

Analyst Coverage, Forecasting Bias, and Corporate Innovation: Evidence from China

Xinping MA

*School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100049,
China*

Yiru WANG

School of Finance, Nankai University, Tianjin 300071, China

Jianping LI

*School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100049,
China*

Biao SHI*

*Institutes of Science and Development, Chinese Academy of Sciences, Beijing 100190, China
E-mail: shibiao@casisd.cn*

Abstract Due to information asymmetry and strategic innovation, firms often encounter challenges related to insufficient driving forces and low-quality innovation outcomes. Analysts always act as information intermediaries who help foster the advancement of corporate innovation activities and the conversion of innovation output. This study examines the impact of analyst coverage and forecasting bias on corporate innovation, employing data from China A-shared listed firms spanning the period 2007 to 2019. We measure corporate innovation from two perspectives: Input and output. Specifically, we use the ratio of research and development (R&D) expenditure to sales as a proxy for the innovation input and the number of patent citations excluding self-citations to measure innovation output. We find that analyst coverage promotes corporate innovation, which is consistent with the “bright” side of analyst coverage. However, the positive effect of analyst coverage hinges on effectively transmitting and disclosing accurate information to investors in the capital market. Based on this, analysts’ forecasting bias includes forecasting dispersion and optimism bias. We find evidence that an increase in analysts’ forecast dispersion leads to a decrease in corporate innovation quality. Moreover, this paper presents a novel approach by employing the regression discontinuity method to examine the effect of analyst optimistic bias on firm innovation. The empirical findings reveal that overly optimistic forecasts by analysts exacerbate innovation quality. These analyses enrich the research on analyst coverage and corporate innovation, providing an empirical basis for improving the capital market with the help of analysts.

Keywords analyst coverage; forecasting bias; corporate innovation; innovation quality

Received April 21, 2023, accepted July 31, 2023

* Corresponding author

1 Introduction

The dictum “Innovate or Perish” is a guiding principle for companies seeking survival and prosperity in today’s dynamic business environment^[1]. However, investing in innovation activities is risky and has uncertain benefits^[2]. Cohen, *et al.*^[3] and Li, *et al.*^[4] found information asymmetry aggravated the negative impact on corporate innovation. Investors typically underestimate the value of firms with higher innovation activities because the capital market is information-driven^[5], and the professionalism and uncertainty of innovation operations raise the degree of information asymmetry within and outside the firm^[6], making it challenging for them to predict future earnings.

Security analysts have been considered an information intermediary in the financial markets, and they significantly change the institutional environment and corporate governance, bringing opportunities and challenges for innovation activities. The positive impact of analysts can be attributed to two functions in the market: 1) Information discovery. They expand the information set available to investors^[4] and enhance the quality of information disclosure^[7–10]. Analysts’ reports complement firm-provided disclosures, which are more valuable, especially in information asymmetry times^[11, 12]. 2) Information interpretation. Analysts possess strong earnings forecasting abilities^[13] and engage in on-site investigation, face-to-face communication with company management, or conducting conference calls to directly monitor managerial behavior^[14]. In this way, it can reduce adverse externalities, including short-termism, opportunistic behavior, and rent-seeking^[15, 16]. Analysts’ information role implies two assumptions. First, these analysts who cover the same firm are a homogeneous community^[17], and they are expected to provide consistent earnings forecasts because analysts’ disagreement is associated with earnings uncertainty^[18] and lower information transparency^[19]. Second, they issue reliable reports or reasonable recommendations, consistent with analyst forecast rationality^[20]. In addition, analysts are subject to various pressures that may distort their motivation and limit their role in corporate governance. More seriously, analysts may also issue false reports to cater to noise traders. These reports are divorced from the fundamentals of the enterprises. For example, the graphene event in 2011 (a listed company with a stock code of 000009) and the significant price fluctuations of Vanke stocks in 2016 were attributed to the false promotion and misleading by analysts, causing losses to numerous investors. Therefore, based on the logical framework of “analyst coverage — forecasting bias — corporate innovation”, we take Chinese listed companies as samples to explore the impact of analyst coverage on innovation and further examine the impact of forecasting bias (forecasting dispersion and forecasting optimism bias) on corporate innovation quality.

While some exploratory attempts have examined the impact of analyst coverage on corporate innovation, a consensus has not yet been reached. Supporters mainly emphasize the information role of analysts^[21, 22], while opponents consider the performance pressure imposed by analysts on firms^[23, 24]. Compared to the developed markets of Europe and America, the Chinese market has a late start and a relatively poor information environment^[25]. Which effect dominates is an empirical question. Previous literature mainly elaborates on and analyzes the relationship between analyst coverage and corporate innovation, with few studies exploring forecasting bias and innovation quality. Innovation quality emphasizes the effectiveness and

sustainability of innovation activities, which is a higher-level pursuit than strengthening innovation investment^[26, 27]. Accurate and objective transmission of capital market information requires analysts to fulfill their information role. In addition, existing literature investigating the impact of forecasting optimism bias has commonly employed instrumental variable methods to address endogeneity. However, it inevitably introduces sample selection bias, which affects the robustness of the results.

Based on this, we investigate the effects of analyst coverage and forecasting bias on innovation using China A-shared public firms from 2007–2019. Our findings show that analyst coverage improves corporate innovation, which is consistent with the “bright” side of analyst coverage. The positive effect is still significant even with comprehensive robustness tests (such as the instrumental variable approach, replacing the innovation variables, and firm-level fixed effect). Moreover, we explore the relationship between forecasting bias and innovation. We find evidence that an increase in analysts’ forecasting dispersion leads to a decrease in corporate innovation quality. Moreover, this paper presents a novel approach by employing the regression discontinuity method to examine the effect of analyst optimistic bias on firm innovation. The empirical findings reveal that overly optimistic forecasts by analysts exacerbate innovation quality.

Our paper contributes to the existing literature in several ways. Firstly, it helps to extend the literature on factors influencing corporate innovation. Previous studies have mainly focused on firm characteristics^[28–30] or external market environments^[31, 32] in examining their impact on firm innovation. In recent years, scholars have gradually turned their attention to the influence of analyst coverage on firm innovation. However, there remains a debate on whether analyst coverage promotes^[21, 22] or inhibits^[23, 33] firm innovation. We provide robust evidence supporting the notion that analyst coverage improves corporate innovation. Secondly, our study contributes to a deeper insight into the role of analysts in the capital market. Previous literature on analyst coverage has primarily focused on stock pricing efficiency^[34], stock price crashes^[33, 35], and information transparency^[16] but ignored the specific differences in the characteristics of analyst coverage^[11, 36]. In this study, we adopt a perspective based on firm innovation input and innovation output to examine the relationship between analyst coverage, forecast bias, and firm innovation. Thirdly, our research provides a novel approach to address the unexplored endogeneity. We creatively employ the discontinuity near earnings pressure thresholds to test the impact of analyst optimism on corporate innovation quality. Our findings are more robust and compelling than earlier studies on analyst optimism bias^[37].

2 Theoretical Analysis and Hypothesis

2.1 Analyst Coverage and Corporate Innovation

Securities analysts’ participation in the market essentially constitutes the acquisition, transmission, and absorption of information. First, analysts can collect and generate the relevant information via financial statements, conference calls and face-to-face communication with the managers. They constantly develop closer relationships with the management to obtain and produce valuable information about the firm for their clients^[38, 39]. And analysts have rich information transmission channels, such as providing earnings forecast reports, issuing recom-

mendations to investors, and expressing opinions on television, newspapers, or other media. [40] proposed limited attention, which shows that these investors are more inclined to invest in stocks that catch their attention when they have limited time and resources. Since securities analysts are competent at processing information, they can incorporate critical information from complicated financial statements and interpret them in simpler ways for investors to comprehend. Analysts' information collection skill exceeds institutional and individual investors^[13]. They always provided information about the company's current and future financial performance^[41, 42], recent corporate events, business strategies, management effectiveness, competitive landscape, and macroeconomic environment. Sun, et al.^[43] argued that analysts can act as a magnifying glass and monitor the earning management behavior^[28, 44], which can alleviate the information asymmetry between insiders and outsiders of enterprise and has a positive impact on corporate innovation. Additionally, analysts constantly used and react to incremental information not included in quarterly earnings, so their forecasts outperform time series models^[45, 46], providing important evidence for investors to make investment decisions^[47]. Zheng, et al.^[48] found analysts' earnings forecasts often contain important information on a firm's intangible assets^[49], including general investments such as R&D and advertising and the firm's labor force. Therefore, companies that obtain more analyst coverage always have a lower chance of being undervalued, which can promote corporate innovation. The preceding discussion leads to our first hypothesis.

H1: Analyst coverage promotes corporate innovation, supporting the information hypothesis.

2.2 Forecasting Bias and Corporate Innovation

2.2.1 Forecasting Dispersion and Corporate Innovation

Research report scandals frequently occur in the Chinese capital market, and whether analysts can form a clear judgment and understanding of the company's operating conditions can affect forecasting accuracy^[36]. Previous studies find the predictive and informational power of consensus target prices (e.g., [50, 51]).

Diether, et al.^[52] first put forward the measure of target price dispersion, providing evidence of a negative relationship between stock returns and the dispersion of analysts' earnings forecasts. The dispersion may come from the uncertainty of the firm's future earnings. Li, et al.^[53] also suggest the dispersion in analysts' target prices directly measures ex-ante uncertainty of stock prices and is likely a proxy of stock return risk. In this case, investors are affected by biased analysts' earnings forecasts. Their forecasts of a firm's future profitability should be similarly biased. Consistent with the risk hypothesis, when there is a significant divergence in analysts' forecastings, investors may face higher decision-making risks and require higher returns^[54], which is unfavorable for implementing corporate innovation activities.

In addition, there are persistent differences in ability and information sets across analysts. Specifically, individual analysts' forecast accuracy systematically differs for reasons including analysts' varying experiences^[55–57], brokerage house association and underwriting relationships^[58, 59], proximity to the firm^[60], lead analyst and star status categorization^[61], or work habits^[62]. Information asymmetry among analysts refers to the consistent and predictable discrepancies in ratings between analysts covering the same companies due to heterogeneity^[63, 64]. The effect of coordinating investor beliefs is weaker when there is greater disagreement among

analysts (cite), which causes information asymmetry^[65] and thus inhibits corporate innovation. The preceding discussion leads to our second hypothesis.

H2: Analyst forecasting dispersion inhibits corporate innovation.

2.2.2 Forecasting Optimism Bias and Corporate Innovation

Analysts always report optimistic forecasts^[66–68] because they want to get more nonpublic company information^[69, 70] and trading commission fees^[71, 72]. And managers also prefer favorable forecasts because these support higher capital market valuations and above-average compensation. They may limit or eliminate an analyst’s flow of information if the analyst issues unfavorable forecasts, even if these are justified. Mayew^[73] evidence presents evidence of management discrimination among analysts during earnings conference calls. Managers use discretion to discriminate among analysts by giving privileged access to meetings and allowing more favorable analysts to ask questions. Analysts’ self-selection behavior occurs when analysts decide not to release their forecasts since their information processing results in low forecasted earnings^[18]. And analysts are also likely to reduce the coverage after receiving bad news and vote with their feet^[74]. In this way, analysts generally tend to make optimistic earnings forecasts and recommendations.

Analysts’ optimism bias can easily mislead investors’ decisions because the negative information of the firms cannot be revealed quickly to outside investors, which means increasing information asymmetry between investors and corporate insiders^[75, 76]. When the accumulated negative information reaches a tipping point, it will suddenly be released to the stock market, resulting in a stock price crash^[35], which can reduce investors’ confidence and thus has a negative impact on firms’ innovation quality. Furthermore, analysts often collude with trading-oriented institutional investors when issuing optimistic forecasts, turning analysts into tools for these investors’ profitability^[77]. This collusion exacerbates speculative behavior in the capital market, undermining stock price stability. Moreover, the excessive focus of corporate management on stock prices hinders their dedication to research and development activities, ultimately reducing the quality and efficiency of corporate innovation. The preceding discussion leads to our third hypothesis.

H3: Analyst forecasting optimism bias inhibits corporate innovation.

3 Research Design

3.1 Data

The sample used in this paper includes information on China public firms from 2007 to 2019. Analyst, innovation, and financial and trading data are from the Chinese Research Data Services Platform (CNRDS) and the China Stock Market and Accounting Research Database (CSMAR). Following the innovation literature^[24], we exclude financial firms, special treatment firms, and firms with missing financial information. We winsorize the continuous variable at the 1% and 99% levels. After the above process, we obtained a sample of 18059 firm years, including 3112 firms.

3.2 Key Variables

We identify corporate innovation from two main channels. First, firms can invest in R&D

activities to increase the share of their earnings dedicated to innovation. Thus, R&D intensity (R&D expenditures scaled by Sales) can reflect the importance of innovation activities^[78]. Second, we measure innovation quality by the number of non-self-citations each patent receives in subsequent years. Analyst coverage is the main independent variable in our regressions. Lang and Lundholm^[79] believed that analyst behaviors always include analyzing the firms' fundamental information (operational and financial data, etc.) and providing earnings forecasts and investment recommendations to brokers, managers, and investors. Therefore, for each fiscal year of a firm, we take the total number of analysts as a raw measure of analyst coverage (Analysts). This measure relies on the fact that most analysts following a firm issue at least one earnings forecast for that firm before its fiscal year ending date. And our final measure of the number of analysts is Lncoverage, which is the natural logarithm of one plus the raw measure of coverage (Analysts).

Following the finance and innovation literature^[23], we control for a rich set of firm and industry characteristics likely to affect firms' innovation. The control variables include firm size (Size); profitability (ROA); asset liability ratio (Lev); market-to-book ratio (TobinQ); firm age (Age); capital expenditure scaled by total assets (Capex AT); asset tangibility (Fix AT); growth ability (Sale Growth); Herfindahl-Hirschman Index calculated as the sum of sales revenue scaled by sales (HHI) and Squared Herfindahl-Hirschman Index (HHI2). A detailed definition of all the variables used in our analysis is provided in Table 1.

Table 1 Variable definitions

Variables	Definitions
RD_Sales	R&D expenditures scaled by Sales
cites	The number of patent citations per year of a firm
Cites	Natural logarithm of one plus the number of patent citations per year of a firm
Analysts	The number of analyst coverage per year of a firm
Lncoverage	Natural logarithm of one plus the number of analysts per year of a firm
Dispersion	the standard deviation of the forecast earning of firm i in year t from analyst j divided by the stock price
EPSP	The mean value of forecast earning of firm i in year t from analyst j minus the actual earnings per share
Size	Natural logarithm of the total assets
ROA	Return on asset
Leverage	Total debt-to-total assets
TobinQ	Market-to-book ratio
Age	Number of years a firm has existed
Capex_AT	Capital expenditures scaled by total assets
Fix_AT	Fixed assets scaled by total assets
Sale_Growth	The growth rate of operating income
HHI	Industry Herfindahl index
HHI ²	The square of industry Herfindahl index

Note: This table describes definitions for all the variables constructed based on the sample of China public firms from 2007 to 2019.

3.3 Model Specification

To empirically test the effect of analyst coverage on corporate innovation, whether there are significant changes in innovation following analyst coverage increase. Based on this, we estimate the following model:

$$\text{Innovation}_{i,t+1/t+2} = \beta_0 + \beta_1 \text{Lncoverage}_{i,t} + \beta_2 \text{Control}_{i,t} + \tau_i + \mu_t + \varepsilon_{i,t}, \quad (1)$$

where $\text{Innovation}_{i,t}$ denotes the innovation activities for firm i over its fiscal year t . The reason for the dependent variable (innovation) is selected as time forward $t+n$ are as follows: Innovation is characterized by a long cycle, high uncertainty, high risk, forward-looking, and professional breakthrough. More analyst coverage can reduce information asymmetry and improve external supervision, which may promote corporate innovation. Therefore, innovation is a long-time process that inevitably exists in time lags. In addition, since the patent is counted at the end of the year, we put the innovation patent data ahead for one or more years to ensure data synchronization. $\text{Lncoverage}_{i,t}$ represents the number of analysts covering a firm in year t . The remaining variables are described in Table 1. All specifications are estimated using OLS and include industry and year-fixed effects, and standard errors are clustered at the firm level.

3.4 Descriptive Statistics

Table 2 provides descriptive statistics and the correlation matrix for all variables. As can be seen from Panel A, R&D expenditure accounted for about 4.55% of the operating income on average, with a notable variation between the minimum (0.02%) and the maximum (25.7%), which fully reflects the varying importance of R&D investment among industries and corporates. In addition, on average, a firm in our final sample receives 47 patent non-self citations per year, indicating that China's economy has entered the 'New Normal,' with the development mode shifting from high speed to high efficiency and the development driving force shifting from labor to innovation. The average of Analysts is 22, which indicates that about a firm is covered by 22 analysts in a year. And the control variables are in a reasonable range. Before regression analysis, we test the correlation between variables. Panel B of Table 2 shows the Pearson correlation coefficients. In Panel B, we find a significant positive correlation between analyst coverage and corporate innovation. Simultaneously, the correlation coefficients between variables are less than 0.4, showing no obvious multicollinearity. In addition, when considering R&D investment and patent citations as the dependent variables, the regression variance inflation factors (VIF) are 4.53 and 5.76, respectively. Notably, both VIF values are less than 10, indicating the absence of severe multicollinearity concerns within the data. Consequently, this implies that the dataset is well-suited for regression analysis, affirming the suitability of employing these variables in the empirical investigation.

Table 2 Summary statistics and correlation matrix

Panel A Descriptive statistics							
	(1)	(2)	(3)	(4)	(5)		
VARIABLES	<i>N</i>	Mean	SD	Min	Max		
RD_Sales	18,059	0.0455	0.0452	0.0002	0.2570		
cites	12,791	47.06	408.1	0	18,818		
Cites	12,791	2.1320	1.5300	0.0000	6.3440		
Analysts	18,059	22.81	19.75	1	127		
Lncoverage	18,059	2.7770	0.9620	0.6930	4.4190		
Dispresion	17,027	0.0248	0.0321	0.0000	1.0460		
EPSP	17,994	0.4026	0.4856	−0.4022	2.6029		
Size	18,059	22.110	1.2680	19.680	26.020		
ROA	18,059	0.0474	0.0626	−0.2280	0.2170		
Leverage	18,059	0.3980	0.1990	0.0502	0.8980		
TobinQ	18,059	2.9420	2.1060	0.9040	12.780		
Age	18,059	15.490	5.7790	3.0000	30.000		
Capex_AT	18,059	0.0543	0.0480	0.0002	0.2380		
Fix_AT	18,059	0.2080	0.1460	0.0021	0.7160		
Sale_Growth	18,059	0.2710	0.5030	−0.7330	1.8940		
HHI	18,059	0.1210	0.1240	0.0195	0.7770		
HHI ²	18,059	0.0300	0.0788	0.0004	0.6030		
Panel B Correlation matrix							
	RD_Sales	Cites	Lncoverage	Size	Leverage	ROA	TobinQ
RD_Sales	1						
Cites	0.067***	1					
Lncoverage	0.061***	0.195***	1				
Size	−0.284***	0.322***	0.331***	1			
ROA	0.003	0.020**	0.290***	−0.088***	−0.395***	1	
TobinQ	0.314***	−0.023**	0.033***	−0.425***	−0.384***	0.301***	1

Note: Panel A reports the descriptive statistics, such as the mean, standard deviation, and the number of observations of the variables used in our regressions. Panel B presents the correlation matrix of the key variables. The data correspond to an unbalanced panel of China public firms from 2007 to 2019. The number of observations is at the firm-year level. All variables are defined in Table 1.

4 Analyst Coverage and Corporate Innovation

We first estimate Eq.(1) using the ordinary least squares (OLS) to assess how analyst coverage affects innovation. Table 3 reports regressions of innovation variables (R&D scaled by sales; one-year-ahead and two-year-ahead patent citations) on analyst coverage and other control variables.

Table 3 Baseline regression of corporate innovation on analyst coverage

VARIABLES	(1)	(2)	(3)	(4)
	RD_Sales _{<i>i,t</i>+1}	RD_Sales _{<i>i,t</i>+2}	Cites _{<i>i,t</i>+1}	Cites _{<i>i,t</i>+2}
Lncoverage _{<i>i,t</i>}	0.0049*** (8.5056)	0.0045*** (7.3386)	0.0816*** (3.6039)	0.0945*** (3.9480)
RD_Sales _{<i>i,t</i>}			5.5835*** (8.8885)	5.5070*** (8.4697)
Size _{<i>i,t</i>}	-0.0014** (-2.1736)	-0.0012* (-1.7230)	0.5810*** (21.0464)	0.5938*** (21.1577)
Leverage _{<i>i,t</i>}	-0.0440*** (-10.9275)	-0.0373*** (-9.0189)	0.3278** (2.5484)	0.3566*** (2.5947)
ROA _{<i>i,t</i>}	-0.0903*** (-7.9307)	-0.0755*** (-5.4087)	0.9067** (2.4522)	0.8818** (2.2709)
TobinQ _{<i>i,t</i>}	0.0031*** (7.7385)	0.0034*** (8.1092)	-0.0162 (-1.5812)	0.0058 (0.5635)
Capex_AT _{<i>i,t</i>}	0.0427*** (4.2532)	0.0343*** (3.4177)	-0.1120 (-0.3175)	-0.2551 (-0.7013)
Age _{<i>i,t</i>}	-0.0004*** (-3.2948)	-0.0003*** (-2.7074)	0.0101** (2.4300)	0.0076* (1.7574)
Sale_Growth _{<i>i,t</i>}	0.0040*** (3.7052)	0.0047*** (4.1631)	-0.0057 (-0.1701)	-0.0151 (-0.4276)
Fix_AT _{<i>i,t</i>}	-0.0169*** (-4.1468)	-0.0177*** (-4.3382)	-0.2197 (-1.3301)	-0.3178* (-1.8350)
HHI _{<i>i,t</i>}	0.0017 (0.1115)	0.0055 (0.3485)	2.1026*** (2.9918)	3.0253*** (3.8136)
HHI _{<i>i,t</i>} ²	-0.0229 (-1.0828)	-0.0257 (-1.1231)	-2.4309*** (-2.7023)	-3.6722*** (-3.6263)
Constant	0.0578*** (3.5449)	0.0483*** (2.8356)	-13.3405*** (-21.1810)	-13.5128*** (-21.2092)
Ind FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	16,362	14,507	11,254	9,549
Adj- <i>R</i> ²	0.4344	0.4254	0.5329	0.5514

Note: This table reports regressions of corporate innovation variables (one-year-ahead, two-year-ahead, R&D expenditure scaled by sales and patent citations) on analyst coverage and other control variables. RD Sales is the R&D expenditures scaled by sales. Cites is the natural logarithm of one plus the number of patent citations. All variables are defined in Table 1. Each regression includes a separate intercept. We include industry fixed effects and year fixed effects. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

The coefficients estimated on Lncoverage are economically and statistically positively significant at the 1% level, suggesting a positive association between analyst coverage and future innovation input and output. Specifically, for a firm experiences an analyst coverage increase of one standard deviation, it will add the R&D expenses by about 10.57 percentage points ($0.005 * 0.962 / 0.0455$), increase patent citations by about 0.36 percentage points ($0.008 * 0.962 / 2.132$) on average. These results suggest that analyst coverage improves corporate innovation. H1 is supported.

4.1 Baseline Regression

With regard to control variables, firms with higher Tobin's Q and lower leverage are more innovative. Larger R&D expenditures are associated with more innovation output. At the same time, there are some interesting findings: When R&D expenditures scaled by sales as the dependent variable, the coefficients estimated on size and ROA are negative. On the contrary, when innovation outputs as dependent variables, the coefficients change to positive. The possible reason is that small and medium firms are more energetic in innovation, which means that policy support such as the ChiNext and the Science and Technology Innovation Board (STAR Market) encourage innovative enterprises to input more funds. However, the innovation outcomes still need to rely on the firms' scale and profitability.

4.2 Robustness Test

In the baseline regression, we find that the analyst coverage improves corporate innovation. In this section, we first conduct the instrumental variable approach to address reverse causality problems. And we find the baseline results are robust to alternative proxies for innovation activities and alternative empirical specifications.

Existing literature shows that firms with more transparent information can attract more financial analysts^[79–82]. However, this type of firm is more likely to prefer innovation activities. In this case, analyst coverage is not exogenous and may have a mixed influence on our findings. Our first identification strategy is to construct an instrument for analyst coverage and use the 2SLS approach to address the endogeneity. The ideal instrument should help capture the variation in analyst coverage that is exogenous to corporate innovation activities. As Yu^[16] argued, the size of brokerage houses, which means the number of analysts employed by brokerages usually depend on their performance or profitability, is unlikely to be related to the corporate innovation the analyst covered. Therefore, the instrumental variable is based on the number of analysts in the brokerage house owned in the benchmark year, expanding the same proportion in the following years and calculating the expected coverage each year. Furthermore, the first year in which analysts are employed in the brokerage house was chosen as the benchmark year because each has a different established time. We construct the instrumental variable as follows:

$$\text{Expcoverage}_{i,j,t} = \frac{\text{Analyst}_{j,t}}{\text{Analyst}_{j,0}} \times \text{Coverage}_{i,j,0}, \quad (2)$$

$$\text{Expcoverage}_{i,t} = \sum_{j=1}^n \text{Expcoverage}_{i,j,t}, \quad (3)$$

where $\text{Analyst}_{j,0}$ and $\text{Analyst}_{j,t}$ are the number of analysts employed by broker j in year t

and the benchmark year, respectively. $Coverage_{i,j,0}$ is the number of analysts from broker j following firm i in the benchmark year. $Expcoverage_{i,j,t}$ and $Expcoverage_{i,t}$ are the expected coverage of firm i in year t from brokerage house j and the total expected number of analysts of firm i from all the broker houses in year t , respectively. Table 4 shows the results of the IV strategy, which investigates the impact of analyst coverage on corporate innovation. Column (1) of Panel A shows the first stage regression result, the coefficient of the expected coverage ($Expcoverage$) is significantly positive at the 1% level, indicating that the instrument is highly correlated with analyst coverage ($Lncoverage$). And the Cragg-Donald Wald F statistic (75.43) is greater than the Stock-Yogo weak ID test critical value (16.38), we reject the null hypothesis that the instrument is weak. Columns (2) to (5) of Panel A show the second-stage regression results estimating the model (1) with fitted analyst coverage from the first-stage regression. The coefficients of the fitted analyst coverage are positive and significant, which is consistent with the baseline regressions.

Table 4 Robustness test

Panel A the instrumental variable approach					
	First	Second			
	(1)	(2)	(3)	(4)	(5)
VARIABLES	$Lncoverage_{i,t}$	$RD_Sales_{i,t+1}$	$RD_Sales_{i,t+2}$	$Cites_{i,t+1}$	$Cites_{i,t+2}$
$Expcoverage_{i,t}$	0.0237*** (8.68)				
$Lncoverage_{i,t}$		0.0127** (2.3972)	0.0123* (1.7127)	0.4849* (1.6463)	0.4337 (1.4523)
$RD_Sales_{i,t}$				6.3348*** (4.2561)	7.5887*** (5.0682)
Constant	-2.0512*** (-4.86)	0.1022*** (3.6096)	0.0939*** (2.7227)	-13.4795*** (-8.7949)	-13.8003*** (-8.8227)
Controls	YES	YES	YES	YES	YES
Ind FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
CD Wald F		285.553	238.376	222.177	208.116
Observations	4,338	4,338	3,307	3,157	2,780
Adj- R^2	0.31	0.5195	0.5004	0.5269	0.5348
Weak identification test	75.43 < 16.38 >				
Underidentification test	91.43 [0.0000]				

Table 4 (Continued)

Panel B Alternative innovation variables				
	(1)	(2)	(3)	(4)
VARIABLES	RD_AT _{<i>i,t+1</i>}	RD_AT _{<i>i,t+2</i>}	Grant _{<i>i,t+1</i>}	Grant _{<i>i,t+2</i>}
Lncoverage _{<i>i,t</i>}	0.0029*** (8.5337)	0.0025*** (5.9967)	0.1156*** (4.5216)	0.1367*** (4.7646)
RD_Sales _{<i>i,t</i>}			3.9377*** (6.4325)	4.1560*** (6.4257)
Constant	0.0536*** (5.8477)	0.0356*** (2.7257)	-7.5271*** (-9.4054)	-8.0197*** (-9.1728)
Controls	YES	YES	YES	YES
Ind FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	14,110	11,277	10,480	8,414
Adj- <i>R</i> ²	0.2752	0.2330	0.2380	0.2476
Panel C Firm fixed effects				
	(1)	(2)	(3)	(4)
VARIABLES	RD_Sales _{<i>i,t+1</i>}	RD_Sales _{<i>i,t+2</i>}	Cites _{<i>i,t+1</i>}	Cites _{<i>i,t+2</i>}
Lncoverage _{<i>i,t</i>}	0.0011*** (2.8678)	0.0012*** (2.6272)	0.0297* (1.8547)	0.0054 (0.2970)
RD_Sales _{<i>i,t</i>}			1.5213*** (3.8973)	1.8408*** (4.1626)
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	14,110	11,277	10,384	8,590
Firms	2,925	2,574	2,214	2,017
Adj- <i>R</i> ²	0.0482	0.0113	0.3462	0.3651

Note: Panel A reports IV 2SLS regressions of corporate innovation on analyst coverage, with expected analyst coverage (Expcoverage) as the instrumental variable. Expcoverage is the number of analysts in which the brokerage house owned in the benchmark year, expanding the same proportion in the following years and then calculating the expected coverage in each year. All variable definitions are provided in Table 1. All specifications include industry and year fixed effects. The robust standard errors, clustered at the firm level, are displayed in parentheses. *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively.

We also measure innovation using alternative proxies. Specifically, we employ the R&D expenditure scaled by assets to measure innovation input. Regarding innovation output, we use granted patents to measure innovation quality rather than patent citations in the benchmark regression. The coefficients in Panel B of Table 4 are significantly positive, which means the

analyst coverage improves corporate innovation.

In addition, we also conducted our analyses using the fixed effect model. After controlling for firm-level fixed effects, the results shown in Panel C of Table 4 remain robust and consistent with the findings of the benchmark regression.

5 Forecasting Bias and Corporate Innovation

The previous section shows that analyst coverage can promote corporate innovation activities. It seems clear that increasing R&D and patent citations result from security analysts conveying the information along various dimensions. However, whether analysts provide objective and accurate information is related to affect the innovation activities. According to existing research, analysts' suggestions contribute to market value in an imperfect capital market because of their specific skills in gathering and assessing value-relevant information^[83]. And analysts can facilitate the valuation process by translating a mixture of public and private information into forecasts of future earnings, which could affect company innovation. For example, suppose analysts accurately communicate information about a company's innovative activities to other financial market participants (especially investors) and help them understand the true value of these long-term investments. In that case, the company's management will not endeavor to speed up the innovation process. Based on the above discussions, we propose that analyst forecast accuracy shows lower disagreement among analysts and is closer to the real earnings^[37].

5.1 Forecasting Dispersion and Corporate Innovation

Analyst forecasts exist heterogeneity due to their different information sources and forecast methods. The strategic deviation hypothesis assumes that forecast errors impose limited costs on analysts. They strategically issue bold forecasts deviating from their peers to gain greater public attention^[64, 84]. On the contrary, the relative performance evaluation method suggests that analyst bonuses and career prospects are chiefly determined by forecasts relative to their peers. And [85] showed that an analyst is more likely to turn over if his forecast accuracy is lower than his peers. Barinov^[86] concluded that firms with high dispersion of analyst forecasts earn low future returns. More specifically, low dispersion indicates that analysts have reached a consensus about the covered firms, and high dispersion illustrates that the target firm's future earnings are unpredictable. To some extent, analysts' behavioral consistency reflects the information overlap. Analysts collect the more similar information, the more consistent the earnings forecasts are. Based on this, we believe that the consensus prediction can convey a certain signal to the capital market, produce an anchoring effect, increase information transparency, and thus create a good external environment for high-quality innovation activities.

Following Wang, et al.^[64], we construct the analyst dispersion ($\text{Dispersion}_{i,t}$) variable as follows:

$$\text{Dispersion}_{i,t} = \frac{\text{Sd}(\text{ForecastEPS}_{i,j,t})}{P_{i,t}}, \quad (4)$$

where $\text{ForecastEPS}_{i,j,t}$ is the forecast earnings of firm i in year t from Analyst $_i$. $\text{Sd}(\text{Forecast}_{i,j,t})$ is the standard deviation of $\text{ForecastEPS}_{i,j,t}$. $P_{i,t}$ is the closing price of firm i in year t . And the larger value of $\text{Dispersion}_{i,t}$ represents greater analyst dispersion.

Table 5 reports the OLS regression results regarding the innovation input and output. The first two columns report the effects of analyst dispersion on the R&D expenses one and two years forward. We find the coefficients of analyst dispersion in Columns (1) and (2) are negative but insignificant. The possible reasons are as follows: Firstly, research and development (R&D) investments serve as the fundamental driving force behind firm development, which makes investment decisions sensitive to industry prospects and long-term strategy planning rather than being easily influenced by short-term market forecasts fluctuations^[87]. Even if analysts have significant disagreements about future performance, firms may persist in their long-term R&D strategies and are unlikely to alter the scale and direction of their R&D investments. Secondly, firms may possess crucial information and insights that analysts cannot access, leading to a greater reliance on internal judgment for R&D investments, thereby minimizing the direct impact of external analyst forecast dispersion.

Table 5 Forecasting dispersion and corporate innovation

VARIABLES	(1) RD_Sales _{t+1}	(2) RD_Sales _{t+2}	(3) Cites _{t+1}	(4) Cites _{t+2}
Dispersion _{i,t}	-0.0055 (-0.4078)	-0.0011 (-0.0703)	-2.1802*** (-3.5704)	-2.5447*** (-3.6118)
RD_Sales _{i,t}			6.1644*** (9.4458)	6.1172*** (8.9058)
Constant	0.0337* (1.8519)	0.0185 (0.8487)	-14.2670*** (-21.5645)	-14.3115*** (-20.7847)
Controls	YES	YES	YES	YES
Ind FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	13,617	10,952	10,093	8,355
Adj_R ²	0.4327	0.4209	0.5394	0.5589

Note: This table reports regressions of corporate innovation variables (one-year-ahead, two-year-ahead, R&D expenditure scaled by sales and patent citation) on analyst dispersion and other control variables. All variables are defined in Table 1. Each regression includes a separate intercept. We include industry fixed effects and year fixed effects.

***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

Columns (3) and (4) report the effects of analyst dispersion on the patent citations one and two years forward. The results show that the coefficients of analyst dispersion are negative and statistically significant at the 1% level, and the statistical significance is explained as analyst coverage increased by 1%, resulting in a 2.18% (2.54%) decrease in patent citations for firm i in year $t + 1$ ($t + 2$). The economic significance of coefficients suggests that a firm experiencing a one standard deviation increase in analyst dispersion will decrease the patent citations by about 3.3 percentage points ($-2.2 * 0.0321/2.132$). The possible reasons are as follows: Firstly, Krishnaswami and Subramaniam^[88] highlight analyst forecast dispersion as a proxy for information asymmetry. The dispersion among analysts implies increased uncertainty and risk for firms, which leads to a decrease in information transparency between firms and

capital markets, ultimately affecting resource allocation decisions. Consequently, firms may allocate fewer resources toward supporting high-quality innovation. Secondly, analyst forecast disagreement may impose market pressure on firms. Therefore, firms may engage in value-detracting investment behaviors, ultimately decreasing the innovation quality. Lastly, The dispersion among analysts can divert firms' attention away from innovation activities. Rather than prioritizing quality, firms may become overly concerned with meeting the quantifiable analysts' expectations, leading to a decline in patent quality, supporting H2.

5.2 Forecasting Optimism Bias and Corporate Innovation

Under the information asymmetry between analysts and brokers in the capital market, stock analysts always suffer from optimism since they announce earnings forecasts bigger than the real earnings because of personal reputation and career concerns^[89]. For example, analysts tend to stop issuing forecasts instead of low earnings forecasts when they have negative opinions of the stocks. In terms of information supply, security analysts are unable to comprehend all of a company's information. Therefore, they prefer to provide optimistic earnings forecasts and positive recommendations. The prevalent practice of positive earnings management and window dressing in reported earnings might cause analyst forecasts to be optimistic when it comes to information demand. An extensive body of literature has been dedicated to investigating the phenomenon of analysts' forecasting biases and their implications. Analysts, as information gatherers and processors in capital markets, play a crucial role in shaping the information flow. However, it is imperative to acknowledge that biased forecastings made by analysts have the potential to mislead investors and undermine the efficiency of forecast information. In terms of the motivations behind the forecasting bias, economic incentives^[90], managerial constraints^[69], and cognitive biases^[91] contribute to analyst forecasting bias. Regarding the economic consequences, Michaely and Womack^[92] emphasize the significance of forecasting bias in shaping asset valuation. Moreover, Fuller and Jensen^[93] argued that analysts' overly optimistic earnings forecasts create pressure on company management, which may result in value-detrimental investment behavior. Guo, et al.^[23] first uncovered a discontinuity in the likelihood of decreasing R&D expenditures around an earnings pressure threshold, and then we exploit this discontinuity to test whether cutting R&D expenses has a causal effect on firms' innovation outcomes.

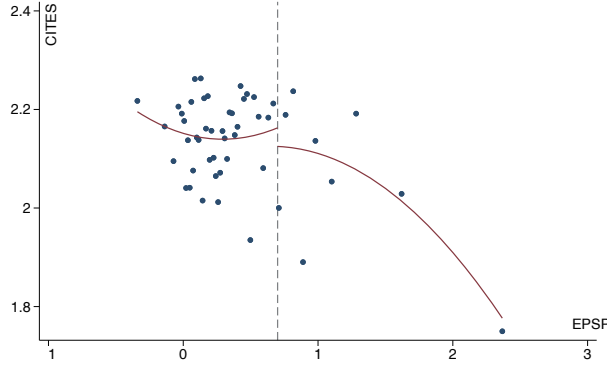
However, the current research still has some shortcomings: In terms of forecasting bias definition, few studies have considered the sample self-selection and the distribution of forecasting bias. Specifically, there are two asymmetric distributions within analyst forecasting bias: Tail asymmetry, where extreme negative bias is more prevalent than extreme positive bias, and middle asymmetry, where slight positive bias are more prevalent than slight negative bias. The asymmetry in sample distribution results in variations in research outcomes depending on the weights assigned to different observations. Regression discontinuity design, by utilizing specific thresholds of independent variables to divide the sample and compare the observation around the threshold, thereby mitigating the influence of sample selection bias. Furthermore, there exists heterogeneity in the impact of optimistic and non-optimistic forecasting bias on corporate innovation, implying that the relationship between analyst forecasting bias and corporate innovation is not simply linear. Therefore, regression discontinuity design can provide more ac-

curate estimate results under conditions of local heterogeneity. Based on this, we consider the sample distribution of analyst forecasting bias and employ the regression discontinuity design to examine the impact of optimistic forecast bias on corporate innovation.

Following Guo, et al.^[23] and Dong, et al.^[37], we construct the optimism bias variable ($EPSP_{i,t}$) as follows:

$$EPSP_{i,t} = \text{mean}(\text{ForecastEPS}_{ijt}) - \text{EPS}_{i,t}, \quad (5)$$

where $\text{mean}(\text{ForecastEPS}_{ijt})$ is the mean forecast earnings per share of firm i in year t from analyst j . $\text{EPS}_{i,t}$ is the actual earnings per share. The optimism bias ($EPSP_{i,t}$) is right-skewed, the samples with $EPSP$ bigger than 0 are far more than those with $EPSP$ smaller than 0, which supports that analysts generally make optimistic forecasts. Therefore, we take 0.7 (80% quantile) as the threshold. When $EPSP > 0.7$ is considered an optimistic forecast, we define $\text{Optimum} = 1$; while $EPSP \leq 0.7$ is considered as a reasonable forecast and $\text{Optimum} = 0$. Figure 1 suggests the presence of a discontinuity in firms' patent citations around the $EPSP = 0.7$ threshold. We find that analyst optimistic forecasts lead to the patent citations decline.



Note: This figure plots the patent citations by the end of the fiscal year as a function of $EPSP$ measured by the distance between analysts' consensus forecasts and the actual firms' EPS. For every $EPSP$ bin, the dots represent the natural logarithm of one plus the number of patent citations per year of a firm. The lines are second-order polynomials fitted through the estimated probabilities on each side of the $EPSP = 0.7$ threshold.

Figure 1 Forecasting optimism bias and innovation quality

Specifically, we uncover a discontinuity ($EPSP$ 80th percentile) depicted in Figure 1 and examine the effect of analyst forecasting bias and corporate patent citations. The findings reveal that overly optimistic forecasts by analysts lead to a decline in innovation quality. The estimation of Regression Discontinuity Design can be approached through two methods: Parametric and non-parametric. In this study, we adopt the parametric approach. Drawing upon the methodology proposed by Imbens and Kalyanaraman^[94] for estimating local treatment effects in Regression Discontinuity Design, we construct the following parametric model:

$$\text{Cites}_{i,t+n} = \beta_0 + \beta_1 \text{optimum}_{i,t} + \beta_2 EPSP_{i,t} + \beta_3 EPSP_{i,t}^2 + \beta_4 \text{Control}_{i,t} + \tau_i + \mu_t + \varepsilon_{i,t}, \quad (6)$$

where $(c - h) < EPSP < (c + h)$. Where h is the optimal bandwidth. The dependent variable

is the patent citations selected as time forward $t + n$, Optimum is an indicator variable equal to one for firms with EPSP > 0.7; those analysts generally make optimistic forecasts.

The choice of bandwidth (h) is correlated with the results. A smaller bandwidth (h) leads to a smaller bias but a larger variance, while a larger bandwidth (h) results in a smaller variance but a larger bias. In this study, we adopt the method proposed by Imbens and Kalyanaraman^[94] based on data-driven local density. The optimal bandwidth is selected by minimizing the mean squared error (MSE) at the cutoff of two equation specifications. The optimal bandwidth is presented in Table 6. For a cutoff value of 0.7, the optimal bandwidth is 0.407.

Therefore, we examine the impact of analyst optimism bias on innovation quality under the 0.407 optimal bandwidth. Table 7 reports the results of regression (6). The coefficients on Optimum are negative and statistically significant at the 5% level, which shows that analysts' optimistic earnings forecasts have a negative impact on innovation quality and prove that the improvement of innovation quality needs analysts' accurate forecasts. Innovation involves a long process full of uncertainty and exclusivity. If analysts continue to issue overly optimistic

Table 6 The selection of optimal bandwidth

Cutoff = 0.7	Left of cutoff	Right of cutoff
BW est.(h)	0.407	0.407
BW bias.(b)	0.561	0.561
Rho(h/b)	0.725	0.725

Table 7 Forecasting optimism bias and corporate innovation

	(1)	(2)	(3)
VARIABLES	Cites _{t+1}	Cites _{t+1}	Cites _{t+1}
Optimum _{i,t}	-0.06675 (-1.03)	-0.12914** (-2.13)	-0.10360** (-2.07)
EPSP _{i,t}	0.15913* (1.84)	0.44129*** (5.22)	-0.11393 (-1.41)
EPSP _{i,t} ²	0.05052 (1.11)	-0.12327*** (-2.85)	0.03206 (0.79)
Constant	2.10905*** (88.61)	-7.09816*** (-21.45)	-13.79395*** (-21.16)
Controls	NO	YES	YES
Ind FE	NO	NO	YES
Year FE	NO	NO	YES
Observations	10,359	10,359	10,359
Adj- R^2	0.003	0.127	0.526

Note: This table reports regression results of the innovation quality, defined as patent citations on analyst optimism bias. All variables are defined in Table 1. We include industry fixed effects and year fixed effects. ***, ** and * indicate significance at the 1%, 5%, and 10% level, respectively.

forecasts that fail to appropriately reflect a company's true value and express it to the capital market, investors will confront increasing information constraints, which will negatively impact innovation quality. H3 is supported.

The Regression Discontinuity Design should satisfy three requirements^[95]. First, we examine whether there is a significant decrease in firm patent quality around the “cutoff” of analyst optimism bias. Second, it is necessary to eliminate the interference of other factors and examine the continuity of control variables near the “cutoff”. Third, we investigate whether individuals can actively manipulate the estimation results.

Firstly, we examine whether there is a noticeable discontinuity in the dependent variable (patent citations) around the “cutoff” of analyst optimism bias. The results from Fig. 1 indicate a significant downward jump in patent quality at the “cutoff”, suggesting that analyst optimism forecasts can decrease the innovation quality. These findings also demonstrate that the “cutoff” associated with analyst optimism serves as a valid indicator of the evident relationship with $(EPSP_{i,t} = \text{mean}(\text{ForecastEPS } S_{ijt}) - EPS_{i,t})$ variables. Therefore, it is appropriate to conduct the Regression Discontinuity Design method to identify the relationship between analysts' optimism bias and innovation quality.

Secondly, to ensure that the decrease in patent quality can be attributed to optimism bias, Figure 2 examines the “cutoff” effects of other control variables (Size, Capex, ROA, TobinQ). The results indicate no significant discontinuity is observed in the other control variables at the cutoff, thus meeting the robust test.

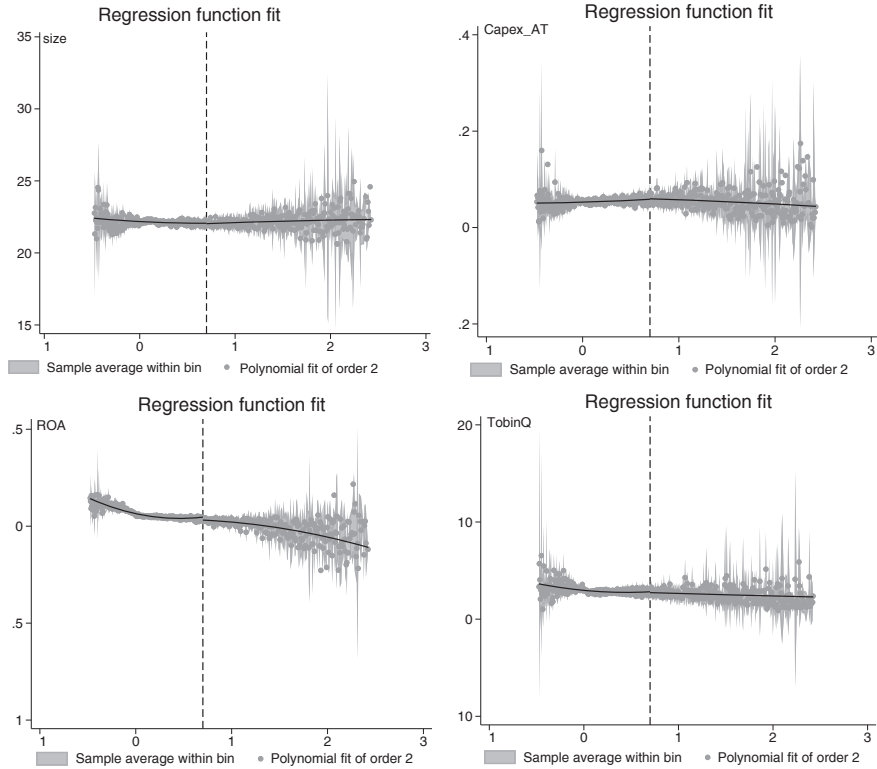


Figure 2 The “cutoff” effects of other control variables (Size, Capex, ROA, TobinQ)

Thirdly, we conduct the following tests to examine the individual manipulation near the cutoff. Firstly, The histogram Figure 3 indicates a continuous around the threshold of 0.7 for analyst optimism bias, with no apparent cutoff. Secondly, Figure 4 shows a density continuity test of the driving variable (EPSP), following the method proposed by McCrary^[96]. The results show no significant differences in the density functions of analyst optimism bias on both sides of the cutoff.

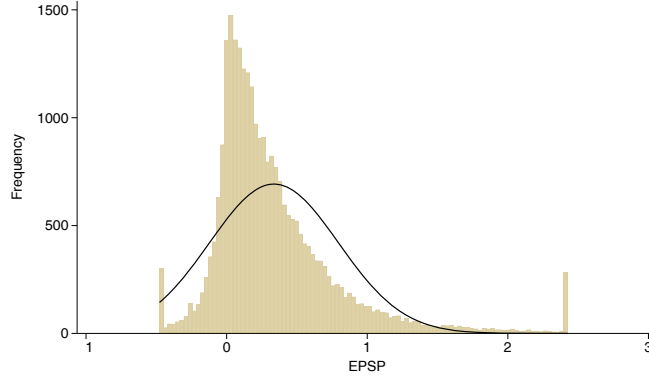


Figure 3 EPSP histogram

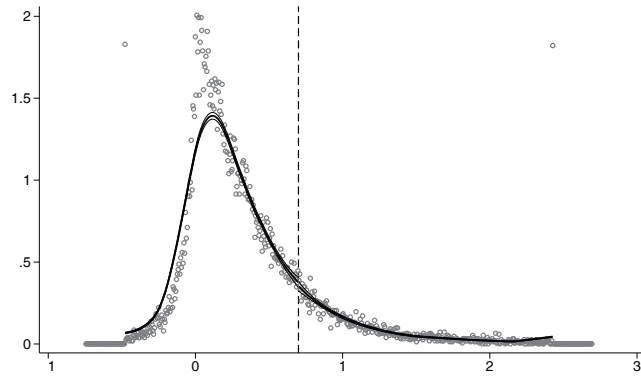


Figure 4 Density distribution of EPSP

6 Conclusion

China is the world's second-largest economy, actively pursuing economic transformation and innovation-driven development strategies. Meanwhile, China's capital market has undergone a remarkable transformation and is progressing toward a multi-level capital market. As crucial participants in the capital market, securities analysts have changed the corporate governance environment and introduced new opportunities and challenges for corporate innovation activities. We focus on the 2007–2019 Chinese A-share listed firms to study the role of analyst coverage and forecasting bias in corporate innovation by using ordinary least squares regression and regression discontinuity from the perspectives of “input” and “output”. Firstly, we find evidence that firms followed by more analysts are more likely to increase their R&D expenditure and patent citations, which provides evidence of their information hypothesis. The positive effects still exist after a series of robustness tests (Instrumental variables approach, replacing

the dependent variables, and fixed effect model). Secondly, the innovation quality is affected by analysts' disagreement. It is only when there is lower disagreement among analysts, particularly the analysts who cover the same company release consensus forecasts, can it reflect the firm value and motivate anchoring effects^[97], thereby improving the innovation quality. Thirdly, analyst optimistic bias can reduce the innovation quality. Specifically, this paper takes a different perspective and explores the threshold of optimistic bias through regression discontinuity, where the difference between analysts' predicted earnings per share and the actual earnings per share exceeds the 80th percentile. After a series of placebo tests, the results prove the rationality of using the 80th percentile as the threshold for defining analyst optimistic bias. Furthermore, the analysis reveals that optimistic bias in analyst forecasting has a negative impact on the quality of firm innovation.

Furthermore, our findings have important practical implications. The securities analyst industry has experienced an initial nascent stage followed by rapid development, and it has now reached a stage where specialization has become increasingly refined. Analysts have significantly changed the corporate governance environment, thereby playing the information and monitoring role in corporate innovation. Based on this study, we propose the following suggestions for enterprises, securities analysts, and investors to improve corporate innovation and purify the investment environment in the capital market. Firstly, the baseline results indicate that analyst coverage can play an information and monitoring role in corporate innovation. Therefore, improving information transparency requires firms to take diversified incentive measures to disclose corporate governance information and pay more attention to exchanging information with analysts (increasing the frequency of telephone communication and on-site interviews with analysts) to realize information communication and complementarity. Secondly, analysts forecasting bias can lead investors to confront increasing information constraints, which negatively impacts innovation quality. Analysts should issue reasonable recommendations and suggestions combined with the firm's conditions and avoid blind optimism. Lastly, it is crucial for investors to adhere to the principles of value investing and avoid "herd behavior". In this way, they can mitigate the influence of analysts' overly optimism and optimize the investment environment in the Chinese capital market.

References

- [1] Chkir I, Hassan B E H, Rjiba H, et al. Does corporate social responsibility influence corporate innovation? International evidence. *Emerging Markets Review*, 2021, 46: 100746.
- [2] Cheah S L Y, Yuen-Ping H O. Commercialization performance of outbound open innovation projects in public research organizations: The roles of innovation potential and organizational capabilities. *Industrial Marketing Management*, 2021, 94: 229–241.
- [3] Cohen L, Diether K, Malloy C. Misvaluing innovation. *The Review of Financial Studies*, 2013, 26(3): 635–666.
- [4] Li K. Does information asymmetry impede market efficiency? Evidence from analyst coverage. *Journal of Banking & Finance*, 2020, 118: 105856.
- [5] Chen W, Zhang L, Jiang P, et al. Can digital transformation improve the information environment of the capital market? Evidence from the analysts' prediction behaviour. *Accounting & Finance*, 2022, 62(2): 2543–2578.
- [6] Jia N. Corporate innovation strategy and disclosure policy. *Review of Quantitative Finance and Accounting*, 2019, 52(1): 253–288.

- [7] Derrien F, Kecskés A, Mansi S A. Information asymmetry, the cost of debt, and credit events: Evidence from quasi-random analyst disappearances. *Journal of Corporate Finance*, 2016, 39: 295–311.
- [8] Dyck A, Morse A, Zingales L. Who blows the whistle on corporate fraud? *The Journal of Finance*, 2010, 65(6): 2213–2253.
- [9] Yao S, Liang H. Analyst following, environmental disclosure and cost of equity: Research based on industry classification. *Sustainability*, 2019, 11(2): 300.
- [10] Zhu L, Chen Q, Yang S, et al. The role of analysts in negative information production and disclosure: Evidence from short selling deregulation in an emerging market. *International Review of Economics & Finance*, 2021, 73: 391–406.
- [11] Hsieh S J, Su Y. The effect of financial analysts on the economic implications of disclosed lease information—a note. *Journal of Applied Accounting Research*, 2022, 23(2): 340–361.
- [12] Loh R K, Stulz R M. Is sell-side research more valuable in bad times? *The Journal of Finance*, 2018, 73(3): 959–1013.
- [13] Huang A H, Zang A Y, Zheng R. Evidence on the information content of text in analyst reports. *The Accounting Review*, 2014, 89(6): 2151–2180.
- [14] Han M, Lin H, Sun D, et al. The eco-friendly side of analyst coverage: The case of green innovation. *IEEE Transactions on Engineering Management*, 2022, 71: 1–16.
- [15] Lin Z, Wang L. Analyst following, financial constraint, and audit opinion shopping: From the perspective of earning management. *Journal of International Financial Management & Accounting*, 2023, 34(1): 71–96.
- [16] Yu F F. Analyst coverage and earnings management. *Journal of Financial Economics*, 2008, 88(2): 245–271.
- [17] Dische A. Dispersion in analyst forecasts and the profitability of earnings momentum strategies. *European Financial Management*, 2002, 8(2): 211–228.
- [18] Wu L, Long Y, Li W, et al. Analysts’ disagreement, self-selection, and stock returns. *Journal of Business Economics and Management*, 2023, 24(1): 37–53.
- [19] Gao J, Chu D, Zheng J, et al. Environmental, social and governance performance: Can it be a stock price stabilizer? *Journal of Cleaner Production*, 2022, 379: 134705.
- [20] Hou D, Meng Q, Chan K C. Does short selling reduce analysts’ optimism bias in earnings forecasts? *Research in International Business and Finance*, 2021, 56: 101356.
- [21] Bai G, Li T, Xu P. Can analyst coverage enhance corporate innovation legitimacy? — Heterogeneity analysis based on different situational mechanisms. *Journal of Cleaner Production*, 2023, 405: 137048.
- [22] Fiorillo P, Meles A, Mustilli M, et al. How does the financial market influence firms’ Green innovation? The role of equity analysts. *Journal of International Financial Management & Accounting*, 2022, 33(3): 428–458.
- [23] Guo B, Pérez-Castrillo D, Toldrà-Simats A. Firms’ innovation strategy under the shadow of analyst coverage. *Journal of Financial Economics*, 2019, 131(2): 456–483.
- [24] He J J, Tian X. The dark side of analyst coverage: The case of innovation. *Journal of Financial Economics*, 2013, 109(3): 856–878.
- [25] Piotroski J D, Wong T J, Zhang T. Political incentives to suppress negative information: Evidence from Chinese listed firms. *Journal of Accounting Research*, 2015, 53(2): 405–459.
- [26] Nowacki C, Monk A. Ambidexterity in government: The influence of different types of legitimacy on innovation. *Research Policy*, 2020, 49(1): 103840.
- [27] Villani E, Linder C, Lechner C, et al. How do non-innovative firms start innovation and build legitimacy? The case of professional service firms. *Journal of Business Research*, 2021, 137: 614–625.
- [28] Chen Y, Wang Y, Nevo S, et al. IT capabilities and product innovation performance: The roles of corporate entrepreneurship and competitive intensity. *Information & Management*, 2015, 52(6): 643–657.
- [29] Lin C, Lin P, Song F M, et al. Managerial incentives, CEO characteristics and corporate innovation in China’s private sector. *Journal of Comparative Economics*, 2011, 39(2): 176–190.
- [30] Yuan R, Wen W. Managerial foreign experience and corporate innovation. *Journal of Corporate Finance*, 2018, 48: 752–770.
- [31] Cornaggia J, Mao Y, Tian X, et al. Does banking competition affect innovation? *Journal of Financial Economics*, 2015, 115(1): 189–209.
- [32] He F, Ma Y, Zhang X. How does economic policy uncertainty affect corporate innovation? — Evidence

- from China listed companies. *International Review of Economics & Finance*, 2020, 67: 225–239.
- [33] Kim J B, Lu L Y, Yu Y. Analyst coverage and expected crash risk: Evidence from exogenous changes in analyst coverage. *The Accounting Review*, 2019, 94(4): 345–364.
 - [34] Israelsen R D. Does common analyst coverage explain excess comovement? *Journal of Financial and Quantitative Analysis*, 2016, 51(4): 1193–1229.
 - [35] Xu N, Jiang X, Chan K C, et al. Analyst coverage, optimism, and stock price crash risk: Evidence from China. *Pacific-Basin Finance Journal*, 2013, 25: 217–239.
 - [36] Huang L, Li W, Wang H, et al. Stock dividend and analyst optimistic bias in earnings forecast. *International Review of Economics & Finance*, 2022, 78: 643–659.
 - [37] Dong R, Fisman R, Wang Y, et al. Air pollution, affect, and forecasting bias: Evidence from Chinese financial analysts. *Journal of Financial Economics*, 2021, 139(3): 971–984.
 - [38] Green T C, Jame R, Markov S, et al. Access to management and the informativeness of analyst research. *Journal of Financial Economics*, 2014, 114(2): 239–255.
 - [39] Soltes E. Private interaction between firm management and sell-side analysts. *Journal of Accounting Research*, 2014, 52(1): 245–272.
 - [40] Aboody D, Lehavy R, Trueman B. Limited attention and the earnings announcement returns of past stock market winners. *Review of Accounting Studies*, 2010, 15(2): 317–344.
 - [41] Lui D, Markov S, Tamayo A. What makes a stock risky? Evidence from sell-side analysts' risk ratings. *Journal of Accounting Research*, 2007, 45(3): 629–665.
 - [42] Lui D, Markov S, Tamayo A. Equity analysts and the market's assessment of risk. *Journal of Accounting Research*, 2012, 50(5): 1287–1317.
 - [43] Sun J, Liu G. Does analyst coverage constrain real earnings management? *The Quarterly Review of Economics and Finance*, 2016, 59: 131–140.
 - [44] Bradley D, Gokkaya S, Liu X. Before an analyst becomes an analyst: Does industry experience matter? *The Journal of Finance*, 2017, 72(2): 751–792.
 - [45] Brown L D, Rozeff M S. The superiority of analyst forecasts as measures of expectations: Evidence from earnings. *The Journal of Finance*, 1978, 33(1): 1–16.
 - [46] Fried D, Givoly D. Financial analysts' forecasts of earnings: A better surrogate for market expectations. *Journal of Accounting and Economics*, 1982, 4(2): 85–107.
 - [47] Jegadeesh N, Kim J, Krische S D, et al. Analyzing the analysts: When do recommendations add value? *The Journal of Finance*, 2004, 59(3): 1083–1124.
 - [48] Zheng X, Yang Y, Shen Y. Labor protection, information disclosure and analyst forecasts: Evidence from China's Labor Contract Law. *China Journal of Accounting Research*, 2022, 15(3): 100251.
 - [49] Barth M E, Kasznik R, McNichols M F. Analyst coverage and intangible assets. *Journal of Accounting Research*, 2001, 39(1): 1–34.
 - [50] Da Z, Schaumburg E. Relative valuation and analyst target price forecasts. *Journal of Financial Markets*, 2011, 14(1): 161–192.
 - [51] Da Z, Hong K P, Lee S. What drives target price forecasts and their investment value? *Journal of Business Finance & Accounting*, 2016, 43(3–4): 487–510.
 - [52] Diether K B, Malloy C J, Scherbina A. Differences of opinion and the cross section of stock returns. *The Journal of Finance*, 2002, 57(5): 2113–2141.
 - [53] Li X, Feng H, Yan S, et al. Dispersion in analysts' target prices and stock returns. *The North American Journal of Economics and Finance*, 2021, 56: 101385.
 - [54] Doukas J A, Kim C F, Pantzalis C. Divergence of opinion and equity returns. *Journal of Financial and Quantitative Analysis*, 2006, 41(3): 573–606.
 - [55] De Franco G, Zhou Y. The performance of analysts with a CFA® designation: The role of human-capital and signaling theories. *The Accounting Review*, 2009, 84(2): 383–404.
 - [56] Hirst D E, Hopkins P E, Wahlen J M. Fair values, income measurement, and bank analysts' risk and valuation judgments. *The Accounting Review*, 2004, 79(2): 453–472.
 - [57] Jacob J, Lys T Z, Neale M A. Expertise in forecasting performance of security analysts. *Journal of Accounting and Economics*, 1999, 28(1): 51–82.
 - [58] Clement M B. Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics*, 1999, 27(3): 285–303.

- [59] Lin H W, McNichols M F. Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics*, 1998, 25(1): 101–127.
- [60] Malloy C J. The geography of equity analysis. *The Journal of Finance*, 2005, 60(2): 719–755.
- [61] Cooper R A, Day T E, Lewis C M. Following the leader: A study of individual analysts' earnings forecasts. *Journal of Financial Economics*, 2001, 61(3): 383–416.
- [62] Rubin A, Segal B, Segal D. The interpretation of unanticipated news arrival and analysts' skill. *Journal of Financial and Quantitative Analysis*, 2017, 52(4): 1491–1518.
- [63] Fracassi C, Petry S, Tate G. Does rating analyst subjectivity affect corporate debt pricing? *Journal of Financial Economics*, 2016, 120(3): 514–538.
- [64] Wang Z, Sun L, Wei K J. Does competition induce analyst effort? Evidence from a natural experiment of broker mergers. *Journal of Banking & Finance*, 2020, 119: 105914.
- [65] Leippold M, Lohre H. The dispersion effect in international stock returns. *Journal of Empirical Finance*, 2014, 29: 331–342.
- [66] Edelen R M, Ince O S, Kadlec G B. Institutional investors and stock return anomalies. *Journal of Financial Economics*, 2016, 119(3): 472–488.
- [67] Groyberg B, Healy P M, Maber D A. What drives sell-side analyst compensation at high-status investment banks? *Journal of Accounting Research*, 2011, 49(4): 969–1000.
- [68] Hu J, Long W, Luo L, et al. Share pledging and optimism in analyst earnings forecasts: Evidence from China. *Journal of Banking & Finance*, 2021, 132: 106245.
- [69] Libby R, Hunton J E, Tan H T, et al. Relationship incentives and the optimistic/pessimistic pattern in analysts' forecasts. *Journal of Accounting Research*, 2008, 46(1): 173–198.
- [70] Lim T. Rationality and analysts' forecast bias. *The Journal of Finance*, 2001, 56(1): 369–385.
- [71] Gu Z Y, Li Z, Yang Y G. Monitors or predators: The influence of institutional investors on sell-side analysts. *The Accounting Review*, 2013, 88(1): 137–169.
- [72] Irvine P J. Analyst' forecasts and brokerage-firm trading[J]. *Accounting Review*, 2004, 79(1): 125–149.
- [73] Mayew W J. Evidence of management discrimination among analysts during earnings conference calls. *Journal of Accounting Research*, 2008, 46(3): 627–659.
- [74] Liu X G, Natarajan R. The effect of financial analysts' strategic behavior on analysts' forecast dispersion. *The Accounting Review*, 2012, 87(6): 2123–2149.
- [75] Shi S. Investor attention, analyst optimism, and stock price crash risk. *Proceedings of Business and Economic Studies*, 2021, 4(3): 63–72.
- [76] Yu Y. Analyst earnings forecast optimism during the COVID-19 pandemic: Evidence from China. *Sustainability*, 2022, 14(19): 12758.
- [77] Guo Y, Yang S, Wang Y, et al. Star analysts' voting in emerging market: A perspective of analysts' optimistic bias. *Emerging Markets Finance and Trade*, 2023, 59(5): 1498–1518.
- [78] Brav A, Jiang W, Ma S, et al. How does hedge fund activism reshape corporate innovation? *Journal of Financial Economics*, 2018, 130(2): 237–264.
- [79] Lang M H, Lundholm R J. Corporate disclosure policy and analyst behavior. *The Accounting Review*, 1996, 71(4): 467–492.
- [80] Bhushan R. Firm characteristics and analyst following. *Journal of Accounting and Economics*, 1989, 11(2–3): 255–274.
- [81] Bushman R M, Piotroski J D, Smith A J. Insider trading restrictions and analysts' incentives to follow firms. *The Journal of Finance*, 2005, 60(1): 35–66.
- [82] Francis J, Hanna J D, Philbrick D R. Management communications with securities analysts. *Journal of Accounting and Economics*, 1997, 24(3): 363–394.
- [83] Jegadeesh N, Kim W. Value of analyst recommendations: International evidence. *Journal of Financial Markets*, 2006, 9(3): 274–309.
- [84] Laster D, Bennett P, Geoum S. Rational bias in macroeconomic forecasts. *The Quarterly Journal of Economics*, 1999, 114(1): 293–318.
- [85] Mikhail M B, Walther B R, Willis R H. Does forecast accuracy matter to security analysts? *The Accounting Review*, 1999, 74(2): 185–200.
- [86] Barinov A. Analyst disagreement and aggregate volatility risk. *Journal of Financial and Quantitative Analysis*, 2013, 48(6): 1877–1900.

- [87] Chen J, Cumming D, Hou W, et al. Does the external monitoring effect of financial analysts deter corporate fraud in China? *Journal of Business Ethics*, 2016, 134: 727–742.
- [88] Krishnaswami S, Subramaniam V. Information asymmetry, valuation, and the corporate spin-off decision. *Journal of Financial Economics*, 1999, 53(1): 73–112.
- [89] Ashour S. Do analysts really anchor? Evidence from credit risk and suppressed negative information. *Journal of Banking & Finance*, 2019, 98: 183–197.
- [90] Beyer A, Guttman I. The effect of trading volume on analysts’ forecast bias. *The Accounting Review*, 2011, 86(2): 451–481.
- [91] Ding D K, Charoenwong C, Seetoh R. Prospect theory, analyst forecasts, and stock returns. *Journal of Multinational Financial Management*, 2004, 14(4–5): 425–442.
- [92] Michaely R, Womack K L. Conflict of interest and the credibility of underwriter analyst recommendations. *The Review of Financial Studies*, 1999, 12(4): 653–686.
- [93] Fuller J, Jensen M C. Just say no to Wall Street: Putting a stop to the earnings game. *Journal of Applied Corporate Finance*, 2010, 22(1): 59–63.
- [94] Imbens G, Kalyanaraman K. Optimal bandwidth choice for the regression discontinuity estimator. *The Review of Economic Studies*, 2012, 79(3): 933–959.
- [95] Chen Y, Shi S, Tang Y. Valuing the urban hukou in China: Evidence from a regression discontinuity design for housing prices. *Journal of Development Economics*, 2019, 141: 102381.
- [96] McCrary J. Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, 2008, 142(2): 698–714.
- [97] Cen L, Hilary G, Wei K C, et al. The role of anchoring bias in the equity market: Evidence from analysts’ earnings forecasts and stock returns. *Journal of Financial and Quantitative Analysis*, 2013, 48(1): 47–76.