**Doctor of Philosophy**

# Environmental Taxation and Eco-conscious Technology Innovation, Multi-channel Investor Sentiment and Stock Returns

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# Environmental Taxation and Eco-conscious Technology Innovation, Multi-channel Investor Sentiment and Stock Returns

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# Abstract

This dissertation is a collection of essays examining current issues in environmental protection taxation and eco-conscious technology innovation, and multi-channel investor sentiment and stock returns. Chapter 1 of this dissertation focus on the environmental taxation and eco-conscious technology innovation. We explored the shock of environmental taxation policy on eco-conscious technology innovation of enterprises. Here, the study determines the environmental taxation significantly incentivize eco-conscious technology innovation by firms in areas with increased pollutant levy standards. The policy shock is more significant for eco-conscious technology innovation in non-SOE enterprises, large-scale enterprises, and non-heavy polluters. Further, the study find that environmental taxation has had a significant impact on sustainable and collaborative innovation, but not on symbolic and independent innovation. Overall, the quality of innovation has really improved, and the innovation organization is dominated by firms working together. Chapter 2 discusses the relationship between multi-channel investor sentiment and stock returns. The study discusses different information channels of investor sentiment on stock returns and their mechanisms, such as market-based, news-based, and social media-based in. We find that our multi-channel investor sentiment has a positive and statistically significant effect on individual stock returns. These findings are robust to different models and specifications. This relationship is heterogeneous, with different turnover rates, seasons, and industries, and market-based investor sentiment has the most extensive influence.

**Key words:** environmental taxation; eco-conscious technology innovation; substantive innovation; symbolic innovation; independent innovation; collaborative innovation; investor sentiment; stock returns

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# 1 Environmental Taxation and Eco-conscious Technology Innovation

## 1.1 Introduction

A new generation of technological revolution is leading the world economy to undergo historical changes, and global warming poses new challenges to the human living environment. These two factors drive ecology development to become one of the breakthroughs in today's innovation changes and the direction of future high-quality, sustainable development. In the highest meeting of the ruling party and the economic work conference, China constantly emphasized that eco-conscious technology innovations are the primary motivating factor to steer the direction of environmentally sustainable development, and the emphasis point to promoting ecological civilization suggestions. Compared with advanced economies, the structural, root, and trend pressures on ecological and environmental protection in China have not been fundamentally alleviated overall. The problematic situation of a fundamental shift has yet to occur regarding pollutant emissions and ecological degradation (Sun & Huang, 2021). As expected, achieving the goal of high-quality development relies heavily on the Chinese government's rational environmental regulation policies. Environmental regulatory means all policies, laws, and implementation processes that aim to curb environmental degradation and preserve natural ecosystems necessitate measures for mitigating economic activities' negative environmental impact. Compared with regulatory standards relying on command-type mechanisms, incentive-type protections have more notable effects on promoting firms' technological innovations. (Weitzman, 1974). The environmental taxation policy in 2018 has generated noticeable interest in incentive-type environmental regulation instruments, where command-type environmental regularities are still predominant in China. Meanwhile, enterprises are the core carriers of societal and economic prosperity creation and claimants of natural resources and the crucial factor in reconciling economic growth and environmental sustainability. To address this, it is essential to investigate how enterprises can respond to incentive-oriented environmental regulations to implement China's current environmental regulation policy and enhance the “double dividend” of enterprises’ green competitiveness.

On the one hand, research on environmental regulations affecting corporate eco-conscious technology innovational behavior has been a cutting-edge academic concern. The existing studies have been richly discussed, but more consensus has yet to be reached. Many eco-friendly regulations on firms’ eco-conscious technology innovations have been found to generate advantageous effects (Jaffe & Palmer, 1997; Ley, Stucki, & Woerter, 2016; Lovely & Popp, 2011; Popp, 2002, 2006). As posited in references (M. Porter & Van der Linde, 1995; M. E. Porter, 1991), Porter's theory suggests that appropriately designed environmental regulations, particularly those employing incentive-oriented mechanisms, can benefit innovation. This is because incentive-oriented regulatory mechanisms for pollution control are more favorable to fostering innovation than technical standards. The reason is that these instruments are more flexible and give companies more room for technical solutions, which can help reduce compliance costs. For polluters, maintaining a great level of environmental-friendly technology innovations and green patents holding allows to stay ahead and maintain market share (M. E. Porter & Kramer, 2006). Greenstone, List, and Syverson (2012) argue that environmental measures have a disincentive effect on firms' technological innovations by increasing their costs. Brunnermeier and Cohen (2003), based on the US manufacturing sector data, identify that environmental regulations do not provide additional incentives to innovate. Subsequent studies have found that this irrelevance may be related to the geographical location of firms (Brunnermeier & Levinson, 2004). From a production efficiency perspective, Van Leeuwen and Mohnen (2017) show that environmental regulations can even inhibit technological innovation efficiency and reduce manufacturing productivity. Similarly, Zhengge and Renjun (2015) do not uncover any indications of a Porter-effect from the Chinese trial policy for trading $S0_2$ emissions.

On the other hand, Shi, Feng, Qiu, and Ekeland (2018) assess the contribution of China carbon emissions pilot policy and corporate innovation trading. Their findings indicate that this policy has a considerable negative effect on innovation in both regulated and unregulated companies. Therefore, Yuan and Xiang (2018) also find that while significantly increasing firm profitability, environmental regulation does not promote strong innovation by examining China's cleaner production standards. Although empirical testing of this research continues to progress, studies have yet to reach a consensus due to differences in environmental regulations across countries based on different samples and research methods.

Overall, the current empirical literature presents divergent findings on the potential of environmental regulations to foster technological innovations. Such inconsistent results offer two valuable perspectives for empirical environmental-friendly technology innovations. Firstly, most established studies focus on conventional environmental policies, including command-and-control mechanisms and emissions trading programs, and less on market-incentivized ecological approaches. China’s environmental regulatory policies rely predominantly on command-and-control approaches (Blackman, Li, & Liu, 2018; C. Wang, Yang, & Zhang, 2015). Moreover, environmental taxation belongs to the incentive-oriented environmental policy, and its study helps enrich and improve the analysis of market-incentive environmental policy. Secondly, finding ways to pinpoint corporate environmental-friendly innovation in technology is still challenging. Most prior research has utilized indirect measures, such as research and development spending, intensity, and sustainable productivity, to gauge firms' innovative activities in the eco-conscious technologies. Although with the disclosure of patent data, some researchers have also utilized patent information to assess innovation in eco-conscious tech innovations(Ley et al., 2016; Popp, 2006; K.-H. Wang, Umar, Akram, & Caglar, 2021). However, prior research has primarily concentrated on investigating how environmental taxation affects technology innovations within firms. The quality and organization of corporate eco-conscious technology innovations has received limited attention from researchers, i.e., are companies' eco-conscious technology innovations substantive or just symbolic? Is the organization of eco-conscious technologies typically an independent or collaborative format?

China has enacted the environmental taxation law since Jan 1, 2018, formerly known as the sewage charge collection system. After the law's implementation, partial provinces and cities have raised the taxation rate of taxable pollutants, i.e., the increased environmental protection tax rate. In contrast, certain provinces and municipalities have altered their emission fee systems to adhere to the "no alteration in taxpayer burden" principle, keeping the environmental taxation rate unchanged from the previous emission charge rate. Our study explored the effects of ecological taxation reform on eco-conscious technology innovations in enterprises. To achieve this, a natural experiment was conducted by comparing firms operating in regions where the environmental protection tax rate was raised to those where it remained unchanged, both before and after the implementation of the tax. Further, heterogeneity discussions and robustness tests were conducted on the policy incentives for environmental-friendly technology innovation in line with green patents' type, enterprise ownership property, and size. Firstly, the eco-conscious technology innovations promote the corporate eco-conscious technology innovations. Secondly, the mechanism test finds that the eco-conscious technology innovations are "substantive innovation" but not "symbolic innovation". The quality of eco-conscious technology innovation is high and significant. In addition, enterprises tend to favor collaborative organizational structures for eco-technological innovations. Finally, the environmental tax reform mainly induced eco-conscious technology innovational activities of non-SOE, large-size, and non-heavy polluting enterprises. The dependency path of eco-conscious technological innovation is evident.

In contrast to prior research, possible contributions of this study include: first, it enriches and improves the evidence related to the market-incentivized environmental policies and eco-conscious technology innovations. Empirical evidence on the repercussions of environmental taxation on eco-conscious technology innovations is scarce. Using the difference-in-difference (DID) method, this paper precisely assesses the shock of environmental taxation to firms' eco-conscious technology innovations, offering micro-level evidence of the Porter hypothesis in developing countries and enhancing the comprehension of the effects of incentive-oriented environmental legislation on firms' eco-conscious technology innovations. Second, assessing the effect of environmental protection tax on the adoption and advancement of eco-friendly technology by businesses was examined in depth, and it was found that eco-conscious technology innovations resulting from the eco-tax were substantive innovations but not symbolic innovation; the green tax had a significant impact in the cooperative mode but not in an independent way. This paper provides fresh insights into evaluating the environmental taxation effectiveness in promoting eco-conscious technological innovation. We contribute to the existing literature on the subject and help to expand our understanding of the topic.

The paper has the following structure: Section 1.2 provides the institutional background, theoretical basis, and mechanism of action. Section 1.3 gives the theoretical basis. Section 1.4 outlines the research design, while Section 1.5 presents the benchmark results. Robustness tests are discussed in Section 1.6, followed by heterogeneity analysis in Section 1.7. Further discussion is provided in Section 1.8, with Section 1.9 offering the paper's conclusion and policy suggestions.

## 1.2 Institutional Overview, Literature Review, and Mechanism

### 1.2.1 Institutional Overview

Environmental taxation originated from the sewage charging system that started in 1979. To implement the environmental policy of "who pollutes, who controls," China legally established a sewage charging system in 1979 and started a pilot program, which was gradually implemented nationwide. The system has facilitated preventing contamination and protecting the environment by encouraging enterprises to strengthen environmental management and reduce pollutant emissions through charges. However, there are problems in the actual implementation, such as insufficient enforcement measures and increased administrative intervention. To solve these problems, China advocated protecting the environment by replacing environmental protection fees with taxes and enforcing a stringent legal system to safeguard the ecology. After the reform, emission units will not pay pollution fees but will instead pay environmental protection tax.

Several differences between the environmental protection tax and the system for charging sewage fees have been implemented to fully exploit environmental regulation and mitigation's intrinsic restraint and positive incentive role. Firstly, the legal status of the eco-tax is enforced by law, providing more substantial legal effects. In contrast, the emission fee system is an administrative regulatory act supported by administrative regulations. It is not incorporated into the tax law management system, leading to weaker legal effects and lax enforcement and supervision (Youliang, Junren, & Huixiang, 2020). Secondly, the incentives for emission reduction under the tax have been enhanced. The eco-tax system increases the incentives for enterprises to reduce emissions by providing concessions such as a 75% reduction in tax if the taxpayers emit pollutants subject to taxation under air or water regulations at a concentration of 30% below the prescribed standard. Additionally, expanding the "fewer emissions less levy" preferential coverage stimulates enterprises to participate in environmental protection and increases investments in this area. Thirdly, the mode of collection and management differs from the sewage charging system. To reduce redundancy, the eco-tax uses a model that involves business declaration, revenue collection, collaboration on environmental protection, and information exchange. This change promotes supervisory synergy between taxation and conservation agencies, leading to greater standardization and transparency in tax collection. Fourthly, revenue allocation between central and local authorities is altered, with the eco-tax providing all local revenue and the foremost authority not anymore participating in revenue sharing. This pattern incentivizes local governments to prioritize environmental policies and measures for conservation, reducing the risk of government collusion with enterprises to increase tax revenue. Finally, the rate under the eco-tax is set to facilitate a seamless transition from the sewage charging system. The law of tax sets the current sewage charge rate as the lower limit, and local governments can float the applicable tax amount of taxable pollutants based on specified tax standards. The upper limit of the tax is set to at most ten times the minimum standard, considering the capacity of the region's environment to support human activities sustainably, current pollutant emissions, and ecological and socio-economic development objectives. Therefore, the environmental protection tax achieves tax burden leveling and upward adjustment, preserving the environment while promoting sustainable progress.

The primary purpose of introducing environmental taxation is to allow emission units to bear the controlling cost of pollution control and environmental damage repair rather than to acquire fiscal revenue. The tax system is designed with the principle of 'more payment for higher emissions, less payment for lower emissions, and no payment for zero emissions' to utilize fiscal leverage as a regulatory tool to guide emission units toward raising environmental awareness, improving waste management, accelerating transformation, and upgrading, reducing pollutant emissions, and contributing to building an ecological civilization.

### 1.2.2 Literature Review and Mechanism

As a critical incentive-oriented environmental regulatory, environment taxation is a practical, active, and sustainable policy tool that addresses environmental and economic issues over the long term, which is an essential component of the broader ecological, economic, and policy framework. We analyze the mechanism and the effect of environmental taxation on eco-conscious technology innovations in enterprises in this part.

#### 1.2.2.1 Environmental Taxation and Corporate Eco-conscious Technology Innovations

Scholars have debated the influence of environmental taxation on enterprises' eco-conscious technology innovations. Some believe that green regulatory can stimulate eco-conscious technology innovations in enterprises. Moreover, compared with command-oriented environmental regulations, the taxation has a greater stimulating power on enterprises' technological innovations (Weitzman, 1974). Amber proved in the empirical test that incentive-motivated environmental legislation does promote enterprises to improve innovations. Environmental taxation enhances enterprises' eco-conscious technology innovations by internalizing external costs (Ambec & Lanoie, 2008). Introducing environmental protection tax brings enterprises double economic and environmental dividends and enhances environmental-friendly technological innovations through the "innovation compensation" effect (Montero, 2002). According to Nesta, Vona, and Nicolli (2014), environmental regulation is vital to fostering the creation of innovative patents for eco-friendly technology. Green regulation can efficiently promote environmental-friendly technology innovation at the regional and micro-enterprise levels (Chakraborty & Chatterjee, 2017; Shang, Tan, Feng, & Zhou, 2022). To incentivize enterprises to enhance their endeavors in environmental-friendly technology innovation research and development (Sen, Bohidar, Shrivas, Sharma, & Modi, 2015) and to boost the eco-patents in heavily polluting sectors (Fang, Kong, Sensoy, Cui, & Cheng, 2021), thus reducing pollutant emissions, command-based regulations motivate powerful incentives for enterprises' eco-conscious technology innovations (Cai, Zhu, Zhang, Li, & Xie, 2020).

On the contrary, some scholars argue that eco-tax inhibits enterprises' eco-conscious technology innovations. Jaffe, Peterson, Portney, and Stavins (1995) and

Kemp, Parto, and Gibson (2005) say that environmental taxes force firms to improve their processes, increasing the cost of environmental equipment and labor and reducing their profit margins. The eco-tax discourages technological innovations. Investing in environmental protection is not voluntary but is more about lowering environmental compliance expenses(Kurzban, Burton-Chellew, & West, 2015). Accordingly, making eco-conscious technology innovations is not the principal motivation behind their environmental investments but rather a way to achieve social and economic value, which ultimately pursued its economic effects (Ukko, Saunila, Rantala, & Havukainen, 2019). Firms will proactively engage in environmentally friendly technology innovation only if its benefits offset expenditures and inputs. Otherwise, environmental taxation would not escalate eco-conscious technology innovations but will even suppress the enterprises' incentive(Xiang-ju & Na, 2018). Wagner (2007) used the manufacturing industry in the United States to study the correlation among eco-technological innovation, green regulation, and patent applications. Furthermore, Chintrakarn (2008) empirically analyzes the manufacturing firms in more than 40 US and other OECD countries states and represents that stringent environmental legislations may hinder the efficiency of eco-conscious technology innovations. This phenomenon is more evident in the US manufacturing industry than in other OECD countries. Environmental regulations even inhibit technical innovation efficiency and reduce manufacturing industries' productivity (Van Leeuwen & Mohnen, 2017).

Different from the previous two views, according to some scholars, environmental taxation has an unclear or insignificant influence on enterprises' eco-conscious technology innovations. Lanjouw and Mody (1996) believed that increasing investment in environmental regulation and emission reduction did not significantly impact the enthusiasm for enterprise innovation. Jaffe and Palmer (1997) analyzed how the government's ecological regulation measures influence the innovation activities of the manufacturing industry. Finally, they found that the strict regulation measures increased the pollution reduction cost of these enterprises, although they increased the expenditure on research and development. However, it does not significantly affect the output of invention patents. By investigating China's standards for cleaner production, Yuan and Xiang (2018) discovered that environmental regulation greatly boosted the enterprises' profitability but did not encourage corporate innovations. Krass, Nedorezov, and Ovchinnikov (2013) studied several factors affecting enterprises' environmental-friendly technological innovations and discovered a modest environmental protection tax could incentivize the adoption of environmentally friendly technologies by enterprises. However, if the tax burden is too heavy, it will produce the opposite results. The environmental-friendly technological innovation exhibits an inverted U-shaped response to the environmental protection tax. Shang et al. (2022) also support the relationship that eco-tax promotes and hinders eco-conscious technology innovations. Jiang, Xu, and Zhou (2023) found in their empirical research on environmental conservation subsidies, eco-tax levies, and sustainable innovations. An inverted U-shaped correlation was observed between eco-tax and corporate innovation toward ecological sustainability, initially hindering and subsequently promoting it.

The available literature provides a logical starting point for the follow-up research. Further research is required to clarify businesses' effectiveness of environmental tax and eco-conscious technology innovations. Therefore, we put forward the first hypothesis,

H1: Environmental taxation has incentivized the eco-conscious technology innovations in enterprises.

#### 1.2.2.2 Property Heterogeneity and Corporate Eco-conscious Technology Innovations

China's economy is still in transition, with public ownership still dominant, while at the same time shifting to an entire economic system that emphasizes the co-development of multiple ownership systems. In addition, SOEs are essential players in Chinese culture and historical tradition. In traditional Chinese culture, SOEs represent the interests of the state and society and therefore enjoy comprehensive support from society and the people. In this context, SOEs and non-SOEs often exhibit different characteristics in developing eco-conscious technological innovations. Therefore, regarding the impact of environmental taxes on eco-conscious technological innovation, it is necessary to consider the impact of different natures of enterprises on eco-conscious technological innovation.

On the one hand, in terms of innovation capacity, the leaders of Chinese SOEs are traditionally Communist Party members or government officials, so SOEs have higher political status and influence than private enterprises. SOEs have more strongly financial resources and government support, and the incentive effect of environmental regulations may be challenging to work for SOEs. On the other hand, in terms of innovation incentives, non-SOEs have weaker risk resistance and less stability, forcing them to continuously improve their products to gain a firm foothold for continuous development in a more competitive market non-SOEs usually have more substantial innovation incentives. Therefore, we propose Hypothesis 2,

H2: More eco-conscious technology innovations are promoted in non-SOEs than in SOEs through the implementation of environmental taxation.

#### 1.2.2.3 Size Heterogeneity and Corporate Eco-conscious Technology Innovations

Environmental taxes have varying implications for environmental and technological innovation among enterprises of different sizes. Larger companies must pay more environmental levies due to higher pollution and emissions. To alleviate the burden of these taxes, larger enterprises must prioritize environmental protection and work to enhance their innovation in environmental protection technologies and equipment to mitigate pollution and emissions. Consequently, ecological taxation occupies a more influential role in facilitating the implementation of eco-conscious technology innovations and environmental management measures for large enterprises. Because of their relatively scale, small and growing businesses (SGBs) generate less environmental pollution and emissions and need to pay less ecological taxation. This situation also leads to insufficient motivation for some SGBs to promote eco-conscious technology innovations and equipment and implement environmental governance measures.

In addition, the resources available to enterprises of different sizes differ, with large enterprises having an inherent advantage in resources such as talent, technology, and capital(Lian, Xu, & Zhu, 2022). Prominent entrepreneurs have relatively abundant resources and better management systems. Their managers are willing to consider the enterprise’s long-term development, so they have the strength and the motivation to innovate green technology. Therefore, large entrepreneurs are eager to put more energy and resources into sustainable tech innovation activities and obtain corresponding green innovation output. However, SGBs have fewer resources and are likelier to be short-sighted in their management decisions. Therefore, although SGBs are also pressured to conduct the environmental protection tax, they prefer to pay the taxes or purchase environmental protection equipment from outside rather than innovate greenly. Therefore, we present hypothesis 3, H3: More eco-conscious technology innovations are promoted in large-sized entrepreneurs than in SGBs through the implementation of environmental taxation.

#### 1.2.2.4 Pollution Heterogeneity and Corporate Eco-conscious Technology Innovations

Simultaneously, non-highly polluting entrepreneurs are stronger susceptible to environmental taxation than highly polluting companies. Given the previous standard about environmental fees, non-highly polluting enterprises pay fewer fees if they produce less environmental pollution and emissions in the production process. With the fee-to-tax reform, paying environmental protection fees will change from the traditional way of charging fees based on pollutant emissions to charging fees based on pollutant emission concentration and pollutant treatment costs, which will lead to an increase in environmental protection fees paid by non-heavy polluters. Under environmental taxation, all environmental fees entrepreneurs pay will be subsumed into the government’s environmental protection fund, which will be used for environmental projects and treatment. The environmental protection fee is relatively high for heavy-polluting enterprises, but it also means they will invest more in environmental management and thus receive more government financial support. For non-highly polluting companies, on the other hand, although they pay relatively less in environmental protection fees, they often suffer more from a lack of financial support and have difficulty obtaining government funding. In addition, heavily polluting companies usually invest more money and human resources in environmental technology to comply with government environmental standards. These enterprises have higher innovation capacity in environmental technology and can reduce emissions and pollutant concentrations through technical means, thus achieving better environmental results. In contrast, non-highly polluting enterprises have less investment in environmental technology and lower innovation ability. They have difficulty reducing pollutant emissions through technical means and must rely more on paying environmental fees to meet the government's requirements, leading to their more significant impact. Therefore, we put forward hypothesis 4,

H4: More eco-conscious technology innovations are promoted in non-heavy polluting enterprises than in heavy polluting enterprises through enforcing environmental taxation.

#### 1.2.2.5 Substantive or Symbolic Innovation

Different motivations for implementing eco-conscious technology innovations in enterprises can lead to varying outcomes. For this reason, eco-conscious technology innovations can be classified as either substantive or symbolic. Substantive innovation involves complex invention patents with high technological content that can increase a company's market value and are considered high-level specialized projects. Symbolic innovation generally prefers utility and design patents, which are of a lower level and less complicated and belong to low-level innovation to meet government policies. Some studies have shown that "quantitative over qualitative" strategic innovations are a significant drag to businesses' profitability, and "flooding" of non-invention patents is only a response of firms to seek support from industrial and regulatory policies (Wenjing & Manni, 2016), the actual innovation capacity of firms has not increased (Zhifan, Jinmin, & Xiaoxuan, 2021), and only substantive innovation can promote economic growth. The purpose of symbolic innovation is to receive government R&D subsidies and tax benefits (Wenjing & Manni, 2016), obtain government funding for patent incentives (Jie & Wenping, 2018), and pass specific technical qualifications (Hao & Zhifeng, 2016). However, these do not lead to real economic growth (Shan-cheng &

Lai-qun, 2021). On the contrary, they can trigger a “patent bubble” in enterprises (Zhifan et al., 2021). J. Hu, Pan, and Huang (2020) also found that environmental legislation considerably contributes to the volume and standard of eco-innovation. However, its effect on superior innovation is less than on inferior innovation.

Regarding eco-conscious technology innovations, Feng, Jin-yu, and Hao (2021) proved that enforcing eco-friendly policies boosted the volume and decreased standard. However, the research was based on the command-based policy of the eco-responsibility system, which has a clear “hard” veto. Does the relationship between flexible eco-regulation and firms’ different forms of eco-conscious technology innovations differ? This question has yet to be addressed in previous studies and therefore needs to be explored in depth.

Moreover, during the pilot period of Chinese environmental taxation, the incentive-driven environmental protection and the regulatory mechanism for information disclosure are in the exploratory stage of development. Differences in incentives for eco-conscious technology innovations among companies may arise due to asymmetric information on pollution emissions between them and the government. Therefore, should firms undertake substantive or symbolic eco-conscious technology innovations to respond to the eco-tax? The quasi-natural experiment of China’s environmental-friendly tax provides an experimental scenario to investigate whether incentive-oriented environmental policies can promote corporate eco-conscious technology innovations. Upon the basis, we put forward hypothesis 5,

H5: Environmental taxation has spurred substantive eco-conscious technology innovations in enterprises.

#### 1.2.2.6 Independent or Collaborative Innovation

Technological innovations are complex activities with considerable investment, high risk, and significant profit, and it is a crucial instruments for companies to create and sustain a competitive edge (Ahuja & Katila, 2001). Whether or not firms adopt a collaborative innovation strategy, technological innovation activities are classified into independent and collaborative models. Different innovation models' connotations and potential advantages also differ, and scholars have different perceptions of their relationship. Regarding the meaning of independent and collaborative innovation, scholars have defined their meanings from different perspectives. Early economists and management scholars described independent and collaborative innovation as the connection between the subjects of tech innovations and the external economic environment. The former refers to innovation activities in which enterprises explore technology development entirely through their efforts, commercialize the R&D results, and eventually gain profits; the latter denotes the joint advancement of novel technologies among enterprises, universities, and research institutes (T. Wang, Yu, & Cui, 2020). Zhongfeng, Hairong, and Wenhong (2016) pointed out that the distinction between independent and collaborative innovation is based on whether the firm dominates the whole R&D process and has control of the final benefit. Thus, independent innovation has two characteristics: endogenous technology and internal resource access. In contrast, joint innovation is an R&D organization based on inter-organizational heterogeneity of resources to acquire complementary knowledge to achieve expected benefits. The collaborating parties generally focus on controlling the output of collaborative innovation.

With the rapid progression in information and network technology, technological diffusion capacity and spillover effects have increased significantly, with some of them spilling over and being applied for free in the manufacturing of other firms (K.-L. Wang, Sun, Xu, Miao, & Cheng, 2022). The adverse effects of such technology spillover can dampen firms' enthusiasm for innovation, especially independent innovation. Joint innovation allows firms to reduce the risk of innovation failure and stimulate more creativity. However, the collaboration also means firms have less exclusivity over innovation patents and property rights, reducing profitability (Chesbrough, 2003). To internalize the external effects of technology spillovers, collaborative innovation is the best strategic choice (Pai, Tseng, & Liou, 2012). However, independent innovation can be more beneficial than collaborative innovation, particularly in companies with high product substitutability (Huiying & Hui, 2011). What is certain is that both separate and joint innovation enhance firms' innovation output, and increasing the resources invested in a particular innovation can lead to higher innovation performance (Radicic & Balavac, 2019). At the same time, it still needs to be made clear how eco-tax affects eco-conscious technological patterns and the differing impacts. On this basis, we posit that,

H6: Environmental taxation has spurred collaborative eco-conscious technology innovations in enterprises.

### 1.3 Theoretical Basis

The externality theory, Pigou tax theory, and Porter hypothesis, which we focus on in this section, are the theoretical foundation of the environmental taxation and firms' eco-conscious technological innovation.

#### 1.3.1 Externality Theory

The term "externality theory" in economics refers to an economic theory that analyzes market failures. It emphasizes that in a market economy, production or consumption activities may have effects on third parties other than market participants, and these effects are called “externalities”.

Externalities are the effects of production or consumption activities beyond the transactions between the direct participants and are classified as positive and negative externalities. A positive externality is an externality in which the behavior of a market participant benefits other non-participants outside the market, adding additional welfare to them and benefiting society more than the individual. A negative externality is an externality that reduces the welfare of others outside the market and, therefore, results in a higher cost to society than to the individual. The central idea of externality theory is that because market participants cannot consider the effects of externalities on third parties, they may create market failures that result in less than fully efficient market outcomes. Therefore, governments may need to take measures to correct market failures, such as through taxes, subsidies, or regulations to incentivize market participants to consider the effects of externalities.

Environmental problems are typical of negative externalities (Samuelson & Nordhaus, 2009). In the production process, the producer releases the pollution produced during the production process directly into the natural environment to reduce costs and maximize profits. As a result, a large amount of pollution is generated, and people other than the producers suffer from all the negative consequences of this pollution, such as health risks and disruptions in their lives. This negative externality also causes damage to the living environment of future generations. The solution to this phenomenon is to internalize the externality. Internalizing externalities means that the external costs of consumers or producers enter their consumption and production decisions and are borne by them to make up for the difference between social and private costs to solve the externality problem (Goodstein & Polasky, 2017).

Environmental protection taxes are designed to internalize negative environmental externalities through the government's "visible hand" (Andersen, 2007).

### 1.3.2 Pigou Tax Theory

Pigou tax theory (also known as Pigou theorem) is a theory developed by Pigou (1924) that states that by collecting taxes and spending them on public facilities and infrastructure, governments can incentivize businesses and individuals to increase investment, thereby promoting economic growth. The theory's central idea is that through policy interventions in tax collection and spending, the government can create a favorable economic environment that makes markets more efficient and encourages economic growth.

When a firm engages in production activities that pollute the environment, this pollution is not simply an act but an aversive public good that brings about negative externalities (Pigou, 1924). In the absence of state policy intervention, the environmental problems caused by the production and operation of enterprises will spread to the surrounding factories, and the cost of other enterprises to maintain the original scale of production (such as the purchase of pollution control equipment) will be further increased by the impact of environmental pollution. As rational economic agents, enterprises will reduce social benefits in exchange for personal benefits, eventually resulting in social welfare loss. Therefore, the Pigou tax theory suggests that a pollution tax can induce firms to feel the social cost of their pollution behavior economically and thus reduce their taxes by lowering their pollution levels.

The Pigou tax theory has had a profound impact on environmental protection taxes. An environmental tax is a tax on pollution levied on the amount of pollution a company emits, motivating companies to adopt more environmentally friendly behavior.

Consistent with the core idea of the Pigou tax theory, an environmental tax is a mechanism that provides economic incentives for companies to reduce their emissions. Specifically, the impact of the Pigou tax theory on the environmental protection tax is mainly manifested in the following aspects: (1) the establishment of the tax collection mechanism. The Pigou tax theory suggests that a tax on pollution can motivate enterprises to feel the social cost of their polluting behavior economically and thus reduce their pollution emissions. This idea has inspired establishing and improving environmental protection tax, making it an effective environmental protection tool. (2) Determination of tax rate. The Pigou tax theory argues that the rate of pollution tax should be high enough to motivate companies to adopt more environmentally friendly behaviors. This idea has also been applied to environmental protection taxes. To make the cost of reducing pollution emissions felt economic, the environmental protection tax rate should be appropriately higher than the cost to the enterprise of reducing pollution. (3) The purpose of collecting the tax. The Pigou tax theory suggests that the tax collected should promote environmental protection and ecology to encourage businesses to take environmental actions. Taxes on environmental protection should also be used for environmental protection and pollution control to achieve the dual goals of environmental protection and economic benefits. In conclusion, the Pigou tax theory provides theoretical support and guidance for formulating and implementing environmental protection tax, which makes environmental protection tax a crucial environmental protection tool.

### 1.3.3 Porter Hypothesis

Concerning the impact of environmental regulation on technological innovation, the classical economics view is that, under constant production technology and demand conditions. However, environmental regulation can effectively curb firms' pollution emissions. It inevitably increases firms' investment in governance, crowding out productive and profitable investment, resulting in a loss of potential output and profits and thus weakening firms' competitiveness (Gray & Shadbegian, 2003). Through numerous case studies, M. Porter and Van der Linde (1995) argue that strict and adequately designed environmental regulations can stimulate technological innovation and that the benefits of innovation compensation can partially or even completely offset the costs of regulation, thus giving firms a more significant competitive advantage. Although the validity of the Porter hypothesis is controversial, it is the first systematic exposition of the possibility of a "win-win" outcome between environmental protection and growth. It has attracted widespread attention and research.

On the one hand, scholars have first constructed the theoretical basis of the hypothesis regarding behavioral economics, market failure, and organizational failure. From the behavioral economics perspective, Ambec and Barla (2006) argue that firm rationality depends on the behavior of professional managers. Since innovation investment increases firm costs, professional managers with current preferences will delay innovation investment, while environmental regulation can inhibit this behavioral preference. At the same time, although firms aim at profit maximization, market failures lead to the inability of firms to fully realize their potential profits, including aspects such as imperfect competition (Boden, Marland, & Andres, 2009) and asymmetric information (Mohr & Saha, 2008). In addition, Ambec and Barla (2002) argue that environmental regulations help to overcome organizational inertia and thus reduce the organizational costs of firm innovation.

On the other hand, to empirically validate the Porter hypothesis, Jaffe and Palmer (1997) subdivide it into the "Narrow Porter Hypothesis", the "Weak Porter Hypothesis", and the “Strong Porter Hypothesis”. The “Narrow Porter Hypothesis” emphasizes that a flexible environmental regulatory system is more conducive to firm innovation than prescriptive regulations, such as technical standards. Market-regulated regulations are more likely to increase firms’ innovation ability than command-and-control regulations. The “Weak Porter Hypothesis” assumes that well-designed environmental regulations will stimulate firms to innovate. The “Strong Porter Hypothesis” suggests that firm innovation triggered by environmental regulation can offset the additional regulatory costs, thereby increasing competitiveness and productivity.

For the “Narrow Porter hypothesis”, it is generally accepted that market-based incentives are more flexible than command-and-control regulatory instruments regarding emission reduction and incentive longevity. This is because market-incentivized environmental regulation, represented by trading permits, promotes environmentally friendly invention, innovation, and technology diffusion by firms (Jaffe, Newell, & Stavins, 2002). A dynamic and flexible environmental policy significantly impacts sustainable development and technological innovation (Yuan & Zhang, 2020). Rubashkina, Galeotti, and Verdolini (2015) examine the relationship between firm competitiveness and the stringency of environmental regulation in manufacturing industries in 17 European countries. It was found that in the “weak Porter hypothesis”, tighter environmental regulation positively impacts the increase in the number of corporate patent applications. Lanoie, Laurent-Lucchetti, Johnstone, and Ambec (2011) empirically tested three different variants of the Porter hypothesis and found strong support for the weak Porter hypothesis and general support for the narrow Porter hypothesis but not for the strong Porter hypothesis. Petroni, Bigliardi, and Galati (2019) even argue that the validity of Porter’s hypothesis cannot be confirmed in any case. Y. Wang, Sun, and Guo (2019) use a panel of data from the industrial sector of

OECD countries and find that environmental policies can have a positive impact on green productivity growth when the innovation offset effect is higher than the compliance cost effect within a certain level of stringency of environmental regulations, which supports the strong Porter hypothesis. X. Wang, Zhang, Nathwani, Yang, and Shao (2022) show that the weak Porter hypothesis holds in the short run because innovation can be stimulated by environmental regulation, while the strong Porter hypothesis holds in both the short and long run because energy efficiency and emission reductions can be achieved under strict regulation. Can only hold in specific scenarios, depending on the type of environmental innovation (Rexhäuser & Rammer, 2014).

In summary, most studies support the “Narrow Porter hypothesis” and the “Weak Porter hypothesis”, which generally agree that reasonably well-designed environmental regulations can increase firms’ technological innovation.

## 1.4 Research Design

### 1.4.1 Data Sources and Indicator Processing

(1) Data source. The eco-conscious technology innovations data derived from the Chinese Research Data Services (CNRDS) includes all patent requests and grants of listed companies in China since 1991 and patent categories grouped into three types: invention, utility model, and design. To reflect eco-conscious technology innovations more accurately, we use the percentage of green patent requests to overall patent requests to represent. Since this paper focuses on how the environmental taxation on green effect eco-conscious technology innovations of Chinese listed companies, we choose year from 2010 to 2021 as the research period to respond more comprehensively to the impact of the policy. Meanwhile, the companies’ annual financial data are obtained from the China Stock Market & Accounting Research Database (CSMAR). In

addition, we exclude ST, *ST, and companies with missing severe data. In addition, to eliminate the effect of extreme values, all continuous variables involved were winsorized at each upper and lower 1% quantile.

(2) The explained variable. Eco-conscious technology innovations. Innovation activities are one of the hot issues in economic research. Various indicators are used in empirical studies to measure eco-conscious technology innovations as different literature approaches the subject from diverse research perspectives. In the context of this paper, we use the percentage indicator (*ETI*) to measure eco-conscious technology innovations. This treatment reflects triple strengths. First, the ratio can refine the measurement of eco-conscious technology innovations. Both patent and green patent data are based on national or international common standards, and data availability and accuracy are guaranteed. Second, the ratio better reflects the importance of eco-conscious technology innovations of enterprises facing environmental protection tax. Third, the ratio could weigh the quantity and quality of eco-conscious technology innovations. Moreover, we calculate the fraction of green invention patent requests to green patent requests and the fraction of green utility model patent requests to green patent requests to identify whether the eco-conscious technology innovations of enterprises are substantive or symbolic; and the proportion of independent green patent applications to green patent applications, and the percentage of collaborative green patent requests to green patent requests to identify whether the eco-conscious technology innovations of enterprises are independent or collaborative.

(3) The explanatory variable. The explanatory variables in this paper are *Treat* and *Post*. If the enterprise is the experimental group sample, $Treat \times Post$ is 0 before implementing the environmental taxation policy, and $Treat \times Post$ is 1 after implementing the environmental protection tax policy. If the enterprise is the control

group sample, no matter whether before or after implementing the environmental protection tax policy, *Treat*×*Post* is 0.

(4) Control variables. To obtain objective estimates of policy effects and to take into account other elements at the firm level that may potentially affect eco-innovation, this paper takes reference from Shaozhou, Shen, and Jingbo (2018),Youliang et al. (2020) and others controlling the variables that affect eco-conscious technology innovations over time as follows. 1) Company size (*lnsize*). The company size is a critical determinant of innovation (M. Bu, Qiao, & Liu, 2020). Usually, to sustain their technological progress, larger firms prioritize continual investment in research and development. Therefore, we measure company size by using the natural logarithm of its total year-end capital. 2) Company Age (*lnCompanyAge*). The firm's age usually represents the entrepreneurs' maturity, and higher maturity tends to be more innovative (Gimenez-Fernandez, Sandulli, & Bogers, 2020). 3) Market value-to-replacement cost ratio, also called the Tobin Q (*lnTobinQ*). The ratio indicates a company's capacity for social value creation. One common belief is that a firm with a higher value tends to generate more social wealth and possess a greater level of innovative spirit. Since the value of Tobin Q fluctuates more, we use the natural logarithm of Tobin Q. 4) Corporate leverage ratio (*Lev*). A firm's leverage ratio reflects the market's assessment of its creditworthiness. Moderate debt enables companies to allocate more resources to innovative activities such as technological improvements to equipment and process improvements (Geelen, Hajda, & Morellec, 2021). 5) Cash ratio of the enterprise (*CashRatio*). Adequate and stable sources of capital are important prerequisites for ensuring the sustainability of innovation. Firms' technological innovation is generally subject to more severe external financing constraints and more dependent on cash holdings for financial support (Z. He & Ciccone, 2020). 6) Variables related to

corporate effectiveness and management framework. Given the influence that factors such as corporate effectiveness and management framework can have on corporate innovation, we simultaneously control for return on total assets (*ROA*), return on total equity (*ROE*), controlling shareholder proportion (*ContrshrProportion*), proportion of separation between the effective controller and owner (*Seperation*), CEO duality (*IsDuality*), Board size (*lnBoardsize*), independent director representation on the board (*IndDirectorRatio*), the property rights (*SOE*) and industry pollution level (*Pollute*). The definitions of the variables are detailed in Table 1.4.1.

**Table 1.4.1 Definitions and descriptions of the key variables.**

| Variable | Symbol | Variable definition and description |
|---|---|---|
| Explained | $ETI_1$ | The green requests to overall patent requests ratio. |
| | $ETI_2$ | The green invention patent requests to overall patent requests ratio. |
| | $ETI_3$ | The green utility model patent requests to overall patent requests ratio. |
| | $ETI_4$ | The independent green requests to overall patent requests ratio. |
| | $ETI_5$ | The collaborative green requests to overall patent requests ratio. |
| Explanatory | Treat | If the area increases the tax rate after the policy implementation, the value is 1; otherwise, 0. |
| | Post | If the year after 2018 and later, the value is 1; otherwise,0. |
| Control | lnsize | The natural logarithm of company year-end total capital. |
| | lnCompanyAge | The natural logarithm of company age. |
| | lnTobin Q | The natural logarithm of market value-to-replacement cost ratio. |
| | Lev | Debt to assets ratio. |
| | CashRatio | The closing balance of cash and cash equivalents to current liabilities ratio. |
| | ROA | Return to assets ratio. |
| | ROE | Return to equity ratio. |
| | ContrshrProportion | The shareholding proportion of the controlling shareholder. |
| | Seperation | The effective controller's proportion minus ownership proportion. |
| | IsDuality | If the chairman is also the CEO, the value is 1; otherwise, 0. |
| | lnBoardsize | The natural logarithm of the board. |
| | InddirectorRatio | The independent directors to board ratio. |
| | SOE | If the corporate is state-owned, the value is 1; otherwise, 0. |
| | Pollute | If the industry is heavy polluting, the value is 1; otherwise, 0. |

### 1.4.2 Model Design

The research work aims to examine whether environmental taxation can promote eco-conscious technology innovations. The most mentioned approach in the literature is the difference-in-difference (DID). This method divides the study population into experimental and comparison groups. It could identify the net policy effect by separating the temporal trends pre- and post-policy adoption and the group variances. It eliminates other unseen factors that fluctuate with time. This methodology is already widely used in existing policy investigations. Through this article, we will quantitatively assess the eco-friendly tax from the perspective of enterprises' eco-conscious technology innovations by companies located in areas with higher tax burdens, which comprise the experimental group. In contrast, regions with stable tax burdens serve as the comparison group. The design of the specific model is outlined below:

$$\boldsymbol{ETI_{1,it} = \beta_0 + \beta_1 Treat_i + \beta_2 Post_t + \beta_3 After_i \times Post_t + \gamma X_{it} + \varepsilon_{it}} \quad (1)$$

Where, $ETI_{1,it}$ denotes eco-conscious technology innovation, which means the green patent requests to overall patent requests ratio of listed companies. $Treat_i$ is the group dummy variable for tax increase area post-environmental taxation adoption is set to 1 for enterprises located within the impacted region. Otherwise takes the value of 0. $Post_t$ is the stage dummy variable, used to represent both the pre- and post-policy pilot periods. The value of 1 is assigned during the post-policy pilot period (i.e., 2018 and later), and 0 is assigned during the pre-policy pilot period. $Treat_i \times Post_t$ is the interaction term about the group dummy variable and stage dummy variable. $X_{it}$ is the listed company matrix of control variables for the economic characteristics mentioned above. Additionally, $\varepsilon_{it}$ is random disturbance terms.

The actual meaning of each coefficient $\beta_1$, $\beta_2$, $\beta_3$ can be understood by conditional expectation:

The mean value of $ETI_{1,it}$ in the treatment group before the event is A: $E(ETI_{1,it}|Treat_i = 1, Post_t = 0) = \beta_0 + \beta_1$

The mean value of $ETI_{1,it}$ in the treatment group after the event is B: $E(ETI_{1,it}|Treat_i = 1, Post_t = 1) = \beta_0 + \beta_1 + \beta_2 + \beta_3$

The mean value of $ETI_{1,it}$ in the control group before the event is C: $E(ETI_{1,it}|Treat_i = 0, Post_t = 0) = \beta_0$

The mean value of $ETI_{1,it}$ in the control group after the event is D: $E(ETI_{1,it}|Treat_i = 0, Post_t = 1) = \beta_0 + \beta_2$

Therefore, the mean difference in $ETI_{1,it}$ between the treatment and control groups before the occurrence of the environmental tax is $A - C = \beta_1$; the mean change in $ETI_{1,it}$ in the control group before and after the occurrence of the environmental tax is $D - C = \beta_2$. $\beta_3$ is the net effect of the environmental tax policy intervention that needs to be measured. If $\beta_3$ is remarkably optimistic it indicates that environmental taxation contributes to promoting eco-conscious technology innovations among companies in areas with rising tax burdens. More detail shown in the table 1.4.2.

**Table 1.4.2 The coefficients' meaning of DID.**

| | Before the policy | After the policy | Difference |
|---|---|---|---|
| Treatment group | $\beta_0 + \beta_1$ | $\beta_0 + \beta_1 + \beta_2 + \beta_3$ | $\beta_2 + \beta_3$ |
| Control group | $\beta_0$ | $\beta_0 + \beta_2$ | $\beta_2$ |
| Difference | $\beta_1$ | $\beta_1 + \beta_3$ | $\beta_3$ (D-in-D) |

### 1.4.3 Statistical Summarization

Table 1.4.3 provides the statistical summarization of the critical variables. The results show that the average $ETI_1$ of Chinese listed companies during the sample period is 0.0678. Coupled with the different kinds of eco-conscious technology innovations, the mean value of $ETI_2$ is 0.0343, which is almost one percentage points higher than the $ETI_3$. Moreover, the average of the $ETI_4$ is 0.0625, while the mean value of the $ETI_5$ is 0.0162. Generally, the substantive and independent organization looks like higher than the symbolic and collaborative pattern of corporate eco-conscious technology innovations. The remaining control variables are all in the normal range. Detailed statistics are shown in the table 1.4.3.

**Table 1.4.3 Statistical summarization of key variables.**

| Variable | Obs | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|
| $ETI_1$ | 25,721 | 0.0678 | 0.135 | 0 | 0.500 |
| $ETI_2$ | 25,721 | 0.0343 | 0.0764 | 0 | 0.286 |
| $ETI_3$ | 25,721 | 0.0230 | 0.0533 | 0 | 0.200 |
| $ETI_4$ | 25,721 | 0.0625 | 0.158 | 0 | 1 |
| $ETI_5$ | 25,721 | 0.0162 | 0.0802 | 0 | 1 |
| Treat | 25,721 | 0.285 | 0.451 | 0 | 1 |
| After | 25,721 | 0.402 | 0.490 | 0 | 1 |
| lnsize | 25,721 | 22.10 | 1.184 | 20.35 | 24.61 |
| lnCompanyAge | 25,721 | 2.770 | 0.331 | 2.079 | 3.258 |
| lnTobinQ | 25,721 | 1.094 | 0.308 | 0.714 | 1.814 |
| Lev | 25,721 | 0.420 | 0.201 | 0.101 | 0.779 |
| CashRatio | 25,721 | 0.802 | 0.984 | 0.0669 | 3.873 |
| ROA | 25,721 | 0.0426 | 0.0409 | -0.0439 | 0.125 |
| ROE | 25,721 | 0.0800 | 0.0769 | -0.101 | 0.229 |
| ContrshrProportion | 25,721 | 0.370 | 0.140 | 0.151 | 0.638 |
| Seperation | 25,721 | 0.0458 | 0.0696 | 0 | 0.213 |
| IsDuality | 25,721 | 0.276 | 0.447 | 0 | 1 |
| IndDirectorRatio | 25,721 | 0.373 | 0.0493 | 0.333 | 0.500 |
| SOE | 25,721 | 0.365 | 0.481 | 0 | 1 |
| Pollute | 25,721 | 0.236 | 0.424 | 0 | 1 |

## 1.5 Analysis of Benchmark Results

The outcomes of the environmental taxation's effect on eco-conscious technology innovations of enterprises are presented in Table 1.5.1. In the average treatment effect column (1), leaving out the control variables, we find the DID coefficient is 0.0093, showed a significant level of 0.05. Column (2), incorporating the control variables and controlling for both time and firm fixed effects, the coefficient increases from 0.0093 to 0.0104, and show positively and significantly at 0.05. This result implies that environmental tax policy especially incentivizes eco-conscious technology innovations by enterprises in areas with increased pollutant levy standards, regardless of whether control variables are included. The result proves Porter's hypothesis is applicable in China, and hypothesis 1 holds. Considering the control variables, the coefficient of *lnsize*, *Lev*, *CashRatio*, *ROE*, *Pollute* are positive and significant. Furthermore, the coefficient of *lnCompanyAge*, *ROA*, *ContrshrProportion*, *IndDirectorRatio*, *SOE* are negative and significant, which means these variables have inverse impact of corporate eco-conscious technology innovations.

**Table 1.5.1 Benchmark regression results.**

| VARIABLES | (1)<br>$ETI_1$ | (2)<br>$ETI_1$ |
|---|---|---|
| DID | 0.0093** | 0.0104** |
| | (0.0042) | (0.0042) |
| Treat | 0.0529*** | 0.0561*** |
| | (0.0025) | (0.0026) |
| After | 0.0093*** | 0.0078*** |
| | (0.0019) | (0.0019) |
| lnsize | | 0.0041*** |
| | | (0.0009) |
| lnCompanyAge | | -0.0298*** |
| | | (0.0028) |
| lnTobinQ | | -0.0026 |
| | | (0.0029) |
| Lev | | 0.0139* |
| | | (0.0073) |
| CashRatio | | 0.0021* |
| | | (0.0011) |
| ROA | | -0.1647** |
| | | (0.0677) |
| ROE | | 0.0809** |
| | | (0.0332) |
| ContrshrProportion | | -0.0294*** |
| | | (0.0061) |

| | | |
|---|---|---|
| Seperation | | -0.0189 |
| | | (0.0118) |
| IsDuality | | 0.0028 |
| | | (0.0020) |
| IndDirectorRatio | | -0.0611*** |
| | | (0.0164) |
| SOE | | -0.0096*** |
| | | (0.0020) |
| Pollute | | 0.0045** |
| | | (0.0020) |
| Constant | 0.0479*** | 0.0714*** |
| | (0.0011) | (0.0222) |
| Observations | 25,721 | 25,721 |
| R-squared | 0.0382 | 0.0470 |

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The same applies to the following table.

### 1.6 Robustness Tests

To ensure the result robust, we conduct robustness tests such as parallel trend testing with dynamic effects, placebo tests, change the explained variable.

#### 1.6.1 Parallel Trend Testing and Dynamic Effects

According to Angrist and Pischke (2009), the precondition for precise identification is that the environmental-friendly technological innovations of firms in the experimental and comparison group pre-policy must satisfy parallel trends. That is, the experimental group should have the identical temporal tendency of the dependent variable as the comparison group without receiving the policy shock. Therefore, we adopt the event study method using the method of Jacobson, LaLonde, and Sullivan (1993) and Deschenes, Greenstone, and Shapiro (2017) and construct the following regression equation,

$$\boldsymbol{ETI_{1,it}} = \sum_{k=-4}^{3} \boldsymbol{\beta_t} \boldsymbol{Treat_t} * \boldsymbol{u_k} * \boldsymbol{After_i} + \boldsymbol{\gamma X_{it}} + \boldsymbol{Post_t} + \boldsymbol{After_i} + \boldsymbol{\varepsilon_{it}} \tag{2}$$

Where, $u_k$ is a time dummy variable. $\{\beta_t\}$ captures the change in the difference between the treatment and comparison groups pre- and post-the taxation reform. The pre-policy period (denoted as the “-1” period) is the baseline period. And the subscript k denotes the period’s number that differs from the baseline period.

From Figure 1.6.1, we can see that the variances between the treatment and control groups are not significant before the environmental taxation reform. There exists no systematic change in eco-conscious technology innovations between the groups, and the model passes the parallel trend test. Simultaneously, the figure also represents the eco-conscious technology innovations of enterprises in the experimental group gradually showed a significant rising movement after environmental taxation reform. As shown in Figure 1.6.1, the eco-conscious technology innovations of the experimental group firms surge and significantly from period zero to one after the taxation reform. As time passes, the eco-conscious technology innovations in the experimental group in the two to third period after the reform, the trend is starting to slowly decline, but remains significant. This result implies that environmental taxation positively incentivizes enterprises’ eco-conscious technology innovations, strengthening the benchmark regression outcomes.

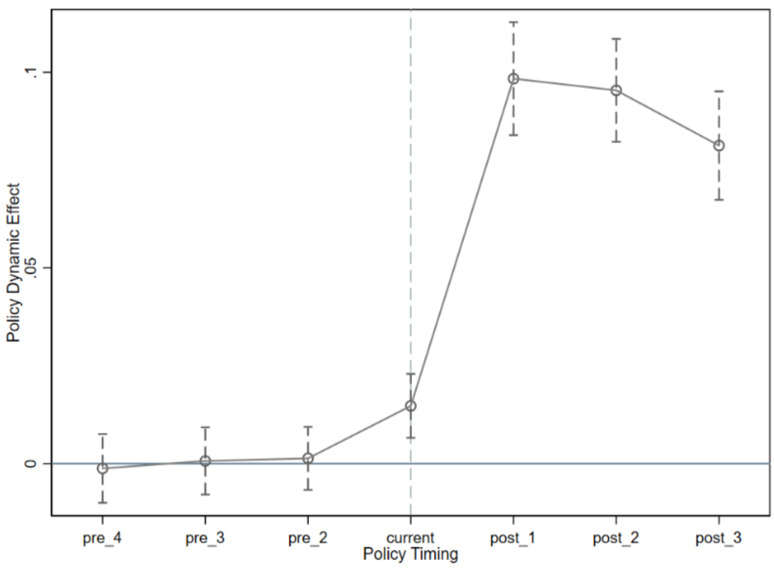


**Figure 1.6.1 Parallel trend testing.**

### 1.6.2 Placebo Tests

The placebo test is a standard procedure for testing the validity of the parallel trend assumption in the DID framework. The placebo test consists of introducing a “dummy” treatment or intervention that does not affect the outcome variable and then running a DID regression with this “dummy” treatment as the treatment variable. The aim is to determine whether the coefficients on the interaction terms for the dummy and post-treatment periods are statistically significant.

To conduct the placebo test, the researchers first identified a pre-treatment period in which the actual treatment should not influence the outcome variable. This was the period in which the placebo treatment was introduced. The placebo treatment variable was set to 1 in the pre-treatment period and 0 in all other periods, while the actual treatment variable was set to 0 in all periods.

If the DID coefficient for placebo treatment was not statistically significant, this indicated that the parallel trend hypothesis was valid. This is because placebo treatment does not affect the outcome variable, so any difference in the outcome variable between the treatment and control groups in the post-treatment period could be due to the actual treatment.

The placebo test coefficient is the interaction coefficient between the placebo treatment and indicator variables in the post-treatment period. If the assumption of parallel trends holds, the coefficients on the interaction terms should not be statistically significant because the “dummy” treatment should not affect the outcome variable.

The placebo test is a powerful tool for assessing the validity of DID methods. It allows researchers to determine whether the parallel trend assumption is appropriate before estimating the causal effect of a treatment. If the parallel trend assumption is violated, the DID approach may lead to biased treatment effect estimates. Therefore, the placebo test is an essential step in evaluating program interventions.

#### 1.6.2.1 Change the Policy Timing

The government officially issued the environmental taxation law in 2016. Although the government did not launch the specific implementation plans around the country then, firms may have reacted to the policy in advance. So, we accelerated the timing of the policy to 2016, replaced the test interval with 2010-2017, and re-regressed to exclude the possibility that the findings may reflect time-series variations in the innovative behavior of the experimental and comparison groups. We found that the DID coefficient is 0.0012, positive but insignificant. This result indicates no expected effect on environmental taxation. No noticeable variation in firms' eco-innovation behavior occurs in the absence of a policy shock, representing the environmental taxation's impact is unique, indicating that the exogenous shocks constructed in this paper are accurate and that the policy onset is indeed in 2018, supporting the benchmark regression findings (see Table 1.6.1 for details).

**Table 1.6.1 Placebo test: change the policy timing.**

| VARIABLES | $ETI_1$ |
|---|---|
| DIDnew | 0.0012 |
| | (0.0055) |
| Treatnew | 0.0113*** |
| | (0.0034) |
| After | 0.0066*** |
| | (0.0022) |
| lnsize | 0.0060*** |
| | (0.0011) |
| lnCompanyAge | -0.0372*** |
| | (0.0033) |
| lnTobinQ | 0.0037 |
| | (0.0035) |
| Lev | 0.0097 |
| | (0.0084) |
| CashRatio | 0.0027** |
| | (0.0013) |

| | |
|---|---|
| ROA | -0.0299 |
| | (0.0765) |
| ROE | 0.0148 |
| | (0.0368) |
| ContrshrProportion | -0.0296*** |
| | (0.0071) |
| Seperation | 0.0138 |
| | (0.0139) |
| IsDuality | 0.0045* |
| | (0.0025) |
| IndDirectorRatio | -0.0682*** |
| | (0.0193) |
| SOE | -0.0097*** |
| | (0.0022) |
| Pollute | 0.0103*** |
| | (0.0023) |
| Constant | 0.0385 |
| | (0.0267) |
| | |
| Observations | 15,306 |
| R-squared | 0.0174 |

### 1.6.2.2 Randomly Set the Experimental group

Also, to ensure that random factors do not interfere with the regression results, we randomly set the experimental group and then regressed 500 times according to model (1). Figure 1.6.2 documents the distribution outcomes of the estimated coefficients of the placebo test. The estimated parameters are generally distributed around zero, as expected from the placebo test, revealing that the baseline results are reliable.

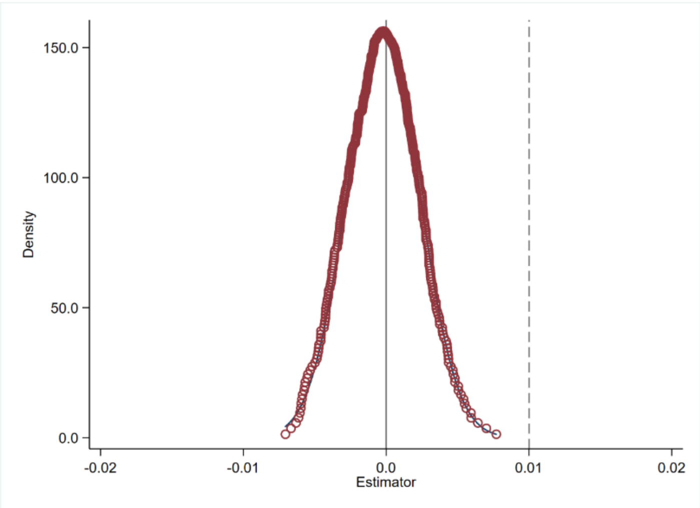


**Figure 1.6.2 The distribution results of placebo test estimation coefficients.**

### 1.6.3 Exclude Disruptive Policies

Considering that many similar or related policies between regions are implemented simultaneously or cross-over, it is evident that there is a specific policy overlap effect. Therefore, this paper considers that other policies with a high correlation with environmental taxes and corporate eco-conscious technological innovation were implemented during the sample period, which may impact the regression results. To exclude shocks from other contemporaneous policies, we control for the effects of the carbon emissions trading pilot and the low-carbon city pilot policies on *ETI*. Specifically, this paper includes the above two policy dummy variables in the baseline regressions to examine the causal relationship between environmental taxes and firms' eco-conscious technological innovation after controlling for other policy interferences.

Table 1.6.2 reports the results of the above regressions, columns (1)-(2) are the regressions with other policy dummy variables added separately and column (3) is the result of adding other policy dummy variables to the regression equation at the same time. All results show that after controlling for other policy shocks, the coefficient of $ETI_1$ remains significantly positive, and the magnitude of the coefficient does not change significantly from the baseline results, indicating that other policy shocks do not affect the causal relationship between environmental taxes and corporate eco-conscious technology innovation, and the previous findings still hold.

**Table 1.6.2 Robustness test: exclude disruptive policies.**

| | (1) | (2) | (3) |
|---|---|---|---|
| VARIABLES | $ETI_1$ | $ETI_1$ | $ETI_1$ |
| DID | 0.0140*** | 0.0106** | 0.0135*** |
| | (0.0042) | (0.0042) | (0.0042) |
| Treat | 0.0504*** | 0.0551*** | 0.0508*** |
| | (0.0027) | (0.0026) | (0.0027) |
| After | 0.0096*** | 0.0096*** | 0.0102*** |
| | (0.0019) | (0.0019) | (0.0019) |

| | | | |
|---|---|---|---|
| lnsize | 0.0029*** | 0.0035*** | 0.0028*** |
| | (0.0009) | (0.0009) | (0.0009) |
| lnCompanyAge | -0.0319*** | -0.0311*** | -0.0322*** |
| | (0.0028) | (0.0028) | (0.0028) |
| lnTobinQ | -0.0068** | -0.0041 | -0.0069** |
| | (0.0030) | (0.0029) | (0.0030) |
| Lev | 0.0165** | 0.0150** | 0.0166** |
| | (0.0073) | (0.0073) | (0.0073) |
| CashRatio | 0.0020* | 0.0020* | 0.0020* |
| | (0.0011) | (0.0011) | (0.0011) |
| ROA | -0.1435** | -0.1590** | -0.1439** |
| | (0.0676) | (0.0677) | (0.0676) |
| ROE | 0.0755** | 0.0812** | 0.0765** |
| | (0.0331) | (0.0332) | (0.0331) |
| ContrshrProportion | -0.0311*** | -0.0300*** | -0.0311*** |
| | (0.0061) | (0.0061) | (0.0061) |
| Seperation | -0.0072 | -0.0153 | -0.0071 |
| | (0.0119) | (0.0119) | (0.0119) |
| IsDuality | 0.0018 | 0.0023 | 0.0018 |
| | (0.0020) | (0.0020) | (0.0020) |
| IndDirectorRatio | -0.0663*** | -0.0634*** | -0.0666*** |
| | (0.0163) | (0.0163) | (0.0163) |
| SOE | -0.0088*** | -0.0090*** | -0.0086*** |
| | (0.0020) | (0.0020) | (0.0020) |
| Pollute | 0.0065*** | 0.0057*** | 0.0068*** |
| | (0.0020) | (0.0020) | (0.0020) |
| CarbonTrdDid | 0.0187*** | | 0.0159*** |
| | (0.0022) | | (0.0024) |
| LowCarbonCityDid | | 0.0109*** | 0.0053*** |
| | | (0.0017) | (0.0018) |
| Constant | 0.1044*** | 0.0829*** | 0.1051*** |
| | (0.0224) | (0.0222) | (0.0224) |
| Observations | 25,721 | 25,721 | 25,721 |
| R-squared | 0.0499 | 0.0485 | 0.0502 |

### 1.6.4 Change the Explained Variable

We change the explained variable to make sure the robustness of the results. We choose the green authorizes to overall patent authorizes ratio (*ETI_get*) instead $ETI_1$. Table 1.6.3 shows that the $DID$ coefficient is statistically significant at the 5% level, therefore the environmental taxation policy does positively boost the enterprises' eco-technology innovation, providing evidence that the benchmark results are sturdy.

**Table 1.6.3 Robustness test: change the explained variable.**

| VARIABLES | (1)<br>ETI_get |
|---|---|
| DID | 0.0062** |
| | (0.0029) |
| Treat | 0.0454*** |
| | (0.0018) |
| After | 0.0036*** |
| | (0.0011) |
| lnsize | 0.0022*** |
| | (0.0006) |
| lnCompanyAge | -0.0139*** |
| | (0.0018) |
| lnTobinQ | 0.0036* |
| | (0.0019) |
| Lev | 0.0104** |
| | (0.0047) |
| CashRatio | 0.0006 |
| | (0.0007) |
| ROA | -0.0476 |
| | (0.0424) |
| ROE | 0.0033 |
| | (0.0206) |
| ContrshrProportion | -0.0075* |
| | (0.0039) |
| Seperation | -0.0041 |
| | (0.0077) |
| IsDuality | 0.0016 |
| | (0.0013) |
| IndDirectorRatio | -0.0249** |
| | (0.0106) |
| SOE | -0.0078*** |
| | (0.0012) |
| Pollute | 0.0038*** |
| | (0.0013) |
| Constant | 0.0190 |
| | (0.0140) |
| Observations | 25,721 |
| R-squared | 0.0638 |

## 1.7 Heterogeneity Analyses

### 1.7.1 Property Heterogeneity

Do eco-conscious technology innovations have diverging responses to environmental taxation depending on properties? To address this question, this paper investigates whether environmental taxation has a heterogeneous influence on eco-conscious technology innovations with different property rights. The heterogeneity results are represented in Table 1.7.1. In column (1) (State-Owned=0), the $DID$ coefficient is 0.0096 (std. value =0.0052) and significant at the 10% significance level. In contrast, in column (2) (State-owned=1), the coefficient is 0.0113 (std. value=0.0071) and insignificant. Based on this result, we inferred that environmental taxation contributes significantly more to the eco-conscious technology innovations of non-SOEs, and the result supports hypothesis 2.

There is the possible reason for this result: Compared to non-SOEs, SOEs are distinctly administrative and profit maximization may not be their core pursuit. In addition, SOEs are more closely tied to the administration and have stronger bargaining power, and many incentives may not be effective for SOEs. For example, when studying the effect of environmental regulation policies on firms' green innovation in China, Shuqiang and Zhenpeng (2021)find that the regulation effect exists only for private firms and is not significant for SOEs. similar results are found by G. He, Wang, and Zhang (2020), which is environmental regulation has no significant effect on SOEs.

**Table 1.7.1 Regression results by property ownership grouping.**

| VARIABLES | (1)<br>$ETI_1$ | (2)<br>$ETI_1$ |
|---|---|---|
| DID | 0.0096* | 0.0113 |
| | (0.0052) | (0.0071) |
| Treat | 0.0508*** | 0.0660*** |
| | (0.0032) | (0.0046) |
| After | 0.0065** | 0.0098*** |
| | (0.0025) | (0.0027) |
| lnsize | 0.0012 | 0.0085*** |
| | (0.0013) | (0.0014) |
| lnCompanyAge | -0.0257*** | -0.0370*** |
| | (0.0034) | (0.0047) |
| lnTobinQ | -0.0098*** | 0.0154*** |
| | (0.0036) | (0.0051) |

| | | |
|---|---|---|
| Lev | 0.0149 | 0.0096 |
| | (0.0095) | (0.0117) |
| CashRatio | 0.0018 | 0.0004 |
| | (0.0013) | (0.0021) |
| ROA | -0.2419*** | -0.1227 |
| | (0.0891) | (0.1084) |
| ROE | 0.1458*** | 0.0294 |
| | (0.0461) | (0.0489) |
| ContrshrProportion | -0.0283*** | -0.0421*** |
| | (0.0081) | (0.0092) |
| Seperation | -0.0557*** | 0.0301 |
| | (0.0153) | (0.0187) |
| IsDuality | 0.0015 | 0.0040 |
| | (0.0022) | (0.0044) |
| IndDirectorRatio | -0.0644*** | -0.0686*** |
| | (0.0210) | (0.0260) |
| Pollute | -0.0098*** | 0.0217*** |
| | (0.0026) | (0.0030) |
| Constant | 0.1372*** | -0.0328 |
| | (0.0304) | (0.0354) |
| Observations | 16,339 | 9,382 |
| R-squared | 0.0391 | 0.0735 |
| StateOwned | 0 | 1 |

### 1.7.2 Size Heterogeneity

Enterprises' sizes are exposed to different degrees of environmental regulation, and their responses may differ. We examine whether the environmental taxation's effect on corporate eco-conscious technology innovations differs among different companies' sizes. Those sizes surpassing the median are classified as large enterprises, and those more minor than the average is categorized as small and growing businesses (SGBs). The regressions were grouped by enterprise size by the model (1). Table 1.7.2 shows the results. The $DID$ coefficient in the SGBs sample (size=0) is 0.0065 (std. value =0.0060) and insignificant. However, in the other group (size=1), the environmental protection tax stimulates eco-conscious technological innovation in large firms with a 95% confidence interval. This result explores that environmental taxation has a more pronounced positive incentive effect on eco-conscious technology innovations in large firms are more significant. Hypothesis 3 is confirmed.

SGBs are less resilient and seek to meet the threshold of environmental requirements under compliance. Eco-conscious technological innovation with high investment, high risk, long cycle time, and uncertain returns will not be the primary choice for SGBs (Chien et al., 2022). On the contrary, large firms are economically strong. They have the ability and energy to undertake green innovation, and the scale effect of sustainable innovations could offset the environmental taxation cost and enhance corporate profits (Z. Chen, Hao, & Chen, 2022). In addition, eco-friendly innovation has strategic implications for large firms, helping to build a better corporate image and strengthen their market influence (Mukonza & Swarts, 2020). Large firms have broader access to resources and networks within and outside their walls. For example, they can recruit specialist consulting firms to locate latent opportunities for environmental-friendly innovation and gain fresh knowledge of eco-innovation (Martínez-Ros & Kunapatarawong, 2019). Therefore, large companies are keener on environmental innovation to establish a competitive advantage over smaller resource-constrained firms (Lu & Beamish, 2001).

**Table 1.7.2 Regression results by entrepreneur's size grouping.**

| VARIABLES | (1)<br>$ETI_1$ | (2)<br>$ETI_1$ |
|---|---|---|
| DID | 0.0065 | 0.0145** |
| | (0.0060) | (0.0058) |
| Treat | 0.0568*** | 0.0505*** |
| | (0.0038) | (0.0037) |
| After | 0.0116*** | 0.0035 |
| | (0.0027) | (0.0026) |
| lnsize | 0.0153*** | 0.0063*** |
| | (0.0025) | (0.0015) |
| lnCompanyAge | -0.0297*** | -0.0271*** |
| | (0.0039) | (0.0040) |
| lnTobinQ | -0.0115*** | 0.0163*** |

| | | |
|---|---|---|
| | (0.0040) | (0.0049) |
| Lev | 0.0068 | 0.0261** |
| | (0.0098) | (0.0114) |
| CashRatio | 0.0029** | 0.0009 |
| | (0.0013) | (0.0023) |
| ROA | -0.3895*** | -0.1148 |
| | (0.1036) | (0.0990) |
| ROE | 0.2347*** | 0.0205 |
| | (0.0555) | (0.0441) |
| ContrshrProportion | -0.0391*** | -0.0218*** |
| | (0.0094) | (0.0081) |
| Seperation | -0.0209 | -0.0209 |
| | (0.0181) | (0.0155) |
| IsDuality | 0.0007 | 0.0043 |
| | (0.0026) | (0.0031) |
| IndDirectorRatio | -0.0415* | -0.0732*** |
| | (0.0239) | (0.0225) |
| SOE | -0.0093*** | -0.0089*** |
| | (0.0030) | (0.0026) |
| Pollute | -0.0106*** | 0.0177*** |
| | (0.0028) | (0.0027) |
| Constant | -0.1544*** | -0.0099 |
| | (0.0553) | (0.0351) |
| | | |
| Observations | 12,863 | 12,858 |
| R-squared | 0.0564 | 0.0469 |
| Size | 0 | 1 |

### 1.7.3 Industry Pollution Level Heterogeneity

Against the background of implementing environmental protection tax, the heavily polluting industries face greater cost pressures. Their motives for green innovation are chiefly to substantially improve the effectiveness of environmental technologies in production processes, increase and enhance resource utilization, and decrease pollutant releases. Moreover, the medium and light-polluting industries have less pressure to reduce emissions. Their motives for green innovation are more strategic, such as capturing profits and creating an environmental image. In 2008, the Chinese ministry of environmental protection formulated a list of environmental protection verification industries for listed companies, specifying that previous scholars’ criteria for defining heavy-polluting sectors (Ailing, Xin, Jinlong, & Yu, 2019; Jinglin, Zhen, Jin, &

Wenqing, 2021; Ye, Caizhen, & Yi, 2019; Yipan & Yuan, 2021) divides the behavior into industries that heavily pollute and non-heavily pollute. Then we use the two groups to investigate the heterogeneity of environmental taxation's impact on eco-conscious technology innovations for businesses in industries with different pollution degrees. The analysis yielded interesting results, which are presented in Table 1.7.3. The $DID$coefficient is significantly positive in column (1) (std. value =0.0048, p<1%); and is not significant in column (2). This result indicates that environmental protection tax encourages eco-friendly technological innovation in non-heavily polluters but does not significantly impact eco-innovation in heavy-polluting industries, support hypothesis 4.

Implementing environmental taxation puts more pressure on non-heavily polluters, thus prompting these enterprises to give more weight to environmental protection and reinforce the input of eco-conscious technology innovations. In contrast, heavily polluting firms, under the pressure of eco-tax, may choose to lower the expenses of pollutant treatment more than to boost the research and implementation of environmental protection technologies. Thus, the increase in green innovation is relatively tiny. In addition, severely polluting entrepreneurs tend to have a high degree of monopoly and capital intensity and face relatively little pressure from environmental protection tax, which may also make the environmental tax less effective in fostering their eco-conscious technological innovation than non-heavy polluters.

**Table 1.7.3 Regression results by industry pollution degree grouping.**

| VARIABLES | (1)<br>$ETI_1$ | (2)<br>$ETI_1$ |
|---|---|---|
| DID | 0.0130*** | 0.0069 |
| | (0.0048) | (0.0085) |
| Treat | 0.0575*** | 0.0458*** |
| | (0.0029) | (0.0056) |
| After | 0.0056*** | 0.0139*** |
| | (0.0021) | (0.0039) |
| lnsize | 0.0009 | 0.0128*** |

| | | |
|---|---|---|
| | (0.0010) | (0.0019) |
| lnCompanyAge | -0.0287*** | -0.0309*** |
| | (0.0031) | (0.0063) |
| lnTobinQ | -0.0039 | 0.0044 |
| | (0.0033) | (0.0067) |
| Lev | 0.0215*** | -0.0126 |
| | (0.0083) | (0.0152) |
| CashRatio | 0.0023* | 0.0016 |
| | (0.0012) | (0.0026) |
| ROA | -0.1811** | -0.1236 |
| | (0.0750) | (0.1564) |
| ROE | 0.0885** | 0.0891 |
| | (0.0373) | (0.0740) |
| ContrshrProportion | -0.0286*** | -0.0434*** |
| | (0.0070) | (0.0126) |
| Seperation | -0.0446*** | 0.0287 |
| | (0.0135) | (0.0242) |
| IsDuality | 0.0022 | 0.0027 |
| | (0.0022) | (0.0045) |
| IndDirectorRatio | -0.0496*** | -0.1075*** |
| | (0.0186) | (0.0342) |
| SOE | -0.0168*** | 0.0112*** |
| | (0.0022) | (0.0043) |
| Constant | 0.1360*** | -0.1028** |
| | (0.0253) | (0.0463) |
| Observations | 19,659 | 6,062 |
| R-squared | 0.0531 | 0.0468 |
| Pollute | 0 | 1 |

## 1.8 Further Discussion

The innovation activities of companies are not generalized and can be of high or low quality. High-quality innovation activities include original and disruptive innovations and strategic innovations with a long-term strategic vision. Furthermore, less capable innovative activities may be simple improvements of existing technologies or mere imitations of other firms' innovations, lacking originality and innovation. Therefore, firms must give full play to their technical and strategic planning capabilities when conducting creative activities and continuously enhance the quality and level of innovation to achieve a more significant commercial edge in the marketplace and chronic development potential. Wenjing and Manni (2016) refer to R&D behaviors that aim to support the companies' technological progress and the innovations' quality as substantive innovation and to seek other R&D behavior that seeks other benefits and pursues the quantity and speed of innovation is called symbolic innovation. In short, substantive innovation is mainly invention patents, while symbolic innovation is mainly non-invention patents.

Unlike developed market economies, China is in a phase of institutional transition. The government is deeply involved in the incentive process of innovation activities, resulting in an imperfect system of stimulation-based environmental supervision. So, does the environmental protection tax lead to distorted incentives during eco-conscious technological innovation, thus creating a bubble of technological innovation?

In addition, independent innovation is preferable when firms conduct innovative activities to acquire financial benefits such as subsidies and tax breaks. At the same time, enterprises are increasingly likely to choose collaborative innovation to reduce innovation uncertainty (Krishnan, Yen, Agarwal, Arshinder, & Bajada, 2021). In this light, this paper investigates how environmental taxation affects eco-conscious technology innovations' behavior by discriminating between quality and pattern.

### 1.8.1 Eco-conscious Technology Innovations' Quality: Substantive or Symbolic Innovation?

The primary purpose of incentive-based environmental regulation is not to capture fiscal revenue but to make emission units bear the necessary expenses of pollution control and ecological damage repair, and through the taxation system where more emissions result in higher payments and fewer emissions result in lower payments, the ecological regulating effect of tax leverage can be harnessed, thus leading emitters to facilitate environmental friendliness. In the fierce market competition, to win market share and stay at the forefront of the market, enterprises must engage in eco-innovate and seek technological progress and product upgrading (Cooper, 2011), enhance green innovation potential, improve the eco-friendly innovations' quality, and develop a competitive superiority. Meanwhile, the government provides incentives such as tax breaks and subsidies for firms' innovation activities in incentive-based environmental regulation.

Therefore, we follow the kinds of green patents to measure the quality of the eco-conscious technology innovations of enterprises. Green invitational patents are characterized as substantive innovations, while green utility model patents are symbolic innovations. To capture eco-conscious technology innovations' quality more precisely, we use percentages to express both types of innovations. Table 1.8.1, column (1), is the green invention patent requests ratio as the dependent variable, defined as substantial innovation. Column (2) takes the green utility model patent requests ratio as the explanatory variable, defined as symbolic innovation. Findings show that $DID$ coefficients are significantly and positively in both two columns, but the column (1) (std. value =0.0024, p<5%) is more significant than column (2) (std. value =0.0017, p<10%). This result indicates that the environment tax policy promotes both substantive and symbolic eco-conscious technology innovations by firms, but it provides a more significant boost to substantive innovations. The conclusion supports hypothesis 5.

**Table 1.8.1 Substantive vs. symbolic innovation.**

| VARIABLES | (1)<br>$ETI_2$ | (2)<br>$ETI_3$ |
|---|---|---|
| DID | 0.0054** | 0.0029* |
| | (0.0024) | (0.0017) |
| Treat | 0.0314*** | 0.0162*** |
| | (0.0015) | (0.0011) |
| After | 0.0052*** | 0.0010 |
| | (0.0010) | (0.0007) |
| lnsize | 0.0045*** | 0.0005 |

| | | |
|---|---|---|
| | (0.0005) | (0.0004) |
| lnCompanyAge | -0.0136*** | -0.0116*** |
| | (0.0015) | (0.0011) |
| lnTobinQ | 0.0068*** | -0.0077*** |
| | (0.0017) | (0.0012) |
| Lev | 0.0018 | 0.0058** |
| | (0.0042) | (0.0029) |
| CashRatio | 0.0019*** | -0.0013*** |
| | (0.0006) | (0.0004) |
| ROA | -0.0661* | -0.0475* |
| | (0.0381) | (0.0263) |
| ROE | 0.0377** | 0.0195 |
| | (0.0186) | (0.0129) |
| ContrshrProportion | -0.0228*** | 0.0005 |
| | (0.0034) | (0.0024) |
| Seperation | -0.0074 | -0.0043 |
| | (0.0066) | (0.0049) |
| IsDuality | 0.0042*** | -0.0003 |
| | (0.0011) | (0.0008) |
| IndDirectorRatio | -0.0312*** | -0.0138** |
| | (0.0093) | (0.0066) |
| SOE | -0.0008 | -0.0067*** |
| | (0.0011) | (0.0008) |
| Pollute | 0.0036*** | -0.0015* |
| | (0.0011) | (0.0008) |
| Constant | -0.0311** | 0.0543*** |
| | (0.0127) | (0.0088) |
| | | |
| Observations | 25,721 | 25,721 |
| R-squared | 0.0463 | 0.0329 |
| Quality | substantive | symbolic |

### 1.8.2 Eco-conscious Technology Innovations' Organization: Independent or Collaborative Innovation?

Various factors are associated with the impact of environmental taxes on innovative forms of organization. Environmental taxes can raise production costs, especially for more polluting firms. Such cost pressures may force firms to adopt a more conservative strategy in their innovation activities, including choosing a more cautious approach to innovation, scaling back R&D investments, and slowing down the pace of innovation. In this case, collaborative innovation has lower R&D costs and more technical support than independent innovation, and it is easier to adapt to the pressure from environmental protection taxes (Petti, Spigarelli, Lv, & Biggeri, 2021). At the same time, with the continuous technological renewal and the rapid increase of market uncertainty, enterprises rely on their strength to perform closed innovation. They need to be adapted to the requirements of the times. Hence, they must take an open stance, such as actively seeking complementary external resources, information technology, and knowledge, and maintain their competitive advantage through collaborative innovation to improve innovation performance.

We constructed separate subsamples of independent and collaborative applications based on the green patent application information, thus further examining how the environmental protection tax affects different organizational forms of environmental-friendly technological innovation. In the table 1.8.2, only column (2) demonstrates that the $DID$ term has a positive and significant coefficient (std. value =0.0027, p<5%). Consequently, the outcomes imply that environmental taxation favors firms' collaborative organization of eco-conscious technology innovations. The conclusion supports hypothesis 6.

**Table 1.8.2 Independent vs. collaborative innovation.**

| VARIABLES | (1)<br>$ETI_4$ | (2)<br>$ETI_5$ |
|---|---|---|
| DID | 0.0056 | 0.0064** |
| | (0.0049) | (0.0027) |
| Treat | 0.0513*** | 0.0124*** |
| | (0.0032) | (0.0016) |
| After | 0.0074*** | 0.0020* |
| | (0.0022) | (0.0011) |
| lnsize | -0.0032*** | 0.0071*** |
| | (0.0011) | (0.0006) |
| lnCompanyAge | -0.0330*** | -0.0045*** |
| | (0.0034) | (0.0015) |
| lnTobinQ | -0.0057 | 0.0012 |
| | (0.0035) | (0.0017) |
| Lev | 0.0189** | 0.0003 |
| | (0.0088) | (0.0044) |
| CashRatio | 0.0010 | 0.0017*** |

| | | |
|---|---|---|
| | (0.0013) | (0.0006) |
| ROA | -0.2894*** | 0.0572 |
| | (0.0779) | (0.0414) |
| ROE | 0.1526*** | -0.0418** |
| | (0.0374) | (0.0208) |
| ContrshrProportion | -0.0343*** | -0.0032 |
| | (0.0072) | (0.0037) |
| Seperation | -0.0277** | -0.0013 |
| | (0.0136) | (0.0073) |
| IsDuality | 0.0025 | 0.0009 |
| | (0.0024) | (0.0011) |
| IndDirectorRatio | -0.0632*** | -0.0069 |
| | (0.0194) | (0.0102) |
| SOE | -0.0138*** | 0.0016 |
| | (0.0023) | (0.0011) |
| Pollute | 0.0030 | 0.0029** |
| | (0.0023) | (0.0012) |
| Constant | 0.2445*** | -0.1329*** |
| | (0.0259) | (0.0135) |
| Observations | 25,721 | 25,721 |
| R-squared | 0.0292 | 0.0187 |
| Organization | independent | collaborative |

## 1.9 Research Conclusions and Policy Implications

Using green patent data as the basis, this paper constructs percentage indicators that could better reflect the characteristics of eco-conscious technology innovations. And we empirically test how the incentive-oriented environmental regulations, and environmental taxation imposed on January 1, 2018, affect the eco-tech innovation behavior of manufacturing firms. The investigation demonstrates that (1) environmental taxation significantly contributes to corporate eco-conscious technology innovation. (2) The environmental protection tax's effects on environmental innovation are heterogeneous depending on the entrepreneurs' nature, size, and pollution degree. The environmental tax encourages eco-conscious technological innovations in non-nationalized, large, and non-heavy pollution companies. (3) Environmental protection taxes have a different bearing on corporate ecotechnological innovation's qualitative and organizational aspects. The environmental protection tax more significantly impacts the substantive ecotechnological innovation of enterprises rather than the symbolic eco-conscious technology innovation. This result suggests that eco-conscious technology innovation is likely to be formal, and the quality of eco-conscious technology innovation is really improved. Furthermore, the environmental protection tax noticeable improved enterprises' eco-conscious technology innovation ability in the collaborative organization. With these findings in mind, the following policy recommendations are given:

(1) Reinforce the responsibility of enterprises to treat pollution and reduce emissions. As a green tax, an environmental taxation is essentially a kind of "ad valorem tax" on pollution, a positive incentive mechanism, i.e., more emission, less emission, and no emission. For enterprises with low pollutant emissions, environmental taxes can play a less tax incentive; for pollution-intensive industries, by raising costs, eliminating and "squeezing out" excess capacity and outdated technologies, products, and processes. The implementation and collection of environmental protection tax guide enterprises to improve technology and processes, reduce pollutant emissions, improve industrial competitiveness, can make sustainable technological innovation products market share higher, crack the problem of overcapacity, the industrial structure is heavy, to achieve sustainable economic and social development.

(2) Develop a market assessment system for sustainable technological innovation. Governments are often unable to accurately assess the quality-quantity characteristics of sustainable technological innovation of enterprises due to their lack of expertise in technological innovation. Therefore, local governments can use market competition mechanisms to help them identify high-quality, sustainable innovation technologies and establish a market assessment system to stimulate growth in the quality and capacity of

sustainable innovation. By doing so, the positive effects of sustainable technology innovation can be fully reflected in environmental protection and other areas.

(3) It is conducive to forming a flexible green tax system. For a long time, China still has tended to emphasize government over the market in environmental protection, making environmental protection a market failure. By levying environmental protection tax and using tax leverage to make enterprises with high pollutant emission intensity pay more tax and those with low pollution emission intensity pay less tax, it can effectively promote the country’s green development and is conducive to the formation of a green taxation system. In addition, it is essential to note that the ownership, size, degree of pollution in the industry, and other factors can affect the technological innovation strategy of an enterprise. Therefore, local management should also consider enterprises’ heterogeneity when levying environmental taxes. Dynamically adjust environmental taxes to the specific characteristics of enterprises to guide them to adopt sustainable technological innovation.

# 2 Multi-Channel Investor Sentiment and Stock Returns

## 2.1 Introduction

The efficient market hypothesis (Fama, 1970), modern portfolio theory (MPT) (Markowitz, 1952), capital asset pricing model (CAPM) (Sharpe, 1964), arbitrage pricing theory (APT) (Ross, 1976), and option pricing model (OPM) (Black & Scholes, 1973) constitute the theoretical cornerstone of modern financial theory. The modern financial theory implies two hypothetical premises, rational economic man, and efficient markets. Modern financial theory assumes that investors conform to the "rational man" assumption and do not misunderstand information or get distorted by emotions in their investments. Also, the modern financial theory assumes that investors are homogeneous and have no individual differences but are not the same. The reality of information asymmetry and the high cost of information acquisition suggest that perfect markets do not exist and that most markets are inefficient. As a result, the credibility of modern financial theory in describing the decision-making process of investors has been challenged and questioned, and the practical guidance for investors has been difficult to meet.

Behavioral finance has gradually developed and grown with the continuous challenges to modern financial theory. The main research problem of behavioral finance theory, i.e., how investors misunderstand information and how emotions sway them, has also attracted more and more attention from scholars. Behavioral finance theory integrates disciplines such as finance, psychology, and behavioral science. It analyzes the motivation of investors' investment behavior from a psychological and social perspective, i.e., what investors "actually do" to study the operation of the whole stock market. Behavioral finance theory goes beyond the framework of modern financial theory to explore the characteristics of market price trends, volatility, and investor portfolio characteristics from the perspective of investor psychology and behavior and then provide reasonable explanations for many “anomalies” in the real financial market.

With the widespread use of investor beliefs, preferences, and psychological research, behavioral finance research has paid attention to the importance of investor emotions, psychology, and decision-making. So behavioral finance theory considers the psychological characteristics of investors’ cognition, feelings, and attitudes in the decision-making process and then analyzes its impact on the market. Research on investor sentiment measurement, investor sentiment pricing, and the mechanism of investor sentiment on the stock market has emerged and has achieved some results. However, there is still no uniformity in the framework of investor sentiment research. Especially for the characteristics of the Chinese stock market, as an emerging market, its market stability is crucial. However, the research on investor sentiment is still in its infancy, and many research questions deserve in-depth analysis and discussion.

China is an emerging stock market; although its market operation mechanism gradually improved, the role of capital financing and resource allocation optimization is becoming more mature, but the surge and plunge of the market still alternate. Speculation in the market remains a serious phenomenon. Speculation brings about serious deviation of stock prices from the fundamental value of stocks, resulting in high market volatility, frequent and excessive investor operations, and irrational behavior of investors in the market. In addition, political, economic, and market policies intervene in the Chinese stock market to a much higher degree than in developed markets, leading to a strong dependence of investors on policies. At the same time, the financial literacy of small and medium-sized investors is generally low, and they tend to follow investment behavior blindly. All these factors limit the function of the stock market itself and hinder the healthy development of the stock market. These anomalies in the stock market are closely related to the irrational behavior of investors and provide a realistic basis for studying investor sentiment.

Therefore, it is highly relevant and instructive to gain insight into the impact of investor sentiment on the stock market. This paper attempts to measure firm-specific investor sentiment from multiple channels to verify the impact of multi-channel investor sentiment on the stock market. Multi-channel investor sentiment is highly relevant to investors in interpreting market information, achieving healthy investments, and maintaining the regular operation of financial markets, among other core issues. Multi-channel investor sentiment also helps to grasp more deeply the development rules of the Chinese stock market and ensure its good operation.

The remainder of the paper proceeds as follows: Section 2.2 details the relevant theory and literature review, Section 2.3 describes the methodology and data, Section 2.4 examines the results; Section 2.5 and 2.6 are robustness tests and heterogeneity analyses, Section 2.7 discusses, Section 2.8 concludes.

### 2.2 Theory and Literature Review

Modern financial theory assumes that asset prices are determined by the intrinsic value of assets in efficient markets, even when there is a bias in market pricing, and rational arbitrage corrects asset prices. However, extensive behavioral finance research proves that irrational or noisy traders exist, and their sentiments will have a persistent and systematic effect on the stock market. Black (1986) points out that noise traders deeply impact the world and our worldview. Noise traders are usually controlled by market sentiment and individual subjective cognitive biases, making the decision process systematically and persistently noisy. Numerous experiments in psychology have also demonstrated that people do not deviate from rationality by accident; they frequently deviate from rationality in the same way (Barberis, Shleifer, & Vishny, 1998; Daniel, Hirshleifer, & Subrahmanyam, 1998; Shefrin, 2002; Tversky & Kahneman, 1974).

The current research on investor sentiment mainly revolves around three aspects: one is to find evidence of the existence of investor sentiment from experiments or surveys, which mainly revolves around psychology and experimental economics; the second is to consider investor sentiment variables in asset pricing models, which mainly revolves around the theoretical model of sentiment pricing, to use the research findings to explain some financial anomalies, which mainly starts with This type of research is mainly based on the specific psychological bias of investors in one aspect; third is based on a quantitative indicator system to directly measure investor sentiment and examine the impact of changes in sentiment on the return and volatility of financial assets.

Despite the richness of investor sentiment research results, a unified research framework has yet to be formed. There are still many differences in research perspectives, methods, and findings. Therefore, this chapter will analyze and summarize the existing research in terms of grounded theory and empirical results. At the theoretical level, we clarify the definition, influencing factors, and measures of investor sentiment; at the practical level, we compare and analyze the existing research methods and results of investor sentiment affecting stock returns.

### 2.2.1 The Definition of Investor Sentiment

Investor sentiment reflects the changes in the mindset and behavioral characteristics of investors in the market during the investment process. Investigating investor sentiment is a hot topic in behavioral finance and is one of the bases for behavioral finance theory to explain financial anomalies. Although investors’ preferences differ, investors learn from each other, imitate, and influence each other in the market. Eventually, investors' emotional characteristics and investment behavior will tend to be the same, which causes the price of financial assets to deviate from the actual value. This result is consistent with Long, Shleifer, Summers, and Waldmann (1990) finding that the unpredictability of noise traders' beliefs can also cause asset prices to deviate significantly from their fundamental values. However, there is no consensus on the definition of investor sentiment in the current research findings.

The most classic definitions of investor sentiment are summarized in the research pieces of literature. Smidt (1968), Zweig (1973), and Black (1986) studied the relationship between investor sentiment and speculative bubbles, expectation bias, and noise trading behavior, and Black (1986) demonstrated that noise traders are the source of investor sentiment. C. M. Lee, Shleifer, and Thaler (1991) first detailed investor sentiment and defined it as price expectations that are not explained by fundamental factors. Barberis et al. (1998) defined noise traders' beliefs about stock price pricing as investor sentiment. Shleifer (2000) pointed out that sentiment reflects common misjudgments of different investors. Hirshleifer and Jiang (2010) find that mispricing can be correlated across firms and affect stock returns in different sectors. Hirshleifer, Li, and Yu (2015) and Frydman, Barberis, Camerer, Bossaerts, and Rangel (2014) argue that mispricing can also be related to economic fundamentals. Mehra and Sah (2002) and Brown and Cliff (2004, 2005) argue that investor sentiment is related to mispricing and reflects the overall degree of optimism or pessimism of stock market investors. Baker and Wurgler (2006, 2007); Baker, Wurgler, and Yuan (2012) define investor sentiment as a combination of judgments or beliefs based on cash flows and risk expectations that depend on investors' characteristics, such as endowments and risk preferences. Fong and Toh (2014) argue that investors can optimally overestimate the likelihood of good outcomes by maximizing current utility. Future likelihood by maximizing current utility. Stambaugh, Yu, and Yuan (2012) also argue that investor sentiment can simultaneously affect the market in the same direction.

In general, the connotation of investor sentiment includes cognitive factors and subjective judgments. Investors have different cognitive structures and subjective judgments, thus forming individual beliefs called "sentiment." In addition, due to different sources of information, sentiment can also be divided into market-based, survey-based, and media-based sentiment. Different investor sentiment channels affect each other, communicate with each other, and infect each other, ultimately affecting the return of financial assets in the market. Investor sentiment research breaks through the traditional financial theory research framework and aims to analyze the impact of irrational groups' beliefs or investment behaviors on the stock market.

### 2.2.2 The Psychological Basis of Investor Sentiment

After years of battling with the traditional efficient market hypothesis, behavioral finance theory has established two critical theoretical cornerstones on which it is based: investor psychology and limited arbitrage. Due to the existence of arbitrage costs and risks, the theory of full arbitrage under the efficient market hypothesis is invalid. Therefore, the price of securities is not only determined by the intrinsic value of securities but also primarily influenced by the behavior of the investor body. Furthermore, the emotions generated by the changes in investor psychology allow investors to achieve only limited rational behavior. Therefore, the emotions and behavior of investors have a non-negligible influence on price determination and its movement in the securities market.

Realizing the limitations of expected utility theory, Tversky and Kahneman (1974) proposed "prospect theory" as an alternative to expected utility theory. Prospect theory provides a reasonable explanation for the experimental results of individual preferences to a certain extent. When an individual makes a decision, he or she is choosing between "expectations," which are the expected outcomes of various risks. Unlike the axiomatic form of expected utility theory, prospect theory is descriptive. Tversky and Kahneman (1974) present their main ideas based on the results of a series of psychological experiments: people value the change in wealth more than the final amount; people tend to take risks when faced with comparable losses and accept certainty when faced with comparable profits. The pleasure of profit is not equal to the pain of an equivalent loss, and the latter is greater than the former. Overall, prospect theory reveals the irrational psychological factors that influence choice behavior from human psychological traits and behavioral characteristics and lays the theoretical foundation for investor mindset analysis.

In addition to prospect theory, many other theories on investor sentiment analysis can be used to explain the anomalies of fundamental financial markets. We can classify the psychological factors influencing investors' trading behavior into three main categories: cognitive biases, psychological biases, and non-standard preferences.

#### 2.2.2.1 Cognitive Biases

Modern cognitive psychology tells us that under uncertainty, investors' judgment and decision-making process is a complex information-processing process, which often has various biases that lead to deviations from rational decisions. There are two information processing systems in investors' decision-making process, the "fast system" based on intuition and heuristics and the "slow system" based on cognitive reasoning (Evans, 2008). Heuristic bias refers to investors' reliance on rules of thumb rather than algorithms to make judgments in decision-making. The possible cognitive biases are：

(1) representativeness biases due to inference based on the similarity of things.

(2) availability bias due to inference based on the strength of one's memory.

(3) anchoring and adjustment bias due to anchoring on some irrelevant information; and

(4) emotional bias because one's emotions, intuition, and instincts.

The framing dependence bias refers to the framing dependence bias that occurs in investors' decision-making due to changes in how things are presented or the context. This bias leads to a violation of the dominance and constancy of rational decision-making.

#### 2.2.2.2 Psychological Biases

Psychological phenomena that arise when decision-makers engage in cognitive activities such as identifying, compiling, and evaluating external information that differs from the assumption of a rational person are called psychological biases. Psychological biases that are prevalent among investors in financial markets include.

(1) Overreaction and underreaction. Overreaction is a phenomenon in which investors fail to make rational evaluations, leading to fluctuations in the price of securities beyond the expected level and then reversing the correction so that the price falls back to the average level. Overreaction temporarily causes the price of a security to deviate from its fundamental value. Barberis et al. (1998) state that the existence of overreaction and underreaction is due to the "anchoring effect" and "confirmation bias"

of investor psychology.” Daniel et al. (1998) use overreaction and underreaction to explain market anomalies that cannot be explained by efficient market theory.

(2) Overconfidence and self-attribution. Overconfidence is a pervasive psychological bias that becomes more pronounced when the decision task is challenging. Individuals are more inclined to be overconfident when their information feedback is delayed or undecided. Investors often need to be more confident in their level of trading. Odean (1998) studied the investment behavior of individual investors in the United States and found that investors sold stocks not because of liquidity needs, tax considerations, or risk reduction but because they were confident that they should sell. The study demonstrates that overconfident investors “trade too much” and that overtrading reduces investors’ returns. Overconfidence is closely related to self-attribution, the tendency to attribute good results to one’s abilities and bad results to external circumstances. Self-attribution fosters overconfidence rather than focusing on accurate self-assessment. Overconfidence may lead to behavioral failure because overconfident expectations are unrealistic.

(3) Herd behavior and the herd effect. The herd effect refers to the psychological tendency of people to change their perceptions or behaviors to conform to the group (Asch, 1951). Herd behavior is manifested by adopting the same thinking activities, performing similar behaviors, and psychologically relying on thinking, feeling, and behaving like most people. In financial markets, herding behavior may lead to herding effects in stock investments. Other investors influence investors with uncertain information, imitate the decisions of others, or rely excessively on public opinion without considering private information to reduce the cost of acting and obtain the most significant returns.

The main reasons for herding behavior in investor decision-making are as follows. 1) Investors have asymmetric and incomplete information and save themselves the cost of finding information by mimicking the behavior of others. The more information people need, the more likely they listen to others. 2) The need to shirk responsibility. Regret aversion makes decision-makers choose the same strategy as others or follow the advice of others to avoid the regret and pain that may come from personal decision errors. 3) The need to reduce fear. Humans are group animals; deviation from the group can cause loneliness and fear. 4) Lack of knowledge, experience, and other personality reasons.

#### 2.2.2.3 Non-standard Preferences

Preference is an economic concept that discerns people's preferences in terms of value and utility for different scenarios or states of events. The behavior of decision-makers is based on their subjective perceptions of objective things. Due to psychological and cognitive biases, the decisions made by decision-makers in real situations often differ from the inferences of neoclassical economics, i.e., they are non-standard preferences.

(1) Regret aversion. "Regret" is an emotional experience when a decision maker does not make the right decision and is a sad state of mind when he or she realizes that he or she should have done better. Regret aversion was introduced by Thaler (1980) and developed by Loomes and Sugden (1982), Kahneman and Tversky (1982), and others. "Regret aversion" refers to people's distress about their actions when they make a wrong decision. To avoid regrets, people often make irrational behaviors, such as making decisions only after getting specific information, even though the information may not be necessary, and they can make decisions without it. For example, decision-makers will give up their independent judgment in the choice of certain vital matters

and make the same choice as others with the general trend to reduce the regret caused by regrets in case of bad decisions. The decision maker will give up his or her independent judgment in certain important matters and make the same choice as others to reduce the loss to his or her spirit if the decision is wrong. Regret aversion is widespread in investment decisions in financial markets. Investors make decisions by comparing current situations with those they have encountered. If they realize that other choices would put them in a better position, they will blame themselves for making the wrong decision. Conversely, if they get a better result from the current choice, they will feel a sense of elation.

(2) Ambiguity aversion and familiarity preferences. In general, people always tend to avoid uncertainty. Ambiguity aversion means that people prefer the familiar one between familiar things and strange things and avoid choosing strange things to do. People loathe subjective or vague uncertainty and even hate objective uncertainty. Their aversion and avoidance of such vagueness are even more potent when it is a possibility of significant future loss. In contrast to vagueness, people tend to prefer what is familiar to them. Behavioral economists believe that familiarity preferences cause investors to alter their risk perceptions based on their familiarity with risky events. The more frequently a person is exposed to a particular stimulus, the more familiar she will be with it and the more she will like it. There is a close correlation between the frequency of exposure to a particular thing and the degree of liking, a phenomenon that social psychology calls the “pure exposure effect,” which is also commonly known as “love over time”.

### 2.2.3 Measure of Investor Sentiment

The sentiment is an essential indicator of investors’ behavior and psychological characteristics to express their expectations about the market’s future. The sentiment index is a measure of investors' various sentiments. In the study of investor sentiment, whether it is an empirical analysis or a theoretical study, it is necessary to construct some indices to measure investor sentiment. There are three main measurement methods for the measurement of investor sentiment: one is to use a direct survey to understand investors' judgment of future market sentiment, called a direct index (or explicit index). The second is to collect actual trading data in the financial market and use one or more relevant variables to build a single sentiment proxy index or composite sentiment index called an indirect index (or implicit index). Third, based on text and media and other Internet platforms, we use text mining techniques to extract information and build investor sentiment indices, which are called text sentiment indices.

(1) Survey-based Investor Sentiment Index

Survey-based investor sentiment indices collect polls from market participants to infer their views. For example, the U.S. market typically uses two standard survey-based indexes of investor sentiment, the American Association of Individual Investors Index (AAII) and the Investor Intelligence Index (II). The AAII index is primarily a survey of American Association of Individual Investors members and is often used as a proxy for individual investor sentiment. The II index, on the other hand, is a survey of over The II Index, is a survey of the sentiment of more than 130 newspaper commentators and is based on the difference between the bullish and bullish percentages of commentators and is often considered an indicator of institutional investor sentiment (W. Y. Lee, Jiang, & Indro, 2002). In addition, there are also survey indicators for the overall market sentiment that focus on the state of investors' perceptions or confidence held about the macroeconomic environment and prospects, such as the Consumer Confidence Index (Salhin, Sherif, & Jones, 2016) and the

Investor Confidence Index (Shiller, 2000). The Chinese market's two commonly accepted direct investment sentiment indices are CCTV Watch and JUCHAO Investor Confidence Index.

Survey-based indicators of investor sentiment have certain shortcomings. Many quantitative indicators in the survey only partially reflect investor sentiment, while investors' responses to the questionnaire are subjective. They will be more rational and cautious in the face of accurate investment judgments and choices. Therefore, the investor sentiment indices extracted from the survey can only partially reflect the genuine sentiment of investors in the actual investment decision process. These direct survey data are likely to be biased. In contrast, trading data in the actual capital market contains investors' psychological and behavioral biases, which may be more accurately used to measure investor sentiment.

(2) Market-based Investor Sentiment Index

Market-based investor sentiment indices use quantitative indicators of actual trading data from financial markets to represent investor sentiment. It can be classified as a single sentiment proxy index and a composite sentiment index according to the number of proxy variables used. For example, single proxy variables such as trading volume (Hou, Xiong, & Peng, 2009; Kumar & Lee, 2006), percentage of stock gains and losses (Arms Jr, 1989), and closed-end fund discounts (C. M. Lee et al., 1991), can be used to measure investor sentiment. In addition to using single indicators as a proxy for investor sentiment, Baker and Wurgler (2006)sentiment index (BW index) is the most classic. They used a composite investor sentiment index constructed to capture investor sentiment using six indicators: closed-end fund discount, volume, number of

IPOs, first-day IPO returns, dividend yield, and security issuance. BW index is currently the most widely used composite indicator to measure investor sentiment indirectly.

Using a single indicator to measure investor sentiment will inevitably be biased. A composite indicator will provide a more comprehensive and realistic reflection of investor sentiment. However, investors forecasts of future stock returns are also influenced by economic fundamentals, which are partly part of investors’ rational reactions. This part of investors’ rational reactions should be excluded from the measurement of investor sentiment to depict irrational sentiment better and ensure the measurement’s accuracy and objectivity. In addition, a comprehensive investor sentiment index relies on the scientific selection of proxy variables. These proxy variables vary due to the limited availability of relevant data. There is a need for a more uniform understanding and a more standardized approach to selecting reasonable sentiment proxy variables. Although indirect indicators of investor sentiment are readily available and objective, the indirect nature of proxy variables inevitably leads to errors and lags. Therefore, it is not easy to measure sentiment in investors’ behavioral decisions in a timely and direct manner in traditional research methods. With the rapid development of information technology, active online media have provided researchers with new perspectives to measure investor sentiment. Much of the recent literature extracts textual sentiment from social media such as Twitter and online forums.

(3) Text and media-based Investor Sentiment Index

Text and media-based investor sentiment indexes are direct measures of investor sentiment based on text data from news websites, social media, Internet stock message boards, and other online platforms. For example, Dougal, Engelberg, Garcia, and Parsons (2012), Ahern and Sosyura (2014), and Kelley and Tetlock (2017) measured investor sentiment through the lexical information of news websites. Y. He, Qu, Wei, and Zhao (2022) found in the text analysis of newspapers that investor sentiment was positively correlated with stock returns in the short term, while in the long term, the sentiment negatively correlated with stock returns. Antweiler and Frank (2004) and Das (2007) all mined information texts from Yahoo! and other stock message boards to construct investor sentiment indicators. In addition, H. Chen, De, Hu, and Hwang (2014), Sprenger, Tumasjan, Sandner, and Welpe (2014), and Bartov, Faurel, and Mohanram (2017) constructed Twitter investor indicators by collecting posts published on Twitter. Zhou (2018), compared with the calculation methods based on the trading and survey, it is surprising that the investor sentiment based on text analysis performs better than the first two methods.

Similarly, Changyun and Jiawei (2015) constructed a media tone to measure firm-level investor sentiment using data on positive and negative terms in mainstream financial media coverage. Based on stock message board posts on Eastmoney.com and a naive Bayesian approach, H. BU, XIE, LI, and WU (2018) propose an investor sentiment index that integrates bullish and bearish expectations of stock comments and investor attention levels. As a result, many Chinese researchers have obtained relevant data from the Internet to measure investor sentiment. In addition to text analysis methods, some scholars also use machine learning methods to extract textual content. As research results from information disciplines continue to emerge, future measures of investor sentiment will likely be more objective, accurate, and timely.

### 2.2.4 Impact of Investor Sentiment on Stock Returns

Many scholars have conducted empirical studies based on various measures of investor sentiment indices. The most empirical analysis revolves around determining the explanatory power of investor sentiment on expected stock market returns. Generally believed that high investor sentiment increases current returns, but then returns decline, i.e., changes in investor sentiment positively affect stock returns in the short run, but the effect fades in the long run. Some studies have concluded that there is no significant correlation between investor sentiment and future stock market returns (Brown & Cliff, 2004; Clarke & Statman, 1998; Solt & Statman, 1988). However, most empirical studies have insisted that investor sentiment impacts stock market returns, including on the market and individual stock, i.e., aggregate, and cross-sectional effects.

#### 2.2.4.1 Aggregate Effect

From the market perspective to study whether investor sentiment affects the overall market return and forms systemic risk, that is, the aggregate effect of investor sentiment. W. Y. Lee et al. (2002) used the investor intelligence index to find that investor sentiment is a systematic factor and that there is a positive relationship between sentiment and returns. Brown and Cliff (2005), Kumar and Lee (2006), and Baker and Wurgler (2006, 2007); Baker et al. (2012) pointed out that investor sentiment will promote stock price changes and then affect investors' expected returns. Baker, Stein, and Wurgler (2003) believed that the difference in the level of investor sentiment would affect their sensitivity to changes in stock returns, resulting in the asymmetric impact of investor sentiment on stock return expectations.

Research on investor sentiment asymmetry has focused on three main areas: first, the asymmetric effects of different sentiment cycles on sentiment forecasting ability. This perspective concerns stocks in different economic life cycles, such as growth periods and recessions; or stocks in different trading cycles, such as bull or bear markets; or studies on the medium- and short-term sentiment issues on return forecasting. Fisher and Statman (2003) find that investor sentiment is positively correlated with S&P returns in the short run and negatively correlated in the long run. Brown and Cliff (2005) confirm the negative relationship in the long run. Berger and Turtle (2015) find that investor sentiment is positively related to stock market returns in the short run and negatively related in the long run. Chung, Hung, and Yeh (2012); Li, Guo, and Park (2017) studied the asymmetry of investor sentiment on stock returns in both boom and recession states.

Second, the asymmetric impact of different sentiment states on returns. This research perspective studies the positive or negative impact of positive or negative investor sentiment on returns. Charoenrook (2005), Brown and Cliff (2005), and Lemmon and Portniaguina (2006) use the Consumer Confidence Index (CCI) to capture investor sentiment and confirm that after investor optimism is followed by a decline in asset returns. Hung (2016) examines investor sentiment, order submission decisions, and investment performance on the Taiwan Stock Exchange. Hung finds that: people's order submission behavior differs significantly between optimistic and sad periods and buy and sell orders exhibit different patterns and asymmetric effects. The sensitivity of order submission decisions to investor sentiment varies significantly across trader categories. Yu and Yuan (2011) argue that the higher involvement of noise traders makes the market less rational during optimistic periods and expected excess stock market returns are only positively related to conditional variance during pessimistic periods. Stambaugh et al. (2012) hypothesize that when market sentiment is associated with arguments about the impact of short-selling barriers, overpricing due to high sentiment is more likely to occur than underpricing due to low sentiment.

Third, the asymmetry in the degree of impact of different emotional states. Whether positive and negative sentiments carry different effects is also of interest.

Dergiades (2012) and Ni, Wang, and Xue (2015) find that the effect of investor sentiment on stock market returns is asymmetric and inverted.

#### 2.2.4.2 Cross-sectional Effect

Considering that there are often cross-sectional differences between stocks of different firms, several scholars have studied the cross-sectional impact of investor sentiment on stock returns of different characteristics. Fisher and Statman (2000) find that the sentiment of large and individual investors has an inverse prediction on the returns of large-cap stocks, while the sentiment of medium-sized investors negatively but insignificantly correlated with the future returns of large-cap stocks. The correlation between either type of investor sentiment or future returns of small-cap stocks is negative but insignificant. However, changes in individual investor sentiment are significant for asset allocation. Baker and Wurgler (2006) find that investor sentiment significantly affects small-cap stocks, emerging stocks, and high-volatility stocks. Baker et al. (2003), Eckbo and Norli (2005), Glushkov (2006) found that stocks that are young or have high short-selling restrictions or low dividends also susceptible to investor sentiment in addition to the stock types mentioned by Baker and Wurgler (2006). Bae and Wang (2012), by comparing US-listed companies with or without the word “China,” find that listed companies with the word “China” are a more significant impact on investor sentiment. Stambaugh et al. (2012), Kumari and Mahakud (2016) analyze the impact of investor sentiment from the perspective of stock anomalies.

Due to the lack of a unified measurement method for investor sentiment, the impact of investor sentiment on investment returns has yet to reach a consensus. There are different conclusions, such as positive, negative, and irrelevant. Investor sentiment, an important market signal, cannot be effectively described and interpreted, which is highly unfavorable to the income output and risk prevention and control of the financial market. Therefore, this study attempts to conduct a more detailed study on the impact of multi-channel investor sentiment measurement on returns. It aims to explain the role of investor sentiment in different activity degrees, industries, and time effects at a more subtle level and provide a helpful reference for exploring the impact of investor sentiment on financial market returns.

## 2.3 Methodology and Hypotheses

Investors are the subjects of transactions in the securities market. They will collect relevant information from various channels before trading to help them make correct investment decisions as much as possible. Taking investors' information sources as the entry point, constructing a multi-channel market reaction, and conducting a comprehensive study on the market reaction caused by investors' decisions can effectively reflect the sentiment of market investors. From the viewpoint of investors' information channels, there are mainly two types of information. One is investors' attention to the overall market trend reflected by historical trading data, which constitutes the investor sentiment based on market transactions. The other is investors' stock market information learned through the Internet. There is much professional financial news on the Internet and many "grassroots" stockholders' messages on stock forums. These texts reflect investors' beliefs about the stock market, which is an expression of sentiment and can be helpful information to mine and measure investor sentiment. Although theoretically, investors can obtain all publicly available stock information through search, the lack of information search ability and the high cost of information search constrain people from browsing and processing all information due to their limited time and energy. Therefore, what information investors browse and what channels can reflect investors' concerns and, thus, investor sentiment in different channels deserve further research.

### 2.3.1 Market-based Measurement of Investor Sentiment

Currently, the most classical market-based investor sentiment indicator is the BW index. The BW index introduces six market sentiment indicators: closed-end fund discount rate, turnover rate, number of IPOs, IPO first-day return, equity financing ratio, and dividend premium. After selecting the variables, they regressed these six market sentiment indicators on macroeconomic variables to obtain the residuals of the regressed indicators. The residuals of each sub-indicator of sentiment are then downscaled with the help of principal component analysis to obtain a composite investor sentiment index. This method excludes the influence of fundamental market information, so the investor sentiment index only contains sentiment information. The BW index can effectively reflect comprehensive investor sentiment, but the disadvantages are on the one hand, it is primarily used in the field of measuring macro market sentiment; on the other hand, the data used are mostly monthly data, and the data frequency is low. What drives changes in investor sentiment is usually individual stock sentiment and short-term trends, thus requiring more accurate and timely tracking. We introduce daily-frequency individual stock trading data in our market-based investor sentiment measurement to address this issue. There are two reasons for using daily-frequency individual stock trading data. On the one hand, individual stock trading data directly results from investors' trading and is a true reflection of investors' sentiments and decisions. On the other hand, daily frequency data is updated more frequently and allows for timely market tracking.

### 2.3.1.1 Sample Selection of Market-based Investor Sentiment

For stock market cycle and individual stock data availability considerations, we select individual stock trading data for the 176 stocks in the CSI 300 Index (CSI300) constituents for the trading days from January 1, 2014, to December 31, 2020. The 176 stocks in the sample cover thirteen industries, such as energy, raw materials, and other industrials (see Appendix 1). The sample period includes two complete bull and bear periods (as shown in Figure 2.3.1), which can provide a more comprehensive interpretation of market-based investor sentiment under the general trend of strength or weakness.

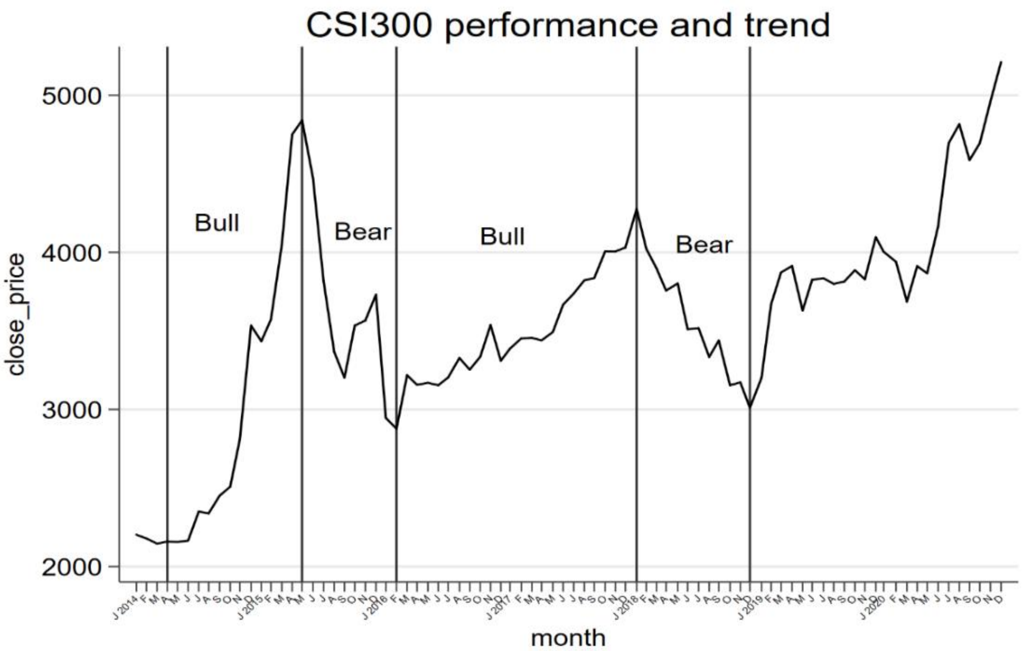


**Figure 2.3.1 CSI300 performance and trend.**

### 2.3.1.2 Indicator Construction for Market-based Investor Sentiment

Considering the actual trading situation and data availability in the Chinese stock market, we draw on the construction method of the BW indicator to construct an investor sentiment indicator based on daily trading. Again, we do not consider the macroeconomic impact on sentiment. We only consider trading indicators that can directly reflect market investor sentiment. We finally selected stock price amplitude (*PA*), market turnover volume (*TURN*), realized range volatility (*RRA*), market main net flow (*MMNetFlow*), and individual stock trading imbalance indicators (*Unbalance*) to construct the market-based investor sentiment. This paper's stock market trading data stand from the CSMAR platform and Choice platform, and the data span from January 1, 2014, to December 31, 2020.

1. Selection of market-based proxies for investor sentiment

(1) Stock Price Amplitude (*PA*)

Stock price amplitude (*PA*) is an indicator of the daily price movement of a stock, which shows to some extent, how active the stock is. If the *PA* is low, the stock is not active enough, and vice versa, the stock is more active. The definition of this indicator is:

$$PA = \frac{Abs(P_{max} - P_{min})}{P_{close\_1}} \tag{1}$$

Where, $PA$ indicates the stock price amplitude, $P_{min}$ indicates the maximum daily price, $P_{min}$ indicates the minimum daily price, and $P_{close\_1}$ indicates the stock's closing price on the previous day. This indicator indicates the degree of daily price volatility of the stock.

(2) Realized Range Volatility (*RRV*)

Realized range volatility (*RRV*) (ZENG & XIANG, 2016) is a method of estimating realized volatility based on price extremes, which is an effective measure of the volatility effect of stocks. They segmented the high-frequency intra-day data at a specific sampling frequency and took the difference between the highest and lowest asset price in each period as the difference in price. The square of each difference was multiplied by the differencing coefficient and summed up as a measure of the asset volatility effect. They define it as volatility based on realized range. The extreme differences obtained by this method contain more comprehensive market information than the returns obtained from the two endpoints. Therefore, the estimates obtained are more accurate than those based on returns. The indicator is defined as,

$$RRV = \sum_{i=1}^{48} (H_{t,i} - L_{t,i})^2 \tag{2}$$

where, $RRV$ denotes realized extreme volatility, $H_{t,i}$ denotes the 5-minute-high price of the stock, and $L_{t,i}$ denotes the 5-minute-low price of the stock.

(3) Market Turnover Volume ($TURN$)

Market turnover volume ($TURN$) reflects some extent, the liquidity of the market (Baker & Stein, 2004; Baker & Wurgler, 2006), and in addition, it reflects the level of investor participation and reflects investor sentiment towards stocks. When investors' sentiment is high, their motivation to invest in stocks increases. The movement of the market volume reflects the speed at which investors transmit their sentiments to the financial market. Therefore, we divide the daily trading volume of the Shanghai and Shenzhen markets by the market capitalization outstanding in Shanghai and Shenzhen markets to reflect the market trading volume to exclude the effect of different trading sizes of different stocks. The indicator is defined as:

$$TURN = \frac{\sum TURN_i}{\sum MEV_i} \tag{3}$$

Where, $TURN$ denotes market turnover volume, $TURN_i$ denotes Shanghai or Shenzhen daily turnover volume, and $MEV_i$ denotes Shanghai or Shenzhen daily market exchange value.

(4) Market Main Net Inflow (*MMNetFlow*)

The market capital flow reflects the willingness of the long and short sides of the market and the gaming of the main and retail investors. By analyzing the willingness to buy and sell as well as the gaming behavior of the main and retail investors to analyze and predict the stock price behavior, it has a high reference value for investors' trading.

In China, the main flow of capital is the money that can influence the stock market and even control the stock market's short and medium-term movements. We only consider the main net flow in the Shanghai and Shenzhen markets in here. If the difference between the main inflow and outflow in the market is positive, the market is in a net inflow state on that day. If the difference between the main inflow and outflow in the market is negative, it means that the market is in a net outflow state on that day. Usually, when the market is rising, the market is often in a net inflow state, which means that the main buying power of the market is relatively large, increasing market price.

Conversely, when the market is falling, the market is often in a state of net outflow, which means that the market has a relatively enormous selling power, which leads to a decline in the market price trend. The definition of this indicator is:

$$MMNetFlow = MMInFlow_t - MMOutFlow_t \tag{4}$$

Where, $MMNetFlow$ indicates the market main net flow, $MMInFlow_t$ indicates the amount of market main capital inflow, and $MMOutFlow_t$ indicates the amount of market main capital outflow.

(5) Individual stock trading imbalance indicator (*Unbalance*)

The individual stock trading unbalance indicator (*Unbalance*) represents the intensity of investors' capital for stock trading. We refer to the methodology of Kaniel et al. (2008) and use the daily active net trading volume as an indicator of individual stock trading unbalance. The indicator is defined as:

$$Unbalance = ACTVBuy_{i,t} - ACTVSell_{i,t} \tag{5}$$

Where $Unbalance$ denotes the individual stock trading unbalance amount, $ACTVBuy_{i,t}$ denotes the active buying amount, and $ACTVSell_{i,t}$ denotes the active selling amount.

Our selected sentiment proxies cover stock volatility (*PA*, *RRV*), market turnover (*TURN*), and capital flow (*MMNetFlow*, *Unbalance*), which provide a comprehensive picture of market-based investor sentiment.

2. A method for constructing market-based investor sentiment indicators

This paper draws on the construction method of Baker and Wurgler (2006), which uses principal component analysis (PCA) to construct market-based investor sentiment indicators. Because single sentiment indicators can only reflect the sentiment level of investors for a specific market segment, they can only reflect a particular aspect of investor sentiment. Therefore, this paper uses a comprehensive investor sentiment indicator constructed by principal component analysis. Compared with a single sentiment indicator, the composite indicator can reflect the stage of market-based investor sentiment and the corresponding changes more realistically and comprehensively.

Principal Component Analysis (PCA) is a data dimensionality reduction technique (Hotelling, 1933). This method seeks to recombine multiple variables with strong correlations into a small number of mutually unrelated composite variables, from which a few fewer sum variables can be removed to reflect as much information as possible about the original variables according to actual needs. The statistical method reflects as much information about the original variables as possible. The specific model is as follows:

$$Y_i = a_{i1}X_1 + a_{i2}X_2 + a_{i3}X_3 \cdots + a_{im}X_m = A_iX; i = 1,2, \ldots, n; \quad (6)$$

$$D(Y_i) = D(A_i^1X) = A_i^1D(X)A_i = \lambda_i; A_i^1A_i = 1; A_i^1A_j = 0 \quad (7)$$

Where, $X_j$ denotes the relevant proxy indicator of investor sentiment, $Y_i$ denotes the ith principal component, and $\lambda_i$ denotes the ith principal component eigenvalue. There are mainly three methods to determine the number of extracted principal components.

(1) Eigenvalues greater than 1. In general, if the eigenvalue of a principal component is less than 1, then we consider that the principal component explains less variance in the data than the individual variables and should be excluded. The disadvantage, however, is that if the eigenvalues of some principal components in the study results are very close to 1, this method will become insignificant in suggesting the number of extracted principal components.

(2) The proportion of data variance explained. Previous studies suggest that the extracted principal components should explain at least 5-10% of the data variance, or the extracted principal components should explain at least 70-80% of the data variance cumulatively.

(3) Scree plot test. A scree plot is a plot based on the degree of explanation of the variance of the data by each principal component. The number of extracted principal components is judged by the position where the scree slope tends to level off.

In this paper, we use the second method to extract the number of principal components and follow the criterion of using the extracted principal components with a cumulative variance explanatory power greater than 80% for extraction.

3. Principal component analysis of market-based investor sentiment indicators

We subject the selected proxies of investor sentiment and their lagged terms to principal component analysis, which yields five current period indicators and their corresponding lagged terms for a total of ten indicators based on the five indicators selected above. Since each proxy variable of investor sentiment in the trading market may have some lead-lag effect, making these variables reflect investor sentiment in different periods. To determine whether lagged terms are needed, this paper introduces lagged terms by drawing on the treatment of Baker and Wurgler (2006) and YI and MAO (2009). To eliminate the effect of magnitude, all variables are standardized in this paper. The specific steps for conducting the principal component analysis method are:

First, to determine whether there is a correlation between the ten selected indicators. This step is the prerequisite for conducting PCA. If there is no correlation between the variables, it is not possible to reduce the dimensionality, and not possible to perform principal component analysis. We usually use Bartlett test of sphericity and the KMO test to check the correlation among the variables. The specific test results are as follows.

```
Determinant of the correlation matrix
Det                =     0.006


Bartlett test of sphericity

Chi-square         =          2.42e+05
Degrees of freedom =                45
p-value            =             0.000
H0: variables are not intercorrelated


Kaiser-Meyer-Olkin Measure of Sampling Adequacy
KMO               =     0.706
```

We use Bartlett's sphericity test to test whether the correlation matrix is an identity matrix, i.e., whether the variables are independent. The test starts with the correlation coefficient matrix of the variables, and the null hypothesis is that the correlation coefficient matrix is an identity matrix. Suppose the value of the statistic of the Bartlett sphericity test is considerable and the corresponding value of the probability of companionship is less than the significance level given by the user. In that case, we should reject the null hypothesis. Conversely, we cannot reject the null hypothesis. The correlation coefficient matrix may be an identity matrix, and the variables are unsuitable for principal component analysis. From the results of the Bartlett test above, the P-value is 0, and the original hypothesis of independence among the variables is rejected, indicating that the variables we have selected can be done for principal component analysis.

The KMO statistic value is used to judge the correlation between variables by comparing the simple and partial correlation coefficients between variables. When the correlation is strong, the partial correlation coefficient is much smaller than the simple correlation coefficient, and the KMO value is close to 1. $KMO \geq 0.9$ indicates that the variables are very suitable for principal component analysis. $0.8 < KMO < 0.9$ means the variables are suitable for principal component analysis. KMO above 0.7 is acceptable; 0.6 is very poor, and below 0.5 is unsuitable for factor analysis. According to the above, the KMO statistical value results are 0.706, indicating that the selected variables are acceptable for principal component analysis.

In the second step, the composite indicator is constructed to determine whether the lagged term is needed. Correlation analysis is performed with the variables to determine whether the lagged term is needed. The specific results of the correlation analysis are shown in Table 2.3.1. The correlation between the variables in column 1 and the composite indicator shows that the composite indicator has a stronger correlation with the five variables in the current period, so we only consider the current period variables when constructing the investor sentiment indicator for market trading.

In the third step, based on the results of the correlation analysis, the final selection of five variables, namely, *PA*, *TURN*, *RRV*, *MMNetFlow*, and *Unbalance*, as the component indicators, was made by principal component analysis using the criterion of 80% or more cumulative explanatory power. Moreover, the principal component scores were calculated using the variable values after promax rotation. The specific results are shown in Tables 2.3.2 to 2.3.4.

Table 2.3.2 reports the results of the principal component analysis. As can be seen from the table, the cumulative variance contribution of the first three principal components reaches 84.4%. Therefore, according to the criterion of 80% or more cumulative explanatory power, extracting the first three principal components can reflect the composite market-based investor sentiment well.

Table 2.3.3 reports the loadings matrix of each principal component. The table shows that Factor 1 has large loading values on the first three metrics and can be considered a principal component reflecting *PA*, *TURN*, and *RRV*. Factor2 has large loading values on *MMNetFlow* and *Unbalance* and can be considered a principal component reflecting *MMNetFlow* and *Unbalance*. Factor 3 has the most significant loading value on *TURN* and can be considered the principal component reflecting turn.

**Table 2.3.1 Correlation analysis of PCA.**

| | Composite index | PA | TURN | RRV | MMNetFlow | Unbalance | LPA | LTURN | LRRV | LMMNetFlow | LUnbalance |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Composite index | 1 | | | | | | | | | | |
| PA | 0.802*** | 1 | | | | | | | | | |
| TURN | 0.698*** | 0.408*** | 1 | | | | | | | | |
| RRV | 0.789*** | 0.773*** | 0.398*** | 1 | | | | | | | |
| MMNetFlow | -0.138*** | -0.210*** | -0.379*** | -0.192*** | 1 | | | | | | |
| Unbalance | 0.337*** | 0.192*** | 0.013*** | 0.085*** | 0.141*** | 1 | | | | | |
| LPA | 0.763*** | 0.592*** | 0.379*** | 0.575*** | -0.101*** | 0.079*** | 1 | | | | |
| LTURN | 0.692*** | 0.365*** | 0.910*** | 0.363*** | -0.299*** | 0.035*** | 0.424*** | 1 | | | |
| LRRV | 0.757*** | 0.563*** | 0.377*** | 0.633*** | -0.069*** | 0.055*** | 0.778*** | 0.417*** | 1 | | |
| LMMNetFlow | -0.250*** | -0.217*** | -0.283*** | -0.237*** | 0.384*** | -0.032*** | -0.204*** | -0.389*** | -0.165*** | 1 | |
| LUnbalance | 0.217*** | 0.075*** | 0.046*** | 0.046*** | -0.062*** | 0.120*** | 0.198*** | 0.016*** | 0.083*** | 0.121*** | 1 |

**Table 2.3.2 Explanatory power of each principal component under the PCA method.**

| Factor | Eigenvalue | Difference | Proportion | Cumulative |
|---|---|---|---|---|
| Factor1 | 2.239 | 1.045 | 0.448 | 0.448 |
| Factor2 | 1.194 | 0.408 | 0.239 | 0.687 |
| Factor3 | 0.786 | 0.222 | 0.157 | 0.844 |
| Factor4 | 0.563 | 0.346 | 0.113 | 0.957 |
| Factor5 | 0.218 | 0.000 | 0.043 | 1.000 |

**Table 2.3.3 Coefficients of each principal component under the PCA method.**

| Variable | Factor1 | Factor2 | Factor3 | Uniqueness |
|---|---|---|---|---|
| PA | 0.870 | 0.258 | 0.218 | 0.129 |
| TURN | 0.708 | -0.271 | -0.281 | 0.346 |
| RRV | 0.854 | 0.186 | 0.351 | 0.113 |
| MMNetFlow | -0.479 | 0.637 | 0.424 | 0.185 |
| Unbalance | 0.146 | 0.783 | -0.597 | 0.009 |

**Table 2.3.4 Rotated factor loadings and unique variances.**

| Variable | Factor1 | Factor2 | Factor3 | Uniqueness |
|---|---|---|---|---|
| PA | 0.9198 | 0.0015 | 0.0634 | 0.1293 |
| TURN | 0.2689 | -0.6674 | 0.0832 | 0.3458 |
| RRV | 0.9743 | 0.0580 | -0.0895 | 0.1125 |
| MMNetFlow | 0.1342 | 0.9335 | 0.0675 | 0.1846 |
| Unbalance | -0.0269 | 0.0281 | 0.9979 | 0.0088 |

Table 2.3.4 reports the rotated principal component loadings matrix and unique variances. Based on the rotated loadings matrix, we can write expressions for the three principal components to find the principal component scores.

$$Factor\ 1 = 0.9198 * PA + 0.2689 * TURN + 0.9743 * RRV + 0.1342 * MMNetFlow + (-0.0269) * Unbalance \tag{8}$$

$$Factor\ 2 = 0.0015 * PA + (-0.6674) * TURN + 0.0580 * RRV + 0.9335 * MMNetFlow + 0.0281 * Unbalance \tag{9}$$

$$Factor\ 3 = 0.0634 * PA + 0.0832 * TURN + (-0.0895) * RRV + 0.0675 * MMNetFlow + 0.9979 * Unbalance \tag{10}$$

We will select the above three principal components based on the criterion of 80% or more cumulative explanatory power to construct a composite market-based investor sentiment indicator. According to Table 2.3.2, using the formula, we can obtain the composite market-based investor sentiment indicator $Senti_{mkt}$ as follows.

$$Senti_{mkt} = \left(\frac{2.239}{2.239 + 1.194 + 0.786}\right) * Factor1 + \left(\frac{1.194}{2.239 + 1.194 + 0.786}\right) * Factor2 + \left(\frac{0.786}{2.239 + 1.194 + 0.786}\right) * Factor3 \quad (11)$$

Equation (11) constructs a composite market-based investor sentiment value. The coefficients of the three parameters are calculated by the PCA method to calculate the market-based investor sentiment value. Taking Vanke (0000002SZ.) as an example, the results of its investor sentiment value are shown in Figure 2.3.2.

From Figure 2.3.2, we can see that Vanke's investor sentiment shows fluctuations in the daily trading cycle for seven years from 2014 to 2020. Regarding fluctuations, the maximum value of sentiment reaches 2.822578, and the minimum value is -1.612891.

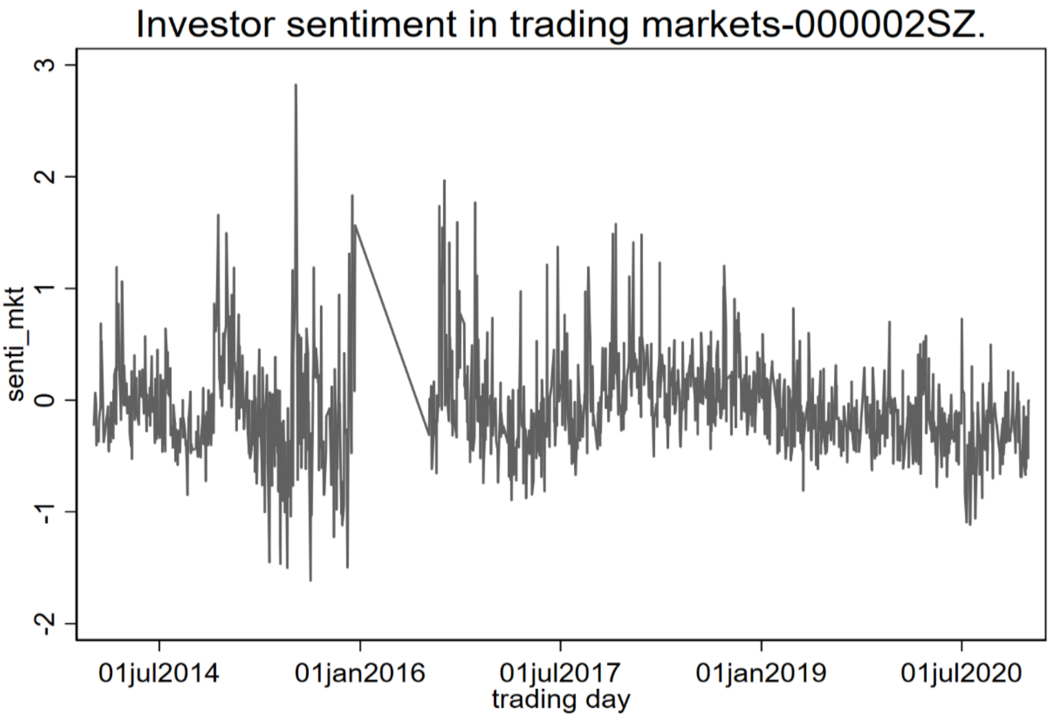


**Figure 2.3.2 Investor sentiment in trading markets-000002SZ.**

### 2.3.1.3 Sentiment Analysis of Market-based Investor Sentiment indicators

We conducted descriptive statistics on market-based investor sentiment for 176 stocks. The specific results are shown in Table 2.3.5. In Table 2.3.5, the mean value of investor sentiment in the trading market is 0, generally in a state of emotional equanimity. Regarding extreme values, the minimum value of investor sentiment based on trading is -2.513, and the maximum value is 14.669, which is highly volatile. From the percentile, the sentiment of the sample is negative at the 10%, 25%, and 50% quartiles, indicating that the overall sentiment of market-based investors tends to be negative.

On the other hand, the 75% and 90% quartiles have a more positive sentiment but do not represent a high proportion of the overall sample. At the 90% quartile, investor sentiment is 0.646, which shows that market-based investors have very few sentiment values above 1. Overall, the overall market -based investor sentiment is dominated by negative peace and sentiment.

**Table 2.3.5 Descriptive statistics of market-based indicators of investor sentiment.**

| Index | Mean | Std.Dev. | Min | Max | Variance | 10% | 25% | 50% | 75% | 90% |
|---|---|---|---|---|---|---|---|---|---|---|
| Senti_mkt | 0 | 0.576 | -2.513 | 14.669 | 0.332 | -0.559 | -0.347 | -0.094 | 0.223 | 0.646 |

### 2.3.1.4 Summary of Market-based Investor Sentiment

We select trading day individual stock trading data from January 1, 2014, to December 31, 2020, for 176 stocks in the CSI 300 Index (CSI300) constituents as the sample for constructing market-based investor sentiment indicators based on Chinese stock market cycles and data availability considerations. We conducted principal component analysis on five indicators: stock price amplitude, realized range volatility, turnover volume, market main net flow, and stock trading unbalance indicator were subjected to principal component analysis. The three indicators of price amplitude realized range volatility and turnover volume were finally selected to construct market-based investor sentiment indicators according to the criterion of cumulative variance contribution rate of 80%. Finally, a descriptive statistical analysis of the market-based investor sentiment indicators was conducted.

The work in this section completes the measurement of market-based investor sentiment, starting with the trading market, and is an essential component of the multichannel investor sentiment measurement effort. In the next section, this paper will measure investor sentiment from the financial news and stock online message board channels, starting from the Internet.

### 2.3.2 News-based and Media-based Measurements of Investor Sentiment

The Internet has become the primary source of public opinion in China today. On the one hand, investors use the fragmented time to browse online news reports and make their interpretations and adaptations after paying attention to numerous social media reports. On the other hand, professional financial websites, stock forums, and other information have become essential references for many investors in the stock market. Many professional financial news published on the Internet end, as well as investors' discussions about the stock market on stock bar forums, all reflect the honest thoughts of investors and their confidence and emotions about the stock market. The investor sentiment embedded in online news and social media texts has recently attracted much attention. Investor sentiment in such texts can have an impact on investors themselves as well as on investor communities in the "herd effect." Online news and social media have become essential channels for measuring investor sentiment(Antweiler & Frank, 2004; Kelley & Tetlock, 2017).

Therefore, we realized the measure of investor sentiment based on online news and social media channels from two perspectives: online financial news and social media, by extracting the sentiment polarity words in the texts of financial news and stock forums and message boards, according to the sentiment calculation method(Antweiler & Frank, 2004).

#### 2.3.2.1 Sample Selection of News-based and Media-based Investor Sentiment

To match with market-based investor sentiment data, we select online financial news and stock forum texts for 176 stocks in the CSI 300 Index (CSI300) constituents for trading days from January 1, 2014, to December 31, 2020. The text data are obtained from the China Research Data Service Platform (CNRDS). Specific examples are shown in Table 2.3.6.

Table 2.3.6 shows the tweets of the total number (*tpostnum*), positive number (*pospostnum*), negative number (*negpostnum*), and neutral number (*neupostnum*) in stock forums and message boards on trading day. Furthermore, can see the total online financial news number (*newsnum_cont*), positive news number (*posnews_all*), negative news number (*negnews_all*), and neutral news number(*neunews_all*).

#### 2.3.2.2 Indicator Construction for News-based and Media-based Investor Sentiment

In this paper, we define the bullish sentiment index according to the construction method of Antweiler and Frank (2004) and classify each post into bullish, bearish, and bearish. We use $pos_{i,t}$ to denote the posting volume of bullish stock *i* on day *t*, and $neg_{i,t}$ to denote the posting volume of bearish stock *i* on day *t*. The specific calculation formula is,

$$B_t^* = ln\left[\frac{1+pos_{i,t}}{1+neg_{i,t}}\right] \tag{12}$$

Where $B_t^*$>0 means bullish, $B_t^*$=0 means flat, and $B_t^*$<0 means bearish, and the indicator takes values from negative infinity to positive infinity. Taking Vanke (0000002SZ.) as an example, the results of its news-based and media-based investor sentiment values are shown in Figure 1.3.3.

Figure 2.3.3 shows the fluctuation status of the news-based and media-based investor sentiment of Vanke over a seven-year trading day cycle from 2014 to 2020. In terms of volatility, news-based investor sentiment reaches a maximum value of 2.288196 and a minimum value of -1.94591. In contrast, media-based sentiment reaches a maximum value of 2.360854 and a minimum value of -0.8919981.

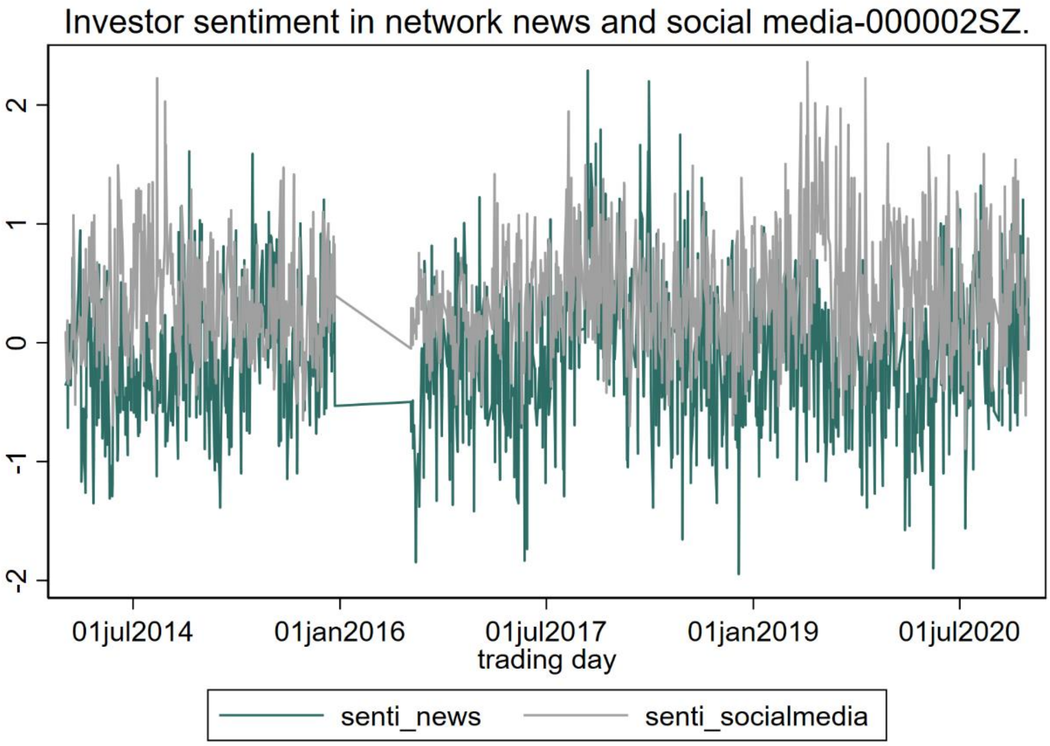


**Figure 2.3.3 Investor sentiment in network news and social media-000002SZ.**

**Table 2.3.6 Example of online financial news and stock forums and message boards statistics about sample stocks on trading days.**

| stkcd | trddt | tpostnum | pospostnu | negpostnum | neupostnum | newsnum_cont | posnews_all | negnews_all | neunews_all |
|---|---|---|---|---|---|---|---|---|---|
| 000002SZ | 2014-01-02 | 108 | 31 | 27 | 50 | 137 | 72 | 43 | 22 |
| 000002SZ | 2014-01-03 | 138 | 46 | 42 | 50 | 154 | 51 | 73 | 30 |
| 000002SZ | 2014-01-06 | 207 | 58 | 68 | 81 | 115 | 30 | 49 | 37 |
| 000002SZ | 2014-01-07 | 118 | 27 | 37 | 54 | 110 | 35 | 49 | 26 |
| 000002SZ | 2014-01-08 | 139 | 52 | 43 | 44 | 70 | 28 | 24 | 18 |
| 000002SZ | 2014-01-09 | 136 | 38 | 54 | 44 | 93 | 22 | 46 | 26 |
| 000002SZ | 2014-01-10 | 116 | 35 | 40 | 41 | 90 | 33 | 39 | 18 |
| 000002SZ | 2014-01-13 | 252 | 66 | 99 | 87 | 81 | 23 | 39 | 19 |
| 000002SZ | 2014-01-14 | 130 | 39 | 46 | 45 | 99 | 42 | 36 | 21 |
| 000002SZ | 2014-01-15 | 143 | 39 | 53 | 51 | 61 | 17 | 23 | 21 |
| 000002SZ | 2014-01-16 | 126 | 41 | 45 | 40 | 94 | 30 | 35 | 29 |
| 000002SZ | 2014-01-17 | 155 | 39 | 48 | 68 | 123 | 34 | 49 | 41 |
| 000002SZ | 2014-01-20 | 84 | 34 | 24 | 26 | 88 | 26 | 25 | 38 |
| 000002SZ | 2014-01-21 | 60 | 25 | 19 | 16 | 86 | 40 | 29 | 17 |
| 000002SZ | 2014-01-22 | 82 | 25 | 17 | 40 | 94 | 48 | 23 | 23 |
| 000002SZ | 2014-01-23 | 85 | 29 | 28 | 28 | 182 | 76 | 59 | 47 |
| … | … | … | … | … | … | … | … | … | … |
| 000002SZ | 2020-12-29 | 67 | 23 | 9 | 35 | 70 | 30 | 16 | 24 |
| 000002SZ | 2020-12-30 | 120 | 38 | 20 | 62 | 96 | 33 | 35 | 28 |
| 000002SZ | 2020-12-31 | 101 | 27 | 18 | 56 | 69 | 25 | 20 | 24 |

### 2.3.2.3 Sentiment Analysis of News-based and Media-based Investor Sentiment

We conducted descriptive statistics on news-based and media-based investor sentiment for 176 stocks. The specific results are shown in Table 2.3.7. As seen in Table 2.3.7, the mean value of investor sentiment for online news is 0.332, which is in a slightly positive sentiment state overall. Regarding extreme values, the minimum value of investor sentiment for online news is -3.714, and the maximum value is 3.784, which does not fluctuate much. In terms of percentile, the sentiment of the sample at the 50%, 75%, and 90% quartiles is positive, indicating that the investor sentiment of online news tends to be positive. The 10% and 25% quartiles are more negative but do not represent a high proportion of the overall sample. Overall, investor sentiment on online news is generally dominated by positive sentiment. Similarly, investor sentiment in social media shows a similar trend to online news, with more significant fluctuations than online news, and investor sentiment in social media is also dominated by positive sentiment overall.

**Table 2.3.7 Descriptive statistics of news-based and media-based investor sentiment.**

| Index | Mean | Std.Dev. | Min | Max | Variance | 10% | 25% | 50% | 75% | 90% |
|---|---|---|---|---|---|---|---|---|---|---|
| Senti_news | 0.332 | 0.910 | -3.714 | 3.784 | 0.829 | -0.693 | -0.288 | 0.405 | 0.916 | 1.386 |
| Senti_media | 0.347 | 0.642 | -2.773 | 5.043 | 0.412 | -0.405 | -0.074 | 0.316 | 0.693 | 1.131 |

### 2.3.2.4 Summary of News-based and Media-based Investor Sentiment

We constructed the news-based and media-based investor sentiment indicators using online financial news and social media text data for 176 stocks in the CSI 300 Index (CSI300) constituents. The trading days are from January 1, 2014, to December 31, 2020. We used Antweiler and Frank (2004) construction method and conducted their overall descriptive statistical analysis. Our preliminary findings show that news-based and media-based investor sentiment tends to be generally positive, while media-based investor sentiment is more volatile.

### 2.3.3 Hypotheses of Investor Sentiment and Stock Returns

The subject of investment behavior in the securities market is the investor. Investors make judgments based on the information they obtain, which impacts their investments. There are multiple sources of investor sentiment, mainly measured by investors' attention to trading market information, browsing financial media news, browsing and communication in stock forums and message boards, and so on. A comprehensive analysis of multiple sources of investor information and a study of sentiment corresponding to multiple sources of information can effectively reflect investor sentiment. Therefore, the measurement of multi-channel investor sentiment mainly includes trading markets, online news, and social media.

Investors will judge the stock movements based on the trading data of the market. While online financial news contains a wealth of information, investors can notice them as a possible prerequisite for market reaction. Investors can read and digest the news to understand the meaning behind the news text. By following financial news reports on specific stocks, investors can determine whether a particular stock has value as an investment. The sentiment in these financial news reports is the basis for investor sentiment. In addition, investors like to refer to other investors' opinions on stocks to increase their desire to invest. Stock forums and message boards gather many retail stockholders who communicate through social media channels, generating investor sentiment. Overall, investors obtain information from different channels such as trading markets, financial news, and stock forums, interpret the information, and translate it into investor sentiment, affecting stock market returns eventually.

(1) Market-based investor sentiment and stock returns

Investor sentiment has an essential impact on stock returns and is an important reason for the predictability of asset returns (Barberis et al., 1998). Investor sentiment in the trading market is mainly measured by stock trading volume (Baker & Wurgler, 2006; Baker et al., 2012; Brown & Cliff, 2004, 2005), stock volatility (Christensen & Podolskij, 2007; C. Hu, Liu, & Zhu, 2019; Martens & Van Dijk, 2007), capital flows (Cohen & Frazzini, 2008), and other aspects of measuring. Investor sentiment has a vital role in influencing risk decisions (Callen, Isaqzadeh, Long, & Sprenger, 2014), and when investor sentiment is high, investors tend to make optimal decisions. Investor sentiment-driven investment tendencies can cause stock prices to deviate from their underlying values, ultimately affecting expected stock returns (Ang & Bekaert, 2007; Campbell & Yogo, 2006; Giglio, Kelly, & Xiu, 2022; Rapach & Zhou, 2013).

It is generally believed that changes in investor sentiment positively affect asset prices in the short run. However, this effect gradually returns to normal, which, from an empirical perspective, means that high investor sentiment raises current stock returns, but future stock returns decline (Ni et al., 2015). Based on the above analysis, we propose the following hypothesis,

H1: In the short run, the higher the market-based investor sentiment, the higher the return on the stock.

(2) News-based investor sentiment and stock returns

With the development of big data and artificial intelligence technologies, Internet texts have become an important source for capturing investor sentiment. Internet texts can be divided into news media, social media, and company announcements. For news, the current literature focuses on mainstream financial newspapers such as The Wall

Street Journal and The New York Times as data sources for news texts (Hanna, Turner, & Walker, 2020; Tetlock, 2007). Financial news usually represents the main views of investment experts and professionally educated analysts.

The tone of news reports affects consumers and can influence investors' expectations about the future and their decision-making behavior, which in turn affects asset prices. Tetlock (2007) uses the text of popular Wall Street Journal columns to measure investor sentiment. He finds that high pessimism in news texts predicts downward pressure on market prices, followed by a return to fundamentals. In contrast, unusually high or low pessimism predicts higher market trading volume. YOU and WU (2012) use the "spiral of silence" theory in communication to explain the media effect on asset pricing. With the mighty communication power of news, the sentiment conveyed by news will resonate among investors and trigger their convergence behavior, eventually making stock pricing deviate from its fundamental value level. Hanna et al. (2020) use the tone of the Financial Times coverage as a proxy for sentiment to test whether investors react differently to sentiment in bull and bear markets. The results found that the tone of the Financial Times influenced trading volume during bull markets. News affects investors' judgments and investment decisions on the stock market, affecting stock prices and returns. Based on the above analysis, this paper proposes the following hypothesis,

H2: In the short-term, the higher the news-based investor sentiment, the higher the stock market return.

(3) Stock forums and message boards-based investor sentiment and stock returns

Compared to standard news texts, informal social media texts reflect more of the personal emotions of the content publisher and are more liberal in their expression.

Social media text data is mainly derived from Twitter (Duz Tan & Tas, 2021), Google search (Gao, Ren, & Zhang, 2020) , and stock forums and message boards (Das, 2007). The social media texts reflect mainly retail investors' discussions about the stock market and represent the investment sentiment of a wide range of individual investors.

Antweiler and Frank (2004) extracted sentiment information from 1.5 million posts about 45 companies on Yahoo Finance and RagingBull and found that the number of posts predicted stock market volatility. Leung and Ton (2015) analyzed 2.5 million posts on the Australian stock forum Hotcopper. They found that posting volume-based investor sentiment showed a significant positive relationship with contemporaneous stock returns for poor market performance and high growth but not for large-cap stocks. Danbolt, Siganos, and Vagenas-Nanos (2015) constructed text sentiment based on Facebook network information and found that text sentiment has some explanatory power for abnormal stock returns. The greater the divergence in investor sentiment, the greater the divergence in investor opinion about future stock return expectations. This result ultimately led to increased stock trading volume and stock price volatility. Whitelaw (2001) find that investors who buy and sell investment recommendations in stock forums do not contain any information that predicts sector-adjusted stock returns. Kim and Kim (2014), based on Yahoo! 3.2 million posts of 91 companies' stocks on the stock forum, found that when investors held optimistic sentiments about a stock, the stock's return had increased in the previous period. However, sentiment had no predictive power for future trading volume, return, or volatility. In addition, some studies have attempted to integrate the textual content of media information into stock trading strategies using techniques such as text analysis and machine learning to build an intelligent trading framework for automated strategies (Kratzwald, Ilić, Kraus, Feuerriegel, & Prendinger, 2018). Based on the above analysis, this paper proposes the following hypothesis,

H3: In the short-term, the higher the stock forums and message boards-based investor sentiment, the higher the stock market return.

## 2.4 Results

### 2.4.1 Model Setting

We construct a theoretical model of the impact of multi-channel investor sentiment on stock returns, divide investor sentiment into market-based sentiment, news-based sentiment, and stock forums-based sentiment, and construct the following econometric model,

$$Returns_{it} = \alpha + \beta_1 Senti_{mkt,it} + \beta_2 Senti_{news,it} + \beta_3 Senti_{media,it} + \gamma X_{it} + \mu_t + \lambda_i + \varepsilon_{it} \quad (13)$$

Equation (13) represents the impact of market-based, news-based, and media-based investor sentiment on stock returns. Where subscript $i$ denotes a sample individually, $t$ denotes a trading day, $Return_{it}$ denotes stock $i$'s return on day t, $Senti_{mkt,it}$ denotes stock $i$'s market-based investor sentiment on day $t$, $Senti_{news,it}$ denotes stock $i$'s news-based investor sentiment on day $t$, $Senti_{media,it}$ denotes stock $i$'s social media-based investor sentiment on day $t$. $X_{it}$ is a control variable for firm characteristics affecting stock returns. $\mu_t$ is a time-fixed effect, $\lambda_i$ is an individual-fixed effect, and $\varepsilon_{it}$ is a random disturbance term.

### 2.4.2 Description of Main Variables and Data Selection

(1) Explained variables. The explained variable is the return on stocks, expressed using the daily individual stock returns considering cash dividend reinvestment from the CSMAR database.

(2) Key explanatory variables. The key explanatory variables are three indicators of market-based, news-based, and stock media-based investor sentiment.

(3) Control variables. The control variables refer to the firm characteristics variables in Ali and Hirshleifer (2020) using Baker and Wurgler (Baker & Wurgler, 2006) BW portfolio and Keloharju, Linnainmaa, and Nyberg (2016) KLN portfolio, and seven control variables were selected, namely the nature logarithmic of firm market capitalization (*Stkmktvalue)*), book-to-market ratio (*BM*), net profit growth (*NetPorfitGrow*), leverage ratio (*Lev*), return on equity (*ROE*), price-to-earnings ratio (*EP*), and dividend distribution ratio (*Dvd_payout*), as shown in Table 2.4.1.

(4) Sample selection. Considering the stock market cycle and the availability of individual stock data, the sample in this paper is 176 stocks of the CSI300 index, and the sample data are selected for the trading days from January 1, 2014, to December 31, 2020, totaling 1,707 trading days. To match the trading day data with the quarterly company characteristics data, the company characteristics data of the same quarter are expanded into the trading days within the quarter to ensure the data integrity of each trading day. For example, if the *Lev* of 000002SZ is 0.794 in the first quarter of 2014, then the *Lev* of the stock is 0.794 for all trading days within the first quarter to ensure data integrity. The data for the other company characteristics are used similarly. In addition, we removed the missing values of the data after the data matching. Finally, we obtained a total of 74,694 observations.

**Table 2.4.1 Variable definition and source.**

| Variables | Definition | Source |
|---|---|---|
| Returns | Stock’s returns | CSMAR |
| Senti_mkt | Investor sentiment in the trading market | CSMAR |
| Senti_news | Investor sentiment in the online financial news | CNRDS |

| | | |
|---|---|---|
| Senti_media | Investor sentiment in the online stock forums and message boards | CNRDS |
| Stkmktvalue | The nature logarithmic of Stock Market Value | CSMAR |
| BM | Book-to-market ratio | CSMAR |
| NetPorfitGrow | Net profit growth rate | CSMAR |
| Lev | Leverage Ratio | CSMAR |
| ROE | Return on equity | CSMAR |
| EP | Earnings-to-price ratio | CSMAR |
| Dvd_payout | Dividend payout ratio | CSMAR |

### 2.4.3 Descriptive Statistics

Table 2.4.2 shows the descriptive statistics. From Table 2.4.2, we can see that the maximum daily return of individual stocks is 10.1%, the minimum is -10.1% and the fluctuation range of return is insignificant. The market-based investor sentiment fluctuates more, while the news-based and stock media-based investor sentiment fluctuate less. Except for market-based investor sentiment, which is slightly negative overall, news-based, and media-based investor sentiment is positive. In addition, the means and standard deviations of the control variables are within acceptable limits.

**Table 2.4.2 Descriptive statistics.**

| variable | N | mean | p50 | sd | min | max |
|---|---|---|---|---|---|---|
| Returns | 74694 | 0.001 | 0.000 | 0.028 | -0.101 | 0.101 |
| Senti_mkt | 74694 | -0.002 | -0.094 | 0.571 | -2.513 | 14.669 |
| Senti_news | 74694 | 0.334 | 0.405 | 0.909 | -3.714 | 3.784 |
| Senti_media | 74694 | 0.349 | 0.318 | 0.642 | -2.773 | 5.043 |
| Stkmktvalue | 74694 | 10.938 | 10.879 | 1.061 | 6.528 | 14.657 |
| BM | 74694 | 0.622 | 0.596 | 0.323 | 0.036 | 1.496 |
| Lev | 74694 | 0.500 | 0.509 | 0.194 | 0.022 | 0.895 |
| NetPorfitGrow | 74694 | 0.855 | 0.040 | 15.819 | -17.961 | 1078.776 |
| ROE | 74694 | 0.101 | 0.084 | 0.078 | 0 | 0.681 |
| EP | 74694 | 0.070 | 0.051 | 0.082 | 0 | 3.313 |
| Dvd_payout | 74694 | 0.101 | 0.000 | 0.213 | 0 | 4.020 |

### 2.4.4 Benchmark regression

After correlation analysis (see table 2.4.3 for details), it was found that the correlation coefficients of Returns and *Senti_mkt*, *Senti_news*, and *Senti_media* are 0.401, 0.163, and 0.284, respectively, all of which are significantly positively correlated at the 1% level, tentatively supporting hypotheses 1 to 3 proposed in the previous section.

We used clustered standard errors for the regressions to reduce the impact of heteroskedasticity and autocorrelation on estimation. In addition, we control for both time and individual fixed effects in the regressions to reduce endogeneity due to omitted variables. The regression analysis of the relationship between market-based, news-based, and stock media-based investor sentiment and stock returns is performed according to the benchmark regression equation (1). The results are presented in table 2.4.4.

Columns (1)-(3) in table 2.4.4 show the results of the one-dimensional regressions of market-based, news-based, and stock bar media-based investor sentiment with stock returns, respectively. This result shows that all three different channels of investor sentiment are significantly and positively related to stock returns. In the short run, the higher the market-based, news-based, and stock media-based investor sentiment, the higher the stock market returns. Columns (4)-(6) show the results of the multiple regressions with the inclusion of control variables. After adding the control variables, investor sentiment in different channels is still significantly and positively correlated with stock returns. Overall, the above results support hypotheses 1 to 3.

**Table 2.4.3 Correlation analysis of variables.**

| | Returns | Senti_mkt | Senti_news | Senti_forum | Stkmktvalue | BM | Lev | NetPorfitGlow | ROE | EP | Dvd_payout |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Returns | 1 | | | | | | | | | | |
| Senti_mkt | 0.401*** | 1 | | | | | | | | | |
| Senti_news | 0.163*** | 0.055*** | 1 | | | | | | | | |
| Senti_media | 0.284*** | 0.059*** | 0.080*** | 1 | | | | | | | |
| Stkmktvalue | 0.004 | -0.133*** | 0.006* | 0.012*** | 1 | | | | | | |
| BM | -0.031*** | -0.122*** | -0.023*** | -0.008** | 0.206*** | 1 | | | | | |
| Lev | -0.005 | 0.001 | 0.004 | -0.021*** | 0.146*** | 0.625*** | 1 | | | | |
| NetPorfitGlow | -0.005 | 0.011*** | -0.008** | -0.010*** | -0.045*** | 0.026*** | 0.014*** | 1 | | | |
| ROE | 0.005 | -0.026*** | 0.015*** | 0.017*** | 0.129*** | -0.350*** | -0.134*** | 0.041*** | 1 | | |
| EP | -0.015*** | -0.055*** | -0.037*** | 0.016*** | 0.149*** | 0.350*** | 0.260*** | 0.073*** | 0.129*** | 1 | |
| Dvd_payout | 0.009** | -0.056*** | 0.032*** | 0.007* | 0.066*** | -0.015*** | -0.075*** | -0.002 | 0.267*** | -0.051*** | 1 |

**Table 2.4.4 Benchmark regression results.**

| VARIABLES | (1)<br>FE1<br>Returns | (2)<br>FE2<br>Returns | (3)<br>FE3<br>Returns | (4)<br>FE4<br>Returns | (5)<br>FE5<br>Returns | (6)<br>FE6<br>Returns |
|---|---|---|---|---|---|---|
| Senti_mkt | 0.022*** | | | 0.022*** | | |
| | (0.001) | | | (0.001) | | |
| Senti_news | | 0.005*** | | | 0.005*** | |
| | | (0.000) | | | (0.000) | |
| Senti_media | | | 0.014*** | | | 0.014*** |
| | | | (0.001) | | | (0.001) |
| Stkmktvalue | | | | 0.001** | 0.002*** | 0.002*** |
| | | | | (0.001) | (0.000) | (0.000) |
| BM | | | | 0.004** | -0.004*** | -0.003** |
| | | | | (0.002) | (0.001) | (0.002) |
| Lev | | | | -0.005* | 0.003 | -0.001 |
| | | | | (0.003) | (0.002) | (0.002) |
| NetPorfitGrow | | | | -0.000** | 0.000 | 0.000** |
| | | | | (0.000) | (0.000) | (0.000) |
| ROE | | | | -0.004* | -0.012*** | -0.006*** |
| | | | | (0.003) | (0.002) | (0.002) |
| EP | | | | 0.002 | -0.006** | -0.009*** |
| | | | | (0.005) | (0.002) | (0.003) |
| Dvd_payout | | | | 0.003*** | 0.001*** | 0.002*** |
| | | | | (0.001) | (0.001) | (0.001) |
| Constant | 0.001*** | -0.001*** | -0.004*** | -0.016* | -0.020*** | -0.020*** |
| | (0.000) | (0.000) | (0.000) | (0.008) | (0.005) | (0.005) |
| Observations | 74,694 | 74,694 | 74,694 | 74,694 | 74,694 | 74,694 |
| Adjusted R-squared | 0.181 | 0.030 | 0.092 | 0.182 | 0.032 | 0.093 |

## 2.5 Robustness Tests

To avoid coincidence of the results caused by the data statistics, we will conduct further robustness tests to ensure the robustness of the baseline regression results.

### 2.5.1 Investor Sentiment Lagged One Period

Considering the lagged effect of investor sentiment on stock returns, we add the lagged term of the investor sentiment index from different channels to model (1) and re-run the regression test. That is,

$$Returns_{it} = \alpha + \beta_1 Senti_{mkt,it} + \beta_2 Senti_{news,it} + \beta_3 Senti_{media,it} + \delta_1 LSenti_{mkt,it} + \delta_2 LSenti_{news,it} + \delta_3 LSenti_{media,it} + \gamma X_{it} + \mu_t + \lambda_i + \varepsilon_{it} \quad (14)$$

Where, $LSenti_{mkt,it}$, $LSenti_{news,it}$, and $LSenti_{media,it}$ are the lagged one period terms of market-based investor sentiment, news-based investor sentiment, and stock bar media-based investor sentiment, respectively. The regression results are shown in table 2.5.1. After adding investor sentiment with one period lagged to model (1), there is a significant negative relationship between the lagged terms of market-based, news-based, and bar-based investor sentiment and stock returns. This result also verifies that investor sentiment changes positively affect stock returns in the short run. However, future stock returns decline, i.e., a negative relationship exists between investor sentiment and expected market returns. The result is in line with the findings of Fisher and Statman (2003), Brown and Cliff (2005), Schmeling (2009), Berger and Turtle (2015), and others.

**Table 2.5.1 Robustness test: Investor sentiment lagged one period.**

| VARIABLES | (1)<br>FE1<br>Returns | (2)<br>FE2<br>Returns | (3)<br>FE3<br>Returns |
|---|---|---|---|
| Senti_mkt | 0.025*** | | |
| | (0.001) | | |
| LSenti_mkt | -0.006*** | | |
| | (0.001) | | |
| Senti_news | | 0.005*** | |
| | | (0.000) | |
| LSenti_news | | -0.001*** | |
| | | (0.000) | |
| Senti_media | | | 0.015*** |
| | | | (0.001) |
| LSenti_media | | | -0.004*** |
| | | | (0.000) |
| Stkmktvalue | 0.001** | 0.002*** | 0.002*** |
| | (0.001) | (0.001) | (0.001) |
| BM | 0.008*** | 0.002 | 0.002 |
| | (0.002) | (0.002) | (0.002) |
| Lev | -0.006* | 0.001 | -0.001 |

| | | | |
|---|---|---|---|
| | (0.003) | (0.003) | (0.002) |
| NetPorfitGrow | -0.000* | -0.000* | -0.000 |
| | (0.000) | (0.000) | (0.000) |
| ROE | 0.003 | -0.001 | 0.003 |
| | (0.003) | (0.002) | (0.002) |
| EP | 0.007** | -0.004 | -0.009* |
| | (0.003) | (0.004) | (0.005) |
| Dvd_payout | 0.003*** | 0.001* | 0.002*** |
| | (0.001) | (0.001) | (0.001) |
| Constant | -0.017** | -0.023*** | -0.024*** |
| | (0.007) | (0.006) | (0.007) |
| | | | |
| Observations | 45,986 | 45,986 | 45,986 |
| Adjusted R-squared | 0.207 | 0.031 | 0.103 |

### 2.5.2 A U-shaped Test

To test whether there is an inverse relationship between investor sentiment and stock returns, we introduce the quadratic term of investor sentiment into the model (1) and use the quadratic term to conduct a U-shaped relationship test between investor sentiment and stock returns. The model is as follows.

$$Returns_{it} = \alpha + \beta_1 Senti_{mkt,it} + \beta_2 Senti_{news,it} + \beta_3 Senti_{media,it} + \theta_1 Senti^2_{mkt,it} + \theta_2 Senti^2_{news,it} + \theta_3 Senti^2_{media,it} + \gamma X_{it} + \mu_t + \lambda_i + \varepsilon_{it} \tag{15}$$

Where, $Senti^2_{mkt,it}$, $Senti^2_{news,it}$, and $Senti^2_{media,it}$ are the quadratic terms of market-based, news-based, and media-based investor sentiment, respectively. After adding the quadratic terms of investor sentiment into the model, the regression results (see table 2.5.2) show that the regression coefficients of $Senti_{mkt,it}$ and $Senti^2_{mkt,it}$ are 0.026 and -0.003 respectively, which are symbol opposite and significant. Similarly, the regression coefficients of $Senti_{media,it}$ and $Senti^2_{media,it}$ are also symbol opposite and significant. We can initially determine an inverted U-shaped relationship between the market-based and media-based investor sentiment and stock returns. When market-based investor sentiment and stock media-based investor sentiment rise more, the more they positively affect stock returns, but when they exceed a certain range, they reduce stock returns. In addition, the U-shaped relationship between news-based investor sentiment and stock returns does not exist.

**Table 2.5.2 Robustness test: The quadratic investor sentiment.**

| | (1) | (2) | (3) |
|---|---|---|---|
| | FE1 | FE2 | FE3 |
| VARIABLES | Returns | Returns | Returns |
| Senti_mkt | 0.026*** | | |
| | (0.001) | | |
| Senti_mkt2 | -0.003*** | | |
| | (0.001) | | |
| Senti_news | | 0.005*** | |
| | | (0.000) | |
| Senti_news2 | | -0.000 | |
| | | (0.000) | |
| Senti_media | | | 0.018*** |
| | | | (0.001) |
| Senti_media2 | | | -0.004*** |
| | | | (0.000) |
| Stkmktvalue | 0.001** | 0.002*** | 0.002*** |
| | (0.001) | (0.000) | (0.000) |
| BM | 0.007*** | -0.004*** | -0.003** |
| | (0.002) | (0.001) | (0.002) |
| Lev | -0.006** | 0.003 | -0.000 |
| | (0.003) | (0.002) | (0.002) |
| NetPorfitGrow | -0.000*** | 0.000 | 0.000** |
| | (0.000) | (0.000) | (0.000) |
| ROE | -0.003 | -0.012*** | -0.006*** |
| | (0.003) | (0.002) | (0.002) |
| EP | 0.002 | -0.006** | -0.010*** |
| | (0.005) | (0.002) | (0.003) |
| Dvd_payout | 0.003*** | 0.001*** | 0.002*** |
| | (0.001) | (0.001) | (0.001) |
| Constant | -0.015* | -0.020*** | -0.017*** |
| | (0.008) | (0.005) | (0.005) |
| Observations | 74,694 | 74,694 | 74,694 |
| Adjusted R-squared | 0.198 | 0.032 | 0.106 |

Although it has been tentatively determined that there is an inverted U-shape relationship between market-based investor sentiment and stock returns, a subsequent exact test for the existence of the inverted U-shape relationship is still needed. The null hypothesis is: Monotone or U shape, and the alternative hypothesis is: Inverse U shape. The specific results of the U-test are as follows.

**Table 2.5.3 Robustness test: U-shaped test between investor sentiment and stock returns.**

| Senti_mkt2<br>(Extreme point: 4.425091) | Lower bound | Upper bound |
|---|---|---|
| Interval | -2.513 | 14.669 |
| Slope | 0.041 | -0.061 |
| t-value | 11.372 | -3.584 |
| P>\|t\| | 0.000 | 0.000 |
| Senti_news2<br>(Extreme point: 119.8781) | Lower bound | Upper bound |
| Interval | -3.714 | 3.784 |
| Slope | 0.005 | 0. 005 |
| Senti_media2<br>(Extreme point: 2.1137) | Lower bound | Upper bound |
| Interval | -2.773 | 5.043 |
| Slope | 0.042 | -0.025 |
| t-value | 15.174 | -8.439 |
| P>\|t\| | 0.000 | 0.000 |

Table 2.5.3 shows that the extreme value points calculated by $Senti_{mkt}^2$ and $Senti_{media}^2$ are in the interval range. At the same time, the slope in the interval is of negative sign, so we can formally conclude that the relationship between $Senti_{mkt}^2$ and $Senti_{media}^2$ and stock returns is an inverted U-type relationship. Furthermore, the extreme value point $Senti_{news}^2$ is not within the interval, so we can also determine that there is no inverted U-type relationship between it and stock returns.

Finally, when market-based and media-based investor sentiment rises, the more it positively affects stock returns, but exceeding a specific interval, reduces stock returns.

### 2.5.3 Adding More Control Variables

We add more control variables to the model to minimize the endogeneity problem caused by omitted variables, including the nature logarithmic of total market value (*Marketvalue*), cash ratio (*Cash_Ratio*), return on assets (*ROA*), and fixed asset growth rate (*FixAssetGrow*). In table 2.5.4, the regression results show that investor sentiment and stock returns in the three different channels remain significantly positive after adding more control variables.

**Table 2.5.4 Robustness test: Add more control variables.**

| | (1) | (2) | (3) |
|---|---|---|---|
| | FE1 | FE2 | FE3 |
| VARIABLES | Returns | Returns | Returns |
| Senti_mkt | 0.022*** | | |
| | (0.001) | | |
| Senti_news | | 0.005*** | |
| | | (0.000) | |
| Senti_media | | | 0.014*** |
| | | | (0.001) |
| Stkmktvalue | 0.002*** | 0.002*** | 0.002*** |
| | (0.001) | (0.000) | (0.000) |
| BM | 0.003 | -0.005*** | -0.004** |
| | (0.002) | (0.002) | (0.002) |
| Lev | -0.006* | 0.001 | -0.002 |
| | (0.003) | (0.003) | (0.002) |
| NetPorfitGrow | -0.000** | 0.000 | 0.000** |
| | (0.000) | (0.000) | (0.000) |
| ROE | 0.003 | 0.000 | 0.002 |
| | (0.005) | (0.004) | (0.004) |
| EP | 0.001 | -0.007*** | -0.010*** |
| | (0.005) | (0.002) | (0.003) |
| Dvd_payout | 0.003*** | 0.002*** | 0.003*** |
| | (0.001) | (0.001) | (0.001) |
| Marketvalue | -0.000** | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) |
| Cash_ratio | 0.000 | -0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) |
| ROA | -0.015 | -0.025*** | -0.016* |
| | (0.010) | (0.008) | (0.008) |
| FixAssetGrow | 0.000 | -0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) |
| Constant | -0.017** | -0.020*** | -0.021*** |
| | (0.008) | (0.005) | (0.005) |
| Observations | 74,694 | 74,694 | 74,694 |
| Adjusted R-squared | 0.182 | 0.032 | 0.093 |

## 2.6 Heterogeneity Analyses

Did we confirm in the previous benchmark regressions and robustness tests that multi-channel investor sentiment has a significant positive effect on stock returns in the short term, but does the transmission of this mechanism differ across samples or groups? The heterogeneity analysis allows us to observe whether the empirical results are consistent with the theoretical results, which helps to prove the validity of our theoretical mechanism. Therefore, next, we run group regressions on the sample based on turnover rate and seasonal and industry segmentation criteria to test whether the benchmark regression results still hold across different samples.

### 2.6.1 Heterogeneity Analysis of Turnover Rate

A stock's turnover rate is one indicator reflecting the stock's liquidity strength and the activity of investment in market trading. The greater the turnover rate, the more active the trading is, and the more investors are involved in the trading; conversely, the trading is light, and there are more investors on the sidelines. In the Chinese industry, a daily turnover rate of 3% is usually used to determine whether a stock is actively traded. Therefore, we divided the sample into the inactive trading group (turnover rate<=3%) and the active trading group (turnover rate >3%) according to the stock daily turnover rate of 3% as the cut-off. The regression results are shown in Table 2.6.1.

**Table 2.6.1 Heterogeneity test: Turnover rate.**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | FE1 | FE2 | FE3 | FE4 | FE5 | FE6 |
| VARIABLES | Returns | Returns | Returns | Returns | Returns | Returns |
| Senti_mkt | 0.022*** | | | 0.023*** | | |
| | (0.001) | | | (0.002) | | |
| Senti_news | | 0.005*** | | | 0.010*** | |
| | | (0.000) | | | (0.002) | |
| Senti_media | | | 0.013*** | | | 0.019*** |

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | | (0.001) | | | (0.004) |
| Stkmktvalue | 0.002** | 0.002*** | 0.002*** | 0.002 | 0.002** | 0.002** |
| | (0.001) | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) |
| BM | 0.004* | -0.003** | -0.002 | -0.001 | -0.012** | -0.006 |
| | (0.002) | (0.001) | (0.002) | (0.008) | (0.006) | (0.005) |
| Lev | -0.004 | 0.003 | -0.002 | -0.008 | 0.004 | 0.006 |
| | (0.003) | (0.002) | (0.002) | (0.012) | (0.008) | (0.006) |
| NetPorfitGrow | -0.000 | 0.000 | 0.000 | -0.000 | -0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| ROE | -0.006** | -0.012*** | -0.005** | -0.000 | -0.018** | -0.018* |
| | (0.003) | (0.002) | (0.003) | (0.007) | (0.006) | (0.010) |
| EP | 0.013*** | -0.005 | -0.014* | -0.004 | -0.007* | -0.004* |
| | (0.005) | (0.003) | (0.007) | (0.006) | (0.004) | (0.002) |
| Dvd_payout | 0.004*** | 0.002*** | 0.002*** | 0.002 | 0.001 | 0.003 |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) |
| Constant | -0.017* | -0.024*** | -0.024*** | -0.014 | -0.019 | -0.028** |
| | (0.009) | (0.005) | (0.005) | (0.021) | (0.015) | (0.012) |
| Observations | 70,505 | 70,505 | 70,505 | 4,189 | 4,189 | 4,189 |
| Adjusted R-squared | 0.184 | 0.030 | 0.091 | 0.155 | 0.068 | 0.123 |

Columns (1) to (3), shows the regression results for the inactive trading group, and column (4) to (6) shows the regression results for the active group of trading. By comparing the results, it is easy to see that the regression coefficient of investor sentiment is more significant in the active group, indicating that investor sentiment in the active group has a more significant impact on stock returns than in the inactive group. The main reason is that a high turnover rate generally means that the stock has good liquidity and is relatively easy to enter and exit the market. The stock does not appear unable to buy or sell and has strong liquidity, which attracts a high level of investor attention. As a result, actively traded stocks are usually perceived by investors as having specific investment value, thus contributing to the more profound impact of investor sentiment on stock returns for these stocks. This finding is more consistent with the findings of Baker and Stein (2004).

### 2.6.2 Heterogeneity Analysis of Season

"Seasonal effect", also known as the "month effect", is the phenomenon that economic activities change regularly throughout the year with the change of seasons (months). In the U.S. stock market, there is the proverb "Sell in May and go away". In China, A-shares also have "seasonal mania". Bouman and Jacobsen (2002) find that the Sell in May phenomenon is prevalent in 36 of 37 markets, including both developed and emerging markets. World Index's performance of monthly returns between 1970 and 2003 also finds that monthly returns are significantly lower than the average for all other months from May to September, while historical average returns for these months are significantly higher than the average from November to April (except February). Hirshleifer, Jiang, and DiGiovanni (2020), in their study of cross-sectional seasonality effects on security returns, also acknowledge that specific securities outperform in the fall. Compared to developed markets, research on seasonal effects in China needs to be more cohesive. ZHANG (2005) empirically tested the seasonal effect in Shanghai and Shenzhen markets using a GARCH model based on the generalized error distribution. The study showed a seasonal and monthly effect in the A-share market, which exhibits a positive first-quarterly effect and a negative three-quarterly effect, with the highest return in January throughout the year. Guo, Luo, and Zhang (2014) also found significant January and February effects in the Chinese market by analyzing the performance of the GTA CSMAR index between 1997 and 2013, and this seasonal effect appears in all tested industries. Chui, Cheng, Chow, and Ya (2020) propose the "Eastern Halloween" effect of "May is bad, June is bad, July will be better", that is, May's returns are low, June's returns are even lower, but July bounces back to an uptrend.

Three main views explain the seasonal effect: (1) the vacation effect. The northern hemisphere usually classifies the period from May to October as summer (summer varies from country to country), during which investors usually take vacations, resulting in a high-risk aversion. The lack of market popularity leads to low returns for stocks. (2) Seasonal Affective Disorder (SAD): Kamstra, Kramer, and Levi (2003) found that people tend to become more depressed as the days get shorter in the fall and winter. This result is evidenced by increased susceptibility to sadness, fatigue, and loss of interest in social activities. Experimental psychological studies have shown that emotional depression triggers risk aversion, including financial risk. (3) Investor optimism cycle: Doeswijk (2008) suggest that analysts are overly optimistic when estimating earnings growth for the next year, thinking that “tomorrow will be better” and having positive expectations for the future. As the quarterly reports are disclosed, analysts gradually emerge from the illusion of over-optimism bias and gradually revise downward the earnings growth for the year from the second quarter onwards.

Based on the theory above, we divide the samples into four sub-samples: spring, summer, autumn, and winter. We take spring as the reference group to conduct group regression to study whether there are seasonal differences in investor sentiment and differences in investor sentiment’s impact on stock returns in different seasons. The specific results are reported in Table 2.6.2.

**Table 2.6.2 Heterogeneity test: Seasonal effect.**

| | (1) | (2) | (3) |
|---|---|---|---|
| | FE1 | FE2 | FE3 |
| VARIABLES | Returns | Returns | Returns |
| Senti_mkt | 0.022*** | | |
| | (0.001) | | |
| Senti_mkt (Summer) | 0.001*** | | |
| | (0.000) | | |
| Senti_mk t(Autumn) | -0.002*** | | |

| | | | |
|---|---|---|---|
| | (0.000) | | |
| Senti_mkt (Winter) | 0.001** | | |
| | (0.001) | | |
| Senti_news | | 0.005*** | |
| | | (0.000) | |
| Senti_news (Summer) | | -0.000 | |
| | | (0.000) | |
| Senti_news (Autumn) | | -0.001** | |
| | | (0.000) | |
| Senti_news (Winter) | | 0.001 | |
| | | (0.000) | |
| Senti_media | | | 0.014*** |
| | | | (0.001) |
| Senti_media (Summer) | 0.001*** | -0.000 | -0.001** |
| | (0.000) | (0.000) | (0.000) |
| Senti_media (Autumn) | -0.002*** | -0.001** | -0.000 |
| | (0.000) | (0.000) | (0.000) |
| Senti_media (Winter) | 0.001** | 0.001 | 0.001*** |
| | (0.001) | (0.000) | (0.000) |
| Stkmktvalue | 0.001** | 0.002*** | 0.002*** |
| | (0.001) | (0.000) | (0.000) |
| BM | 0.006*** | -0.004*** | -0.004** |
| | (0.002) | (0.002) | (0.002) |
| Lev | -0.005* | 0.003 | -0.000 |
| | (0.003) | (0.002) | (0.002) |
| NetPorfitGrow | -0.000*** | -0.000 | 0.000** |
| | (0.000) | (0.000) | (0.000) |
| ROE | -0.001 | -0.011*** | -0.011*** |
| | (0.004) | (0.003) | (0.003) |
| EP | 0.001 | -0.006** | -0.008*** |
| | (0.005) | (0.003) | (0.003) |
| Dvd_payout | -0.000 | -0.000 | 0.000 |
| | (0.001) | (0.001) | (0.001) |
| Constant | -0.016** | -0.020*** | -0.020*** |
| | (0.008) | (0.005) | (0.005) |
| Observations | 74,694 | 74,694 | 74,694 |
| Adjusted R-squared | 0.184 | 0.032 | 0.093 |

In Table 2.6.2, market-based investor sentiment in column (1) is significant in all four seasons, indicating a significant seasonal effect of market-based investor sentiment. Investor sentiment is negatively related to investment returns in the fall, i.e., investor sentiment in the trading market has a lower impact on stock returns than in other seasons. In column (2), news-based investor sentiment has a negative seasonal sensitivity in the fall, which has a lower impact on stock returns than in other seasons. In column (3), stock media-based investor sentiment has opposite seasonal effects in summer and winter, with investor sentiment having a lower impact on stock returns in summer than in the other seasons. In contrast, the opposite is true in winter. To conclude, there is a negative seasonal effect of investor sentiment in different channels in summer and autumn.

In addition to the disturbance of sentiment stemming from factors such as holidays and seasons, the seasonal effect has a different logic: one is that May to October is in the fundamental validation period, and the market faces a more significant test. At the beginning of each year, many policy highlights, an abundance of funds, and empty windows of economic data, prone to spring mania market. With the macroeconomic data in April and May, the annual report, and the quarterly report, performance into the verification period, because the market has been manic before, only the data continues to improve and better than expected, the market will continue to rise momentum. Second, the May to October in China's policy cycle in the off-season, the market sentiment could be more peaceful than in other months. The basic rhythm of the policy cycle in China is as follows: Every January to February, the local government held the "two sessions"; and the ministry held the annual work conference. March held the national "two sessions". October to November held the plenary session of the Communist Party of China, and December held the Central Economic Work Conference. In comparison, May to October is the policy off-season, mainly the implementation of the policy implementation period, which is one of the factors affecting risk appetite. To a certain extent, this also explains in more depth why investor sentiment has a negative seasonal effect in the summer and autumn.

### 2.6.3 Heterogeneity Analysis of Industry

In this paper, we group the sample by industry according to the China Securities Regulatory Commission's 2012 industry classification level one criterion to study the industry impact of investor sentiment. The regression results are reported in Table 2.6.3. Among the thirteen industries in which 176 stocks, the eight industries in which multi-channel investor sentiment significantly and positively affects stock returns. Only market-based investor sentiment significantly affects stock returns in leasing and business services ($L$). All other remaining industries have a non-significant effect of multi-channel investor sentiment on stock returns. Overall, investor sentiment in the trading market has the broadest effect on stock returns across industries, with positive and significant effects on stock returns in eight industries.

The results of the above heterogeneity tests show that the conclusion that multi-channel investor sentiment positively and significantly affects stock returns still holds even when the sample data are divided into different subsamples according to different criteria for regression analysis. The results also indicate that investors should pay sufficient attention to the impact of different channel investor sentiments on stock returns.

**Table 2.6.3 Heterogeneity test: Industry.**

| INDUSTRIES | A | B | C | D | E | F | G | I | K | L | N | P | Q |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | FE1 | FE2 | FE3 | FE4 | FE5 | FE6 | FE7 | FE8 | FE9 | FE10 | FE11 | FE12 | FE13 |
| VARIABLES | Returns | Returns | Returns | Returns | Returns | Returns | Returns | Returns | Returns | Returns | Returns | Returns | Returns |
| Senti_mkt | 0.033 | 0.018*** | 0.021*** | 0.018*** | 0.019*** | 0.021** | 0.020*** | 0.023*** | 0.023*** | 0.023** | 0.024 | 0.017 | 0.037 |
| | (0.000) | (0.002) | (0.001) | (0.002) | (0.001) | (0.004) | (0.002) | (0.002) | (0.002) | (0.001) | (0.000) | (0.000) | (0.000) |
| Senti_news | 0.001 | 0.004*** | 0.004*** | 0.003* | 0.004*** | 0.011* | 0.003*** | 0.005*** | 0.002*** | 0.003 | -0.002 | 0.004 | 0.008 |
| | (0.000) | (0.001) | (0.000) | (0.001) | (0.000) | (0.003) | (0.001) | (0.001) | (0.000) | (0.001) | (0.000) | (0.000) | (0.000) |
| Senti_media | 0.027 | 0.011*** | 0.011*** | 0.009*** | 0.011*** | 0.013** | 0.010*** | 0.017*** | 0.011*** | 0.006 | 0.006 | 0.025 | 0.011 |
| | (0.000) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) | (0.001) | (0.002) | (0.001) | (0.004) | (0.000) | (0.000) | (0.000) |
| Stkmktvalue | -0.010 | 0.004** | 0.002** | -0.003 | 0.001 | 0.025 | -0.001 | -0.003* | 0.003* | 0.026 | -0.014 | -0.080 | 0.218 |
| | (0.000) | (0.002) | (0.001) | (0.003) | (0.002) | (0.014) | (0.001) | (0.001) | (0.001) | (0.010) | (0.000) | (0.000) | (0.000) |
| BM | 0.027 | 0.011** | 0.007*** | -0.001 | -0.037 | 0.100 | 0.009 | -0.014 | -0.003 | 0.027 | -0.014 | -1.393 | -3.591 |
| | (0.000) | (0.005) | (0.003) | (0.010) | (0.028) | (0.045) | (0.008) | (0.020) | (0.007) | (0.006) | (0.000) | (0.000) | (0.000) |
| Lev | -0.121 | -0.003 | -0.010*** | -0.015 | 0.001 | -0.008 | 0.013** | -0.010 | -0.029 | -0.104 | -0.320 | 0.009 | -6.119 |
| | (0.000) | (0.008) | (0.003) | (0.009) | (0.042) | (0.015) | (0.004) | (0.006) | (0.037) | (0.081) | (0.000) | (0.000) | (0.000) |
| NetPorfitGrow | 0.012 | 0.000 | 0.000 | 0.000*** | -0.001 | -0.000 | 0.000 | -0.000 | -0.000 | 0.001** | 0.005 | 0.026 | -0.015 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| ROE | 0.035 | 0.012 | -0.006* | 0.008 | -0.011 | -0.085 | 0.010 | 0.022* | 0.011 | -0.060 | -0.029 | 0 | -1.725 |
| | (0.000) | (0.007) | (0.003) | (0.008) | (0.029) | (0.042) | (0.020) | (0.010) | (0.012) | (0.039) | (0.000) | (omitted) | (0.000) |
| EP | 0 | 0.006 | 0.004 | -0.036 | 0.085* | 0.043 | 0.124** | 0.039 | 0.033** | -0.010 | -0.031 | 0 | 15.594 |
| | (omitted) | (0.010) | (0.011) | (0.025) | (0.042) | (0.020) | (0.043) | (0.038) | (0.011) | (0.002) | (0.000) | (omitted) | (0.000) |
| Dvd_payout | 0 | -0.000 | 0.004*** | 0.005*** | 0.015** | 0.017** | 0.007* | 0.008** | -0.000 | 0.011* | 0.006 | 0 | 0.784 |
| | (omitted) | (0.001) | (0.001) | (0.001) | (0.005) | (0.004) | (0.003) | (0.003) | (0.007) | (0.002) | (0.000) | (omitted) | (0.000) |
| Constant | 0.138 | -0.063** | -0.021** | 0.048 | 0.010 | -0.299 | 0.008 | 0.028 | -0.019 | -0.254 | 0.374 | 0.881 | 0.050 |
| | (0.000) | (0.023) | (0.009) | (0.040) | (0.073) | (0.163) | (0.017) | (0.022) | (0.049) | (0.074) | (0.000) | (0.000) | (0.000) |
| Observations | 175 | 5,335 | 49,646 | 1,691 | 3,705 | 602 | 3,427 | 3,561 | 5,707 | 495 | 275 | 37 | 38 |
| Adjusted R-squared | 0.447 | 0.231 | 0.266 | 0.208 | 0.254 | 0.298 | 0.258 | 0.311 | 0.312 | 0.201 | 0.203 | 0.245 | 0.280 |

## 2.7 Discussion

Current research on investor sentiment focuses on trading market data or a single information channel, which is at variance with reality. Investors consider information from multiple channels when making stock investments. Therefore, research on investor sentiment should be considered from multiple channels and multiple dimensions to analyze investor sentiment more comprehensively.

This paper examines the relationship between market-based, news-based, and stock bar media-based investor sentiment and stock returns using 176 stocks in the CSI300 index. First, in the benchmark regression, all three different channels of investor sentiment are found to have a significant positive effect on stock returns. This benchmark regression result still holds in the robustness test. This is consistent with the results of previous studies (Fisher & Statman, 2000; McGurk, Nowak, & Hall, 2020). We also find that more active stock investors have more positive sentiment and higher stock returns. This is consistent with the theoretical prediction that investor sentiment increases stock market liquidity (Baker & Stein, 2004; Liu, 2015). There is a general seasonal effect on investor sentiment, especially in the summer and fall. Previous research suggests that stock market returns tend to be much lower in the summer and fall than in the winter and spring (Bouman & Jacobsen, 2002). This is consistent with our findings. Market-based investor sentiment has the broadest effect across industries. This is consistent with previous findings.

In our information channel selection, we only consider three main information channels, namely, the trading market, financial news, and stock forums and message boards. In addition, the impact of multi-channel investor sentiment on the stock investment is complex and diversified, and this paper only digs deeper into the impact of multi-channel investor sentiment on stock returns. Future research can integrate more information channels and continue to explore the impact mechanism of multi-channel investor sentiment on stock investment from more perspectives. Forming more useful supplements to investor sentiment-related research and, at the same time providing stock investment practice. More guidance can be drawn from this study.

### 2.8 Conclusion

Based on theoretical frameworks such as prospect theory and cognitive bias, this paper constructs a multi-channel investor sentiment based on a sample of 176 constituent stocks in the China CSI300 index from 2014-2020, using information from three different sources: trading market, financial news, and stock bar forums, and empirically tests the mechanism of the influence of multi-channel investor sentiment on stock returns. The benchmark regression found that all three different channels of investor sentiment have a significant positive effect on stock returns. This benchmark regression result still holds in the robustness test. In the robustness test, it is verified by lagging one period that multi-channel investor sentiment positively affects stock returns in the short run but plays a negative role in the long run. And the U-shaped test finds that only news-based investor sentiment does not have a U-shaped relationship with stock returns. We still find that the more market-based and stock media-based investor sentiment rises, the more it positively affects stock returns, but after a certain level, it reduces stock returns. In addition, when we add more control variables to reduce the effect of endogeneity, the benchmark regression results still hold.

In the heterogeneity analysis, we subdivide the sample data by three criteria: turnover rate, season, and industry, verifying that the benchmark regression results still hold even across different data. We find that more active stocks have more positive investor sentiment and higher stock returns. There is a general seasonal effect of investor sentiment, especially in summer and fall, with different channels of investor sentiment negatively affecting stock returns. Furthermore, among different industries, trading markets have the broadest effect on investor sentiment. Overall, the results of the heterogeneity analysis similarly support the benchmark regression results that multi-channel investor sentiment has a positive effect on stock returns. This paper provides a valuable theoretical addition to the research on investor sentiment and provides empirical evidence on the factors influencing stock returns.

## References


[1]Ahern, K. R., & Sosyura, D. (2014). Who writes the news? Corporate press releases during merger negotiations. *The Journal of Finance, 69*(1), 241-291.

[2]Ahuja, G., & Katila, R. (2001). Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic Management Journal, 22*(3), 197-220.

[3]Ailing, P., Xin, L., Jinlong, Q., & Yu, S. (2019). Can Green M&A of Heavy Polluting Enterprises Achieve Substantial Transformation under the Pressure of Media. *China Industrial Economics(in China)*(02), 174-192. doi:10.19581/j.cnki.ciejournal.20190131.005.

[4]Ali, U., & Hirshleifer, D. (2020). Shared analyst coverage: Unifying momentum spillover effects. *Journal of Financial Economics, 136*(3), 649-675. doi:https://doi.org/10.1016/j.jfineco.2019.10.007

[5]Ambec, S., & Barla, P. (2002). A theoretical foundation of the Porter hypothesis. *Economics Letters, 75*(3), 355-360.

[6]Ambec, S., & Barla, P. (2006). Can environmental regulations be good for business? An assessment of the Porter hypothesis. *Energy studies review, 14*(2).

[7]Ambec, S., & Lanoie, P. (2008). Does it pay to be green? A systematic overview. *The Academy of Management Perspectives*, 45-62.

[8]Andersen, M. S. (2007). An introductory note on the environmental economics of the circular economy. *Sustainability science, 2*(1), 133-140.

[9]Ang, A., & Bekaert, G. (2007). Stock return predictability: Is it there? *The Review of Financial Studies, 20*(3), 651-707.

[10]Angrist, J. D., & Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*: Princeton university press.

[11]Antweiler, W., & Frank, M. Z. (2004). Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards. *The Journal of Finance, 59*(3), 1259-1294. doi:10.1111/j.1540-6261.2004.00662.x

[12]Arms Jr, R. W. (1989). The Arms Index (TRIN). *Dow Jones-Irwin*.

[13]Asch, S. E. (1951). Effects of group pressure upon the modification and distortion of judgments. *Groups, leadership, and men*, 177-190.

[14]Bae, K. H., & Wang, W. (2012). What's in a "China" name? A test of investor attention hypothesis. *Financial Management, 41*(2), 429-455.

[15]Baker, M., & Stein, J. C. (2004). Market liquidity as a sentiment indicator. *Journal of Financial Markets, 7*(3), 271-299.

[16]Baker, M., Stein, J. C., & Wurgler, J. (2003). When does the market matter? Stock prices and the investment of equity-dependent firms. *The Quarterly Journal of Economics, 118*(3), 969-1005.

[17]Baker, M., & Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance, 61*(4), 1645-1680. doi:10.1111/j.1540-6261.2006.00885.x

[18]Baker, M., & Wurgler, J. (2007). Investor Sentiment in the Stock Market. *Journal of Economic Perspectives, 21*(2), 129-151. doi:10.1257/jep.21.2.129

[19]Baker, M., Wurgler, J., & Yuan, Y. (2012). Global, local, and contagious investor sentiment. *Journal of Financial Economics, 104*(2), 272-287.

[20]Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics, 49*(3), 307-343.

[21]Bartov, E., Faurel, L., & Mohanram, P. S. (2017). Can Twitter Help Predict Firm-Level Earnings and Stock Returns? *The Accounting Review, 93*(3), 25-57. doi:10.2308/accr-51865

[22]Berger, D., & Turtle, H. J. (2015). Sentiment bubbles. *Journal of Financial Markets, 23*, 59-74.

[23]Black, F. (1986). Noise. *The Journal of Finance, 41*(3), 528-543.

[24]Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy, 81*(3), 637-654.

[25]Blackman, A., Li, Z., & Liu, A. A. (2018). Efficacy of command-and-control and market-based environmental regulation in developing countries. *Annual Review of Resource Economics, 10*, 381-404.

[26]Boden, T. A., Marland, G., & Andres, R. J. (2009). Global, regional, and national fossil-fuel CO2 emissions. *Carbon dioxide information analysis center, Oak ridge national laboratory, US department of energy, Oak Ridge, Tenn., USA doi, 10*.

[27]Bouman, S., & Jacobsen, B. (2002). The Halloween indicator,"sell in May and go away": Another puzzle. *American Economic Review, 92*(5), 1618-1635.

[28]Brown, G. W., & Cliff, M. T. (2004). Investor sentiment and the near-term stock market. *Journal of Empirical Finance, 11*(1), 1-27.

[29]Brown, G. W., & Cliff, M. T. (2005). Investor sentiment and asset valuation. *The Journal of Business, 78*(2), 405-440.

[30]Brunnermeier, S. B., & Cohen, M. A. (2003). Determinants of environmental innovation in US manufacturing industries. *Journal of Environmental Economics and Management, 45*(2), 278-293.

[31]Brunnermeier, S. B., & Levinson, A. (2004). Examining the evidence on environmental regulations and industry location. *The Journal of Environment & Development, 13*(1), 6-41.

[32]BU, H., XIE, Z., LI, J.-h., & WU, J.-j. (2018). Investor sentiment extracted from internet stock message boards ank its effect on Chinese stock market. *Journal of Management Science in CHINA, 21*(04), 86-101.

[33]Bu, M., Qiao, Z., & Liu, B. (2020). Voluntary environmental regulation and firm innovation in China. *Economic Modelling, 89*, 10-18.

[34]Cai, X., Zhu, B., Zhang, H., Li, L., & Xie, M. (2020). Can direct environmental regulation promote green technology innovation in heavily polluting industries? Evidence from Chinese listed companies. *Science of The Total Environment, 746*, 140810. doi:https://doi.org/10.1016/j.scitotenv.2020.140810

[35]Callen, M., Isaqzadeh, M., Long, J. D., & Sprenger, C. (2014). Violence and risk preference: Experimental evidence from Afghanistan. *American Economic Review, 104*(1), 123-148.

[36]Campbell, J. Y., & Yogo, M. (2006). Efficient tests of stock return predictability. *Journal of Financial Economics, 81*(1), 27-60.

[37]Chakraborty, P., & Chatterjee, C. (2017). Does environmental regulation indirectly induce upstream innovation? New evidence from India. *Research Policy, 46*(5), 939-955.

[38]Changyun, W., & Jiawei, W. (2015). Media Tone, Investor Sentiment and IPO Pricing. *Journal of Financial Research (in China)*(9), 174-189.

[39]Charoenrook, A. (2005). Does sentiment matter. *Unpublished working paper. Vanderbilt University*.

[40]Chen, H., De, P., Hu, Y. J., & Hwang, B.-H. (2014). Wisdom of crowds: The value of stock opinions transmitted through social media. *The Review of Financial Studies, 27*(5), 1367-1403.

[41]Chen, Z., Hao, X., & Chen, F. (2022). Green innovation and enterprise reputation value. *Business Strategy and the Environment, n/a*(n/a). doi:https://doi.org/10.1002/bse.3213

[42]Chesbrough, H. W. (2003). *Open innovation: The new imperative for creating and profiting from technology*: Harvard Business Press.

[43]Chien, F., Kamran, H. W., Nawaz, M. A., Thach, N. N., Long, P. D., & Baloch, Z. A. (2022). Assessing the prioritization of barriers toward green innovation: small and medium enterprises Nexus. *Environment, Development and Sustainability, 24*(2), 1897-1927. doi:10.1007/s10668-021-01513-x

[44]Chintrakarn, P. (2008). Environmental regulation and US states' technical inefficiency. *Economics Letters, 100*(3), 363-365.

[45]Christensen, K., & Podolskij, M. (2007). Realized range-based estimation of integrated variance.

*Journal of Econometrics, 141*(2), 323-349.
[46]Chui, D., Cheng, W. W., Chow, S. C., & Ya, L. (2020). Eastern Halloween effect: A stochastic dominance approach. *Journal of International Financial Markets, Institutions and Money, 68*, 101241.
[47]Chung, S.-L., Hung, C.-H., & Yeh, C.-Y. (2012). When does investor sentiment predict stock returns? *Journal of Empirical Finance, 19*(2), 217-240.
[48]Clarke, R. G., & Statman, M. (1998). Bullish or bearish? *Financial Analysts Journal, 54*(3), 63-72.
[49]Cohen, L., & Frazzini, A. (2008). Economic links and predictable returns. *The Journal of Finance, 63*(4), 1977-2011.
[50]Cooper, R. G. (2011). Perspective: The Innovation Dilemma: How to Innovate When the Market Is Mature. *Journal of Product Innovation Management, 28*(s1), 2-27. doi:https://doi.org/10.1111/j.1540-5885.2011.00858.x
[51]Danbolt, J., Siganos, A., & Vagenas-Nanos, E. (2015). Investor sentiment and bidder announcement abnormal returns. *Journal of Corporate Finance, 33*, 164-179.
[52]Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under-and overreactions. *The Journal of Finance, 53*(6), 1839-1885.
[53]Das, S. R., & Chen, M. Y. (2007). Yahoo! for Amazon: Sentiment extraction from small talk on the web. *Management Science*.
[54]Dergiades, T. (2012). Do investors' sentiment dynamics affect stock returns? Evidence from the US economy. *Economics Letters, 116*(3), 404-407.
[55]Deschenes, O., Greenstone, M., & Shapiro, J. S. (2017). Defensive investments and the demand for air quality: Evidence from the NOx budget program. *American Economic Review, 107*(10), 2958-2989.
[56]Doeswijk, R. Q. (2008). The optimism cycle: Sell in May. *De Economist, 156*(2), 175-200.
[57]Dougal, C., Engelberg, J., Garcia, D., & Parsons, C. A. (2012). Journalists and the stock market. *The Review of Financial Studies, 25*(3), 639-679.
[58]Duz Tan, S., & Tas, O. (2021). Social media sentiment in international stock returns and trading activity. *Journal of Behavioral Finance, 22*(2), 221-234.
[59]Eckbo, B. E., & Norli, Ø. (2005). Liquidity risk, leverage and long-run IPO returns. *Journal of Corporate Finance, 11*(1-2), 1-35.
[60]Evans, J. S. B. (2008). Dual-processing accounts of reasoning, judgment, and social cognition. *Annu. Rev. Psychol., 59*, 255-278.
[61]Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance, 25*(2), 383-417. doi:10.2307/2325486
[62]Fang, Z., Kong, X., Sensoy, A., Cui, X., & Cheng, F. (2021). Government's awareness of environmental protection and corporate green innovation: A natural experiment from the new environmental protection law in China. *Economic Analysis and Policy, 70*, 294-312.
[63]Feng, T., Jin-yu, Z., & Hao, Z. (2021). Does Environmental Regulation Improve the Quantity and Quality of Green Innovation Evidence from the Target Responsibility System of Environmental Protection. *China Industrial Economics(in China), 2*, 136-154.
[64]Fisher, K. L., & Statman, M. (2000). Investor sentiment and stock returns. *Financial Analysts Journal, 56*(2), 16-23.
[65]Fisher, K. L., & Statman, M. (2003). Consumer confidence and stock returns. *The Journal of Portfolio Management, 30*(1), 115-127.
[66]Fong, W. M., & Toh, B. (2014). Investor sentiment and the MAX effect. *Journal of Banking & Finance, 46*, 190-201.
[67]Frydman, C., Barberis, N., Camerer, C., Bossaerts, P., & Rangel, A. (2014). Using neural data to test a theory of investor behavior: An application to realization utility. *The Journal of Finance, 69*(2), 907-946.
[68]Gao, Z., Ren, H., & Zhang, B. (2020). Googling investor sentiment around the world. *Journal of Financial and Quantitative Analysis, 55*(2), 549-580.

[69]Geelen, T., Hajda, J., & Morellec, E. (2021). Can Corporate Debt Foster Innovation and Growth? *The Review of Financial Studies, 35*(9), 4152-4200. doi:10.1093/rfs/hhab129
[70]Giglio, S., Kelly, B., & Xiu, D. (2022). Factor models, machine learning, and asset pricing. *Annual Review of Financial Economics, 14*, 337-368.
[71]Gimenez-Fernandez, E. M., Sandulli, F. D., & Bogers, M. (2020). Unpacking liabilities of newness and smallness in innovative start-ups: Investigating the differences in innovation performance between new and older small firms. *Research Policy, 49*(10), 104049. doi:https://doi.org/10.1016/j.respol.2020.104049
[72]Glushkov, D. (2006). Sentiment beta. *Available at SSRN 862444*.
[73]Goodstein, E. S., & Polasky, S. (2017). *Economics and the Environment*: John Wiley & Sons.
[74]Gray, W. B., & Shadbegian, R. J. (2003). Plant vintage, technology, and environmental regulation. *Journal of Environmental Economics and Management, 46*(3), 384-402.
[75]Greenstone, M., List, J. A., & Syverson, C. (2012). *The effects of environmental regulation on the competitiveness of US manufacturing*. Retrieved from
[76]Guo, B., Luo, X., & Zhang, Z. (2014). Sell in May and go away: Evidence from China. *Finance Research Letters, 11*(4), 362-368.
[77]Hanna, A. J., Turner, J. D., & Walker, C. B. (2020). News media and investor sentiment during bull and bear markets. *The European Journal of Finance, 26*(14), 1377-1395.
[78]Hao, M., & Zhifeng, Y. (2016). Is Chinese enterprises' patent maintenance market driven or policy driven? *Science Research Management (in China), 37*(7), 134-144.
[79]He, G., Wang, S., & Zhang, B. (2020). Watering down environmental regulation in China. *The Quarterly Journal of Economics, 135*(4), 2135-2185.
[80]He, Y., Qu, L., Wei, R., & Zhao, X. (2022). Media-based investor sentiment and stock returns: a textual analysis based on newspapers. *Applied Economics, 54*(7), 774-792.
[81]He, Z., & Ciccone, S. (2020). Too much liquidity? Seemingly excess cash for innovative firms. *Financial Review, 55*(1), 121-144. doi:https://doi.org/10.1111/fire.12210
[82]Hirshleifer, D., & Jiang, D. (2010). A financing-based misvaluation factor and the cross-section of expected returns. *The Review of Financial Studies, 23*(9), 3401-3436.
[83]Hirshleifer, D., Jiang, D., & DiGiovanni, Y. M. (2020). Mood beta and seasonalities in stock returns. *Journal of Financial Economics, 137*(1), 272-295.
[84]Hirshleifer, D., Li, J., & Yu, J. (2015). Asset pricing in production economies with extrapolative expectations. *Journal of Monetary Economics, 76*, 87-106.
[85]Hotelling, H. (1933). Analysis of a complex of statistical variables into principal components. *Journal of educational psychology, 24*(6), 417.
[86]Hou, K., Xiong, W., & Peng, L. (2009). A tale of two anomalies: The implications of investor attention for price and earnings momentum. *Available at SSRN 976394*.
[87]Hu, C., Liu, Y.-J., & Zhu, N. (2019). De-leverage and illiquidity contagion. *Journal of Banking & Finance, 102*, 1-18.
[88]Hu, J., Pan, X., & Huang, Q. (2020). Quantity or quality? The impacts of environmental regulation on firms' innovation–Quasi-natural experiment based on China's carbon emissions trading pilot. *Technological Forecasting and Social Change, 158*, 120122.
[89]Huiying, Z., & Hui, W. (2011). The Effects of Spillovers on the Enterprise's Innovation Decision Under the Premise of Innovation Uncertainty. *Journal of Xinjiang University(Philosophy and Social Sciences) (in China), 39*(5), 1-7.
[90]Hung, P.-H. (2016). Investor sentiment, order submission, and investment performance on the Taiwan Stock Exchange. *Pacific-Basin Finance Journal, 39*, 124-140.
[91]Jacobson, L. S., LaLonde, R. J., & Sullivan, D. G. (1993). Earnings losses of displaced workers. *The American economic review*, 685-709.
[92]Jaffe, A. B., Newell, R. G., & Stavins, R. N. (2002). Environmental policy and technological change. *Environmental and resource economics, 22*, 41-70.
[93]Jaffe, A. B., & Palmer, K. (1997). Environmental regulation and innovation: a panel data study.

*Review of economics and statistics, 79*(4), 610-619.
[94]Jaffe, A. B., Peterson, S. R., Portney, P. R., & Stavins, R. N. (1995). Environmental regulation and the competitiveness of US manufacturing: what does the evidence tell us? *Journal of Economic Literature, 33*(1), 132-163.
[95]Jiang, Z., Xu, C., & Zhou, J. (2023). Government environmental protection subsidies, environmental tax collection, and green innovation: evidence from listed enterprises in China. *Environmental Science and Pollution Research, 30*(2), 4627-4641.
[96]Jie, Z., & Wenping, Z. (2018). Has Catch-up Strategy of Innovation Inhibited the Quality of China's Patents? *Economic Research Journal (in China), 53*(5), 28-41.
[97]Jinglin, L., Zhen, Y., Jin, C., & Wenqing, C. (2021). Study on the Mechanism of ESG Promoting Corporate Performance:Based on thePerspective of Corporate Innovation. *Science of Science and Management of S.& T.(in China)*(09), 71-89.
[98]Kahneman, D., & Tversky, A. (1982). The psychology of preferences. *Scientific American, 246*(1), 160-173.
[99]Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2003). Winter blues: A SAD stock market cycle. *American Economic Review, 93*(1), 324-343.
[100]Kelley, E. K., & Tetlock, P. C. (2017). Retail short selling and stock prices. *The Review of Financial Studies, 30*(3), 801-834.
[101]Keloharju, M., Linnainmaa, J. T., & Nyberg, P. (2016). Return seasonalities. *The Journal of Finance, 71*(4), 1557-1590.
[102]Kemp, R., Parto, S., & Gibson, R. B. (2005). Governance for sustainable development: moving from theory to practice. *International journal of sustainable development, 8*(1-2), 12-30.
[103]Kim, S.-H., & Kim, D. (2014). Investor sentiment from internet message postings and the predictability of stock returns. *Journal of Economic Behavior & Organization, 107*, 708-729.
[104]Krass, D., Nedorezov, T., & Ovchinnikov, A. (2013). Environmental taxes and the choice of green technology. *Production and Operations Management, 22*(5), 1035-1055.
[105]Kratzwald, B., Ilić, S., Kraus, M., Feuerriegel, S., & Prendinger, H. (2018). Deep learning for affective computing: Text-based emotion recognition in decision support. *Decision Support Systems, 115*, 24-35.
[106]Krishnan, R., Yen, P., Agarwal, R., Arshinder, K., & Bajada, C. (2021). Collaborative innovation and sustainability in the food supply chain- evidence from farmer producer organisations. *Resources, Conservation and Recycling, 168*, 105253. doi:https://doi.org/10.1016/j.resconrec.2020.105253
[107]Kumar, A., & Lee, C. M. (2006). Retail investor sentiment and return comovements. *The Journal of Finance, 61*(5), 2451-2486.
[108]Kumari, J., & Mahakud, J. (2016). Investor sentiment and stock market volatility: Evidence from India. *Journal of Asia-Pacific Business, 17*(2), 173-202.
[109]Kurzban, R., Burton-Chellew, M. N., & West, S. A. (2015). The Evolution of Altruism in Humans. *Annual Review of Psychology, 66*(1), 575-599. doi:10.1146/annurev-psych-010814-015355
[110]Lanjouw, J. O., & Mody, A. (1996). Innovation and the international diffusion of environmentally responsive technology. *Research Policy, 25*(4), 549-571.
[111]Lanoie, P., Laurent-Lucchetti, J., Johnstone, N., & Ambec, S. (2011). Environmental Policy, Innovation and Performance: New Insights on the Porter Hypothesis. *Journal of Economics & Management Strategy, 20*(3), 803-842. doi:https://doi.org/10.1111/j.1530-9134.2011.00301.x
[112]Lee, C. M., Shleifer, A., & Thaler, R. H. (1991). Investor sentiment and the closed-end fund puzzle. *The Journal of Finance, 46*(1), 75-109.
[113]Lee, W. Y., Jiang, C. X., & Indro, D. C. (2002). Stock market volatility, excess returns, and the role of investor sentiment. *Journal of Banking & Finance, 26*(12), 2277-2299.

[114]Lemmon, M., & Portniaguina, E. (2006). Consumer confidence and asset prices: Some empirical evidence. *The Review of Financial Studies, 19*(4), 1499-1529.
[115]Leung, H., & Ton, T. (2015). The impact of internet stock message boards on cross-sectional returns of small-capitalization stocks. *Journal of Banking & Finance, 55*, 37-55.
[116]Ley, M., Stucki, T., & Woerter, M. (2016). The impact of energy prices on green innovation. *The Energy Journal, 37*(1).
[117]Li, H., Guo, Y., & Park, S. Y. (2017). Asymmetric Relationship between Investors' Sentiment and Stock Returns: Evidence from a Quantile Non-causality Test. *International Review of Finance, 17*(4), 617-626.
[118]Lian, G., Xu, A., & Zhu, Y. (2022). Substantive green innovation or symbolic green innovation? The impact of ER on enterprise green innovation based on the dual moderating effects. *Journal of Innovation & Knowledge, 7*(3), 100203. doi:https://doi.org/10.1016/j.jik.2022.100203
[119]Liu, S. (2015). Investor sentiment and stock market liquidity. *Journal of Behavioral Finance, 16*(1), 51-67.
[120]Long, J. B. D., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise Trader Risk in Financial Markets. *Journal of Political Economy, 98*(4), 703-738. doi:10.1086/261703
[121]Loomes, G., & Sugden, R. (1982). Regret theory: An alternative theory of rational choice under uncertainty. *The economic journal, 92*(368), 805-824.
[122]Lovely, M., & Popp, D. (2011). Trade, technology, and the environment: Does access to technology promote environmental regulation? *Journal of Environmental Economics and Management, 61*(1), 16-35.
[123]Lu, J. W., & Beamish, P. W. (2001). The internationalization and performance of SMEs. *Strategic Management Journal, 22*(6-7), 565-586.
[124]Markowitz, H. (1952). The Utility of Wealth. *Journal of Political Economy, 60*(2), 151-158. doi:10.1086/257177
[125]Martens, M., & Van Dijk, D. (2007). Measuring volatility with the realized range. *Journal of Econometrics, 138*(1), 181-207.
[126]Martínez-Ros, E., & Kunapatarawong, R. (2019). Green innovation and knowledge: The role of size. *Business Strategy and the Environment, 28*(6), 1045-1059.
[127]McGurk, Z., Nowak, A., & Hall, J. C. (2020). Stock returns and investor sentiment: textual analysis and social media. *Journal of Economics and Finance, 44*(3), 458-485. doi:10.1007/s12197-019-09494-4
[128]Mehra, R., & Sah, R. (2002). Mood fluctuations, projection bias, and volatility of equity prices. *Journal of Economic Dynamics and Control, 26*(5), 869-887.
[129]Mohr, R. D., & Saha, S. (2008). Distribution of environmental costs and benefits, additional distortions, and the porter hypothesis. *Land Economics, 84*(4), 689-700.
[130]Montero, J.-P. (2002). Market structure and environmental innovation. *Journal of applied economics, 5*(2), 293-325.
[131]Mukonza, C., & Swarts, I. (2020). The influence of green marketing strategies on business performance and corporate image in the retail sector. *Business Strategy and the Environment, 29*(3), 838-845. doi:https://doi.org/10.1002/bse.2401
[132]Nesta, L., Vona, F., & Nicolli, F. (2014). Environmental policies, competition and innovation in renewable energy. *Journal of Environmental Economics and Management, 67*(3), 396-411.
[133]Ni, Z.-X., Wang, D.-Z., & Xue, W.-J. (2015). Investor sentiment and its nonlinear effect on stock returns—New evidence from the Chinese stock market based on panel quantile regression model. *Economic Modelling, 50*, 266-274.
[134]Odean, T. (1998). Are investors reluctant to realize their losses? *The Journal of Finance, 53*(5), 1775-1798.
[135]Pai, D.-C., Tseng, C.-Y., & Liou, C.-H. (2012). Collaborative innovation in emerging economies: Case of India and China. *Innovation, 14*(3), 467-476. doi:10.5172/impp.2012.14.3.467

[136]Petroni, G., Bigliardi, B., & Galati, F. (2019). Rethinking the Porter Hypothesis: The Underappreciated Importance of Value Appropriation and Pollution Intensity. *Review of Policy Research, 36*(1), 121-140. doi:https://doi.org/10.1111/ropr.12317
[137]Petti, C., Spigarelli, F., Lv, P., & Biggeri, M. (2021). Globalization and innovation with Chinese characteristics: the case of the automotive industry. *International journal of emerging markets, 16*(2), 303-322.
[138]Pigou, A. C. (1924). *The economics of welfare*: Macmillan.
[139]Popp, D. (2002). Induced innovation and energy prices. *American Economic Review, 92*(1), 160-180.
[140]Popp, D. (2006). International innovation and diffusion of air pollution control technologies: the effects of NOX and SO2 regulation in the US, Japan, and Germany. *Journal of Environmental Economics and Management, 51*(1), 46-71.
[141]Porter, M., & Van der Linde, C. (1995). Green and competitive: ending the stalemate. *The Dynamics of the eco-efficient economy: environmental regulation and competitive advantage, 33*, 120-134.
[142]Porter, M. E. (1991). Towards a dynamic theory of strategy. *Strategic Management Journal, 12*(S2), 95-117.
[143]Porter, M. E., & Kramer, M. R. (2006). The link between competitive advantage and corporate social responsibility. *Harvard Business Review, 84*(12), 78-92.
[144]Radicic, D., & Balavac, M. (2019). In-house R&D, external R&D and cooperation breadth in Spanish manufacturing firms: is there a synergistic effect on innovation outputs? *Economics of Innovation and New Technology, 28*(6), 590-615.
[145]Rapach, D., & Zhou, G. (2013). Forecasting stock returns. In *Handbook of economic forecasting* (Vol. 2, pp. 328-383): Elsevier.
[146]Rexhäuser, S., & Rammer, C. (2014). Environmental Innovations and Firm Profitability: Unmasking the Porter Hypothesis. *Environmental and resource economics, 57*(1), 145-167. doi:10.1007/s10640-013-9671-x
[147]Ross, S. A. (1976). Options and Efficiency*. *The Quarterly Journal of Economics, 90*(1), 75-89. doi:10.2307/1886087
[148]Rubashkina, Y., Galeotti, M., & Verdolini, E. (2015). Environmental regulation and competitiveness: Empirical evidence on the Porter Hypothesis from European manufacturing sectors. *Energy Policy, 83*, 288-300. doi:https://doi.org/10.1016/j.enpol.2015.02.014
[149]Salhin, A., Sherif, M., & Jones, E. (2016). Managerial sentiment, consumer confidence and sector returns. *International Review of Financial Analysis, 47*, 24-38.
[150]Samuelson, P. A., & Nordhaus, W. D. (2009). *Macroeconomics 19e*: McGraw-Hill Higher Education, Maidenhead.
[151]Schmeling, M. (2009). Investor sentiment and stock returns: Some international evidence. *Journal of Empirical Finance, 16*(3), 394-408.
[152]Sen, P. K., Bohidar, S. K., Shrivas, Y., Sharma, C., & Modi, V. (2015). Study on innovation, research and recent development in technology for green manufacturing. *International Journal of Mechanical Engineering and Robotics Research, 4*(1), 185.
[153]Shan-cheng, H., & Lai-qun, J. (2021). Does Government R&D Subsidy Promote Strategic Innovation or Substantive Innovation?—Theoretical Models and Empirical Analysis. *R&D Management (in China), 33*(3), 109-120.
[154]Shang, L., Tan, D., Feng, S., & Zhou, W. (2022). Environmental regulation, import trade, and green technology innovation. *Environmental Science and Pollution Research, 29*(9), 12864-12874.
[155]Shaozhou, Q., Shen, L., & Jingbo, C. (2018). Do Environmental Rights Trading Schemes Induce Green Innovation? Evidence from Listed Firms in China. *Economic Research Journal (in China), 53*(12), 129-143.

[156]Sharpe, W. F. (1964). CAPITAL ASSET PRICES: A THEORY OF MARKET EQUILIBRIUM UNDER CONDITIONS OF RISK*. *The Journal of Finance, 19*(3), 425-442. doi:10.1111/j.1540-6261.1964.tb02865.x
[157]Shefrin, H. (2002). Behavioral decision making, forecasting, game theory, and role-play. *International journal of forecasting, 18*(3), 375-382.
[158]Shi, B., Feng, C., Qiu, M., & Ekeland, A. (2018). Innovation suppression and migration effect: The unintentional consequences of environmental regulation. *China Economic Review, 49*, 1-23.
[159]Shiller, R. J. (2000). Measuring bubble expectations and investor confidence. *The Journal of Psychology and Financial Markets, 1*(1), 49-60.
[160]Shleifer, A. (2000). *Inefficient markets: An introduction to behavioural finance*: Oup Oxford.
[161]Shuqiang, W., & Zhenpeng, F. (2021). Research on the Influence of Environmental Protection Charge System Improvement on the Effect of Enterprise Green Innovation-A Quasi-natural Experiment Based on the Change of Environmental Protection Fee to Tax. *Journal of industrial Technological Economics, 40*(8), 31-39.
[162]Smidt, S. (1968). A new look at the random walk hypothesis. *Journal of Financial and Quantitative Analysis, 3*(3), 235-261.
[163]Solt, M. E., & Statman, M. (1988). How useful is the sentiment index? *Financial Analysts Journal, 44*(5), 45-55.
[164]Sprenger, T. O., Tumasjan, A., Sandner, P. G., & Welpe, I. M. (2014). Tweets and Trades: the Information Content of Stock Microblogs. *European Financial Management, 20*(5), 926-957. doi:10.1111/j.1468-036x.2013.12007.x
[165]Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics, 104*(2), 288-302.
[166]Sun, J., & Huang, R. (2021, 3 Mar.). Building modernization in harmony between man and nature. *People's Daily*
[167]Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance, 62*(3), 1139-1168.
[168]Thaler, R. (1980). Toward a positive theory of consumer choice. *Journal of Economic Behavior & Organization, 1*(1), 39-60.
[169]Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *Science, 185*(4157), 1124-1131.
[170]Ukko, J., Saunila, M., Rantala, T., & Havukainen, J. (2019). Sustainable development: Implications and definition for open sustainability. *Sustainable Development, 27*(3), 321-336.
[171]Van Leeuwen, G., & Mohnen, P. (2017). Revisiting the Porter hypothesis: an empirical analysis of green innovation for the Netherlands. *Economics of Innovation and New Technology, 26*(1-2), 63-77.
[172]Wagner, J. (2007). Exports and productivity: A survey of the evidence from firm-level data. *World economy, 30*(1), 60-82.
[173]Wang, C., Yang, Y., & Zhang, J. (2015). China's sectoral strategies in energy conservation and carbon mitigation. *Climate policy, 15*(sup1), S60-S80.
[174]Wang, K.-H., Umar, M., Akram, R., & Caglar, E. (2021). Is technological innovation making world" Greener"? An evidence from changing growth story of China. *Technological Forecasting and Social Change, 165*, 120516.
[175]Wang, K.-L., Sun, T.-T., Xu, R.-Y., Miao, Z., & Cheng, Y.-H. (2022). How does internet development promote urban green innovation efficiency? Evidence from China. *Technological Forecasting and Social Change, 184*, 122017. doi:https://doi.org/10.1016/j.techfore.2022.122017
[176]Wang, T., Yu, X., & Cui, N. (2020). The substitute effect of internal R&D and external

knowledge acquisition in emerging markets: an attention-based investigation. *European Journal of Marketing, 54*(5), 1117-1146.

[177]Wang, X., Zhang, T., Nathwani, J., Yang, F., & Shao, Q. (2022). Environmental regulation, technology innovation, and low carbon development: Revisiting the EKC Hypothesis, Porter Hypothesis, and Jevons' Paradox in China's iron & steel industry. *Technological Forecasting and Social Change, 176*, 121471. doi:https://doi.org/10.1016/j.techfore.2022.121471

[178]Wang, Y., Sun, X., & Guo, X. (2019). Environmental regulation and green productivity growth: Empirical evidence on the Porter Hypothesis from OECD industrial sectors. *Energy Policy, 132*, 611-619. doi:https://doi.org/10.1016/j.enpol.2019.06.016

[179]Weitzman, M. L. (1974). Prices vs. quantities. *The Review of Economic Studies, 41*(4), 477-491.

[180]Wenjing, L., & Manni, Z. (2016). Is it Substantive Innovation or Strategic Innovation?—Impact of Macroeconomic Policies on Micro-enterprises' Innovation. *Economic Research Journal (in China), 51*(4), 60-73.

[181]Whitelaw, T. (2001). News or Noise? Internet Postings and Stock Prices. *Financial Analysts Journal*.

[182]Xiang-ju, L., & Na, H. (2018). Regional competition environmental tax and enterprise green technology innovation. *China Population,Resources and Environment(in China), 28*(9), 73-81.

[183]Ye, G., Caizhen, S., & Yi, Z. (2019). Does corporate social responsibility disclosure improve the company's market performance? *Systems Engineering-Theory & Practice(in China)*(04), 881-892.

[184]YI, Z., & MAO, N. (2009). Research on measuring investor sentiment in Chinese stock market: construction of CICSI. *Journal of Financial Research (in China)*(11), 174-184.

[185]Yipan, W., & Yuan, H. (2021). Environmental Regulations,Relocation of Heavy Polluting Enterprises andCollaborative Governance Effect: Evidence Based on the Establishment ofSubsidiaries in Different Places. *Economic Science(in China)*(05), 130-145.

[186]YOU, J., & WU, J. (2012). Spiral of Silence: Media Sentiment and the Asset Mispricing. *Economic Research Journal (in China), 7*, 141-152.

[187]Youliang, J., Junren, G., & Huixiang, Z. (2020). Does "Environmental Protection Fees Replaced with Environmental ProtectionTaxes" Affect Corporate Performance? *Accounting Research(in China)*(5), 117-133.

[188]Yu, J., & Yuan, Y. (2011). Investor sentiment and the mean–variance relation. *Journal of Financial Economics, 100*(2), 367-381.

[189]Yuan, B., & Xiang, Q. (2018). Environmental regulation, industrial innovation and green development of Chinese manufacturing: Based on an extended CDM model. *Journal of Cleaner Production, 176*, 895-908.

[190]Yuan, B., & Zhang, Y. (2020). Flexible environmental policy, technological innovation and sustainable development of China's industry: The moderating effect of environment regulatory enforcement. *Journal of Cleaner Production, 243*, 118543. doi:https://doi.org/10.1016/j.jclepro.2019.118543

[191]ZENG, Y., & XIANG, X. (2016). An Extension to Stochastic Volatility Model: the Theory and Empirical Analysis of Chinese Stock Market. *China Economic Quarterly, 15*(4), 205-228.

[192]ZHANG, B. (2005). Research on calendar effect of Chinese stock market: a method based on rolling sample test. *Journal of Financial Research (in China), 07*, 33-44.

[193]Zhengge, T., & Renjun, S. (2015). Can Emissions Trading Scheme Achieve the Porter Effect in China? *Economic Research Journal (in China), 50*(7), 160-173.

[194]Zhifan, L., Jinmin, D., & Xiaoxuan, L. (2021). Helping Hand or Punching Fist?How Stock Liquidity Affects Corporate Innovation in China. *Finance Research (in China), 489*(3), 188-206.

[195]Zhongfeng, S., Hairong, W., & Wenhong, Z. (2016). Synergizing independent and cooperative

R&D activities: The effect of absorptive capacity. *Science Research Management (in China), 37*(11), 11-17.

[196]Zhou, G. (2018). Measuring Investor Sentiment. *Annual Review of Financial Economics, 10*(1), 239-259. doi:10.1146/annurev-financial-110217-022725

[197]Zweig, M. E. (1973). An investor expectations stock price predictive model using closed-end fund premiums. *The Journal of Finance, 28*(1), 67-78.

# Appendix

**Appendix 1 List of sample stocks.**

| No. | Stock code | Avg. annual turnover rate | Industry | Ind. code | No. | Stock code | Avg. annual turnover rate | Industry | Ind. code |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 000002.SZ | 1.032 | Real estate | K | 89 | 600050.SH | 0.899 | Information transmission, software, and information technology services | I |
| 2 | 000063.SZ | 2.329 | Manufacturing | C | 90 | 600085.SH | 0.833 | Manufacturing | C |
| 3 | 000066.SZ | 2.396 | Manufacturing | C | 91 | 600089.SH | 1.844 | Manufacturing | C |
| 4 | 000069.SZ | 1.269 | Water conservancy, environment, and public facilities management | N | 92 | 600104.SH | 0.319 | Manufacturing | C |
| 5 | 000100.SZ | 2.339 | Manufacturing | C | 93 | 600111.SH | 2.581 | Manufacturing | C |
| 6 | 000157.SZ | 1.176 | Manufacturing | C | 94 | 600115.SH | 0.811 | Transportation, storage, and postal services | G |
| 7 | 000301.SZ | 1.676 | Production and supply of electricity, heat, gas, and water | D | 95 | 600132.SH | 1.002 | Manufacturing | C |
| 8 | 000333.SZ | 0.754 | Manufacturing | C | 96 | 600150.SH | 1.581 | Manufacturing | C |
| 9 | 000338.SZ | 1.749 | Manufacturing | C | 97 | 600161.SH | 1.174 | Manufacturing | C |
| 10 | 000408.SZ | 2.642 | Manufacturing | C | 98 | 600176.SH | 1.415 | Manufacturing | C |
| 11 | 000425.SZ | 1.482 | Manufacturing | C | 99 | 600183.SH | 1.679 | Manufacturing | C |
| 12 | 000538.SZ | 0.742 | Manufacturing | C | 100 | 600188.SH | 0.775 | Mining | B |
| 13 | 000568.SZ | 1.042 | Manufacturing | C | 101 | 600196.SH | 1.457 | Manufacturing | C |
| 14 | 000596.SZ | 0.995 | Manufacturing | C | 102 | 600219.SH | 1.728 | Manufacturing | C |
| 15 | 000625.SZ | 1.329 | Manufacturing | C | 103 | 600276.SH | 0.501 | Manufacturing | C |
| 16 | 000651.SZ | 1.14 | Manufacturing | C | 104 | 600309.SH | 1.213 | Manufacturing | C |
| 17 | 000661.SZ | 1.447 | Manufacturing | C | 105 | 600332.SH | 1.077 | Manufacturing | C |
| 18 | 000703.SZ | 1.078 | Manufacturing | C | 106 | 600346.SH | 1.759 | Manufacturing | C |

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| No. | Stock code | Avg. annual turnover rate | Industry | Ind. code | No. | Stock code | Avg. annual turnover rate | Industry | Ind. code |
|---|---|---|---|---|---|---|---|---|---|
| 19 | 000708.SZ | 1.303 | Manufacturing | C | 107 | 600352.SH | 1.997 | Manufacturing | C |
| 20 | 000725.SZ | 2.297 | Manufacturing | C | 108 | 600362.SH | 1.624 | Manufacturing | C |
| 21 | 000768.SZ | 1.285 | Manufacturing | C | 109 | 600383.SH | 0.772 | Real estate | K |
| 22 | 000786.SZ | 1.46 | Manufacturing | C | 110 | 600406.SH | 1.193 | Information transmission, software, and information technology services | I |
| 23 | 000792.SZ | 1.321 | Manufacturing | C | 111 | 600426.SH | 1.597 | Manufacturing | C |
| 24 | 000800.SZ | 1.728 | Manufacturing | C | 112 | 600436.SH | 0.911 | Manufacturing | C |
| 25 | 000858.SZ | 0.833 | Manufacturing | C | 113 | 600438.SH | 1.409 | Manufacturing | C |
| 26 | 000876.SZ | 1.195 | Manufacturing | C | 114 | 600460.SH | 3.705 | Manufacturing | C |
| 27 | 000877.SZ | 3.586 | Manufacturing | C | 115 | 600489.SH | 1.569 | Mining | B |
| 28 | 000895.SZ | 0.922 | Manufacturing | C | 116 | 600519.SH | 0.33 | Manufacturing | C |
| 29 | 000938.SZ | 2.375 | Manufacturing | C | 117 | 600547.SH | 1.738 | Mining | B |
| 30 | 000963.SZ | 1.042 | Wholesale and retail trade | F | 118 | 600570.SH | 2.666 | Information transmission, software, and information technology services | I |
| 31 | 000977.SZ | 2.989 | Manufacturing | C | 119 | 600584.SH | 3.755 | Manufacturing | C |
| 32 | 001979.SZ | 4.028 | Real estate | K | 120 | 600585.SH | 0.832 | Manufacturing | C |
| 33 | 002001.SZ | 1.405 | Manufacturing | C | 121 | 600588.SH | 1.427 | Information transmission, software, and information technology services | I |
| 34 | 002007.SZ | 1.476 | Manufacturing | C | 122 | 600600.SH | 0.806 | Manufacturing | C |
| 35 | 002008.SZ | 2.464 | Manufacturing | C | 123 | 600606.SH | 1.765 | Real estate | K |
| 36 | 002027.SZ | 3.006 | Leasing and business service | L | 124 | 600655.SH | 1.237 | Wholesale and retail trade | F |
| 37 | 002032.SZ | 0.423 | Manufacturing | C | 125 | 600660.SH | 0.896 | Manufacturing | C |
| 38 | 002049.SZ | 3.293 | Manufacturing | C | 126 | 600690.SH | 0.82 | Manufacturing | C |

***Continued.***

| No. | Stock code | Avg. annual turnover rate | Industry | Ind. code | No. | Stock code | Avg. annual turnover rate | Industry | Ind. code |
|---|---|---|---|---|---|---|---|---|---|
| 39 | 002050.SZ | 1.14 | Manufacturing | C | 127 | 600741.SH | 0.634 | Manufacturing | C |
| 40 | 002064.SZ | 1.584 | Manufacturing | C | 128 | 600745.SH | 2.091 | Manufacturing | C |
| 41 | 002074.SZ | 3.853 | Manufacturing | C | 129 | 600763.SH | 1.109 | Health and social work | Q |
| 42 | 002120.SZ | 2.238 | Manufacturing | C | 130 | 600795.SH | 0.882 | Production and supply of electricity, heat, gas, and water | D |
| 43 | 002129.SZ | 2.952 | Manufacturing | C | 131 | 600809.SH | 0.909 | Manufacturing | C |
| 44 | 002179.SZ | 1.212 | Manufacturing | C | 132 | 600845.SH | 0.873 | Information transmission, software and information technology services | I |
| 45 | 002202.SZ | 1.674 | Manufacturing | C | 133 | 600886.SH | 0.799 | Production and supply of electricity, heat, gas and water | D |
| 46 | 002230.SZ | 2.767 | Information transmission, software, and information technology services | I | 134 | 600887.SH | 1.151 | Manufacturing | C |
| 47 | 002236.SZ | 2.355 | Manufacturing | C | 135 | 600893.SH | 1.236 | Manufacturing | C |
| 48 | 002241.SZ | 1.904 | Manufacturing | C | 136 | 600900.SH | 0.282 | Production and supply of electricity, heat, gas, and water | D |
| 49 | 002252.SZ | 0.592 | Manufacturing | C | 137 | 600989.SH | 3.136 | Manufacturing | C |
| 50 | 002271.SZ | 1.736 | Manufacturing | C | 138 | 601006.SH | 0.358 | Transportation, storage, and postal services | G |
| 51 | 002304.SZ | 0.481 | Manufacturing | C | 139 | 601012.SH | 2.002 | Manufacturing | C |
| 52 | 002311.SZ | 0.528 | Manufacturing | C | 140 | 601021.SH | 1.311 | Transportation, storage, and postal services | G |
| 53 | 002352.SZ | 2.369 | Manufacturing | C | 141 | 601088.SH | 0.21 | Mining | B |

***Continued.***

| No. | Stock code | Avg. annual turnover rate | Industry | Ind. code | No. | Stock code | Avg. annual turnover rate | Industry | Ind. code |
|---|---|---|---|---|---|---|---|---|---|
| 54 | 002371.SZ | 2.348 | Manufacturing | C | 142 | 601100.SH | 1.34 | Manufacturing | C |
| 55 | 002410.SZ | 1.424 | Information transmission, software, and information technology services | I | 143 | 601111.SH | 0.616 | Transportation, storage, and postal services | G |
| 56 | 002414.SZ | 1.363 | Manufacturing | C | 144 | 601117.SH | 0.984 | Construction | E |
| 57 | 002415.SZ | 0.613 | Manufacturing | C | 145 | 601138.SH | 3.147 | Manufacturing | C |
| 58 | 002460.SZ | 5.969 | Manufacturing | C | 146 | 601155.SH | 3.457 | Real estate | K |
| 59 | 002466.SZ | 4.013 | Manufacturing | C | 147 | 601186.SH | 0.685 | Construction | E |
| 60 | 002475.SZ | 0.866 | Manufacturing | C | 148 | 601216.SH | 1.372 | Manufacturing | C |
| 61 | 002493.SZ | 0.386 | Manufacturing | C | 149 | 601225.SH | 2.06 | Mining | B |
| 62 | 002555.SZ | 2.941 | Manufacturing | C | 150 | 601238.SH | 0.509 | Manufacturing | C |
| 63 | 002568.SZ | 1.483 | Manufacturing | C | 151 | 601390.SH | 0.616 | Construction | E |
| 64 | 002594.SZ | 1.634 | Manufacturing | C | 152 | 601618.SH | 0.805 | Construction | E |
| 65 | 002600.SZ | 6.169 | Manufacturing | C | 153 | 601633.SH | 0.55 | Manufacturing | C |
| 66 | 002601.SZ | 2.657 | Manufacturing | C | 154 | 601668.SH | 0.782 | Construction | E |
| 67 | 002602.SZ | 1.579 | Manufacturing | C | 155 | 601669.SH | 1.973 | Construction | E |
| 68 | 002607.SZ | 3.972 | Education | P | 156 | 601766.SH | 0.611 | Manufacturing | C |
| 69 | 002648.SZ | 1.625 | Manufacturing | C | 157 | 601799.SH | 0.762 | Manufacturing | C |
| 70 | 002709.SZ | 5.196 | Manufacturing | C | 158 | 601800.SH | 1.113 | Construction | E |
| 71 | 002714.SZ | 2.042 | Agriculture, forestry, animal husbandry and fishery | A | 159 | 601808.SH | 0.449 | Mining | B |
| 72 | 002791.SZ | 3.433 | Manufacturing | C | 160 | 601857.SH | 0.055 | Mining | B |
| 73 | 002812.SZ | 4.126 | Manufacturing | C | 161 | 601877.SH | 0.6 | Manufacturing | C |
| 74 | 002821.SZ | 3.573 | Manufacturing | C | 162 | 601888.SH | 0.575 | Leasing and business service | L |
| 75 | 002841.SZ | 2.031 | Manufacturing | C | 163 | 601898.SH | 0.374 | Mining | B |
| 76 | 002916.SZ | 5.295 | Manufacturing | C | 164 | 601899.SH | 1.294 | Mining | B |

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| No. | Stock code | Avg. annual turnover rate | Industry | Ind. code | No. | Stock code | Avg. annual turnover rate | Industry | Ind. code |
|---|---|---|---|---|---|---|---|---|---|
| 77 | 002920.SZ | 2.59 | Manufacturing | C | 165 | 601966.SH | 1.911 | Manufacturing | C |
| 78 | 002938.SZ | 4.448 | Manufacturing | C | 166 | 601985.SH | 1.938 | Production and supply of electricity, heat, gas, and water | D |
| 79 | 600009.SH | 1.066 | Transportation, storage, and postal services | G | 167 | 601989.SH | 1.046 | Manufacturing | C |
| 80 | 600010.SH | 1.461 | Manufacturing | C | 168 | 603019.SH | 4.161 | Manufacturing | C |
| 81 | 600011.SH | 0.344 | Production and supply of electricity, heat, gas and water | D | 169 | 603160.SH | 2.258 | Manufacturing | C |
| 82 | 600018.SH | 0.223 | Transportation, storage, and postal services | G | 170 | 603288.SH | 0.859 | Manufacturing | C |
| 83 | 600019.SH | 0.467 | Manufacturing | C | 171 | 603369.SH | 2.46 | Manufacturing | C |
| 84 | 600025.SH | 5.567 | Production and supply of electricity, heat, gas, and water | D | 172 | 603799.SH | 5.747 | Manufacturing | C |
| 85 | 600028.SH | 0.182 | Mining | B | 173 | 603806.SH | 2.413 | Manufacturing | C |
| 86 | 600029.SH | 1.147 | Transportation, storage, and postal services | G | 174 | 603899.SH | 1.624 | Manufacturing | C |
| 87 | 600031.SH | 1.168 | Manufacturing | C | 175 | 603986.SH | 3.842 | Manufacturing | C |
| 88 | 600048.SH | 1.015 | Real estate | K | 176 | 603993.SH | 1.219 | Mining | B |

# 국문요약

이 논문은 주로 환경보호세와 생태를 의식하는 기술혁신, 다채널 투자자의 정서와 주식 수익의 관계를 연구합니다. 이 논문의 첫 번째 장은 주로 환경세와 생태를 의식하는 기술혁신 사이의 관계에 대해 논의합니다. 우리는 환경과 관련된 세금 정책이 기업의 생태를 의식하는 기술 혁신에 미치는 영향에 대해 논의했습니다. 이 연구는 환경세가 오염물질 징수 기준을 높인 지역에서 기업에게 생태를 의식하는 기술을 혁신시키게 하는 상당한 인센티브 효과가 있음을 확인했습니다. 이 정책의 영향은 비공기업, 대기업 및 심한 오염물질을 배출하지 않는 기업의 생태를 의식하는 기술 혁신에 더 중요합니다. 또한 연구에 따르면 환경세는 지속가능한 혁신과 협력적 혁신에 상당한 영향을 미치지만 상징적 혁신과 개별적 혁신에는 영향을 미치지 않는 것으로 나타났습니다. 일반적으로 혁신의 질이 향상되었으며, 혁신과 관련된 조직은 협력 기업이 주도합니다. 제 2 장에서는 다채널의 투자자 정서와 주식 수익 사이의 관계에 대해 논의합니다. 이 연구는 시장, 뉴스, 소셜미디어 기반 투자자 정서와 같은 투자자의 다른 정보 채널이 주식 수익과 메커니즘에 미치는 영향을 연구합니다. 우리는 다채널 투자자 정서가 개별 주식의 주식 수익에 긍정적이고 통계적으로 유의한 영향을 미친다는 것을 발견했습니다. 이러한 결과는 다양한 모델과 분석방식을 적용해도 일관적입니다. 상황에 따라 달라지는 관계를 보이며, 거래율, 계절 및 업계에 따라 달라집니다. 그리고 시장에 기반한 투자자 정서가 가장 넓게 영향을 미칩니다.