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Learning by doing or catering: Firm-specific experience and analyst forecast accuracy[☆]

Xu Ji [a], Shanhui Wu [b], Yan Dong [a,*], Xiaoqi Yang [a,1]

[a] Department of Finance, Research Institute of Economics and Management, Southwestern University of Finance and Economics, Chengdu, China
[b] Department of Enterprise Management, Research Institute of Economics and Management, Southwestern University of Finance and Economics, Chengdu, China

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ABSTRACT

This article explores catering behavior among security analysts by examining how firm-specific experience impacts forecast accuracy. Using analyst forecasts on listed companies in China from 2014 to 2018, we find that firm-specific experience significantly reduces analyst forecast accuracy, which indicates the existence of catering behavior. Heterogeneity analysis reveals that catering behavior primarily exists for analysts employed by large brokerage firms or who issue forecasts for large companies. Further analysis shows that catering behavior is more prevalent when analysts make forecasts for SOEs. These findings suggest multi-faced implications of firm-specific experience and call for better regulations on refraining analysts' catering behavior.

1. Introduction

As active information intermediaries, security analysts play a critical role in alleviating information asymmetry in capital markets (Amiram et al., 2016; Fang, 2007). Because investors rely heavily on analysts' research reports for their investing decisions, yet analysts differ substantially in their capacity to correctly predict the earnings performance of listed companies, investigating factors that determine analysts' forecast accuracy remains an important undertaking for both market participants and researchers(Clement, 1999; Fan and Song, 2010).

Firm-specific experience, defined as the length of time during which an analyst has issued forecasts for a specific company, is a key variable for research in analysts' forecast accuracy. According to learning-by-doing theory(Arrow, 1962), analysts can accumulate knowledge and experience while issuing forecasts for the same listed company over time. As analysts issue more forecasts for a company, they will gain a deeper understanding of the company's operations and financial data and thus become more capable of

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* Corresponding author.
E-mail addresses: wush@swufe.edu.cn (S. Wu), ydong@swufe.edu.cn (Y. Dong).

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making accurate forecasts. On that count, previous studies have provided empirical evidence for this hypothesis of learning by doing. That is, the forecasting accuracy of analysts tends to increase as they obtain more firm-specific experience(Clement, 1999; Mikhail et al., 1997).

However, firm-specific experience does not always promote analyst forecast accuracy. A key assumption of learning-by-doing theory is that analysts can remain sufficiently independent and objective when they make financial forecasts for companies. The principle of independence is often violated, however, because analysts' decision-making is influenced by shareholders and other beneficiary agents. As research has demonstrated, under pressures from the brokerage firms that they work for or the listed companies that they analyze, analysts are more likely to issue positive forecasts—In other words, the analysts cater to the companies in their reports when facing pressure(Dugar and Nathan, 1995; Lin and Mcnichols, 2004). From a perspective of catering, firm-specific experience may imply deep long-term relationships between analysts and listed companies which strengthens the former's tendency to cater and therefore issue favorable forecasts for listed companies.

Using sell-side security analyst forecasts data from China, this article aims to investigate the possible negative effect of firm-specific experience on analyst forecast accuracy, a perspective that is largely ignored in past research. Although analysts worldwide play similar roles insofar as they provide earnings forecasts for market participants to aid their investment decisions, analysts in China are more likely than their counterparts elsewhere to engage in catering for two reasons. First, China's stock markets and analyst industry emerge late and have a relatively short history of development comparing to those in developed countries, and for that reason, regulations concerning analysts' behavior remain in their infancy. Although the China Securities Regulatory Commission established a firewall system in 2015 in a bid to preclude conflicts of interests between investment bank and research departments within brokerage firms, the regulation's ambiguous clauses and problems associated with its execution have prevented the realization of its full impact on enhancing analysts' independence. Second, unlike sell-side analysts in many other countries who may work for an investment bank, a brokerage firm, or as a free agent, nearly all sell-side analysts in China are affiliated with brokerage firms that typically have very broad scope of business and diverse internal interests. Altogether, because analysts' behavior in China is highly influenced by pressure from brokage firms, it has been very difficult for them to achieve and maintain independence when issuing forecasts(Cao and Zhu, 2011; Pan et al., 2011; Wu et al., 2018).

Against that backdrop, our analysis of the earnings-per-share (EPS) data of listed companies issued by 1880 analysts from 78 brokerage firms in China from 2014 to 2018 reveals that, in general, firm-specific experience has a significantly negative effect on analyst forecast accuracy, which suggests the existence of catering behavior among analysts. Moreover, heterogeneity analysis shows that catering behavior primarily occurs among analysts who are employed by large brokerage firms or who issue forecasts for large listed companies. For forecasts made by analysts from small brokerage firms or made for small listed companies, firm-specific experience actually increases forecast accuracy. We also test the impact of firm-specific experience on analyst forecast accuracy between state-owned enterprises (SOEs) and non-SOEs, whose difference in market share and status in the Chinese economy may influence analysts' catering behavior differently. On that point, we find that firm-specific experience exerts a significantly negative effect on analyst forecast accuracy for SOEs but a non-significant impact when the forecasts are issued for non-SOEs.

With these findings, this article makes several contributions to the literature. First, it sheds some new lights on the relationship between firm-specific experience and analyst forecast accuracy. From the perspective of learning-by-doing theory, authors such as Mikhail et al. (1997) and Clement (1999) mostly interpret firm-specific experience as indicating knowledge growth and emphasize its positive effect on analyst forecast accuracy. By contrast, our findings suggest that a catering mechanism associated with firm-specific experience may decrease analyst forecast accuracy, which to some extent reconcile the conflicting results in previous studies and call for a more comprehensive investigation into the role that firm-specific experience plays for analyst forecast accuracy. Second, this article extends the literature on analysts' catering behavior. Past research on analysts' catering to listed companies (Dugar and Nathan, 1995; Lin and Mcnichols, 2004) primarily attributes catering behavior to specific business relationships—for instance, underwriting or investment banking—between brokerage firms and listed companies. Our findings, by extension, characterize analysts' catering behavior in three dimensions—the size of brokerage firms, the size of listed companies, and the state ownership of listed companies—and improve current understandings of the catering phenomenon in China. Third, because Chinese stock markets are relatively young and dominated by retail investors without much investment expertise, our findings can help such investors to better understand the pattern of analysts' forecasting behavior and use their advice wisely. Finally, our findings provide important insights and implications for policymaking when it comes to regulating analysts' behavior.

In what follows, Section 2 presents literature review, after which Section 3 describes the study's sample, data processing, and research design. Next, Section 4 reports the empirical results of our main regressions, heterogeneity analyses, and robustness testing. Last, Section 5 concludes the article by articulating policy implications of our findings.

2. Literature review

Arrow (1962)'s learning-by-doing theory ascribes people's improved performance during production processes to learning and maintains that learning is essentially the product of experience. Since its proposal, the learning-by-doing theory has been widely used for research on the relationship between experience and performance. To our knowledge, Mikhail et al. (1997) first introduce the theory on the study in analyst forecast accuracy and find that firm-specific experience significantly improves analyst forecast accuracy. Taking firm-specific experience as a proxy of analysts' personal ability, Clement (1999) observes similar results. In general, previous studies have shown that, as analysts accumulate firm-specific experience, their forecasts tend to be more accurate(Fan and Song, 2010; Kumar, 2010; Luo et al., 2018; Yang et al., 2019).

However, some researchers find that firm-specific experience does not always lead to better forecasting performance. For instance, Hong et al. (2000) show that more experienced analysts do not forecast better than their less experienced counterparts, although they use general experience instead of firm-specific experience in their study.[2] Meanwhile, Jacob et al. (1999) find that when the "talent" or special knowledge of analysts on a specific listed company is controlled for, firm-specific experience does not influence analyst forecast accuracy. These findings suggest that the learning-by-doing theory may not fully explain the relationship between firm-specific experience and analyst forecast accuracy. Indeed, some factors or processes may counteract the benefits of learning by doing and reduce or even negate the positive effect of firm-specific experience on analyst forecast accuracy. One possible counteracting factor is analysts' catering behavior during forecasting. As the tendency of catering rises with firm-specific experience, analysts' forecasting bias is likely to increase and thus reduce the positive outcomes of firm-specific experience as predicted by learning-by-doing theory.

Among many reasons for analysts to cater, an important one is the environment under which the analysts function. According to the literature, at least two factors in that environment can induce analysts' catering behavior. The first source is brokerage firms. To build and maintain good customer relations, the brokerage firms where analysts work often force them to cater to listed companies with whom they have business contracts and to issue optimistic forecasts for them. Lin and Mcnichols (2004) demonstrate that, when brokerage firms have underwriting business with the companies being analyzed, their analysts tend to give relatively optimistic growth forecasts and positive investment recommendations. In that vein, Dugar and Nathan (1995) find that earnings forecasts and investment recommendations provided by analysts at investment banks are significantly more positive than those by analysts in other sectors. Lin and Mcnichols (2004) add that not only existing business relationships but also potential business opportunities could lead analysts to engage in catering. In particular, when issuing securities, listed companies tend to choose brokerage firms that have been optimistic about them in the past; thus, in order to ensure future collaboration opportunities with listed companies, brokerage firms often request their analysts to provide relatively optimistic forecasts for them.

The management team from the listed companies is another source that can enforce analysts to issue optimistic forecasts. Because analysts' reports could influence the stock price of listed companies(Dugar and Nathan, 1995; Lin and Mcnichols, 2004), analysts who issue negative forecasts for listed companies often make a bad impression and thus receive tremendous pressure from the companies, which not only creates obstacles for their future research with the companies but also affects their career prospects(Laderman and Hawkins, 1990). Analysts also cater to listed companies in order to increase trade volumes and brokerage commissions, and to remain on good terms with the management of listed companies as a means to access private information(Chen and Jiang, 2006; Francis and Philbrick, 1993; Zhao et al., 2013).

In sum, past research has generally shown that firm-specific experience leads to the accumulation of knowledge and the enhancement of skills, which consequently improves analyst forecast accuracy. Taking a perspective of catering, our study hypothesizes an alternative mechanism by which firm-specific experience negatively impacts analyst forecast accuracy. Specifically, we argue that firm-specific experience does not just reflect analysts' knowledge growth, but indicates a deep relationship between listed companies and analysts that may induce the latter's catering behavior. Because two conflicting mechanisms exist at the same time for firm-specific experience, its full impact on analyst forecast accuracy depends on the strength of each and, for that reason, warrants further investigation.

Although analysts generally have incentives to cater to listed companies by issuing favorable forecasts, the intensity of catering may vary for different groups of analysts. Dugar and Nathan (1995) and Lin and Mcnichols (2004) suggest that analysts' catering behavior in large brokerage firms is more intense than that of analysts in small ones. Due to limited resources and capacities, it is relatively more difficult for small brokerage firms to foster business relations with listed companies. As a consequence, the leaders of small brokerage firms are less motivated to force optimistic forecasts. Analysts in those brokerage firms, in turn, tend to observe the principle of independence when issuing forecasts. On the contrary, analysts at large brokerage firms are more likely to cater to listed companies. Because analysts at small brokerage firms are less likely to cater, firm-specific experience to a larger extent reflects improved knowledge for them, which positively affects analyst forecast accuracy. By contrast, for analysts at large brokage firms, the catering mechanism associated with firm-specific experience becomes dominant, which may reduce or even negate the positive impact of accumulated knowledge. Altogether, the firm-specific experience of analysts at large brokerage firms may decrease analyst forecast accuracy.

The intensity of analysts' catering behavior may also differ for listed companies with different sizes. Generally speaking, large listed companies have a wide range of resources and more business dealings with brokerage firms; thus, analysts may have stronger incentives to cater to them than to small listed companies. Therefore, we expect that the firm-specific experience of analysts would positively affect the accuracy of forecasts for small listed companies, whereas the impact for large listed companies would be negative.

Last, SOEs, as opposed to non-SOEs, have a significant market share and play important roles in the Chinese economy. The particular roles that SOEs play(Liu, 2001) afford them an implicit guarantee from the government(Han and Hu, 2015), which creates an edge for them in obtaining bank loans(Brandt and Li, 2003) and reducing financing constraints(Zhang and Liu, 2018). Taken together, the special status and power of SOEs may make analysts more likely to cater to them when issuing forecasts. Therefore, we expect firm-specific experience to exert a significantly negative impact on analyst forecast accuracy for SOEs but only a limited impact when forecasts are issued for non-SOEs.

[2] Because analysts, limited by professional background and personal energy, tend to track several industries or companies, their general experience and firm-specific experience are highly correlated.

3. Sample, data processing and research design

3.1. Sample and data source

Our study's sample derives from the forecasted EPS data for all listed companies on Chinese A-share Main Board and Small and Medium Enterprise Board, issued by sell-side analysts in China from 2014 to 2018. We match those companies and forecasts with the China Stock Market & Accounting Research Database (CSMAR) to collect information about analysts' firm-specific experience and their personal characteristics, along with forecast-related data, brokerage firms' characteristics, and the financial data of listed companies.

From the sample, we exclude some observations based on various criteria: forecasts issued by a team of analysts in which the contribution of any one analyst's firm-specific experience is difficult to identify, forecasts issued by analysts whose personal information is incomplete, forecasts for listed companies with abnormal stock trading, forecasts for listed companies covered by fewer than three analysts in a given year, and forecasts for listed companies over future years. We also winsorize the data by removing the top and bottom 1% of observations in order to eliminate extreme outliers. Our final sample thus contains 71,891 forecasts for 1802 listed companies issued by 1880 analysts at 78 brokerage firms.

3.2. Variable selection and measurement

3.2.1. Dependent variable

Following the method proposed by Mikhail et al. (1997), we construct the variable of analyst forecast error ($Forerror_{ijmn}$) by

Table 1
Definitions of variables.

Type of variable		Variable	Definition
Dependent variable		Accuracy	A dummy variable that equals 1 if the analyst forecast error is less than or equal to the year-industry average forecast error and 0 otherwise
Independent variable		SpecificFirmEx	The number of prior quarters in which the analyst has issued forecasts for a specific listed company
Control variables	Analysts' characteristics	Gender	A dummy variable that equals 1 if the analyst is a man and 0 if a woman
		Degree	A dummy variable that equals 1 if the analyst has a bachelor's degree, 2 if a master's degree, and 3 if a doctoral degree
		LAnalystRank	A dummy variable that equals 1 if the analyst's rank on *New Fortune*'s list last year equals 5; 2 if its rank equals 4; 3 if its rank equals 3; 4 if its rank equals 2; 5 if its rank equals 1; and 0 if the analyst does not appear on the list last year
		GeneralEx	The number of prior quarters in which the analyst has issued forecasts for any listed company
	Forecasts' characteristics	RHorizon	The number of days between the date of the analyst's forecast and the date of their most recent prior forecast for the same listed company in the same year
		FHorizon	The number of days between the date of the analyst's forecast and the earnings announcement date of the same listed company in the same year
		DayElapsed	The number of days between the date of the analyst's forecast and the date of the most recent prior forecast issued by any other analyst for the same listed company in the same year
		CoverIndus	The number of small industries followed by analysts in the year
		Frequency	The number of times that analysts issue forecasts for the same listed company in the year
	Brokerage firms' characteristics	BrokerEx	The number of quarters between the date of the analyst's forecast and the date of the establishment of the brokerage firm to which the analyst belongs
		Colisted	A dummy variable that equals 1 if the brokerage firm to which the analyst belongs is listed in the year and 0 otherwise
		BrokerSize	The total number of analysts employed by the brokerage firm who issue forecasts in the year
	Listed companies' characteristics	AnaAttention	The number of analysts following the listed company in the year
		CompanyAge	The number of quarters between the date of the analyst's forecast and the listing date of the listed company
		CompanySize	The natural logarithm of total assets of listed companies in the year when the analyst issues forecasts
		ROE	The ratio of net profit to shareholders' equity of listed companies in the year when the analyst issues forecasts
		Leverage	The ratio of total liabilities to the total assets of listed companies in the year when the analyst issues forecasts
		SalesGrowth	The growth rate of the sales income of the listed company in the year when the analyst issues forecasts

Note: *LAnalystRank* is based on the last year's ranking of analysts on *New Fortune*' s best analyst list in the same industry as the firm forecasted in the year. The industry classification guidelines for listed companies (2012 edition) by the China Securities Regulatory Commission (CSRC) divides the industries of listed companies into 19 categories (i.e., A through S) and 90 subcategories. The number of small industries in our study is based on the 90 subcategories. The industry classification standards of listed companies in the CSMAR database differ, such that companies listed before 2014 are classified according to the CSRC's 2001 guidelines for listed companies, whereas companies listed after 2014 are classified according to the CSRC's 2012 guidelines. Due to stark differences between the two sets of guidelines, we manually classify all listed companies according to the 2012 version of the guidelines in order to unify the standards.

calculating the absolute value of the difference between the analyst-forecasted EPS and the actual EPS of the listed company in the given year. The measure is divided by the year-end stock closing price of the listed company in order to eliminate the impact of the stock prices of different listed companies. The formula for measuring analyst forecast error is shown in Eq. 1:

$$Forerror_{ijmn} = \frac{|FEPS_{ijmn} - REPS_{ij}|}{Price_{ij}} \tag{1}$$

in which $FEPS_{ijmn}$ and $Forerror_{ijmn}$ respectively represent the forecasted EPS and analyst forecast error of the ith forecast issued by analyst m at brokerage firm n for company j, and $REPS_{ij}$ and $Price_{ij}$ respectively represent the actual EPS and the year-end stock closing price of listed company j corresponding to the forecast i.

Using the value of $Forerror_{ijmn}$, we further construct the dummy variable of analyst forecast accuracy ($Accuracy_{ijmn}$). Due to differences in analyst forecast error between different years and industries(Jacob et al., 1999), we use the relative accuracy of forecasts. First, based on the classification standard of the Shenzhen Stock Exchange for listed companies, we divide our sample of listed companies into six industries: manufacturing, commerce, finance, real estate, public utilities, and comprehensive industries. Second, we calculate the mean analyst forecast error for each industry in each fiscal year. Third, we compare $Forerror_{ijmn}$ with the mean analyst forecast error for the industry that listed company j belongs to in the fiscal year of ith forecast ($MForerror_{ij}$). If the former is less than or equal to the latter, then we conclude that analyst m's forecast level in the ith forecast is higher than or equal to the average level of the corresponding industry in the corresponding fiscal year. In that case, $Accuracy_{ijmn}$ equals 1 but 0 otherwise. We perform those calculations according to Eq. 2:

$$Accuracy_{ijmn} = \begin{cases} 1, if Forerror_{ijmn} \leq MForerror_{ij} \\ 0, if\ Forerror_{ijmn} > MForerror_{ij} \end{cases} \tag{2}$$

3.2.2. Independent variable

It has been suggested that measuring analysts' experience in years cannot sufficiently capture their actual experience(Bonner and Lewis, 1990; Davis and Solomon, 1989). Therefore, we measure firm-specific experience as the number of prior quarters in which the analyst has issued forecasts for a specific listed company ($SpecificFirmEx_{ijmn}$).

3.2.3. Control variables

Our analysis includes four groups of control variables: analysts' characteristics, forecasts' characteristics, brokerage firms' characteristics, and listed companies' characteristics. Those variables are important factors of analyst forecast accuracy, as shown in previous studies(Clement, 1999; Fan and Song, 2010; Kerl and Ohlert, 2015; Kumar, 2010; Mikhail et al., 1997; Stickel, 1992). The variables included in each classification and their definitions appear in Table 1.

3.3. Empirical model

To empirically test the impact of firm-specific experience on analyst forecast accuracy, we use the logit regression model shown in Eq. 3:

Table 2
Descriptive statistics ($N = 71{,}891$).

Variable	*M*	*SD*	*Min.*	*Max.*
SpecificFirmEx	3.92	6.29	0.00	30.49
Gender	0.74	0.44	0.00	1.00
Degree	2.01	0.38	1.00	3.00
LAnalystRank	0.01	0.20	0.00	5.00
GeneralEx	13.81	11.98	0.00	48.78
RHorizon	51.43	65.86	0.00	306.00
FHorizon	278.64	96.12	96.00	461.00
DayElapsed	15.13	25.91	0.00	126.00
CoverIndus	7.70	5.42	1.00	28.00
Frequency	3.67	2.81	1.00	15.00
BrokerEx	76.87	25.61	27.44	121.94
Colisted	0.68	0.47	0.00	1.00
BrokerSize	44.14	21.40	5.00	93.00
AnaAttention	21.07	11.81	4.00	54.00
CompanyAge	45.15	27.43	1.29	100.11
CompanySize	23.38	1.67	20.79	29.19
ROE	0.12	0.07	−0.09	0.35
Leverage	0.47	0.20	0.09	0.93
SalesGrowth	0.24	0.36	−0.33	2.40

Table 3
Correlation matrix.

Variable	Accuracy	SpecificFirmEx	Gender	Degree	LAnalystRank	GeneralEx	RHorizon	FHorizon	DayElapsed	CoverIndus
Accuracy	1.000									
SpecificFirmEx	−0.012	1.000								
Gender	−0.030	−0.049	1.000							
Degree	0.013	0.000	0.073	1.000						
LAnalystRank	−0.007	−0.007	0.002	−0.003	1.000					
GeneralEx	0.004	0.389	−0.068	−0.023	0.002	1.000				
RHorizon	−0.013	0.278	−0.026	0.018	−0.001	0.084	1.000			
FHorizon	−0.294	−0.007	0.013	−0.004	0.006	−0.008	0.026	1.000		
DayElapsed	0.021	−0.012	0.023	0.011	0.000	0.006	0.045	−0.190	1.000	
CoverIndus	−0.030	−0.069	0.019	−0.100	0.048	0.162	−0.015	0.003	0.024	1.000
Frequency	0.005	0.210	0.027	0.006	0.042	0.045	−0.073	0.040	−0.066	−0.006
BrokerEx	0.015	0.019	0.017	0.070	0.004	−0.039	0.020	−0.027	0.028	0.023
Colisted	0.002	0.049	0.012	0.069	0.003	0.027	0.017	0.005	0.022	0.065
BrokerSize	−0.023	0.126	0.054	0.078	0.045	0.057	0.023	0.051	−0.014	−0.129
AnaAttention	0.103	0.085	−0.057	−0.016	−0.005	0.031	0.012	0.000	−0.271	−0.064
CompanyAge	0.003	0.109	0.013	0.003	−0.080	0.030	0.021	−0.043	0.003	0.024
CompanySize	−0.066	0.196	0.013	−0.026	0.014	0.075	0.057	−0.009	−0.074	−0.020
ROE	0.141	0.023	−0.042	−0.019	0.007	0.015	0.005	−0.029	−0.126	−0.068
Leverage	−0.128	0.078	0.022	−0.014	0.036	0.034	0.016	0.004	−0.003	0.016
SalesGrowth	0.040	−0.068	−0.004	−0.003	0.028	0.009	−0.046	−0.024	−0.014	0.048
Variable	Frequency	BrokerEx	Colisted	BrokerSize	AnaAttention	CompanyAge	CompanySize	ROE	Leverage	SalesGrowth
Frequency	1.000									
BrokerEx	0.023	1.000								
Colisted	0.026	0.452	1.000							
BrokerSize	0.091	0.118	0.216	1.000						
AnaAttention	0.155	0.045	−0.023	0.055	1.000					
CompanyAge	0.022	0.007	0.012	0.048	0.073	1.000				
CompanySize	0.076	−0.010	−0.006	0.096	0.282	0.294	1.000			
ROE	0.091	−0.002	−0.019	0.028	0.408	0.021	0.077	1.000		
Leverage	0.021	−0.002	0.003	0.071	0.032	0.211	0.662	−0.077	1.000	
SalesGrowth	0.036	0.017	0.013	0.006	0.010	−0.040	−0.054	0.146	0.024	1.000

$$Accuracy_{ijmn} = \alpha_0 + \alpha_1 \cdot SpecificFirmEx_{ijmn} + \sum\nolimits_{X=1}^{4} \alpha_{1+X} \bullet MX_{im} + \sum\nolimits_{X=1}^{7} \alpha_{5+X} \bullet IX_{ijmn} + \sum\nolimits_{X=1}^{3} \alpha_{12+X} \bullet NX_{in} + \sum\nolimits_{X=1}^{5} \alpha_{15+X} \bullet JX_{ij} + IndustriesDummy + YearDammy + \varepsilon_{ijmn} \tag{3}$$

in which $Accuracy_{ijmn}$ and $SpecificFirmEx_{ijmn}$ respectively represent the analyst forecast accuracy and firm-specific experience measured by quarters of the ith forecast issued by analyst m at brokerage firm n for listed company j; MX_{im} refers to analyst m's characteristics when issuing the ith forecast, which does not change by brokerage firm or listed company; IX_{ijmn} refers to forecast i's characteristics of analyst m at brokerage firm n for listed company j; NX_{in} indicates the brokerage firm n's characteristics corresponding to forecast i, which does not change by analyst or listed company; and JX_{ij} refers to listed company j's characteristics corresponding to forecast i, which does not change by analyst or brokerage firm.

3.4. Descriptive statistics

Table 2 reports the descriptive statistics of the independent variable and control variables. The average value of firm-specific experience is 3.92, but the standard deviation is 6.29, which indicates a significant difference in firm-specific experience between different analysts. On average, analysts issue forecasts 278.64 days before the earnings announcement of the listed companies and re-forecast 51.43 days later. Each analyst covers an average of 7.70 industries and issues 3.67 reports per year for the same listed

Table 4
Results of the main regression.

Type of variable		Variable	(1) Accuracy	(2) Accuracy
Independent variable		SpecificFirmEx	−0.006*** (−3.719)	−0.005*** (−3.269)
	Analysts' characteristics	Gender	−0.095** (−2.021)	−0.078* (−1.764)
		Degree	0.085*** (3.438)	0.063*** (2.879)
		LAnalystRank	0.017 (0.249)	0.005 (0.088)
		GeneralEx	0.003*** (5.228)	0.003*** (3.827)
	Forecasts' characteristics	RHorizon	−0.000 (−0.064)	0.000 (0.021)
		FHorizon	−0.008*** (−13.261)	−0.008*** (−13.226)
		DayElapsed	−0.001*** (−4.935)	−0.001*** (−5.981)
		CoverIndus	−0.011*** (−3.382)	−0.011*** (−3.719)
		Frequency	−0.000 (−0.020)	0.002 (0.386)
Control variables	Brokerage firms' characteristics	BrokerEx	0.000 (0.302)	0.000 (0.603)
		Colisted	0.052* (1.877)	0.029 (0.987)
		BrokerSize	−0.001 (−1.592)	−0.001 (−0.901)
	Listed firms' characteristics	AnaAttention	0.016*** (5.824)	0.019*** (6.765)
		CompanyAge	0.002 (1.277)	0.003*** (2.969)
		CompanySize	−0.042 (−0.578)	−0.106* (−1.701)
		ROE	3.244*** (5.262)	3.144*** (5.166)
		Leverage	−1.331*** (−12.854)	−1.522*** (−10.058)
		SalesGrowth	0.137 (1.338)	0.168 (1.471)
		Constants	4.047** (2.119)	5.512*** (3.351)
Year-fixed effect			No	Yes
Industry-fixed effect			No	Yes
N			71,891	71,891
R^2			0.1124	0.1177

Note: Z statistics, calculated using robust standard errors that take into account clustering at the industry level, are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

company. Table 3 shows the correlation coefficients of the variables, all of which are under 0.7, thereby indicating that collinearity is limited in the data of our sample.

4. Empirical results

4.1. Impact of firm-specific experience on analyst forecast accuracy

Table 4 presents the empirical results obtained by applying Eq. 3, which we use to calculate the impact of firm-specific experience on analyst forecast accuracy in the full sample. Columns 1 and 2 show the results with and without controlling the year-fixed effect and industry-fixed effect, respectively. As shown in those columns, the coefficients of firm-specific experience are negative (i.e., −0.006 and − 0.005) and significant at the 1% level, which indicates that with the increase of firm-specific experience, analyst forecast accuracy decreases. This finding contradicts with what learning-by-doing theory would predict and provides evidence of the existence of analysts' catering behavior.

The results for the control variables are mostly consistent with what the literature has shown. First, for analysts' characteristics, forecast accuracy improves when the analysts have a higher level of education and more general experience. Women have higher analyst forecast accuracy, whereas the analyst's rank does not significantly improve forecast accuracy.

With regards to forecasts' characteristics, we control for the number of days between the date of the analyst's forecast and the date of their most recent prior forecast for the same listed company in the same year; the number of days between the date of the analyst's forecast and the date of any other analyst's most recent prior forecast for the same listed company in the same year; and the number of days between the date of the analyst's forecast and the earnings announcement for the same listed company in the same year. We find that analysts' forecasts are more accurate if they cover fewer industries, whereas forecast frequency does not impact analyst forecast accuracy.

Next, for the characteristics of the brokerage firms where the analysts work, analyst forecast accuracy is higher if the brokerage firm is a listed company, although this effect becomes not significant after year- and industry-fixed effects are controlled for. The impacts of brokerage firms' experience and size on analyst forecast accuracy are not significant.

Last, for the characteristics of the listed companies, analyst coverage, length of time listed, and return on equity rate positively impact analyst forecast accuracy, whereas the size and leverage of listed companies are negatively correlated with analyst forecast accuracy. Sales growth has no significant effect on analyst forecast accuracy.

4.2. Heterogeneity based on the size of brokage firms and listed companies

We expect that the tendency of catering would be higher for analysts at large brokage firms or when they issue forecasts for large listed companies. In this section, we examine the heterogeneous effects of firm-specific experience based on the size of brokage firms and listed companies.

First, we divide the full sample into two subgroups—small and large brokerage firms—based on the ranking of the size of the brokerage firms where the analysts work, with the 50th percentile as the dividing point, and, for each sample, perform regression analysis using Eq. 3. The results, reported in Table 5, show that in up to the 50th percentile of brokerage firms, the coefficient of firm-specific experience is significantly positive (i.e., 0.014 and significant at the 1% level). In the 50th–100th percentile of brokerage firms, the coefficient of firm-specific experience is significantly negative (i.e., −0.008 and significant at the 1% level). These results suggest that, in small brokerage firms, the independence of analysts is not significantly interfered with and thus firm-specific experience enhances analyst forecast accuracy as learning-by-doing theory predicts. By contrast, in large brokerage firms, due to stronger interference with analysts' independence, firm-specific experience does not improve analyst forecast accuracy but decreases it. These findings verify our hypothesis concerning the heterogeneous effects of firm-specific experience for differently sized brokerage firms.

Second, we divide the full sample into small and large listed companies based on the ranking of the size of the listed companies covered by the analysts, again with the 50th percentile as the dividing point, and, for each sample, perform regression according to Eq.

Table 5
Results of heterogeneity analysis based on the size of brokerage firms.

Variable	Up to the 50th percentile Accuracy	50th–100th percentile Accuracy
SpecificFirmEx	0.014*** (3.718)	−0.008*** (−3.809)
Constants	6.736*** (5.774)	5.233*** (3.077)
Control variables	Yes	Yes
Year-fixed effect	Yes	Yes
Industry-fixed effect	Yes	Yes
N	12,832	59,059
R^2	0.1425	0.1139

Note: *Z* statistics, calculated using robust standard errors that take into account clustering at the industry level, are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

3. The results are shown in Table 6. In up to the 50th percentile of the listed companies, the coefficient of firm-specific experience is significantly positive (i.e., 0.013 and significant at the 10% level). In the 50th–100th percentile of listed companies, the coefficient of firm-specific experience is significantly negative (i.e., −0.008 and significant at the 1% level). These results suggest that when issuing forecasts for small listed companies, analysts' catering behavior is weak and firm-specific experience reflects knowledge growth and improves analyst forecast accuracy. While issuing forecasts for large listed companies, firm-specific experience seems to indicate strong catering behavior of analysts and therefore reduces analyst forecast accuracy. These findings confirm our hypothesis regarding the heterogeneous effects of firm-specific experience for listed companies of different size.

Third, we investigate the impact of firm-specific experience on analyst forecast accuracy based on the combinations of differently sized brokerage firms and listed companies. The results are shown in Fig. 1 and Table 7. In the combination of small brokerage firms and small listed companies, firm-specific experience significantly improves analyst forecast accuracy (i.e., 0.013 and significant at the 1% level). In the combination of small brokerage firms and large listed companies, firm-specific experience also significantly enhances analyst forecast accuracy (i.e., 0.058 and significant at the 1% level). In the group combining large brokerage firms and small listed companies, firm-specific experience has no significant impact on analyst forecast accuracy (0.014). In the group combining large brokerage firms and large listed companies, the impact of firm-specific experience on analyst forecast accuracy is significantly negative (i.e., −0.008 and significant at the 1% level).

4.3. Differentiated effects of firm-specific experience for SOEs and non-SOEs

In this section, we divide the full sample into non-SOEs and SOEs and perform regressions using Eq. 3. The results are shown in Table 8. In the subsample of non-SOEs, the coefficient of firm-specific experience is non-significantly negative (i.e., −0.001). By contrast, in the subsample of SOEs, the coefficient of firm-specific experience is significantly negative (i.e., −0.009 and significant at the 1% level). These results indicate that when issuing forecasts on non-SOEs, analysts' catering behavior tends to be weak. For forecasts on SOEs, firm-specific experience compromises analyst forecast accuracy, suggesting strong catering behavior of analysts. These findings confirm our hypothesis regarding the differentiated effects of firm-specific experience for SOEs and non-SOEs and suggest that state ownership is a critical factor influencing analysts' catering behavior and forecast accuracy in the Chinese context.

4.4. Robustness tests

For robustness tests, we recalculate analyst forecast accuracy based on different industry classification standards—that is, the industry classification guidelines of listed companies issued by the CSRC in 2012. The results are consistent with the findings in previous regressions, as detailed in Tables 9–12.

5. Conclusions and policy recommendations

Using forecasted EPS data issued by sell-side analysts in China from 2014 to 2018, we examine the impact of firm-specific experience on analyst forecast accuracy from a perspective of catering. The results first suggest that, overall, firm-specific experience has a significantly negative impact on analyst forecast accuracy, which indicates the existence of analysts' catering behavior. Second, the results of heterogeneity analysis imply that catering behavior exists primarily for analysts who are employed by large brokerage firms or who issue forecasts for large listed companies. Specifically, the impact of firm-specific experience on analyst forecast accuracy seems to be positive when forecasts are made by analysts from small brokerage firms or issued for small listed companies but negative when the analysts work for large brokerage firms or cover large listed companies. Third, the results of our analysis comparing SOEs and non-SOEs show that the effect of firm-specific experience on analyst forecast accuracy is not significant when analysts issue forecasts for non-SOEs and significantly negative when analysts cover SOEs, which indicates that catering behavior exists primarily among analysts who cover SOEs.

Our findings have important implications for policymakers. For one, these findings confirm that analysts indeed cater in the

Table 6
Results of heterogeneity analysis based on the size of listed companies.

Variable	Up to the 50th percentile Accuracy	50th–100th percentile Accuracy
SpecificFirmEx	0.013* (1.887)	−0.008*** (−3.921)
Constants	6.844*** (5.329)	5.137*** (3.010)
Control variables	Yes	Yes
Year-fixed effect	Yes	Yes
Industry-fixed effect	Yes	Yes
N	14,783	57,108
R^2	0.1397	0.1134

Note: *Z* statistics, calculated using robust standard errors that take into account clustering at the industry level, are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

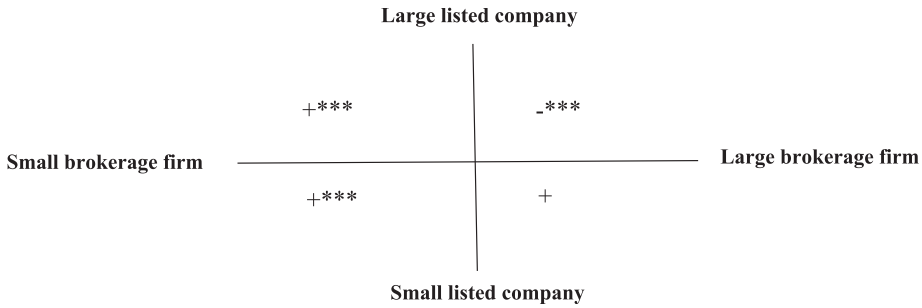

Fig. 1. Impacts of firm-specific experience on analyst forecast accuracy for combinations of differently sized brokerage firms and listed companies.

Table 7
Results based on combinations of differently sized brokerage firms and listed companies.

Variable	Small brokerage firms and small listed companies	Small brokerage firms and large listed companies	Large brokerage firms and small listed companies	Large brokerage firms and large listed companies
SpecificFirmEx	0.013*** (2.886)	0.058*** (7.643)	0.014 (1.006)	−0.008*** (−3.995)
Constants	6.569*** (5.297)	−883.167 (−1.278)	2.801 (1.367)	5.093*** (2.966)
Control variables	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes
Industry-fixed effect	Yes	Yes	Yes	Yes
N	12,368	464	2415	56,644
R^2	0.1411	0.2625	0.1514	0.1129

Note: *Z* statistics, calculated using robust standard errors that take into account clustering at the industry level, are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 8
Results of further analysis between SOEs and non-SOEs.

Variable	Non-SOEs Accuracy	SOEs Accuracy
SpecificFirmEx	−0.001 (−0.304)	−0.009*** (−3.381)
Constants	7.488*** (8.171)	5.208** (2.278)
Control variables	Yes	Yes
Year-fixed effect	Yes	Yes
Industry-fixed effect	Yes	Yes
N	44,894	26,997
R^2	0.1424	0.1051

Note: *Z* statistics, calculated using robust standard errors that take into account clustering at the industry level, are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

forecasting process and such behavior reduces analyst forecast accuracy. Catering behavior is especially strong among analysts at large brokerage firms, among analysts who cover large listed companies, and among analysts who issue forecasts for SOEs. In the process of China's capital market reform, a major challenge is how to protect the interests of small and medium investors. Because analysts' reports act as an important source of information for investors, the decline in the quality of such information not only risks the investment outcomes of investors but also hurt the healthy development of Chinese capital markets.

For another, with the in-depth development of capital markets in China, the business of brokerage firms has become increasingly diversified, and their business exchanges with listed companies have intensified. As a result, the working environment for sell-side security analysts who are generally affiliated with specific brokerage firms becomes increasingly complex environment under which maintaining independence of analysts confronts ever-greater challenges. To ensure the independence of analysts and the objectivity of their reports, the reform of Chinese capital markets should strengthen the regulation on brokerage firms and listed companies to reconcile the diverse interests (i.e., firewall system) between different departments within brokerage firms and prevent illegal benefit transfer between analysts and the top management of listed companies.

This paper has explored the analyst behavior in a Chinese context. Extension of this research to other emerging financial markets

Table 9
Robustness test on the results of the main regression.

Variable	**(1)** wjAccuracy	**(2)** wjAccuracy
SpecificFirmEx	−0.005***	−0.004***
	(−2.676)	(−3.138)
Constants	3.616**	4.888***
	(1.895)	(2.573)
Control variables	Yes	Yes
Year-fixed effect	Yes	Yes
Industry-fixed effect	Yes	Yes
N	71,891	71,891
R^2	0.1128	0.1187

Note: *wjAccuracy* refers to the dummy variable of analyst forecast accuracy constructed in the robustness tests. *Z* statistics, calculated using robust standard errors that take into account clustering at the industry level, are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 10
Robustness test on the results of heterogeneity analysis based on differently sized brokerage firms.

Variable	Up to the 50th percentile wjAccuracy	50th–100th percentile wjAccuracy
SpecificFirmEx	0.012*	−0.006***
	(1.909)	(−3.201)
Constants	6.317***	4.669***
	(4.617)	(2.686)
Control variables	Yes	Yes
Year-fixed effect	Yes	Yes
Industry-fixed effect	Yes	Yes
N	12,832	59,059
R^2	0.1463	0.1132

Note: *Z* statistics, calculated using robust standard errors that take into account clustering at the industry level, are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 11
Robustness test on the results of heterogeneity analysis based on differently sized listed companies.

Variable	**Up to the 50th percentile** wjAccuracy	**50th–100th percentile** wjAccuracy
SpecificFirmEx	0.014*	−0.007***
	(1.714)	(−3.714)
Constants	6.307***	4.590***
	(4.726)	(2.596)
Control variables	Yes	Yes
Year-fixed effect	Yes	Yes
Industry-fixed effect	Yes	Yes
N	14,783	57,108
R^2	0.1425	0.1128

Note: *Z* statistics, calculated using robust standard errors that take into account clustering at the industry level, are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

can test the generalizability of our findings and contribute to their financial market development. We suggest multi-faceted examinations on firm-specific experience and imply possible sources for catering behavior of analysts. It is important to further investigate the relationship among analysts, security companies and listed companies in order to get a full understanding of the mechanisms of catering. Exploration on the conditions that modify catering behavior will be helpful to better protect the independence of analysts. Finally, it will be interesting to examine whether our findings on analysts' forecasts have any impact on investor decision-making and stock performance.

Declaration of competing interest

None.

Table 12
Robustness test on the results between SOEs and non-SOEs.

Variable	Non-SOEs wjAccuracy	SOEs wjAccuracy
SpecificFirmEx	−0.001 (−0.308)	−0.008*** (−2.881)
Constants	7.398*** (6.534)	4.369** (1.961)
Control variables	Yes	Yes
Year-fixed effect	Yes	Yes
Industry-fixed effect	Yes	Yes
N	44,894	26,997
R^2	0.1426	0.1033

Note: *Z* statistics, calculated using robust standard errors that take into account clustering at the industry level, are reported in brackets. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Data availability

we have upload the Mendeley dataset link
Learning by Doing or Catering: Firm-Specific Experience and Analyst Forecast Accuracy (Original data) (Mendeley Data)

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