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Stock market reactions and optimism bias in analysts' earnings forecasts: An analysis of China's stock markets

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ABSTRACT

This paper examines analysts' catering behavior to current investor demand, proxied by the unbalanced stock market reaction toward optimistic forecasts and non-optimistic forecasts (i.e., optimism premium). Using data on earnings forecasts issued by sell-side analysts in China from 2014 to 2018, we show that the optimism premium significantly increases analysts' tendency to issue optimistic forecasts—in short, that analysts do cater to investor demand. The implications of our findings for theory and practices are discussed.

1. Introduction

As important information intermediaries, financial analysts are expected to issue unbiased research reports to reduce a market's information asymmetry and thereby increase its efficiency (Guo et al., 2023; Huang et al., 2022; Zhang et al., 2020). However, facing conflicts of interest, analysts often make their forecasts rosier in order to achieve personal gains, for the result of generally optimistic reports (Hong and Kubik, 2003; Hou and Gao, 2021; Karmaziene, 2023; Lehmer et al., 2022).

Focusing on the optimism bias in analysts' earnings per share (EPS) forecasts as their most salient output (Huang et al., 2022; Lehmer et al., 2022), previous studies have examined a wide range of determinants related to conflicts of interest originating from both the supply side, including among brokers where the analysts work (Cowen et al., 2006; Hong and Kubik, 2003; Jackson, 2005; Lehmer et al., 2022) and the management of listed companies covered by analysts (Agrawal et al., 2008; Francis and Philbrick, 1993; Ke and Yu, 2006), and the demand side. Concerning the latter research stream, which our paper seeks to contribute to, Zhang et al. (2022) and Guo et al. (2023) have shown that analysts issue optimistically biased EPS forecasts to cater to institutional investors for commission fees and market ranking (see also Karmaziene, 2023). Drawing on a theory of media bias, Lai (2004) has additionally revealed that analysts' optimism bias in EPS forecasts could result from their catering to institutional investor beliefs for the purpose of generating business for their brokerages. Acknowledging those contributions, we complement studies on the demand side, which have largely focused on analysts' catering to a specific agent (e.g., fund clients or institutional investors), with the consideration of market-level factors, specifically investor demand for optimistic forecasts. Although some literature provides evidence of analysts' catering to investor demand, it focuses either on analysts' bias in target price forecasts (Chen et al., 2016) or on their shift in coverage (Jansen

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et al., 2023), whereas no literature addresses analysts' issuance of optimistically biased EPS forecasts as an act of catering to investor demand.

This paper draws specifically on catering theory (Baker et al., 2009; Baker and Wurgler, 2004), which holds that managers of firms attempting to secure a stock price increase pay dividends in order to cater to current investor demand for dividend payers. It therefore investigates whether analysts issue optimistically biased EPS forecasts to cater to current investor demand for optimistic forecasts for a given stock. According to Baker and Wurgler (2004, 2004b), investors in imperfect markets are assumed to have heterogeneous preferences, and some detect analysts' forecasts bias, albeit to various extents (Kumar and Lee, 2006), and even appreciate their content, particularly when the biased EPS forecasts match their own preferences (Mullainathan and Shleifer, 2005). For example, scholars have observed that financial markets, particularly those in which short sales are limited (Miller, 1977), are populated by behaviorally optimistic investors (Barberis et al., 1998), mostly individuals, who hold long positions in stocks whose prices they naively believe will fundamentally increase in the future (Barber and Odean, 2001) and, as such, demand information that endogenously confirms their optimistic beliefs (Caplin and Leahy, 2001; Karlsson et al., 2009). Although naive in their trading strategy given limits to arbitrage (Shleifer, 2000), scholars have noted that, via optimistic preferences, investors can even generate high returns by holding risks that are self-induced in markets and that other investors do not want to bear (DeLong et al., 1990). To the same extent, institutional investors, including hedge funds, with short-term trading strategies may generate a demand for optimistic analysts' forecasts, because, as observed by scholars, those forecasts not only facilitate lucrative trades, particularly with retail traders (Bilinski et al., 2019), but also generate the bulk of trading fees (Goldstein et al., 2009) and create the potential for rewarding brokerage companies and their analysts (Chen et al., 2016).

The presence of investor demand for optimistic EPS forecasts causes divergent stock market reactions to optimistic versus non-optimistic EPS forecasts. However, the magnitude and direction of the divergence is time-variant depending on the composition of investors and their preferences. Because analysts bear a negative charge for inaccuracy, by looking at stock market reactions to EPS forecasts with different degrees of optimism they can infer the investors' current appreciation of optimistic forecasts and fine-tune the issuance of future forecasts accordingly. In other words, investor demand for analysts' optimistic EPS forecasts is time-variant, which causes the relative aggregate market value of stocks with and without optimistic forecasts to fluctuate. As a result, analysts attempt to manage their current clientele in ways that are assumed to directly or indirectly reward the most analysts whose EPS forecasts meet their preferences (Lai, 2004), namely by shouldering the costs of inaccurate EPS forecasts, by catering to investor demand for optimistic EPS forecasts, and by issuing upwardly biased forecasts when investors place a premium on those forecasts, as well as vice versa.

Similar to the *dividend premium*, defined by Baker and Wurgler (2004, 2004b) as current investor demand for dividend payers, in this paper we introduce *optimism premium* (*OP*), defined as the difference between a stock market's reaction to the most recent optimistic forecast and its reaction to the most recent non-optimistic forecast of a stock. In that sense, a positive *OP* means higher current investor demand for optimistic forecasts for a stock. To some extent, the *OP* reflects market mispricing but with a certain optimistic direction, thereby making catering behavior under its influence appropriate for analysts. In such an imperfect market, analysts may engage in opportunistic behavior by issuing optimistic EPS forecasts in response to previously positive market reactions to optimistic versus non-optimistic reports. Such a conceptualization relates to Lehmer et al.'s (2022) conception of the informativeness of future analysts' reports of changes in volume in response to the prior stock market reaction and to Abarbanell's (1991) argument that analysts pay attention to prior changes in stock prices while revising their EPS forecasts. Along similar lines, other scholars have also empirically observed that analysts strategically utilize investors' optimistic sentiment during particular periods (Huang et al., 2022) and flex their market influence (Lehmer et al., 2022) in issuing optimistically biased EPS forecasts in order to cater to those investors and, in turn, reap personal gain (e.g., compensation through investment banking, commission from analysts' brokers, and private information via access to the management of covered firms). For that reason, a positive association between the *OP* and the issuance of analysts' subsequent optimistic EPS forecasts can be expected. In addition, for robustness we introduce the difference in future stock market reactions to optimistic EPS forecasts compared with non-optimistic ones and suggest a negative association with analysts' current issuance of optimistic EPS forecasts. If current investor demand for optimistic EPS forecasts is especially high, then the underlying stock is likely to be currently overpriced, which implies that the same stock's future returns will be relatively low (Baker and Wurgler, 2004).

We test the association between past *OP* and the analysts' subsequent issuance of optimistic EPS forecasts in a longitudinal sample of 1664 security analysts in China's stock markets from 2014 to 2018, for 42,999 total observations. Controlling for changes in stock market prices and excess trading volume generated by such optimistic forecasts, we show that the higher the previous (future) *OP* of an individual analyst, the more likely (less likely) the analyst is to issue an optimistically biased EPS forecast. In specification tests and additional robustness tests, that primary association remains constant.

This paper's chief contribution is its identification of a new source of analysts' optimism bias in EPS forecasts by linking the occurrence of such bias to the implied investors' excess demand for optimistic forecasts captured by the variable of the *OP*. In following the *OP*, analysts prioritize the goal of catering to investors' unbalanced demand, a finding that extends the scope of catering theory initially developed in the field of dividend payments in North American stock markets (Baker and Wurgler, 2004). We also contribute to literature on the relationship between analysts' behavior and investor demand (Chen et al., 2016) by providing theoretical arguments and empirical evidence that, controlling for imbalance in trading volumes and general market sentiments, investors' demand for optimistic EPS forecasts is another driver of analysts' catering behavior via the issuance of optimistically biased forecasts. Our work demonstrates our theory that analysts cater to investors not only amid excess demand for a given stock but also because investors appreciate analysts' issuance of optimistic reports for stocks that they are interested in, as expressed by the *OP*. Our work also suggests that the catering effect driven by investor demand for information observed from analysts' coverage strategies (Jansen et al., 2023) extends to EPS forecasts as well. Moreover, given that EPS forecasts are analysts' most salient output and widely used to assess their performance, the relevance of the *OP* in analysts' issuance of biased reports indicates, on the one hand, the presence and relevance of investors, particularly retail traders, with potentially biased preferences and noise trading strategies in China's financial market. On the other, that sell-side analysts in China may face more severe conflicts of interest originating from brokerages, the management of listed companies, and institutional investors, which drive their optimism bias in their chief output.

2. Data and method

2.1. Sample data

Our sample consists of data from the China Stock Market & Accounting Research Database (CSMAR) representing EPS forecasts for all non-financial listed companies on the A-share main board and small and medium-sized board issued by sell-side analysts in China as well as the stock prices of listed companies from 2014 to 2018. Compared with developed stock markets dominated by more professional and experienced institutional investors such as in the United States, China's stock markets constitute an emerging market and, as such, differ considerably from their developed counterparts. First, the short sales constraint in China means that investment interests can be obtained primarily by the increase of stock prices, which makes investor demand for optimistic forecasts material information. Second, retail investors without much investment training or experience form a large proportion of investors in China's stock markets, thereby making the demand more likely to indicate irrational preferences, even for optimistic EPS forecasts, which are more likely to induce catering among analysts (Chen et al., 2016; Jansen et al., 2023). Third, retail investors rely heavily on analysts' forecasts to make investment decisions, which may reinforce the market influence of analysts and, in turn, create strong catering incentives for them (Lehmer et al., 2022).

Because the severe lockdown procedure adopted in China during the COVID-19 pandemic strongly affected periods after 2020, we exclude observations representing those periods from our analysis. From initial data based on 486,521 observations, we also exclude forecasts issued by a team of analysts ($n = 229{,}033$), because the contribution of individual analysts therein is difficult to identify; forecasts for listed companies for future years ($n = 169{,}261$), because the forecast period is too long to be informative; forecasts for listed companies with abnormal stock trading ($n = 1500$), because analysts' forecasts can be disturbed by those anomalies; forecasts for listed companies covered by less than three analysts in that year ($n = 4481$), because there are not enough forecasts for analysts to refer to; and all forecasts with missing information for variables ($n = 39{,}247$). Our final sample contains 42,999 analyst-listed company-reporting day-level forecasts.

2.2. Dependent variable

Based on the methods of Mikhail et al. (1999) and Hong and Kubik (2003), we first construct the forecast's optimism error variable ($Optierror_{d,m,\ y,\ j,\ i}$) for each forecast in Eq. (1), in which $FEPS_{d,m,\ y,\ j,\ i}$ and $Optierror_{d,m,\ y,\ j,\ i}$ respectively represent the *EPS* forecast and forecast error of analyst *i*for listed company *j* at day *d*, month *m*, and year *y*. Meanwhile,$REPS_{y,j}$ and $Price_{y-1,\ j}$ represent the actual EPS value and the prior year-end stock closing price of listed company *j* corresponding to each forecast, respectively.

$$Optierror_{d,m,y,j,i} = \frac{FEPS_{d,m,y,j,i} - REPS_{y,j}}{Price_{y-1,j}} \tag{1}$$

Next, we use a moving average method to define whether an analyst's forecast is optimistic. If $Optierror_{d,m,\ y,\ j,\ i}$ is higher than or equals the consensus average forecast optimism error of the previous 180 days issued for the same listed company by all analysts, then the forecast is regarded as optimistic. In that case, $Optimism_{d,m,\ y,\ j,\ i}$ equals 1 but 0 if otherwise (Jackson, 2005).

2.3. Independent variable

Similar to Lacina and Karim (2004), we first use a Capital Asset Pricing Model (CAPM) with the previous 180 days as the prediction window to measure the theoretical daily return of the covered stock and, in turn, derive the cumulative abnormal return (CAR) of the stock by calculating the difference between the theoretical and the real daily return based on the [−1,3] window with 0 as the forecasting day.[1]

For each forecast, the *optimism premium* (*OP*) is the daily average difference between the CAR of the most recent optimistic forecast and the CAR of the most recent non-optimistic forecast issued by any analyst before the forecast on the same stock. Fig. 1 shows three scenarios for the construction of the *OP*. If both optimistic forecasts and non-optimistic forecasts exist before the forecast issued by analyst *i* on firm *j* at day *d*, month *m*, and year *y*, then the *OP* is defined as the daily average difference between the CAR[−1,3] of the most recent optimistic forecast issued by analyst *a* on firm *j* at day $d - r - h$ and the CAR[−1,3] of the most recent non-optimistic forecast issued by analyst *b* on firm *j* at day $d - r$. However, if only optimistic (non-optimistic) forecasts exist before the forecast issued by analyst *i* on firm *j* at day *d*, month *m*, and year *y*, then the *OP* is defined as the (minus) daily average CAR[−1,3] of the most recent optimistic (non-optimistic) forecast issued by analyst *a* (*b*) on firm *j* at day $d - r - h$ ($d - r$). For a robustness check, we add a dummy variable to control for the latter two cases and obtain consistent results.

[1] If the forecasting day is a non-trading day for the stock, then the next day is used as the forecasting day; if that day is also a non-trading day, then the next day is used, and so on, for up to 7 days.

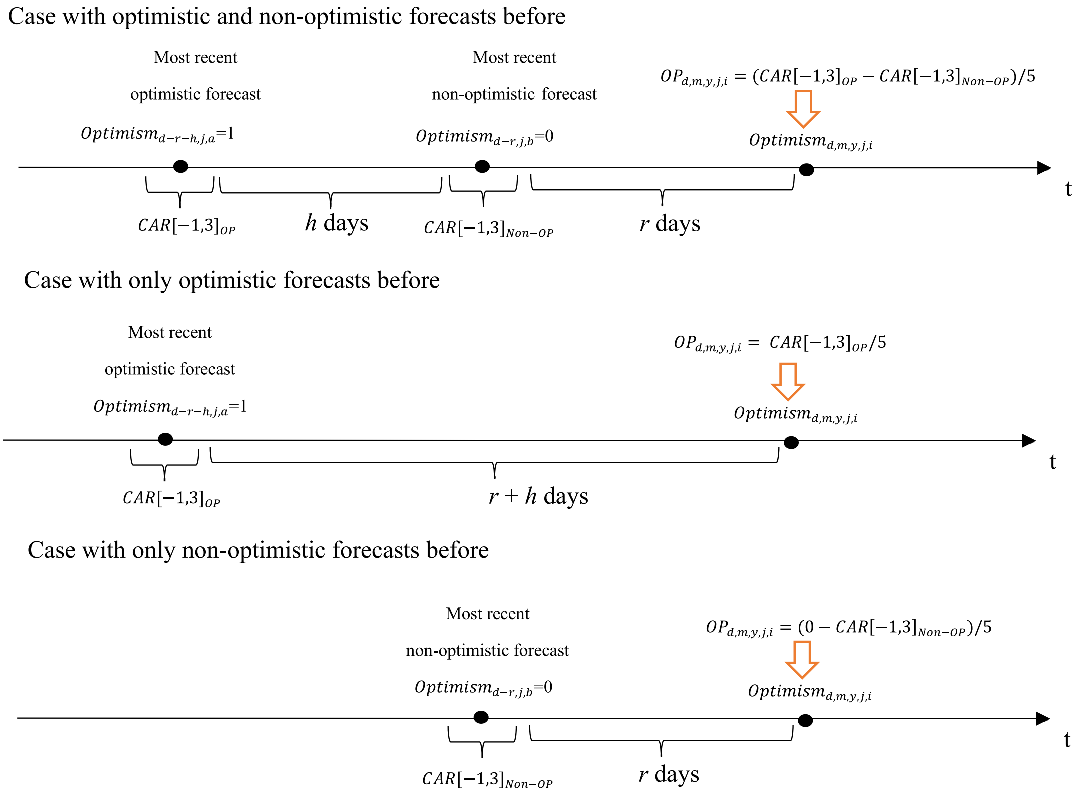

Fig. 1. Method of estimating the *optimism premium* (*OP*).

2.4. Controls

The control variables are categorized as existing at five levels. At the forecast level, other than the forecast horizon (Zhang et al., 2022), namely *ForeHorizon*, we include the revision horizon (*RevHorizon*) and day elapsed (*DayElapsed*) to control the number of days between analysts' forecasts and their own last forecast on the same stock and the number of days between analysts' forecasts and the most recent forecast issued by any other analyst on the same stock. At the analyst level, we control analysts' reputation (Guo et al., 2023), namely *AnaRank*. At the listed company level (Chen et al., 2016; Zhang et al., 2022), we control companies' size (*FirmSize*), Return on Equity (*ROE)*, and analysts' attention (*AnaAttention*). To further control the possible effect of market mispricing on analysts' issuance of biased forecasts, particularly the effect that analysts' optimism is merely an opportunistic reaction to market inefficiency, we use discretional accruals (*AccRatio*) at the firm level as a control variable for market mispricing (Kraft et al., 2006; Polk and Sapienza, 2008). At the broker level, we control for potential supply-side sources of conflicts of interest, as captured by underwriting relationship (*Underwriting*) and fee affiliation relationship (*FeeAffiliation*), following Wu et al. (2018). At that level, additional controls include brokers' size (*BrokerSize*) and reputation (*BroRank*), following Zhang et al. (2022). At the market level, we control unbalanced trading volume (*VolExcess*) and investor sentiment (*ISI*), which can induce analysts' optimism bias in EPS forecasts (Chen et al., 2016; Lehmer et al., 2022; Wu et al., 2018). Because the *OP* is based on the market return, we add the CSI 300 Index return to control the general market return trend (*MIndex*). We also incorporate the *OP* based on the future window (*FReturn*) to rule out the possibility that analysts issue optimistic forecasts to cater to future instead of current investor demand (Baker and Wurgler, 2004).

Data representing the underwriting and fee affiliation relationships derive from the Wind Economic Database (EDB), while data representing other control variables come from the CSMAR database. Table A0 in the Supplementary Materials shows the definition and descriptive statistics of the variables. Concerning optimism, the table clarifies that analysts are generally optimistic toward the listed companies.

2.5. Estimation method

We use a fixed-effect logit model that controls year-, industry-, and analyst-level effects. A fixed-effect model can help to rule out the impact of fixed omitted correlated variables on our results, including certain analysts' career paths. Our choice of a fixed-effect model is controlled with the standard Hausman test. We also use Variance Inflation Factor (VIF) for multicollinearity and δ-Oster for unobservable selection bias in variables (Oster, 2019).

To test the effect of the *OP* on analysts' issuance of optimistically biased EPS forecasts, we use a logit model specified in Eq. (2), in which $F(z) = e^z/(1+e^z)$ is the cumulative logistic distribution and X is a vector of control variables. If our hypothesis is true, then β should be significantly positive.

$$\Pr\left(Optimism_{d,m,y,j,i} = 1\right) = F\left(\alpha + \beta \cdot OP_{d,m,y,j,i} + \gamma \cdot X_{d,m,y,j,i}\right) \tag{2}$$

3. Results and discussion

3.1. Descriptive statistics

Table 1, showing the correlation coefficients of the variables, reveals that the correlation coefficients are all less than 0.7, which indicates that collinearity is limited in our sample.

3.2. Main effect of OP on optimism

Table 2 presents the number of optimistic forecasts in each year and the corresponding mean market reactions. As demonstrated, compared with non-optimistic forecasts, the market reacts more visibly to optimistic forecasts, meaning that excess investor demand for optimistic forecasts may exist in the market. Next, Table 3 presents the results of Eq. (2) with and without controlling different groups of control variables. As shown, the coefficients of the *OP* are all positive and significant at the 1 % level, which indicates that as the *OP* increases, analysts are more likely to issue optimistic EPS forecasts. Such a result holds constant when using optimism as a continuous variable in a fixed-effect regression model (see Table A2 in the Supplementary Materials). The difference in future stock market reactions to optimistic EPS forecasts compared with non-optimistic ones reveals a negative association with current analysts' issuance of optimistic EPS forecasts, thereby providing additional evidence of analysts' tendency of catering to current investor demand for optimistic forecasts.

4. Concluding remarks

Testing the effect of investors' appreciation of optimistic forecasts proxied by the *OP* on analysts' optimism in future EPS forecasts, our analysis reveals a previously undocumented catering effect in security analyst forecasts originated from demand-side sources. Our findings provide robust evidence that *OP* can significantly increase analysts' tendency to issue optimistically biased EPS forecasts (see Tables A3 and A4 in the Supplementary Materials). That association stays constant even when accounting for other potential sources of optimism bias in analysts' forecasts, including the underwriting relationship, fee affiliation relationship, excess trading volume, and investor sentiments (see Table A1 in the Supplementary Materials). Moreover, to test whether our results are simply driven by market

Table 1
Correlation coefficients of the variables.

Variables	*Optimism*	*OP*	*RevHorizon*	*ForeHorizon*	*DayElapsed*	*AnaRank*	*AnaAttention*	*FirmSize*	*ROE*
Optimism	1.000								
OP	0.026	1.000							
RevHorizon	−0.002	0.002	1.000						
ForeHorizon	0.218	0.024	0.001	1.000					
DayElapsed	−0.015	0.001	0.058	−0.147	1.000				
AnaRank	−0.006	−0.002	0.008	0.028	−0.012	1.000			
AnaAttention	0.035	−0.011	0.014	0.075	−0.293	−0.003	1.000		
FirmSize	0.035	−0.004	0.023	0.027	−0.072	0.017	0.268	1.000	
ROE	0.011	−0.001	0.032	0.026	−0.108	−0.010	0.313	0.057	1.000
AccRatio	−0.009	−0.002	0.003	0.038	0.007	−0.016	0.007	−0.067	0.172
Underwriting	−0.006	−0.008	−0.012	0.007	−0.014	−0.017	0.039	0.058	−0.006
FeeAffiliation	0.029	0.006	−0.010	0.041	−0.101	0.026	0.259	0.191	0.138
BrokerSize	0.018	0.000	0.006	0.037	0.014	0.176	−0.035	0.068	0.000
BroRank	0.025	−0.008	0.006	0.036	−0.032	0.126	0.042	0.047	0.019
VolExcess	0.034	0.125	−0.007	0.007	−0.014	0.005	0.003	0.001	−0.003
FReturn	−0.056	−0.102	−0.029	−0.061	0.023	0.008	−0.049	−0.049	−0.016
MIndex	−0.024	−0.002	−0.018	−0.045	0.040	0.019	−0.047	−0.029	−0.024
ISI	−0.018	0.024	−0.068	0.168	−0.007	0.038	−0.096	−0.032	−0.053

Variables	*AccRatio*	*Underwriting*	*FeeAffiliation*	*BrokerSize*	*BroRank*	*VolExcess*	*FReturn*	*MIndex*	*ISI*
AccRatio	1.000								
Underwriting	−0.020	1.000							
FeeAffiliation	−0.008	0.024	1.000						
BrokerSize	−0.018	0.081	0.079	1.000					
BroRank	0.001	0.067	0.047	0.398	1.000				
VolExcess	−0.007	0.008	0.005	0.004	0.004	1.000			
FReturn	0.020	0.009	0.006	0.017	−0.033	−0.054	1.000		
MIndex	−0.010	−0.005	0.014	−0.018	−0.003	0.000	−0.005	1.000	
ISI	−0.024	0.019	−0.051	0.001	−0.038	−0.004	0.074	0.031	1.000

Table 2
Optimistic forecast numbers and corresponding mean market reactions.

Optimism(=0/1) Year	*N* (=0)	CAR3 *M* (=0)	*N* (=1)	CAR3 *M* (=1)	*N* (Total)	CAR3 *M* (Total)
2014	3497	0.008	3176	0.012	6673	0.010
2015	3414	0.021	2371	0.025	5785	0.023
2016	4742	0.008	3736	0.015	8478	0.011
2017	5723	0.004	5729	0.012	11,452	0.008
2018	4903	0.008	5707	0.014	10,610	0.011
Total	22,279	0.009	20,719	0.015	42,998	0.012

Table 3
Main effect of *optimism premium (OP)*.

Variables	*Optimism*	*Optimism*	*Optimism*	*Optimism*	*Optimism*
OP	2.674***	2.623***	2.606***	2.595***	1.810***
	(4.020)	(3.933)	(4.732)	(3.884)	(2.661)
RevHorizon	–	−0.001***	−0.001***	−0.001***	−0.001***
		(−3.098)	(−1.730)	(−3.136)	(−3.292)
ForeHorizon	–	0.002***	0.002***	0.002***	0.002***
		(14.081)	(40.932)	(13.985)	(14.553)
DayElapsed	–	0.000	0.001	0.001*	0.001*
		(1.056)	(3.654)	(1.655)	(1.888)
AnaRank	–	−0.055***	−0.058***	−0.060***	−0.060***
		(−3.653)	(−3.921)	(−3.964)	(−3.932)
AnaAttention	–	–	0.001	0.001	0.000
			(−1.232)	(0.446)	(0.421)
FirmSize	–	–	0.032***	0.028***	0.027***
			(3.062)	(2.943)	(2.802)
ROE	–	–	0.028	0.008	0.007
			(0.571)	(0.061)	(0.056)
AccRatio			−0.737***	−0.731***	−0.714***
			(−3.833)	(−3.801)	(−3.703)
Underwriting	–	–	–	−0.206**	−0.207**
				(−2.104)	(−2.106)
FeeAffiliation	–	–	–	0.068***	0.072***
				(2.825)	(2.968)
BrokerSize	–	–	–	0.001	0.001
				(0.430)	(0.430)
BroRank	–	–	–	0.063	0.064
				(1.084)	(1.106)
VolumeExcess	–	–	–	–	1.262***
					(6.368)
FResurn	–	–	–	–	−22.888*
					(−1.909)
MIndex	–	–	–	–	−0.653***
					(−3.260)
ISI	–	–	–	–	−0.003***
					(−4.260)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes
N	42,280	42,280	42,280	42,280	42,280
R^2	0.1048	0.0821	0.1092	0.1095	0.1109
δ-Oster	245.454	14.449	13.770	13.652	3.773
VIF	1.00	1.01	1.08	1.11	1.09

Note: *Z* statistics are shown in parentheses, δ-Oster represents the coefficient of the omitted variable bias robustness test, VIF is the variance inflation factor, and *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

mispricing, we calculate *OP_fake* by bootstrapping randomly selected dates on which analysts issue EPS forecasts. Our *OP_fake* is non-significant, however, which shows that mispricing cannot be the sole driver of analysts' optimism bias in EPS forecasts (see Table A5 in the Supplementary Materials). We also empirically document that regulatory changes on conflicts of interest at the environmental level can decrease analysts' dependence on *OP* in issuing optimistically biased EPS forecasts (see Table A1 in the Supplementary Materials).

Such an effect offers some evidence of how regulating conflicts of interest in analyst services, thereby making inaccurate reports less desirable to investors and to analysts via increased negative costs for inaccuracy and the reduced possibility for brokerage firms to profit from issuing such reports by conducting business with institutional investors, paves the way to limiting additional conflicts originating from analysts' pursuit of the *OP* in issuing EPS forecasts. To the same extent, because demand for optimistic forecasts is fueled by optimistic investors, policymakers should also pay attention to the enhancement of investors' financial capabilities and skills as a way to increase analysts' independent status, in addition to regulating stakeholders who interfere with analysts' forecasts.

Our findings have some limitations. Although we focus on EPS forecasts only, we envision the possibility of extending the catering effect to analysts' stock coverage as well (Jansen et al., 2023). Because we also empirically analyze the effect of a proxy of market mispricing, further studies should elaborate, distinguish, and separate the effect of market mispricing and implied demand for optimistic forecasts in analysts' issuance of optimistically biased forecasts. Last, whereas we focus on the Chinese financial market, future studies could involve evaluating the association between the *OP* and optimistic forecasts across financial markets with different regulations and institutions.

CRediT authorship contribution statement

Xu Ji: Conceptualization, Data curation, Writing – review & editing. **Yan Dong:** Writing – review & editing, Supervision. **Gianluca Vagnani:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Xiaoqi Yang:** Conceptualization, Data curation.

Declaration of Competing Interest

The authors have no relevant financial or non-financial interests to disclose.

Data availability

Data will be made available on request.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2023.104822.

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