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The cross-board spillover effect of innovation information: Establishment of the Star Market and Main Board analyst forecasts

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ABSTRACT

Studies show that innovation information disclosed by listed firms affects the decision of non-listed firms and their stakeholders. This paper explores whether innovation information disclosed within a specific list board (i.e., market) also spills over to other list boards. Based on the establishment of China's Star Market, we conduct an empirical test from the perspective of analyst forecasts. We find that (1) The accuracy of analyst forecasts of Main Board firms with greater information similarity to Star Market firms is significantly higher than that of Main Board firms with lower information similarity. (2) This effect is significantly stronger in samples with a substantially lower listing threshold for innovation firms, for Main Board firms with stronger innovation characteristics and when market innovation information needs are greater. (3) This affect is enhanced by analysts' tendency to track Star Market firms with similar information to their tracked Main Board firms. These results enrich research on the spillover effects of innovation information and factors affecting analyst forecasts.

1. Introduction

Innovation information disclosed by firms has positive externalities and can affect the decisions of other firms and their stakeholders (Lück et al., 2020; Kim and Valentine, 2021; Hegde et al., 2023), i.e., the spillover effect of innovation information. The literature mainly focuses on this spillover effect at the firm level, studying

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how innovation information spills over from firms with higher disclosure levels to firms with lower disclosure levels.[1] Considering that a country's listed boards (i.e., markets) usually focus on different types of firms[2] and provide information with different characteristics, the above-mentioned firm-level innovation information spillover effect is also likely to exist between specific listed boards. Accordingly, this paper explores whether a listed board focusing on innovation firms has innovation information spillover effects on other listed boards.

In 2019, China established the Star Market on the Shanghai Stock Exchange, providing an opportunity to study the above issues. First, the Star Market focuses on supporting high-tech and strategic emerging industries such as the new-generation information technology, high-end equipment, new materials, new energy, energy conservation and environmental protection and biomedicine industries[3]; thus, it has innovative attributes distinct from those of other listed boards in China. Second, from 2019 to 2022, the Shanghai and Shenzhen Main Boards added about 400 listed firms, while the Star Market added about 500 listed firms. The Star Market has a clear and important impact on the number of listed firms in China. Third, the establishment of Star Market has a certain level of exogeneity, which enhances the effectiveness of causal identification of the innovation information spillover effect.

The literature mainly studies the innovation information spillover effect from the perspectives of corporate investment and disclosure, patent transactions and investors' investment (e.g., Badertscher et al., 2013; Wu Cen et al., 2022; Kim and Valentine, 2023). In theory, innovation information spillover may affect any user of innovation information. In particular, innovation information is important for analysts (e.g., Jones, 2007; Palmon and Yezegel, 2012; Bellstam et al., 2021). However, few studies explore the innovation information spillover effect from the perspective of analyst forecasts. In addition, no research on the factors influencing analyst forecasts is focused on the innovation information spillover effect. Therefore, in contrast to the literature, this paper takes the establishment of the Star Market in China as an opportunity to examine whether innovation information has a spillover effect at the level of listed boards from the perspective of analyst forecasts.

Specifically, we use the similarity of management discussion and analysis (MD&A) texts to identify the impact of the establishment of the Star Market on Main Board firms in terms of innovation information and construct a difference-in-differences (DID) model for empirical testing. The results show that (1) After the establishment of the Star Market, the analyst forecasts of Main Board firms with a higher level of information similarity to Star Market firms improve significantly compared with the forecasts of Main Board firms with a lower level of information similarity. The results pass the parallel trend and placebo tests, as well as alternate robustness tests such as controlling for the impact of the ChiNext registration system reform, adjusting the method used to identify the key variable, a time-varying DID and an analysis report level test. (2) This effect is stronger in samples with a substantially lower listing threshold for innovative firms, for Main Board firms with stronger innovation characteristics and when investors' innovation information needs are greater. (3) This effect is also enhanced by analysts' tendency to track Star Market firms that have similar information to the Main Board firms they are tracking.

This paper contributes to the bodies of literature on the spillover effect of innovation information and the factors influencing analyst forecasts. Recent literature confirms the spillover effect of innovation information at the firm level (e.g., Badertscher et al., 2013; Cotei and Farhat, 2013; Li et al., 2022) but does not address whether innovation information also has a spillover effect at the listed board level. In this paper, different listed boards are shown to have differentiated positioning, and a spillover effect of innovation information between listed boards is proposed. This effect is confirmed by the establishment of the Star Market in China, an exogenous shock, and thus contributes to the literature on the spillover effect of innovation information. Furthermore, the literature mainly explores the factors influencing analyst forecasts in terms of the characteristics of the analysts and the analyzed firms (e.g., Christensen et al., 2013; Gu et al., 2019). In contrast, there is little

[1] For example, spillover from listed firms to non-listed firms (Badertscher et al., 2013) or from inventors to citers (Hegde et al., 2023).

[2] For example, Nasdaq claims that it "became home to many of the growth-oriented companies and industries ... providing a market for these innovative companies," and the New York Stock Exchange claims that it has "been the place where world leaders come to raise capital ... include the boldest leaders across all verticals." See https://www.nasdaq50.com/stories/30, https://www.nyse.com/network.

[3] See "Implementation Opinions on Establishing Star Market and Piloting a Registration System at the Shanghai Stock Exchange", https://www.gov.cn/zhengce/zhengceku/2019-10/18/content_5441532.htm.

focus on how innovation information from one listed board can spill over to analysts and affect their forecasts regarding firms on other listed boards. Therefore, this paper fills the gap in the literature on the factors influencing analyst forecasts.

2. Literature review

As noted above, our study stands at the intersection of two strands of literature, namely the strands on the information spillover effect and the factors influencing analyst forecasts.

The information spillover effect can be described as the impact of information disclosed by one firm on the decisions of other related firms and their stakeholders. The relevant literature can be roughly divided into three aspects. The first aspect is the type of information, including accounting statement information (Lu et al., 2019), research and development (R&D) information (Merkley, 2014; Kim and Valentine, 2023), internal control information (Gao and Zhang, 2019), competition information (Fang et al., 2018; Kim et al., 2008), regulated information (Brown et al., 2018) and initial public offering (IPO) inquiry information (Wu et al., 2022). The second aspect concerns the paths of this spillover effect, including a shared industry (Badertscher et al., 2013; Gao and Zhang, 2019; Li et al., 2021; Wu et al., 2022), supply chain (Chiu et al., 2019) and auditors (Christoph et al., 2023). The third aspect comprises economic consequences, including corporate investment (Badertscher et al., 2013), cash holdings (Chen et al., 2014; Di et al., 2020), risk information disclosure (Brown et al., 2018), tax pressure (Dai et al., 2023), accounting manipulation (Gao and Zhang, 2019), earnings forecasts (Kim et al., 2008), stock price synchronization (Wu et al., 2022) and patent transactions (Kim and Valentine, 2023).

The factors influencing analyst forecasts can also be roughly divided into three categories. The first category pertains to the information quality of analyzed firms, including the information disclosure quality (Fang, 2007), information transparency (Christensen et al., 2013), information available to management (Liu and Chen, 2019), annual report readability (Xu et al., 2021; Li et al., 2023) and online sales (Liu et al., 2022). The second category concerns the ability of analysts to obtain and interpret information, including basic characteristics (Clement, 1999), industry expertise (Liu and Gao, 2014), overseas experience (Guan et al., 2020), understanding of IFRS (Barniv and Myring, 2015), attendance of conference calls (Mayew et al., 2013), site visits (Cheng et al., 2016) and personal relationships with management (Gu et al., 2019). The third category involves information sources external to the analyzed firms, including the comparability of accounting information between other firms and the analyzed firms (De Franco et al., 2011), information disclosed by firms with economic ties to the analyzed firms (Guan et al., 2015), media reports (Tan et al., 2016) and economic policy uncertainty (Dai and Yang, 2020).

In summary, different types of information, such as accounting information, innovation information and governance information, can produce spillover effects through multiple paths, such as a shared industry, supply chain and auditor, but few publications focus on innovation information spillover between different listing boards. Furthermore, analyst forecasts are affected by factors such as the quality of information about the analyzed firms, analysts' ability and information sources external to the analyzed firms, but no literature focuses on the listing of innovation firms, an important factor related to the innovation information environment. This paper studies how the IPO wave of the Star Market affects the forecasts of analysts of Main Board firms through the innovation information spillover effect, thus helping to fill the two above-described gaps in the literature.

3. Hypothesis development

3.1. Institutional background

The Star Market has distinct innovation attributes. The *Regulations on the Registration Administration of Initial Public Offering of Stocks on the Star Market (Trial)* state that "priority will be given to supporting enterprises that are in line with national strategies, possess key core technologies, have outstanding scientific and technological innovation capabilities, and mainly rely on core technologies to carry out production and operations … and have strong growth potential." First, in terms of industry, the Star Market focuses

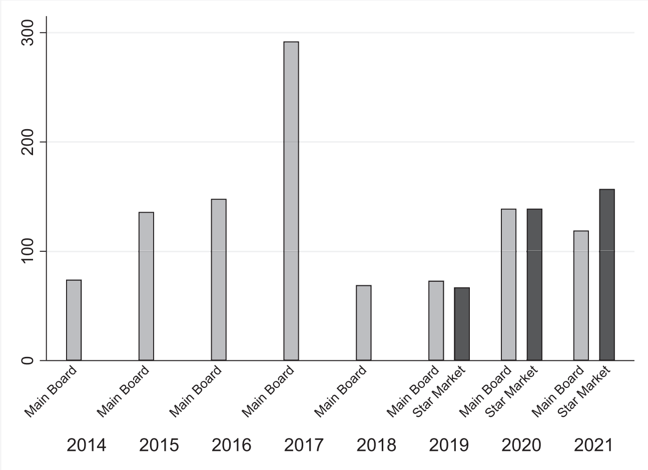

Fig. 1. Numbers of IPOs on the Main Board and the Star Market over time (years).

on supporting the listing of enterprises in high-tech fields such as new-generation information technology, high-end equipment, new materials, new energy, energy conservation and environmental protection and biomedicine. Second, in terms of listing conditions, the Star Market has five financial conditions for listing, among which some clauses do not require net profit, some clauses require R&D investment and some clauses do not require traditional financial indicators such as net profit and operating income but only require innovation indicators. Compared with other boards, the Star Market has substantially weakened traditional financial indicators and strengthened innovation indicators. Third, in terms of the number of IPOs over the years (as shown in Fig. 1), the Star Market and Main Board report similar numbers, and the number of IPOs on the Main Board has not decreased significantly compared with that in previous years, indicating that Star Market firms have not reduced the number of IPOs on the Main Board. Fourth, in terms of the actual financial indicators of listed firms in the IPO year (as shown in Fig. 2), Star Market firms have significantly higher R&D expenditures than Main Board firms but significantly lower net profits, operating income and net cash flow from operating activities, indicating that the Star Market mainly supports innovative firms that cannot easily meet the listing conditions of the Main Board. In summary, based on the listing system arrangements and the actual situations of listed firms, the Star Market has added a batch of innovative listed firms to the capital market.

3.2. Theoretical analysis

First, the Star Market provides incremental information about innovation to the capital market. Compared with non-listed firms, listed firms face extensive and strict information disclosure requirements and are obliged to publicly publish their financial statements and other information related to shareholders' equity (Aghamolla and Thakor, 2022). In addition, given the need to make reasonable valuations and investment decisions for listed firms, investors, analysts and other capital market entities usually have substantial requirements regarding the level and quality of information disclosed by listed firms (Chapman and Green, 2018). In fact, many firms choose not to go public, or to make a trade-off between going public and avoiding information proprietary costs, precisely to avoid the proprietary costs generated by the increased information disclosure requirements after listing (Marra and Suijs, 2004).

In addition, although the disclosure of innovation information generates proprietary costs (Cao et al., 2018) and thus restricts firms after listing, this restriction only occurs after listing leads to an increase in information disclosure. Therefore, even when proprietary costs are considered, the net effect of listing on innovation information disclosure should be positive rather than negative. In short, it can be inferred that the listing of innovative firms should result in an increase in innovation information. Analysis of the institutional background reveals that the Star Market has successfully listed many innovative firms in a short period of time, thus

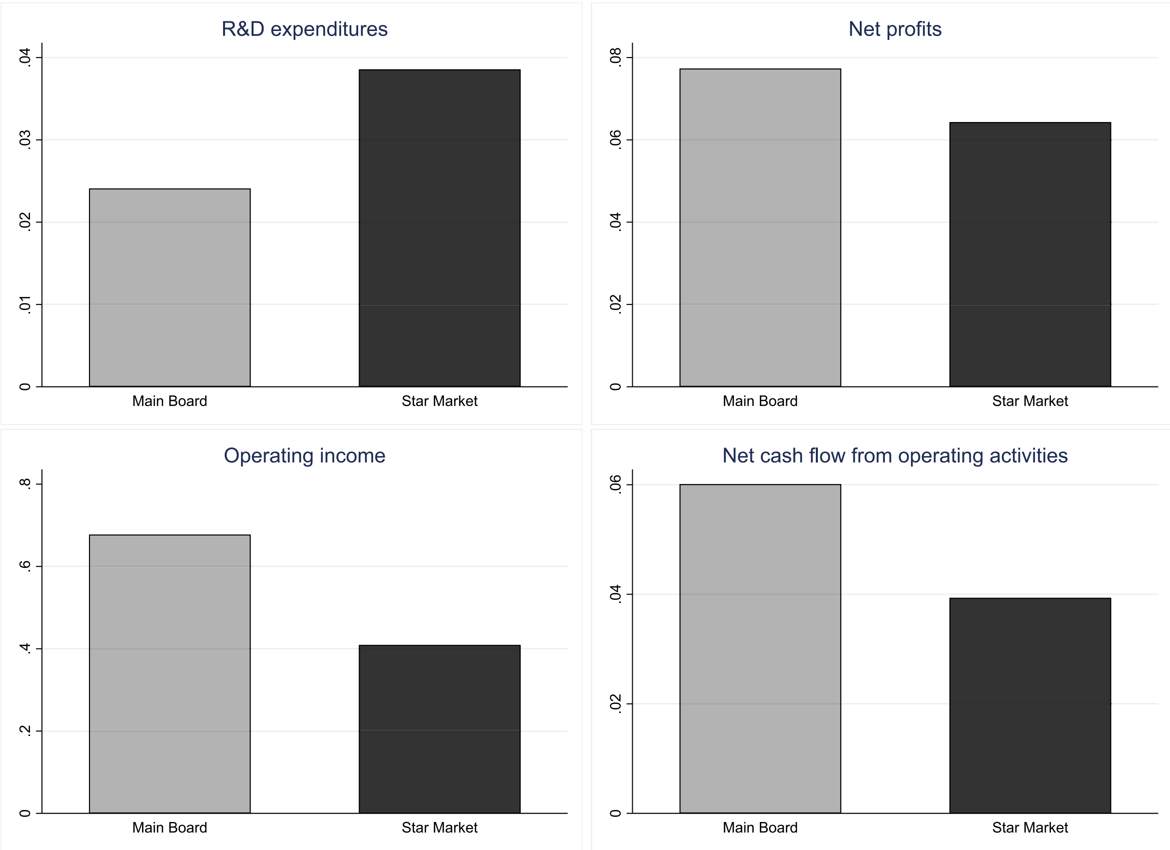

Fig. 2. Financial indicators of firms listed on the Main Board and Star Market in the year of listing.

resolving the paucity of innovative listed firms in China's capital market to a certain extent. In addition, a series of institutional arrangements implemented by the Star Market, such as registration system reform, IPO review inquiry and the disclosure system, have further strengthened the information disclosure of its listed firms. In summary, the Star Market is expected to result in an increase in innovation information within the capital market.

Second, innovation information has positive externalities. In economics, a positive externality is defined as the positive impact of the behavior of an entity on other entities in society. At the firm level, the positive externalities of innovation information are reflected by impacts on similar R&D activities. Information contained in innovation disclosures, such as new technologies, products or business models, can inspire other firms. These other firms can formulate their own innovative ideas, thereby promoting their own innovation activities. Research also supports this point. For example, Lück et al. (2020) show that the disclosure of innovation information can reduce repetitive research, thus reducing the wastage of social resources and subsequently helping other innovators quickly achieve more differentiated innovation results. Kim and Valentine (2018) and Hegde et al. (2023) provide evidence supporting these findings based on the US Inventor Protection Act. Li et al. (2022) show that the innovation information disclosed by listed firms reduces the uncertainty surrounding the innovation activities of non-listed firms. In short, in the context of positive externalities, the innovation information provided by the Star Market should affect the innovation information environment for other related firms.

Finally, the innovation information provided by the Star Market can help analysts make predictions about Main Board firms. First, innovation has a positive impact on the future profitability and market value of enterprises, but this impact is often underestimated by investors (Dong et al., 2021). Therefore, innovation information helps investors and other outsiders estimate the future profitability and value of an enterprise. Research also shows that innovation information is an important supplement to financial statement information. Gu and Li (2003) find that when the availability of current profit information decreases or uncertainty about future profits increases, firms increase their innovation disclosure. Merkley (2014) finds that earnings adjusted for R&D expenses are negatively correlated with narrative R&D disclosure. Second, the source of innovation information is very important to analysts. Due to serious information asymmetry, corporate R&D investment reduces the accuracy of analysts' forecasts (Amir et al., 2003; Gu and Wang, 2007; Chalmers et al., 2011). Therefore, analysts who lack sources of innovation information find it difficult to provide useful forecasts for R&D-intensive companies (Palmon and Yezegel, 2012). In contrast, the disclosure of innovation information helps analysts' forecasts. For example, disclosure in the development stage helps reduce uncertainty regarding the conversion of R&D into future sales, thereby improving the accuracy of analysts' forecasts (Jones, 2007). Analysts also use innovation information when describing a company's characteristics (Bellstam et al., 2021). Third, analysts benefit from information complementarity between different firms (Guan et al., 2015). Firms may face certain common challenges and risks in innovation, such as industry competition, technical difficulties and regulatory changes. Analysts can incorporate such information into their forecasts to better understand certain common problems in the innovation field and increase the accuracy and comprehensiveness of their conclusions.

In summary, the Star Market provides the capital market with incremental innovation information, which has positive externalities: It affects the innovation information environment of other firms, and the availability of sufficient innovation information helps analysts make forecasts. Therefore, the Star Market should have a positive impact on the forecast accuracy of analysts of Main Board firms. Based on this, we propose the following research hypothesis:

Hypothesis 1 (H1). The establishment of the Star Market improves the accuracy of analysts' forecasts for Main Board firms.

4. Research design

4.1. Sample selection and data sources

As this paper explores the spillover effect of the establishment of the Star Market, the initial sample should comprise companies listed outside the Star Market, including those listed on the Shanghai Stock Exchange Main Board, Shenzhen Stock Exchange Main Board[4] and ChiNext. However, ChiNext implemented a registration system reform in 2020, which may interfere with the explained variables of the sample companies in the treatment window (see below) and lead to deviations in the results of testing the consequences of the establishment of the Star Market. In addition, the establishment of the Star Market provides the proposed listed companies with additional options regarding the listing board. Main Board firms newly listed before and after the establishment of the Star Market may have systematic differences. For these reasons, we select only companies listed on the Shanghai and Shenzhen Main Boards before 2019 as our sample.

Regarding the time range of sample selection, we follow two principles. First, we ensure that the length of the control window (before the establishment of the Star Market) and the treatment window (after the establishment of the Star Market) are consistent. Second, we include as many observations as possible while not substantially expanding the time window to ensure that the test results best reflect the impact of the establishment of Star Market, rather than other events. In addition, due to a data update situation at the time of the study, the final time range is set from 3 years before and to 3 years after the establishment of the Star Market, or 2016–2021. Following research conventions, we also exclude financial industry companies, special treatment companies and observations with missing variables. As data from 2016 to 2018 are needed to construct variables in subsequent tests, we also exclude companies that do not fully span the time range to ensure balanced panel data.

The MD&A texts are obtained from the annual reports disclosed by listed companies on the Juchao Information Network. Accounting statement data, stock returns, stock prices, book-to-market ratios, analysts'

[4] The Shenzhen Stock Exchange's ChiNext was merged into the Main Board in 2021. Prior to 2021, ChiNext actually assumed the functions of the Main Board; accordingly, we do not list it separately.

forecasts of earnings per share and actual earnings per share are obtained from the China Stock Market & Accounting Research Database, and other data are from the Chinese Research Data Services Platform. Data on the number of innovative questions are obtained from SSE E-interactive and SZSE Interactive Easy. Finally, following research conventions, all the continuous variables are winsorized at the 1% and 99% levels to eliminate the effects of extreme values.

4.2. Empirical model and variable description

We establish the following DID model to test H1:

$$Accuracy_{it} = \beta_0 + \beta_1 Post_t \times Treat_i + \beta_C Control_{it} + Firm_i + Year_t + \varepsilon_{it} \tag{1}$$

where $Accuracy_{it}$ represents the accuracy of the analyst forecast of Main Board company i in year t. $Post_t$ represents a dummy variable indicating whether year t is after the establishment of Star Market. $Treat_i$ represents the intensity of treatment of Main Board company i by the establishment of Star Market. $Control_{it}$ represents a vector composed of control variables, with reference to Han et al. (2018), and includes the number of analysts following (*Follow*), number of analyst research reports (*FCFreq*), number of analyst on-site inspections (*Visits*), company size (*Size*), asset–liability ratio (*Lev*), return on total assets (*ROA*), loss or not (*Loss*), company age (*Age*), number of media reports (*Media*), stock returns (*Stkret*), book-to-market ratio (*BTM*), corporate transparency (*Opacity*), whether the chairman and general manager are the same person (*Dual*), ownership concentration (*Sharehd*) and institutional holdings (*Inst*). *Firm* and *Year* represent firm and year fixed effects, respectively. We mainly focus on the coefficient β_1. A positive and significant coefficient indicates that the establishment of the Star Market improves the accuracy of analyst forecasts for Main Board firms, thus confirming H1.

Referring to the approach of Han et al. (2018), we use the mean value of analyst forecast accuracy at the company-year level to measure *Accuracy*, which is calculated as follows:

$$Accuracy_{it} = -\frac{1}{n_{it}}\sum_{1}^{n_{it}} \left|ForecastEPS_{ijt} - EPS_{it}\right| / P_{it}$$

where i represents the company, j represents the analyst, t represents the fiscal year and n_i represents the number of times the analyst predicts the earnings per share of company i in fiscal year t. *Accuracy* represents the accuracy of the forecast, *ForecastEPS* represents the earnings per share predicted by the analyst, *EPS* represents the company's actual earnings per share and *P* represents the stock price at the end of the year.

In the absence of ideal experimental and control groups, the effectiveness of the DID model depends on the accurate measurement of treatment intensity. It is difficult to determine which Main Board firms are completely unaffected by the incremental innovation information resulting from the establishment of the Star Market. Therefore, empirical testing depends on how the treatment intensity (*Treat*) of the impact of the establishment of the Star Market on Main Board firms is measured. Obviously, the more similar the innovation information disclosed by Main Board firms is to the innovation information resulting from the establishment of the Star Market, the greater the intensity of treatment the Main Board firms will receive. As MD&A texts are important carriers of corporate non-financial information and the main source of information used to measure innovation disclosure in research (Li and Yao, 2020; Zhou et al., 2022), we use the MD&A similarity between Main Board firms and Star Market firms to identify *Treat*. In addition, considering that the MD&A similarity between Main Board firms and Star Market firms may contain time trends, we also use the MD&A similarity between Main Board firms and Main Board firms listed after 2019 for deflation,[5] a process described in detail below.

[5] For example, the industry of Main Board firms x has developed rapidly in recent years, and the number of IPOs has grown rapidly; the situation for Main Board firms y is the opposite. Directly using the MD&A similarity between Main Board firms and Star Market firms to measure *Treat* would result in a value of $Treat_x$ greater than that of $Treat_y$, but this would be caused by the different development trends of the industries described by the two variables, rather than the establishment of the Star Market. The growth in the number of IPOs due to this time trend is not limited to the Star Market. Therefore, using the MD&A similarity between Main Board firms and newly listed Main Board firms from 2019 to 2021 for deflation can eliminate the above time trend to a certain extent.

First, the similarity between the MD&A of the Main Board firms in fiscal year 2018[6] and that of the Star Market firms listed in 2019 in fiscal year 2019[7] (*SimStar19*), of Star Market firms listed in 2020 in fiscal year 2020 (*SimStar20*) or of Star Market firms listed in 2021 in fiscal year 2021 (*SimStar21*) is calculated. Second, the similarity between the MD&A of Main Board firms in fiscal year 2018 and the MD&A of Main Board firms listed in 2019 in fiscal year 2019 (*SimMain19*), of Main Board firms listed in 2020 in fiscal year 2020 (*SimMain20*) or the MD&A of Main Board firms listed in 2021 in fiscal year 2021 (*SimMain21*) is calculated. Finally, *Treat* is calculated as follows:

$$Treat_x = \left(\frac{1}{m} \times \sum_{y=1}^{m} \left(SimStar19_{xy} + SimStar20_{xy} + SimStar21_{xy}\right)\right) / \left(\frac{1}{n} \times \sum_{z=1}^{n} (SimMain19_{xz} + SimMain20_{xz} + SimMain21_{xz})\right)$$

where x represents Main Board firms listed before 2019, y represents Star Market firms, z represents Main Board firms listed between 2019 and 2021, m represents the number of y and n represents the number of z.

We use the cosine of the angle between text vectors to measure similarity. The specific calculation steps are as follows. First, segment the MD&A text according to *Jieba*. Second, use the term frequency–inverse document frequency (TF-IDF) method to calculate the inverse document frequency for each word as follows[8]:

$$idf(w) = log(N/df(w))$$

where $idf(w)$ represents the inverse text frequency of word w, N represents the total number of texts and $df(w)$ represents the number of texts in which w appears. Third, calculate the TF-IDF value of all words in each text as follows:

$$TF\text{-}IDF(w) = tf(w) \times idf(w)$$

where $tf(w)$ represents the frequency of word w in the text. Fourth, each text is vectorized: the elements of the vector are all words, and the value of the element is the TF-IDF value of the word. Finally, the cosine of the vector angle is calculated as follows:

$$SIM = cos(\theta) = \sum_{i=1}^{n} (X_i \times Yi) / \sqrt{\sum_{i=1}^{n} (X_i)^2} \times \sqrt{\sum_{i=1}^{n} (Y_i)^2}$$

where n represents the vector length (total number of words), and X_i and Y_j represent the value of each element in the MD&A text vector of firm i and the MD&A text vector of firm j, respectively. The larger the *SIM*, the smaller the angle and the greater the cosine similarity of the text.

The definitions of other variables are shown in Table 1.

5. Empirical results and discussion

5.1. Descriptive statistics

The descriptive statistics are presented in Table 2. The mean value of *Accuracy* is –0.0374, indicating that on average, the absolute value of the ratio of the earnings per share to the stock price predicted by analysts

[6] Factors such as the macroeconomic situation may affect the MD&A of both Main Board firms and Star Market firms simultaneously, thereby affecting the text similarity between the two, and these factors may also affect analysts' forecasts; accordingly, using the MD&A of Main Board firms after the establishment of the Star Market may lead to endogeneity. Therefore, we use the MD&A of Main Board firms in the fiscal year 2018, which is temporally close to but before the establishment of the Star Market.

[7] If the MD&A of the Star Market firms listed in 2019 were used to calculate the *SIM* in 2020, the treatment intensity attributable to 2019 would be absorbed. Therefore, we use the MD&A of the newly listed Star Market firms in that year and do not include the MD&A of the Star Market firms that were listed in the prior year or before.

[8] Using inverse text frequency, lower weights can be assigned to words with higher frequency and higher weights to words with lower frequency. This is based on two empirical observations: the greater the term frequency of a word in a text, the more relevant it is to the text; the more texts a word appears in, the weaker its ability to distinguish texts.

Table 1
Variable definitions.

Variable	Definition
Accuracy	The average of the absolute differences between analysts' forecasts of earnings per share and the firms' actual earnings per share, divided by the stock price; the inverse is taken.
Post	A dummy variable equal to 1 after 2019, and 0 otherwise.
Treat	See above.
Follow	The number of securities firms tracking the firms.
FCFreq	The natural logarithm of the number of analyst research reports plus 1.
Visits	The number of on-site visits by analysts.
Size	The natural logarithm of the total assets.
Lev	The total debts divided by the total assets.
ROA	The net profit divided by the total assets.
Loss	A dummy variable equal to 1 if the net profit is negative, and 0 otherwise.
Age	The number of years the company has been listed.
Media	The number of online media reports about a firm.
Stkret	The annual stock returns.
BTM	The net assets at the end of the period, divided by the market value at the end of the period.
Opacity	Manipulability accruals, calculated using the modified Jones model.
Dual	A dummy variable equal to 1 if the chairman and general manager are the same person, and 0 otherwise.
Sharehd	The shareholding ratio of the top 10 shareholders.
Inst	The shareholding ratio of institutional investors.

Table 2
Descriptive statistics.

Variables	N	Mean	SD	Min	Max
Accuracy	7,026	–0.0374	0.0564	–0.3428	–0.0002
Post	7,026	0.5000	0.5000	0.0000	1.0000
Treat	7,026	0.7650	0.1109	0.5731	1.0812
Follow	7,026	2.4672	0.8115	0.6931	3.8501
FCFreq	7,026	2.4046	1.3780	0.0000	4.9200
Visits	7,026	1.4883	1.9696	0.0000	6.4693
Size	7,026	23.1895	1.2814	20.8735	27.0987
Lev	7,026	0.4666	0.1884	0.0829	0.8845
ROA	7,026	0.0435	0.0557	–0.1876	0.2022
Loss	7,026	0.0796	0.2706	0.0000	1.0000
Age	7,026	2.5785	0.5615	0.6931	3.3673
Media	7,026	4.2683	0.8879	2.5649	7.0405
Stkret	7,026	0.0628	0.4319	–0.5563	1.8561
BTM	7,026	0.6950	0.2656	0.1401	1.2350
Opacity	7,026	0.0483	0.0494	0.0007	0.2647
Dual	7,026	0.2202	0.4144	0.0000	1.0000
Sharehd	7,026	59.4538	14.8094	26.8700	91.7200
Inst	7,026	5.3340	6.0537	0.0005	27.5994

differs from the actual situation by about 3.74%. The mean value of *Post* is 0.5000, which is because we use balanced panel data, and the mean value of *Treat* is 0.7650.

5.2. Baseline results

Table 3 presents the regression results of model (1). When no control variables are included, the coefficient of *Post* × *Treat is* 0.0654, which is significant at the 1% level. After including control variables, the coefficient of *Post* × *Treat* is 0.0525, which is also significant at the 1% level, indicating that the establishment of the Star Market is associated with improved forecast accuracy among the analysts of Main Board firms.

Table 3
Results of testing *H1*.

	(1) *Accuracy*	(2) *Accuracy*
Post × *Treat*	0.0654***	0.0525***
	(5.69)	(5.85)
Follow		–0.0186***
		(–8.62)
FCFreq		0.0145***
		(14.81)
Visits		0.0019***
		(2.94)
Size		0.0044
		(1.19)
Lev		–0.0086
		(–0.82)
ROA		0.2278***
		(6.33)
Loss		–0.0727***
		(–14.30)
Age		–0.0025
		(–0.43)
Media		–0.0036**
		(–2.16)
Stkret		–0.0129***
		(–5.76)
BTM		–0.0282***
		(–3.57)
Opacity		–0.0973***
		(–5.72)
Dual		0.0011
		(0.49)
Sharehd		0.0005***
		(3.13)
Inst		0.0005***
		(4.19)
Constant	–0.0192***	–0.1059
	(–18.64)	(–1.37)
Observations	7,026	7,026
R-squared	0.098	0.474
Firm	Yes	Yes
Year	Yes	Yes

Note: Asterisks denote the level of statistical significance: ***, $p < 0.01$; **, $p < 0.05$; *, $p < 0.1$. The t values are in parentheses.

5.3. Robustness tests

5.3.1. Parallel trend test

One important prerequisite for using the DID model is that the experimental group and the control group meet the parallel trend condition; that is, before the exogenous shock occurs, the outcome variables of the two groups should have a consistent change trend. To test whether model (1) satisfies the parallel trend assumption, we construct the following model:

$$\begin{aligned} Accuracy_{it} = {} & \beta_0 + \beta_1 Post2017_t \times Treat_i + \beta_2 Post2018_t \times Treat_i + \beta_3 Post2019_t \times Treat_i \\ & + \beta_4 Post2020_t \times Treat_i + \beta_5 Post2021_t \times Treat_i + \beta_C Control_{it} + Firm_i + Year_t + \varepsilon_{it} \end{aligned} \tag{2}$$

where *Post2017–Post2021* respectively are dummy variables representing 2017–2021; the definitions of the other variables are the same as in model (1). We focus on the regression coefficients of *Post2017* × *Treat* and *Post2018* × *Treat*. If these are not significant, then within the comparison window, the analyst forecast accuracy of Main Board firms will not be differentiated by a difference in *Treat* and the change trends will be consistent with the parallel trend condition.

The regression results of model (2) are shown in column 1 of Table 4. The coefficients of *Post2017* × *Treat* and *Post2018* × *Treat* are not significant, consistent with the expectations of the parallel trend test. In addition, the coefficients of *Post2019* × *Treat*, *Post2020* × *Treat* and *Post2021* × *Treat* are all positive and significant, and the absolute values of the coefficients exhibit a gradually increasing trend, implying a gradually increasing trend in the effect predicted in H1. This trend may be related to the growing number of firms listed on the Star Market.

5.3.2. Placebo test

A common problem affecting empirical analyses of policy consequences is that due to the complexity of the real economy and society, as well as the policy impacts covered by the research itself, firm behavior may be affected by many unobservable factors. Therefore, even if the model setting satisfies the parallel trend assumption, this does not guarantee that the empirical results are caused by policy implementation. Our results may be similarly affected. For this reason, we designed a placebo test. Generally, we select a year other than the actual year of establishment and set this as the assumed year of establishment and then conduct the same test as in model (1). If the result is not significant, then the results of model (1) do not exist without policy implementation; in other words, the placebo test is passed.

To set the macro-environment of the alternative sample as closely as possible to model (1) and obtain as sufficient a sample as possible, while ensuring that the assumed treatment window does not coincide with the actual treatment window, we use 2016, 2017 and 2018, the years the closest to the actual treatment win-

Table 4
Robustness testing.

	(1) *Accuracy*	(2) *Accuracy*	(3) *Accuracy*	(4) *Accuracy*	(5) *Accuracy*	(6) *Accuracy*	(7) *Accuracy1*
Post2017 × *Treat*	–0.0040						
	(–0.56)						
Post2018 × *Treat*	0.0030						
	(0.37)						
Post2019 × *Treat*	0.0305***						
	(2.89)						
Post2020 × *Treat*	0.0360***						
	(3.27)						
Post2021 × *Treat*	0.0621***						
	(4.76)						
Post × *Treat*		–0.0068	0.0598***				0.4300***
		(–0.95)	(5.94)				(3.99)
Post × *ChiNext*			0.0157				
			(1.64)				
Post × *Treat1*				0.0027***			
				(4.00)			
Post × *Treat2*					0.0585***		
					(5.00)		
Star						0.0280***	
						(5.79)	
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	–0.0235	0.0360	–0.1076	–0.1354*	–0.1855*	–0.1376*	2.9114***
	(–1.31)	(0.69)	(–1.39)	(–1.72)	(–1.75)	(–1.78)	(2.97)
Observations	7,026	6,840	7,026	7,026	4,752	7,026	348,654
R-squared	0.465	0.431	0.474	0.472	0.382	0.474	0.211
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Asterisks denote the level of statistical significance: ***, $p < 0.01$; **, $p < 0.05$; *, $p < 0.1$. The t values are in parentheses.

dow, as the assumed treatment window, and use 2013, 2014 and 2015 as the comparison window. We trace *Treat* in model (1) back to the time window of the placebo test; that is, *Treat* for each company remains unchanged, and only the value of *Post* is changed. The other settings are consistent with model (1). The regression results are shown in column 2 of Table 4. The coefficient of *Post* × *Treat* is not significant, indicating that the regression results of model (1) do not exist without policy implementation, and the placebo test is passed.

5.3.3. Controlling the impact of the ChiNext registration system reform

One year after the establishment of the Star Market, on 24 August 2020, the Shenzhen Stock Exchange organized the first batch of companies under the ChiNext registration system to go public. Compared with the period before the registration system reform, the listing conditions of ChiNext have undergone significant changes since the reform, including clauses without profit requirements and clauses requiring R&D performance. The ChiNext registration system reform may also result in an increase in innovative listed firms, which would produce the same effect as H1 and thus threaten our baseline results. To this end, we incorporate ChiNext-related variables into model (1): We use the same method as that used to construct *Treat* and calculate the ChiNext impact variable *ChiNext* using firms listed on ChiNext after 2020, and construct the following model:

$$Accuracy_{it} = \beta_0 + \beta_1 Post_t \times Treat_i + \beta_2 Post_t \times ChiNext_i + \beta_C Control_{it} + Firm_i + Year_t + \varepsilon_{it} \tag{3}$$

The regression results are shown in column 3 of Table 4. The coefficient of *Post* × *Treat* is positive and significant at the 1% level, indicating that the effect indicated in H1 holds even if the impact of the ChiNext registration system reform is considered.

5.3.4. Adjust the method of identifying Treat

The previous identification of *Treat* is mainly based on the MD&A similarity between Main Board firms and Star Market firms. We next adjust the method of identifying *Treat*. First, Badertscher et al. (2013) find that the number of listed companies in an industry is positively related to the industry's information environment. Therefore, the greater the number of newly listed companies in the same industry on the Star Market, the more impact Main Board analysts should have on the establishment of the Star Market. Second, we focus on the innovation information provided by the Star Market rather than on general information, allowing us to further identify the similarity of innovative texts in MD&A based on the similarity of the MD&A texts. Accordingly, we use the natural logarithm of the number of listed companies on the Star Market in the same industry plus 1 to identify the treatment intensity of the establishment of the Star Market (*Treat1*); we also determine whether a sentence comprises innovative text based on whether it contains innovative keywords, obtain the innovative text in MD&A and calculate the treatment intensity variable (*Treat2*) using the same method used to calculate *Treat1*. In model (1), *Treat* is replaced by *Treat1* or *Treat2*. The regression results are shown in columns 4 and 5 of Table 4. The coefficients of *Post* × *Treat1* and *Post* × *Treat2* are positive and significant at the 1% level.[9]

5.3.5. Using multi-period DID model

Model (1) treats the establishment of the Star Market as an exogenous shock to the DID model and constructs a firm-level treatment intensity variable, *Treat*, that does not change over time. In essence, this model assumes that the impact of Star Market firms on Main Board analysts is uniformly distributed within the treatment window. However, the number of Star Market listings fluctuates within the treatment window, and thus the information provided may not be uniformly distributed. Therefore, to ensure the robustness of the conclusion as much as possible, we treat the Star Market IPOs in each year as an exogenous shock

[9] The industry classification used to calculate *Treat1* is the 2012 version of the industry classification of the China Securities Regulatory Commission; when calculating *Treat2*, the MD&A texts of A-share listed firms from 2016 to 2021 are used as the corpus, and word2vec is used to expand the seed words "innovation" and "R&D" to obtain the following innovation keywords: technology, cutting-edge, industry-university-research, original, creation, new type, key breakthroughs, scientific research, research, development, science, patents, processes, intellectual property rights, research and development, new projects, new products and new businesses. The reduction in sample size is due to the elimination of some samples with insufficient innovative texts.

and construct a firm-year level variable of treatment intensity, *Star*, that changes over time. We then construct a multi-period DID model:

$$Accuracy_{it} = \beta_0 + \beta_1 Star_{it} + \beta_C Control_{it} + Firm_i + Year_t + \varepsilon_{it} \quad (4)$$

where $Star_{it}$ represents the impact of the IPOs of Star Market firms on Main Board firm i in fiscal year t. This measurement method is basically the same as the method previously used to measure *Treat*. It differs in that here, *Treat is* a firm-level variable, while *Star* is a firm-year level variable. The other variable definitions are consistent with model (1). The regression results of model (4) are shown in column 6 of Table 4. The coefficient of *Star* is positive and significant at the 1% level, which is in line with the expectations of H1.

5.3.6. Test at the analysis report level

Some studies use the data structure at the analysis report level when testing the factors influencing analysts' forecasts. As our main explanatory variable is a firm- or firm-year level variable, the firm-year level variable (*Accuracy*) is used in model (1). To ensure robustness, we also include the analysis report level variable (*Accuracy1*):

$$Accuracy1_{ijt} = \beta_0 + \beta_1 Post_t \times Treat_i + \beta_C Control_{ijt} + Firm_i + Year_t + \varepsilon_{ijt} \quad (5)$$

where *Accuracy1* represents the absolute value of the difference between analysts' predicted earnings per share and the actual earnings per share, which is calculated as the inverse of the difference after dividing by the stock price. The definitions of the other variables are consistent with model (1). The regression results of model (5) are shown in column 7 of Table 4. The coefficient of *Post* × *Treat* is positive and significant at the 1% level, which is also in line with the expectations of H1.

6. Further analysis

6.1. Cross-sectional analysis

We argue that the logical chain of H1 contains three influencing factors. First, the premise that the Star Market provides incremental innovation information is that before the establishment of the Star Market, the Main Board restricted the listing threshold for innovation firms' IPOs. The stronger this restriction, the stronger the innovation information spillover effect caused by the establishment of the Star Market would be. Second, because the incremental information provided by the Star Market has distinct attributes of scientific and technological innovation, the affected Main Board firms should mainly be firms with strong innovation characteristics. Third, the greater the demand of information users for innovation information provided by Main Board firms, the greater the impact of the incremental innovation information provided by the Star Market on these users' decision-making. We conduct a cross-sectional analysis to address these three factors.

6.1.1. Extent to which the listing threshold is lowered

One of the premises of H1 is that the Star Market has lowered the listing threshold for innovative enterprises. As mentioned in the institutional background section, the traditional financial indicators of Star Market firms are significantly worse than those of Main Board firms in the year of listing. The larger this gap, the greater the extent to which the establishment of Star Market has lowered the listing threshold for innovation firms and the more it helps Main Board firms utilize innovation information; that is, the effect of H1 should be stronger when this gap is larger. We test this using the following specific approach.

Based on the three financial indicators included in the Main Board listing financial conditions, namely net profit, operating income and net operating cash flow, we calculate the difference between the listing financial indicators of the Star Market firms and the Main Board firms (*Diff*). The formula is as follows:

$$Diff_i = \sum_{z=1}^{3} (MeanX_{zt} - X_{zit})$$

where i represents the Star Market firms, and t represents the listing year. X_1, X_2 and X_3 represent the net profits, operating income and net operating cash flow, respectively (all deducted by total assets). *MeanX* rep-

Table 5
Cross-sectional analysis.

	(1) Greater reduction *Accuracy*	(2) Lesser reduction *Accuracy*	(3) Innovative *Accuracy*	(4) Non-innovative *Accuracy*	(5) Greater needs *Accuracy*	(6) Lesser needs *Accuracy*
Post × *Treat*	0.0601***	0.0387**	0.0573***	0.0302**	0.0736***	0.0296**
	(5.13)	(2.31)	(4.93)	(2.25)	(5.96)	(2.32)
Difference		0.0214*		0.0271*		–0.0440***
P-value		0.08		0.06		0.000
Control	Yes	Yes	Yes	Yes	Yes	Yes
Constant	–0.1938*	–0.0594	–0.0454	–0.2028**	0.0273	–0.1919*
	(–1.80)	(–0.54)	(–0.43)	(–2.03)	(0.24)	(–1.69)
Observations	3,558	3,468	3,679	3,347	3,558	3,468
R-squared	0.495	0.462	0.465	0.473	0.458	0.497
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes

Note: Asterisks denote the level of statistical significance: ***, p < 0.01; **, p < 0.05; *, p < 0.1. The t values are in parentheses.

resents the mean of *X* for all newly listed Main Board firms in that year. Obviously, the larger the value of *Diff*, the stronger the effect of the Star Market in terms of lowering the listing threshold. Subsequently, using *SIM* as the weight, *Diff* is "mapped" to the Main Board firm level[10]:

$$Threshold_i = 1/n\sum_{j=1}^{n} Diff_j * SIM_{ij}$$

where *i* represents a Main Board firm, *j* represents a Star Market firm, *n* represents the number of Star Market firms and *Threshold* represents the degree to which the Star Market reduces the listing threshold. Finally, according to whether *Threshold* is above or below the industry median, the full sample is divided into two sub-samples having either a greater or lesser reduction in listing thresholds (greater or lesser reduction, respectively).

The regression results of model (1), run using the two sub-samples, are shown in columns 1 and 2 of Table 5. Compared with the lesser reduction sample, the absolute value of the coefficient of *Post* × *Treat* for the greater reduction sample is larger, and the difference is significantly different from 0 at the 10% level. This means that as the negative effect of the establishment of the Star Market on the listing threshold for innovation firms increases, its positive effect on the accuracy of analysts' forecasts for Main Board firms is strengthened, which is in line with previous expectations.

6.1.2. Innovation characteristics of Main Board firms

Another important premise of H1 is that the establishment of the Star Market provides incremental innovation information to the capital market. Here, "information" refers to innovation information rather than general information. Therefore, not all Main Board firms are affected by the establishment of the Star Market. For innovation-poor Main Board firms, the innovation information provided by the Star Market is less relevant, and its usefulness for analysts' forecasts may no longer hold or be relatively weak. We expect that the effect of H1 is stronger among innovation-focused Main Board firms.

We use the ratio of R&D investment to total assets (*RD*) to measure the innovation characteristics of enterprises. Specifically, to avoid the possible impact of the establishment of the Star Market on the R&D investment of Main Board firms, we use the ratio of Main Board firms before the establishment of the Star Market to measure innovation characteristics. Based on whether *RD* is above or below than the industry median, we divide the full sample into two sub-samples with (innovative) or without innovation characteristics (non-innovative).

[10] To conduct a cross-sectional test, it is necessary to construct a cross-sectional difference variable for Main Board firms. *Diff* is a Star Market firm-level variable and thus needs to be converted into a Main Board firm-level variable. *SIM* enables this conversion.

The regression results of model (1) using the two sub-samples are shown in columns 3 and 4 of Table 5. Compared with the non-innovation sample, the absolute value of the coefficient of $Post \times Treat$ for the innovation sample is greater, and the difference is significantly different from 0 at the 10% level. This means that the positive effect of the establishment of the Star Market on the accuracy of analysts' forecasts is stronger among Main Board firms with more prominent innovation characteristics, which is in line with previous expectations.

6.1.3. Market innovation information needs

Investors of different firms vary in their demands for innovation information. It is difficult for non-professional investors to understand when a company's innovation activities have a certain technical threshold; accordingly, innovation information disclosure is necessary. Additionally, companies are located in different information environments. When the information environment is poorer, investors need more innovation information related to the company. Investors' demand for innovation information determines the marginal benefits of firms' disclosed innovation information. The greater the demand, the greater the marginal benefits. Therefore, we expect that the effect of H1 is stronger for Main Board firms whose investors have a greater demand for innovation information.

In recent years, exchanges' online platforms have become important means of communication between investors and listed firms. By asking questions on an online platform, investors can obtain the required information directly from the managers of listed firms (Tan et al., 2016). Accordingly, we use the number of questions about innovation activities posted on the exchange network platform (deflated by the total number of questions) to measure investors' demand for innovation information from Main Board firms. Using this variable, the full sample is divided into two sub-samples with greater (greater needs) and lesser innovation information needs (lesser needs).

The regression results of model (1) for the two sub-samples are shown in columns 5 and 6 of Table 5. Compared with the lesser needs sample, the absolute value of the coefficient of $Post \times Treat$ for the greater needs sample is larger, and the difference is significantly different from 0 at the 1% level. This means that the positive effect of the establishment of the Star Market on the accuracy of analysts' forecasts is stronger when innovation information needs are greater, which is in line with previous expectations.

6.2. Transmission path analysis

According to our theoretical analysis, a possible transmission path by which the establishment of the Star Market affects the forecasts of Main Board analysts is as follows. First, since the establishment of the Star Market, the analysts of Main Board firms have paid attention to Star Market firms with similar innovation information to that of the Main Board firms they track. Second, the analysts of Main Board firms use the incremental innovation information provided by these Star Market firms to enhance their ability to produce forecasts for Main Board firms. To test the first link in the above transmission path, we construct the following model:

$$AnalyStar_{it} = \beta_0 + \beta_1 Treat_i + \beta_C Control_{it} + \varepsilon_{it} \tag{6}$$

where $AnalyStar_{it}$ indicates whether the analysts of Main Board firm i choose to follow Star Market firms in year t; the definitions of the other variables are the same as in model (1). The sample period for model (6) is 2019–2021 because analysts have had the possibility of choosing whether to track Star Market firms only since the establishment of that market. If the first link in the above transmission path holds, the coefficient of *Treat* is expected to be positive and significant.

To test the second link in the possible transmission path, we construct the firm-level variable *DumFollow*. If the analysts of a Main Board firm choose to follow Star Market firms, then *DumFollow* is assigned a value of 1 during the entire sample period of this Main Board firm; otherwise, it is assigned a value of 0. On this basis, the full sample is divided into two sub-samples comprising analysts who choose and choose not to follow Star Market firms (''Follow'' and ''Not Follow,'' respectively). If the second link in the possible transmission path holds, the regression results of model (1) should be stronger for the ''Follow'' sample and weaker or nonexistent for the ''Not Follow'' sample.

Table 6
Transmission path analysis.

	(1)	(2)	(3)
	AnalySTAR	**Follow** *Accuracy*	**Not Follow** *Accuracy*
Treat	**0.6081******		
	(6.56)		
Post **×** ***Treat***		**0.0547******	**0.0489**
		(5.13)	**(1.20)**
Control	Yes	Yes	Yes
Constant	–1.3962***	–0.2828***	0.2208
	(–5.62)	(–3.51)	(1.47)
Observations	3,513	6,114	912
R-squared	0.289	0.345	0.442
Industry	Yes	Yes	Yes
Year	Yes	Yes	Yes

Note: Asterisks denote the level of statistical significance: ***, $p < 0.01$; **, $p < 0.05$; *, $p < 0.1$. The t values are in parentheses.

The results of testing the first link are shown in column 1 of Table 6. The coefficient of *Treat* is positive and significant at the 1% level, which is in line with expectations. The results of testing the second link are shown in columns 2 and 3 of Table 6. The coefficient of *Post* × *Treat* is positive and significant only for the "Follow" sample, which is also in line with expectations.

7. Conclusions

Drawing on the establishment of China's Star Market, this paper studies whether the innovation information provided by a specific listing board can spill over to another list board. The main conclusions are as follows. (1) After the establishment of the Star Market, the accuracy of analysts' forecasts for Main Board firms with higher (but not lower) information similarity to the Star Market firms significantly improved. (2) This effect is stronger in samples with greater reductions in listing thresholds, more innovation characteristics and greater innovation information needs. (3) Since the establishment of the Star Market, analysts have tended to follow Star Market firms that have similar information to the Main Board firms they follow, which also enhances the baseline effect.

The above conclusions have three implications. First, the number of listed firms can have a positive effect on the information environment through analysts, an information intermediary that is crucial to the efficiency of the capital market. The results also show that information sources outside the tracked firm are potentially important factors affecting analysts' forecasts. Second, innovation information has both professional thresholds and confidentiality requirements; consequently, corporate innovation disclosure faces agency problems and proprietary costs, forming the so-called "innovation disclosure dilemma." Potentially, further improving the corporate listing system could fill the gap in innovative listed firms and alleviate the innovation disclosure dilemma via the overall innovation information supply of the capital market. Third, the institutional arrangement of the listing threshold for innovation companies has important economic consequences and should be treated with caution.

This paper has certain limitations. First, it mainly examines the impact of the Star Market on analysts' forecasts. However, financial forecasting is only one aspect of analyst behavior. The increase in innovation information may also affect other analyst behaviors, such as tracking target selection, field research and stock ratings. Future research may consider an expanded scope to explore these aspects. Second, this paper mainly provides evidence from the level of Main Board firms regarding how analysts' forecasts of these firms are affected by the Star Market, but does not provide analyst-level evidence. Future research may consider mining the text data of analyst research reports to explore how Main Board analysts use the increase in innovation information due to the Star Market to provide more intuitive empirical evidence.

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