硕士研究生学位论文

题目：金融分析师关注提高了企业的生产率吗？

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Does Analyst Coverage Increase Firm Productivity?

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ABSTRACT

While many papers try to find the effects of finance on the real economy, the roles played by the financial analysts, one of the most important information agents in the financial market, are not well understood. In this paper, I examine the effect of analyst coverage on the total factor productivities of listed firms in the Chinese stock market. Following the methods proposed by Olley and Pakes (1996), and Levinsohn and Pertin (2003), I estimate the total factor productivities of listed firms in the Chinese A-share market. Using firm-annual observations of Chinese A-share listed companies from 2007 to 2020, I conduct a panel data fixed-effect regression, and the result shows that the total factor productivities of a firm in the future years are positively correlated with current analyst coverage. To establish the causality, I adopt an instrumental variable approach and I also use brokerage mergers and acquisitions as quasi-natural experiments to solve the potential endogeneity problems. These results show that analyst coverage leads to an increase in the productivity of firms.

Regarding the potential mechanisms of how analyst coverage affects firm productivity, I conjecture that financial analysts may influence firm productivity through two opposing mechanisms: the information mechanism and the managerial pressure mechanism. The empirical results find that two mechanisms coexist. On one hand, the result indicates that financial analysts may alleviate firms' financial constraints, promote firms' innovation activities and thus increase the total factor productivities. These findings are consistent with the information mechanism. On the other hand, I find that the positive effect of analyst coverage on firm productivity is weaker when an analyst does not severely overestimate the earnings. When financial analysts significantly overestimate the level of corporate earnings, analysts can even predict a decrease in productivity. These findings are consistent with the managerial pressure mechanism. Because financial analysts are likely to systematically overestimate the profitability of firms when they cannot maintain their independence, I argue that Chinese regulators should strengthen the regulation on the analyst.

KEYWORDS: Financial analyst, Total factor productivity, Information asymmetry, Financial friction

Content

Chapter I Introduction

1.1 Background

How does finance serve the real economy? Does the development of a country's financial sector contribute to the productivity of that country's enterprises? This is a hot topic in economics research and one of the most important concerns of our society. The outline of *the 14th Five-Year Plan* also requires China to "build the institution to let finance support to the real economy. It can be seen that serving the real economy is an important goal of China's financial industry.

The finance theory suggests that the transparency of stock market information is an important factor affecting the efficiency of the financial system. Financial analysts are important information intermediaries in the financial market and have a pivotal role. In China, there are a large number of financial practitioners engaged in financial analysis. According to the data released by China Securities Association, as of 2020, more than 3,000 financial analysts are working in China. And according to data gathered by CSMAR, from 2015 to 2020, sell-side stock analysts on the stock market published 284,900 research reports. It means that on average, one research report is published in less than 10 minutes. As a think tank for investors, financial analysts' research reports can influence the investor’s behavior, which in turn has a huge impact on the stock price.

Existing academic studies also show that financial analysts can influence the decisions of the firm they cover through a variety of mechanisms. Some of these researchers have a positive view: They argue that financial analysts can reduce the level of information asymmetry in firms (Hong et al., 2000; Frankel & Li, 2004; etc.), loose financial constraints (Brennan & Subrahmanyam, 1995; Derrien & Kecskés, 2013 etc.), and provide external monitoring of management (Yu, 2008; Luo et al, 2015; etc.). Other researchers have taken a negative view: These studies found that financial analysts systematically tend to issue reports that overestimate corporate earnings (Dugar & Nathan, 1995; Ke & Yu, 2006; et al.) and exert pressure on firms to perform, raising the the myopic problem of the management team (He & Tian, 2013; et al.).

1.2 Motivation

While researchers have found both good and bad effects of financial analysts on firms, and they have provided solid theoretical backgrounds and empirical tests, little research has focused on the productivity of the firms. A natural question is: Does financial analyst increase the productivity of the firms? If financial analysts do affect firms' productivity, through what mechanisms do these effects occur? It is worth noting that the benefits of analysts for firms do not necessarily translate into productivity. More financing, for example, does not necessarily mean higher firm productivity, because it may instead trigger overinvestment problems. If firms use cheap financing to invest heavily in low-productivity activities, their productivity will decrease. To answer this question, To et al. (2018) estimate the total factor productivity (TFP) of U.S. public firms. Their empirical results find that analyst coverage increases the TFP of U.S. public firms. After searching the literature, I find that few scholars have yet studied the relationship between financial analyst coverage and TFP in the Chinese market. The existing literature also suggests that the impact of financial analysts on listed firms may differ between China and the US: For example, He and Tian (2013) find that financial analyst coverage in the US stock market leads to a decline in the number of corporate patents, while Yu et al. (2017) find that analyst in the Chinese stock market leads to an increase of patent filled by firms the Chinese stock market. Therefore, this paper tries to study the relationship between financial analyst coverage and the TFP of public firms in the Chinese stock market.

The light regulation and low independence of financial analysts in China add unique value to this paper. Developed countries generally have heavy regulations for financial analysts. In the United States, in order to maintain the independence of analysts, U.S. law requires institutional and physical segregation of the analyst division from other businesses of the brokerage firm. Violators face serious penalties. The regulations on financial analysts in the European Union are even stricter: *The Markets in Financial Instruments Directive II* (*MiFID II*), which came into force in the EU on January 3, 2018, requires investment institutions to pay analysts separately from the commission fee because the bundling payment of analyst fee and commission fee can lead to a loss of independence. (Xue et al., 2022). This means that the "research-for-commission" or soft dollar business model in China and the US is no longer legal in the European Union since 2018. The regulation of financial analysts in China is relatively loose, and the penalties for violation are far less severe than those in Europe and the US. In recent years, various financial analyst scandals have occurred, such as the "graphite mining scandal" of Xiangcai Securities in 2011, the "photo scandal" of Founder Securities in 2018, and the "research report scandal" of Guosen Securities in 2020.

What are the consequences if analysts cannot maintain independence? A large body of literature has found that if analysts fail to maintain independence, they produce biased reports that systematically overestimate the profitability of firms (Dugar & Nathan, 1995; Hong & Kubi, 2003; Ke & Yu, 2006; Cao & Zhu, 2011; Zhao et al, 2013; etc.). My research further finds that when financial analysts significantly overestimate firm profitability, the more analysts focus on a firm, the lower the future productivity of that firm. This suggests that if analysts lack independence, then the reports they issue are likely to be unhelpful or even harmful to the productivity of the real economy.

1.3 Research Methodology and Main Findings

This paper would like to answer the following research questions: Does financial analyst coverage improve the TFP of Chinese listed firms? If the financial analyst leads to changes in the TFP, through what mechanisms do such changes occur?

To measure the productivity of firms, I use the method proposed by Olley and Pakes (1996) and Levinsohn and Pertin (2003). I estimated the TFP of A-share listed firms in China from 2007 to 2020 using Stata software. This paper also constructs a series of variables measuring firms' financial constraints and firm innovation for studying the potential channels. In particular, when measuring corporate innovation, I not only consider the number of patents of listed companies but also use the patent citation data from Google Patent to measure the quality of patents issued by listed companies. This is a contribution to the existing literature studying corporate innovation in China.

This paper first investigates the relationship between financial analysts and TFP using fixed-effect regression analysis. Considering possible endogeneity, I test the main results of the benchmark regression using the instrumental variables approach and a natural experiment approach.

The results of this paper indicate that financial analyst in the Chinese stock market improves the TFP of firms. Further, I find that financial analyst coverage may improve firm TFP through two channels: reducing firms' financing constraints and increasing firms' innovation. In addition, this paper also finds that the effect of analyst coverage on improving firm TFP is more significant when analysts underestimate the level of firm profitability. When financial analysts significantly overestimate the level of corporate earnings, the more analyst coverage on a firm, the lower the future TFP of that firm. These results suggest that managerial pressure mechanism may also exist in China.

1.4 Contributions

(1) Although there is a large existing literature that focuses on financial analysts and TFP, I find that there are few papers on the impact of financial analysts on the TFP in the Chinese stock market. To et al. (2018) conducted an empirical study on the impact of financial analysts on the TFP in the U.S. market. This paper adopts their research methodology and finds a positive impact of financial analysts on firm TFP, which enriches the related literature.

(2) In this paper, empirical studies are conducted to verify the mechanisms between financial analysts and TFP, including the information mechanism and the managerial pressure mechanism. Regarding the information mechanism, the empirical study on the information mechanism finds that analyst coverage can improve firm TFP through two channels: reducing firm financing constraints and increasing firm innovation. In addition to the mechanisms found by To et al. (2018), this paper provides support for the managerial pressure mechanism of financial analysts. This paper finds that the more financial analysts overestimate the profitability of firms, the weaker the analysts' effect on total factor productivity improvement. When financial analysts significantly overestimate the profitability of a firm, the more analyst coverage on a firm, the lower the future total factor productivity of this firm. These findings provide some insights for China's financial regulators: Existing studies have found that analysts in China may systematically give forecasts that overestimate corporate earnings for the benefit of their employers and the management team of listed companies. Thus, the empirical analysis of the managerial pressure mechanism in this paper emphasizes the importance of analyst independence. Based on this analysis, this paper argues that China's financial regulators should strengthen the regulation of financial analysts.

1.5 Thesis Structure

The paper is divided into eight main chapters: Chapter I introduces the background and the motivations, and provides an overview of the research methodology and findings. Chapter II is a literature review, which focuses on the studies of analyst coverage and TFP. Chapter III provides the theoretical analysis and empirical hypotheses. This chapter analyzes the theories on how financial analysts can have an impact on firm TFP and develops empirical hypotheses that can be tested. Chapter IV introduces the sample and variables used in this paper. Chapter V disucsses the methods used in the empirical analysis of this paper, including panel fixed effects regression, panel instrumental variables estimation, and quasi-natural experiment of brokerage mergers. In Chapter VI, I show the main empirical findings of this paper. Chapter VII covers the robustness tests in which the robustness of my main findings is supported. Chapter VIII summarizes the main findings of this paper, discusses the policy implication, and provides an outlook on the possible of further research.

In addition, the paper contains an appendix: Appendix A of the paper provides a detailed discussion of the estimation methods for the TFP, the core variable of the paper.

Chapter II　Literature Review

In this chapter, I provide a review of the relevant existing literature. This paper examines the impact of financial analysts on firm productivity and the potential mechanisms. Therefore, in section 2.1 of this chapter, I review the existing literature on financial analysts and discover the possible impact of analysts on the firms. Subsequently, in section 2.2 of this chapter, I briefly introduce the concept of total factor productivity (TFP) and review the estimation method of firm TFP. In addition, I summarize the founded factors related to firm TFP.

2.1　Financial Analyst

Financial analysts are important information intermediaries in the financial markets. This paper focuses on stock market analysts. Their daily works are to gather and analyze the information of the stock market and companies and write research reports based on the information and the analyst's professional judgment. In the report, stock analysts forecast financial indicators such as earnings per share (EPS), determine a reasonable range of stock prices, and give investors recommendations for each stock, such as "buy", "hold", "sell", etc.

Hired by different employers, financial analysts can be divided into buy-side analysts and sell-side analysts. A small fraction of financial analysts is buy-side analysts. They are directly employed by institutional investors, mainly working in funds, venture capitals, asset management companies, and other investment institutions. Buy-side analysts provide their research results only to his or her employer and keep the findings strictly confidential to the public. In contrast, the vast majority of financial analysts are sell-side analysts employed by the research departments of brokerage houses or multi-business investment banks. They publicly release research reports to the market and recommend stocks with investment value to investors. After investors are served, they will pay a portion of the commission to the analysts.

Since the vast majority of financial analysts in both China and developed countries are sell-side analysts, and since buy-side analysts do not publicly release their data so their data is unavailable, existing studies generally focus only on sell-side analysts (i.e. He & Tian, 2013; To et al., 2018; Guo et al., 2019; etc.). The existing literature finds that sell-side analysts can have an impact on the firms under focus through multiple channels.

2.1.1 Analyst and Information Asymmetry

Currently, there is a large body of academic research focusing on the information transmission role of analysts in financial markets. Scholars argue that financial analysts can transmit information related to stock prices, thereby reducing the degree of information asymmetry between investors and corporate managers.

Some studies have argued that information asymmetry can generate excess returns for some investors and that financial analysts reduce thees excess returns. This phenomenon provides evidence for the information transmission role of financial analysts. For example, Hong et al. (2000) study the profitability of momentum trading strategies in the U.S. stock market from 1980 to 1996. The empirical results find poorer profits for momentum trading in stocks covered by analysts. Based on the results of Hong and Stein (1999), Hong et al. (2000) argue that the reason why momentum tradings are profitable is that information affecting stock prices is not quickly known to all trading participants, but it takes a long time to disseminate. Therefore, Hong et al. (2000) claim that analysts contribute to more rapid information dissemination. Frankel and Li (2004) study the trading volume and profitability of insider traders in the U.S. stock market between 1975 and 1997. It was found that analysts significantly reduced the trading volume and profitability of insider traders. The authors argue that insider traders with private information about firms can be profitable only if there is a high level of information asymmetry. Thus, this result suggests that financial analysts can reduce the level of information asymmetry in firms.

Durnev et al. (2003) and Durnev et al. (2004) show that if there is less idiosyncratic information about a company in the stock market, the share price of that company will rise and fall in line with the market. Therefore, the synchronization of the stock price with the market can be used as a measure of the quantity of firm information in the secondary market. Based on this study, Zhu et al. (2007) use data from 2004 to 2005 for listed companies in China and find that analyst reduces the stock price synchronization of the firm they cover. Therefore, the authors argue that financial analysts increase the information in stock prices by conveying information related to stock prices. Yi et al. (2019) further apply a machine learning approach to analyze the text of investment research reports in the Chinese stock market using data from 2009 to 2015. The results find that the richer the idiosyncratic information of the firms in the research reports, the lower the synchronization of the stock price with the market. In addition, the authors find that research reports rich in idiosyncratic information are more valued by investors and trigger stronger market price movements.

Other studies point out that financial analysts not only convey information to the financial markets but also use their expertise to interpret the information so that information becomes more understandable. For example, Huang et al. (2018) use machine learning to compare analyst reports and earnings presentations of listed companies in the U.S. stock market. Huang et al. (2018) find that analysts not only repeat information from earnings presentations but also interpret complex information. Investors give more weight to analysts' views when earnings presentations are difficult to understand.

2.1.2 Analyst and Financial Constraints

Finance theory suggests that information asymmetry between firm managers and investors can lead to principal-agent problems if it leads to the inability of firms to obtain effective financing (Stiglitz & Weiss, 1981; Myers & Majluf, 1984). Existing empirical studies have found that financial analysts' attention can prevent financing constraints in firms by reducing the degree of information asymmetry.

Brennan and Subrahmanyam (1995) use trading data of US stocks and find that the agency costs due to information asymmetry decrease significantly after the stocks of listed firms are covered by financial analysts. Derrien and Kecskés (2013) treat broker mergers as quasi-natural experiments and estimate the impact of a decline in financial analysts on firms: Their results suggest that a reduction in analyst coverage significantly depresses a firm's financing activity and reduces the level of investment. In brokerage mergers, for a firm that loses an analyst, the decline in financing equals 2.0% of total assets and the decline in investment equals 1.9% of total assets. The authors show that these effects are more pronounced in firms with high information asymmetry and severe financing constraints. Similar results were found in our study: Zhang and Lu (2007) measured the degree of financing constraints of Chinese listed firms from 2004 to 2006 using the methodology proposed by Almeida (2004). Then, they find that the higher the degree of analyst coverage, the fewer financing constraints the firm faces.

2.1.3 Analyst and Innovation

The relationship between financial analysts and corporate innovation is currently a hot research topic. Currently, there are two different views on this issue. Some researchers argue that financial analysts are overly optimistic about the short-term performance of firms and give earnings forecasts that are difficult for firms to achieve, leading to the problem of managerial myopia. He and Tian (2013) study the impact of analyst coverage on corporate patent applications in the US market. The results show that the number and quality of patents obtained by firms in the future declined significantly after analyst coverage.

In contrast, both Yu et al. (2017) and Chen et al. (2017) find that analysts in the Chinese stock market lead to an increase in the number of patents filed by firms. To explain this result, which differs from He and Tian (2013), both papers argue that the share concentration in the Chinese market is higher than in the US, which inhibits the negative effect of managerial pressure. Yu et al. (2017) argue that financial analysts can increase corporate innovation by alleviating financial constraints. Chen et al. (2017) argue that in addition to the financing constraint, analysts can increase innovation by showing the value of corporate R&D innovation to investors and reducing agency problems in R&D.

Guo et al. (2019) further investigate the effect of analyst coverage on innovation in the US stock market, and their empirical results somewhat refute the findings of He and Tian (2013): Guo et al. (2019) find that analyst coverage does reduce firms' capital investment in R&D by exerting pressure on management. However, firms choose to innovate more through mergers and acquisitions (M&A) or by corporate venture capital (CVC). The negative impact of analysts on firm innovation is no longer significant when innovation obtained from M&A and CVC are included. The authors found that although analyst leads to a decrease in innovation inputs, analyst helps to increase efficiency of firm innovation. Further, the increase in the efficiency improves the quantity and quality of firm patents as well as the novelty of firm patents.

2.1.4 Analysts' Optimistic Bias and Managerial Pressure

A large number of existing studies have found that financial analysts systematically tend to give research reports that overestimate the profitability of companies. This is at least partly because of the conflict of interest between the financial analysts' investor clients, employers, and the companies they cover. If financial analysts do not maintain independence from their employers and the listed firm they study, they are likely to produce biased investment reports.

First, analysts may overestimate the profitability of the companies they follow in the interest of their employers. The vast majority of financial analysts are sell-side analysts employed by brokerage houses or multi-business investment banks. In addition to investment analysis services, these firms usually operate other businesses, such as investment banking, which helps issue securities, and proprietary trading business, which uses the brokerage houses’ own funds to make investments in the secondary market. If a sell-side analyst issues an unfavorable profit forecast for a stock underwritten by his or her employer’s investment banking department, or heavily held by the employer’s proprietary trading department, his or her report will affect the profits of these businesses. Therefore, if sell-side analysts cannot maintain their independence, analysts may issue research reports that overestimate the profitability of firms for the profit of their employers. This idea is supported by a large body of research: Dugar and Nathan (1995) compare earnings forecasts for firms in the U.S. market and find that sell-side analysts employed by investment banks produce significantly more optimistic earnings forecasts than other analysts. Hong and Kubik (2003) study the careers of 12,336 financial analysts at 8,441 brokerage firms in the U.S. and find that when two analysts are equally accurate in their forecasts, the analyst with more optimistic forecasts is more likely to be valued by their employers. Further, the authors also find that forecast upward bias was more helpful for retention and promotion than forecast accuracy when the securities they focused on were underwritten by their own employers. Cao and Zhu (2011) study 55,903 sell-side analysts' investment recommendations in China between 2005 and 2009 and find that sell-side analysts tended to recommend stocks invested by their employer's proprietary business.

Second, the literature also points out that financial analysts will issue investment research reports that overestimate the profitability of companies to please the manager of the companies under research. This can help financial analysts to get managers’ insider information to help them predict the performance of a firm more accurately in the future. For example, Ke and Yu (2006) study the earnings forecasts of analysts in the US between 1983 and 2000 and find that if an analyst initially forecasted a firm's earnings higher, that analyst's future forecasts for that firm were more accurate compared to other analysts. This effect was shown to be more pronounced in firms with more serious insider trading and in firms with earnings more difficult to estimate. Zhao, et al. (2013) find that analysts who issue optimistic reports during big event of Chinese listed companies are given more opportunities to visit listed companies for field research.

Whatever the purpose, if an analyst issues an overly high earnings forecast for a company under study, then management may be too busy trying to achieve that forecast and neglect to invest in the beneficial long-term project. Matsunaga and Park (2001) find that Chief Executive Officer (CEO) bonuses reduces a lot even if a firm just slightly misses the quarterly earnings predicted by analysts. Graham et al. (2005) survey the Chief Executive Officers (CFOs) of 401 US-listed companies and find that the majority of CFOs were not willing to make investments that might lead to a miss of short-term earnings forecasts, even if the investment opportunity adds value to the firm. Fuller and Jensen (2010) observe that the CEOs and CFOs of US-listed companies often succumb to the short-term performance pressure of financial analysts and force their middle and lower managers to achieve earnings forecasts. He and Tian (2013) examine the relationship between analyst coverage and corporate innovation in the U.S. and find that firms that are followed by analysts witness reductions in innovation outputs. He and Tian (2013) argue that analysts put excessive pressure on firms' management team and let them forgo beneficial R&D.

2.2 Total Factor Productivity

In this paper, total factor productivity (TFP) is used to measure the production efficiency of listed companies in China. TFP is one of the most important concepts in economics, and the analysis of TFP has been integrated into various subfields of economic research. In the economic sense, TFP refers to the total output produced by a firm per unit of the total input, or the part of total output that cannot be explained by tangible inputs such as labor and capital. Thus, TFP measures the contribution to output growth due to technological advances in production, human capital accumulation, and improved management capabilities. Unlike other performance indicators such as total revenue and net profit, TFP is less influenced by the size of a firm, because the contributions of labor and capital are deducted. Lu and Lian (2012) point out that although TFP is conceptually a microeconomic indicator, in the early years it was usually estimated based on macroeconomics data due to the lack of micro data. In contrast, estimating TFP using firm data can help us to analyze the factors that affect productivity.

2.2.1 Estimating Total Factor Productivity

TFP can be estimated by deducting factor contribution from the actual output. TFP is generally calculated by considering both capital and labor inputs and the Cobb-Douglas type production functions:

$$Y_{it} = A_{it} L_{it}^{\beta_l} K_{it}^{\beta_k} \tag{2.1}$$

By taking the logarithm of the production function, we can obtain the log-linearized production function:

$$y_{it} = a_{it} + \beta_l l_{it} + \beta_k k_{it} \tag{2.2}$$

From the above equation, we can see that if we can accurately estimate the coefficients of log capital and log labor (i.e., the elasticities of labor capital and labor with respect to output), then we can obtain the log TFP of a firm by subtracting the firm's output predicted using labor and capital from the firm's actual log output. However, Marschak and Andrews (1944) point out the problem of simultaneity bias in estimating the above coefficients directly by regression: Managers of firms can predict at least part of the productivity of the firm before deciding on factor inputs, but this level of productivity is unobservable to outsiders. When the managers know that the productivity is high, then they will increase human and capital inputs, which makes the regression term correlate with the residuals. Therefore, the coefficients of the log production function (2.2) cannot be estimated directly by the Ordinary least squares (OLS) method.

To address this issue, Olley and Pakes (1996) propose a method based on semi-parametric estimation: Olley and Pakes (1996) argue that a firm will increase investment when productivity is high. Therefore, the level of investment in the firm's current period can be used to control for the unobservable level of productivity. This can address the simultaneity bias problem.

Levinsohn and Pertin (2003) propose an alternative idea to solve the simultaneity bias based on Olley and Pakes (1996). Levinsohn and Pertin (2003) argue that the Olley and Pakes (1996) approach requires that investment must monotonically increase with productivity. Therefore, their approach cannot measure total factor productivity for a sample of firms with zero values of investment. This results in a large number of missing samples. Levinsohn and Pertin (2003) find that although firms may not invest in a year, they commonly purchase intermediate inputs during production. Therefore, controlling for unobservable productivity levels using intermediate inputs instead of investment can address this problem relatively well.

2.2.2 Influencing Factors of Total Factor Productivity

The existing literature identifies a large number of factors influencing the TFP of firms, which are partly firm-specific and partly from outside the firm.

First, the existing literature suggests that a range of firm-specific characteristics are related to a firm's TFP. First, some firm financial indicators may be related to a firm's TFP. İmrohoroğlu and Tüzel (2014) systematically study this problem: they estimate TFP for US -listed firms from 1963 to 2009, and construct a series of firm indicators. Then, they divide firms into different groups according to their TFP and find that some variables are monotonically related to firms' TFP. Overall, large firms with more total assets have higher TFP than small firms, and growth firms with a lower book-to-market ratio have higher TFP than value firms. İmrohoroğlu and Tüzel (2014) also found that firms' capital growth rate, the ratio of investment to total capital, the ratio of new employees to all employees, and the inventory level are also positively related to firms' TFP.

Second, a large number of studies point out that R&D increases firm productivity: Griliches (1986), a study of major U.S. manufacturing firms from the 1960s to 1970s, finds that firm R&D innovation significantly increases firm productivity. Moreover, their result shows that basic research has a stronger effect on firm productivity than other types of R&D. Hall et al. (2010) conduct a systematic review of the literature on the returns to corporate R&D. The results show that although different researchers have used different data and estimation methods, studies consistently show that corporate R&D capital significantly increases corporate output and R&D has a spillover effect on the economy as a whole. Studies in China have also found that corporate R&D increases firm productivity (Wu, 2006; Mao et al., 2013).

Besides, the literature also finds that firm ownership also has a significant impact on TFP. The current empirical study on the change of ownership of Chinese firms finds that public ownership can hinder TFP. First, research finds that the privatization of state-owned enterprises (SOEs) can help increase firm productivity: For example, Chen et al. (2021) use the Industrial Enterprise Survey database to study the privatization of SOEs in China from 1998 to 2007. It shows that the productivity of private firms in China is 53% higher than that of SOEs. Liu et al. (2016) and Zhang et al. (2021) use the Industrial Enterprise Survey database and data of listed companies in China respectively and find that mixed-ownership reforms of SOEs significantly increase their TFP. Second, the existing literature also finds that private firms experience TFP declines after receiving state-owned capital. For instance, using the Industrial Enterprise Survey database, Dong and Liu (2021) find that after state-owned capital injection, firms' TFP and return on assets (ROA) both show significant declines.

In addition to the firm-specific factor, existing studies also find a number of factors from outside of the firm that are related to the TFP.

First, it is found that industrial organization affects the TFP: In a competitive industry, firms with high productivity choose to enter the market and expand their production, while firms with lower productivity choose to downsize or even exit the market. This market selection mechanism of superiority leads to higher productivity of firms in competitive industries (Jovanovic, 1982; Hopenhayn, 1992). Using the Chinese Industrial Enterprise Survey database from 1998 to 2007, Li et al. (2012) find that firm entry and exit increase the productivity of firms in China's industrial sector. Using the same data, Wang and Liu (2016) find that SOEs monopolization of the upstream of the value chain leads to the entry of inefficient SOEs into the downstream market. It squeezes high-productivity non-SOEs out of the market.

Second, existing studies also find that government intervention can have an impact on the TFP of firms. On the one hand, the existing literature finds that government subsidies may have a positive effect on the productivity of subsidized firms: Ren et al. (2014) study equipment manufacturing firms covered in the Chinese Industrial Enterprise Survey database from 2000 to 2007, and find that government subsidies can increase firms' productivity by alleviating their financing constraints. Li et al. (2019) find that the promotion effect of government subsidies on firms' total factor productivity is also present in listed firms. Based on the thoughts of Lin (2017), Li et al. (2019) argue that government subsidies can also improve the productivity of firms by motivating them to invest capital in industries with bright market prospects. In contrast to this optimistic view, some studies on China's industrial policy have found that China's industrial policy might have reduced firms' productivity: Qian et al. (2018) use China's *Ten Industry Revitalization Plans* introduced in 2009 as a natural experiment. They find that firms in the planned industries showed significant decreases in productivity compared to those in other industries. Moreover, this effect is stronger in regions with stronger government intervention and the effect is stronger in SOEs.

Finally, To et al. (2018) finds that analyst coverage increases the productivity of firms in the US stock market. This is the most relevant research to my paper. To et al. (2018) first conduct a panel data fixed effects regression and find that analyst coverage positively predicts a firm's TFP in the future. To address the endogeneity, To et al. (2018) construct an instrumental variable following Yu (2008). Also, they identify the causal relationship using a quasi-natural experiment of brokerage mergers. The authors find that all findings consistently support that financial analysts increase the TFP of firms. In this paper, I use the methodology of To et al. (2018) and investigate the impact of financial analysts in the Chinese securities market. Different from To et al. (2018), this paper also empirically tests the managerial pressure due to financial analysts' overestimation of firms' profitability, which is not studied by To et al. (2018). Considering that the regulation of securities analysts in China may not be as strict as that in Europe and the US, and that weak financial regulation is a common problem in financial markets of developing countries. I think that my study has some contribution to existing literature.

Chapter III Theory and Research Hypothesis

3.1 Theory

3.1.1 Theoretical Framework

Based on the literature review in the previous chapter, I find two opposing views on the relationship between analyst coverages and total factor productivity (TFP).

On the one hand, the information mechanism suggests that financial analysts can reduce the degree of information asymmetry between firm managers and investors, thus reducing the financing constraints of firms. This helps firms to seize fleeting investment opportunities, thus increasing their productivity. Besides, more transparent information also helps investors to recognize the importance of firms' innovative R&D activities and alleviate the problem of undervaluation of firms' innovation results due to information asymmetry, thus improving firms' innovation.

On the other hand, the managerial pressure mechanism suggests that analysts have an incentive to publish research reports that overestimate the profitability of firms. If a firm's managers fail to meet the analysts' profitability forecasts, they may cause institutional investors to reduce their holdings, leading to a decline in the stock price or even a hostile takeover, which could ultimately lead to the failure of the manager’s career. This analyst pressure on the manager can lead to the myopic problem: Managers will focus on short-term performance, neglecting investments that are beneficial to the long-term growth of the company, thus negatively impacting productivity.

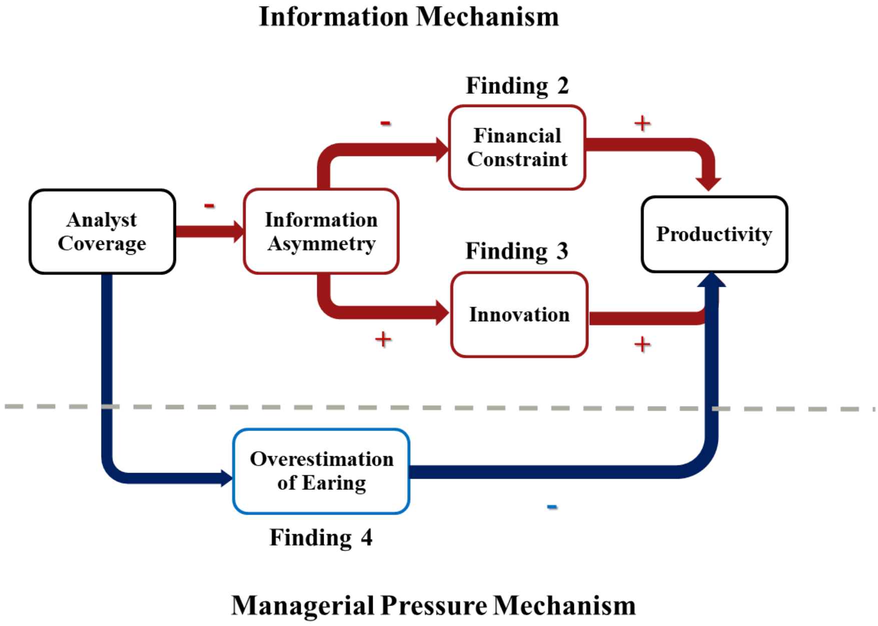

Figure 3.1 The Theoretical Framework

3.1.2 Information Mechanism

Information mechanism suggests that, as an important information intermediary in financial markets, the analyst may reduce the degree of information asymmetry, thus reducing the financing constraints of firms and ultimately increasing their TFP.

In the 1980s, the problem of financial constraints due to information asymmetry attract the attention of economists: Stiglitz and Weiss (1981) construct a model of debt financing in information-asymmetric markets. In their model, borrowers have more information than lenders: Before borrowing, lenders have difficulty in judging the default risk of borrowers, which can lead to high-risk borrowers crowding out low-risk borrowers. This causes the problem of adverse selection. After lending, lenders cannot prevent borrowers from investing the funds in high-risk projects because they cannot observe the borrowers' actions, so problem of the moral hazard also arosed. Stiglitz and Weiss (1981) suggest that information asymmetry between borrowers and lenders can lead to credit rationing problems: Some demanders of funds are unable to obtain borrowing. After Stiglitz and Weiss (1981), Myers and Majluf (1984) construct a model of equity financing in an information asymmetric market. In this model, information asymmetry leads to similar problems when firm managers have an information advantage over equity investors, and these effects stop firms from obtaining sufficient equity financing. Due to the lack of funds, firms have to cut back on valuable investments, which ultimately affects firm productivity.

Financial analysts, as information intermediaries in financial markets, provide information on firms' investment behavior, and this is especially the case when sell-side analysts make their research reports available to the whole market. This will help the financial market to understand the true risk level of corporate investments, thus helping to prevent adverse selection problems. In addition, the market can be informed whether companies are investing in risky activities. This also helps to avoid the problem of moral hazard. Therefore, I argue that financial analyst coverage can reduce financing constraints due to information asymmetry, which in turn may increase the long-term productivity of firms.

In addition to reducing firms' financing constraints, financial analysts may also increase R&D investment in public firms by reducing the likelihood that firms are undervalued by financial markets. Research in behavioral finance suggests that if the information affecting stock prices is complex, investors may exhibit an underreaction to this information (You & Zhang, 2009; Hirshleifer et al., 2009). The knowledge, patents, and highly sophisticated products coming out from R&D may be difficult for investors to understand. This leads to the undervaluation of corporate innovation outputs and reduces the incentives of corporate management to invest in R&D. Hirshleifer et al. (2018) find that the originality of a listed company's patents positively predicts the long-term stock price return. Moreover, the fewer investors pay attention to the company's stock, the stronger the relationship between patent originality and future stock price returns. This predictive nature of patent originality for long-term stock price returns suggests that prices in stock markets fail to reflect the value represented by a firm's innovation in the short run. Further, Shu et al. (2022) find that some patent examiners in the United States Patent and Trademark Office (USPTO) are busy. The patents approved by these busy examiners are generally of poor quality. If most of a firm's patents are examined and approved by these busy patent examiners, then, all else equal, these companies have lower long-term returns. This evidence also suggests that trading prices in financial markets do not reflect the value represented by corporate innovation in the short run. Given that the Chinese stock market is currently dominated by individual investors, individual investors are likely to have more difficulty realizing the actual value of complex innovation outcomes than institutional investors with investment expertise. I suspect that the problem of investors underreacting to innovation outcomes may be more acute in the Chinese stock market than in the US market.

Financial analysts are typically better able to accumulate expertise in a particular industry they cover compared to investors who usually hold diversified portfolios. These abilities make it easier for financial analysts to realize the value of a firm's innovative output and reduce mispricing due to investors' inadequate response to complex information. Existing research also provides some evidence for this mechanism: Li (2020) finds that reduced analyst coverage increases stock mispricing. Thus, I conjecture that financial analyst coverage can reduce the risk that a firm's innovation is undervalued by the market, facilitating firms' innovations and, and finally, increasing their productivity.

3.1.3 Managerial Pressure Mechanism

The managerial pressure mechanism, on the other hand, suggests that financial analysts will systematically give high earnings forecasts, which will trigger the short-termism behavior of corporate managers and finally reduce corporate productivity. Financial analysts will systematically overestimate firms' earnings forecasts because sell-side analysts face conflicts of interest between clients and employers, and between clients and listed firms: on the one hand, the securities firms that employ sell-side analysts usually also operate other businesses such as investment banking and proprietary investment. If the company that the sell-side analyst focuses on is underwritten by the employer's investment banking department or is held by the employer's proprietary investment department. Then colleagues in other departments or even his or her supervisors may make the analyst issue a report that overestimates the profitability of the company (Hong and Kubik, 2003; Cao and Zhu, 2011). However, if the analysts issue a report with an upward earning bias, the firm is likely to succumb to the short-term pressure. The managers may abandon beneficial projects to achieve the forecasts (Fuller & Jensen, 2010; Graham et al., 2005).

In addition, sell-side analysts may also issue reports that overestimate the profitability of a company to maintain good relationships with the management of the company under investigation. If sell-side analysts can maintain a good relationship with the management of the firm, the analysts may get insider information from the management team of the firm (Ke & Yu, 2006) or have the opportunity to conduct field research on the firm (Zhao, et al., 2013). This enables financial analysts to make more accurate predictions about the firm in the future and it does good for the career development of financial analysts. From the perspective of company managers, analyst reports that overestimate corporate earnings levels can lead to higher stock prices in the short term, which allow corporate owners to overestimate the capabilities of corporate managers. However, in order to achieve analysts' forecasts, corporate management may focus on the short-term performance of the company, investing money in short-term projects such as marketing and forgoing long-term productivity investments that benefit the company.

3.2 Hypothesis Development

3.2.1 Analyst Coverage and Total Factor Productivity

This paper focuses on the relationship between analyst coverage and firm performance in the Chinese capital market. As pointed out by Yu et al. (2017), unlike the mature stock markets in developed countries such as the US, Chinese stock markets have a high degree of information asymmetry. I conjecture that this may cause the information dissemination theory more applicable to China.

The phenomenon of share price synchronization in China's stock market indicates that there is serious information asymmetry between the firm and the investors (Durnev et al., 2003; Gul et al., 2010). And if firm-specific information is not integrated into the stock price, the value discovery role of the financial market will collapse and it can seriously affect the efficiency of resource allocation. Yi et al. (2019) point out that financial analysts in China can reduce the synchronization of stock prices by mining company-specific information, which enhances the signaling role of stock prices in resource allocation in financial markets.

In my opinion, financial analysts can promote firm performance through the information mechanism and may also inhibit firm performance through the performance pressure mechanism. The relationship between financial analysts' coverage and corporate productivity should be the combined effect of both mechanisms. Considering the characteristics of China’s financial market, I conjecture that the information mechanism may have a greater effect in our stock market. Based on the above analysis, this paper proposes empirical hypothesis H1.

H1: In the Chinese stock market, analyst coverage improves firms’ TFP.

3.2.2 Possible Channels

Research shows that Chinese firms face more serious financial constraints. Bailey et al. (2011) found that state-owned banks tend to provide loans to low-performing enterprises in order to prevent unemployment and therefore maintain social stability. Ren and Lv (2014) found that serious financing constraints prevail in China's equipment manufacturing enterprises. Economic theory suggests that the degree of information asymmetry of enterprises is an important factor affecting enterprise financing. The higher the degree of information asymmetry, the less easy it is for enterprises to obtain external financing. Therefore, I conjecture that financial analysts' attention can make corporate information more transparent and thus alleviate the financing constraint problem of enterprises to some extent. Based on the above analysis, I propose the empirical hypothesis H2.

H2: In the Chinese stock market, analyst coverage can improve firms' TFP by alleviating their financial constraints.

In addition to this, research on firms' innovation capability is an important part of financial analysts' work. Yu et al. (2017) point out that financial analysts in China pay much attention to corporate innovation. Their report helps investors to realize the value of corporate innovation activities, thus reducing the risk of corporate innovation being undervalued by the market, which ultimately helps firms to innovate and improve their performance. Based on the above analysis, I propose the empirical hypothesis H3.

H3: In the Chinese stock market, analyst coverage can improve firms' TFP by increasing corporate innovation.

3.2.3 Heterogeneity of Analysts' Earning Forecasts

If financial analysts in the Chinese stock market contribute to corporate TFP, does it mean that the managerial pressure theory does not apply to China? I think this is not the case. Developed Western countries have strict regulatory requirements for financial analysts to ensure their independence: first, the US and EU require a "China wall" between the investment banking and analyst departments of securities firms. That is, from the securities company management system to isolate the two departments, the investment banking department is prohibited to intervene in the sell-side analysts. Secondly, the US, EU, and other developed countries also strictly require the independence between analysts and researched companies, and strict disclosure of potential conflicts of interest. However, compared to developed Western countries, the regulatory development of financial analysts in China is relatively late and the regulatory requirements are loose. For example, *MiFID II*, an EU law that came into effect on January 3, 2018, mandates that the research service fees paid by investors to sell-side analysts must be paid separately and cannot be tied to brokerage payments to securities firms for This regulatory requirement fundamentally cuts off the ability of investors to pay sell-side analysts for research services. This regulatory requirement has fundamentally cut off the relationship between financial analysts and other departments of the employer, greatly enhancing the independence of sell-side analysts. However, China's laws and regulations do not have similar requirements, which makes China's sell-side analysts generally use the business model of "service for commission", which is bad for the independence of sell-side analysts, so China's analysts may be more inclined to give research reports that overestimate corporate earnings.

On the other hand, in recent years, empirical studies have found that the phenomenon of managerial short-sightedness also exists among listed companies in China. For example, Yu (2022) finds that the shorter the expected tenure of a firm's president, the higher the degree of financialization of the firm. Based on this phenomenon, the authors suggest that management short-sightedness may have contributed to the financialization of Chinese firms. Hu et al. (2021) use a machine learning approach to analyze the text of managerial discussion and analysis in the annual reports of Chinese listed companies and identify the language related to managerial myopia. The authors find that the more myopic the management is, the less capital investment and R&D expenditure the firm has.

Based on the theoretical analysis in Section 3.1.3, I think that that financial analysts will put pressure on a firm's managers only when their earnings forecasts are so high that the firm has difficulty meeting this target. Therefore, if the performance pressure theory applies to China, analysts' forecasts that do not overestimate firms' short-term earnings levels should be more able to promote firms' long-term productivity than analysts' forecasts that overestimate firms' short-term earnings levels. Based on the above analysis, I propose the empirical hypothesis H4.

H4: In the Chinese stock market, the positive relationship between analyst coverage and firms’ TFP is weaker when analysts overestimate the level of firm earnings.

Chapter IV Samples and Variables

4.1 Samples

This paper examines the relationship between financial analysts' coverage and firm productivity in the Chinese stock market. Since financial analysts only publish research reports on listed companies, the samples used are firm-year observations of A-share listed companies from 2007 to 2020. The sample of this paper starts in 2007 because the split-share structure reform which started in April 2005, had a large impact on China's stock market, and this reform was completed by the end of 2006.

Following Li et al., (2016) and Yu et al. (2017), this paper drops some of the samples:

(1) The samples of listed companies in the financial sector are removed due to different accounting standards;

(2) Because stocks on the verge of delisting may have financial fraud and incomplete information disclosure, this paper removes the firm-year sample with the following exchange mark: ST (Special Treatment), ST* (Special Treatment*), and PT (Particular Transfer);

(3) The samples with missing values of important variables are dropped.

Finally, this paper obtains 28,585 company-annual samples from 3,643 listed companies.

4.2 Variables

4.2.1 Dependent Variables

The main explanatory variable in this paper is the total factor productivity (TFP) of listed firms, which is estimated using the method proposed by Olley and Pakes (1996) (hereafter referred to as the OP method), and the method proposed by Levinsohn and Pertin (2003) (hereafter referred to as the LP method), respectively. For robustness, I also use the firm's return on assets (ROA) as an alternative measure of firm productivity.

(1) OP method TFP（TFP_OP）

This paper uses the OP method proposed by Olley and Pakes (1996) to estimate the TFP of listed firms. To address the problem of simultaneity bias, the OP method uses firm investment to control for the unobservable productivity levels of firms. To avoid the influence of inflation, I use the Producer Price Index (PPI), the Consumer Price Index (CPI), and the investment price index are used to adjust the nominal variables to real values with 2007 as the base year. Since fixed assets are accumulated over years, I also follow To et al. (2018) to estimate the average age of a firm's fixed assets and adjust prices based on the estimated age. For the other variables, I adjust prices using the fiscal year of the firm's financial report. In Section A.1 of the Appendix, I provide a detailed discussion of the raw data and calculation procedures of the OP method to estimate the TFP.

(2) LP method TFP（TFP_LP）

The alternative TFP estimation method used in this paper is proposed by Levinsohn and Pertin (2003). The LP method is similar to the OP method. The difference is that the LP method uses intermediate inputs instead of firm investment to control for simultaneity bias. Similarly, the nominal variables required for the LP method are all adjusted to the real values using 2007 as the base year. In Section A.2 of the Appendix, I provide a detailed discussion of the raw data, and computational procedures for the LP method to estimate TFP.

(3) Return on assets（ROA）

Because the TFP of a firm is an indicator estimated based on a structural model, for robustness, I use the ROA as an alternative measure of firm productivity. Mathematically, a firm's ROA is the net profit divided by the average of year-beginning and year-end total assets.

4.2.2 Independent Variables

(1) Log analyst (LnAnalyst), Log report (LnReport)

The explanatory variable in this paper is analyst coverage. Financial analysts can be classified as sell-side analysts employed by securities firms, and buy-side analysts employed by investment institutions such as funds. Same as other studies in this area (e.g., He & Tian, 2013; To et al., 2018; Guo et al., 2019; etc.), the empirical study in this paper focuses on sell-side analysts for two reasons: First, the vast majority of financial analysts in the current financial markets in China and other developed countries are sell-side analysts. Second, unlike sell-side analysts who publish research reports publicly, buy-side analysts generally only publish research results and investment recommendations internally to investment institutions, so there is the problem of the unavailability of data.

In the benchmark regression section, the number of sell-side analyst teams that publish earnings forecasts for a listed company within a fiscal year is used as a measure of analyst coverage. If a team of analysts issued multiple earnings forecasts for a listed company, the analyst coverage is still considered to be one. Because the data of analyst coverage has a large positive skewness, i.e., a few "star companies" attract a large number of analysts' attention, while a large number of companies do not have analyst coverage, this paper adds 1 to the analyst coverage indicator and then takes the natural logarithm. The above measure of analyst coverage is consistent with He and Tian (2013), To et al. (2018), and Guo et al. (2019). In the robustness check section of this paper, I also use the number of all research reports issued for a listed company in a year plus one taking the natural logarithm (LnReport) as a measure of analyst coverage, and the results are not significantly different from those found in the benchmark regression.

(2) Log overestimating analyst (LnAnaHigh), Log underestimating analyst (LnAnaLow)

To investigate the heterogeneity of the impact of different analysts' earnings forecasts on firm performance, this paper also divides the analyst coverage received by firms into two parts: Overestimating analysts (LnAnaHigh) and underestimating analysts (LnAnaLow). First, I calculate the optimistic bias of analysts.

$$Error_{kit} = \frac{ForecastEPS_{kit} - RealizedEPS_{it}}{StockPrice_{it}} \tag{4.1}$$

In equation (4.1), $ForecastEPS_{kit}$ refers to the analyst k's forecast of firm i's earnings per share (EPS) at the end of year t. $RealizedEPS_{it}$ refers to the real EPS realized by firm i at the end of year t. To normalize, I divide the difference between the two by the firm's stock price on the day the analyst issues the forecast to obtain the standardized optimistic bias $Error_{kit}$ for firm i in year t. If the optimistic bias $Error_{kit}$ is greater than 0, it means that the analyst overestimates the firm's earnings in that year. Conversely, if the error is lower than 0, it means that the analyst underestimates the profitability of the firm in that year.

However, because analysts may be influenced by the overall market sentiment, research shows that they tend to overestimate firms' earnings when market sentiment is high (Xu et al., 2012; Wu et al., 2012). Therefore, using zero to classify analysts' overestimation and underestimation of firms' performance may be affected by the overall market sentiment. Therefore, this paper chooses to use the average optimistic bias of all analysts' forecasts in the current year as the criterion for classifying analysts' overestimation or underestimation of corporate earnings levels. Mathematically, the two indicators of overestimating analysts (LnAnaHigh) and underestimating analysts (LnAnaLow) are calculated as follows.

$$LnAnaHigh_{it} = ln(\, 1 + \textstyle\sum_k \mathbb{1}\,(Error_{kit} > meanError_t)) \tag{4.2}$$

$$LnAnaLow_{it} = ln(\, 1 + \textstyle\sum_k \mathbb{1}\,(Error_{kit} < meanError_t)) \tag{4.3}$$

$meanError_t$ refers to the average optimistic bias of all analysts' forecasts for the year, and $\mathbb{1}()$ is the indicator function, which takes 1 if the condition in parentheses is met and 0 otherwise. $\sum_k \mathbb{1}\,(Error_{kit} > meanError_t)$ is the number of analysts whose optimistic bias is higher than the average optimistic bias for the year.

It is worth noting that the sum of the number of overestimating and underestimating analysts does not equal the total number of analysts as defined in the previous section, because a team of analysts may make multiple different forecasts in a year, with some forecasts being overestimation and others being underestimation. In this case, this analyst is counted as both overestimating and underestimating.

Since it may be arbitrary to use the mean to classify overestimating and underestimating analysts, I also use quartiles of optimism bias to divide the analysts into four groups. The results support the conclusions drawn in this paper.

4.2.3 Control Variables

Following existing research literature on firm productivity (e.g., To et al., 2018; Dong & Liu, 2021; et al.), I control for the following variables that may affect TFP.

First, to remove the effects of different firm characteristics on firm productivity, this paper controls for the following variables.

(1) Firm size (Size)

In this paper, I use the natural logarithm of the firm's total assets at the end of the year as a control of firm size. İmrohoroğlu and Tüzel (2014) find that in the US stock market, the TFP level is higher for larger listed firms. Also, larger firms may be held by more investors and therefore attract more analyst coverage. Because firm size may be correlated to both our dependent and independent variables, not controlling for firm size may lead to omitted variable bias.

(2) Firm age (Age)

This paper uses one plus the number of years after firm establishment taking the natural logarithm to control for the effect of firm age. On the one hand, new market entrants may have open corporate cultures; on the other hand, older firms may have established technological barriers or have stable supply chain relationships. All these factors can have impacts on the productivity of the firm.

(3) Book-to-market ratio (BM)

This paper uses the book-to-market ratio, i.e., the total book assets at the end of the year divided by its total market capitalization, to control for productivity differences due to the level of the firm valuation. İmrohoroğlu and Tüzel (2014) find that growth firms with low book-to-market ratios are more productive than value firms with high book-to-market ratios. Because the level of firm valuation may also affect financial analysts' coverage on firms, not controlling for book-to-market ratio may lead to omitted variable bias.

Second, to remove the effects of firm operation on firm productivity, this paper controls for the following variables.

(4) Revenue growth (Growth)

Following Song et al. (2021), this paper uses the growth rate of total revenue relative to the previous year's total revenue as a control for the impact of firm growth. Because firms with rapid revenue growth may have higher productivity and also attract more analysts, I think that not controlling for firm growth will lead to omitted variable bias.

(5) Investment expenditures (CapEx)

Following To et al. (2018), this paper uses firm investment divided by firm operating income as a control variable. Firm investment is measured as cash paid for the purchase and construction of fixed assets, intangible assets, and other long-term assets reported in the annual cash flow statement. On the one hand, higher corporate investment spending may imply that firms have higher productivity and want to achieve higher profits by expanding production. On the other hand, high investment spending may also mean that the firm's capital is relatively old and needs to be maintained or renewed, and therefore less productive.

(6) Cashflow from operations (Cashflow)

This paper uses the net cash flow from operating activities over total assets at the end of the year as a control variable. Firms with higher operating cash flow are likely to be in the rapid growth phase of their business and therefore they may have higher productivity.

(7) Fixed assets (PPEratio)

In this paper, I use the ratio of fixed assets over total assets as a control variable. On the one hand, high fixed capital intensity may imply that firms have expensive and highly sophisticated production equipment and therefore have high productivity; on the other hand, firms with high fixed capital intensity may also adopt inefficient production technology and therefore have lower productivity.

Third, considering the effect of different firm ownership on firm productivity, this paper controls for the following variables.

(8) State-owned enterprises (SOEs)

In order to control the effect of enterprise ownership on enterprise productivity, this paper introduces a SOE dummy variable, which is taken as 1 for state-owned enterprises and 0 for enterprises with other ownership. An enterprise is considered to be state-owned if its state-owned shares account for more than 50% or if the controlling shareholder is a state-owned enterprise. The existing literature shows a negative effect of SOEs on firm productivity (Chen et al., 2021; Dong & Liu, 2021; et al.). Because analysts may prefer to focus on non-SOEs, not controlling for firm size may lead to omitted variable bias.

(9) Control shareholding (FirstOwn)

In this paper, we use the largest shareholder's shareholding over total firm shares as a control of the power of large shareholders. On the one hand, a high control power may lead to a lack of oversight on large shareholders, which triggers a type II agency problem and negatively affects productivity. On the other hand, a high control power may also ease control contests and benefit firm productivity.

(10) Institutional shareholding (InstOwn)

This paper uses institutional investors' shareholding over total shares to control the effect of institutional shareholding. On the one hand, a high institutional shareholding may have a supervisory effect on firm managers, which is beneficial to the productivity of the firm. On the other hand, the threat of reduction of institutional investors' holdings may also put pressure on the performance of corporate managers and induce the problem of managerial short-termism. Because sell-side analysts mainly serve institutional investors, sell-side analysts may be more inclined to focus on stocks heavily held by institutional investors, and thus the percentage of institutional investors' holdings also correlates to the explanatory variables. I argue that not controlling for the percentage of institutional investors' holdings may lead to omitted variable bias.

Fourth, to control for industry competition, this paper controls for the following variables.

(11) Herfindahl-Hirschman Index (HHI) and its squared term (HHI_sq)

In this paper, the Herfindahl-Hirschman Index (HHI) of the industry is used to control for the competition in the industry. Mathematically, the Herfindahl-Hirschman Index is the sum of the squares of the market shares of all firms in an industry. Where market share is the ratio of the revenue from the main business of a listed company over the total revenue from the main business of all listed companies in that industry. Industries are classified using the 2012 edition of the SEC industry classification codes. Because the effect of industry competition on TFP may not be linear, this paper also controls for the squared term of the Herfindahl-Hirschman index (HHI_sq).

Fifth, in order to control for the effect of subsidies on firm productivity, the paper concludes by also controlling for the following variables.

(12) Log subsidies (LnSubsidy) and its squared term (LnSubsidy_sq)

This paper controls for the effect of government subsidies using the one plus government subsidies taken as the natural logarithm. Ren et al. (2014) and Zheng Li et al. (2019) argue that government subsidies can alleviate firms' financing constraints thus increasing their productivity. Because excessive subsidies may also have a depressive effect on firm productivity, this paper also controls for the squared term of log government subsidies (LnSubsidy_sq).

4.2.4 Variables Related to Mechanisms

(1) Average Optimistic Bias (MeanError)

To further investigate the heterogeneity of forecast bias on firm performance, this paper I follow Gentry and Shen (2013) and Guo et al. (2019) to construct the variable of average earnings optimistic bias. This indicator is positive if, on average, analysts overestimate a firm's earnings per share, and negative if the opposite is true.

$$MeanError_{jt} = \frac{1}{K}\sum_{k} Error_{kit} \tag{4.5}$$

(2) KZ index (KZindex)

Following He and Tian (2013), this paper uses the KZ index proposed by Kaplan and Zingales (1997) as a measure of the financial constraints faced by a listed firm. Kaplan and Zingales (1997) use a variety of different financial data to measure the financing constraints faced by firms, including operating cash flow over total assets, cash dividends over total assets, cash holding over total assets, the firm's gearing ratio and the firm's Tobin's Q.

(3) Cash holding ratio (CashRatio)

Following Yu et al. (2017), this paper also adopts the cash holding ratio, i.e., the ratio of cash to total assets, as a measure of corporate financing constraints. More cash means that the firm has more funds available and therefore faces fewer financing constraints.

(4) Log patent (LnPatent)

This paper measures the innovation outputs based on the invention patents filed. Because listed companies may achieve innovation through mergers and acquisitions of innovative companies or by corporate venture capital (CVC), it is not enough to focus only on the innovation activities of listed companies themselves (Guo et al., 2019). Therefore, this paper considers not only invention patents of listed companies themselves, but also invention patents filed by subsidiaries, joint ventures, and associates of listed companies.

In addition to invention patents, patents in China also include utility model patents and design patents. I only considered invention patents. The reason is that the existing literature points out that utility model and design patents do not represent a sufficient level of innovation: After an invention patent is filed, it must undergo a substantive examination by the patent office, and only patent applications with novel, creative and useful applications can be granted. In contrast, China's Intellectual Property Office conducts few examinations on utility model patents and design patents. This makes the level of innovation represented by utility model patents and design patents much less than that of invention patents (Dang & Motohashi, 2015). Some studies have even found that the increase in utility model patents in China has hurt TFP (Mao et al., 2018), and that a large number of utility model patents of low-quality are used as patent trolls (Mao, et al., 2017). Therefore, this paper does not consider utility model patents and design patents.

In this paper, two patent-based indicators are used to measure the innovation outcomes of companies: the natural logarithm number of invention patents (LnPatent) and the natural logarithm of the total number of invention patent citations (LnCite). The number of invention patents is the total number of invention patents filed by listed companies and their subsidiaries, affiliates and joint ventures in a year.

(5) Log patent citation (LnCite)

Patents represent very different levels of innovation. Some patents are groundbreaking in the field and others are only minor contributions. Therefore, I also use the patent citation to measure the innovation quality. Since the China Intellectual Property Office does not collate the citation relationship between patents in China, this paper follows Lin et al. (2021) and Sun et al. (2021) and uses the Google Patents as the original data source. The data was collected from Google by the China Research Data Service Platform (CNRDS).

I performed careful data cleaning: First, Chinese invention patents use patent numbers ending with A (e.g., *CN101183371A*) when they are filled before official approval, and use patent numbers ending with B (e.g., *CN101183371B*) when they are granted. This results in the two different patent numbers for granted patents. Both Google Patents and CNRDS do not adjust for the double-counting problem. In this paper, this problem is adjusted when calculating the number of company patents and patent citations, and I finally obtain information on 900,754 invention patents applied by our listed companies and their subsidiaries, associates and joint ventures between 2007 and 2017 with 2,456,605 citations from other patents. Second, there is a data truncation problem because patents are cited by other patents over a longer period of time. However, future citations to current patents are not observable. In this paper, we refer to the adjustment method proposed by Hall et al. (2001) to adjust for the truncation problem. To adjust for the truncation problem, I divide the citation by the average citation of patents in same technology type and filed in the same year:

$$Cite_{it} = \sum_j \frac{PatCite_{isjt}}{meanPatCite_{st}} \tag{4.5}$$

$PatCite_{isjt}$ refers to the patent numbered j filed by enterprise i in year t, which belongs to technology type s. $meanPatCite_{st}$ refers to the average citation amount of all patents of technology type s filed in year t. Then, after summing up the citations for each firm for each year, the total number of citations $Cite_{jt}$ for invention patents filed by firm i in year t is obtained.

In the analysis, I use the first digits of the International Patent Classification (IPC) code, i.e., the IPC sector, to classify the technology type s of the enterprise's patent applications. I also use the first two digits of the IPC code, and the industry the enterprise belongs to classify the technology type s of the enterprise's patent applications, and the results obtained are not significantly different from the benchmark analysis.

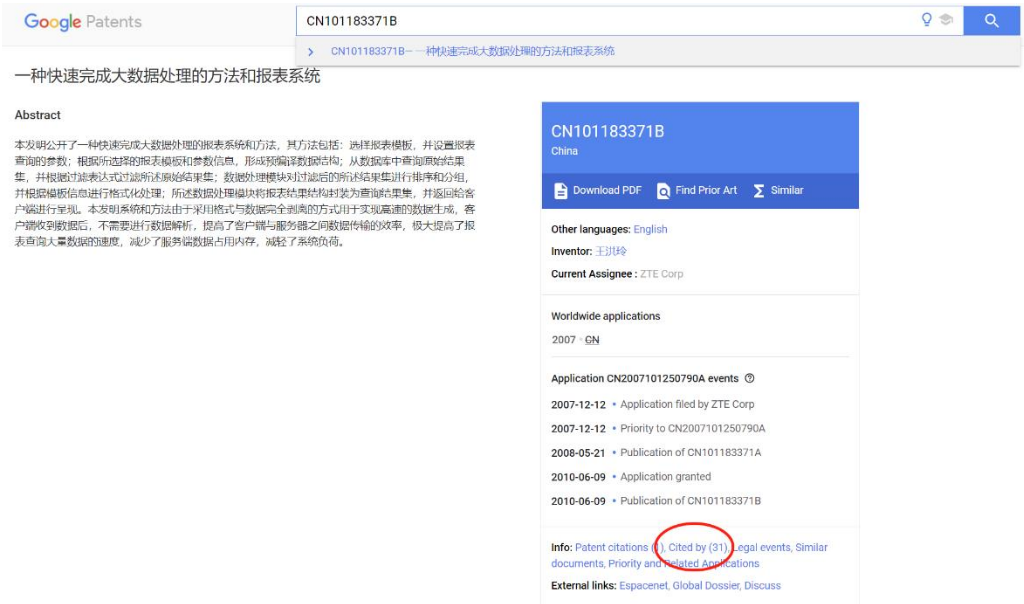

Figure 4.1　A Record of Patent Citations in Google Patents

In Table 4.1, I conclude the variables used in this paper:

Table 4.1 Main Variables Used in This Paper

Symbols	Name	Definition	Source
TFP_OP	OP method TFP	Estimated following Olley and Pake (1996)	Wind
TFP_LP	LP method TFP	Estimated following Levinsohn and Pertin (2003)	Wind
ROA	Return on assets	2*net income / (year-beginning total assets + year-end total assets)	Wind
LnAnalyst	Log analyst	ln(1 + the number of analysts issuing earnings forecasts for the firm)	CSMAR
LnReport	Log report	ln(1 + the number of research reports)	CSMAR
LnAnaHigh	Log overestimating analyst	ln(1 + the number of analysts whose optimistic bias is higher than the mean)	CSMAR
LnAnaLow	Log underestimating analyst	ln(1 + the number of analysts whose optimistic bias is lower than the mean)	CSMAR
Size	Firm size	ln(1 + total assets) Total assets in thousand RMB yuan	Wind
Age	Firm age	ln(1 + years since the establishment of the enterprise)	CSMAR
BM	Book-to-market ratio	Total assets / total market value	Wind
Growth	Revenue growth	(Total revenue - prior year's total revenue) / prior year's total revenue	Wind
CapEx	Investment expenditures	Cash paid for the acquisition of fixed assets, intangible assets and other long-term assets / total revenues	Wind
Cashflow	Cashflow from operations	Cash flow from operating activities / total assets	Wind
PPEratio	Fixed assets ratio	Fixed assets / total assets	Wind
SOE	State-owned enterprises	1 for state-owned enterprises, 0 otherwise	CSMAR
FirstOwn	Control shareholding	Shares of the first largest shareholder / total shares	Wind
InstOwn	Institutional shareholding	Institutional investor shares / total shares	Wind

Table 4.1 The Main Variables Used in This Paper (Continued)

Symbols	**Name**	**Definition**	**Source**
HHI	Herfindahl-Hirschman Index	The sum of squared revenue share of each enterprise in an industry	CSMAR
HHI_sq	Herfindahl-Hirschman Index Squared	Squared HHI	CSMAR
LnSubsidy	Log government subsidies	ln(1 + subsidy) Government subsidy in thousands of RMB yuan	Wind
LnSubsidy_sq	Log government subsidies squared	Squared LnSubsidy	Wind
MeanError	Average optimistic bias	Average of analysts' optimistic bias on corporate earnings forecasts	CSMAR
KZindex	Cash holding ratio	Defined as Kaplan and Zingales (1997)	CSMAR
CashRatio	KZ index	Cash and cash equivalents / total assets	Wind
LnPatent	Log patent	ln(1 + number of enterprise invention patents)	CNRDS
LnCite	Log Patent citation	ln(1 + number of standardized citations of corporate invention patents)	CNRDS

Chapter V Empirical Strategy

First, I investigate the relationship between analyst coverage and firm productivity in China using a panel data fixed effects regression. The advantage of this empirical strategy is that it includes as many firm-annual observation samples as possible, which helps us to examine the relationship between financial analyst coverage and firm productivity as a whole. However, the drawback of this approach is also obvious: reverse causality and omitted variables may lead to serious endogeneity problems, so that we cannot make clear judgments about causality with baseline regression analysis alone.

To address the endogeneity problems, this paper further adopts two methods: first, I use the instrumental variables proposed by Yu (2008) to test the main results in the benchmark regression. Second, I also follow Hong and Kacperczyk (2010) and Li et al. (2016), and use the three major mergers and acquisitions (M&As) of Chinese brokerage houses as quasi-natural experiments to investigate the impact of the decline in analyst coverage brought about by M&As among securities firms on TFP.

5.1 Panel Data Fixed-Effects Regression

This paper first test each of the above empirical hypotheses using a panel data fixed-effects regression, specifically, the models are as follows:

5.1.1 Panel Regression Test for the Hypothesis H1

The empirical hypothesis H1 in this paper is exploring the relationship between TFP and analyst coverage. I run panel fixed effects regressions using firm TFP one year forward, two years forward, and so on, as the dependent variable. Log analyst coverage in the current year and the control variables described in Section 4.2.3 of this chapter are independent variables. Considering the possibility of and heteroskedasticity autocorrelation in firm TFP, I use robust standard errors clustering at firm level in the benchmark regressions. If the regression analysis indicates that β_1 is significantly positive, then the empirical results can be considered to provide some evidence for the empirical hypothesis H1.

$$TFP_{it+\tau} = \beta_0 + \beta_1 LnAnalyst_{it} + \boldsymbol{X'_{it}\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.1}$$

$TFP_{it+\tau}$ is the TFP of firm i in year $t+\tau$, measured using the OP method and LP method. $LnAnalyst_{it}$ is the log analyst coverage of firm i in year t. $\boldsymbol{X}_{it}'$ is the control variable described in Section 4.2.3 and represented as a row vector. μ_i is the firm fixed effect to control for firm characteristics that do not vary over time. θ_t is the annual time fixed effect to control for productivity fluctuations that vary only over time.

5.1.2 Panel Regression Test for the Hypothesis H2

The empirical hypothesis H2 in this paper aims to investigate whether analysts' coverage can improve the TFP of firms by relaxing their financial constraints. In the benchmark regression analysis, this paper first use the classical three step regression analysis of with mediator recommended by Baron and Kenny (1986), and Wen and Ye (2014) to test H3 in a panel regression:

$$KZindex_{it+1} = \beta_0 + a\ LnAnalyst_{it} + \boldsymbol{X}_{it}'\boldsymbol{\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.2}$$

$$TFP_{it+1} = \beta_0 + c\ LnAnalyst_{it} + \boldsymbol{X}_{it}'\boldsymbol{\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.3}$$

$$TFP_{it+1} = \beta_0 + c'\ LnAnalyst_{it} + b\ KZindex_{it+1} + \boldsymbol{X}_{it}'\boldsymbol{\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.4}$$

In the first step, I regress the mediator next year $KZindex_{it+1}$ on the current analyst coverage $LnAnalyst_{it}$, and continue if the coefficient a is significantly smaller than 0. In the second step, I regress the next year TFP TFP_{it+1} on current period analyst coverage $LnAnalyst_{it}$, and continue if the coefficient c is significantly larger than 0. In the third step, I regress the next year TFP TFP_{it+1} on current period analyst coverage $LnAnalyst_{it}$ after adding the mediating variable $KZindex_{it+1}$. If the coefficient c' decreases comparing to c but is still significantly larger than 0, then the result suggests that financing constraints should play a part in the relationship between analyst coverage and long-term firm performance. This result provides some evidence for the empirical hypothesis H2.

In addition, this paper also uses the next year cash holding ratio $Cashratio_{it+1}$ as an alternative measure of corporate financial constraints.

5.1.3 Panel Regression Test for the Hypothesis H3

The empirical hypothesis H3 of this paper aims to investigate whether analyst coverage can improve the TFP of firms by increasing their innovation. In the same way as the test of the empirical hypothesis H3, this paper estimates the following models in turn.

$$LnPatent_{it+1} = \beta_0 + a\ LnAnalyst_{it} + \boldsymbol{X}_{it}'\boldsymbol{\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.5}$$

$$TFP_{it+1} = \beta_0 + c\ LnAnalyst_{it} + \boldsymbol{X'_{it}\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.6}$$

$$TFP_{it+1} = \beta_0 + c'\ LnAnalyst_{it} + b\ LnPatent_{it+1} + \boldsymbol{X'_{it}\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.7}$$

In addition, this paper also uses the total citations of the firm's patent applications in the following year $LnCite_{it+1}$ to replace $LnPatent_{it+1}$ in the above model as another measure of the firm's innovation outcomes.

5.1.4 Panel Regression Test for the Hypothesis H4

The empirical hypothesis H4 in this paper investigates the moderating effect of analysts' overestimation on earnings forecasts. I use two different approaches to test H4.

First, I add the average optimistic bias (MeanError) and the product term of the average optimistic bias and analyst coverage to model (5.1). If the coefficient of the product term, β_3, is significantly less than 0, this empirical result is considered to provide some evidence for the empirical hypothesis H4.

$$TFP_{it+1} = \beta_0 + \beta_1 LnAnalyst_{it} + \beta_2 MeanError_{it} + \beta_3 LnAnalyst_{it} * MeanError_{it} + \boldsymbol{X'_{it}\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.8}$$

Despite the simplicity of this empirical approach, however, there are potential problems: The use of the product term to test for moderating effects is prone to spurious significance (Zhu & Zhang, 2021). Second, it also implicitly assumes the same effect of the control variables. Third, because firms need to have at least one analyst focus in order to calculate the indicator of average earnings forecast bias, this implies that samples in the regression without analyst focus are excluded, which may lead to sample selection bias. Therefore, I also used an alternative approach to test hypothesis H4. In equation (5.8), I include analysts who overestimate and underestimate corporate earnings in the regression model:

$$TFP_{it+1} = \beta_0 + \beta_1\ LnAnaHigh_{it} + \beta_2\ LnAnaLow_{it} + \boldsymbol{X'_{it}\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.9}$$

If the result shows that the coefficient β_1 is significantly smaller than the coefficient β_2 then it provides some support for the empirical hypothesis H4.

5.2 Endogeneity Problems

One potential problem with the benchmark regression analysis in this paper is endogeneity. I conjecture that both reverse causality and omitted variables in the benchmark regression analysis may lead to serious bias in estimation.

5.2.1 Reverse Causality

First, reverse causality may lead to endogeneity problems in the benchmark regression results of this paper. This is because a productive firm may attract analysts. Although this paper uses the future productivities of firms as dependent variables, which can somewhat weaken the reverse causality. However, analysts may cover firm with high future productivity in advance because they can predict the productivity of firm. This mechanism can lead to a bias in coefficient estimation, Thus, reverse causality is one of the potential reasons for the endogeneity of benchmark regressions.

5.2.2 Omitted Variables

Second, omitted variables may also lead to the endogeneity problem of the baseline regression results in this paper. This is because some hard-to-observe factors may affect both analyst coverage and firm productivity. The supply chains of high-productivity companies are usually complex. However, studying this complex information requires additional effort, which can inhibit analysts from covering these firms. Failure to control for this factor can lead to a downward bias in estimation. However, because supply chains complexity is difficult to measure, they are also difficult to control for in panel regressions.

5.3 Solving Endogeneity Problems Using an Instrumental Variable

To address the endogeneity issue, I first construct as an instrumental variable of analyst coverage following Yu (2008) using the variation of the size of the analyst team of the securities firms. On the one hand, the number of analysts employed by a securities firm is determined by the managers of the securities firm and is determined by the securities firm's own business strategy and profitability. It is not likely to be influenced by the characteristics of the firm that analysts cover. Therefore, the instrumental variable satisfies exclusivity. On the other hand, the size of a brokerage firm's analyst team directly affects how busy the analysts are. When the size of a securities firm's analyst team is small, analysts are forced to pay less attention to each firm. Therefore, the instrumental variable correlated with actual analyst coverage.

Mathematically, the variable of expected analyst coverage is constructed as follows.

$$ExpectedCoverage_{ijt} = \frac{Brokersize_{jt}}{Brokersize_{j0}} * Coverage_{i0j} \quad (5.10)$$

$$ExpectedCoverage_{it} = \sum_{j=1}^{J} ExpectedCoverage_{ijt} \quad (5.11)$$

In (5.10), $Brokersize_{jt}$ is the total number of analysts employed by security firm j in year t, and $Brokersize_{j0}$ is the total number of analysts employed by security firm j in the base year. $Coverage_{i0j}$ represents whether securities company j have analyst that cover the company i in the base year. If it did, it takes 1, it takes 0. Therefore, $ExpectedCoverage_{ijt}$ measures the change in the degree of coverage to listed company i by analysts belonging to security firm j due to the change in the size of the security analyst team. In (5.11), I sum up the attention of all securities firms to listed company i in year t. When estimating the regressions using instrumental variables, only firms that were followed by at least one analyst in the base year are included.

The choice of the base year does not affect the exclusivity and relevance of the instrumental variables. In this paper, I first choose the last year of the sample, i.e., 2020, as the base year. This is because the securities industry in China is in quick growth, with new firms going public and new analysts joining the market. Using the last year of the sample as the base year includes as much of the firm-annual sample as possible. In addition, Yu (2008) suggest deleting the observed sample in the base year. In this paper, the regression analysis uses the productivity of the forward years as the explanatory variable, and the sample in this paper ends in 2020, so the independent variables used in the regression analysis is only used up to the value of 2019. Therefore, using 2020 as base year further retains more observations.

It is worth noting that Yu (2008) does not require that the initial period of the subsample be selected as the base year. In fact, Yu (2008) chooses the middle year of the sample as the base year to include the largest sample of firm-year observations. Although we construct the instrumental variable using the last period of the sample, this instrumental variable avoids the reverse causality problem caused by analysts' selection of firms to focus on because we do not use the information of whether analysts cover a specific firm in years other than the base year. Instead, fluctuations are generated entirely using the size of the analyst team at the securities firm. Nevertheless, in order to further show robustness, section 7.1.3 of this paper reconstructs the instrumental variable by changing the base period selection and performs a robustness check on the main results of this paper

5.4 Solving Endogeneity Problems Using Quasi-Natural Experiment

I also follow Hong and Kacperczyk (2010) and Derrien and Kecskés (2013) to identify the impact of a decline in analyst coverage by using a quasi-natural experiment.

Hong and Kacperczyk (2010) show that mergers between brokerage firm cause an exogenous analyst coverage decline. Hong and Kacperczyk (2010) argue that, in general, at most one analyst team of a brokerage firm follows a particular firm. Therefore, mergers between securities firms can lead to redundancy of analyst coverage after the merger. If analysts from both firms focused on the same firm, then after the merger the securities firm would fire at least one analyst due to redundancy. Thus, companies that were followed by both securities firms prior to the mergers are generally left with only one analyst team after the merger. Thus, mergers between brokerage firms can lead to a decline in analyst coverage. From the perspective of exogeneity, mergers between securities firms are determined by the business strategy of the securities firm and is not related to the firms followed by the analyst.

Li et al. (2016) apply this natural experiment to the study of financial analysts in China, and they also include brokerage acquisitions in addition to mergers. However, Li, et al. (2016) did not show which merger and acquisition (M&A) events they include. To find mergers and acquisitions among Chinese brokerages during the sample period, I use the CSMAR analyst forecast database to screen the list of brokerage firms that publish research reports between 2007 and 2020. Then, I compare the list of brokerage firms that publish research reports in different years. For brokerages that disappeared, I used Baidu to search for relevant information and finally screened out three brokerage M&A events that could be used during the sample period. Table 5.1 shows information related to three mergers and acquisitions among brokerage firms.

Table 5.1 M&A Events of Brokerage Firms in the Sample Period

Brokerage A	**Brokerage B**	**Year**	**Stocks Covered by Both Firms**	**Stocks Covered Before and After Event**
Founder Securities	Minzu Securities	2014	77	43
Shenyin Wanguo Securities	Hongyuan Securities	2015	299	174
CICC	CIC Securities	2017	154	125

The fourth column of Table 5.1 shows the number of firms covered both securities firms at least one time in the two years prior to the M&As. As in Hong and Kacperczyk (2010), I remove the samples of listed firms that analysts no longer continue to follow after the brokerage M&As. This is because the analyst team may stop following a listed firm because they believe that the firm has no research value. If this fraction of firms is included in the sample period, then the decline in analyst coverage is not entirely due to brokerage firm M&As. The fifth column of Table 5.1 shows the sample of firms that were followed by both securities firms before the mergers and continued to be followed after the merger. Finally, a firm may be affected by multiple brokerage mergers. For this type of firms, I only keep the observations around the last brokerage mergers.

As we can see from the sample selection process above, firms in the experimental group are continuously followed by teams of analysts at a securities firm before and after a brokerage firm merger. In reality, many firms do not attract enough analyst coverage. This means that firms in the experimental group tend to be larger and stronger than average listed firms. This can lead to sample selection problem of treatment effect estimation if all other untreated firms are used as the control group. Therefore, I use propensity score matching (PSM) to screen unshocked firms with similar firm characteristics to the experimental group as a control group by using firm size (Size), firm book-to-market ratio (BM), operating cash flow (Cashflow), and analyst coverage without taking logarithms (Analyst) as matching covariates. I estimate propensity scores using logit model and perform nearest neighbor matching with a caliper of 0.05. Finally, I find 231 pairs of matched firm.

In this paper, we use the difference-in-difference (DID) method to estimate the treatment effect from the decline in analyst coverage. To further eliminate the effects of firm characteristics, year, and control variables on firm productivity, the following fixed-effects model with control variables is used to estimate the treatment effect:

$$TFP_{it} = \beta_0 + \beta_1 treated_{it} + \boldsymbol{X}'_{it}\boldsymbol{\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.12}$$

In model (5.12), $treated_{it}$ takes 1 for the experimental group sample after the merger occurs and 0 before the merger occurs; it is always 0 for the control group sample. μ_i is a firm fixed effect to control for firm characteristics that do not vary over time. θ_t is an annual time fixed effect to control for productivity fluctuations that vary only over time.

Chapter VI Empirical Result

6.1 Descriptive Statistics

The sample in this paper contains 28,585 firm-year observations from 3,643 publicly traded companies. Only 20,723 average optimistic bias (MeanError) observations are available because it requires that firms have at least one analyst following them in a year. Because I require at least 3 years data to adjust for the truncation problem of patent citations, there are no observation of log citation (LnCite) for firm-year observations in 2018, 2019, and 2020, resulting in only 19,464 observations of LnCite.

To avoid the effect of extreme values, all continuous variables in this paper are winsorized at the 1% and 99% quartiles. The results of descriptive statistics after winsorization are presented in Table 6.1.

Table 6.1 Descriptive Statistics after Winsorization

Variable	N	Mean	St. Dev.	Min	Median	Max
TFP_OP	28585	8.921	0.961	5.095	8.872	11.57
TFP_LP	28585	7.924	0.905	4.407	7.875	10.45
ROA	28585	0.064	0.056	-0.098	0.055	0.313
LnAnalyst	28585	1.528	1.159	0.000	1.609	3.912
LnReport	28585	1.871	1.419	0.000	1.946	4.852
LnAnaLow	28585	1.071	1.110	0.000	0.693	3.829
LnAnaHigh	28585	0.783	0.972	0.000	0.000	3.401
Size	28585	15.13	1.299	12.30	14.95	19.50
Age	28585	2.773	0.380	1.099	2.833	3.555
BM	28585	0.937	0.996	0.051	0.612	7.935
Growth	28585	0.210	0.496	-0.616	0.124	5.223
CapEx	28585	0.120	0.158	0.001	0.067	1.267
Cashflow	28585	0.047	0.072	-0.223	0.047	0.297
PPEratio	28585	0.224	0.167	0.002	0.190	0.772
SOE	28585	0.405	0.491	0.000	0.000	1.000
FirstOwn	28585	0.356	0.150	0.083	0.338	0.758
InstOwn	28585	0.459	0.244	0.001	0.483	0.936
HHI	28585	0.106	0.116	0.014	0.069	0.951
HHI_sq	28585	0.025	0.075	0.000	0.005	0.905
LnSubsidy	28585	8.554	2.657	0.000	9.016	13.43
LnSubsidy_sq	28585	80.24	34.69	0.000	81.30	180.2
MeanError	20723	0.009	0.017	-0.044	0.005	0.129
KZindex	28585	1.427	2.082	-8.568	1.596	8.489
CashRatio	28585	0.180	0.127	0.006	0.146	0.838
LnPatent	28585	1.756	1.549	0.000	1.609	6.397
LnCite	19464	1.500	1.502	0.000	1.245	6.227

6.2 Aggregate Effect of Analysts on Productivity

6.2.1 Baseline Regression for Hypothesis H1

The baseline regression model (5.1) is first used to test the empirical hypothesis H1. In columns (1) to (3) of Table 6.2, the explanatory variable is OP method TFP one year ahead. From column (1) to column (3), I gradually add control variables to the regressions and control for three fixed effects of firm, industry, and year. I control for industry fixed effects in addition to firm fixed effects because more than 20% of companies change industries. Not controlling for industry fixed effects may lead to omitted variable bias because there are significant differences in TFP across industries. The results show coefficient of LnAnalyst are 0.153, 0.086, and 0.078, and the coefficients are all significantly greater than 0 at the 1% level. this one result suggests that there is an increase in TFP after financial analysts focus on a particular firm. This result provides some support for the empirical hypothesis H1.

For robustness, in column (4) I change the explanatory variable to LP method TFP. The results show that the coefficient of LnAnalyst is also significantly greater than zero and is not different from column (3). In addition to this, in the robustness testing section of Chapter 7 of this paper, I further test the empirical hypothesis H1 using the firm's return on assets (ROA) as an alternative measure of firm productivity. The results find that the coefficient of analyst coverage on a firm's ROA in the coming year is significantly positive. These results provide further support for the empirical hypothesis H1.

Table 6.2 Regression Test for Empirical Hypothesis H1

VARIABLES	(1) TFP_OP t+1	(2) TFP_OP t+1	(3) TFP_OP t+1	(4) TFP_LP t+1
LnAnalyst	**0.153*** **	**0.086*** **	**0.078*** **	**0.078*** **
	(0.006)	**(0.005)**	**(0.005)**	**(0.005)**
Size		0.371***	0.366***	0.312***
		(0.013)	(0.013)	(0.013)
Age		-0.058	0.003	-0.019
		(0.050)	(0.050)	(0.049)

Table 6.2 Regression Test for Empirical Hypothesis H1 (Continued)

BM		-0.067***	-0.059***	-0.060***
		(0.008)	(0.008)	(0.009)
Growth		0.126***	0.117***	0.118***
		(0.008)	(0.008)	(0.008)
CapEx		-0.192***	-0.203***	-0.290***
		(0.034)	(0.033)	(0.032)
Cashflow		0.813***	0.813***	0.815***
		(0.058)	(0.058)	(0.056)
PPEratio		-0.091	-0.061	-0.414***
		(0.059)	(0.058)	(0.059)
SOE			-0.110***	-0.099***
			(0.035)	(0.034)
FirstOwn			0.171**	0.170**
			(0.082)	(0.082)
InstOwn			0.350***	0.342***
			(0.050)	(0.050)
HHI			-0.092	-0.160
			(0.171)	(0.168)
HHI_sq			0.093	0.141
			(0.195)	(0.189)
LnSubsidy			0.004	0.004
			(0.006)	(0.006)
LnSubsidy_sq			-0.001*	-0.001*
			(0.001)	(0.000)
Constant	7.936***	2.783***	2.562***	2.559***
	(0.117)	(0.232)	(0.246)	(0.241)

Table 6.2 Regression Test for Empirical Hypothesis H1 (Continued)

Observations	28,585	28,585	28,585	28,585
Number of stockcode	3,643	3,643	3,643	3,643
Adjusted R-squared	0.388	0.466	0.471	0.442
Firm FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: This table reports the empirical results using the benchmark regression model (5.1) for the empirical hypothesis H1. Robust standard errors clustering at the firm level are marked in parentheses. *** , ** and * indicate that the regression coefficients are significant at the 1%, 5% and 10% levels, respectively.

6.2.2 Longer-Term Productivity

Because analyst coverage may affect firms over a longer period of time, in Table 6.3 I report the results of regressions of analyst coverage on longer-term firm productivity. The explanatory variables are chosen to be the OP method TFP of the firm one year to five years in the future. Figure 6.1 plots the regression coefficients for log analyst coverage (LnAnalyst), with 95% confidence intervals represented using short vertical lines.

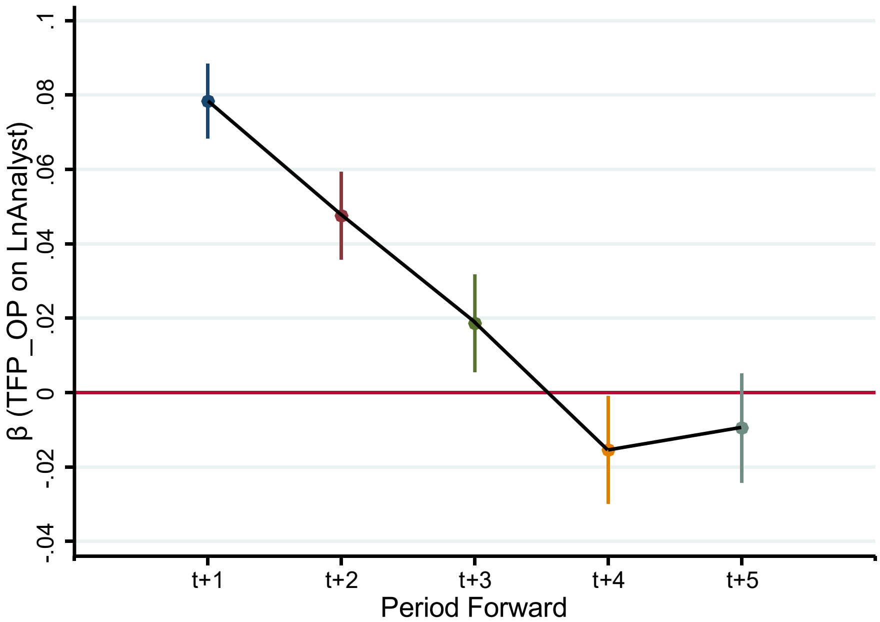

Figure 6.1 Estimated Coefficient of LnAnalyst on TFP_OP

The results show that the regression coefficients of TFP_OP on LnAnalyst for 1, 2, and 3 year ahead are significantly greater than 0, and the coefficient gradually decays. The regression coefficient on TFP_OP four year in the future is significantly negative, but the absolute value and statistical significance of the coefficient are relatively weak. Eventually, the coefficient is no longer significant if I use TFP_OP five year in the future. I also do the similar regression using the LP method, and the result is similar. These results suggest that the increase in firm productivity persists for some time.

Table 6.3 Regression Test Result for Empirical Hypothesis H1: Long Term

VARIABLES	(1) TFP_OP t+1	(2) TFP_OP t+2	(3) TFP_OP t+3	(4) TFP_OP t+4	(5) TFP_OP t+5
LnAnalyst	**0.078*** **	**0.048*** **	**0.019*** **	**-0.015** **	**-0.009**
	(0.005)	**(0.006)**	**(0.007)**	**(0.007)**	**(0.007)**
Size	0.366***	0.202***	0.067***	-0.021	-0.072***
	(0.013)	(0.015)	(0.016)	(0.018)	(0.020)
Age	0.003	0.059	0.087	0.078	0.117
	(0.050)	(0.058)	(0.068)	(0.074)	(0.077)
BM	-0.059***	-0.035***	-0.020*	-0.008	0.011
	(0.008)	(0.009)	(0.011)	(0.011)	(0.010)
Growth	0.117***	0.079***	0.041***	0.039***	0.017*
	(0.008)	(0.008)	(0.009)	(0.010)	(0.010)
CapEx	-0.203***	-0.035	0.088**	0.135***	0.166***
	(0.033)	(0.037)	(0.040)	(0.048)	(0.046)
Cashflow	0.813***	0.491***	0.266***	-0.032	-0.159**
	(0.058)	(0.067)	(0.068)	(0.076)	(0.078)
PPEratio	-0.061	0.092	0.206***	0.241***	0.314***
	(0.058)	(0.065)	(0.071)	(0.069)	(0.071)
SOE	-0.110***	-0.060	-0.036	-0.015	0.006
	(0.035)	(0.039)	(0.044)	(0.046)	(0.046)

Table 6.3 Regression Test Result for Empirical Hypothesis H1: Long Term (Continued)

FirstOwn	0.171**	0.084	0.110	0.023	0.023
	(0.082)	(0.094)	(0.104)	(0.109)	(0.114)
InstOwn	0.350***	0.337***	0.244***	0.181***	0.120*
	(0.050)	(0.059)	(0.062)	(0.067)	(0.068)
HHI	-0.092	-0.096	-0.381*	-0.176	-0.113
	(0.171)	(0.195)	(0.208)	(0.222)	(0.234)
HHI_sq	0.093	0.065	0.351	0.113	0.078
	(0.195)	(0.207)	(0.220)	(0.243)	(0.255)
LnSubsidy	0.004	0.005	0.007	0.005	0.003
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
LnSubsidy_sq	-0.001*	-0.001	-0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	2.562***	5.068***	7.470***	8.920***	9.364***
	(0.246)	(0.284)	(0.313)	(0.328)	(0.341)
Observations	28,585	25,218	21,969	18,858	16,193
Number of stockcode	3,643	3,512	3,394	2,958	2,722
Adjusted R-squared	0.471	0.359	0.283	0.256	0.262
Firm FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Note: This table reports the empirical results using the benchmark regression model (5.1) for the empirical hypothesis H1. The explanatory variable is TFP of the OP method from one year ahead to five years ahead. The robust standard errors clustering at the firm level are marked in parentheses. *** , ** and * denote regression coefficients significant at the 1%, 5% and 10% levels, respectively.

6.2.3 Instrumental Variable Estimation

To address the endogeneity problems, this paper uses ExpectedCoverage as an instrumental variable for LnAnalyst to further test the empirical hypothesis H1. Table 6.3 reports the results of the two-stage least squares (2SLS) estimation result. Column (1) reports the results of the first stage regression. It can be seen that the coefficient of LnAnalyst on LnAnalyst is significantly positive. In addition, the Kleibergen-Paap F-statistic reaches 269.35, much larger than the critical value. This result indicates that expected analyst coverage is not a weak instrumental variable.

In columns (2) to (3) I report the results of the second-stage regressions where the explanatory variables are OP method TFP and LP method TFP in the next year. The results show that the coefficients are significantly positive. Since the instrumental variable of expected analyst coverage is constructed by the size of the analyst team of the securities firm, which is generally independent of the characteristics of the firm being followed by the analyst, it satisfies the requirement of exogeneity of the instrumental variable. Therefore, the use of expected analyst coverage can somewhat address the endogeneity problem posed by reverse causality and omitted variables. This result further suggests that financial analysts contribute to firm productivity.

Table 6.4 Regression Using Instrumental Variables for Hypothesis H1

	First Stage	Second Stage	
	(1)	(2)	(3)
VARIABLES	LnAnalyst	TFP_OP	TFP_LP
	t	t+1	t+1
ExpectedCoverage	**0.095*** **		
	(0.006)		
LnAnalyst		**0.160*** **	**0.156*** **
(instrumented)		**(0.032)**	**(0.031)**
Size	0.484***	0.312***	0.272***
	(0.027)	(0.023)	(0.023)
Age	-0.372***	0.036	0.018
	(0.098)	(0.057)	(0.056)

Table 6.4 Regression Using Instrumental Variables for Hypothesis H1 (Continued)

BM	-0.217***	-0.047***	-0.048***
	(0.017)	(0.011)	(0.011)
Growth	-0.035**	0.125***	0.126***
	(0.016)	(0.012)	(0.011)
CapEx	0.177**	-0.205***	-0.303***
	(0.073)	(0.043)	(0.044)
Cashflow	0.797***	0.936***	0.945***
	(0.111)	(0.086)	(0.084)
PPEratio	-0.601***	-0.045	-0.384***
	(0.114)	(0.072)	(0.073)
SOE	-0.228***	-0.064	-0.058
	(0. 067)	(0.045)	(0.042)
FirstOwn	-0.362**	0.148	0.128
	(0.177)	(0.099)	(0.097)
InstOwn	1.221***	0.285***	0.284***
	(0.121)	(0.074)	(0.074)
HHI	-0.659*	0.193	0.141
	(0.385)	(0.215)	(0.207)
HHI_sq	0.796*	-0.077	-0.054
	(0.460)	(0.260)	(0.236)
LnSubsidy	0.031***	0.008	0.009
	(0.011)	(0.008)	(0.008)
LnSubsidy_sq	-0.002**	-0.001**	-0.001**
	(0.001)	(0.001)	(0.001)

Table 6.4 Regression Using Instrumental Variables for Hypothesis H1 (Continued)

Observations	15,306	15,306	15,306
Number of Stock	1,864	1,864	1,864
R-squared	0.340	0.535	0.497
Firm FE	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Cragg-Donald Wald F		595.69	
Kleibergen-Paap Wald F		269.35	

Note: This table reports the empirical results using an instrumental variable to the test of empirical hypothesis H1. Robust standard errors clustering at the firm level are marked in parentheses. *** , ** and * indicate that the regression coefficients are significant at the 1%, 5% and 10% levels, respectively.

6.2.4 Quasi-Natural Experiment.

This paper further tests the empirical hypothesis H1 using a quasi-natural experiment of securities firm mergers. This paper uses a difference-in-difference (DID) method to identify the impact of exogenous analyst coverage decline due to securities firm mergers on firms' TFP. A firm is classified in experimental group if analysts from two brokerage firms published at least one research report two years prior to the brokerage mergers. It is worth noting to our readers that this method of data screening is more lenient than Hong and Kacperczyk (2010), which requires that both firms' analysts have published at least one research report on a listed firm in the year prior to the brokerage mergers. I believe this is a necessary compromise: Hong and Kacperczyk (2010) use more than 43 brokerage mergers in the U.S. securities market, but there are only three brokerage mergers in China in the sample period of this paper. If the data processing method of Hong and Kacperczyk (2010) is strictly followed, the treatment group sample is too small. Nevertheless, I try to repeat the estimation strictly following Hong and Kacperczyk (2010). There were no significant differences in the estimated coefficient, although the sample size is small.

Table 6.5 in this paper reports the results of the DID estimation of the empirical hypothesis H1. Among them, columns (1) and (2) report the DID estimation result after propensity score matching (PSM). Following To et al. (2018), I perform PSM using characteristics of the firm in year prior to the event. Matching covariates includes firm size

(Size), firm book-to-market ratio (BM), operating cash flow (Cashflow), and analyst coverage (Analyst) before take logarithm. In this paper, propensity scores are estimated using Logit, with one-to-one nearest neighbor matching with a caliper of 0.05. The samples contain 231 pairs of firms. Finally, I retain the sample for only the three years before the event, the year of the event, and the three years after the event. The final sample contains 3,094 firm-year observations from 462 firms. I estimate treatment effects for the natural experiment of brokerage mergers using the regression model (5.12), and the results show that the treatment effect is significantly negative. This result suggests that the decline in financial analyst coverage from brokerage mergers significantly reduces the TFP of firms.

In addition to this, columns (3) and (4) report the results of direct DID estimation without matching. The results also shows that the decline in financial analyst coverage from brokerage mergers significantly reduces the TFP of firms.

Table 6.5 Natural Experiment Test of the Hypothesis H1

	PSM-DID		DID without Match	
	(1)	(2)	(3)	(4)
VARIABLES	TFP_OP	TFP_LP	TFP_OP	TFP_LP
Treated	**-0.065*** **	**-0.068*** **	**-0.065*** **	**-0.066*** **
	(0.024)	**(0.024)**	**(0.019)**	**(0.018)**
Size	0.526***	0.464***	0.544***	0.480***
	(0.039)	(0.039)	(0.011)	(0.011)
Age	0.131	0.107	-0.143***	-0.165***
	(0.192)	(0.195)	(0.046)	(0.045)
BM	-0.094***	-0.093***	-0.105***	-0.105***
	(0.019)	(0.019)	(0.008)	(0.008)
Growth	0.130***	0.134***	0.129***	0.128***
	(0.029)	(0.030)	(0.007)	(0.007)
CapEx	-0.139	-0.172	-0.297***	-0.326***
	(0.126)	(0.123)	(0.034)	(0.033)

Table 6.5 Natural Experiment Test of the Hypothesis H1 (Continued)

Cashflow	1.333***	1.348***	1.293***	1.274***
	(0.198)	(0.195)	(0.060)	(0.057)
PPEratio	-0.584***	-1.120***	-0.552***	-1.097***
	(0.185)	(0.184)	(0.054)	(0.054)
SOE	-0.033	-0.037	-0.109***	-0.100***
	(0.085)	(0.080)	(0.029)	(0.028)
FirstOwn	0.275	0.311	0.342***	0.348***
	(0.206)	(0.206)	(0.073)	(0.072)
InstOwn	0.057	0.060	0.315***	0.308***
	(0.103)	(0.104)	(0.043)	(0.043)
HHI	0.722	0.682	-0.200	-0.224
	(0.517)	(0.517)	(0.163)	(0.155)
HHI_sq	-0.414	-0.362	0.193	0.220
	(0.674)	(0.663)	(0.192)	(0.172)
LnSubsidy	-0.022	-0.025	0.010*	0.008
	(0.024)	(0.024)	(0.006)	(0.006)
LnSubsidy_sq	0.002	0.002	-0.001	-0.001
	(0.002)	(0.001)	(0.000)	(0.000)
Constant	0.700	0.809	0.541**	0.753***
	(0.745)	(0.751)	(0.232)	(0.224)
Observations	3,094	3,094	33,816	33,816
Number of stockcode	462	462	3,902	3,902
Adjusted R-squared	0.466	0.437	0.567	0.547
Firm FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: This table reports the empirical results of testing the empirical hypothesis H1 using the natural experiment. Robust standard errors clustering at the firm level are marked in parentheses. *** , ** and * denote regression coefficients significant at the 1%, 5% and 10% levels, respectively.

A reasonable DID estimation requires that the explanatory variables in the experimental and control groups should satisfy the parallel trend assumption. In other words, if the firms in experimental group are not shocked, then TFP should change exactly the same over time as the firms in the control group. Although it is impossible to strictly prove that the parallel trends, we can test for parallel trends through the event study method. The following model is constructed in this paper.

$$TFP_{it} = \alpha_0 + \sum_{\tau} \beta_{\tau} Period_{\tau} * Treatment_i + \boldsymbol{X}'_{it}\boldsymbol{\delta} + \mu_i + \theta_t + \epsilon_{it} \quad (6.1)$$

In equation (6.1), $\tau \in \{-3, -2, -1, 1, 2, 3\}$ represents the year before and after the event. For instance, $\tau = -1$ represents 1 year before the event. $Period_{\tau}$ is a dummy variable that takes 1 for samples with event year τ. If β_{τ} does not significantly different from 0 before the event but significantly less than 0 after the event. then the parallel trend hypothesis is supported.

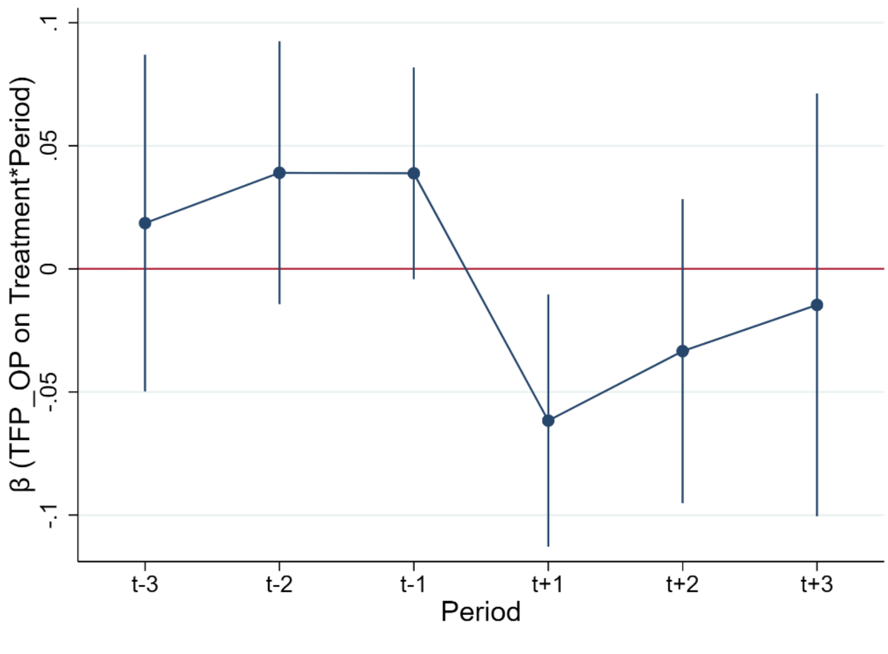

Figure 6.2 Parallel Trend Test

Figure 6.2 shows the individual β_{τ} coefficients and 95% confidence intervals for the above regressions using the OP method of TFP. We can find that β_{τ} is not significantly different from 0 before the event, but there is a significant decrease in the coefficient when mergers take place. The coefficient one year after the event is significantly smaller than 0.

This indicates that the parallel trend hypothesis is supported and the difference between the experimental and control groups should come from the treatment effect. In addition, the coefficients at two and three years after the event gradually decay, which echoes the findings in subsection 6.2.2 of this paper.

6.3 Channel Analysis

6.3.1 Test for Hypothesis H2

In this paper, regression models (5.2), (5.3) and (5.4) are used to test for the empirical hypothesis H2. Columns (1), (2), and (3) of Table 6.6 report the empirical results using the KZindex as a mediating variable. In column (1), I regress the KZ index on LnAnalyst, and the results show that the coefficient is significantly smaller than 0. This result indicates that there is a significant decrease in the KZ index of firms in the following year after analyst coverage to a firm. In columns (2) and (3), I report the results of the regression of the firm's analyst coverage on the firm's TFP calculated by the OP method in the following year, where column (3) adds the firm's KZ index in the next year to the dependent variable. We can find that the coefficient of LnAnalyst in column (3) shows a decline. This indicates that part of the impact of analyst coverage on firm productivity should be achieved by reducing the firm's financing constraints.

In columns (4), (5) and (6), I repeat the above test using the cash holding ratio. It is found that the regression coefficient of log financial analyst coverage on CashRatio is positive. And comparing column (5) and column (6), the coefficient of LnAnalyst in column (6) also shows a certain degree of decrease. These results provide support for empirical hypothesis H2.

Table 6.6 Regression Test Result for Empirical Hypothesis H2

VARIABLES	(1) KZindex t+1	(2) TFP_OP t+1	(3) TFP_OP t+1	(4) CashRatio t+1	(5) TFP_OP t+1	(6) TFP_OP t+1
LnAnalyst	**-0.167*** **	**0.078*** **	**0.064*** **	**0.008*** **	**0.078*** **	**0.076*** **
	(0.014)	**(0.005)**	**(0.005)**	**(0.001)**	**(0.005)**	**(0.005)**
KZindex			**-0.084*** **			
t+1			**(0.003)**			
CashRatio						**0.293*** **
t+1						**(0.047)**
Size	0.336***	0.366***	0.394***	-0.031***	0.366***	0.375***
	(0.038)	(0.013)	(0.013)	(0.003)	(0.013)	(0.014)
Age	1.783***	0.003	0.153***	-0.165***	0.003	0.051
	(0.170)	(0.050)	(0.050)	(0.014)	(0.050)	(0.051)
BM	0.138***	-0.059***	-0.047***	0.005***	-0.059***	-0.060***
	(0.018)	(0.008)	(0.008)	(0.001)	(0.008)	(0.008)
Growth	0.003	0.117***	0.117***	-0.002	0.117***	0.117***
	(0.022)	(0.008)	(0.008)	(0.001)	(0.008)	(0.008)
CapEx	0.680***	-0.203***	-0.146***	-0.068***	-0.203***	-0.183***
	(0.083)	(0.033)	(0.032)	(0.006)	(0.033)	(0.033)
Cashflow	-2.499***	0.813***	0.602***	0.165***	0.813***	0.765***
	(0.181)	(0.058)	(0.055)	(0.011)	(0.058)	(0.057)
PPEratio	0.997***	-0.061	0.023	-0.199***	-0.061	-0.003
	(0.157)	(0.058)	(0.056)	(0.011)	(0.058)	(0.059)
SOE	0.096	-0.110***	-0.102***	-0.004	-0.110***	-0.109***
	(0.089)	(0.035)	(0.034)	(0.006)	(0.035)	(0.035)
FirstOwn	-0.806***	0.171**	0.103	0.012	0.171**	0.168**
	(0.252)	(0.082)	(0.079)	(0.016)	(0.082)	(0.082)

Table 6.6 Regression Test Result for Empirical Hypothesis H2 (Continued)

InstOwn	-0.504***	0.350***	0.308***	0.066***	0.350***	0.331***
	(0.149)	(0.050)	(0.049)	(0.011)	(0.050)	(0.050)
HHI	-2.213***	-0.092	-0.278*	0.145***	-0.092	-0.134
	(0.500)	(0.171)	(0.169)	(0.041)	(0.171)	(0.172)
HHI_sq	2.523***	0.093	0.305	-0.114**	0.093	0.126
	(0.600)	(0.195)	(0.196)	(0.052)	(0.195)	(0.198)
LnSubsidy	-0.011	0.004	0.003	-0.000	0.004	0.004
	(0.016)	(0.006)	(0.006)	(0.001)	(0.006)	(0.006)
LnSubsidy_sq	0.001	-0.001*	-0.001*	0.000	-0.001*	-0.001*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Constant	-6.439***	2.562***	2.019***	0.994***	2.562***	2.271***
	(0.730)	(0.246)	(0.239)	(0.057)	(0.246)	(0.252)
Observations	28,585	28,585	28,585	28,585	28,585	28,585
Number of stockcode	3,643	3,643	3,643	3,643	3,643	3,643
Adjusted R-squared	0.222	0.471	0.503	0.168	0.471	0.472
Firm FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: This table reports the empirical results using regression models (5.2), (5.3) and (5.4) for empirical hypothesis H2. Robust standard errors clustering at the firm level are marked in parentheses. *** , ** and * indicate that the regression coefficients are significant at the 1%, 5% and 10% levels, respectively.

6.3.2 Test for Hypothesis H3

In this paper, regression models (5.5), (5.6) and (5.7) are used to test for the empirical hypothesis H3. Columns (1), (2), and (3) of Table 6.7 report the empirical results using log patent (LnPatent). In column (1), I regress LnPatent next year on LnAnalyst, and the results show that the coefficient is significantly larger than 0. This result indicates that after analyst coverage, there is a significant increase in patent applications filed by the firm in the following year. This indicates that in China, analyst coverage is beneficial on firm innovation. In columns (2) and (3), I report the regression results of TFP_OP on LnAnalyst, where column (3) adds a LnPatent to the independent variable. Comparing column (2) with column (3), we can find that the coefficient of analyst coverage in column (3) is smaller than in column (2). This result suggests that part of the impact of analyst coverage on firm productivity is achieved by increasing the firm's level of innovation. Therefore, this supports the empirical hypothesis H4.

In columns (4), (5) and (6), I repeat the above regression test using log citation (LnCite) as a mediating variable, and the results are similar to those using the log number of patents. The result provide further support for the empirical hypothesis H3.

Table 6.7 Regression Test Result for Empirical Hypothesis H3

VARIABLES	(1) LnPatent t+1	(2) TFP_OP t+1	(3) TFP_OP t+1	(4) LnCite t+1	(5) TFP_OP t+1	(6) TFP_OP t+1
LnAnalyst	**0.057*****	**0.078*****	**0.077*****	**0.047*****	**0.070*****	**0.069*****
	(0.010)	**(0.005)**	**(0.005)**	**(0.010)**	**(0.007)**	**(0.007)**
LnPatent			**0.018*****			
t+1			**(0.005)**			
LnCite						**0.013****
t+1						**(0.006)**
Size	0.313***	0.366***	0.360***	0.250***	0.354***	0.351***
	(0.024)	(0.013)	(0.014)	(0.028)	(0.017)	(0.017)
Age	0.187*	0.003	-0.000	0.375***	0.012	0.007
	(0.103)	(0.050)	(0.050)	(0.117)	(0.061)	(0.062)
BM	-0.016	-0.059***	-0.059***	-0.041**	-0.079***	-0.079***
	(0.015)	(0.008)	(0.008)	(0.017)	(0.011)	(0.011)
Growth	-0.006	0.117***	0.117***	-0.002	0.106***	0.106***
	(0.011)	(0.008)	(0.008)	(0.013)	(0.009)	(0.009)
CapEx	0.034	-0.203***	-0.204***	0.025	-0.223***	-0.223***
	(0.061)	(0.033)	(0.033)	(0.058)	(0.034)	(0.034)

Table 6.7 Regression Test Result for Empirical Hypothesis H3 (Continued)

Cashflow	0.082	0.813***	0.811***	0.068	0.660***	0.659***
	(0.090)	(0.058)	(0.058)	(0.097)	(0.067)	(0.067)
PPEratio	0.042	-0.061	-0.062	0.149	-0.078	-0.080
	(0.099)	(0.058)	(0.058)	(0.101)	(0.066)	(0.066)
SOE	0.107*	-0.110***	-0.112***	0.079	-0.101**	-0.102**
	(0.058)	(0.035)	(0.035)	(0.068)	(0.044)	(0.044)
FirstOwn	-0.351**	0.171**	0.178**	-0.221	0.304***	0.307***
	(0.167)	(0.082)	(0.082)	(0.171)	(0.110)	(0.110)
InstOwn	0.069	0.350***	0.349***	-0.070	0.383***	0.384***
	(0.097)	(0.050)	(0.050)	(0.100)	(0.062)	(0.061)
HHI	0.287	-0.092	-0.097	0.167	-0.537***	-0.539***
	(0.327)	(0.171)	(0.171)	(0.347)	(0.192)	(0.192)
HHI_sq	-0.139	0.093	0.095	0.107	0.459**	0.457**
	(0.367)	(0.195)	(0.195)	(0.360)	(0.217)	(0.217)
LnSubsidy	-0.077***	0.004	0.006	-0.048***	0.006	0.007
	(0.009)	(0.006)	(0.006)	(0.009)	(0.006)	(0.006)
LnSubsidy_sq	0.008***	-0.001*	-0.001**	0.005***	-0.001**	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-4.145***	2.562***	2.637***	-3.447***	2.716***	2.760***
	(0.473)	(0.246)	(0.248)	(0.527)	(0.303)	(0.304)
Observations	28,585	28,585	28,585	19,464	19,464	19,464
Number of stockcode	3,643	3,643	3,643	2,968	2,968	2,968
Adjusted R-squared	0.268	0.471	0.471	0.164	0.388	0.388
Firm FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: This table reports the empirical results using regression models (5.5), (5.6) and (5.7) for empirical hypothesis H3. Robust standard errors for clustering at the firm level are marked in parentheses. *** , ** and * indicate that the regression coefficients are significant at the 1%, 5% and 10% levels, respectively..

6.4 Managerial Pressure Mechanism: Hypothesis H4

In this paper, regression models (5.8) and (5.9) are used to test for the empirical hypothesis H4. Columns (1), (2), and (3) of Table 6.8 report the empirical results using regression model (5.8). In column (1), the coefficient of the product term of LnAnalyst and average optimistic bias (MeanError) is significantly less than zero, which indicates that the positive effect of analyst coverage on firms' TFP decreases with the extent to which analysts overestimate firms' earnings. This result provides evidence for the empirical hypothesis H4. However, someone may argue that if a financial analyst report significantly overestimates the level of corporate earnings, this research report may provide less valid information. Therefore, in columns (2) and (3), I further add the forecast estimation error (AbsError) and analyst forecast dispersion (Dispersion) to the control variables. AbsError is the mean of the absolute value of the optimistic error. Dispersion is the standard deviation of the optimistic error. It is found that the coefficient of the product term is still significantly negative. These results provide evidence for the empirical hypothesis H4.

In columns (4), (5) and (6), LnAnaHigh and LnAnaLow are the natural logarithms of the number of analysts who overestimate and underestimate firms' earnings per share in the current year. In column (5), I control the AbsError, and, in column (6), I control the Dispersion. The results in column (5) and (6) that the number of analysts who overestimate the firm's earnings forecast negatively predicts the firm's productivity in the following year. This result suggests that when financial analysts significantly overestimate the level of firm earnings, the more analysts focus on a firm, the lower the future TFP of that firm. This also provides evidence for the empirical hypothesis H4。

Table 6.8 Regression Test Result for Empirical Hypothesis H4

VARIABLES	(1) TFP_OP t+1	(2) TFP_OP t+1	(3) TFP_OP t+1	(4) TFP_OP t+1	(5) TFP_OP t+1	(6) TFP_OP t+1
LnAnalyst	0.089***	0.090***	0.089***			
	(0.007)	(0.007)	(0.007)			
MeanError	-0.049	-1.386**	-0.395			
	(0.524)	(0.602)	(0.654)			
LnAnalyst*MeanError	**-1.073*** **	**-0.933*** **	**-0.960*** **			
	(0.242)	**(0.242)**	**(0.288)**			
LnAnaLow				**0.081*** **	**0.065*** **	**0.055*** **
				(0.004)	**(0.006)**	**(0.005)**
LnAnaHigh				**0.003**	**-0.018*** **	**-0.018*** **
				(0.003)	**(0.004)**	**(0.004)**
AbsError		1.706***			0.957***	
		(0.387)			(0.300)	
Dispersion			-0.004			-0.010
			(0.015)			(0.015)
Size	0.333***	0.332***	0.331***	0.376***	0.334***	0.335***
	(0.015)	(0.015)	(0.016)	(0.013)	(0.015)	(0.016)
Age	0.071	0.069	0.078	-0.046	0.048	0.057
	(0.053)	(0.053)	(0.053)	(0.050)	(0.053)	(0.052)
BM	-0.049***	-0.052***	-0.048***	-0.055***	-0.051***	-0.047***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Growth	0.111***	0.108***	0.103***	0.105***	0.108***	0.102***
	(0.010)	(0.010)	(0.011)	(0.008)	(0.010)	(0.011)
CapEx	-0.188***	-0.185***	-0.197***	-0.204***	-0.188***	-0.202***
	(0.036)	(0.036)	(0.037)	(0.033)	(0.037)	(0.035)
Cashflow	0.778***	0.769***	0.789***	0.748***	0.752***	0.768***
	(0.065)	(0.065)	(0.068)	(0.058)	(0.065)	(0.066)

Table 6.8 Regression Test Result for Empirical Hypothesis H4 (Continued)

PPEratio	0.056	0.056	0.066	-0.077	0.052	0.062
	(0.060)	(0.060)	(0.061)	(0.058)	(0.060)	(0.060)
SOE	-0.088**	-0.090**	-0.076*	-0.112***	-0.090**	-0.079*
	(0.038)	(0.038)	(0.041)	(0.035)	(0.038)	(0.041)
FirstOwn	0.126	0.123	0.156*	0.185**	0.144*	0.149*
	(0.086)	(0.086)	(0.087)	(0.082)	(0.086)	(0.087)
InstOwn	0.262***	0.270***	0.211***	0.334***	0.241***	0.178***
	(0.053)	(0.053)	(0.053)	(0.050)	(0.053)	(0.052)
HHI	-0.136	-0.154	-0.238	-0.116	-0.150	-0.227
	(0.175)	(0.174)	(0.174)	(0.171)	(0.174)	(0.168)
HHI_sq	0.124	0.141	0.290	0.139	0.159	0.277
	(0.197)	(0.197)	(0.188)	(0.195)	(0.197)	(0.183)
LnSubsidy	-0.007	-0.007	-0.013**	0.004	-0.008	-0.014**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
LnSubsidy_sq	0.000	0.000	0.001	-0.001*	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	2.832***	2.837***	2.869***	2.607***	2.914***	2.942***
	(0.285)	(0.285)	(0.293)	(0.249)	(0.284)	(0.285)
Observations	20,723	20,723	18,595	28,585	20,723	19,067
Number of stockcode	3,340	3,340	3,156	3,643	3,340	3,224
Adjusted R-squared	0.500	0.501	0.507	0.473	0.503	0.517
Firm FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: This table reports the empirical results using regression models (5.8) and (5.9) for the empirical hypothesis H5. The robust standard errors clustering at the firm level are marked in parentheses. *** , ** and * indicate that the regression coefficients are significant at the 1%, 5% and 10% levels, respectively..

Chapter VII Robustness Check

In Chapter 6 of this paper, I test each of the empirical hypotheses presented in Chapter 3 of this paper. In order to avoid spurious results that lead to wrong conclusions in this paper, in this chapter I perform rich robustness tests on the results of this paper. There are two main aspects: First, to avoid spurious results due to variable measures, in subsection 7.1, I construct explanatory variables, explained variables, and instrumental variables using alternative methods. Second, to avoid spurious results due to incorrect use of measures, in subsection 7.2 of this paper I also perform robustness tests on the methodology in this paper. All these results indicate that the main findings of this paper are robust.

7.1 Robustness Tests for Variable Measurements

7.1.1 Using Return on Assets as Dependent Variable

In the analysis in Chapter 6, I use the TFP of the firm as a measure of the firm's productive efficiency. Because the TFP is an indicator calculated based on a structural model, it requires a accurate model settings. In order to avoid the problems that may arise because of the unrobustness of the variable estimation, I follow Dong and Liu (2021) and use the firm's return on assets (ROA) as another measure of the firm's productivity. Mathematically, the firm's return on asset is the net profit divided by the year-beginning and year-end average total assets.

Since ROA represents the profit generated per unit of productive resources, it can also be broadly interpreted as a measurement of productivity. In fact, a firm's return on assets is highly positively correlated with TFP (İmrohoroğlu and Tüzel, 2014). However, we should notice that there are also some differences between firms' return on assets and TFP: first, the numerator of ROA is net profit, which considers non-productive income such as interest income and government subsidy income, but TFP excludes these accounting accounts from the calculation. Second, the denominator of ROA is the average total assets, which includes all asset types of the firm; whereas TFP uses the firm's fixed assets as a proxy variable for the firm's capital investment, without considering other asset types such as intangible assets of the firm. Third, the ROA does not deduct the contribution of the labor input, while TFP deducts the contribution of labor inputs to output. Fourth, the ROA is calculated directly using nominal data without adjusting for price levels, while TFP is calculated using real data after adjusting for price changes.

In Table 7.1, I repeat the baseline regression using ROA from one year ahead to five years ahead as dependent variable. Comparing to the results in subsection 6.2.2 of this paper, we find that the results using ROA are similar in time trend to those using TFP. The difference is that when TFP is used, the coefficient for LnAnalyst starts to become negative four years in the future, while when return on assets is used, the coefficient starts to become negative as early as three years in the future. Why does the log analyst coverage negatively predict the long-term productivity and ROA of a firm? I think that this question requires further research.

Table 7.1 Using Return on Asset as Dependent Variable

	(1)	(2)	(3)	(4)	(5)
VARIABLES	ROA	ROA	ROA	ROA	ROA
	t+1	t+2	t+3	t+4	t+5
LnAnalyst	**0.008*** **	**0.003*** **	**-0.001** **	**-0.004*** **	**-0.002*** **
	(0.000)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Size	-0.016***	-0.021***	-0.021***	-0.019***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Age	-0.004	0.000	0.001	0.002	0.005
	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
BM	-0.004***	0.000	0.004***	0.006***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Growth	0.011***	0.006***	0.002***	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
CapEx	-0.022***	-0.012***	-0.002	0.003	0.004
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)

Table 7.1 Using Return on Asset as Dependent Variable (Continued)

Cashflow	0.107***	0.058***	0.025***	-0.006	-0.025***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
PPEratio	-0.014***	0.005	0.018***	0.016***	0.016***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
SOE	-0.007***	-0.006*	-0.006*	-0.007*	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
FirstOwn	0.003	-0.000	0.002	0.008	0.017*
	(0.007)	(0.008)	(0.008)	(0.009)	(0.009)
InstOwn	0.042***	0.036***	0.024***	0.016***	0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
HHI	0.012	0.021	0.001	-0.017	-0.013
	(0.015)	(0.017)	(0.018)	(0.019)	(0.019)
HHI_sq	-0.015	-0.019	0.000	0.018	0.014
	(0.018)	(0.018)	(0.020)	(0.022)	(0.024)
LnSubsidy	-0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
LnSubsidy_sq	-0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.267***	0.333***	0.366***	0.345***	0.233***
	(0.021)	(0.022)	(0.024)	(0.027)	(0.029)
Observations	28,585	25,218	21,969	18,858	16,193
Number of stockcode	3,643	3,512	3,394	2,958	2,722
Adjusted R-squared	0.138	0.087	0.073	0.060	0.037
Firm FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Note: Robust standard errors clustering at the firm level are marked in parentheses. *** , ** and * indicate that the regression coefficients are significant at the 1%, 5% and 10% levels, respectively.

7.1.2 Using Log Report as Independent Variables

In the analysis in Chapter 6, I use the number of analyst teams that issue earnings forecasts for a firm in a year as a measure of how much attention a firm receives from analysts. Because a team of analysts may issue multiple research reports in a year, in Table 7.2, I use the natural logarithm of the total number of research reports (LnReport) for a firm in a year as another measure of analyst coverage, and the explanatory variables are the OP method TFP, LP method TFP, and ROA in the coming year, respectively. The results are not significantly different from the main results in Chapter 6.

Table 7.2 Using Log Report as Independent Variables

	(1)	(2)	(3)	(4)	(5)
VARIABLES	TFP_OP	TFP_OP	TFP_OP	TFP_LP	ROA
	t+1	t+1	t+1	t+1	t+1
LnReport	**0.128*** **	**0.070*** **	**0.064*** **	**0.063*** **	**0.007*** **
	(0.005)	**(0.004)**	**(0.004)**	**(0.004)**	**(0.000)**
Size		0.369***	0.364***	0.310***	-0.016***
		(0.013)	(0.014)	(0.013)	(0.001)
Age		-0.077	-0.014	-0.036	-0.006
		(0.050)	(0.050)	(0.049)	(0.005)
BM		-0.066***	-0.058***	-0.060***	-0.004***
		(0.008)	(0.008)	(0.009)	(0.001)
Growth		0.125***	0.116***	0.117***	0.011***
		(0.008)	(0.008)	(0.008)	(0.001)
CapEx		-0.194***	-0.205***	-0.292***	-0.022***
		(0.034)	(0.033)	(0.032)	(0.002)
Cashflow		0.807***	0.808***	0.810***	0.106***
		(0.058)	(0.058)	(0.056)	(0.006)
PPEratio		-0.101*	-0.071	-0.424***	-0.014***
		(0.059)	(0.058)	(0.059)	(0.005)

Table 7.2 Using Log Report as Independent Variables (Continued)

SOE			-0.110***	-0.099***	-0.007***
			(0.035)	(0.034)	(0.003)
FirstOwn			0.169**	0.168**	0.003
			(0.082)	(0.082)	(0.007)
InstOwn			0.352***	0.344***	0.042***
			(0.050)	(0.050)	(0.005)
HHI			-0.093	-0.162	0.012
			(0.172)	(0.168)	(0.015)
HHI_sq			0.100	0.149	-0.014
			(0.195)	(0.189)	(0.017)
LnSubsidy			0.005	0.005	-0.000
			(0.006)	(0.006)	(0.000)
LnSubsidy_sq			-0.001*	-0.001**	-0.000
			(0.001)	(0.000)	(0.000)
Constant	7.945***	2.867***	2.637***	2.634***	0.275***
	(0.115)	(0.233)	(0.247)	(0.242)	(0.021)
Observations	28,585	28,585	28,585	28,585	28,585
Number of stockcode	3,643	3,643	3,643	3,643	3,643
Adjusted R-squared	0.390	0.466	0.471	0.442	0.138
Firm FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Note: Robust standard errors clustering at the firm level are marked in parentheses. *** , ** and * indicate that the regression coefficients are significant at the 1%, 5% and 10% levels, respectively.

7.1.3 Changing the Base Year and Reconstructing the Instrument Variable

In the analysis in Chapter 6, the instrument variable ExpectedCoverage, is constructed by selecting 2020 as the base year. I argue that this method of construction is reasonable. Yu (2008) argues that the choice of the base year does not affect the exogeneity and relevance of this instrumental variable. In this section, to avoid spurious results due to the choice of the base year, I reconstruct the instrumental variable by switching to 2016 and 2019 as the base year and repeat the instrumental variable regression analysis in Chapter 6. The results are presented in Table 7.3. We can find that the coefficients of the second regression step are still significantly positive, which supports the conclusions of this paper.

Table 7.3 Changing the Base Year and Reconstructing the Instrument Variable

	Benchmark Year = 2016			Benchmark Year = 2019		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	LnAnalyst	TFP_OP	TFP_LP	LnAnalyst	TFP_OP	TFP_LP
	t	t+1	t+1	t	t+1	t+1
ExpectedCoverage	**0.057*** **			**0.094*** **		
	(0.005)			**(0.005)**		
LnAnalyst		**0.143*** **	**0.147*** **		**0.138*** **	**0.132*** **
(instrumented)		**(0.043)**	**(0.043)**		**(0.027)**	**(0.027)**
Size	0.484***	0.329***	0.277***	0.479***	0.310***	0.268***
	(0.022)	(0.027)	(0.027)	(0.024)	(0.020)	(0.020)
Age	-0.647***	0.048	0.031	-0.502***	0.068	0.052
	(0.093)	(0.059)	(0.058)	(0.098)	(0.057)	(0.056)
BM	-0.241***	-0.043***	-0.042***	-0.232***	-0.044***	-0.046***
	(0.016)	(0.014)	(0.014)	(0.016)	(0.011)	(0.011)
Growth	-0.017	0.127***	0.129***	-0.032**	0.129***	0.130***
	(0.012)	(0.009)	(0.009)	(0.015)	(0.010)	(0.010)
CapEx	0.216***	-0.180***	-0.274***	0.185**	-0.183***	-0.275***
	(0.058)	(0.038)	(0.038)	(0.072)	(0.045)	(0.045)
Cashflow	0.605***	0.824***	0.825***	0.794***	0.830***	0.844***
	(0.093)	(0.072)	(0.070)	(0.109)	(0.081)	(0.078)
PPEratio	-0.551***	-0.043	-0.381***	-0.437***	-0.022	-0.370***
	(0.096)	(0.065)	(0.065)	(0.109)	(0.065)	(0.066)

Table 7.3 Changing the Base Year and Reconstructing the Instrument Variable (Continued)

SOE	-0.202***	-0.077**	-0.070*	-0.189***	-0.055	-0.046
	(0.057)	(0.039)	(0.039)	(0.071)	(0.041)	(0.039)
FirstOwn	-0.401***	0.174*	0.170*	-0.533***	0.163*	0.154*
	(0.147)	(0.090)	(0.090)	(0.158)	(0.091)	(0.088)
InstOwn	1.294***	0.284***	0.270***	1.258***	0.291***	0.297***
	(0.103)	(0.077)	(0.077)	(0.113)	(0.067)	(0.067)
HHI	-0.375	-0.072	-0.158	-0.379	0.204	0.131
	(0.320)	(0.187)	(0.182)	(0.355)	(0.205)	(0.197)
HHI_sq	0.625*	0.114	0.180	0.579	-0.111	-0.065
	(0.375)	(0.211)	(0.199)	(0.431)	(0.242)	(0.221)
LnSubsidy	0.012	0.003	0.004	0.034***	0.002	0.003
	(0.009)	(0.007)	(0.007)	(0.010)	(0.008)	(0.008)
LnSubsidy_sq	0.000	-0.001	-0.001*	-0.002**	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	22,016	22,016	22,016	16,492	16,492	16,492
Number of stockcode	2,414	2,414	2,414	1,964	1,964	1,964
R-squared	0.400	0.448	0.411	0.355	0.591	0.558
Firm FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Cragg-Donald F		330.00			719.934	
Kleibergen-Paap F		146.84			314.694	

Note: This table reports the empirical results of testing the empirical hypothesis H1 using expected analyst coverage as an instrumental variable for log analyst coverage. When constructing the instrumental variables, the base years are chosen to be 2016 and 2019, respectively. The robust standard errors clustering at the firm level are marked in parentheses. *** , ** and * indicate that the regression coefficients are significant at the 1%, 5% and 10% levels, respectively.

To further test the robustness of the instrumental variables in this paper, I try all years from 2007 to 2020 as the base years to construct the instrumental variables. It turns out that constructing instrumental variables using 2016 to 2019 as the base year gives similar results. However, if the instrumental variables are constructed using 2007 to 2015 as the base years, the F-statistics of the weak instrumental variable tests are small, which indicates that the instrumental variables are weaker. In addition to this, the results of the second-stage regression are not significant if the instrumental variables are constructed using 2007 to 2015 as the base year. To some extent, this result questions the robustness of the results of this paper. However, because the China's securities industry is in rapid development with new companies going public and new analysts entering the industry, using earlier years as the base year to construct the instrumental variables would lead to a large number of missing samples. Therefore, I believe that this phenomenon is is in line with expectations. In addition to this, considering that this paper also uses a natural experiment of securities firm mergers, and the results still support the empirical hypothesis of this paper, I think that the main findings of this paper are relatively robust.

7.2 Robustness Tests for Econometric Methods

7.2.1 Using Instrumental Variables in Channel Analysis

In Chapter 6 of this paper, I use Baron and Kenny's (1986) classic three step regression approach to test how analyst coverage increase firm productivity. However, reverse causality and omitted variable bias may still lead to biased estimates in the regression estimations. To solve the potential endogeneity problem in these channel analysis, I further tested the channels using the instrumental variables estimation.

Table 7.4 reports the results of the regression using KZindex, CashRatio and LnPatent as dependent variables. The results show that analyst coverage significantly release the financing constraints in the next year and increases the firm's innovation outcomes in the next year. The results further provide support for the mediation mechanism in this paper.

Table 7.4 Using Instrumental Variables in Channel Analysis

	First Stage	Second Stage		
	(1)	(2)	(3)	(4)
VARIABLES	LnAnalyst	KZindex	CashRatio	LnPatent
	t	t+1	t+1	t+1
ExpectedCoverage	**0.095*** **			
	(0.006)			
LnAnalyst		**-0.266** **	**0.018** **	**0.209*** **
(instrumented)		**(0.110)**	**(0.008)**	**(0.075)**
Size	0.484***	0.526***	-0.035***	0.210***
	(0.027)	(0.079)	(0.006)	(0.053)
Age	-0.372***	1.750***	-0.164***	-0.002
	(0.098)	(0.216)	(0.017)	(0.144)
BM	-0.217***	0.123***	0.009***	0.018
	(0.017)	(0.034)	(0.002)	(0.025)
Growth	-0.035**	-0.064**	0.001	-0.006
	(0.016)	(0.033)	(0.002)	(0.018)
CapEx	0.177**	0.888***	-0.089***	-0.097
	(0.073)	(0.121)	(0.008)	(0.088)
Cashflow	0.797***	-2.987***	0.176***	-0.016
	(0.111)	(0.275)	(0.018)	(0.161)
PPEratio	-0.601***	0.995***	-0.208***	0.092
	(0.114)	(0.218)	(0.016)	(0.157)
SOE	-0.228***	0.232*	-0.010	0.176**
	(0. 067)	(0.131)	(0.009)	(0.081)
FirstOwn	-0.362**	-0.684**	0.021	-0.286
	(0.177)	(0.340)	(0.021)	(0.239)
InstOwn	1.221***	-0.404*	0.050***	-0.105
	(0.121)	(0.245)	(0.018)	(0.170)

Table 7.4 Using Instrumental Variables in Channel Analysis (Continued)

HHI	-0.659*	-1.907***	0.135***	-0.180
	(0.385)	(0.664)	(0.050)	(0.472)
HHI_sq	0.796*	2.393***	-0.122**	0.504
	(0.460)	(0.704)	(0.057)	(0.514)
LnSubsidy	0.031***	-0.010	-0.002	-0.084***
	(0.011)	(0.025)	(0.002)	(0.016)
LnSubsidy_sq	-0.002**	0.001	0.000	0.009***
	(0.001)	(0.002)	(0.000)	(0.001)
Observations	15,306	15,306	15,306	15,306
Number of Stock	1,864	1,864	1,864	1,864
R-squared	0.340	0.135	0.080	0.232
Firm FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: This table reports regression results using expected analyst coverage as an instrumental variable for log analyst coverage. Robust standard errors for clustering at the firm level are marked in parentheses. *** , ** and * denote regression coefficients significant at the 1%, 5% and 10% levels, respectively.。

7.2.2 Placebo Test for Quasi-natural Experiment

I conducted a placebo test for a natural experiment on brokerage mergers. The placebo variable (PlaceboTreated) was obtained by shifting the treatment variable Treated back in time by three years. The coefficient on the placebo variable was found to be insignificant. This is in line with out expectations. Table 7.5 shows the results of the placebo test.

Table 7.5 Placebo Test for Quasi-natural Experiment

VARIABLES	(1) TFP_OP t+1	(2) TFP_LP t+1
PlaceboTreated	**-0.058**	**-0.048**
	(0.061)	**(0.055)**
Size	0.518***	0.460***
	(0.038)	(0.036)
Age	-0.051	-0.070
	(0.115)	(0.112)
BM	-0.122***	-0.117***
	(0.021)	(0.021)
Growth	0.151***	0.151***
	(0.026)	(0.026)
CapEx	-0.177*	-0.194**
	(0.091)	(0.089)
Cashflow	0.939***	0.929***
	(0.153)	(0.152)
PPEratio	-0.555***	-1.104***
	(0.149)	(0.149)
SOE	-0.101	-0.099
	(0.079)	(0.071)
FirstOwn	0.328	0.341*
	(0.211)	(0.202)
InstOwn	0.179*	0.189**
	(0.098)	(0.096)
HHI	-0.610	-0.805**
	(0.370)	(0.358)
HHI_sq	0.577	0.875**
	(0.457)	(0.415)

Table 7.5 Placebo Test for Quasi-natural Experiment (Continued)

LnSubsidy	-0.002	0.000
	(0.013)	(0.013)
LnSubsidy_sq	0.001	0.001
	(0.001)	(0.001)
Constant	1.258**	1.409**
	(0.589)	(0.566)
Observations	2,834	2,834
Adjusted R-squared	0.607	0.580
Firm FE	YES	YES
Industry FE	YES	YES
Year FE	YES	YES

Note: This table reports a placebo test for the natural experiment of brokerage merger. The placebo dummy variable PlaceboTreated is constructed by shifting the Treated variable three periods into the past. Robust standard errors clustering at firm level are marked in parentheses. *** , ** and * denote regression coefficients significant at the 1%, 5% and 10% levels, respectively.

7.2.3 Increasing of Control Variables

In the empirical analysis in Chapter 6 of this paper, I have controlled for a rich set of control variables and controlled for firm, industry, and year fixed effects to minimize the problem of omitted variable bias. Notably, Chapter 6 of this paper does not control for firm's ROA and firm's leverage ratio (Leverage) in the benchmark regression analysis. I do not control for ROA because ROA itself can be considered as another measure of firm productivity (cf. subsection 7.1.1 of this chapter). Moreover, return on assets is highly positively correlated with TFP (İmrohoroğlu and Tüzel, 2014), so controlling for ROA would absorb some of the analysts' concerns about the impact on firm productivity. Chapter 6 of this paper also does not control for the firm's leverage ratio because the firm's leverage ratio is related to the financial constraint channel studied in this paper. Therefore, controlling for the leverage ratio in the regression analysis would absorb some of the productivity changes due to the financing constraints.

However, to further prevent spurious results due to omitted variable bias, the results of the benchmark regressions that further control for the firm's return on assets (ROA) and the firm's leverage ratio (Leverage) are reported in Table 7.6. The results show that the coefficients of interest LnAnalyst remain significantly larger than 0. This provides further support for my results.

Table 7.6 Regression Test for Empirical Hypothesis H1: Increasing Control Variables

VARIABLES	(1) TFP_OP t+1	(2) TFP_OP t+2	(3) TFP_OP t+3	(4) TFP_LP t+1	(5) TFP_LP t+2	(6) TFP_LP t+3
LnAnalyst	**0.053*** **	**0.040*** **	**0.019*** **	**0.052*** **	**0.038*** **	**0.017** **
	(0.005)	**(0.006)**	**(0.007)**	**(0.005)**	**(0.006)**	**(0.007)**
ROA	2.022***	0.636***	0.058	2.041***	0.619***	0.060
	(0.117)	(0.128)	(0.137)	(0.113)	(0.124)	(0.131)
Leverage	0.133***	0.105*	0.133**	0.160***	0.118**	0.148***
	(0.047)	(0.054)	(0.059)	(0.044)	(0.051)	(0.057)
Size	0.369***	0.199***	0.059***	0.313***	0.155***	0.026
	(0.013)	(0.016)	(0.017)	(0.013)	(0.015)	(0.016)
Age	0.032	0.060	0.067	0.005	0.046	0.052
	(0.047)	(0.058)	(0.068)	(0.046)	(0.057)	(0.067)
BM	-0.047***	-0.032***	-0.026**	-0.049***	-0.033***	-0.025**
	(0.008)	(0.009)	(0.011)	(0.008)	(0.009)	(0.011)
Growth	0.074***	0.065***	0.038***	0.074***	0.068***	0.041***
	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)
CapEx	-0.160***	-0.023	0.088**	-0.247***	-0.130***	0.005
	(0.032)	(0.037)	(0.041)	(0.031)	(0.036)	(0.040)
Cashflow	0.521***	0.403***	0.264***	0.522***	0.390***	0.245***
	(0.057)	(0.066)	(0.070)	(0.055)	(0.064)	(0.068)
PPEratio	0.050	0.117*	0.189***	-0.306***	-0.092	0.091
	(0.057)	(0.065)	(0.071)	(0.057)	(0.065)	(0.069)

Table 7.6 Regression Test for Empirical Hypothesis H1: Increasing Control Variables (Continued)

SOE	-0.097***	-0.058	-0.037	-0.086***	-0.048	-0.030
	(0.034)	(0.039)	(0.044)	(0.033)	(0.039)	(0.043)
FirstOwn	0.114	0.063	0.108	0.110	0.057	0.103
	(0.076)	(0.092)	(0.104)	(0.076)	(0.093)	(0.104)
InstOwn	0.293***	0.328***	0.255***	0.288***	0.317***	0.237***
	(0.047)	(0.059)	(0.063)	(0.047)	(0.058)	(0.062)
HHI	-0.067	-0.076	-0.359*	-0.131	-0.185	-0.487**
	(0.166)	(0.194)	(0.208)	(0.162)	(0.192)	(0.204)
HHI_sq	0.060	0.039	0.332	0.104	0.139	0.469**
	(0.197)	(0.207)	(0.220)	(0.187)	(0.205)	(0.217)
LnSubsidy	0.008	0.007	0.007	0.008	0.008	0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
LnSubsidy_sq	-0.001***	-0.001	-0.000	-0.001***	-0.001*	-0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Constant	2.286***	5.033***	7.563***	2.307***	4.811***	7.115***
	(0.242)	(0.288)	(0.316)	(0.236)	(0.275)	(0.294)
Observations	28,585	25,218	21,969	28,585	25,218	21,969
Number of stockcode	3,643	3,512	3,394	3,643	3,512	3,394
Adjusted R-squared	0.486	0.361	0.284	0.459	0.334	0.260
Firm FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: This table reports the empirical results using the benchmark regression model (5.1) for the empirical hypothesis H1. The explanatory variables are future one-year, two-year, and three-year OP method TFP and LP method TFP. The robust standard errors clustering at the firm level are marked in parentheses. *** , ** and * indicate that the regression coefficients are significant at the 1%, 5% and 10% levels, respectively.

Chapter VIII Conclusion

8.1 Main Findings and Conclusions

In this article, I empirically investigate whether financial analysts in China can improve the productivity of listed companies in China using samples of A-share listed companies.

I find that two different mechanisms have been proposed in the existing literature to elucidate the relationship between financial analysts' coverage and firms' productivity. The information mechanism suggests that financial analysts can alleviate the financial constraints of firms and increase firm’s innovation. Therefore, the information mechanism predict that financial analysts are beneficial to firms' productivity. The managerial pressure mechanism, in contrast, argues that financial analysts have an incentive to overestimate a firm's earnings. Overly optimistic short-term earnings forecasts can put pressure on firm management to forgo investments that benefit firm performance in the long run, which in turn reduces firm productivity.

In order to verify the above mechanisms, I estimated TFP of China's listed companies using methods proposed by Olley and Pakes (1996) and Levinsohn and Pertin (2003). Finally, I use a sample of 28,585 firm-year observations of 3,643 listed firms from 2007 to 2020. The baseline regression results indicate that the analyst coverage in the Chinese stock market increases the productivity of firms. Further, I find that analyst coverage may increase firm productivity through two channels: reducing firms' financing constraints and increasing firms' innovation. In addition, the empirical study in this paper also finds that the effect of analyst coverage on firm productivity is more significant when analysts do not significantly overestimate the level of firm profitability. This result suggests that the managerial pressure mechanism may also exist in China.

To solve endogeneity problems in the benchmark regressions, I also follows Yu (2008) to estimate the effect of analyst coverage using the instrumental variable of expected analyst coverage. In addition, this paper also follows Hong and Kacperczyk (2010) and Derrien and Kecskés (2013) to identify the impact of the decline in analyst coverage on firm productivity by using the decline in analyst coverage due to mergers and acquisitions between securities firm. The results support the findings in the benchmark regression of this paper.

8.2 Policy Implication

This paper finds that the productivity-enhancing effect of analyst coverage exists only when analysts do not significantly overestimate firm short-term earnings levels. A large body of existing academic research points to the lack of analyst independence as the reason for analysts' systematic overestimation of firm earnings (Dugar & Nathan, 1995; Hong & Kubi, 2003; Ke & Yu, 2006; Cao, Sheng & Zhu, 2011; Zhao, et al. 2013; etc.). A natural question then is what regulatory policies can further enhance the independence of analysts in China.

It is worth noting that sell-side analysts in the Chinese securities market adopt a business model of "research for commission". This business model is also known as "bundling payment" or "soft dollar". While there is some justification for "research-for-commission," this business model is also considered to do harm to the independence of analyst (Xue et al., 2022). I believe that *the Markets in Financial Instruments Directive II* (*MiFID II*), which came into force in the European Union on January 3, 2018, may have implications for analyst regulation in China.

8.2.1 Soft Dollar and Analyst Independence

In Figure 8.1, I depict the business model of sell-side analysts: based on research on each listed company, sell-side analysts provide research services for investment institutions. The research services include not only the research reports issued by the sell-side analysts, but also other service such as data collection. The core feature of "research for commission" is that investment institutions such as fund companies generally do not pay sell-side analysts directly for their services in China and the US. Institutional investors choose to buy and sell securities through the sales and trading offices of brokerage companies with good research services and pay more commission. This allows sell-side analysts to generate revenue for securities firms. After enjoying the research service, investment institutions will also rate the research service of each sell-side analyst, and the securities company can pay part of the position commission to the sell-side analyst as free according to the rating.

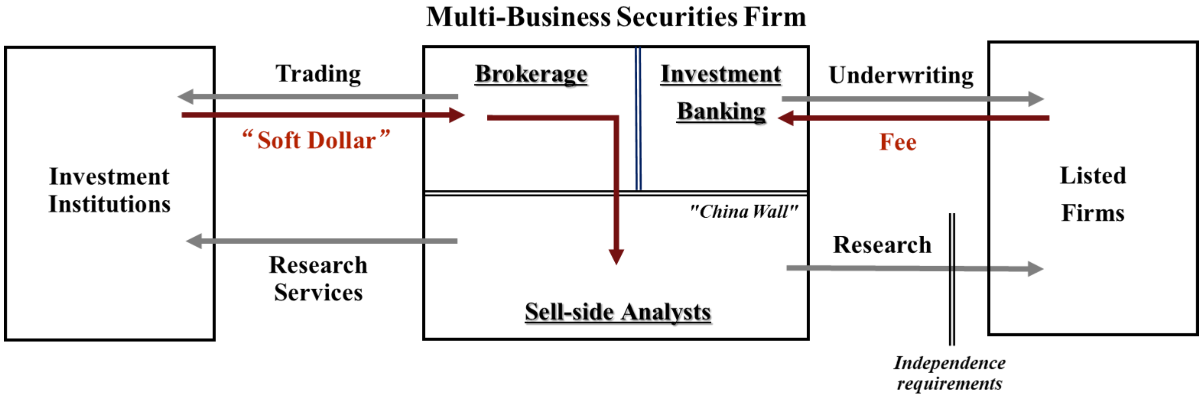

Figure 8.1 The Business Model of Sell-side Analysts in China

This business model is sustainable for at least two reasons: First, it is simple and feasible for investment institutions to pay a lump sum fee to securities firms. This method of payment simplifies the flow of funds between the investment institution and the securities firm. Second, neither the U.S. nor the Chinese law and regulators require investment firms to pay analysts independently: In 1975, the U.S. Congress amended the U.S. Securities Exchange Act of 1934, which added a new Section 28(e) allowing investment firms to make bundling payments (Guo & Mota, 2021). The Chinese law also does not require investment firms to pay analysts separately.

However, the "research-for-commission" business model is detrimental to the independence of sell-side analysts. Although both U.S. and Chinese laws require the establishment of a "Chinese wall" between the research department and other departments of the securities firm, the research department itself does not receive independent service fee income because the investment institution makes a bundling payment to the securities firm. In practice, the securities company executives decide the income of each sell-side analyst. This makes sell-side analysts still have the incentive to consider the overall interests of their employer and issue research reports in favor of the securities company's other business.

In addition, this bundling payment business model is also very opaque. Since it is not clear how much of the fees from the investment institution to the securities firm is given to the analyst, it is also difficult for regulators to detect misconduct between the sell-side analyst and the investment institution. For example, an investment institution may choose to trade with a brokerage firm that issues optimistic reports for its investment positions, thereby inducing bias in analyst's forecast (Xue et al., 2022).

8.2.2 Insights from *MiFID II*

In order to eliminate the disadvantages of "research-for-commission", the European Union has made active attempts in regulating analysts. *MiFID II*, an EU law comming into force on January 3, 2018, explicitly requires investment institutions to pay for analysts' services separately. Guo and Mota (2021) study the impact of *MiFID II* on the financial analyst market in the EU. Their empirical results find that *MiFID II* significantly improves the accuracy of analysts' forecasts.

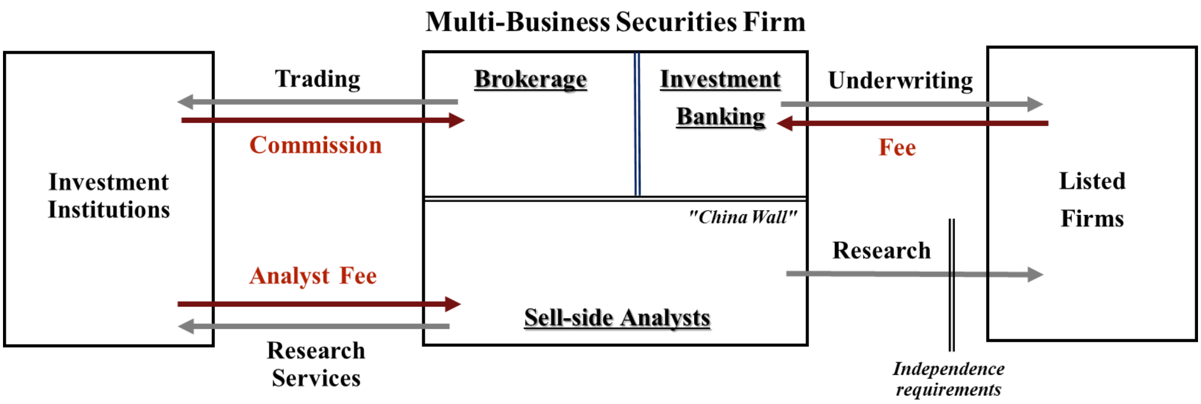

Figure 8.2 The Business Model of Sell-side Analysts in EU after *MiFID II*

Based on the above analysis, I believe that China can learn from the regulatory requirements for financial analysts in *MiFID II*, requiring Chinese investment institutions to pay separate fees to sell-side analysts. This will help maintain the independence of sell-side analysts, curb sell-side analysts from issuing reports that overestimate corporate profitability, and ultimately allow financial analysts to better serve China's real economy.

8.3 Shortcomings and Prospects

As a preliminary research result, there are some limitations and shortcomings in this paper, which need further analysis and research.

First, the heterogeneity of the role of financial analysts among different enterprises still needs to be studied. China's listed companies are in different places, in all industries, and there are significant differences in the ownership structure and management system of each firm. Although this paper finds that, the financial analysts in China's stock market has improved the performance of enterprises in general, I do not conducted in-depth research on the heterogeneity of the effect among different enterprises.

Second, the differences in the role of financial analysts over time are yet to be studied. Since the establishment of China's stock market, China's stock indexes have experienced several ups and downs. Especially, there are two market crashes in 2008 and 2015 after the stock market bubbles. Economic theory suggests that the bursting of financial bubbles can exacerbate the financing constraints of firms and may lead to a decline in the productivity of the economy (e.g., Miao & Wang, 2012). Considering that financial analysts can make corporate information more transparent, and that information asymmetry is an important cause of corporate financing constraints (Myers & Majluf , 1984), a natural question is: Is the enhancing effect of financial analysts on corporate performance more pronounced in bear markets following the bursting of financial bubbles? This question is subject to further in-depth study in the future.

Third, the effect of financial analysts on the overall productivity of an economy remains to be studied. In this paper, I focus on the relationship between analyst coverage and the performance of the firms being followed. Although this paper finds that analyst coverage helps improve the performance of firms, however, analyst coverage is also likely to have externalities on the performance of other firms. One possible scenario is that if the supply of funds in a financial market is constant, analyst coverage, in relaxing the financing constraints of the firms under attention, also deprives other firms of financing at the same time. This mechanism is likely to exist because listed firms have much less difficulty raising funds than unlisted firms. Unfortunately, regression analysis can only tell us the results of partial equilibrium in the A-share market, but not the total effect on the Chinese economy as a whole. This issue also needs to be further investigated in depth in the future.

Fourth, the regulation on financial analysts needs to be further studied. I think that China's securities regulators could learn from the EU's approach to regulating financial analysts. However, because there are huge differences between two financial market, copying the EU regulatory requirements is not the optimal solution. Due to my lack of background knowledge in law and regulation, this paper does not explore the policy recommendations in more depth. How to introduce regulatory policies based on the reality of China's financial market? This is a question that needs to be further studied.

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Appendix A. Total Factor Productivity Estimation

A.1 Total Factor Productivity Estimation Using OP Method

A.1.1 Introduction

Mathematically, Cobb-Douglas production function is often used to describe the production of firms.

$$Y_{it} = A_{it} L_{it}^{\alpha} K_{it}^{\beta} \tag{A.1}$$

Y_{it} represents the total output of firm i in year t. L_{it} is the total labor input, K_{it} is the total capital input, and α and β are the elasticities of output with respect to labor input and capital input. If the effects of labor and capital are excluded, A_{it} is the TFP of firm i in year t.

To estimate the TFP of the firm, take the natural logarithm of the above production function:

$$y_{it} = \alpha l_{it} + \beta k_{it} + u_{it} \tag{A.2}$$

The lowercase letters y_{it}, l_{it}, and k_{it} are the logarithmic forms of the uppercase letters Y_{it}, L_{it}, and K_{it}. u_{it} is the fraction of log output that cannot be explained by labor and capital, which is the logarithmic TFP of firm. Thus, it might be possible to estimate the logarithmic TFP of a firm by subtracting the estimated output from the realized output:

$$\widehat{TFP}_{it} = y_{it} - \hat{y}_{it} = y_{it} - (\hat{\alpha} l_{it} + \hat{\beta} k_{it}) \tag{A.3}$$

However, Olley and Pakes (1996) point out that the above estimates of TFP suffer from both simultaneity bias: Firms with high productivity will invest a lot of labor and capital in pursuit of profits, which will lead to biased coefficients in OLS estimates.

To address these issues, Olley & Pakes (1996) argue that the following production functions can be considered.

$$y_{it} = \alpha l_{it} + \beta k_{it} + w_{it} + \epsilon_{it} \tag{A.4}$$

In the above equation, u_{it} in equation (A.2) is divided into two parts: the error term ϵ_{it} is an exogenous shock affecting the production level that cannot be forecasted by the firm and therefore does not affect the firm's factor inputs. w_{it} represents the productivity level known by the firm. The firm determines the level of log investment i_{it} based on w_{it}

and the existing log capital stock k_{it}:

$$i_{it} = f_t(w_{it}, k_{it}) \tag{A.5}$$

Olley and Pakes (1996) assume that the optimal investment function $f_t()$ is monotonically increasing in w_{it}, then the inverse function $h_t()$, which can be taken, is obtained.

$$w_{it} = h_t(i_{it}, k_{it}) \tag{A.6}$$

Taking the above equation into the production function (A.4), we get

$$y_{it} = \alpha l_{it} + \beta k_{it} + h_t(i_{it}, k_{it}) + \epsilon_{it} \tag{A.7}$$

It can be further rewritten as

$$y_{it} = \alpha l_{it} + \phi_{it} + \epsilon_{it} \tag{A.8}$$

$$\phi_{it} = \beta k_{it} + h_t(i_{it}, k_{it}) \tag{A.9}$$

To estimate the labor elasticity α, Olley and Pakes (1996) use a quadratic polynomial containing i_{it} and k_{it} to approximate $\phi_{it} = \phi_{it}(i_{it}, k_{it})$. A consistent estimate of labor elasticity $\hat{\alpha}$ can be obtained by estimating equation (4.8).

To estimate the capital elasticity β, one can define $V_{it} = y_{it} - \hat{\alpha} l_{it}$ and then estimate the following function:

$$V_{it} = y_{it} - \hat{\alpha} l_{it} = \beta k_{it} + g(\phi_{it-1} - \beta k_{it-1}) + \mu_{it} + e_{it} \tag{A.10}$$

The $g()$ function above can also be approximated by a higher order polynomial containing ϕ_{it-1} and k_{it-1}.

Once we estimate the labor elasticity and capital elasticity $\hat{\alpha}$ and $\hat{\beta}$, the logarithmic TFP can be calculated using equation (A.3).

A.1.2 Data and Variables Used for Estimation

To estimate the TFP of firms using the OP method, we need five main variables. All variables in nominal value should be adjusted into real value. I follow methods of To et al. (2018), İmrohoroğlu & Tüzel (2014), and Song Min et al. (2021) in measuring of the following main variables.

(1) Real Output

Following To et al. (2018), the nominal output of the firm is approximated using

Operating Income Before Depreciation and Amortization (OIBDP) plus the labor cost of the firm. OIBDP is the operating profit, plus depreciation and amortization, plus income taxes, and finally, plus finance costs. Labor costs are approximated using cash paid to and for employees as reported in the firm's statement of cash flows. Some literature also directly uses the enterprise's operating income or the enterprise's main business income as the actual output of the enterprise. The reason why I do not use the firm's operating income or main business income is that Foster et al. (2008) show that the firm's operating income is affected by the prices of firm-specific inputs. For example, in times of iron ore shortage, steel prices are also higher, and if TFP is estimated directly based on operating income, the effect of input price fluctuations will be incorrectly included. In contrast, To et al. (2018) argue that using OIBDP plus labor costs as a measure of a firm's real output can address this issue to some extent. After calculating the nominal output of enterprises, I refer to the adjustment method of Xiao and Xue (2019) to adjust the nominal output of enterprises to the real output with 2007 as the base year. For firms in manufacturing sector whose industry code starts with C in the 2012 version of the SEC, the Producer Price Index (PPI) are used in adjusting the price level. For other firms, the Consumer Price Index (CPI) is used to adjust prices. The price indices are obtained from the National Bureau of Statistics of China.

(2) Real Capital Input

The capital investment of an enterprise is calculated using the book value of the fixed assets after depreciation. Since capital is accumulated over years and the price index is not the same in different years, it is necessary to estimate the age of the firm's fixed assets before making price adjustments. In this paper, I follow To et al. (2018) to estimate the age of a firm's fixed assets using the firm's accumulated depreciation divided by the firm's current depreciation. Considering the possible changes in the firm's depreciation accrual policy, I take a three-year moving average of the age of fixed assets for smoothing. To further avoid the effect of extreme values, I winsorize the age of fixed assets at the 5% and 95% quartiles. After calculating the firm's age of fixed assets, I use the fixed asset investment price index reported by the National Bureau of Statistics to convert nominal capital inputs into real capital inputs using 2007 as the price base year.

(3) Labor Input

Following To et al. (2018) and Song Min et al. (2021), the labor input is measured using the number of employees of the enterprise.

(4) Real Investment

In order to control for the problem of simultaneity bias, we also need the firm's investment. Following Xiao and Xue (2019), this paper uses the cash paid for forming fixed assets intangible assets and other long-term assets reported in the cash flow statements of listed firms as a measure of the amount of nominal investment in the firm. Then, I use the fixed asset investment price index to convert the nominal investment amount into the actual investment amount using 2007 as the price base year.

(5) Exit the Market

To control for the problem of sample selection bias due to firm exit from the market, we also need the dummy variable of whether the firm exited the market. In this paper, we consider corporate delisting as corporate exit from the market. In addition to this, because there are shell listings in China's stock market and the shell company generally changes its corporate name abbreviation and main business. Therefore, in this paper, following Xiao and Xue (2019), I also consider the simultaneous change of the enterprise's acronym and its industry as the exit of the enterprise from the market.

In Table A.1, I summarize the data used in the OP method to calculate the TFP of firms.

Table A.1 Data Used for TFP Estimation Using OP Method

Variable	Description	Unit	Source
Real Output	Nominal output = operating profit + depreciation and amortization + income tax + finance costs + cash paid to and for employees Then adjust nominal output to real output using 2007 as benchmark year: For firms in manufacture industry, PPI is used; otherwise, CPI is used.	Thousand RMB	Wind
Real Capital Input	Notional capital input = book value of fixed assets Based on the age of fixed assets, the investment price index for fixed assets was used to adjust to the nominal capital input using 2007 as benchmark year. The age of fixed assets is the firm's accumulated depreciation/current depreciation, taking a three-year moving average and winsorizing at the 5% and 95% quartiles.	Thousand RMB	Wind
Labor Input	Number of employees	1	Wind
Real Investment	Notional investment = Cash paid for forming fixed assets, intangible assets and other long-term assets Use the investment price index to adjust nominal investment to real investment using 2007 as benchmark year.	Thousand RMB	Wind
Exit the Market	Delist, or both abbreviation and industry change in same year		Wind

A.1.3 Estimation Program

Yasar et al. (2008) wrote the stata external command *oprg*, which can easily and reliably estimate firm TFP using the OP method. In this paper, we use this program to estimate the TFP of listed companies in China.

A.2 Total Factor Productivity Estimation Using LP Method

A.2.1 Introduction

Another TFP estimation method used in this paper is proposed by Levinsohn and Pertin (2003) and is referred to as the LP method in this paper. Levinsohn and Pertin (2003) point out that the OP method cannot estimate the TFP of firm-year observations with zero investment. In addition, the authors find that the OP method may also be problematic when firms face non-convex capital adjustment costs. Levinsohn and Pertin (2003) argue that the intermediate inputs have small fraction of zero value. Also, intermediate inputs are consumed in the production process and therefore do not require as large an adjustment cost as long-lived fixed assets. Therefore, using intermediate inputs to replace investment can solve the problems of OP method.

A.2.2 Data and Variables Used for Estimation

The LP method requires data on firms' intermediate goods inputs. In this paper, I follow Qian et al. (2018) and use cash paid for the purchase of goods and services reported in statement of cash flows as a measure of firms' nominal intermediate goods inputs. Then I adjust the nominal intermediate goods inputs to the real value using the PPI and using 2007 as the price base year.

Table A.2 Data Used for TFP Estimation Using LP Method

Variable	Description	Unit	Source
Real Output	Nominal output = operating profit + depreciation and amortization + income tax + finance costs + cash paid to and for employees Then adjust nominal output to real output using 2007 as benchmark year: For firms in manufacture industry, PPI is used; otherwise, CPI is used.	Thousand RMB	Wind
Real Capital Input	Notional capital input = book value of fixed assets Based on the age of fixed assets, the investment price index for fixed assets was used to adjust to the nominal capital input using 2007 as benchmark year. The age of fixed assets is the firm's accumulated depreciation/current depreciation, taking a three-year moving average, and then winsorizing at the 5% and 95% quartiles.	Thousand RMB	Wind
Labor Input	Number of employees	1	Wind
Real Intermediate Input	Nominal intermediate inputs = cash paid for goods and services. Adjusted to real intermediate inputs using the PPI using 2007 as benchmark year	Thousand RMB	Wind
Exit the Market	Delist, or both abbreviation and industry change in same year		Wind

A.2.3 Estimation Program

Petrin et al. (2004) wrote the stata external command *levpet*, which allows easy and reliable estimate firm TFP using the LP method. In this paper, we use this procedure to estimate the TFP of listed companies in China.

摘要

金融如何影响实体经济是目前经济学界的热点问题之一。金融分析师是金融市场中重要的信息中介。然而，金融分析师对于被关注企业的影响还没有被经济学界充分地理解。在本文中，我研究了中国 A 股市场中金融分析师关注对上市公司全要素生产率的影响。参考 Olley and Pakes（1996）以及 Levinsohn and Pertin（2003）提出的方法，我计算了中国 A 股上市公司的全要素生产率。利用 2007 年至 2020 年中国 A 股上市企业的公司-年度观察样本，我对企业未来生产率与分析师关注之间的关系进行了面板固定效应回归分析，结果显示，上市公司未来的全要素生产率水平与当期分析师关注度正相关。为了建立分析师关注对企业生产率的因果关系，我参考 Yu（2008）构造了分析师关注的工具变量。除此之外，我将我国证券公司之间兼并收购导致的外生分析师关注下降纳入研究，用来解决内生性问题。结果显示，分析师覆盖率有助于公司生产力的提高。

针对分析师关注影响公司生产率的潜在机制，我依据现有理论推测金融分析师可能通过两种相反的机制影响公司生产率。其中包括信息解读机制和业绩压力机制。实证结果发现，两种机制在中国市场同时存在。一方面，针对信息解读机制的实证结果显示，金融分析师可以缓解企业的财务约束，并促进企业的创新活动，从而提高企业的全要素生产率。另一方面，针对业绩压力机制的实证结果发现，分析师关注对于企业生产率的提高作用在分析师没有高估企业盈利水平时更加显著。当金融分析师显著地高估企业盈利水平时，分析师关注可能导致企业生产率不增反降。考虑到分析师如果不能保持独立性，那么他们就可能迫于雇主、上市公司的压力系统地出具高估公司的盈利能力的研究报告，进而阻碍分析师关注对生产率的正面作用。本文认为中国的监管机构应该加强对分析师独立性的监管。

关键词：金融分析师，全要素生产率，信息摩擦，金融摩擦

目录

第一章　引言

1.1　选题背景

金融是否真的能为实体经济服务？一个国家金融体系的发展是否有助于该国企业生产率的提高？这既是经济学研究的热点问题，也是中国社会最关注的问题之一。“十四五”规划纲也要求我国“构建金融有效支持实体经济的体制机制”。可见，服务实体经济是我国金融行业的重要目标。

金融学理论认为，股票市场信息的透明度是影响金融体系效率的重要因素。金融分析师是金融市场中重要的信息媒介，在金融市场中有着举足轻重的作用。在我国有大量的金融从业人员从事金融分析工作。根据中国证券业协会发布的数据，截至 2020 年，我国金融分析师从业人员已经超过 3000 人。而根据国泰安（CSMAR）整理的数据，从 2015 年到 2020 年的五年间，我国仅证券公司雇佣的股票市场卖方分析师就发布了多达 28.49 万篇研报，这意味着，平均不到 10 分钟就有一篇研报问世。作为投资者的智囊团，金融分析师的研究报告能左右资金的动向，进而对二级市场中股票的交易价格产生影响。

现有的学术研究也表明，金融分析师能够通过多种机制，对被关注的上市公司产生影响。一些研究者对于金融分析师的作用持正面看法：他们认为，金融分析师能够降低企业的信息不对称程度（Hong et al., 2000; Frankel & Li, 2004; 等），降低企业的融资约束（Brennan & Subrahmanyam, 1995; Derrien & Kecskés, 2013；等）；并对管理层进行外部监督（Yu, 2008; Luo et al., 2015; 等）。另一些研究者则对金融分析师的作用持负面看法：一些研究发现，金融分析师系统性地倾向于出具高估企业盈利水平的报告（Dugar & Nathan, 1995; Ke & Yu, 2006; 等），并对企业产生业绩压力，引发管理层短视的问题（He & Tian, 2013; 等）。

1.2　研究意义

虽然研究者已经发现金融分析师对于企业的影响有好有坏，而且都提供了充分扎实的理论依据与实证检验，但现有文献鲜有关注金融分析师与被关注企业生产效率之间的关系。那么，一个自然的问题是：从整体上来看，金融分析师是否提高了被关注企业的生产率？如果金融分析师的关注影响了企业的生产率，那么这一作用是通过何

种机制实现的？值得注意的是，金融分析师对企业的好处，并不一定能直接转化为企业的生产率。比如更方便地融资并不一定意味着企业生产率的提升，反而可能会引发过度投资问题。如果企业使用廉价融资大量投资到低生产效率的活动中，那么企业的生产率会不增反降。

为了回答这一问题，To et al.（2018）对美国市场中金融分析师关注对于企业生产率的影响进行了研究。他们的实证结果发现，分析师关注提高了美国上市公司的全要素生产率水平。在搜索大量文献后，我发现，目前还没有学者研究我国市场中金融分析师关注与企业生产效率之间的关系。现有文献也表明，由于中美两国的金融市场存在显著的差异，金融分析师对于上市公司的作用在中国与美国存在差异：比如 He and Tian（2013）发现美国股票市场中金融分析师关注会导致企业专利数量的下降，而余明桂 等（2017）则发现在中国股票市场中分析师关注会导致企业专利数量的上升。因此，本文希望能研究在中国股票市场中，金融分析师与被关注企业生产效率之间的关系。

中国金融分析师轻监管、低独立性的特点为本文增添了独特的价值。西方发达国家普遍对金融分析师有极其严格的监管要求。在美国，为了避免证券经纪公司其他部门对金融分析师进行干涉，法律要求证券经纪公司对分析师部门进行制度上、甚至物理上的隔离。违反独立性要求的金融分析师和证券经纪公司将面临严重的处罚，并需要为造成的损失承担赔偿责任。欧盟对于金融分析师的监管要求甚至比美国更加严格：2018 年 1 月 3 日在欧盟正式生效的《金融工具市场指令 II》（*Markets in Financial Instruments Directive Ⅱ*，简称 *Mi FID Ⅱ*），明确要求投资机构必须对分析师服务进行单独付费，而不能与支付给证券公司的佣金进行绑定。这意味着在我国和美国市场流行的“研究换佣金”的商业模式在欧盟不再合法，而这种商业模式也被认为是导致金融分析师独立性丧失的“万恶之源”（薛菲 等, 2022）。我国对于金融分析师的监管发展比较晚，对于分析师与证券公司的处罚力度也不及欧美。近年来，各种金融分析师丑闻也时有发生，如 2011 年湘财证券等证券公司的“石墨矿事件”，2018 年方正证券分析师饭局不雅照事件，2020 年国信证券“研报门”等等。这些事件为我国金融分析师监管敲响了警钟。

金融分析师不能保持独立性有什么后果？大量文献发现，如果分析师无法保持独立性，那么他们会出具有偏误的分析报告，系统性地高估企业未来的盈利水平（Dugar & Nathan, 1995; Hong & Kubi, 2003; Ke & Yu, 2006; 曹胜与朱红军, 2011; 赵良玉 等, 2013; 等）。本文则进一步发现，当金融分析师显著地高估企业盈利水平时，分析师越关注某家企业，这家企业未来的全要素生产率就越低。这表明，如果分析师缺乏独立性，那么他们很可能对被生产率没有益处，甚至是有害的。

1.3　研究方法与主要发现

本文的研究问题是：在中国市场中，金融分析师是否提高了被关注企业的生产效率？如果金融分析师的关注会导致被关注企业生产率发生变化，那么这种改变是通过何种机制产生的？

为了度量企业的生产率，本文参考 Olley and Pakes（1996）和 Levinsohn and Pertin（2003）提出的计算方法，是使用 Stata 软件估计了我国 A 股上市公司 2007 年到 2020 年的全要素生产率。同时，本文还构造了一系列度量融资约束、企业创新的变量用于影响机制的分析。特别是在度量企业创新时，我不仅考虑了上市公司的专利数量，还创新性地使用谷歌专利的专利引用数据度量了上市公司发布专利的质量。

在实证策略上，本文首先采用多元回归分析的方法对金融分析师与企业未来生产率之间的关系进行研究。考虑可能存在的内生性问题，本文采用工具变量法，以及券商合并自然实验对基准回归的结果进行了检验。

本文的结果表明，从总体上来看，金融分析师的关注提高了我国上市企业的生产率。进一步，我通过中介效应分析发现金融分析师关注可能通过降低企业的融资约束与提高企业的创新水平两种渠道提高企业的生产率。然而，本文的实证研究还发现，分析师关注对于企业生产率的提高作用在分析师没有高估企业盈利水平时更加显著。当金融分析师显著地高估企业盈利水平时，分析师越关注某家企业，这家企业未来的全要素生产率就越低。这一结果表明业绩压力机制很可能存在于中国。

1.4　研究贡献

本文在以下方面对现有研究进行了贡献：

（1）尽管现有大量文献关注我国企业的生产率，也有一些文献关注金融发展对于我国企业生产率的影响。然而，在查阅文献之后，我发现目前还鲜有文献关注我国金融分析师对于上市公司全要素生产率的影响。To et al.（2018）对美国市场中金融分析师对于企业全要素生产率的影响进行了实证研究。本文参考了 To et al.（2018）的研究方法，发现了金融分析师对于我国上市公司生产率存在正向影响，丰富了相关文献。

（2）本文通过实证研究，验证了金融分析师对于企业生产率之间的影响机制，包括信息解读机制与业绩压力机制。其中，对于信息解读机制的实证研究发现分析师关注可以通过降低企业融资约束和提高企业创新两种渠道提高企业的生产率。在 To et al.（2018）发现的机制之外，本文还对金融分析师的业绩压力机制提供了支持。本文发现，金融分析师越是高估企业的盈利水平，分析师对全要素生产率的提高作用越弱。当金融分析师显著地高估企业盈利水平时，分析师越关注某家企业，这家企业未来的

全要素生产率就越低。这一发现对我国金融监管政策有一定价值：考虑到现有研究发现我国分析师可能为了雇主、上市公司管理者的利益系统性地高估企业盈利水平，本文对于业绩压力假说的实证分析强调了分析师独立性的重大意义。基于这一分析，本文认为我国金融监管机构应当加强对于金融分析师独立性的监管。

1.5 文章结构

本文共分为八个主要章节：第一章为引言部分，介绍本文的选题背景、研究意义、研究方法、主要结论、研究贡献，并简要介绍本文的结构。第二章为文献综述，主要梳理有关企业生产率与分析师关注的文献。第三章为理论分析与实证假设。本章对金融分析师影响企业生产率的现有理论进行分析，并提出可以验证的实证假设。第四章为样本与数据，介绍本文实证分析所用的样本，然后对各变量的度量方式进行描述。第五章为实证研究设计，介绍本文实证分析所使用的方法，包括面板固定效应回归、面板工具变量法以及券商合并准自然实验。第六章中，我展示了本文主要的实证研究结果。第七章为稳健性检验，进一步检验了本文的主要结论。第八章为结论与展望，总结本文的主要结论，讨论本文结论对于我国金融监管的启示。同时，第八章也指出本文研究的不足，并对未来可能继续的研究方向进行展望。

除此之外，本文还包含两个附录：本文附录 A 对于本文核心被解释变量全要素生产率的估计方法进行了细致探讨。

第二章　文献综述

在本章节，我将对与本文相关的现有文献进行梳理。本文考察的是金融分析师对于企业生产率的影响，以及潜在的作用机制。因此，在本章 2.1 节中，我将回顾现有文献对于金融分析师的研究，发掘金融分析师对于被关注企业可能的影响。随后，在本章 2.2 节，我将依据现有文献剖析企业全要素生产率的概念，探究企业全要素生产率的测量方法，并回顾现有文献中已经发现的全要素生产率的影响因素。

2.1　金融分析师

金融分析师是金融市场中重要的信息媒介。本文研究的是股票市场的金融分析师，他们的日常工作是对市场、行业与企业的调查研究，整理并分析各种影响证券价格的信息。股票市场的金融分析师会基于市场信息与个人的专业判断，撰写投资研究报告。在报告中，股票分析师会对被关注公司的每股收益、市盈率等财务指标进行预测，判断股价合理的区间，并为投资者给出各只股票的投资建议，比如“买入”，“持有”，“卖出”等。

根据雇主性质，金融分析师又可以被分买方分析师和卖方分析师。金融分析师中的小部分是买方分析师。他们直接受投资机构雇佣，主要在共同基金、对冲基金、风险投资公司、资产管理公司工作。买方分析师一般只对投资机构内部发布研究成果，并且对外严格保密。而金融分析师中的绝大多数是证券公司雇佣的卖方分析师。与买方分析师不同，卖方分析师会向市场公开发布研究报告，并向机构投资者推荐股票。

由于股票市场中，绝大多数金融分析师是卖方分析师，而且买方分析师不公开发布研究报告，存在数据不可得的问题。因此，现有研究（如 He & Tian, 2013; To et al., 2018; Guo et al., 2019; 等）大多只关注卖方分析师。现有文献发现，卖方分析师可以通过多种渠道对于被关注企业产生影响：

2.1.1　分析师与信息不对称

目前，学术界有大量研究聚焦于分析师在金融市场中的信息传递作用。学者认为，分析师关注能够传递与股价有关的信息，从而降低投资人与企业管理者之间的信息不对称。

一些研究认为信息不对称能为部分投资人带来超额收益，而金融分析师关注降低了这种超额收益。这一现象为金融分析师的信息传递作用提供了证据。例如 Hong et al.

（2000）研究了美国股票市场 1980 年到 1996 年动量交易策略的盈利能力。实证结果发现被分析师关注的股票动量交易盈利较差。基于 Hong and Stein（1999）的研究结果，Hong et al.（2000）认为动量交易策略能够盈利的原因在于信息没有迅速地被所有交易参与者获知，而是需要较长时间传播。因此，Hong et al.（2000）认为分析师有助于股票市场中的信息传播。Frankel and Li（2004）研究了 1975 年到 1997 年之间的美国股市中内幕交易者的交易量和盈利性。结果发现，分析师关注可以显著降低内幕交易者的交易量和盈利性。作者认为，只有企业存在比较严重的信息不对称时，掌握企业内部信息的内幕交易者才能从交易中获利。因此这一结果表明金融分析师关注可以降低信息不对称。

另一些研究则发现金融分析师关注降低了股价与市场的同步性，这也为金融分析师的信息传递作用提供了证据。Durnev et al.（2003）和 Durnev et al.（2004）认为，如果股票市场中某家上市公司特质性信息比较少，那么公司股价会出现和大盘、行业板块同涨同跌的现象。因此，股价与市场的同步性可以作为二级市场中企业特质性信息含量的度量指标。基于这一研究，朱红军 等（2007）使用我国上市公司 2004 年到 2005 年的数据，发现分析师降低了股价同步性。因此，作者认为金融分析师通过传递与股价有关的信息，提高了股市中的信息含量。伊志宏 等（2019）进一步运用了机器学习的方法，对 2009 年到 2015 年中国股市中的投资研究报告进行了文本分析。结果发现，研究报告中企业的特质性信息越丰富，股价与市场的同步性越低。除此之外，作者还发现，特质性信息丰富的研究报告会更受到投资人重视，引发更强市场价格变动。

另一些研究则指出，金融分析师不仅能向金融市场传递信息，还能使用专业技能对于信息进行解读，从而让信息更加能被投资者理解。例如 Huang et al.（2018）使用了文本分析的方法，对美国股市的分析师报告和上市公司财报说明会的语言主题进行了对比。Huang et al.（2018）发现分析师不仅会重复财报说明会的信息，而且会对复杂信息加以解读。而投资人则会在财报说明会难以理解时更加重视分析师的观点。

2.1.2 分析师与企业融资

金融学理论认为，企业管理者与投资人之间的信息不对称会导致委托代理问题，使得企业无法获得有效的融资（Stiglitz & Weiss, 1981; Myers & Majluf , 1984）。现有实证研究发现，金融分析师的关注可以通过降低企业信息不对称程度，降低企业的融资困难的问题。

Derrien and Kecskés（2013）将 1994 年到 2008 年之间美国券商的兼并视作准自然实验，通过双重差分的方法估计了券商兼并导致的金融分析师关注下降对企业带来的影响。他们的结果表明，分析师关注的减少会抑制企业的融资活动，并降低投资水平。

在券商合并中，一家企业每失去分析师的关注，企业总融资的下降相当于企业总资产的 2.0%，企业总投资的下降相当于企业总资产的 1.9%，这些效应在信息不对称程度高、融资约束严重的企业更加显著。我国的研究也发现了相似的结果：张纯和吕伟（2007）使用 Almeida （2004）提出的方法测量了 2004 到 2006 年我国上市公司的融资约束的程度。张纯和吕伟（2007）进一步发现，对于某家上市公司进行研究的分析师数量越多，企业面临的融资约束就更小。

2.1.3　分析师与企业创新

金融分析师与企业创新之间的关系是学术界目前比较火热的研究课题。目前，学术界对于这一问题有两种不同的看法。一些研究者认为，金融分析师过度关注企业短期绩效，而且会给出企业难以实现的盈利预测，导致管理层短视的问题，最终导致企业创新受到抑制。例如，He and Tian（2013）研究了美国市场中分析师对于企业专利影响。结果显示，分析师关注后企业未来获得专利的数量与质量都出现了显著地下降。

与此相反的是，余明桂 等（2017）和陈钦源 等（2017）均发现在中国股票市场中分析师关注会导致企业申请专利数量的提升。为了解释这一结果与 He and Tian（2013）的不同，两篇文章均认为中国股市中企业股权集中度高于美国，这抑制了分析师对企业管理者压力对于企业创新的负面影响。余明桂 等（2017）认为金融分析师可以通过缓解企业融资约束提高企业创新。陈钦源 等（2017）则认为除了融资约束外，分析师还可以通过向投资人传递企业研发创新的价值，并减少企业研发创新中的代理问题，最终提高企业创新。

Guo et al.（2019）则进一步研究了美国市场中分析师关注对企业创新的影响，他们的实证结果一定程度上否定了 He and Tian（2013）的发现：Guo et al.（2019）发现，分析师关注确实会降低企业对于研发的资金投入。但是，企业会更多兼并收购其他创新型企业，或者设立企业风险投资公司进行创新。而并购、设立企业风险投资公司带来的企业创新成果未被 He and Tian（2013）考虑在内。Guo et al.（2019）发现，如果将这两种包含在内，那么分析师关注对于企业创新的负面影响就不再显著。作者认为，尽管分析师关注会带来创新投入的下降，但是分析师关注有助于提高企业创新的效率。进一步，企业创新效率的提升提高了企业专利的数量、质量以及企业专利的新颖性。

2.1.4　分析师的预测偏误与业绩压力

现有大量研究发现，卖方分析师系统性地给出高估企业盈利水平的研究报告。这可能是因为分析师与雇主以及被研究上市公司之间存在利益冲突。如果卖方分析师不能与雇主、被关注上市公司保持独立，他们就很可能出具有偏误的投资报告：

首先，分析师可能出于雇主利益，高估被关注企业的盈利水平：金融分析师中的绝大多数是受到证券公司雇佣的卖方分析师。除了投资分析服务之外，证券公司通常也经营其他业务：如投资银行业务，帮助企业发行证券；以及券商自营业务，利用证券公司自身的资金进行投资。如果卖方分析师出具了不利于企业的盈利预告，这可能会影响雇主其他业务的利润。因此，分析师可能出于雇主利益的考虑，发布高估企业盈利水平的研究报告。现有大量实证研究支持了这一点：Dugar and Nathan（1995）研究了 1983 年到 1988 年美国股市中金融分析师对企业的盈利预测。结果发现，相比其他分析师，受投资银行雇佣的分析师出具的盈利预测显著地更加乐观。Hong and Kubik（2003）则对美国 1983 年到 2000 年 8,441 家金融企业中 12,336 名金融分析师的职业生涯进行了研究，结果发现：当分析师关注的证券由自己的雇主承销时，预测的乐观程度比准确性更能帮助其留任、升迁。曹胜与朱红军（2011）研究了我国 2005 年到 2009 年间 55,903 个卖方分析师的投资建议，结果发现，卖方分析师更倾向于推荐雇主自营业务投资的股票。这些证据说明，当卖方分析师不能与雇主其他部门保持独立时，分析师有可能出具高估企业盈利水平的研究报告。

除了出于雇主利益，金融分析师也可能为了讨好被调研企业的管理层，出具高估企业盈利水平的投资研究报告。这能帮助金融分析师换取管理层的内幕信息，帮助自己在未来更加准确地预测企业的财务指标。例如，Ke and Yu（2006）研究了美国 1983 年到 2000 年间美国股市中金融分析师，结果发现：如果起初分析师对企业的盈利预测较乐观，未来这名分析师对于该企业的预测就更加准确。而且这种效应在内幕交易比较严重，盈利难以估计的企业更加显著。赵良玉 等（2013）则发现，在中国上市公司重大事件中出具乐观报告的分析师，获得了更多前往上市公司实地调研的机会。这些证据表明，如果卖方分析师不能与被调研企业保持独立时，卖方分析师可能会出具高估企业盈利的研究报告。

无论出于何种目的，如果分析师为被调研企业发布了过高的盈利预测，那么管理层可能会忙于实现这一盈利预测，进而忽视对于企业长期有利的投资。Matsunaga and Park（2001）发现，即使上市公司只是略微错失了金融分析师预测的季度盈利水平，企业总裁的奖金也会减少。Graham et al.（2005）调查了 401 家美国上市公司的财务总监。他们的调查结果发现，如果一项投资会使企业错失金融分析师预测的盈利水平，即使这个投资项目长期有利于企业，绝大多数财务总监也不愿意接受这一项目。Fuller and Jensen（2010）观察到，美国上市公司的总裁与财务总监时常屈服于金融分析师的短期业绩压力，为了实现证券分析师的盈利预测而要求中下层更改公司的既定计划。上文中提到的 He and Tian（2013）则研究了美国分析师关注与企业创新之间的关系。结果发现，被分析师关注的企业三年后申请专利的数量与质量均出现了显著下降。He and Tian（2013）认为分析师的关注给企业管理层带来了过大的压力，使得企业不得不放弃长期有利于企业发展的研发投入，不利于企业的创新。

2.2　全要素生产率

2.2.1　企业全要素生产率的概念

本文使用全要素生产率来度量我国上市公司的生产效率。全要素生产率是经济学最重要的概念之一，对于全要素生产率的分析已经融入到了经济学研究的各个子领域。经济学含义上，全要素生产率指的是单位要素投入的总产量，或者说，是总产出中无法被劳动、资本等投入所解释的部分。因此，全要素生产率度量了由于生产技术进步、人力资本积累、管理能力提高等因素对于产出增长的贡献。由于在计算中对企业投入的劳动、资本进行了扣除，全要素生产率可以很好地度量企业的生产效率，它不会像总收入、净利润等指标，仅仅因为企业的规模变化而变化。鲁晓东与连玉君（2012）指出，虽然全要素生产率从概念上是一个微观企业的特征，然而由于早期企业层面微观数据的不足，通常基于宏观数据进行估计。但是，使用微观数据对全要素生产率进行估计，可以帮助我们从微观经济的层面上对影响企业生产率的因素进行分析。本文希望研究的就是分析师关注这一因素，对于我国企业生产率的影响。

2.2.2　企业全要素生产率的估计方法

企业全要素生产率的测算可以通过从企业实际产出中扣除企业的要素投入贡献得到。全要素生产率在计算时一般考虑企业的资本与劳动两种要素投入，并使用柯布-道格拉斯型生产函数刻画企业生产：

$$Y_{it} = A_{it} L_{it}^{\beta_l} K_{it}^{\beta_k} \tag{2.1}$$

通过对生产函数取对数，我们可以得到对数线性化之后的生产函数：

$$y_{it} = a_{it} + \beta_l l_{it} + \beta_k k_{it} \tag{2.2}$$

从上式中我们可以看出，如果我们可以准确对对数资本与对数劳动的系数（即资本与劳动对产出的弹性），那么就可以用企业实际对数产出减去使用劳动、资本预测的企业产出，得到企业的对数全要素生产率。然而，Marschak and Andrews（1944）指出，如果直接使用普通最小二乘法估计上式系数，会导致同时性偏误（Simultaneity Bias）。这是因为，企业的管理者一般可以在决定要素投入前预测到至少一部分企业的生产率，但这一生产率水平对我们是不可观测的。当企业管理者认为企业的生产率较高，那么管理者便会提高人力、资本的投入，这使得回归项与残差相关。

为了解决这一问题，Olley and Pakes（1996）提出了一种基于半参数估计的方法对企业全要素生产率进行估计： Olley and Pakes（1996）认为，企业生产率越高，那么企业在当期的投资额也就会越高。因此，可以使用企业当期的投资水平对不可观测的生产率水平进行控制，这可以解决同时性偏误的问题。

Levinsohn and Pertin（2003）基于 Olley and Pakes（1996）提出了另一种解决同时性偏误的思路。Levinsohn and Pertin（2003）认为 Olley and Pakes（1996）的方法要求投资与生产率必须保持单调关系，因此，这一方法无法测算投资为零值的企业的全要素生产率，从而导致大量样本丢失。Levinsohn and Pertin（2003）发现，虽然企业可能在一年中不进行投资，但是在生产过程中普遍会购买中间投入品。因此，使用中间品投入替代投资对不可观测生产率水平进行控制，可以比较好地解决这一问题。

2.2.3 企业全要素生产率的影响因素

现有文献发现大量因素与企业的全要素生产率有关，这些因素一部分来自企业本身。

首先，现有文献表明，一系列企业本身的特征与企业的全要素生产率有关。İmrohoroğlu and Tüzel（2014）对这一问题进行了系统性地研究：他们计算了美国上市公司 1963 年到 2009 年的全要素生产率以及一系列指标。随后，他们将企业按照全要素生产率从低到高分成不同组，结果发现，一些特征与企业的全要素生产率单调相关：从整体上来看，上市公司中总资产较多的大企业比小企业全要素生产率高，账面市值比较低的成长型公司比价值型公司全要素生产率高。İmrohoroğlu and Tüzel（2014）还发现企业的资本增长率、投资占总资本的比例、新雇员占全部雇员的比例，以及存货水平也和企业的全要素生产率正相关。

其次，大量研究指出研发创新会提高企业的生产率：Griliches（1986）对上世纪六十年代到七十年代美国主要制造业企业的研究发现，企业的研发创新能显著提高企业的生产率。而且，相比其他类型的研发，基础研究对于企业生产率的提升作用更强。Hall et al.（2010）对企业研发回报的文献进行了系统性梳理。结果显示，尽管不同研究者使用了不同的数据与估计策略，大量研究均一致地表明企业研发资本投入能显著地提高企业的产出，并且对于整个社会存在溢出效应。针对我国的研究也发现企业研发创新能提高企业的生产率（吴延兵, 2006; 毛德凤 等, 2013）。

除此之外，针对我国企业所有制变动的实证研究发现，国有资本可能在一定程度上对企业生产率存在阻碍作用。一方面，文献发现国有企业私有化改革有助于提高企业的生产率：比如 Chen et al.（2021）使用中国工业企业调查数据库研究了 1998 年到 2007 年我国国有企业的民营化。结果显示，在其他条件不变的情况下，样本期内我国

民营企业的全生产率比国有企业高 53%。刘晔 等（2016）与 Zhang et al.（2021）分别使用工业企业调查数据库与我国上市公司数据，发现国有企业接受混合所有制改革显著地提高了企业的生产率。另一方面，现有文献还发现民营企业接受国有资本注入后出现了生产率下降，比如董艳与刘佩忠（2021）利用工业企业调查数据库，发现 1998 年到 2013 年期间接受国有资本注资的企业，全要素生产率与资产收益率（Return on asset; ROA）均出现显著的下降。

除了来自企业本身的因素，研究还发现一些来自企业外部的因素与企业的全要素生产率有关。

首先，现有文献发现产业组织会对企业的生产率产生影响：一方面，在一个竞争性的行业中，拥有高生产力的企业会选择进入市场并扩大生产规模，而生产率较低的企业则会选择缩小规模甚至退出市场，这种优胜略汰的市场选择机制会使竞争性行业内的企业生产率更高（Jovanovic, 1982; Hopenhayn, 1992）。李平 等（2012）使用 1998 年到 2007 年中国工业企业调查数据库，发现行业竞争提高了我国工业部门企业的全要素生产率。另一方面，也有研究发现竞争对于生产率的作用也与价值链有关：王永进和刘灿雷（2016）发现处于价值链上游的国有企业垄断市场，会导致低效率的国有企业进入下游市场。这会将高生产率的非国有企业挤出市场，从而降低行业整体的生产率。

其次，现有研究还发现政府干预能够对企业的全要素生产率产生影响。一方面，现有文献发现政府补贴可能对被补贴企业的生产率有正面作用：任曙明 等（2014）研究了 2000 年到 2007 年中国工业企业调查数据库中覆盖的装备制造业企业，结果发现政府补贴能够通过缓解企业的融资约束提高企业的生产率。李政 等（2019）发现政府补贴对于企业全要素生产率的促进作用同样存在于制造业的上市公司。基于林毅夫（2017）的思想，李政 等（2019）认为政府补贴除了可以缓解企业的融资约束，还可以引导企业将资金投向有市场前景的行业，从而提高企业的生产率。与这种乐观的看法不同的是，一些对于我国产业政策的研究则发现我国的产业政策降低了企业的生产率：例如钱雪松 等（2018）将中国 2009 年出台的十大产业振兴规划作为自然实验，结果发现：相比其他行业，处于振兴规划行业中的企业生产率的企业没有增加，反而出现了下降。而且这一效应在政府干预较强的地区更强，在国有企业中也更强。

最后，To et al.（2018）针对美国市场的实证研究发现金融分析师关注提高了企业的生产率。这是与本文研究最相关的论文。To et al.（2018）使用面板数据固定效应回归发现关注企业的分析师数量可以正向预测企业未来一年、两年的全要素生产率。为了解决内生性问题，To et al.（2018）参考 Yu（2008）构造了工具变量。除此之外，To et al.（2018）还借鉴 Hong and Kacperczyk（2010）和 Kelly and Ljungqvist（2012）将

证券公司合并与停业作为准自然实验，识别了准自然实验中分析师关注下降对企业生产率的作用。作者给出的所有结论均一致性地支持金融分析师能提高企业的全要素生产率。本文研究方法上学习了 To et al.（2018），并对于中国证券市场中金融分析师与企业全要素生产率的影响进行了研究。除此之外，本文还对金融分析师高估企业盈利水平导致的业绩压力进行了实证检验，这一点并没有被 To et al.（2018）的研究覆盖。因此，对于业绩压力机制的实证是本文的主要创新。考虑到我国对证券分析师的监管可能不如欧美严格，而金融监管薄弱是发展中国家金融市场的普遍问题。我认为我的研究有一定的贡献，并有一定的普遍意义。

第三章　理论分析与实证假设

3.1　理论分析

3.1.1　理论框架

基于上一章 2.1 节对于金融分析师的文献综述，我发现，目前经济学理论对于分析师关注与企业生产率之间关系，存在两种相反的看法：

一方面，信息解读假说认为金融分析师可以降低企业管理者与投资人之间的信息不对称程度，从而缓解企业的融资约束。这有助于企业抓住转瞬即逝的投资机会，从而提高企业的生产率。除此之外，更加透明的信息，也有可能有助于投资人认识到企业创新研发活动的重要性，缓解企业研发创新中的代理问题，从而提高企业的创新水平。

另一方面，业绩压力假说则认为分析师有动机发布高估企业盈利状况的研究报告。如果企业管理者不能达到分析师对于企业预估的盈利水平，那么就可能招致投资者减持，导致股价下跌，最终导致管理者“位子”不保。这种分析师对于企业管理层的压力，可能引发管理者短视的问题。管理者会过度关注企业短期业绩，忽视对于企业长期发展有利的投资，进而对企业生产率产生负面影响。

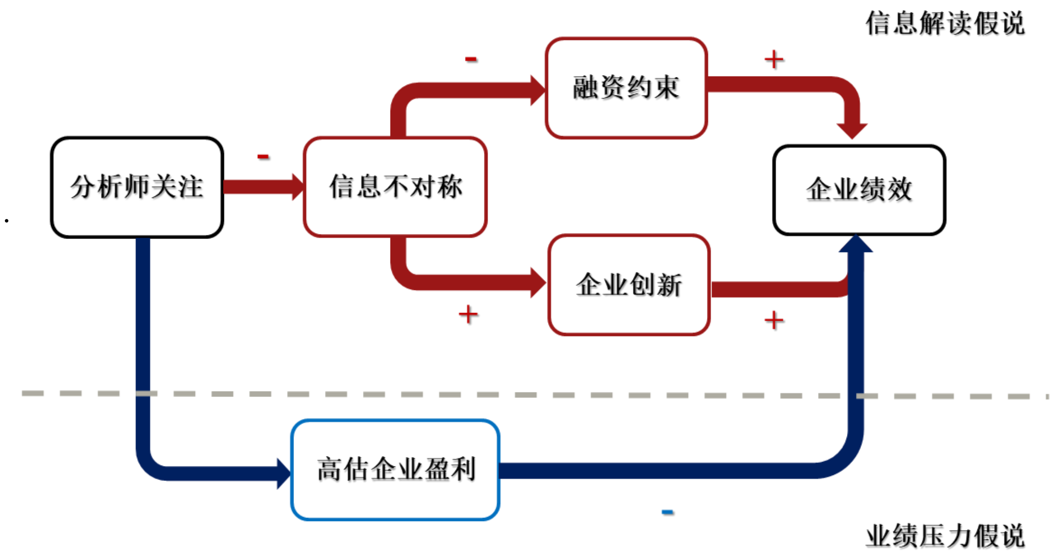

图 3.1　理论分析框架图

3.1.2 信息解读假说

信息解读假说认为，作为金融市场重要的信息媒介，分析师关注可能降低被关注企业的信息不对称程度，从而降低企业的融资约束，最终提高企业的生产率。

早在上世纪八十年代，信息不对称导致的企业融资约束问题就引起了理论经济学界的重视：Stiglitz and Weiss（1981）构建了信息不对称市场中的债务融资模型。在模型中，借款者相比贷款者更有信息优势：借贷之前，贷款者难以判断借款者的违约风险，这导致高风险的借款人挤出低风险的借款人，引发了逆向选择问题。借贷之后，贷款者因为无法观测到借款者的行动，所以无法避免借款人将自己借出的资金投入到高风险的项目中，引发了道德风险问题。最终借款者与贷款者之间的信息不对称会导致一些资金的需求者无法获得借款，导致信贷配给。 Myers and Majluf （1984）则构造了信息不对称市场中的股权融资模型。在这一模型中，当企业管理人比股权投资者拥有信息优势时，信息不对称也会导致相似的委托代理问题，使企业无法获得足够的股权融资。由于缺乏资金，企业不得不削减有价值的投资，最终影响企业生产率。

金融分析师作为金融市场中的信息中介，会对企业的投资行为进行持续的调查。卖方分析师还会将研究报告向市场公开。这会帮助金融市场了解企业投资的真实风险水平，从而有助于防止逆向选择问题。除此之外，通过公开报告，市场可以获知企业是否将已经获得的融资投入到高风险的活动中。这也有助于避免企业管理者的道德风险问题。因此，我认为金融分析师能够降低信息不对称导致的融资约束，进而可能增加企业的生产率。

除了降低企业的融资约束之外，金融分析师还可能通过降低企业被金融市场低估的可能性，提高上市公司的研发创新。行为金融学领域的研究表明，如果影响股价的信息比较复杂，那么投资者对于这一信息可能呈现出反应不足（You & Zhang, 2009；Hirshleifer et al., 2009）。而企业创新产出的知识、专利与高精尖产品，缺乏相关背景知识的投资人可能难以理解其价值，从而导致企业创新的价值被投资者低估，降低企业管理层对于企业研发的投入力度。Hirshleifer et al.（2018）发现，上市公司专利的原创性能正向预测股价长期收益率。而且投资者对该公司股票的关注度越低，专利原创性与未来股价收益率的关系就越强。专利原创性对于股价长期收益率的预测能力，表明金融市场的交易价格在没能在短期之内反映出企业创新所代表的价值。进一步，Shu et al.（2022）发现，在美国专利局中一些专利审查员工作比较忙碌，而这些忙碌审查员批准的专利普遍质量较差。如果一家上市公司的专利大多由这些较为忙碌的专利审查员审核批准，那么这些公司股票的长期收益率会更低。这一证据也表明，金融市场的交易价格不能在短期之内反映出企业创新所代表的价值。考虑到中国股市以个人投资者为主，相比有一定专业知识的机构投资者，个人投资者很可能更难意识到复杂创新

成果的实际价值。因此，我猜想中国股票市场中投资者对创新成果反应不足的问题可能比美国市场更加严重。

相比持有分散化组合的投资人，金融分析师通常会对某一行业的上市公司进行持续跟踪研究，从而更能积累专业知识。目前我国金融分析师也日益专业化。证券公司偏好雇佣高学历、有复合背景的人才从事金融分析工作。这些因素使得金融分析师更容易意识到企业创新产出的价值，从而有利于降低由于投资者对复杂信息反应不足带来的错误定价。现有的研究也对这一机制提供了一些的证据：Li（2020）通过券商关闭与券商合并准自然实验，发现分析师关注的减少增加了上市公司股票价值被错误定价的程度。因此，我认为金融分析师覆盖能够降低企业创新被市场低估的风险，有利于企业创新，进而可能提高企业的生产率。

3.1.3　业绩压力假说

业绩压力假说则认为，金融分析师会系统性地给出过高盈利预测，这将引发企业管理者的短视行为，降低企业生产率。金融分析师会系统性地高估企业的盈利预测，可能源自于卖方分析师面临客户与雇主、客户与上市公司之间的利益冲突：一方面，由于雇佣卖方分析师的证券公司通常也会经营投资银行业务、自营投资业务等其他业务。如果卖方分析师关注的企业恰好是雇主投资银行部门承销的股票，或者雇主自营投资部门重仓的股票，那么雇主其他部门同事就很可能对分析师进行威逼利诱，要求分析师出具高估企业盈利水平的报告（Hong & Kubik, 2003; 曹胜与朱红军，2011）。如果分析师出具了高估企业盈利水平的报告，企业就很可能屈服于金融分析师的短期业绩压力，为了实现金融分析师的盈利预测而要求中下层更改公司的既定计划，并放弃长期收益为正的项目（Fuller & Jensen,2010; Graham et al., 2005）。

除此之外，卖方分析师也可能为了维护和被调查上市公司管理层的良好关系出具有高估企业盈利水平的报告。如果卖方分析师能够与企业管理层保持良好的关系，分析师就可能从企业管理层获得内部信息（Ke & Yu, 2006），或者获得对企业进行实地调研的机会（赵良玉 等, 2013）。这有利于金融分析师在未来对企业进行更加准确的预测，有利于金融分析师的职业发展。而从公司管理者的角度来说，高估企业盈利水平的分析师报告可以在短期内使股价上升，这可以让企业所有者高看企业管理者的能力。然而，为了实现分析师的盈利预测，企业管理层有可能会注重企业当年的短期绩效，将资金投入营销等短期项目中，放弃长期来看有利于企业的投资，最终使企业的生产率降低。

3.2 实证假设

3.2.1 分析师关注与企业生产率

本文关注中国股票市场中分析师关注与企业生产率之间关系。不同于美国等西方发达国家成熟的资本市场，中国股市存在信息不对称程度高的特点。我猜想，这可能使信息解读机制更加适用于中国：

我国的股票市场中存在着较为严重的股价“同涨同跌”现象，这表明中国股市中企业特质性信息少，信息不对称问题严重（Durnev et al.,2003; Gul et al., 2010）。而公司特质性信息如果不能融入股价，那么市场的价值发现作用将失灵，影响资源配置的效率。伊志宏 等（2019）指出，我国金融分析师可以通过挖掘公司特质性信息，降低股价的同步性，加强了股价在金融市场资源配置中的信号作用。

根据 3.1 节中的理论分析，我认为，金融分析师的关注既可能通过信息解读机制促进企业生产率，也可能通过业绩压力机制抑制企业生产率。金融分析师关注与企业生产率之间的关系应当是两种机制的综合效应。考虑到我国金融市场的特点，我猜想信息解读机制在我国股票市场中的影响可能会更大。如果这一猜想正确，那么被分析师关注之后，企业应当有更高的生产率。因此，本文提出实证假设 H1：

H1：在中国股票市场中，分析师关注提高了企业全要素生产率。

3.2.2 可能的影响渠道

改革不彻底的我国金融体系存在较多摩擦，我国企业面临比较严重的融资约束问题。Bailey et al.（2011）发现，我国银行为了防止失业与维护社会稳定，倾向于给低生产率企业发放贷款。任曙明与吕镯（2014）发现我国装备制造业企业普遍存在较为严重的融资约束。经济学理论认为，企业的信息不对称程度是影响企业融资难易程度的重要因素，信息不对称程度越高，委托代理问题越严重，企业越不容易获得外部融资。因此，我猜测，金融分析师关注能够使企业信息更加透明，从而一定程度上缓解企业的融资约束问题。根据以上分析，我提出实证假设 H2：

H2：在中国股票市场中，分析师关注可以通过缓解企业的融资约束，提高企业的全要素生产率。

除此之外，对于企业创新的研究是金融分析师工作的重要部分。余明桂 等（2017）指出，我国金融分析师普遍重视对于企业创新的研究。这一特点有助于投资者意识到企业创新活动的价值，从而降低企业创新被市场低估的风险，最终有助于企业进行创新，提高企业生产率。根据以上分析，我提出实证假设 H3：

H3：在中国股票市场中，分析师关注可以通过提高企业的创新，提高企业的全要

素生产率。

3.2.3　分析师的业绩压力

如果在中国金融市场中金融分析师的关注促进了企业生产率，那么是否意味着业绩压力理论并不适用于中国？一方面，西方发达国家为了保证金融分析师的独立性，对于分析师有着严格的监管要求：首先，美国、欧盟均要求证券公司在投资银行部门与分析师部门之间设立“中国墙”，隔离两个部门，禁止投资银行部门对卖方分析师进行干预。其次，美国、欧盟等发达国家也严格要求分析师与被调研公司之间保持独立，并严格披露潜在的利益冲突。然而，相比西方发达国家，我国对于金融分析师的监管发展比较晚，监管要求也比较松。比如，欧盟 2018 年 1 月 3 日起正式生效的法律《金融工具市场指令 II》（*Markets in Financial Instruments Directive Ⅱ*，简称 *Mi FID Ⅱ*），强制要求投资者支付给卖方分析师的研究服务费，必须单独支付，而不能和支付给证券公司经纪业务的分仓佣金绑定。这一监管要求从根本上断绝了金融分析师与雇主其他部门的利益关系，极大地提高了卖方分析师的独立性。然而我国法律法规则并没有类似的要求，这使得我国卖方分析师则普遍使用“以服务换佣金”的商业模式，这一模式非常不利于卖方分析师的独立性。因此，我国分析师可能更加倾向于给出高估企业盈利的研究报告。

另一方面，研究发现管理者短视的现象同样存在于我国的上市公司中。例如俞鸿琳（2022）发现，企业总裁的预期任职时间越短，企业金融化程度越高。根据这一现象，作者认为管理层短视可能导致了我国企业的“脱实向虚”。胡楠 等（2021）则使用了机器学习的方法对我国上市公司年报中管理者讨论与分析的部分进行了文本分析，识别出其中与管理者短视相关的语言，用于对企业管理者的短视程度进行度量。作者发现，管理层越短视，企业的资本投资和研发支出就越少。

根据本文 2.1.4 节的文献综述和 3.1.3 节的理论分析，我们不难发现，只有当金融分析师对企业的盈利预测过高，以至于企业难以达到这一目标时，金融分析师才会对企业管理层施加压力。因此，如果业绩压力机制存在，那么相比其他分析师预测，高估企业盈利的分析师预测对企业生产率的提高作用应当更弱。基于上述分析，我提出实证假设 H4：

H4：在中国股票市场中，分析师关注对于企业生产率的提高作用，在分析师高估企业盈利水平时更弱。

第四章　样本与数据

4.1　样本构成

本文研究的是中国股票市场中分析师关注与生产率之间的关系。由于分析师一般只对上市公司发布研究报告，本文的公司样本是 A 股上市公司，样本区间为 2007 年至 2020 年。本文的样本开始于 2007 年是因为 2005 年 4 月开始的股权分置改革对我国股票市场有较大影响，而这一改革在 2006 年底基本已经完成。

参考国内文献（如李春涛 等, 2016; 余明桂 等, 2017; 等），本文对观测样本进行了以下筛选：

（1） 由于金融企业会计准则不同，本文删除了金融行业的上市公司样本；

（2） 由于濒临退市的企业可能存在财务造假、信息披露不完整等情况，本文删除了被标记为 ST、ST*、PT 的上市公司样本；

（3） 本文剔除了重要控制变量存在缺失值的样本。

最终，本文得到了 28585 个公司-年度样本，来自于 3643 家上市公司。

4.2　变量构造

4.2.1　被解释变量

本文的被解释变量是上市公司的全要素生产率，分别使用 Olley and Pakes（1996）提出的方法（下称 OP 法），以及 Levinsohn and Pertin（2003）提出的方法（下称 LP 法）进行计算。出于稳健性的考虑，我还使用企业的资产收益率（Return on asset; ROA）作为生产率的另一个度量：

（1）OP 法全要素生产率（TFP_OP）

本文采用主要采用 Olley and Pakes（1996）提出的 OP 法对上市公司的全要素生产率进行估计。为了解决同时性偏误问题，OP 法使用企业投资不可观测的生产率水平进行控制。为了避免价格水平对企业生产率估计带来的偏差，我使用国家统计局公布的工业生产者出厂价格指数、居民消费价格指数和固定资产投资价格指数对各名义变量进行了价格调整，估计所用的变量全部调整为以 2007 年为价格基准年的实际值。其中，由于固定资产是多年投资积累的，我参考 To et al.（2018）对于企业固定资产的年龄进行了估计，然后基于估计的年龄将固定资产调整为以 2007 年为价格基准年的实际值。

对于其他变量，我使用企业财务报告的会计年对价格进行调整。在附录 A.1 节中，我对 OP 法估计我国上市公司全要素生产率的原始数据、计算程序进行了细致的探讨。

（2）LP 法全要素生产率（TFP_LP）

本文采用的另一种全要素生产率估计方法由 Levinsohn and Pertin（2003）提出。LP 方法与 OP 方法类似，不同点在于 LP 方法使用中间品投入替代企业固定资产投资，用于对同时性偏误的控制。同样，LP 法所需的名义变量，也全部被我调整为以 2007 年为基准年的实际值。在附录 A.2 节中，我对 LP 法估计我国上市公司全要素生产率的原始数据、计算程序进行了细致的探讨。

（3）资产收益率（ROA）

考虑到企业的全要素生产率作为一种基于结构模型计算的指标，比较依赖计量模型的准确性。为了避免指标计算方法不稳健可能带来的问题，我参考董艳和刘佩忠（2021）的做法，使用企业的资产收益率（Return on assets, ROA）作为企业生产率的另一个度量。使用资产收益率作为被解释变量的实证结果在本文 7.1.1 节稳健性检验部分报告。数学上，企业的资产收益率是净利润除以年末年初平均资产。

4.2.2　解释变量

（1）对数分析师（LnAnalyst），对数研报（LnReport）

本文的解释变量是分析师关注。金融分析师可以被划分为卖方分析师和买方分析师。与本领域内其他研究（如 He & Tian, 2013; To et al., 2018; Guo et al., 2019; 等）相同，本文的实证研究部分关注于卖方分析师，这样做有以下两点原因：首先，当前中国以及其他发达国家的金融市场中，绝大多数金融分析师是卖方分析师。第二，与公开发布研究报告的卖方分析师不同，买方分析师一般只对投资机构内部发布研究成果与投资建议，因此存在数据不可得的问题。

在基准回归部分，本文采用一个会计年度之内，对于某家上市公司发布盈利预测的卖方分析师团队数量作为分析师关注的度量。如果一个分析师团队，对于某家上市公司发布了多个盈利预测报告，则仍然认为分析师关注度为 1。考虑到分析师关注这一数据有较大的正偏度，即少数“明星企业”吸引了大量分析师的关注，而大量企业没有分析师关注，本文对于分析师关注这一指标加 1 之后再取自然对数，生成对数分析师（LnAnalyst）这一指标。上述分析师关注的度量方法与数据处理方法与 He and Tian（2013），To et al.（2018），以及 Guo et al.（2019）保持一致。在本文的稳健性检验部分，我也使用了对数研报（LnReport），即研报数量加 1 取自然对数作为分析师关注度的另一个度量。

（2）对数高估分析师（LnAnaHigh），对数低估分析师（LnAnaLow）

为了对分析师的业绩压力假说进行实证检验，本文将企业所获得的分析师关注划分为对数高估分析师（LnAnaHigh）和对数低估分析师（LnAnaLow）两个部分：首先，我计算了分析师预测的标准化高估偏差$Error_{kit}$：

$$Error_{kit} = \frac{ForecastEPS_{kit} - RealizedEPS_{it}}{StockPrice_{it}} \tag{4.1}$$

其中$ForecastEPS_{kit}$指的是k分析师在t年初到t年末对i企业在t年末每股收益（Earning per share；EPS）的预测值。在计算这一指标时，我只包括了分析师对企业当年的盈利预测，而不包括对企业未来多年的盈利预测。$RealizedEPS_{it}$指的是i企业在t年末实现的真实每股收益。为了对这一指标进行标准化，我用两者的差除以分析师发布预测当天的企业股价，从而得到了k分析师在t年对i企业的标准化高估偏差$Error_{kit}$。如果标准化预测偏差$Error_{kit}$大于 0，则意味着这一分析师高估了当年的企业盈利水平，反之，若这一指标低于 0，则意味着这一分析师低估了当年企业的盈利水平。

然而，考虑到发现分析师可能会受到市场整体情绪影响，在市场情绪较高、经济形势乐观时可能整体倾向于高估企业的盈利水平（许年行 等, 2012；伍燕然 等, 2012），以 0 值作为分析师高估与低估企业生产率的划分标准可能会受到市场整体情绪的干扰。因此，本文选择使用当年全部分析师预测的平均标准化高估偏差，作为划分分析师高估或低估企业盈利水平的划分标准。数学上，对数高估分析师（LnAnaHigh）和对数低估分析师（LnAnaLow）两个指标的计算方法如下：

$$LnAnaHigh_{it} = ln(1 + \sum_k \mathbb{I}(Error_{kit} > meanError_t)) \tag{4.2}$$

$$LnAnaLow_{it} = ln(1 + \sum_k \mathbb{I}(Error_{kit} < meanError_t)) \tag{4.3}$$

其中$meanError_t$指当年全部分析师预测的标准化预测偏差均值。$\mathbb{I}()$是指示函数，如满足括号内条件则取 1，反之取 0。$\sum_k \mathbb{I}(Error_{kit} > meanError_t)$就是当年预测高估程度高于平均水平的分析师数量。

值得注意的是，高估与低估的分析师数量加和并不等于前文所定义的总分析师数量，原因在于一个分析师团队可能一年之内对企业每股盈利作了多次不同的预测，一些预测高估而另一些低估。因此这一个分析师团队会被同时算入高估和低估的分析师。

考虑到使用均值划分高估、低估分析师可能比较武断，本文还使分析师标准化预测偏差四分位点，将分析师关注划分为四组，对实证假设 H4 进行了进一步检验。

4.2.3 控制变量

借鉴现有对于企业生产率的研究文献（如 To et al., 2018; 董艳与刘培忠, 2021；宋敏 等, 2021），文本控制了以下可能影响全要素生产率的变量：

第一，考虑到企业特征对于生产率的影响，本文控制了以下变量：

（1）企业规模（Size）

本文使用公司年末总资产的自然对数控制企业规模对于企业生产率的影响。一方面，İmrohoroğlu and Tüzel（2014）发现，在美国股市中，规模较大的上市公司全要素生产率水平较高。另一方面，规模较大的企业可能被更多投资者持有，更能吸引分析师关注。考虑到企业规模可能与解释变量和被解释变量均相关，不控制企业规模可能导致遗漏变量偏误。

（2）企业年龄（Age）

本文使用企业成立年数加 1 取自然对数，控制企业年龄对于企业生产率的影响。一方面，新进入市场的企业可能管理制度灵活、企业文化开放；另一方面，老企业则可能建立了技术壁垒，或者拥有稳定的供应链关系。这些因素均会对企业的生产率产生影响。

（3）账面市值比（BM）

本文企业的账面市值比，即企业年末的总资产除以总市值，控制企业估值水平导致的生产率差异。İmrohoroğlu and Tüzel（2014）发现，低账面市值比的成长型公司比高账面市值比的价值型公司生产率高。考虑企业估值水平也可能影响金融分析师对企业的关注，不控制账面市值比可能导致遗漏变量偏误。

第二，考虑到企业经营状况对于企业生产率的影响，本文控制了以下变量：

（4）企业成长性（Growth）

参考宋敏 等（2021），本文使用企业营业收入相对上年的增长率控制企业的成长性的影响。考虑到营业收入快速增长的企业可能生产率较高，而且也会吸引更多分析师关注，我认为不控制企业成长性会导致遗漏变量偏误。

（5）投资开支（CapEx）

参考 To et al.（2018），本文使用企业投资除以企业营业收入控制企业资本开支对于企业生产率的影响。其中企业投资以现金流量表中报告的购建固定资产、无形资产和其他长期资产支付的现金进行度量。一方面，企业投资开支较高可能意味着企业有较高生产率，希望通过扩大生产实现更高利润。另一方面，高投资开支也可能意味着企业资本比较陈旧，需要进行维护或更新换代，因此生产率较低。

（6）经营现金流（Cashflow）

本文使用企业经营活动产生的净现金流占企业年末总资产的比例，控制企业经营活动现金流对企业生产率的影响。经营现金流较高的企业可能业务较好，因此生产率

较高。

（7）固定资产比例（PPEratio）

本文使用固定资产占总资产的比例，控制企业使用固定资产密集程度对于企业生产率的影响。一方面，固定资本密集度高可能意味着企业拥有昂贵的高精尖生产设备，因此生产率高；另一方面，固定资本密集的企业也可能采用低效率高消耗的生产模式，生产率较低。

第三，考虑到企业所有权不同对于企业生产率的影响，本文控制了以下变量：

（8）国有企业（SOE）

为了控制企业所有制对于企业生产率的影响，本文引入了国有企业虚拟变量 SOE，对于国有企业取 1，对于其他所有制企业取 0。如果企业国有股份占比超过 50%，或者控股股东为国有企业，则这家企业被认为是国有企业。现有文献显示国有股权对企业生产率有一定的负面作用（Chen et al., 2021；董艳与刘佩忠，2021；等）。考虑到分析师可能更倾向于关注非国有企业，我认为不控制企业规模可能导致遗漏变量偏误。

（9）第一大股东持股比（FirstOwn）

本文使用第一大股东持股占总企业股份的比例控制控股股东所有权的影响。一方面，大股东持股比例高可能导致大股东缺乏监督，引发第二类代理问题，对生产率产生负面影响。另一方面，大股东持股比例高也可能缓解控制权争夺，有利于企业生产率。

（10）机构投资者持股比（InstOwn）

本文使用机构投资者持股占总股份的比例控制机构持股对于企业生产率的影响。一方面，机构投资者持股比例高可能会对企业管理者有监督作用，有利于企业的生产效率。另一方面，机构投资者的减持威胁也可能对企业管理者带来业绩压力，诱发管理者短视的问题。考虑到卖方分析师主要服务的对象是机构投资者，卖方分析师可能更倾向于关注机构投资者重仓的股票，因此机构投资者持股比例也与解释变量相关。我认为如果不控制机构投资者持股比例可能会导致遗漏变量偏误。

第四，为了控制行业竞争格局，本文控制了以下变量：

（11）赫芬达尔—赫希曼指数（HHI）及其平方项（HHI_sq）

本文使用企业所处行业的赫芬达尔—赫希曼指数（Herfindahl-Hirschman Index，HHI）控制企业所处行业的竞争情况。数学上，赫芬达尔—赫希曼指数是某行业所有企业市场份额的平方和。其中市场份额是某上市公司主营业务收入占该行业上市公司主营业务收入总和的比例。行业使用 2012 版证监会行业分类代码进行分类。考虑到行业

竞争程度对于全要素生产率的影响可能并非线性，缺乏竞争与完全竞争都可能不利于企业生产效率，因此本文还控制了赫芬达尔—赫希曼指数的平方项（HHI_sq）。

第五，为了控制补贴对企业生产率的影响，本文最后还控制了以下变量：

（12）对数政府补贴（LnSubsidy）及其平方项（LnSubsidy_sq）

本文使用企业所接受的政府补贴总量取自然对数，控制政府补贴对于企业生产率的影响。任曙明 等（2014）和李政 等（2019）认为政府补贴可以缓解企业融资约束，引导企业投资，从而提高企业的生产率。考虑到过多补贴也可能会对企业生产率产生抑制作用，本文还控制了对数政府补贴的平方项（LnSubsidy_sq）。

4.2.4　其他变量

（1）平均高估程度（MeanError）

为了进一步研究研究分析师不同的盈利预测对于企业生产率影响的异质性， 本文还仿照 Gentry and Shen（2013），Guo et al.（2019）的做法，构造了平均高估程度这一指标。数学上，该指标是当年全部分析师对某家企业盈利预测标准化高估程度的算数平均值。如果平均来看，分析师高估了企业的每股收益，则这一指标为正，反之为负：

$$MeanError_{jt} = \frac{1}{K}\sum_{k} Error_{kjt} \tag{4.4}$$

（2）KZ 指数（KZindex）

目前，学术界有多种方法对企业面临的融资约束程度进行度量，度量方法可以大致分为两类：使用单一财务指标度量企业的融资约束，以及使用多种财务指标复合度量企业的融资约束。考虑到两种度量方法各有优劣，本文出于结论稳健性考虑，分别选择了企业现金持有水平（CashRatio），以及综合考虑了多个财务指标的 KZ 指数（KZindex）对企业面临的融资约束程度进行度量。

参考 He and Tian（2013），本文使用了 Kaplan and Zingales（1997）所提出的 KZ 指数作为上市公司面临融资约束的一个度量方法。Kaplan and Zingales（1997）对多种不同的财务数据进行整合，用于度量企业面临的融资约束：其中包括经营向现金流占上期末总资产的比例，现金股利占上年末总资产的比例，现金占上年末总资产的比例，企业的资产负债率与企业的托宾 Q 值。

（3）现金比例（CashRatio）

参考余明桂 等（2017），本文还采用了上市公司的现金持有水平，即现金与现金等价物占总资产的比例作为企业融资约束的度量指标。企业持有的现金越多，意味着企业可动用的资金越多，因此面临的融资约束也就越小。

（4）对数发明专利（LnPatent）

本文基于上市公司申请的发明专利度量企业的创新绩效。考虑到上市公司被分析师关注之后，可能会通过兼并收购创新型企业，或者设立公司风险投资机构实现创新，仅仅关注上市公司本身的创新活动是不够的（Guo et al., 2019）。因此，本文不仅考虑了上市公司本身的发明专利，也考虑了上市公司子公司、合营公司和联营公司申请的发明专利。这种处理方法与余明桂 等（2017）保持一致。

在度量企业的创新时，我只考虑了企业申请的发明专利，而将实用新型专利和外观设计专利排除在外。原因在于，实用新型专利和外观设计专利所代表的创新水平不足：发明专利在申请之后，必须经过我国知识产权局的实质性审查，只有具备新颖性、创造性和实用性的专利申请才能获得授权。而我国知识产权局则不会对实用新型专利和外观设计专利进行实质性审查，而是仅仅进行形式审查，确定专利申请书等符合规范即可获得授权。这使得实用新型专利和外观设计专利所代表的创新水平远远不如发明专利（Dang & Motohashi, 2015）。一些研究甚至发现，我国实用新型专利的增加对于我国全要素生产率产生了统计学意义上的负向冲击（毛昊 等，2018），而且，大量低质量的实用新型专利被“专利蟑螂”用于恶意诉讼（毛昊 等，2017）。因此，本文在使用专利度量企业创新时不考虑实用新型专利和外观设计专利。

本文使用基于专利的两种指标度量企业的创新成果：对数发明专利（LnPatent）与对数发明专利引用（LnCite）。发明专利数量是上市公司及其子公司、联营公司、合营公司在某年申请的发明专利总数量。考虑到专利本身代表的创新水平有很大不同，本文还参考 Guo et al.（2019），使用企业发明专利的总引用量作为企业创新产出的度量。

（5）对数发明专利引用（LnCite）

企业发明专利的总引用量是上市公司及其子公司、联营公司、合营公司在某年申请的发明专利，被后来专利的引用的总数量。由于中国知识产权局没有整理我国专利之间的引用关系，本文参考 Lin et al.（2021）与 Sun et al.（2021）采用了谷歌专利中报告的专利被其他专利引用这一指标作为原始数据源。本文使用的原始数据由中国研究数据服务平台（CNRDS）从谷歌公司获取。我在该数据库的基础上进行了细致的数据清洗：

首先，中国发明专利在未经官方审查授权时，使用以 A 结尾的专利公开号（如 CN101183371A），而在官方审查授权后使用以 B 结尾的专利公开号（如 CN101183371B）。这使得获得授权的专利存在两个不同的专利公开号。谷歌公司和中国研究数据服务平台均没有对这一问题进行调整，存在重复计算问题。本文在计算公司专利数量与专利引用量时，对这一问题进行了调整，最终得到了我国上市公司及其子公司、联营公司、合营公司在 2007 年到 2017 年之间申请的 900,754 项发明专利与 2,456,605 次被其他专

利引用的信息。

其次，由于专利会在较长时间被其他专利引用，而未来专利对当前专利的引用不可被观测到，因此存在数据截尾问题。本文参考 Hall et al. (2001)在构造美国经济研究局专利引用数据库时提出的调整方法，对截尾问题进行调整。具体做法是用原始引用量，除以同年同科技分类的平均引用量，得到标准化之后的专利引用量：

$$Cite_{it} = \sum_j \frac{PatCite_{isjt}}{meanPatCite_{st}} \tag{4.5}$$

其中$PatCite_{isjt}$指的是i企业在t年申请的编号为j的专利，该专利属于科技类型s。$meanPatCite_{st}$指的是t年申请的全部科技类型为s的专利的平均引用量。然后，在对每个企业每年的引用量进行加总，即可得到j企业在t年申请发明专利的总引用量$Cite_{jt}$。我使用国际专利分类（IPC）代码的第一位，即 IPC 部，用于划分企业申请专利的科技类型s。

图 4.1　谷歌专利中对专利引用的记录

在表 4.1 中，我整理了本文所使用的主要变量：

表 5.1 本文使用的主要变量

变量符号	变量名	构造方法	数据源
TFP_OP	OP法全要素生产率	参考 Olley and Pakes（1996）估计	Wind
TFP_LP	LP法全要素生产率	参考 Levinsohn and Pertin（2003）估计	Wind
ROA	资产收益率	2*净利润/ (年末资产+年初资产)	Wind
LnAnalyst	对数分析师	ln(1+对企业发布盈利预测的分析师数)	CSMAR
LnReport	对数研报	ln(1+对企业发布盈利预测的研报数)	CSMAR
LnAnaHigh	对数高估分析师	ln(1+预测高估偏差高于均值的分析师数)	CSMAR
LnAnaLow	对数低估分析师	ln(1+预测高估偏差低于均值的分析师数)	CSMAR
Size	企业规模	ln(1+总资产) 其中总资产以千元计	Wind
Age	企业年龄	ln(1+企业成立以来的年数)	CSMAR
BM	账面市值比	总资产/总市值	Wind
Growth	企业成长性	(营业收入-上年营业收入)/上年营业收入	Wind
CapEx	投资开支	购建固定资产、无形资产和其他长期资产支付的现金/营业收入	Wind
Cashflow	经营现金流	经营活动现金流/总资产	Wind
PPEratio	固定资产比例	固定资产/总资产	Wind
SOE	国有企业	国有企业为1，否则为0	CSMAR
FirstOwn	第一大股东持股比	第一大股东股份/总股份	Wind
InstOwn	机构投资者持股比	机构投资者股份/总股份	Wind
HHI	赫芬达尔—赫希曼指数	行业内各企业主营业务收入占比平方和	CSMAR
HHI_sq	赫芬达尔—赫希曼指数平方项	赫芬达尔—赫希曼指数的平方	CSMAR
LnSubsidy	对数政府补贴	ln(1+政府补贴) 其中政府补贴以以千元计	Wind
LnSubsidy_sq	对数政府补贴平方项	对数政府补贴的平方	Wind
MeanError	平均高估程度	分析师对企业盈利预测高估程度的平均值	CSMAR
KZindex	KZ指数	参见Kaplan and Zingales（1997）	CSMAR
CashRatio	现金比例	现金及现金等价物/总资产	Wind
LnPatent	对数发明专利	ln(1+企业发明专利数)	CNRDS
LnCite	对数发明专利引用	ln(1+企业发明专利标准化引用数)	CNRDS

第五章 实证研究设计

参考 To et al.（2018），在基准回归分析中，本文使用面板数据固定效应模型对我国分析师关注与企业生产率之间的关系进行研究。这一实证策略的好处在于包含了尽可能多的企业-年度观测样本，有助于我们从整体上考察金融分析师关注与企业生产率之间的关系。然而，这一方法的缺点也十分明显：反向因果与遗漏变量可能导致比较严重的内生性问题，因此仅仅凭借基准回归分析我们不能对因果关系进行清晰地判断。

为了解决反向因果与遗漏变量导致的内生性问题，本文还采用了另外两种实证研究方法：第一，我使用了 Yu（2008）提出的工具变量对基准回归中的主要结果进行了检验；第二，我还参考 Hong and Kacperczyk（2010）和李春涛 等（2016），将我国证券公司之间三次主要的兼并收购事件作为准自然实验，研究了证券公司之间兼并收购带来的分析师关注下降对于企业全要素生产率的影响。

5.1 基准回归模型

为了验证第三章中本文提出的实证假设，本文首先考虑使用面板数据固定效应模型对上述实证假设进行逐一检验，具体而言，实证模型如下：

5.1.1 对实证假设 H1 的固定效应回归检验

本文实证假设 H1 是在探究企业生产率与分析师关注之间的关系。由于分析师关注对于企业生产率的影响时间可能较长，我使用企业向前一年、两年或多年的全要素生产率作为因变量，使用当年对数分析师关注以及控制变量作为自变量，进行面板固定效应回归分析。考虑到企业生产率可能存在的自相关和异方差，本文在基准回归中使用企业层面的聚类稳健标准误。如果使用模型(5.1)进行回归分析发现β_1显著为正，那么就可以认为实证结果为实证假设 H1 提供了一定证据。

$$TFP_{it+\tau} = \beta_0 + \beta_1 LnAnalyst_{it} + \boldsymbol{X}'_{\boldsymbol{it}}\boldsymbol{\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.1}$$

在上述模型(5.1)中，$TFP_{it+\tau}$是企业i在$t+\tau$年的全要素生产率，分别使用 OP 方法和 LP 方法度量。$LnAnalyst_{it}$是企业i在t年的对数分析师关注。$\boldsymbol{X}'_{\boldsymbol{it}}$是 4.2.3 节描述的控制变量，以一个行向量表示。μ_i是企业固定效应，用于控制企业不随时间变化而变化的特征。θ_t是年度时间固定效应，控制只随着时间变化而不同的生产率波动。

5.1.2 对实证假设 H2 的固定效应回归检验

本文的实证假设 H2 旨在研究分析师关注是否可以通过放松企业的融资约束，提高企业的生产率。在基准回归分析中，本文参考 Baron and Kenny（1986），以及温忠麟与叶宝娟（2014）推荐的经典中介效应分析方法，对 H2 进行面板回归检验。具体分析方法是按顺序估计以下模型：

$$KZindex_{it+1} = \beta_0 + a\ LnAnalyst_{it} + \boldsymbol{X'_{it}\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.2}$$

$$TFP_{it+1} = \beta_0 + c\ LnAnalyst_{it} + \boldsymbol{X'_{it}\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.3}$$

$$TFP_{it+1} = \beta_0 + c'\ LnAnalyst_{it} + b\ KZindex_{it+1} + \boldsymbol{X'_{it}\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.4}$$

第一步，使用当期分析师关注$LnAnalyst_{it}$对中介变量向前一期 KZ 指数$KZindex_{it+1}$进行回归，如果系数a显著小于 0 则继续；第二步，使用当期分析师关注$LnAnalyst_{it}$对向前一期全要素生产率TFP_{it+1}进行回归，若系数c显著大于 0 则继续；第三步，加入中介变量$KZindex_{it+1}$之后，再次使用当期分析师关注$LnAnalyst_{it}$对向前一期全要素生产率TFP_{it+1}进行回归。若系数c'相比c减小但是仍然显著大于 0，则认为融资约束在分析师关注与企业生产率之间发挥了一部分中介效应，即为实证假设 H2 提供了一定证据。

除此之外，本文还使用向前一期现金持有水平$Cashratio_{it+1}$，替换上述模型中的$KZindex_{it+1}$，作为企业融资约束的另一个度量。

5.1.3 对实证假设 H3 的固定效应回归检验

本文的实证假设 H3 旨在研究分析师关注是否可以通过提高企业创新，提高企业的生产率。与对实证假设 H2 的检验方法相同，本文对依次对以下模型进行估计。

$$LnPatent_{it+1} = \beta_0 + a\ LnAnalyst_{it} + \boldsymbol{X'_{it}\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.5}$$

$$TFP_{it+1} = \beta_0 + c\ LnAnalyst_{it} + \boldsymbol{X'_{it}\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.6}$$

$$TFP_{it+1} = \beta_0 + c'\ LnAnalyst_{it} + b\ LnPatent_{it+1} + \boldsymbol{X'_{it}\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.7}$$

除此之外，本文还使用企业下一年申请专利的总引用量$LnCite_{it+1}$，替换上述模型中的$LnPatent_{it+1}$，作为企业融资约束的另一个度量。

5.1.4 对实证假设 H4 的固定效应回归检验

本文实证假设 H4 是在探究分析师盈利预测的高估程度的调节效应，本文采用两种不同方法对 H4 进行检验：

首先，本文在模型(5.1)的基础上加入平均高估程度（MeanError）以及平均高估程度与分析师关注的交乘项，如果交乘项的系数β_3显著小于 0，则认为这一实证结果为实证假设 H4 提供了一定证据。

$$TFP_{it+1} = \beta_0 + \beta_1 LnAnalyst_{it} + \beta_2 MeanError_{it} + \beta_3 LnAnalyst_{it} * MeanError_{it} + \boldsymbol{X}'_{it}\boldsymbol{\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.8}$$

尽管这一实证方法比较简单，然而也存在的潜在问题：首先，使用交乘项检验调节效应容易出现虚假显著（朱家祥与张文睿, 2021），而且隐含性地假设了控制变量的影响相同。其次，由于企业至少需要有一个分析师关注，才能计算平均盈利预告偏差这一指标，这意味着回归中没有分析师关注的样本点会被排除在外，可能会导致样本选择偏误。因此，我还分别计算了对数高估分析师（LnAnaHigh），以及对数低估分析师（LnAnaLow）这两个指标，并进行以下回归：

$$TFP_{it+1} = \beta_0 + \beta_1\, LnAnaHigh_{it} + \beta_2\, LnAnaLow_{it} + \boldsymbol{X}'_{it}\boldsymbol{\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.9}$$

若上述回归发现系数β_1小于系数β_2，那么这一实证结果就一定程度上为实证假设 H4 提供了支持。

5.2　内生性问题

本文基准回归分析的一个潜在问题是可能存在内生性问题。我认为，基准回归分析中反向因果和遗漏变量都可能导致比较严重的内生性问题。

5.2.1　反向因果

首先，反向因果可能导致本文的基准回归结果存在内生性问题。这是因为分析师关注不仅仅可能影响到企业生产率，企业生产率本身也可能反过来对分析师的关注产生影响。尽管本文使用的是企业未来的生产率，一定程度上可以削弱反向因果的可能性。然而，考虑到金融分析师会对企业长期绩效进行预测，分析师可能会因为预测到这家企业明年生产率较高，从而提前关注这家企业。这一机制会导致联立方程偏误，从而使得基准回归分析的系数被高估。因此，反向因果是基准回归存在内生性的潜在原因之一。

5.2.2　遗漏变量

其次，遗漏变量也可能导致本文的基准回归结果存在的内生性问题。这是因为，一些难以观测的因素可能同时影响到分析师关注与企业生产率。比如，高生产率的企业

供应链复杂度可能更高，但是，分析师可能不愿意对信息比较复杂的企业进行覆盖。企业供应链的复杂度可能随着时间变化，而且在对于各个企业也不相同，因此不会被固定效应所吸收。因此，如果不对这一因素进行控制，便会导致分析师关注的影响被低估。但是，由于供应链复杂度本身难以度量，所以也难以放入面板回归中加以控制。

5.3 使用工具变量解决内生性问题

为了解决内生性问题，本文首先参考 Yu（2008）使用证券公司分析师团队规模的变化构造了预期分析师关注（ExpectedCoverage）这一变量，作为分析师关注的工具变量。一方面，证券公司雇佣多少分析师由证券公司的管理层决定，受到证券公司本身经营策略、盈利状况等因素的影响，而一般不受到被分析师关注企业的特征影响。因此，通过证券公司分析师团队的规模构造工具变量满足外生性。另一方面，券商分析师团队的大小，会直接影响到分析师的繁忙程度。当证券公司分析师团队人数较少时，分析师就不得不减少对于企业的关注。因此，使用证券公司分析师团队的数量构造工具变量也满足相关性。

数学上，预期分析师关注这一变量的构造方法如下：

$$ExpectedCoverage_{ijt} = \frac{Brokersize_{jt}}{Brokersize_{j0}} * Coverage_{i0j} \tag{5.10}$$

$$ExpectedCoverage_{it} = \sum_{j=1}^{J} ExpectedCoverage_{ijt} \tag{5.11}$$

(5.10)式中，$Brokersize_{jt}$是在t年证券公司j雇佣的分析师总人数，$Brokersize_{j0}$是基准年j证券公司雇佣的分析师总人数。而$Coverage_{i0j}$代表在基准年证券公司j是否关注了上市公司i，如果关注了则取 1，没有关注则取 0。所以$ExpectedCoverage_{ijt}$度量了由于证券分析师团队规模的变化，导致证券公司j所属分析师对上市公司i关注程度的变化。(5.11)中，我们将所有券商在t年对上市公司i的关注进行加总，那么我们就得到了这一年的预期分析师关注。使用工具变量对回归进行估计时，只包含基准年年被至少一个分析师关注的企业。

基准年的选择并不会影响工具变量的外生性与相关性。在本文中，我首先选择样本最后一年，即 2020 年作为基准年。这是因为我国证券行业在不断发展中，不断有新的企业上市、并不断有新的分析师加入市场，使用样本最后一年作为基准年尽可能多地包含企业-年度样本。除此之外，Yu（2008）建议将基准年的观测样本删去。本文中，回归分析使用了向前一年的生产率作为被解释变量，因为本文样本终结于 2020 年，所以回归分析使用的解释变量只用到了 2019 年的值。使用 2020 年预期分析师关注自然排除了基准年的观测样本，因此进一步保留了更多观测值。

本文读者可能会认为使用样本最后一期作为基准年构造预期分析师这一工具变量，不能体现“预期”这一特征。然而， Yu（2008）并不要求必须将样本初期选为基准年。实际上，Yu（2008）为了包含最多企业-年度观测样本，选择了样本中间年作为分析师关注的基准年。尽管我们使用样本最后一期构造工具变量，但是由于我们没有使用到除了基准期之外的其他年份分析师是否关注企业的信息，而是完全使用证券公司分析师团队的规模产生工具变量的变化，这一工具变量可以避免分析师选择企业进行关注带来的反向因果问题。尽管如此，为了进一步避免基准期选择带来的偶然结果，本文7.1.3 节还是通过改变基准期选择重新构造了工具变量，对本文主要结果进行了稳健性检验。

5.4　使用准自然实验解决内生性问题

除了使用工具变量解决内生性问题，本文还参考 Hong and Kacperczyk（2010），Derrien and Kecskés（2013）的研究方法，将证券公司之间兼并收购导致的分析师关注下降作为准自然实验，用于识别分析师关注下降对于企业生产率的影响。

券商兼并收购导致的分析师关注下降满足相关性与外生性，因此可以很好地识别出企业生产率与分析师关注之间的因果关系。从相关性的角度上看，Hong and Kacperczyk（2010）认为，一般来说，一家证券公司的至多只有一个分析师团队关注某家公司。因此，证券公司之间的相互兼并会导致兼并后分析师关注的冗余。如果两家公司的分析师在兼并前关注同一个行业或者同样的公司，那么兼并之后证券公司会因为冗余解雇其中一名分析师，或者要求这个分析师关注其他企业。那些被兼并收购之前的两家证券公司同时关注的企业，在兼并之后一般只能剩下一个分析师团队关注。因此，使用券商之间的兼并收购会导致分析师关注的下降。从外生性的角度上看，券商之间的兼并收购是证券公司的经营策略决定的，与这家证券公司分析师团队关注的企业无关。

在国内的相关研究方面，李春涛 等（2016）率先将这一自然实验应用于对我国金融分析师的研究。然而，李春涛 等（2016）并未公开他们筛选出的券商合并事件。为了筛选出样本期内我国券商之间的兼并收购事件，我借鉴李春涛 等（2016）的筛选方法，使用国泰安分析师预测数据库，筛选出 2007 到 2020 年之间发布研究报告的券商名录。然后，我对比了不同年发布研究报告的证券公司列表。对于各年份在名录上消失的券商，我使用百度搜索相关信息，最终筛选出 3 个样本期内可以使用的券商合并事件。表 5.1 整理了三次券商之间的兼并收购的相关信息：

表 5.1　样本期内券商兼并收购事件

券商A	券商B	合并年	并购前同时关注企业	并购后继续关注企业
方正证券	中国民族证券	2014	77	43
申银万国证券	宏源证券	2015	299	174
中金公司	中投证券	2017	154	125

表 5.1 的第四列展示了券商合并之前的两年，同时被两家证券公司的分析师团队关注的企业数量。与 Hong and Kacperczyk（2010）相同，我删除了券商合并之后证券公司不再继续关注的上市公司样本。这是因为，分析师团队可能认为被关注企业没有研究价值而停止对某个上市公司跟踪。如果将这部分企业包含在样本期内，那么分析师关注的下降就不完全是由券商合并导致的。现实中，分析师可能会因为预测到某家企业未来生产率较低没有投资推荐价值停止对该企业的跟踪，这就会导致自然实验的双重差分估计量存在样本选择偏误。表 5.1 的第五列展示了合并前被两家证券公司同时关注，且合并后被并购发起方分析师团队继续关注的企业样本。最后，考虑到同一家企业可能受到多次券商合并影响，对于这类企业，我只保留了最后一次企业被券商合并影响的样本。

从上面的样本筛选过程中我们可以看出，一家企业被划分为实验组意味着这家企业在券商兼并前后被证券公司的分析师团队持续跟踪。而现实中，很多企业并不能吸引足够多的分析师关注。这意味着实验组企业是全部上市公司中较大、较强，能吸引很多分析师关注的企业。这导致使用全部未受冲击的上市公司作为对照组，双重差分估计值可能受到企业特征的影响。参考 To et al.（2018），我使用倾向得分匹配的方法筛选与实验组企业特征相似的未受冲击企业作为控制组，具体的方法是：使用企业规模（Size）、企业账面市值比（BM）、经营现金流（Cashflow）和未取对数之前的分析师关注（Analyst）作为匹配协变量，使用 Logit 模型估计倾向得分并进行参数为 0.05 的卡尺最近邻匹配。最终，我为 231 家实验组企业找到了唯一的匹配样本。

本文使用双重差分（Difference-in-difference, DID）方法对分析师关注下降导致的企业全要素生产率变化进行估计。企业-年度样本保留事件前后各三年的样本。为了进一步消除企业特征、年份以及控制变量对于企业生产率的影响，本文使用以下带控制变量的固定效应模型对双重差分估计量进行估计：

$$TFP_{it} = \beta_0 + \beta_1 Treated_{it} + \boldsymbol{X}_{it}'\boldsymbol{\delta} + \mu_i + \theta_t + \epsilon_{it} \tag{5.12}$$

在模型(5.12)中，$Treated_{it}$对于实验组样本在券商合并冲击后取 1，在合并发生前取 0；对于控制组样本则一直取 0。

第六章　实证研究结果

6.1　描述性统计

本文的样本最终包含了来自 3643 家上市公司的 28585 个企业-年度观测值。由于分析师的平均预测偏差（MeanError）要求企业当年至少有一名分析师关注才可以进行计算，因此只有 20723 个年度-公司观测值。由于专利引用量需要至少 3 年的数据进行截尾调整，因此对全部 2018、2019 和 2020 年的样本取空值，因此只有 19464 年度-公司观测值。注意到，在未取自然对数之前，分析师关注、专利数量、专利引用量等变量有着很大的正偏度。本文借鉴 He and Tian（2013）和 To et al.,（2018）的做法，对这些变量取自然对数进行处理，这些变量名称加前缀 Ln 进行表示。除此之外，根据全要素生产率的计算方法，本文的主要被解释变量全要素生产率也是取对数后的指标（详见附录 A）。

为了进一步避免极端值的影响，本文在回归分析中对所有的连续变量在 1%和 99%的分位数进行了缩尾（Winsorize）处理。变量的描述性统计结果见表 6.1：

表 6.1　描述性统计结果

Variable	N	Mean	St. Dev.	Min	Median	Max
TFP_OP	28585	8.921	0.961	5.095	8.872	11.57
TFP_LP	28585	7.924	0.905	4.407	7.875	10.45
ROA	28585	0.064	0.056	-0.098	0.055	0.313
LnAnalyst	28585	1.528	1.159	0.000	1.609	3.912
LnReport	28585	1.871	1.419	0.000	1.946	4.852
LnAnaLow	28585	1.071	1.110	0.000	0.693	3.829
LnAnaHigh	28585	0.783	0.972	0.000	0.000	3.401
Size	28585	15.13	1.299	12.30	14.95	19.50
Age	28585	2.773	0.380	1.099	2.833	3.555
BM	28585	0.937	0.996	0.051	0.612	7.935
Growth	28585	0.210	0.496	-0.616	0.124	5.223
CapEx	28585	0.120	0.158	0.001	0.067	1.267
Cashflow	28585	0.047	0.072	-0.223	0.047	0.297
PPEratio	28585	0.224	0.167	0.002	0.190	0.772
SOE	28585	0.405	0.491	0.000	0.000	1.000
FirstOwn	28585	0.356	0.150	0.083	0.338	0.758
InstOwn	28585	0.459	0.244	0.001	0.483	0.936
HHI	28585	0.106	0.116	0.014	0.069	0.951
HHI_sq	28585	0.025	0.075	0.000	0.005	0.905
LnSubsidy	28585	8.554	2.657	0.000	9.016	13.43
LnSubsidy_sq	28585	80.24	34.69	0.000	81.30	180.2
MeanError	20723	0.009	0.017	-0.044	0.005	0.129
KZindex	28585	1.427	2.082	-8.568	1.596	8.489
CashRatio	28585	0.180	0.127	0.006	0.146	0.838
LnPatent	28585	1.756	1.549	0.000	1.609	6.397
LnCite	19464	1.500	1.502	0.000	1.245	6.227

注：本表报告了基准回归分析中使用的描述性统计结果。样本为2007年至2020年的A股上市公司企业-年度样本，不包括金融行业公司、被标记为ST、ST*、PT的公司、重要变量存在缺失值的公司-年度样本。

6.2　金融分析师对生产率的总效应

6.2.1　对实证假设 H1 的基准回归分析

本文首先采用基准回归模型(5.1)对于实证假设 H1 进行检验。在表 6.2 的列（1）到列（3）中，被解释变量为未来一年的 OP 法计算的全要素生产率（TFP_OP）。从列（1）到列（3），我将控制变量逐步加入到回归中，并控制了企业、行业、年度三个固定效应。结果显示系数估计值为 0.153，0.086 和 0.078，且系数均在 1%水平上显著大于 0。这一个结果初步表明金融分析师关注某家企业之后，企业全要素生产率出现了提升。这一结果一定程度上对实证假设 H1 提供了支持。

从回归模型解释能力的角度上来看，只加入固定效应的回归调整后 R 方就达到了 0.388。进一步加入解释变量后，调整后 R 方最终上升到 0.471，这表明我们的控制变量也有助于解释一部分全要素生产率的差异。

从控制变量的系数上看，企业规模的系数均显著为正，这表明我国上市公司企业规模越大，企业的全要素生产率水平也就越高。这与 İmrohoroğlu and Tüzel（2014）在美国股市的发现一致。从企业的成长性的角度来看，企业账面市值比的系数显著为负，这表明低账面市值比的成长型公司比价值型公司的全要素生产率更高。相似地，企业的营业收入增长率的系数显著为正，这表明企业收入增长越快，企业的全要素生产率越高，这符合我们的经济学直觉。从企业所有者的角度上来看，国有企业的系数显著为负，这表明国有企业在其他条件不变的情况下，生产率不如其他所有制对企业，这与现有文献的共识相一致。第一大股东持股比例、机构持有人比例的系数显著为正，表明大股东持股比例越高、机构持有人比例越高，企业全要素生产率水平也就越高。

出于稳健性考虑，在列（4）我将被解释变量改为未来一年 LP 法计算的全要素生产率（TFP_LP）。结果显示，使用分析师关注的系数也显著大于 0，而且与列（3）没有显著的差异。除此之外，在本文第七章稳健性检验的部分，我还使用企业的资产收益率（ROA）作为企业生产率的另一个度量方法，使用基准回归模型对实证假设 H1 进行了进一步检验。结果发现，分析师关注对企业未来一年资产收益率的系数显著为正。这些结果进一步对实证假设 H1 提供了支持。

表 6.2　对实证假设 H1 的基准回归分析：未来一年生产率

VARIABLES	(1) TFP_OP t+1	(2) TFP_OP t+1	(3) TFP_OP t+1	(4) TFP_LP t+1
LnAnalyst	**0.153***** **(0.006)**	**0.086***** **(0.005)**	**0.078***** **(0.005)**	**0.078***** **(0.005)**
Size		0.371*** (0.013)	0.366*** (0.013)	0.312*** (0.013)
Age		-0.058 (0.050)	0.003 (0.050)	-0.019 (0.049)
BM		-0.067*** (0.008)	-0.059*** (0.008)	-0.060*** (0.009)
Growth		0.126*** (0.008)	0.117*** (0.008)	0.118*** (0.008)
CapEx		-0.192*** (0.034)	-0.203*** (0.033)	-0.290*** (0.032)
Cashflow		0.813*** (0.058)	0.813*** (0.058)	0.815*** (0.056)
PPEratio		-0.091 (0.059)	-0.061 (0.058)	-0.414*** (0.059)
SOE			-0.110*** (0.035)	-0.099*** (0.034)
FirstOwn			0.171** (0.082)	0.170** (0.082)
InstOwn			0.350*** (0.050)	0.342*** (0.050)
HHI			-0.092 (0.171)	-0.160 (0.168)
HHI_sq			0.093 (0.195)	0.141 (0.189)
LnSubsidy			0.004 (0.006)	0.004 (0.006)
LnSubsidy_sq			-0.001* (0.001)	-0.001* (0.000)

续表 6.2　对实证假设 H1 的基准回归分析：未来一年生产率

Constant	7.936***	2.783***	2.562***	2.559***
	(0.117)	(0.232)	(0.246)	(0.241)
Observations	28,585	28,585	28,585	28,585
Number of stockcode	3,643	3,643	3,643	3,643
Adjusted R-squared	0.388	0.466	0.471	0.442
Firm FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

注：本表报告了使用基准回归模型(5.1)对于实证假设H1进行检验的实证结果。被解释变量为未来一年OP法全要素生产率和LP法全要素生产率。括号内标注了企业层面的聚类稳健标准误。*** 、** 和 *分别表示回归系数在1%、5%和10%的水平上显著。

6.2.2　分析师关注对企业的长期影响

考虑到分析师关注可能对企业的影响时间比较长，在表格 6.3 中，我报告了分析师关注对更长期企业生产率的回归结果。被解释变量选择企业未来一年到未来五年的全要素生产率，使用 OP 法进行计算。为了更加清晰直观地展示结果，图 6.1 绘制了对数分析师关注（LnAnalyst）的回归系数，95%置信区间使用垂直短线表示。

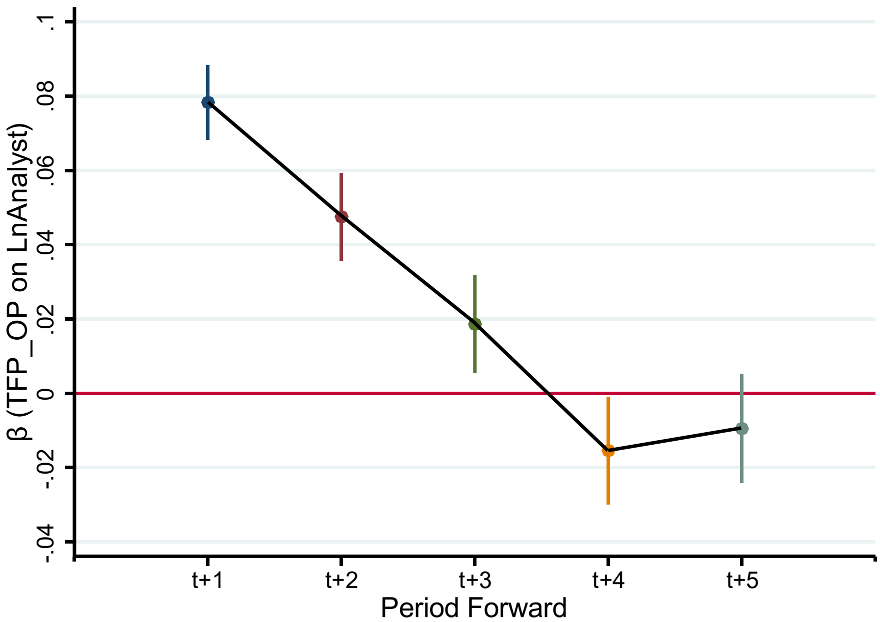

图 6.1　分析师关注对长期企业生产率的回归系数

结果显示，分析师关注对于未来 1 期、2 期、3 期的全要素生产率的回归系数显著大于 0，但是系数的大小随着时间的增长逐渐衰减。分析师关注对于未来 4 期的全要素生产率回归系数呈现负显著，但是系数绝对值和统计学显著性均比较弱。最终分析师关注对于未来 5 期全要素生产率回归系数显著不再显著。这些结果初步表明，金融分析师关注后企业生产率的提升会持续一段时间。

表 6.3 对实证假设 H1 的基准回归分析：未来多年生产率

VARIABLES	(1) TFP_OP t+1	(2) TFP_OP t+2	(3) TFP_OP t+3	(4) TFP_OP t+4	(5) TFP_OP t+5
LnAnalyst	**0.078*****	**0.048*****	**0.019*****	**-0.015****	**-0.009**
	(0.005)	**(0.006)**	**(0.007)**	**(0.007)**	**(0.007)**
Size	0.366***	0.202***	0.067***	-0.021	-0.072***
	(0.013)	(0.015)	(0.016)	(0.018)	(0.020)
Age	0.003	0.059	0.087	0.078	0.117
	(0.050)	(0.058)	(0.068)	(0.074)	(0.077)
BM	-0.059***	-0.035***	-0.020*	-0.008	0.011
	(0.008)	(0.009)	(0.011)	(0.011)	(0.010)
Growth	0.117***	0.079***	0.041***	0.039***	0.017*
	(0.008)	(0.008)	(0.009)	(0.010)	(0.010)
CapEx	-0.203***	-0.035	0.088**	0.135***	0.166***
	(0.033)	(0.037)	(0.040)	(0.048)	(0.046)
Cashflow	0.813***	0.491***	0.266***	-0.032	-0.159**
	(0.058)	(0.067)	(0.068)	(0.076)	(0.078)
PPEratio	-0.061	0.092	0.206***	0.241***	0.314***
	(0.058)	(0.065)	(0.071)	(0.069)	(0.071)
SOE	-0.110***	-0.060	-0.036	-0.015	0.006
	(0.035)	(0.039)	(0.044)	(0.046)	(0.046)
FirstOwn	0.171**	0.084	0.110	0.023	0.023
	(0.082)	(0.094)	(0.104)	(0.109)	(0.114)
InstOwn	0.350***	0.337***	0.244***	0.181***	0.120*
	(0.050)	(0.059)	(0.062)	(0.067)	(0.068)
HHI	-0.092	-0.096	-0.381*	-0.176	-0.113
	(0.171)	(0.195)	(0.208)	(0.222)	(0.234)

续表 6.3　对实证假设 H1 的基准回归分析：未来多年生产率

HHI_sq	0.093	0.065	0.351	0.113	0.078
	(0.195)	(0.207)	(0.220)	(0.243)	(0.255)
LnSubsidy	0.004	0.005	0.007	0.005	0.003
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
LnSubsidy_sq	-0.001*	-0.001	-0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	2.562***	5.068***	7.470***	8.920***	9.364***
	(0.246)	(0.284)	(0.313)	(0.328)	(0.341)
Observations	28,585	25,218	21,969	18,858	16,193
Number of stockcode	3,643	3,512	3,394	2,958	2,722
Adjusted R-squared	0.471	0.359	0.283	0.256	0.262
Firm FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

注：本表报告了使用基准回归模型(5.1)对于实证假设H1进行检验的实证结果。被解释变量是未来一年到未来五年OP法全要素生产率。括号内标注了企业层面的聚类稳健标准误。*** 、** 和*分别表示回归系数在1%、5%和10%的水平上显著。

6.2.3　使用工具变量解决内生性问题

为了解决内生性问题，本文使用了预期分析师关注（ExpectedCoverage）作为对数分析师关注（LnAnalyst）的工具变量，对实证假设 H1 进行进一步检验。表 6.3 报告了两阶段最小二乘法的检验结果：其中列（1）报告了第一阶段的回归结果。可见预期分析师关注对于对数分析师关注的回归显著为正。除此之外， Kleibergen-Paap F 统计量达到了 269.35，远远大于临界值，这表明预期分析师关注不是一个弱工具变量。

在列（2）到列（3）中我报告了被解释变量为未来一年 OP 法全要素生产率和 LP 法全要素生产率的第二阶段回归结果，结果表明系数显著为正。这一结果进一步表明，金融分析师对企业的关注有助于企业生产率的提升。

表 6.4　对实证假设 H1 的工具变量回归分析

	First Stage	Second Stage	
	(1)	(2)	(3)
VARIABLES	LnAnalyst	TFP_OP	TFP_LP
	t	t+1	t+1
ExpectedCoverage	**0.095*****		
	(0.006)		
LnAnalyst		**0.160*****	**0.156*****
(instrumented)		**(0.032)**	**(0.031)**
Size	0.484***	0.312***	0.272***
	(0.027)	(0.023)	(0.023)
Age	-0.372***	0.036	0.018
	(0.098)	(0.057)	(0.056)
BM	-0.217***	-0.047***	-0.048***
	(0.017)	(0.011)	(0.011)
Growth	-0.035**	0.125***	0.126***
	(0.016)	(0.012)	(0.011)
CapEx	0.177**	-0.205***	-0.303***
	(0.073)	(0.043)	(0.044)
Cashflow	0.797***	0.936***	0.945***
	(0.111)	(0.086)	(0.084)
PPEratio	-0.601***	-0.045	-0.384***
	(0.114)	(0.072)	(0.073)
SOE	-0.228***	-0.064	-0.058
	(0. 067)	(0.045)	(0.042)
FirstOwn	-0.362**	0.148	0.128
	(0.177)	(0.099)	(0.097)
InstOwn	1.221***	0.285***	0.284***
	(0.121)	(0.074)	(0.074)
HHI	-0.659*	0.193	0.141
	(0.385)	(0.215)	(0.207)
HHI_sq	0.796*	-0.077	-0.054
	(0.460)	(0.260)	(0.236)
LnSubsidy	0.031***	0.008	0.009
	(0.011)	(0.008)	(0.008)

续表 6.4　对实证假设 H1 的工具变量回归分析

LnSubsidy_sq	-0.002**	-0.001**	-0.001**
	(0.001)	(0.001)	(0.001)
Observations	15,306	15,306	15,306
Number of Stock	1,864	1,864	1,864
R-squared	0.340	0.535	0.497
Firm FE	YES	YES	YES
Industry FE	YES	YES	YES
Year FE	YES	YES	YES
Cragg-Donald Wald F	595.69		
Kleibergen-Paap Wald F	269.35		

注：本表报告了使用预期分析师关注作为对数分析师关注的工具变量对于实证假设H1进行检验的实证结果。括号内标注了企业层面的聚类稳健标准误。*** 、** 和*分别表示回归系数在1%、5%和10%的水平上显著。

6.2.4　使用自然实验解决内生性问题

为了进一步解决内生性问题，本文还使用证券公司合并这一准自然实验对于实证假设 H1 进行了进一步检验。如果券商合并前两年，并购方和被并购方分析师均对某家上市公司发布了至少一篇研报，则这家企业被划分为实验组企业。最终，我们值得读者注意的是，这种数据筛选方法相比 Hong and Kacperczyk（2010）更加宽松，Hong and Kacperczyk（2010）要求券商合并前一年并购方和被并购方分析师均对某家上市公司发布了至少一篇研报。我认为这是一种必要的妥协：Hong and Kacperczyk（2010）使用了美国证券市场多大 43 次券商兼并事件，但是本文样本期内我国券商并购事件只有 3 个。如果严格按照 Hong and Kacperczyk（2010）的数据处理方法，则处理组样本过少。

本文表 6.5 报告了对实证假设 H1 进行双重差分估计的结果。其中列（1）和列（2）报告了进行倾向得分匹配之后再进行双重差分估计的结果。参考 To et al.（2018），我使用企业被券商合并事件冲击前一年的特征进行倾向得分匹配，协变量包括企业规模（Size）、企业账面市值比（BM）、经营现金流（Cashflow）和未取对数之前的分析师关注（Analyst）。本文倾向得分使用 Logit 回归进行估计，匹配方式是卡尺为 0.05 的最近邻匹配。最终 231 家企业匹配到了与之唯一对应的控制组企业。最后，我只保留了事件前三年，事件当年和事件后三年的样本。最终样本包含了 462 家企业的 3094 个企业年度观测值。我使用回归模型(5.12)对券商合并自然实验的处理效应进行了估计，结果显示处理效应显著为负。这一结果表明券商合并带来的金融分析师关注下降，显著

地降低了企业的全要素生产率。

除此之外，列（3）和列（4）还报告了不进行匹配直接进行双重差分估计的结果。结果与倾向得分匹配之后再进行双重差分估计的结果没有显著差异。

表 6.5　对实证假设 H1 的自然实验检验

	PSM-DID		DID without Match	
	(1)	(2)	(3)	(4)
VARIABLES	TFP_OP	TFP_LP	TFP_OP	TFP_LP
Treated	**-0.065*** **	**-0.068*** **	**-0.065*** **	**-0.066*** **
	(0.024)	**(0.024)**	**(0.019)**	**(0.018)**
Size	0.526***	0.464***	0.544***	0.480***
	(0.039)	(0.039)	(0.011)	(0.011)
Age	0.131	0.107	-0.143***	-0.165***
	(0.192)	(0.195)	(0.046)	(0.045)
BM	-0.094***	-0.093***	-0.105***	-0.105***
	(0.019)	(0.019)	(0.008)	(0.008)
Growth	0.130***	0.134***	0.129***	0.128***
	(0.029)	(0.030)	(0.007)	(0.007)
CapEx	-0.139	-0.172	-0.297***	-0.326***
	(0.126)	(0.123)	(0.034)	(0.033)
Cashflow	1.333***	1.348***	1.293***	1.274***
	(0.198)	(0.195)	(0.060)	(0.057)
PPEratio	-0.584***	-1.120***	-0.552***	-1.097***
	(0.185)	(0.184)	(0.054)	(0.054)
SOE	-0.033	-0.037	-0.109***	-0.100***
	(0.085)	(0.080)	(0.029)	(0.028)
FirstOwn	0.275	0.311	0.342***	0.348***
	(0.206)	(0.206)	(0.073)	(0.072)
InstOwn	0.057	0.060	0.315***	0.308***
	(0.103)	(0.104)	(0.043)	(0.043)
HHI	0.722	0.682	-0.200	-0.224
	(0.517)	(0.517)	(0.163)	(0.155)
HHI_sq	-0.414	-0.362	0.193	0.220
	(0.674)	(0.663)	(0.192)	(0.172)

续表 6.5　对实证假设 H1 的自然实验检验

LnSubsidy	-0.022	-0.025	0.010*	0.008
	(0.024)	(0.024)	(0.006)	(0.006)
LnSubsidy_sq	0.002	0.002	-0.001	-0.001
	(0.002)	(0.001)	(0.000)	(0.000)
Constant	0.700	0.809	0.541**	0.753***
	(0.745)	(0.751)	(0.232)	(0.224)
Observations	3,094	3,094	33,816	33,816
Number of stockcode	462	462	3,902	3,902
Adjusted R-squared	0.466	0.437	0.567	0.547
Firm FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

注：本表报告了使用券商合并自然实验对实证假设H1进行检验的实证结果。括号内标注了企业层面的聚类稳健标准误。*** 、** 和*分别表示回归系数在1%、5%和10%的水平上显著。

值得注意的是，一个合理的准自然实验要求实验组和控制组的被解释变量应当是满足平行趋势假设的。换句话说，如果实验组没有受到自然实验冲击，那么全要素生产率在时间上的变化应当和控制组完全一致。尽管无法严格证明实验组和控制组满足平行趋势，我们可以通过事件研究法对平行趋势进行检验。为此，本文构造了以下模型：

$$TFP_{it} = \alpha_0 + \sum_\tau \beta_\tau Period_\tau * Treatment_i + \boldsymbol{X}'_{it}\boldsymbol{\delta} + \mu_i + \theta_t + \epsilon_{it} \qquad (6.1)$$

其中$\tau \in \{-3,-2,-1,1,2,3\}$ 代表距离事件发生的过去的年份，比如$\tau = -1$就代表事件发生前 1 年。$Period_\tau$是一个虚拟变量，对于事件年为τ的样本取 1。如果β_τ在τ小于 0 时不显著，但是在事件后显著小于 0。那么平行趋势假设就得到了一定程度的支持。

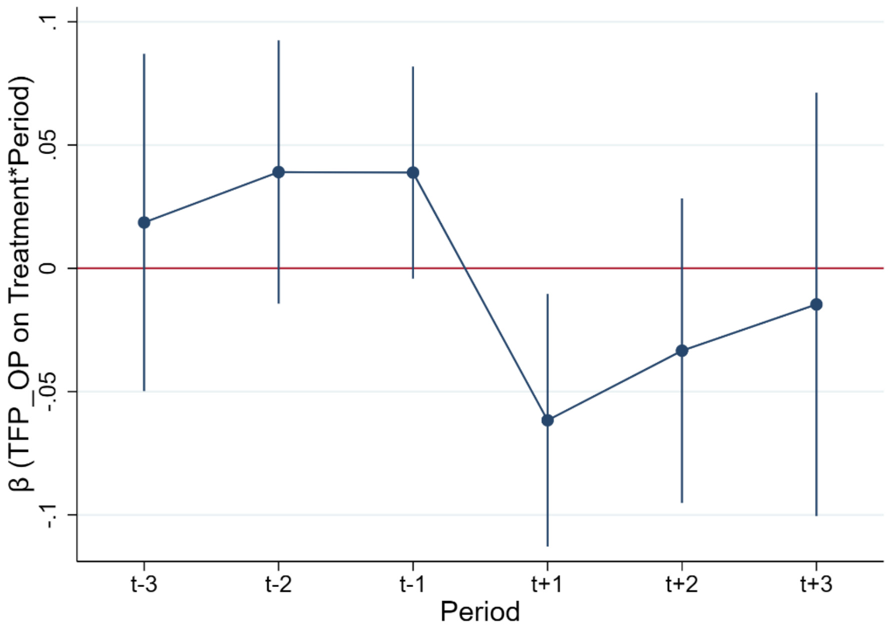

图 6.2　平行趋势检验

图 6.2 展示了使用 OP 法全要素生产率进行上述回归的各个β_τ系数以及 95%置信区间。我们可以发现，事件发生前β_τ与 0 没有显著差异，但是事件发生后系数出现了大幅下降，且事件后一年系数显著小于 0。这表明平行趋势假设得到了支持，实验组与控制组的差异应当来自于处理效应。除此之外，事件发生后两年、三年的系数逐渐衰减，这与本文 6.2.2 小节中的发现形成了呼应。

6.3　影响渠道分析

6.3.1　对实证假设 H2 的检验

本文采用回归模型(5.2)、(5.3)和(5.4)对于实证假设 H2 进行检验。表 6.6 的列（1）、列（2）和列（3）报告了使用 KZ 指数作为中介变量的实证结果。在列（1），我使用当期分析师关注对下期企业的 KZ 指数进行回归，结果表明系数显著小于 0。这一结果表明，分析师关注一家企业之后，下一年企业的 KZ 指数出现了显著的下降。在列（2）和列（3）中，我报告了企业分析师关注对企业下一年 OP 法计算的全要素生产率的回归结果，其中列（3）在自变量中加入了企业下一年的 KZ 指数。我们可以发现，列（3）中的对数金融分析师（LnAnalyst）系数出现了一定程度的下降。这以结果表明，分析师关注对于企业生产率的影响中，一部分可能是通过降低企业的融资约束实现的。

在列（4），列（5）和列（6）中，我使用了企业现金占总资产的比例，重复了上

述检验。结果发现，对数金融分析师关注对企业未来一期现金占总资产比例的回归系数为正。且对比列（5）和列（6），列（6）中对数金融分析师关注的系数也出现了一定程度的下降。这些结果进一步为实证假设 H2 的成立提供了支持。

表 6.6　实证假设 H2 的多元回归检验

VARIABLES	(1) KZindex t+1	(2) TFP_OP t+1	(3) TFP_OP t+1	(4) CashRatio t+1	(5) TFP_OP t+1	(6) TFP_OP t+1
LnAnalyst	**-0.167*** **	**0.078*** **	**0.064*** **	**0.008*** **	**0.078*** **	**0.076*** **
	(0.014)	**(0.005)**	**(0.005)**	**(0.001)**	**(0.005)**	**(0.005)**
KZindex t+1			**-0.084*** **			
			(0.003)			
CashRatio t+1						**0.293*** **
						(0.047)
Size	0.336***	0.366***	0.394***	-0.031***	0.366***	0.375***
	(0.038)	(0.013)	(0.013)	(0.003)	(0.013)	(0.014)
Age	1.783***	0.003	0.153***	-0.165***	0.003	0.051
	(0.170)	(0.050)	(0.050)	(0.014)	(0.050)	(0.051)
BM	0.138***	-0.059***	-0.047***	0.005***	-0.059***	-0.060***
	(0.018)	(0.008)	(0.008)	(0.001)	(0.008)	(0.008)
Growth	0.003	0.117***	0.117***	-0.002	0.117***	0.117***
	(0.022)	(0.008)	(0.008)	(0.001)	(0.008)	(0.008)
CapEx	0.680***	-0.203***	-0.146***	-0.068***	-0.203***	-0.183***
	(0.083)	(0.033)	(0.032)	(0.006)	(0.033)	(0.033)
Cashflow	-2.499***	0.813***	0.602***	0.165***	0.813***	0.765***
	(0.181)	(0.058)	(0.055)	(0.011)	(0.058)	(0.057)
PPEratio	0.997***	-0.061	0.023	-0.199***	-0.061	-0.003
	(0.157)	(0.058)	(0.056)	(0.011)	(0.058)	(0.059)
SOE	0.096	-0.110***	-0.102***	-0.004	-0.110***	-0.109***
	(0.089)	(0.035)	(0.034)	(0.006)	(0.035)	(0.035)
FirstOwn	-0.806***	0.171**	0.103	0.012	0.171**	0.168**
	(0.252)	(0.082)	(0.079)	(0.016)	(0.082)	(0.082)
InstOwn	-0.504***	0.350***	0.308***	0.066***	0.350***	0.331***
	(0.149)	(0.050)	(0.049)	(0.011)	(0.050)	(0.050)

续表 6.6 实证假设 H2 的多元回归检验

HHI	-2.213***	-0.092	-0.278*	0.145***	-0.092	-0.134
	(0.500)	(0.171)	(0.169)	(0.041)	(0.171)	(0.172)
HHI_sq	2.523***	0.093	0.305	-0.114**	0.093	0.126
	(0.600)	(0.195)	(0.196)	(0.052)	(0.195)	(0.198)
LnSubsidy	-0.011	0.004	0.003	-0.000	0.004	0.004
	(0.016)	(0.006)	(0.006)	(0.001)	(0.006)	(0.006)
LnSubsidy_sq	0.001	-0.001*	-0.001*	0.000	-0.001*	-0.001*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Constant	-6.439***	2.562***	2.019***	0.994***	2.562***	2.271***
	(0.730)	(0.246)	(0.239)	(0.057)	(0.246)	(0.252)
Observations	28,585	28,585	28,585	28,585	28,585	28,585
Number of stockcode	3,643	3,643	3,643	3,643	3,643	3,643
Adjusted R-squared	0.222	0.471	0.503	0.168	0.471	0.472
Firm FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

注：本表报告了使用回归模型(5.2)、(5.3)和(5.4)对于实证假设H2进行检验的实证结果。括号内标注了企业层面的聚类稳健标准误。*** 、** 和*分别表示回归系数在1%、5%和10%的水平上显著。

6.3.2 对实证假设 H3 的检验

本文采用回归模型(5.5)、(5.6)和(5.7)对于实证假设 H3 进行检验。表 6.7 的列（1）、列（2）和列（3）报告了使用对数专利申请量的实证结果。在列（1），我使用当期分析师关注对下期企业的对数发明专利申请量进行回归，结果表明系数显著大于 0。这一结果表明，分析师关注一家企业之后，下一年企业申请的专利出现了显著的上升。这意味着在中国，分析师关注有利于企业创新。在列（2）和列（3）中，我报告了企业分析师关注对企业下一年 OP 法计算的全要素生产率的回归结果，其中列（3）在自变量中加入了企业下一年的对数专利申请量。对比列（2）与列（3），我们可以发现列（3）中分析师关注的系数小于列（2）。这一结果表明，分析师关注对于企业生产率的影响中，一部分是通过提高企业的创新水平实现的。因此，这以结果支持了实证假设 H4 成立。

在列（4），列（5）和列（6）中，我使用企业下一年申请发明专利的对数总引用量作为中介变量，重复了上述回归检验，结果与使用对数专利数量的结果相似。这以

结果进一步对实证假设 H3 提供了支持。

表 6.7　实证假设 H3 的多元回归检验

VARIABLES	(1) LnPatent t+1	(2) TFP_OP t+1	(3) TFP_OP t+1	(4) LnCite t+1	(5) TFP_OP t+1	(6) TFP_OP t+1
LnAnalyst	**0.057*****	**0.078*****	**0.077*****	**0.047*****	**0.070*****	**0.069*****
	(0.010)	**(0.005)**	**(0.005)**	**(0.010)**	**(0.007)**	**(0.007)**
LnPatent			**0.018*****			
t+1			**(0.005)**			
LnCite						**0.013****
t+1						**(0.006)**
Size	0.313***	0.366***	0.360***	0.250***	0.354***	0.351***
	(0.024)	(0.013)	(0.014)	(0.028)	(0.017)	(0.017)
Age	0.187*	0.003	-0.000	0.375***	0.012	0.007
	(0.103)	(0.050)	(0.050)	(0.117)	(0.061)	(0.062)
BM	-0.016	-0.059***	-0.059***	-0.041**	-0.079***	-0.079***
	(0.015)	(0.008)	(0.008)	(0.017)	(0.011)	(0.011)
Growth	-0.006	0.117***	0.117***	-0.002	0.106***	0.106***
	(0.011)	(0.008)	(0.008)	(0.013)	(0.009)	(0.009)
CapEx	0.034	-0.203***	-0.204***	0.025	-0.223***	-0.223***
	(0.061)	(0.033)	(0.033)	(0.058)	(0.034)	(0.034)
Cashflow	0.082	0.813***	0.811***	0.068	0.660***	0.659***
	(0.090)	(0.058)	(0.058)	(0.097)	(0.067)	(0.067)
PPEratio	0.042	-0.061	-0.062	0.149	-0.078	-0.080
	(0.099)	(0.058)	(0.058)	(0.101)	(0.066)	(0.066)
SOE	0.107*	-0.110***	-0.112***	0.079	-0.101**	-0.102**
	(0.058)	(0.035)	(0.035)	(0.068)	(0.044)	(0.044)
FirstOwn	-0.351**	0.171**	0.178**	-0.221	0.304***	0.307***
	(0.167)	(0.082)	(0.082)	(0.171)	(0.110)	(0.110)
InstOwn	0.069	0.350***	0.349***	-0.070	0.383***	0.384***
	(0.097)	(0.050)	(0.050)	(0.100)	(0.062)	(0.061)
HHI	0.287	-0.092	-0.097	0.167	-0.537***	-0.539***
	(0.327)	(0.171)	(0.171)	(0.347)	(0.192)	(0.192)

续表 6.7　实证假设 H3 的多元回归检验

HHI_sq	-0.139	0.093	0.095	0.107	0.459**	0.457**
	(0.367)	(0.195)	(0.195)	(0.360)	(0.217)	(0.217)
LnSubsidy	-0.077***	0.004	0.006	-0.048***	0.006	0.007
	(0.009)	(0.006)	(0.006)	(0.009)	(0.006)	(0.006)
LnSubsidy_sq	0.008***	-0.001*	-0.001**	0.005***	-0.001**	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-4.145***	2.562***	2.637***	-3.447***	2.716***	2.760***
	(0.473)	(0.246)	(0.248)	(0.527)	(0.303)	(0.304)
Observations	28,585	28,585	28,585	19,464	19,464	19,464
Number of stockcode	3,643	3,643	3,643	2,968	2,968	2,968
Adjusted R-squared	0.268	0.471	0.471	0.164	0.388	0.388
Firm FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

注：本表报告了使用回归模型(5.5)、(5.6)和(5.7)对于实证假设H3进行检验的实证结果。括号内标注了企业层面的聚类稳健标准误。*** 、** 和*分别表示回归系数在1%、5%和10%的水平上显著。

6.4　识别金融分析师的业绩压力：实证假设 H4

本文采用回归模型(5.8)和(5.9)对于实证假设 H4 进行检验。表 6.8 的列（1）、列（2）和列（3）报告了使用回归模型(5.8)的实证结果。在列（1），我使回归模型(5.8)的交乘项方法对实证假设 H4 进行检验，由于分析师预测的平均高估程度 MeanError 这一指标，要求企业某年至少需要有一名分析师才能计算，因此回归结果列（1）中的观测样本只包括存在至少有 1 名分析师关注的企业-年度观测值。列（1）中的交乘项系数显著小于 0，这表明在这一子样本之中，分析师关注对于企业全要素生产率的正面作用随着分析师高估企业盈利的程度而发生下降，这为实证假设 H4 的成立提供了证据。考虑到如果金融分析师报告显著地高估了企业的盈利水平，那么这个分析师报告的信息含量本身可能就比较少。因此，在列（2）和列（3）中，我在控制变量中进一步加入了预测平均绝对偏差 AbsError 和分析师预测离散程度 Dispersion。其中预测平均绝对偏差 AbsError 是高估偏差取绝对值之后再取平均的结果，分析师预测离散程度 Dispersion 则是标准化高估偏差的标准差。结果发现交乘项的系数仍然显著为负。这些结果对实证假设 H5 提供了证据。

在列（4）中，LnAnaHigh 与 LnAnaLow 分别是高估、低估企业当年每股收益的分析师数量自然对数。结果发现，高估企业盈利的分析师数量对于企业下一年全要素生产率的系数不显著。在列（5）中，我控制了预测平均绝对偏差 AbsError，在列（6）中我控制了预测离散程度 Dispersion。结果发现高估企业盈利预测的分析师数量可以负向预测企业下一年的生产率。这以结果表明，当金融分析师显著地高估企业盈利水平时，分析师越关注某家企业，这家企业未来的全要素生产率就越低。这也对实证假设 H4 供了证据。

表 6.8　实证假设 H4 的多元回归检验

VARIABLES	(1) TFP_OP t+1	(2) TFP_OP t+1	(3) TFP_OP t+1	(4) TFP_OP t+1	(5) TFP_OP t+1	(6) TFP_OP t+1
LnAnalyst	0.089***	0.090***	0.089***			
	(0.007)	(0.007)	(0.007)			
MeanError	-0.049	-1.386**	-0.395			
	(0.524)	(0.602)	(0.654)			
LnAnalyst*MeanError	**-1.073*** **	**-0.933*** **	**-0.960*** **			
	(0.242)	**(0.242)**	**(0.288)**			
LnAnaLow				**0.081*** **	**0.065*** **	**0.055*** **
				(0.004)	**(0.006)**	**(0.005)**
LnAnaHigh				**0.003**	**-0.018*** **	**-0.018*** **
				(0.003)	**(0.004)**	**(0.004)**
AbsError		1.706***			0.957***	
		(0.387)			(0.300)	
Dispersion			-0.004			-0.010
			(0.015)			(0.015)
Size	0.333***	0.332***	0.331***	0.376***	0.334***	0.335***
	(0.015)	(0.015)	(0.016)	(0.013)	(0.015)	(0.016)
Age	0.071	0.069	0.078	-0.046	0.048	0.057
	(0.053)	(0.053)	(0.053)	(0.050)	(0.053)	(0.052)
BM	-0.049***	-0.052***	-0.048***	-0.055***	-0.051***	-0.047***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Growth	0.111***	0.108***	0.103***	0.105***	0.108***	0.102***
	(0.010)	(0.010)	(0.011)	(0.008)	(0.010)	(0.011)

续表 6.8　实证假设 H4 的多元回归检验

CapEx	-0.188***	-0.185***	-0.197***	-0.204***	-0.188***	-0.202***
	(0.036)	(0.036)	(0.037)	(0.033)	(0.037)	(0.035)
Cashflow	0.778***	0.769***	0.789***	0.748***	0.752***	0.768***
	(0.065)	(0.065)	(0.068)	(0.058)	(0.065)	(0.066)
PPEratio	0.056	0.056	0.066	-0.077	0.052	0.062
	(0.060)	(0.060)	(0.061)	(0.058)	(0.060)	(0.060)
SOE	-0.088**	-0.090**	-0.076*	-0.112***	-0.090**	-0.079*
	(0.038)	(0.038)	(0.041)	(0.035)	(0.038)	(0.041)
FirstOwn	0.126	0.123	0.156*	0.185**	0.144*	0.149*
	(0.086)	(0.086)	(0.087)	(0.082)	(0.086)	(0.087)
InstOwn	0.262***	0.270***	0.211***	0.334***	0.241***	0.178***
	(0.053)	(0.053)	(0.053)	(0.050)	(0.053)	(0.052)
HHI	-0.136	-0.154	-0.238	-0.116	-0.150	-0.227
	(0.175)	(0.174)	(0.174)	(0.171)	(0.174)	(0.168)
HHI_sq	0.124	0.141	0.290	0.139	0.159	0.277
	(0.197)	(0.197)	(0.188)	(0.195)	(0.197)	(0.183)
LnSubsidy	-0.007	-0.007	-0.013**	0.004	-0.008	-0.014**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
LnSubsidy_sq	0.000	0.000	0.001	-0.001*	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	2.832***	2.837***	2.869***	2.607***	2.914***	2.942***
	(0.285)	(0.285)	(0.293)	(0.249)	(0.284)	(0.285)
Observations	20,723	20,723	18,595	28,585	20,723	19,067
Number of stockcode	3,340	3,340	3,156	3,643	3,340	3,224
Adjusted R-squared	0.500	0.501	0.507	0.473	0.503	0.517
Firm FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

注：本表报告了使用回归模型(5.8)和(5.9)对于实证假设H4进行检验的实证结果。括号内标注了企业层面的聚类稳健标准误。*** 、** 和*分别表示回归系数在1%、5%和10%的水平上显著。

第七章 稳健性检验

在本文的第六章，我对本文第三章提出的实证假设进行了逐一的检验。为了避免统计学上偶然出现的结果使本文得出错误的结论，在本章中我对本文的结果进行了丰富的稳健性检验。主要有以下两方面：为了避免变量度量方法导致的偶然结果，在 7.1 小节中我使用其他方法构造了解释变量、被解释变量以及工具变量，重复了本文中重要的回归分析。其次，为了避免错误使用计量方法导致的虚假结果，本文 7.2 小节中我对本文中的计量方法也进行了稳健性检验。上述结果均表明，本文的主要结论是稳健的。

7.1 对变量度量方法的稳健性检验

7.1.1 使用资产收益率作为被解释变量

在第六章的分析中，我使用的是企业的全要素生产率作为企业生产效率的度量。考虑到企业的全要素生产率作为一种基于结构模型计算的指标，比较依赖计量模型的准确性。为了避免因为指标计算方法不稳健可能带来的问题，我参考董艳和刘佩忠（2021）的做法，使用企业的资产收益率（Return on assets, ROA）作为企业生产率的另一个度量。数学上，企业的资产收益率是净利润除以年末年初的平均资产。

由于资产收益率代表企业每单位生产资源所产生的利润，因此也可以被广义地理解为一种生产率的度量方式。事实上，企业的资产收益率与全要素生产率是高度正相关的（İmrohoroğlu & Tüzel, 2014）。

不过，应当注意到的是，企业的资产收益率与全要素生产率也存在着一些不同：第一，资产收益率的分子是净利润，这使得企业的利息收入、政府补贴收入等非生产性收入被考虑在内，但是全要素生产率在计算时则将这些会计科目排除在外。第二，资产收益率的分母平均总资产，包括了企业的全部资产类型；而全要素生产率则使用企业的固定资产作为企业资本投入的代理变量，没有考虑企业无形资产等其他资产类型。第三，资产收益率没有扣除企业雇佣劳动力增加对于产出的贡献，而全要素生产率将劳动投入对产出的贡献进行了扣除。第四，资产收益率是直接使用未经价格水平调整的名义数据计算的，而全要素生产率在计算时则使用了经过价格调整的数据。

在表 7.1 中，我使用企业未来一年到未来五年的资产收益率重复了表 6.3 中的统计结果。回顾本文 6.2.2 小节的结果，我们发现使用资产收益率的结果与使用全要素生产

率的结果，在时间趋势上是相似的。差别在于，使用全要素生产率作为被解释变量时，对数分析师的系数在未来四年开始变负；而使用资产收益率作为被解释变量时，对数分析师的系数在未来三年就开始变负。为何对数分析师关注可以负向预测企业长期的生产率和资产收益率？我认为这一问题还有待进一步研究。

表 7.1　使用资产收益率作为被解释变量

VARIABLES	(1) ROA t+1	(2) ROA t+2	(3) ROA t+3	(4) ROA t+4	(5) ROA t+5
LnAnalyst	**0.008*** **	**0.003*** **	**-0.001** **	**-0.004*** **	**-0.002*** **
	(0.000)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**
Size	-0.016***	-0.021***	-0.021***	-0.019***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Age	-0.004	0.000	0.001	0.002	0.005
	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
BM	-0.004***	0.000	0.004***	0.006***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Growth	0.011***	0.006***	0.002***	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
CapEx	-0.022***	-0.012***	-0.002	0.003	0.004
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Cashflow	0.107***	0.058***	0.025***	-0.006	-0.025***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
PPEratio	-0.014***	0.005	0.018***	0.016***	0.016***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
SOE	-0.007***	-0.006*	-0.006*	-0.007*	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
FirstOwn	0.003	-0.000	0.002	0.008	0.017*
	(0.007)	(0.008)	(0.008)	(0.009)	(0.009)
InstOwn	0.042***	0.036***	0.024***	0.016***	0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
HHI	0.012	0.021	0.001	-0.017	-0.013
	(0.015)	(0.017)	(0.018)	(0.019)	(0.019)

续表 7.1　使用资产收益率作为被解释变量

HHI_sq	-0.015	-0.019	0.000	0.018	0.014
	(0.018)	(0.018)	(0.020)	(0.022)	(0.024)
LnSubsidy	-0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
LnSubsidy_sq	-0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.267***	0.333***	0.366***	0.345***	0.233***
	(0.021)	(0.022)	(0.024)	(0.027)	(0.029)
Observations	28,585	25,218	21,969	18,858	16,193
Number of stockcode	3,643	3,512	3,394	2,958	2,722
Adjusted R-squared	0.138	0.087	0.073	0.060	0.037
Firm FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

注：括号内标注了企业层面的聚类稳健标准误。*** 、** 和*分别表示回归系数在1%、5%和10%的水平上显著。

7.1.2　使用研报关注作为解释变量

在第六章的分析中，我使用的是一年中对企业发布盈利预测的分析师团队数量，作为企业被分析师关注的度量。考虑到一个分析师团队可能在一年中发布了多篇研报，表 7.2 中，我使用某家公司在一年中的全部研报数量取自然对数作为分析师关注的另一个度量，被解释变量分别是未来一年企业 OP 法全要素生产率，LP 法全要素生产率以及企业资产收益率。结果与第六章主要的结果没有显著差异。

表 7.2　使用对数研报数量度量分析师关注

VARIABLES	(1) TFP_OP t+1	(2) TFP_OP t+1	(3) TFP_OP t+1	(4) TFP_LP t+1	(5) ROA t+1
LnReport	**0.128*****	**0.070*****	**0.064*****	**0.063*****	**0.007*****
	(0.005)	**(0.004)**	**(0.004)**	**(0.004)**	**(0.000)**
Size		0.369***	0.364***	0.310***	-0.016***
		(0.013)	(0.014)	(0.013)	(0.001)
Age		-0.077	-0.014	-0.036	-0.006
		(0.050)	(0.050)	(0.049)	(0.005)
BM		-0.066***	-0.058***	-0.060***	-0.004***
		(0.008)	(0.008)	(0.009)	(0.001)
Growth		0.125***	0.116***	0.117***	0.011***
		(0.008)	(0.008)	(0.008)	(0.001)
CapEx		-0.194***	-0.205***	-0.292***	-0.022***
		(0.034)	(0.033)	(0.032)	(0.002)
Cashflow		0.807***	0.808***	0.810***	0.106***
		(0.058)	(0.058)	(0.056)	(0.006)
PPEratio		-0.101*	-0.071	-0.424***	-0.014***
		(0.059)	(0.058)	(0.059)	(0.005)
SOE			-0.110***	-0.099***	-0.007***
			(0.035)	(0.034)	(0.003)
FirstOwn			0.169**	0.168**	0.003
			(0.082)	(0.082)	(0.007)
InstOwn			0.352***	0.344***	0.042***
			(0.050)	(0.050)	(0.005)
HHI			-0.093	-0.162	0.012
			(0.172)	(0.168)	(0.015)
HHI_sq			0.100	0.149	-0.014
			(0.195)	(0.189)	(0.017)
LnSubsidy			0.005	0.005	-0.000
			(0.006)	(0.006)	(0.000)
LnSubsidy_sq			-0.001*	-0.001**	-0.000
			(0.001)	(0.000)	(0.000)

续表 7.2　使用对数研报数量度量分析师关注

Constant	7.945***	2.867***	2.637***	2.634***	0.275***
	(0.115)	(0.233)	(0.247)	(0.242)	(0.021)
Observations	28,585	28,585	28,585	28,585	28,585
Number of stockcode	3,643	3,643	3,643	3,643	3,643
Adjusted R-squared	0.390	0.466	0.471	0.442	0.138
Firm FE	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

注：括号内标注了企业层面的聚类稳健标准误。*** 、** 和*分别表示回归系数在1%、5%和10%的水平上显著。

7.1.3　改变基准年重新构造工具变量

在第六章的分析中，我使用的工具变量预期分析师关注 ExpectedCoverage 是通过选择 2020 年作为分析师关注的基准年进行构造的。本文认为这种构造方法是合理的。Yu（2008）认为，基准年的选择不会影响这一工具变量的外生性和相关性。在本节中，为了避免偶然选择基准年导致的统计学上不稳健的结果，我换用 2016 年和 2019 年作为基准年重构造了工具变量，并重复第六章中的工具变量回归分析。结果在表 7.3 中展示。我们可以发现第二步回归的系数仍然显著为正，支持了本文的结论。

表 7.3　对实证假设 H1 的工具变量回归分析：改变基准年

	Benchmark Year = 2016			Benchmark Year = 2019		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	LnAnalyst t	TFP_OP t+1	TFP_LP t+1	LnAnalyst t	TFP_OP t+1	TFP_LP t+1
ExpectedCoverage	**0.057*** **			**0.094*** **		
	(0.005)			**(0.005)**		
LnAnalyst (instrumented)		**0.143*** **	**0.147*** **		**0.138*** **	**0.132*** **
		(0.043)	**(0.043)**		**(0.027)**	**(0.027)**
Size	0.484***	0.329***	0.277***	0.479***	0.310***	0.268***
	(0.022)	(0.027)	(0.027)	(0.024)	(0.020)	(0.020)
Age	-0.647***	0.048	0.031	-0.502***	0.068	0.052
	(0.093)	(0.059)	(0.058)	(0.098)	(0.057)	(0.056)

续表 7.3　对实证假设 H1 的工具变量回归分析：改变基准年

BM	-0.241***	-0.043***	-0.042***	-0.232***	-0.044***	-0.046***
	(0.016)	(0.014)	(0.014)	(0.016)	(0.011)	(0.011)
Growth	-0.017	0.127***	0.129***	-0.032**	0.129***	0.130***
	(0.012)	(0.009)	(0.009)	(0.015)	(0.010)	(0.010)
CapEx	0.216***	-0.180***	-0.274***	0.185**	-0.183***	-0.275***
	(0.058)	(0.038)	(0.038)	(0.072)	(0.045)	(0.045)
Cashflow	0.605***	0.824***	0.825***	0.794***	0.830***	0.844***
	(0.093)	(0.072)	(0.070)	(0.109)	(0.081)	(0.078)
PPEratio	-0.551***	-0.043	-0.381***	-0.437***	-0.022	-0.370***
	(0.096)	(0.065)	(0.065)	(0.109)	(0.065)	(0.066)
SOE	-0.202***	-0.077**	-0.070*	-0.189***	-0.055	-0.046
	(0.057)	(0.039)	(0.039)	(0.071)	(0.041)	(0.039)
FirstOwn	-0.401***	0.174*	0.170*	-0.533***	0.163*	0.154*
	(0.147)	(0.090)	(0.090)	(0.158)	(0.091)	(0.088)
InstOwn	1.294***	0.284***	0.270***	1.258***	0.291***	0.297***
	(0.103)	(0.077)	(0.077)	(0.113)	(0.067)	(0.067)
HHI	-0.375	-0.072	-0.158	-0.379	0.204	0.131
	(0.320)	(0.187)	(0.182)	(0.355)	(0.205)	(0.197)
HHI_sq	0.625*	0.114	0.180	0.579	-0.111	-0.065
	(0.375)	(0.211)	(0.199)	(0.431)	(0.242)	(0.221)
LnSubsidy	0.012	0.003	0.004	0.034***	0.002	0.003
	(0.009)	(0.007)	(0.007)	(0.010)	(0.008)	(0.008)
LnSubsidy_sq	0.000	-0.001	-0.001*	-0.002**	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	22,016	22,016	22,016	16,492	16,492	16,492
Number of stockcode	2,414	2,414	2,414	1,964	1,964	1,964
R-squared	0.400	0.448	0.411	0.355	0.591	0.558
Firm FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Cragg-Donald F		330.00			719.934	
Kleibergen-Paap F		146.84			314.694	

注：本表报告了使用预期分析师关注作为对数分析师关注的工具变量对于实证假设H1进行检验的

实证结果。构造工具变量时，基准年分别选择2016年和2019年。括号内标注了企业层面的聚类稳健标准误。*** 、** 和*分别表示回归系数在1%、5%和10%的水平上显著。

为了进一步检验本文工具变量的稳健性，我遍历地了 2007 年到 2020 年所有年份作为基准年构造工具变量。结果发现，使用 2016 年到 2019 年作为基准年构造工具变量均能给出相似的结果。但是，如果使用 2007 年到 2015 年作为基准年构造工具变量，弱工具变量检验的 F 值比较小，这表明工具变量本身较弱。除此之外，如果使用 2007 年到 2015 年作为基准年构造工具变量，二阶段回归的结果也并不显著。一定程度上，这对本文结果的稳健性提出了质疑。但是考虑到我国证券行业在迅速发展中，不断有新企业上市，同时不断有新的分析师进入行业，使用较早年份作为基准年构造工具变量会导致大量样本缺失。因此，我认为这一现象是是符合预期的。除此之外，考虑到本文还使用了证券公司合并自然实验，结果依然支持了本文的实证假设，我认为本文的主要结论是比较稳健的。

7.2　对计量方法的稳健性检验

7.2.1　使用工具变量进行机制分析

在本文第六章中，我使用 Baron and Kenny（1986）经典的三次回归方法对中介机制进行检验。然而，这一机制分析的方法也会受到内生性问题的困扰。为了进一步表明本文中介机制的稳健性，本文还使用工具变量法对机制检验的第一步回归进行了估计。其结果进一步对本文的中介机制提供了支持。

表 7.4　使用工具变量进行机制分析

	First Stage	Second Stage		
	(1)	(2)	(3)	(4)
VARIABLES	LnAnalyst t	KZindex t+1	CashRatio t+1	LnPatent t+1
ExpectedCoverage	**0.095***** **(0.006)**			
LnAnalyst (instrumented)		**-0.266**** **(0.110)**	**0.018**** **(0.008)**	**0.209***** **(0.075)**
Size	0.484*** (0.027)	0.526*** (0.079)	-0.035*** (0.006)	0.210*** (0.053)
Age	-0.372*** (0.098)	1.750*** (0.216)	-0.164*** (0.017)	-0.002 (0.144)

续表 7.4　使用工具变量进行机制分析

BM	-0.217***	0.123***	0.009***	0.018
	(0.017)	(0.034)	(0.002)	(0.025)
Growth	-0.035**	-0.064**	0.001	-0.006
	(0.016)	(0.033)	(0.002)	(0.018)
CapEx	0.177**	0.888***	-0.089***	-0.097
	(0.073)	(0.121)	(0.008)	(0.088)
Cashflow	0.797***	-2.987***	0.176***	-0.016
	(0.111)	(0.275)	(0.018)	(0.161)
PPEratio	-0.601***	0.995***	-0.208***	0.092
	(0.114)	(0.218)	(0.016)	(0.157)
SOE	-0.228***	0.232*	-0.010	0.176**
	(0. 067)	(0.131)	(0.009)	(0.081)
FirstOwn	-0.362**	-0.684**	0.021	-0.286
	(0.177)	(0.340)	(0.021)	(0.239)
InstOwn	1.221***	-0.404*	0.050***	-0.105
	(0.121)	(0.245)	(0.018)	(0.170)
HHI	-0.659*	-1.907***	0.135***	-0.180
	(0.385)	(0.664)	(0.050)	(0.472)
HHI_sq	0.796*	2.393***	-0.122**	0.504
	(0.460)	(0.704)	(0.057)	(0.514)
LnSubsidy	0.031***	-0.010	-0.002	-0.084***
	(0.011)	(0.025)	(0.002)	(0.016)
LnSubsidy_sq	-0.002**	0.001	0.000	0.009***
	(0.001)	(0.002)	(0.000)	(0.001)
Observations	15,306	15,306	15,306	15,306
Number of Stock	1,864	1,864	1,864	1,864
R-squared	0.340	0.135	0.080	0.232
Firm FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

注：本表报告了使用预期分析师关注作为对数分析师关注的工具变量的回归结果。括号内标注了企业层面的聚类稳健标准误。*** 、** 和*分别表示回归系数在1%、5%和10%的水平上显著。

7.2.2　券商合并自然实验的安慰剂检验

我对券商合并自然实验进行了安慰剂检验。其中安慰剂变量 PlaceboTreated 是通过将 Treated 在时间上向前平移三期得到的。结果发现安慰剂变量的系数不显著。这符合我的预期。表 7.5 展示了安慰剂检验的结果。

表 7.5　券商合并自然实验的安慰剂检验

VARIABLES	(1) TFP_OP t+1	(2) TFP_LP t+1
PlaceboTreated	**-0.058**	**-0.048**
	(0.061)	**(0.055)**
Size	0.518***	0.460***
	(0.038)	(0.036)
Age	-0.051	-0.070
	(0.115)	(0.112)
BM	-0.122***	-0.117***
	(0.021)	(0.021)
Growth	0.151***	0.151***
	(0.026)	(0.026)
CapEx	-0.177*	-0.194**
	(0.091)	(0.089)
Cashflow	0.939***	0.929***
	(0.153)	(0.152)
PPEratio	-0.555***	-1.104***
	(0.149)	(0.149)
SOE	-0.101	-0.099
	(0.079)	(0.071)
FirstOwn	0.328	0.341*
	(0.211)	(0.202)
InstOwn	0.179*	0.189**
	(0.098)	(0.096)
HHI	-0.610	-0.805**
	(0.370)	(0.358)
HHI_sq	0.577	0.875**
	(0.457)	(0.415)

续表 7.5 券商合并自然实验的安慰剂检验

LnSubsidy	-0.002	0.000
	(0.013)	(0.013)
LnSubsidy_sq	0.001	0.001
	(0.001)	(0.001)
Constant	1.258**	1.409**
	(0.589)	(0.566)
Observations	2,834	2,834
Adjusted R-squared	0.607	0.580
Firm FE	YES	YES
Industry FE	YES	YES
Year FE	YES	YES

注：本表报告了对券商合并自然实验的安慰剂检验。安慰剂虚拟变量PlaceboTreated是通过将Treated变量向过去平移三期构造的。括号内标注了企业层面的聚类稳健标准误。*** 、** 和*分别表示回归系数在1%、5%和10%的水平上显著。

7.2.3 进一步增加控制变量

在本文第六章的实证分析中，我已经控制了丰富的控制变量，并控制了企业、行业、年度固定效应以最大程度地解决遗漏变量偏误的问题。值得注意的是，本文第六章没有在基准回归分析中控制企业的资产收益率（ROA）和企业的杠杆比率（Leverage）。我不控制资产收益率是因为资产收益率本身可以视作企业生产率的另一个度量（参考本章 7.1.1 小节）。而且，资产收益率与全要素生产率高度正相关（İmrohoroğlu & Tüzel, 2014），因此控制资产收益率会吸收一部分分析师关注对于企业生产率的影响。本文第六章不控制企业的杠杆比率，是因为企业的杠杆比率与本文研究的融资约束机制相关，如果在回归分析中控制杠杆比例，将会吸收一部分融资约束机制导致的生产率变化。

然而，为了进一步防止遗漏变量偏差导致的虚假结果，表 7.6 中报告了进一步控制企业资产收益率（ROA）和企业的杠杆比率（Leverage）的基准回归结果。结果显示，对数分析师关注的系数仍然显著大于 0。这为我的结果提供了进一步的支持。

表 7.6 对实证假设 H1 的基准回归分析：增加控制变量

VARIABLES	(1) TFP_OP t+1	(2) TFP_OP t+2	(3) TFP_OP t+3	(4) TFP_LP t+1	(5) TFP_LP t+2	(6) TFP_LP t+3
LnAnalyst	**0.053*** **	**0.040*** **	**0.019*** **	**0.052*** **	**0.038*** **	**0.017** **
	(0.005)	**(0.006)**	**(0.007)**	**(0.005)**	**(0.006)**	**(0.007)**
ROA	2.022***	0.636***	0.058	2.041***	0.619***	0.060
	(0.117)	(0.128)	(0.137)	(0.113)	(0.124)	(0.131)
Leverage	0.133***	0.105*	0.133**	0.160***	0.118**	0.148***
	(0.047)	(0.054)	(0.059)	(0.044)	(0.051)	(0.057)
Size	0.369***	0.199***	0.059***	0.313***	0.155***	0.026
	(0.013)	(0.016)	(0.017)	(0.013)	(0.015)	(0.016)
Age	0.032	0.060	0.067	0.005	0.046	0.052
	(0.047)	(0.058)	(0.068)	(0.046)	(0.057)	(0.067)
BM	-0.047***	-0.032***	-0.026**	-0.049***	-0.033***	-0.025**
	(0.008)	(0.009)	(0.011)	(0.008)	(0.009)	(0.011)
Growth	0.074***	0.065***	0.038***	0.074***	0.068***	0.041***
	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)
CapEx	-0.160***	-0.023	0.088**	-0.247***	-0.130***	0.005
	(0.032)	(0.037)	(0.041)	(0.031)	(0.036)	(0.040)
Cashflow	0.521***	0.403***	0.264***	0.522***	0.390***	0.245***
	(0.057)	(0.066)	(0.070)	(0.055)	(0.064)	(0.068)
PPEratio	0.050	0.117*	0.189***	-0.306***	-0.092	0.091
	(0.057)	(0.065)	(0.071)	(0.057)	(0.065)	(0.069)
SOE	-0.097***	-0.058	-0.037	-0.086***	-0.048	-0.030
	(0.034)	(0.039)	(0.044)	(0.033)	(0.039)	(0.043)
FirstOwn	0.114	0.063	0.108	0.110	0.057	0.103
	(0.076)	(0.092)	(0.104)	(0.076)	(0.093)	(0.104)
InstOwn	0.293***	0.328***	0.255***	0.288***	0.317***	0.237***
	(0.047)	(0.059)	(0.063)	(0.047)	(0.058)	(0.062)
HHI	-0.067	-0.076	-0.359*	-0.131	-0.185	-0.487**
	(0.166)	(0.194)	(0.208)	(0.162)	(0.192)	(0.204)
HHI_sq	0.060	0.039	0.332	0.104	0.139	0.469**
	(0.197)	(0.207)	(0.220)	(0.187)	(0.205)	(0.217)

续表 7.6　对实证假设 H1 的基准回归分析：增加控制变量

LnSubsidy	0.008	0.007	0.007	0.008	0.008	0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
LnSubsidy_sq	-0.001***	-0.001	-0.000	-0.001***	-0.001*	-0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Constant	2.286***	5.033***	7.563***	2.307***	4.811***	7.115***
	(0.242)	(0.288)	(0.316)	(0.236)	(0.275)	(0.294)
Observations	28,585	25,218	21,969	28,585	25,218	21,969
Number of stockcode	3,643	3,512	3,394	3,643	3,512	3,394
Adjusted R-squared	0.486	0.361	0.284	0.459	0.334	0.260
Firm FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

注：本表报告了使用基准回归模型(5.1)对于实证假设H1进行检验的实证结果。括号内标注了企业层面的聚类稳健标准误。*** 、** 和*分别表示回归系数在1%、5%和10%的水平上显著。

第八章　结论及展望

8.1　主要研究结论

在这篇文章中，使用我国 A 股上市公司的样本，实证研究了我国金融分析师是否能够提高我国上市公司的生产率。

通过梳理有关文献，我发现已有文献提出了两种不同的理论阐释金融分析师关注与企业生产率之间的关系。其中，信息解读假说认为，金融分析师可能通过降低企业的信息不对称程度，从而缓解企业的融资约束，同时提高企业的创新水平。最终，信息解读理论认为金融分析师关注有利于企业的生产率提高。业绩压力假说则与此相反，认为金融分析师有动机高估企业的盈利水平。过高的短期盈利预测会给企业管理层带来压力，迫使企业放弃长期有利于企业绩效的投资，进而降低企业的生产率。

为了验证上述理论，我选取我国 A 股上市公司作为研究对象，参考 Olley and Pakes（1996）、Levinsohn and Pertin（2003）提出的方法计算了我国上市公司的全要素生产率作为企业生产率的度量。最终，我使用 2007 年到 2020 年 3643 家上市公司的 28585 个企业-年度观测样本进行实证分析。基准回归结果表明，在我国股票市场中金融分析师的关注提高了企业的生产率。进一步，我通过中介效应分析发现金融分析师关注可能通过降低企业的融资约束与提高企业的创新水平两种渠道提高企业的生产率。除此之外，本文的实证研究还发现，分析师关注对于企业生产率的提高作用在分析师低估企业盈利水平时更加显著。这以结果表明业绩压力理论的机制可能同样存在于中国。

考虑到基准回归可能存在比较严重的内生性问题，本文还参考 Yu（2008）的做法使用预期分析师关注这一工具变量对分析师关注的作用进行估计。除此之外，本文还参考 Hong and Kacperczyk（2010），Derrien and Kecskés（2013）的研究方法，将证券公司之间兼并收购导致的分析师关注下降作为准自然实验，用于识别分析师关注下降对于企业生产率的影响。结果支持了本文基准回归中的结论。结果显示，本文的主要结论是比较稳健的。

8.2　政策建议

本文发现，分析师关注对于企业生产率的提高作用，只有在分析师没有显著高估企业短期盈利水平时才存在。学术界现有大量研究则指出，分析师缺乏独立性是分析师系统性地高估企业盈利水平的原因（Dugar & Nathan, 1995; Hong & Kubi, 2003; Ke & Yu,

2006; 曹胜与朱红军, 2011; 赵良玉 等, 2013; 等)。那么一个自然的问题是，何种监管政策可以进一步提高我国分析师的独立性呢？

值得注意的是，中国证券市场中的卖方分析师采用的是以“研究换佣金”的商业模式。这种商业模式也被成为“打包付费”(Bundling Payment)或者“软美元”(Soft Dollar)。虽然“研究换佣金”有一定合理性，但是这种商业模式也被认为是分析师缺乏独立性的“万恶之源”(薛菲 等, 2022)。我认为，2018 年 1 月 3 日在欧盟正式生效的《金融工具市场指令 II》(*Markets in Financial Instruments Directive II*，简称 *Mi FID II*）或许对于我国分析师监管有启示意义。

8.2.1 “研究换佣金”与分析师独立性

在图 8.1 中，我描绘了卖方分析师的商业模式：基于对各家上市公司的调查研究，卖方分析师会为投资机构提供研究服务。研究服务不仅包括卖方分析师出具的研究报告，投资机构也可能委托卖方分析师对上市公司的订单数量等资料进行搜集，或者邀请卖方分析师对上市公司的专利技术进行解读等等。“研究换佣金”的核心特点在于：在中国以及美国的金融市场中，基金公司等投资机构一般不会直接向卖方分析师支付服务费。机构投资者会选择通过研究服务好的证券公司营业部买卖证券，并为证券公司支付更多分仓佣金。这使得卖方分析师能为证券公司带来收入。在享受研究服务之后，投资机构也会对于各个卖方分析师的研究服务进行打分评价，证券公司可以按照打分将一部分分仓佣金支付给卖方分析师作为报酬，这被称为卖方分析师的“派点收入”。

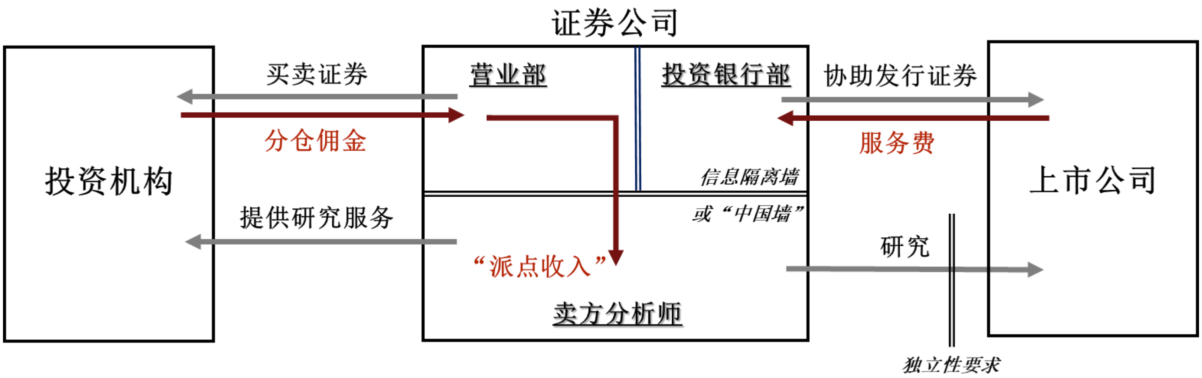

图 8.1 我国卖方分析师的商业模式

这种商业模式能够持续存在有以下两个原因：首先，投资机构每年对证券公司一笔付清费用简单可行。相比投资机构对卖方分析师进行单独付费，这种支付方式大大简化了投资机构与证券公司之间的资金往来。第二，美国与中国的法律与监管机构均没有要求投资机构必须向分析师独立付费。1975 年，美国国会修订了《美国 1934 年证

券交易法》，其中新增加的 28(e)节允许投资机构进行打包付费（Guo & Mota, 2021）。而中国的法律也没有要求投资机构必须对分析师进行单独付费。

然而，“研究换佣金”的商业模式不利于卖方分析师保持其独立性。尽管美国与中国的法律均要求证券公司的研究部门与其他部门之间建立“中国墙”，即从制度上隔离研究部门，禁止其他部门对分析师进行干预。然而，由于投资机构对于证券公司进行打包付款，研究部门本身并不能独立获得服务费收入。在实际操作中，分析师团队能拿到多少“派点收入”，很大程度上还是要证券公司高管说了算。这使得卖方分析师仍然有动机“从雇主整体利益考虑”，出具有利于证券公司其他业务的研究报告。

除此之外，这种打包支付的商业模式也不透明。由于不清楚投资机构给证券公司支付的费用中多少是给予分析师的，监管机构也难以发现卖方分析师与投资机构之间的不当行为。比如，投资机构可能选择为自己重仓股票发布乐观报告的券商进行交易，从而诱导分析师出具有偏差的报告（薛菲　等, 2022）。

8.2.2　欧盟法规的启示

为了革除“研究换佣金”的弊端，欧盟在对分析师监管的方面进行了积极的尝试。其中 2018 年 1 月 3 日正式生效的法律《金融工具市场指令 II》明确要求投资机构必须对分析师服务进行单独付费，而不能与支付给证券公司的佣金进行绑定。这一监管要求意味着“研究换佣金”在欧盟不再合法。Guo and Mota（2021）评估了《金融工具市场指令 II》对于欧盟金融分析师市场的影响。他们的实证结果发现，《金融工具市场指令 II》显著地提高了分析师预测的准确性。

基于上述分析，我认为中国可以适时适当地借鉴欧盟《金融工具市场指令 II》中对金融分析师的监管要求，要求我国投资机构对卖方分析师进行单独付费。这有利于保持卖方分析师的独立性，遏制卖方分析师出具高估企业盈利水平的报告，并最终让金融分析师更好地服务我国实体经济。

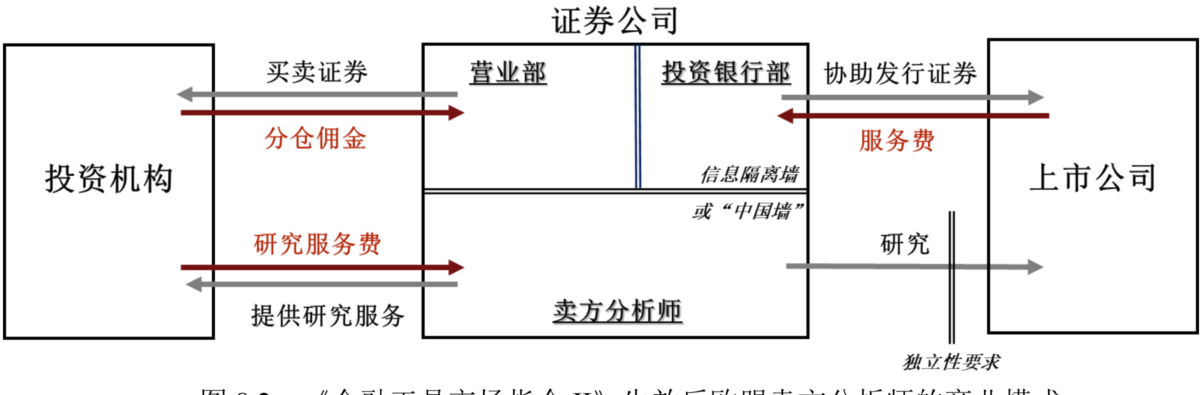

图 8.2　《金融工具市场指令 II》生效后欧盟卖方分析师的商业模式

8.3 本文研究的不足与展望

作为初步的研究成果，本文的研究还存在一些局限与不足，有待进一步分析与研究：

第一，不同企业之间金融分析师作用的异质性还有待研究。我国上市公司分布于五湖四海、林立于各行各业，在企业的所有权结构、管理制度等多个方面存在显著的差异。本文虽然发现，整体上我国股票市场中金融分析师的关注提高了企业的生产率，但是还没有对于不同企业之间作用的差异进行深入地研究。

第二，金融分析师的作用在不同时期的作用差异还有待研究。自我国股票市场建立以来，我国股票指数也经历了几次大起大落，其中 2008 年、2015 年股市“疯牛”之后的大跌也令人刻骨铭心。目前，理论经济学认为金融泡沫的破裂会加剧企业的融资约束，可能导致经济体生产率的下降（如 Miao & Wang, 2012）。考虑到金融分析师可以使企业信息更加透明，而信息不对称是导致企业融资约束的重要原因（Myers & Majluf , 1984），一个自然的问题是：是否金融分析师对于企业生产率的提高作用，在金融泡沫破裂后的熊市更加显著？这一问题还有待未来进一步深入研究。

第三，金融分析师对经济体整体生产率的影响还有待研究。在本文中，我主要研究了分析师关注与被关注的公司的生产率之间的关系。尽管本文发现，分析师的关注有助于提高企业的生产率，然而分析师的关注也很可能会对其他企业的生产率产生外部性。如果资金供给恒定不变，分析师关注在放松被关注企业的融资约束时，也同时剥夺了其他企业的融资。考虑到我国上市公司的融资困难程度远远低于非上市公司，这一机制是很可能存在的。但是，回归分析等微观计量方法只能告诉我们在 A 股市场中“局部均衡”结果，而对于中国整个经济体的作用则不得而知。这一问题也有待未来的进一步深入研究。

第四，对金融分析师的监管方法还有待进一步研究。本文认为欧盟法规《金融工具市场指令 II》对我国金融监管政策有一定参考意义。然而，考虑到中国与欧盟金融市场存在巨大的差异，照搬照抄欧盟的监管要求或许不是最优解。由于我法律知识匮乏，对于金融监管方面的法律法规理解非常粗浅，因此本文没有在政策建议方面进行更加深入地探讨。如何基于中国金融市场的现实出台监管政策，让金融分析师更好地服务实体经济？这一个问题还有待学者进一步研究。

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附录 A　全要素生产率的估计

A.1　OP 法（Olley & Pakes, 1996）估计全要素生产率

A.1.1　方法简介

在经济学中，一般使用柯布-道格拉斯型生产函数刻画企业的生产活动：

$$Y_{it} = A_{it} L_{it}^{\alpha} K_{it}^{\beta} \tag{A.1}$$

其中，Y_{it}代表为i的企业在t年的总产出，L_{it}为总人工投入，K_{it}为总资本投入，α和β分别为产出对于人工投入、资本投入的弹性。如果排除人工和资本的影响，A_{it}就是i的企业在t年的全要素生产率。

为了估计企业的全要素生产率，可以对上述生产函数取对数:

$$y_{it} = \alpha l_{it} + \beta k_{it} + u_{it} \tag{A.2}$$

其中小写字母y_{it}，l_{it}，k_{it}分别是大写字母Y_{it}总产出，L_{it}总人工投入，K_{it}总资本投入的对数形式。u_{it}是对数产出无法被劳动和资本解释的部分，包含了企业全要素生产率的信息。因此，直接的想法是，可以通过企业实现的对数产出水平y_{it}，减去使用l_{it}和k_{it}预测的企业对数总产出水平$\hat{y}_{it}$，即可得到企业对数生产率的估计值：

$$\widehat{TFP}_{it} = y_{it} - \hat{y}_{it} = y_{it} - (\hat{\alpha} l_{it} + \hat{\beta} k_{it}) \tag{A.3}$$

然而， Marschak and Andrews（1944）指出，上述对于全要素生产率的估计存在同时性偏误（Simultaneity Bias）：同时性偏误指的是企业的投入决策与企业的生产率相关：高生产率的企业会为了追逐利润大量投入劳动力和资本，这会导致 OLS 估计的系数有偏。

为解决同时性偏误的问题，Olley and Pakes（1996）提出了一种使用企业投资额对对生产率水平进行控制的方法，在本文中简称 OP 法。OP 法考虑以下生产函数：

$$y_{it} = \alpha l_{it} + \beta k_{it} + w_{it} + \epsilon_{it} \tag{A.4}$$

在上式中，公式(A.2)中的u_{it}被分为两部分：扰动项ϵ_{it}刻画影响生产水平的外生冲击或者测量误差，无法被企业预知，因此不影响企业要素投入。w_{it}代表被企业已知的生产率水平。企业根据w_{it}与现有对数资本存量k_{it}决定下期对数投资水平i_{it}：

$$i_{it} = f_t(w_{it}, k_{it}) \tag{A.5}$$

Olley and Pakes（1996）假设最优投资函数$f_t()$对于w_{it}单调递增的，那么可以取$f_t()$对于w_{it}的反函数，记作$h_t()$，得到：

$$w_{it} = h_t(i_{it}, k_{it}) \tag{A.6}$$

将上式带入到生产函数(A.4)中，可得：

$$y_{it} = \alpha l_{it} + \beta k_{it} + h_t(i_{it}, k_{it}) + \epsilon_{it} \tag{A.7}$$

上式可以进一步改写成：

$$y_{it} = \alpha l_{it} + \phi_{it} + \epsilon_{it} \tag{A.8}$$

$$\phi_{it} = \beta k_{it} + h_t(i_{it}, k_{it}) \tag{A.9}$$

为了估计劳动弹性α，Olley 与 Pakes（1996）使用包含i_{it}和k_{it}的二次多项来近似$\phi_{it} = \phi_{it}(i_{it}, k_{it})$。通过对(A.8)式进行估计即可以获得对于劳动弹性的一致估计$\hat{\alpha}$。

为了估计资本弹性β，可以定义$V_{it} = y_{it} - \hat{\alpha} l_{it}$，然后对以下函数进行估计：

$$V_{it} = y_{it} - \hat{\alpha} l_{it} = \beta k_{it} + g(\phi_{it-1} - \beta k_{it-1}) + \mu_{it} + e_{it} \tag{A.10}$$

其中$g()$函数也可以是用包含ϕ_{it-1}和k_{it-1}的高阶多项式进行近似。获得了劳动弹性与资本弹性的估计值$\hat{\alpha}$和$\hat{\beta}$之后，即可带入公式(A.3)获得 TFP 的估计。

A.1.2　原始数据

在使用 OP 法对企业全要素生产率进行估计时，我们需要 5 个主要变量，其中全部名义变量需要经过价格指数的调整。我参考 To et al.（2018），İmrohoroğlu and Tüzel（2014），宋敏 等（2021）的方法对以下主要变量进行度量：

（1）　企业的实际产出

企业的名义产出使用折旧摊销前营业利润（Operating Income Before Depreciation and Amortization；OIBDP）加企业的劳动力成本近似计算。其中折旧摊销前营业利润是营业利润，加上折旧摊销，再加上所得税，最后加上财务费用。劳动力成本使用企业现金流量表中报告的支付给职工以及为职工支付的现金近似计算。目前国内的文献也有直接使用企业的营业收入或者企业主营业务收入作为企业实际产出。我之所以不直接使用企业营业收入或者主营业务收入度量实际产出，是因为 Foster et al.（2008）的研究表明企业的营业收入会受到企业特质性的投入品价格影响。比如，在铁矿石短缺时，钢材价格也较高，如果直接基于营业收入估计全要素生产率，则将会错误地将投入价格波动产生的影响包含在内。而 To et al.（2018）认为使用折旧摊销前营业利润加劳动力成本作为企业实际产出的度量可以一定程度上解决这一问题。在计算获得企业

的名义产出之后，我参考肖文与薛天航（2019）的调整方法，将企业的名义产出调整为以 2007 年为基准年的实际产出，具体的调整方法是：对于 2012 年版证监会行业代码为 C 开头的制造业企业，使用工业生产者出厂价格指数（Producer Price Index for Industrial Products, PPI）对价格进行调整；对于其他企业，使用居民消费价格指数（Consumer Price Index, CPI）对价格进行调整。价格指数的数据来源于中国国家统计局。

（2） 企业的实际资本投入

企业的资本投入使用企业固定资产的经过折旧后的账面价值进行计算。由于资本由多年的投资进行积累，而不同年份的价格指数并不相同，因此在进行价格调整之前需要估计企业固定资产的年龄。本文参考 To et al.（2018），使用企业累计折旧除以企业当期折旧，估计企业固定资产的年龄。考虑到企业计提折旧的政策可能存在变化，我对固定资产的年龄取三年移动平均值进行平滑处理。为了进一步避免极端值的影响，我对固定资产的年龄在 5%和 95%分位数上进行了缩尾（winsorize）处理。在计算得到企业的固定资产年龄后，我使用国家统计局报告的固定资产投资价格指数，将名义资本投入转化为以 2007 年为基准年的实际资本投入。

（3） 企业的人工投入

参考 To et al.（2018）以及宋敏 等（2021），测算 TFP 时使用的企业的人工投入使用企业的员工人数度量。

（4） 企业的实际投资额

为了控制企业可观测的生产率水平导致的同时性偏误问题，我们还需要企业的投资额。参考肖文与薛天航（2019）的做法，本文使用上市公司现金流量表中报告的购建固定资产无形资产和其他长期资产支付的现金作为企业名义投资额的度量。然后，我使用国家统计局报告的固定资产投资价格指数，将名义投资额转化为以 2007 年为基准年的实际投资额。

（5） 企业是否退出市场

为了控制企业退出市场导致的样本选择偏误问题，我们还需要企业是否退出市场的虚拟变量。本文将企业退市视为企业退出市场。除此之外，考虑到我国股票市场存在借壳上市，即非上市公司通过将资产注入上市公司（壳公司），获得企业的控制权，实现上市融资。此后，被其他公司取得控制权的壳公司一般会变更企业简称和主营业务。因此，本文参考肖文与薛天航（2019）的做法，也将企业的简称和所属行业同时变化视为企业退出市场。

在表 A.1 中，我总结了 OP 法计算企业全要素生产率所使用的数据。

表 A.1　OP 法计算企业全要素生产率所使用的数据

变量	变量描述	单位	数据来源
实际产出	名义产出 ＝ 营业利润+折旧摊销+所得税+财务费用+支付给职工以及为职工支付的现金 对于制造业企业，使用工业生产者出厂价格指数调整为以2007年为基准年的实际产出；对于其他企业，居民消费价格指数调整为以2007年为基准年的实际产出	千元	Wind
实际资本投入	名义资本投入 ＝ 固定资产账面价值 按照固定资产年龄，使用固定资产投资价格指数调整为以2007年为基准年的实际资本投入。固定资产年龄是企业累计折旧/当期折旧，取三年移动平均，再在5%和95%分位数上进行缩尾处理。	千元	Wind
人工投入	员工人数	人	Wind
实际投资额	名义投资额 ＝ 购建固定资产、无形资产和其他长期资产支付的现金 使用固定资产投资价格指数调整为以2007年为基准年的实际资本投入。	千元	Wind
退出市场	企业退市，或者公司简称和所属行业同时发生变化则视为企业退出市场		Wind

A.1.3　计算程序

目前，学术界已经开发了比较成熟的企业全要素生产率估计程序。Yasar et al.（2008）撰写了 stata 外部命令 opreg，可以方便可靠地实现使用实现 OP 方法对全要素生产率进行估计。该程序的具体使用方法可以参考 Yasar et al.（2008）。本文使用这一程序对我国上市公司的全要素生产率进行估计。

A.2　LP 法（Levinsohn & Pertin, 2003）估计全要素生产率

A.2.1　方法简介

本文采用的另一种全要素生产率估计方法由 Levinsohn and Pertin（2003）提出，在本文中简称 LP 法。Levinsohn and Pertin（2003）指出了上述 OP 法的一些不足之处：OP 法在估计企业全要素生产率时要求企业的投资者必须是正数，因此不能计算投资额为零值的企业年度样本。除此之外，作者还发现当企业面对非下凸的资本调整成本时，OP 方法也可能是存在问题的。针对这些问题， LP 法使用中间品投入替代 OP 法中的企业固定资产投资，用于对同时性偏误的控制。Levinsohn and Pertin（2003）认为，企

业购买中间品投入取零值比较少，而且中间投入品在生产过程中被消耗，因此不像长期使用的固定资产那样需要较大的调整成本，因此能够很好地解决 OP 法存在的问题。

A.2.2 原始数据

LP 法需要企业中间品投入的数据。本文参考钱雪松 等（2018），使用企业资产负债表中报告的购买商品、接受劳务支付的现金作为企业名义中间品投入的度量，然后使用工业生产者出厂价格指数将名义中间品投入调整成以 2007 年为基准年的实际中间品投入。

在表 A.2 中，我总结了 LP 法计算企业全要素生产率所使用的数据。

表 A.2 LP 法计算企业全要素生产率所使用的数据

变量	变量描述	单位	数据来源
实际产出	名义产出 = 营业利润+折旧摊销+所得税+财务费用+支付给职工以及为职工支付的现金 对于制造业企业，使用工业生产者出厂价格指数调整为以2007年为基准年的实际产出；对于其他企业，居民消费价格指数调整为以2007年为基准年的实际产出。	千元	Wind
实际资本投入	名义资本投入 = 固定资产账面价值 按照固定资产年龄，使用固定资产投资价格指数调整为以2007年为基准年的实际资本投入。固定资产年龄是企业累计折旧/当期折旧，取三年移动平均，再在5%和95%分位数上进行缩尾处理。	千元	Wind
人工投入	员工人数	人	Wind
实际中间品投入	名义中间品投入 = 购买商品、接受劳务支付的现金。使用工业生产者出厂价格指数调整为以2007年为基准年的实际中间品投入	千元	Wind
退出市场	企业退市，或者公司简称和所属行业同时发生变化则视为企业退出市场		Wind

A.2.3 计算程序

Petrin et al.（2004）撰写了 stata 外部命令 levpet，可以方便可靠地实现 LP 方法对全要素生产率进行估计。该程序的具体使用方法可以参考 Petrin et al.（2004）。本文使用这一程序对我国上市公司的全要素生产率进行估计。

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