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Can strict financial regulation improve analysts' forecast accuracy? Evidence based on a quasi-natural experiment in China

Tao Jiang, Gang Wu *

Business School, Nanjing University, 22 Hankou Road, Gulou District, Nanjing, 210093, Jiangsu, China

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ABSTRACT

The necessity of strict regulation in financial activities remains a topic of ongoing debate. Using China's New Regulation on Asset Management (NRAM) as a quasi-natural experiment, we find that strict financial regulation can improve analysts' forecast accuracy. Mechanism analysis shows that strict financial regulation increases analysts' forecast accuracy by reducing the risk-taking level and increasing the media attention. We further show that this effect is stronger in firms that are followed by more analysts and those with more complex operations. Our findings support the theory regarding the effectiveness of strict financial supervision from the perspective of capital market information efficiency.

1. Introduction

After the financial crisis of 2007–2009, many countries have successively introduced stricter policies for regulating financial activities. However, whether strict regulation of financial activities is a necessary measure has remained a significant theoretical debate, with no definitive consensus reached thus far. The theory supporting strict financial regulation suggests that effective financial regulation is an important factor for the stability of economic development (Duffie, 2018), which can help reduce the bankruptcy risk of firms (Qin et al., 2023). The theories against strict financial regulation argue that it may reduce the quality of credit (Keys et al., 2009), and have adverse effects on corporate risk-taking and innovation (Bens et al., 2023). Therefore, it holds significant importance to further investigate the consequences of financial regulation from different perspectives.

Our intention is to delve into the consequences of strict financial regulation from the perspective of analysts' prediction accuracy. Previous studies predominantly concentrate on financial institutions such as banks or primarily focus on firms' performance, with relatively limited attention devoted to analysts. The existing literature, when exploring the impact of regulation on analysts' behavior, mainly focuses on the impact of laws and regulations aimed at directly constraining analysts' behavior (Bradshaw, 2009; Cowan and Salotti, 2020), while paying little attention to the impact of financial regulation that is not directly related to analysts' behavior. Analysts play an important role in the capital market, whose judgments have a significant impact on the information users in the capital market (Bourveau and Law, 2021), which is closely related to the information efficiency of the capital market. Therefore, studying whether and how strict financial regulation implemented in financial activities will affect the accuracy of analysts' predictions is of great significance for understanding the effectiveness of strict financial regulation.

In 2018, China announced the "Guiding Opinions on Regulating the Asset Management Business of Financial Institutions", known as the New Regulation on Asset Management (NRAM), aimed to enhance regulatory supervision over asset management activities of financial institutions, specifically targeting the containment of shadow banking operations. Using NRAM as a quasi-natural experiment, we demonstrate that strict financial regulation measures significantly enhance the accuracy of analysts' forecasts. The

* Corresponding author.
E-mail address: gwumail@foxmail.com (G. Wu).

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mechanism analysis reveals that analysts' forecast accuracy is enhanced by mitigating firms' risk-taking levels and raising media attention. Our findings passed the parallel trends hypothesis and placebo tests. We further demonstrate that this effect is more pronounced in firms with higher analyst coverage and firms with more complex business operations.

Our paper makes several contributions. First, our findings extend the literature on the positive impacts of strict financial regulation from the perspective of information efficiency in the capital market. Second, existing research on the micro-level impacts of financial regulation primarily concentrates on companies and financial institutions. Our study expands the literature by focusing on the accuracy of analysts' predictions. Third, we enrich the literature on factors affecting the accuracy of analysts' predictions, in which there is limited research on whether financial regulation, not directly related to analysts, will have similar consequences.

2. Literature review

Whether the consequences of strict regulation are positive or negative remains a theoretical question on which there is no agreement.

Many studies have found that strict financial regulation has a significant positive impact on financial activities. For example, Beltratti and Stulz (2012) and Caprio et al. (2014) both find that stricter regulation and enhanced private monitoring contribute to better performance and lower risks for banks during financial crises. However, several scholars have raised concerns about the efficacy of stringent financial regulation. Keys et al. (2009) find that more regulated lenders originate lower-quality loans, indicating that increased regulation may exacerbate moral hazard. Bens et al. (2023) argue that regulatory constraints may hinder firms' risk-taking by providing evidence that deregulation leads to increased risk incentives for borrowing firms.

Similar inconsistent findings emerge in studies on the consequences of NRAM. For instance, Qin et al. (2023) argue that corporate bankruptcy risk is significantly reduced following the introduction of NRAM, while Ma and Hu (2024) report a notable decline in small and medium-sized enterprises' investment after NRAM.

Together, the main focus of the existing literature is on financial entities, such as banks and firms, that are directly affected by strict financial regulation. Analysts also play an important role in financial activities. Therefore, when exploring the consequences of strict financial regulation, we should not only focus on its direct impact on banks and firms, but also on its indirect impact on the information efficiency of the capital market. That is why we choose to conduct our study from the perspective of analysts.

3. Theoretical analysis

The accuracy of analyst predictions depends on both their predictive ability and their opportunistic motives. NRAM can reduce the risk-taking levels of firms with higher levels of financialization and increase the media attention of firms with higher levels of financialization. The impact of these two aspects may enhance the predictive ability of analysts and reduce their opportunistic behavior.

Firstly, NRAM might reduce the risk-taking propensity of firms with heightened financialization. NRAM can constrain firms from investing through shadow banking and reduce their risk-taking levels (Qin et al., 2023). The reduction of risk helps to reduce the uncertainty. On the one hand, this effect helps improve the predictive ability of analysts. Existing research indicates that uncertainty is an important factor affecting the accuracy of analyst forecasts (Zhang, 2006; Amiram et al., 2018). When uncertainty is high, analysts' ability to provide accurate predictions may be compromised, as analysts need to collect more information or conduct more analysis. And when uncertainty is high, analysts' existing behavioral biases such as conservatism or overconfidence will be amplified, leading to an increase in their inadequate response to new information (Zhang, 2006). So NRAM helps to improve analysts' predicting ability for firms with higher levels of financialization. On the other hand, lower level of uncertainty helps constrain the opportunistic behavior of analysts. Existing research has shown that in situations of high uncertainty, analysts publishing biased forecasts have less negative impact on their reputation (Ackert and Athanassakos, 1997). The reduction of uncertainty after the NRAM helps to enhance the degree of damage to the reputation of analysts caused by biased predictions, thereby improving the accuracy of analysts' predictions.

Secondly, NRAM can help increase the media attention of companies with higher levels of financialization. NRAM is a very strict financial regulatory measure for asset management. Before the implementation of NRAM, the scale of asset management business in China were huge. As of 2016, the size of shadow banking assets in China had reached 7011.39 billion US dollars (data source: CSMAR). Therefore, the implementation of NRAM is more likely to attract media attention. Existing research suggests that the media can provide new information to the market through original surveys and analysis (Miller, 2006). This characteristic of the media helps to broaden the sources of analysts' information, thus enhancing the analysts' ability to provide accurate predictions. In addition, media attention helps to monitor the behavior of analysts. Existing research suggests that the media not only relies on the analysts' information (Guest and Kim, 2023), but also rebroadcasts the analysts' content (Miller, 2006). This characteristic means that analysts' biased predictive behavior will receive more attention. Therefore, analysts may provide more accurate predictions to avoid reputation damage.

In summary, we propose research hypothesis.

H: After the implementation of NRAM, the more financialized a firm is, the more likely it is that the accuracy of analysts' forecasts for that firm will increase.

4. Data sources and the model

We select A-share listed companies in the Shanghai and Shenzhen stock markets of China as research samples, excluding the samples of financial industry. The sample period is 2015 to 2021, including three years before and after NRAM. All continuous variables were winsorized at the 1% and 99% levels. Our data are all from the CSMAR and CNRDS databases in China.

Due to the fact that NRAM does not constrain different types of firms, but rather specific financial activities, there is no experimental group or control group, making it impossible to construct a classic DID model. Nevertheless, the impact of this policy on firms with different degrees of financialization varies. Firms with a higher degree of financialization may involve more asset management businesses and be more exposed to this shock. Thus, we draw on Nunn and Qian (2011) to design the following generalized DID model:

$$Accuracy_{i,t} = \beta_0 + \beta_1 Post_{i,t} \times FDegree_{i,t} + Controls_{i,t} + \mu_t + \delta_i + \varepsilon_{i,t}, \tag{1}$$

where *Accuracy* is the accuracy of analysts' forecasts, calculated as $-1 \times |$*average EPS predicted by analysts − actual EPS* $|$/*share price at the beginning of the year*. *FDegree* is the degree of financialization, calculated using the ratio of a firm's financial assets at the end of 2015 to total assets at the end of 2015. The definition of financial assets is shown in the footnote of Table A.6. *Post* is defined as 1 for 2018 and beyond, otherwise it is 0. μ and δ stand for year and firm fixed effects. Variable definitions and descriptive statistics are shown in Table A.6.

5. Empirical results

5.1. Benchmark regression

The benchmark regression results are shown in Table 1, and the coefficient of *Post*×*FDegree* is significantly positive, indicating that after the implementation of NRAM, the accuracy of analysts' predictions for firms with higher levels of financialization will be improved. Taking column (2) as an example, for each one standard deviation increase in the level of firm's degree of financialization before the implementation of the NRAM, the accuracy of analysis forecast will increase by 4.14% ($0.0272 \times 0.0614/|-0.0403|$) of the absolute value of $E(Accuracy)$. The findings of our paper are consistent with the work of Beltratti and Stulz (2012), Caprio et al. (2014), and Duffie (2018), who emphasize the positive implications of financial regulations. Furthermore, this research may offer a partial response to the concerns of Meltzer (1967) and Kane (1988) about the costs of financial regulations, as market participants like analysts may have already experienced the positive effects of strong regulations, indicating that regulatory costs are more likely to be mitigated across the market.

5.2. Robustness tests

5.2.1. Parallel trends test

The DID model requires that before the exogenous shock of NRAM, analysts' accuracy of both the treatment group and the control group have the same growth trend. Following Wu et al. (2024), we conduct the parallel trends analysis by introducing cross-multiplication terms of time variables and *FDegree*. The indicator *Before3* signifies the third year before the application of NRAM, *Current* represents an indicator for the year when NRAM is applied. *Before2*, *Post1* and *Post2* are similarly defined. Table 2 indicates that the coefficients of the interaction terms before the application of NRAM are all insignificant, providing support for the parallel trends assumption.

5.2.2. The placebo test

A potential concern regarding our main findings is that firms with higher levels of financialization may inherently have a stronger tendency to improve the accuracy of analyst forecasts, which could serve as an alternative explanation for the observed effect. Alternatively, the improvement in analyst accuracy is simply a result of changes in macroeconomic cycles. To alleviate the above concerns, we follow Wu et al. (2024) to assume that the policy would be advanced by two years, that is, the policy would be implemented in 2016. The regression results are shown in Table 3, where the cross term's coefficient is no longer significant, indicating that concerns about the above two issues can be alleviated.

5.2.3. Regressions using alternative test windows and alternative measure of analysts' forecast accuracy

To ensure the robustness of our findings, we further conduct 3 kinds of robustness tests. Firstly, we draw on Wu et al. (2024) to change the research period to a nine-year duration (2014 to 2022), in order to observe if this effect still exists in a wider time window. Secondly, we exclude the year of policy from the sample period, to eliminate potential short-term interference or noise associated with the immediate impacts of NRAM. Finally, in order to eliminate potential reverse causality, we use the future value of *Accuracy* (*F.Accuracy*) as the dependent variable. The above regression results are shown in columns (1) to (3) of Table 4, respectively. The above tests help strengthen the overall reliability of the conclusions.

Table 1
Strict financial regulation and analysts' forecast accuracy.

	(1) Accuracy	(2) Accuracy
Post × *FDegree*	0.0282**	0.0272***
	(0.0133)	(0.0102)
Size		0.0132***
		(0.0019)
ROA		0.4776***
		(0.0136)
Lev		−0.0300***
		(0.0070)
BM		−0.0412***
		(0.0039)
Growth		0.0056***
		(0.0010)
Cash		−0.0429***
		(0.0049)
DitorSize		0.0046
		(0.0071)
InditorRtio		0.0057
		(0.0181)
Top1		−0.0000
		(0.0001)
Separation		0.0002
		(0.0002)
Dual		0.0031*
		(0.0017)
Big4		0.0049
		(0.0037)
AuditOpin		0.0447***
		(0.0049)
Constant	−0.0407***	−0.3707***
	(0.0005)	(0.0454)
N	14,222	14,222
Adj. R^2	0.2608	0.6156
Year FE	Yes	Yes
Firm FE	Yes	Yes

Robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The same applies to the tables below.

Table 2
Parallel trends test.

	(1) *Accuracy*
Before3 × *FDegree*	0.0042
	(0.0149)
Before2 × *FDegree*	−0.0114
	(0.0143)
Current × *FDegree*	0.0055
	(0.0152)
Post1 × *FDegree*	0.0556***
	(0.0175)
Post2 × *FDegree*	0.0117
	(0.0204)
Post3 × *FDegree*	0.0296
	(0.0207)
N	14,222
Adj. R^2	0.6157
Controls	Yes
Year FE	Yes
Firm FE	Yes

This table presents the results of parallel trends test. *Before3* and *Before2* mean the third year and second year before the application of NRAM. *Current* represents an indicator for the year when NRAM is applied. *Post1* and *Post2* are defined as the first and second year after the application of NRAM.

Table 3
The placebo test.

	(1) *Accuracy*
FakePost × *FDegree*	0.0069
	(0.0125)
N	14,222
Adj. R^2	0.6154
Controls	Yes
Year FE	Yes
Firm FE	Yes

This table reports the placebo test assuming that the pseudo-event year occurs two years prior to the real event year of NAMR. *FakePost* denotes whether the year is after 2016. We can tell that the coefficient for *FakePost* × *FDegree* is no longer significant, thereby reinforcing the robustness of our findings.

Table 4
Remaining robust tests and mechanism tests.

	(1) *Accuracy*	(2) *Accuracy*	(3) *F.Accuracy*	(4) *StockVol*	(5) *lnNews*
Post × *FDegree*	0.0249***	0.0402***	0.0454***	−0.0037***	0.4376**
	(0.0096)	(0.0127)	(0.0150)	(0.0013)	(0.2019)
N	17,678	11,971	11,886	17,230	17,026
Adj. R^2	0.5883	0.6088	0.3939	0.7010	0.6690
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

Columns (1) to (3) show remaining robust tests, including tests based on alternative test windows and alternative measure of analysts' forecast accuracy. In column (1), we use an extended research period of 2014 to 2022. In column (2), we use a research period of 2015 to 2021 without year 2018. In column (3), we use the future value of *Accuracy* (*F.Accuracy*) as the dependent variable. Columns (4) and (5) present the impact of strong financial regulation on the firms' risk taking and media attention. In column (4), we use firms' stock price volatility as dependent variable to test mechanism of strict financial regulation's impact on firms' risk-taking level. Similarly, in column (5), we use the extent of a firm's coverage by news to denote media attention paid to the firm.

5.3. Mechanism analysis

Existing literature suggests that the mediation effect model of the traditional three regression models may have serious endogeneity issues when conducting mechanism analysis (Aguinis et al., 2017; Pieters, 2017). An alternative approach is to empirically test the relationship between independent variables and mediating variables, and to explain the relationship between mediating variables and dependent variables through theoretical analysis, such as Chen et al. (2020). Therefore, the mechanism analysis in our paper adopts this method. We use Eq. (2) to test the mechanisms:

$$StockVol_{i,t}/lnNews_{i,t} = \beta_0 + \beta_1 Post_{i,t} \times FDegree_{i,t} + Controls_{i,t} + \mu_t + \delta_i + \varepsilon_{i,t}, \tag{2}$$

where *StockVol* denotes firm's risk-taking level, measured as stock price volatility following Bargeron et al. (2010), and *lnNews* stands for media attention, calculated as ln(*The number of sentences mentioning listed companies of online media*+1). Considering that media attention may also be influenced by the performance of the firm's stock market and negative performance, we introduce two more control variables: the turnover rate of stocks (*Turnover*, the sum of daily turnover rates within the year) and the firm's losses (*Loss*, defined as the average of three indicators: *NegEarn*, *l1NegEarn*, and *l2NegEarn*. *NegEarn* takes a value of 1 if the firm reports negative earnings and 0 otherwise. *l1NegEarn* and *l2NegEarn* represent NegEarn in the previous one and two periods, respectively.). The regression results of the mechanism tests are shown in Table 4 columns (4) and (5), which are consistent with the prediction. The implementation of NRAM has resulted in lower levels of risk-taking and increased media attention for more financialized companies.

5.4. Cross-sectional analysis

The supervisory effect under NRAM may be stronger in companies with more analyst followers. The biased forecasting behavior of individual analysts is more pronounced when the target firm has a greater number of analyst followers. Thus, the monitoring effect of the policy may be stronger in firms with a greater number of analyst followers. Therefore, we introduce Eq. (3) to observe the impact of NRAM on the accuracy of analyst forecasts for listed companies under different analyst attention levels:

$$\begin{aligned} Accuracy_{i,t} = {} & \beta_0 + \beta_1 HighAttention_{i,t} \times Post_{i,t} \times FDegree_{i,t} + \beta_2 HighAttention_{i,t} \\ & + \beta_3 Post_{i,t} \times FDegree_{i,t} + Controls_{i,t} + \mu_t + \delta_i + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

where the definition of analyst attention (*HighAttention*) is whether the number of analyst teams following a listed firm exceeds industry median value for the year. If it exceeds, it is assigned a value of 1; otherwise, it is assigned a value of 0.

Table 5
Cross-sectional analysis.

	(1) *Accuracy*	(2) *Accuracy*
HighAttention × *Post* × *FDegree*	0.0580***	
	(0.0162)	
HighAttention	0.0106***	
	(0.0012)	
Complex × *Post* × *FDegree*		0.0292*
		(0.0177)
Complex		−0.0014
		(0.0017)
Post × *FDegree*	0.0131	0.0186
	(0.0118)	(0.0119)
N	14,222	14,222
Adj. R^2	0.6188	0.6156
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes

In column (1), we report the results of DID regression after dividing the treatment group into two subgroups depending on whether a firm's analyst attention is more or less than the cross-sectional median. In column (2), we use similar method on subgroups divided by whether the number of subsidiaries of the sample firms is in the first quartile.

If a listed firm's operations are more complex, its financial activities in asset management may be more difficult to predict. For firms with more complex operations, the extent of uncertainty reduction from constraints on asset management activities may be higher. Thus the policy's enhancing effect on analysts' forecast accuracy is likely to be stronger for such firms. Therefore, we replace *HighAttention* in Eq. (3) with business complexity (*Complex*) to observe the impact of NRAM on the accuracy of analysts' forecasts for listed companies with different operating complexities, where *Complex* is defined as whether the number of subsidiaries of a listed firm is in the top 25% of the industry year, if so, *Complex* is 1, otherwise it is 0.

The results of the cross-sectional analysis are shown in Table 5, showing that the impact of the policy on the accuracy of analysts' predictions is higher in listed companies with more analyst teams following and those with more complex operations, aligning with our previous predictions.

6. Conclusion

The research results of our work indicate that after the release of NRAM, analysts have better accuracy in predicting companies with higher levels of financialization, and the results still exist after robustness testing. The results imply that the accuracy of analysts' predictions is not only influenced by directly related regulatory factors, but also by those that are indirectly related.

The findings suggest that implementing stricter regulations on financial activities can enhance the information efficiency of capital markets. Policymakers could consider strengthening regulatory frameworks to ensure that financial practices are transparent and well-supervised, which can lead to improved market performance and increased information interpreting.

There still remains some limitations of our research. One limitation is that our work only considers a single type of financial regulation. Future research could explore the consequences of different types and levels of financial regulations. Another limitation is that our study does not yet consider how financial institutions may circumvent regulations or the subsequent policy adjustments, which future research could address to provide a more complete analysis.

CRediT authorship contribution statement

Tao Jiang: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Gang Wu:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Variable definitions and descriptive statistics

See Table A.6.

Table A.6
Description and descriptive statistics of variables.

Variable	Description	N	*Mean*	*SD*	*Min*	*Median*	*Max*
Accuracy	The accuracy of analysts' forecasts.	14 222	−0.0403	0.0676	−0.4374	−0.0177	−0.0002
Post	After the implementation of NRAM.	14 222	0.5384	0.4985	0.0000	1.0000	1.0000
FDegree	Firm's degree of financialization.	14 222	0.0317	0.0614	0.0000	0.0086	0.4000
Size	Natural logarithm of firm's total assets.	14 222	22.6562	1.2892	19.6127	22.4908	26.4116
ROA	Net income divided by total assets.	14 222	0.0284	0.0848	−0.5143	0.0343	0.1937
Lev	Total debt divided by total assets.	14 222	0.4457	0.2023	0.0634	0.4392	0.9855
BM	Book value of assets divided by Market value of assets.	14 222	0.6251	0.2678	0.0900	0.6127	1.2074
Growth	Growth rate of operating revenue.	14 222	0.1902	0.5119	−0.6825	0.1063	3.9094
Cash	Net cash flow divided by total assets.	14 222	−0.0047	0.0967	−0.3170	0.0022	0.2802
DitorSize	Natural logarithm of the number of directors plus one.	14 222	2.2394	0.1749	1.7918	2.3026	2.7081
InditorRtio	Proportion of independent directors on the board.	14 222	0.3771	0.0544	0.3333	0.3636	0.5714
Top1	Biggest shareholders' percentage holdings.	14 222	33.4607	14.4053	8.1200	31.2750	71.2400
Separation	The difference between control and ownership.	14 222	4.7784	7.5226	0.0000	0.0000	28.5264
Dual	Whether the chairman also serve as the general manager.	14 222	0.2586	0.4379	0.0000	0.0000	1.0000
Big4	Whether firm's auditing firm is one of the Big Four.	14 222	0.0683	0.2523	0.0000	0.0000	1.0000
AuditOpin	Whether firm has standard unqualified audit opinion.	14 222	0.9587	0.1989	0.0000	1.0000	1.0000

This table presents descriptive statistics for the variables used in the benchmark regression. N stands for the number of observations; SD stands for standard deviation.
For FDegree, The definition of financial assets is the sum of held-to-maturity investments, recoursable financial assets acquired, available-for-sale financial assets, financial assets held for trading, and investment property.

Data availability

The data used in this study were obtained from the CSMAR and CNRDS databases, which were licensed by our institution. Due to the terms of the institutional subscription, we do not have the right to make this data publicly available.

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