International Review of Financial Analysis 89 (2023) 102750

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Learn from peers? The impact of peer firms' analyst earnings forecasts on a focal firm's corporate investment efficiency

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ARTICLE INFO

Keywords:
Peers' analyst earnings forecasts
Learning effect
Information asymmetry
Investment efficiency

ABSTRACT

We explore whether a firm can learn from information on peers produced by analysts. Based on a sample of Chinese firms, we document that analyst earnings forecast accuracy (dispersion or optimism) of peer firms is positively (negatively) associated with the focal firm's investment efficiency. The effect is more salient when the focal firm operates in a competitive industry, when analysts are predicting positive earnings, when peers produce low-quality annual reports, or when the focal firm has high information asymmetry. Overall, our findings provide new insights on learning from peer information produced by a third party and show that analyst earnings forecasts have spillover effects in the product market.

1. Introduction

Prior research finds that peer-firm information helps managers of a focal firm[1] make more informed investment decisions because other firms within a peer group are affected by similar economic conditions (Roychowdhury, Shroff, & Verdi, 2019). The focal firm can leverage information from its peers to guide its corporate activities. For instance, studies show managers of a focal firm can learn from peers' restatements to modify its subsequent investment decisions (Durnev & Mangen, 2009) and from peers' valuations to recognize its investment opportunities (Foucault & Fresard, 2014). These studies, however, focus on peer firms' own disclosures and ignore information disseminated by peers' other important external stakeholders.[2] Among various external stakeholders, we consider analysts and explore whether peer firms' analyst earnings forecasts affect a focal firm's investment efficiency.

Analysts are essential information producers and stakeholders of a covered firm. Their earnings forecasts are mostly useful to other market participants (Durney et al., 2003; Francis & Soffer, 1997; Liu, Thomas, & Jacob, 2000; Lys & Sohn, 1990; Zhang et al., 2022) in terms of timeliness and are not subject to manipulation by peer managers. Generally, there are a number of analysts following a peer firm. Thus, a focal firm can gain insights from the mean value, difference, or dispersion of the analyst earnings forecasts.

We argue that there are two potential mechanisms for how peers' analyst earnings forecasts affect a focal firm's investment. First, from a business intelligence perspective, a focal firm's managers are motivated to learn from these peer forecasts because they inform the managers about the peers' sales, earnings, and sales costs. Then, the focal firm can develop more-precise estimates of aggregate demand and supply of the products in the same industry. Such peer-firm forecasts can enlarge managers' information set and reduce future uncertainty of the focal firm, leading to better investment efficiency. Second, investors of the focal firm can gain a better understanding of a focal firm's market competition from peers' analyst earnings forecasts. As information asymmetry between investors and the focal firm decreases, the adverse selection and moral hazard problems are attenuated, leading to higher investment efficiency of the focal firm.

We test our hypotheses using a sample of Chinese firms. Following prior research (Durnev & Mangen, 2009; Seo, 2021), we identify peers as industry peers who have the same first three digits in their SIC codes

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[1] If there are N firms in an industry, the i[th] firm in the industry faces the remaining N-1 firms in its operation. Hence, every firm is a focal firm. We use the term to avoid the confusion of a generic use.

[2] On August 26, 2022, on an online interactive platform (irm.cninfo.com.cn), an investor asked the company secretary of Rongjie Ltd. (a major lithium battery manufacturer) about his firm's operating performance. He suggested the investor to look into his company's peers and related analyst earnings forecasts. Please refer to http://irm.cninfo.com.cn/ircs/question/questionDetail?questionId=1260536678414499840 (accessed September 22, 2022).

https://doi.org/10.1016/j.irfa.2023.102750
Received 29 September 2022; Received in revised form 5 June 2023; Accepted 27 June 2023
Available online 3 July 2023
1057-5219/

using the 2012 CSRC (China Securities Regulatory Commission) version of industry classification. We document that peers' analyst forecast accuracy is positively related to a focal firm's investment efficiency. In contrast, large dispersion and optimism in forecasts are negatively related to investment efficiency. The results are robust to an alternative investment efficiency proxy and after accounting for endogeneity.

Additional analysis suggests that the impact of peer forecasts on a focal firm's investment efficiency is more salient when peer information and peers' analyst earnings forecasts are useful to the focal firm. Specifically, our results suggest that the impact of peers' analyst earnings forecasts on the focal firm's investment efficiency is stronger when the firm belongs to a competitive industry or analysts' forecasts are on the positive earnings. In a competitive industry, firms need to be particularly careful and precise in investment and operation decisions to maintain their edge in the marketplace. Therefore, these firms rely more on peer information, including peers' analyst earnings forecasts. Similarly, forecasting losses are much harder than those of positive earnings (Ciccone, 2005). Hence, when analysts make operating losses forecasts, the information is less helpful.

Second, we find that the effect of peers' analyst earnings forecasts on the focal firm's investment efficiency is stronger when the quality of the peers' annual reports is low. The results are consistent with the notion that when peers' disclosures are less informative, the focal firm relies more on the insights of analysts. This intuition is similar to the logic of Shroff, Verdi, and Yost (2017), who find that the peer information environment matters only when investors cannot get enough information from a focal firm.

Third, we document that when the focal firm has high information asymmetry, the effect of peers' earnings forecasts by analysts on its investment efficiency is more salient. We interpret that to mean more peer information alleviates the focal firm's information asymmetry. Therefore, stakeholders of the focal firm face lower information uncertainty from an industry context. Accordingly, the focal firm has lower moral hazard and adverse selection issues leading to lesser concerns from external stakeholders and thus lower cost of capital. Consequently, investment efficiency improves.

This paper contributes to the literature in two major ways. First, we advance the literature on analysts. We show that their forecasts on peer firms benefit focal firms' investment efficiency. Previous studies emphasize analyst earnings forecasts of a focal firm, not analyst earnings forecasts of the peers of a focal firm. Our findings contribute to the literature on analysts by documenting that analysts are not only helpful to investors of their covered firms but also are helpful to competitors of their covered firms. To our best knowledge, we offer the first study that explores the spillover effects of analyst earnings forecasts on investment efficiency. Second, we expand the literature on investment efficiency. By showing analyst earnings forecasts of peers are useful to a focal firm in enhancing its investment efficiency, we document that peers' analyst earnings forecasts are a new determinant of investment efficiency.

The remainder of the paper proceeds as follows. Section 2 develops the hypotheses. Section 3 describes the sample construction, the variables, and the model. Section 4 shows the empirical results, and Section 5 concludes.

2. Literature review and hypotheses development

2.1. Literature review

There are two strands of literature related to our study. The first is the literature that considers the relation between accounting information and investment efficiency. Roychowdhury et al. (2019) find that accounting information contributes to a firm's investment efficiency because of its effect on information asymmetry and information uncertainty. Previous studies document that a firm's disclosure decreases information asymmetry between the firm and external stakeholders, leading to easier access to capital and effective monitoring. As the adverse selection and moral hazard costs decrease, the focal firm's investment efficiency increases (Roychowdhury et al., 2019). Roychowdhury et al. (2019)'s argument is consistent with the prior literature finding that a firm's investment efficiency is positively related to its accounting information quality (Biddle, Hilary, & Verdi, 2009).

The second strand of literature articulates that a focal firm learns from its peers' accounting information. Thus, the focal firm's investment efficiency increases because it faces less information uncertainty about its industry and competitors. The logic is that the focal firm and its peers face similar economic conditions and business environments related to the demand, supply, labor availability, and input costs in their product market. Therefore, industry peers can provide useful information to enrich managers' information set, leading to lower uncertainty about growth opportunities and increasing the firm's investment efficiency (Ferracuti & Stubben, 2019). Moreover, managers can learn from or mimic peer-firm investment strategies and then modify their own investment decisions to be more profitable. For instance, Durnev & Mangen (2009) find that competitors can gain information about investment projects from peers' restatements and modify their subsequent investment decisions. Foucault & Fresard (2014) show that a focal firm's investment is positively related to its peers' valuations because peers' valuations convey information to managers about their firm's growth opportunities. Similarly, Yang et al. (2020) show that managers from a sample of Chinese firms imitate successful competitors' decisions to identify investment opportunities to guide their optimal investment project selection. While the literature focuses on a focal firm's own information, we posit that peers' information *from a third party* could also attenuate information asymmetry between the focal firm and external stakeholders leading to an increase in the focal firm's investment efficiency.

2.2. Hypotheses development

We contend that peers' analyst earnings forecasts are an important piece of information. Analyst earnings forecasts provide valuable information about peer firms (Amir, Lev, & Sougiannis, 2003; Barth, Kasznik, & Mcnichols, 2001). The focal firm or investors of the focal firm can learn from peers' analyst earnings forecasts. Earnings forecasts (Lys & Sohn, 1990) and revisions in analysts' long-term growth forecasts (Liu, Thomas, & Jacob, 2000) can provide information related to stock prices for investors, and earnings forecasts revisions can provide useful information accompanied by buy recommendations (Francis & Soffer, 1997). Hutton, Lee, & Shu (2012) show that analysts' forecasts include private information that managers do not have. Beyer et al. (2010) find that for an average firm in their sample from 1994 to 2007, analyst earnings forecasts can provide 22% of the accounting-based information, more than 8% of earnings announcements, and 4% of mandatory disclosures due to the Securities and Exchange Commission. Therefore, a focal firm and its investors can not only learn from peers' own disclosures but peers' analyst earnings forecasts as well.

Compared to firms' financial reporting, analyst earnings forecasts have three strengths. First, peers' analyst earnings forecasts are timelier than their annual reports. Annual reports focus on historical information, while analyst earnings forecasts are forward-looking and are provided frequently in a year by different analysts. Thus, analyst earnings forecasts are more relevant for stakeholders' future decisions. Therefore, a focal firm and its investors can learn more about the peer firm's future and industry conditions from peers' analyst earnings forecasts than from peer firms' annual reports.

Second, peers' analyst earnings forecasts are more reliable than peers' own disclosures. Managers may manipulate earnings or disclosures, but analysts are unlikely to manipulate their research (Bushee, Gow, & Taylor, 2018). Therefore, a focal firm or its investors can learn valuable information from peers' analyst earnings forecasts.

Third, it is common to have multiple analysts following a firm. The focal firm and its stakeholders can learn from more than “one head” by examining the mean, dispersion, or optimism of the forecasts to extract useful information for its own use.

Overall, peers' analyst earnings forecasts are informative, predictive, objective, and timely, which can effectively reduce information asymmetry (between managers and investors of the focal firm), and expand the information set of managers. We argue that high analyst earnings forecast accuracy represents high information quality, smaller forecast dispersion represents less uncertainty, and high analyst earnings forecast optimism suggests less-objective information on focal firm's peers. Based on the discussion above, we form the following hypotheses:

H1. Peers' analyst forecast accuracy is positively associated with a firm's investment efficiency.

H2. Peers' analyst forecast dispersion is negatively associated with a firm's investment efficiency.

H3. Peers' analyst forecast optimism is negatively associated with a firm's investment efficiency.

3. Research design

3.1. Data

We focus on analyst earnings forecasts in our analysis by obtaining the forecasts and financial data from the China Stock Market & Accounting Research Database (CSMAR). We keep only analyst earnings forecasts of year *t* disclosed before annual reports for year *t-1*. We drop observations with missing analyst names, reporting dates, or earnings forecasts. We present the summary statistics of the mean number of analysts making earnings forecast for a year by year in Appendix A. In the table, *N* is the number of firms that received earnings forecasts. The mean is the average earnings forecast that analysts follow firms. For example, in 2007 there are 603 firms followed by analysts, and on average a firm is followed by 4.8 analysts.

Our sample spanning the period of 2007–2021 includes A-share firms from the Shanghai and Shenzhen Stock Exchanges. We exclude 1488 observations that belong to financially stressed firms,[3] 917 financial industry firm observations, 62 observations that have just one industry peer, and 12,072 observations with missing variables.[4] The final sample consists of 26,512 firm-year observations. Appendix B presents the frequency distribution of the sample. We only keep an industry if it has at least 20 observations to calculate investment efficiency.

3.2. Variable measurement

3.2.1. Identifying peers' analyst earnings forecasts

We use analysts' forecast properties to quantify analyst forecasting activity. Specifically, we use analyst earnings forecast accuracy, dispersion, and optimism bias to gauge the property of analyst earnings forecast. From the perspective of firm-level analyst earnings forecast accuracy, we have two measures:

$$ACCU1_{i,t} = -\frac{\left|\text{the mean of all analysts' EPS forecast}_{i,t} - \text{actual EPS}_{i,t}\right|}{\left|\text{actual EPS}_{i,t}\right|} \quad (1)$$

$$ACCU2_{i,t} = -\frac{\text{themean of }\left|\text{each analysts' EPS forecast}_{i,t} - \text{actual EPS}_{i,t}\right|}{\left|\text{actual EPS}_{i,t}\right|} \quad (2)$$

where *EPS* is earnings per share. Hence, high values of *ACCU1* and *ACCU2* suggest the forecasts are accurate.

Forecast dispersion (*DISP*), we define it as:

$$DISP_{i,t} = \frac{\text{the standard deviation of analysts' EPS forecast}_{i,t}}{\left|\text{actual EPS}_{i,t}\right|} \quad (3)$$

Hence, a small *DIS* suggests that analysts have low disagreement on the EPS forecast of the i^{th} firm at *t*.

For analyst earnings forecast optimism (*OPT*), we define it as:

$$OPT_{i,t} = \frac{\left(\text{the mean of all analysts' EPS forecast}_{i,t} - \text{actual EPS}_{i,t}\right)}{\left|\text{actual EPS}_{i,t}\right|} \quad (4)$$

If *OPT* is large, it means that analysts' optimism bias is large.

In calculating *ACCU1, ACCU2, DISP,* and *OPT,* we keep the earnings forecasts made by an analyst one year prior to the analyst's forecasting year. For instance, when we examine the impact of an analyst's earnings forecast for i^{th} firm in 2010 on the firm's investment efficiency in 2010, we use the analyst's earnings forecasts made for 2010 after 2008 annual report release but before 2009 annual report release.

To identify peers as firms in the same industry, For peer consideration, we use a focal firm's three digit SIC code (as defined in the Chinese Securities Regulatory Commission in 2012) to identify its peer firms. If an analyst makes more multiple EPS forecasts in the same interval, we use the analyst's average EPS forecast. Then, we obtain a focal firm's peer accuracy, peer dispersion, and peer optimism by the respective mean values of *ACCU1, ACCU2, DISP*, and *OPT* of the firm's all peers. We denote them as *PEER_ACCU1, PEER_ACCU2, PEER_DISP,* and *PEER_OPT*, respectively.[5]

3.2.2. Identifying investment efficiency

Following Richardson (2006) and Liu, Wu, & Wang (2012), we use the absolute value of residuals from Eq. (5) to measure investment efficiency (*ABSINV*):

$$\begin{aligned} INV_{i,t} = {} & \beta_0 + \beta_1 GROWTH_{i,t-1} + \beta_2 LEV_{i,t-1} + \beta_3 CASH_{i,t-1} + \beta_4 AGE_{i,t-1} \\ & + \beta_5 SIZE_{i,t-1} + \beta_6 RETURN_{i,t-1} + \beta_7 INV_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \quad (5)$$

where *i* and *t* correspond to firm and year, respectively. *INV* represents new investments, which is the value of the sum of capital expenditure and spending on mergers and acquisitions minus the sum of income from the sales of long-term assets and depreciation,[6] deflated by total assets in year *t*. Capital expenditure is cash paid to acquire fixed assets, intangible assets, and other long-term assets. Spending on mergers and acquisitions is net cash paid by subsidiaries and other business units. Income from the sale of long-term assets is net cash received from external fixed assets, intangible assets, and other long-term assets. *GROWTH* is measured

[3] The China Securities Regulatory Commission (CSRC) defines financially distressed firms. The CSRC labeled these firms "ST*". A firm is an ST* firm if it satisfies one of the following criteria: (1) it had two consecutive years of negative earnings; (2) it had a major financial report misstatement or fraudulent financial reports that led to a restatement and negative earnings in most recent two years; (3) it had a major financial report misstatement or fraudulent financial report and did not make a prompt restatement; (4) it did not provide annual or semiannual reports by the legally required date; (5) it was in the period from the trading day when the stock resumed listing to the first annual report disclosure date after the listing resumes; or (6) other circumstances identified by the Exchanges. Firms are eager to remove their ST* status, and therefore, their corporate practices are different from other firms.

[4] A considerable number of missing observations occurred because we keep observations in industries that have more than 20 firms when we calculate the metrics for investment efficiency and earnings management. We also need to delete observations without data at *t-1*.

[5] This approach is consistent with that of Leary and Roberts (2014) and Seo (2021).

[6] Capital expenditure, spending on mergers and acquisitions, and income from sales of long-term assets are from cash flow statements prepared using the direct method. Depreciation is the depreciation amount from cash flow statements prepared using the indirect method. Under Chinese accounting standards, cash flow statements can be prepared by a direct or indirect method.

by the market value deflated by fiscal-year-end total assets (*Tobin's Q*). *LEV* is the asset–liability ratio. *CASH* is the net amount of cash and cash equivalents at the end of the fiscal year. *AGE* is the natural logarithm of the number of years a firm has been listed. *SIZE* is the natural logarithm of a firm's total assets at the end of the fiscal year. *RETURN* is the annual stock return.

3.3. Empirical model

We estimate the association between peers' analyst earnings forecasts and the firm's investment efficiency using the following regression model:

$$ABSINV_{i,t} = \beta_0 + \beta_1 PEER_{i,t} + \beta_k \sum Controls_{i,t} + \sum YEAR + \sum INDUSTRY + \varepsilon_{i,t} \quad (6)$$

The dependent variable is the investment efficiency for firm *i* in year *t*. The explanatory variable is *PEER*, which represents *PEER_ACCU1, PEER_ACCU2, PEER_DISP*, or *PEER_OPT*. Following previous studies (Biddle et al., 2009; Richardson, 2006), we control for financial characteristics including firm size (*SIZE*), return on assets (*ROA*), book-to-market ratio (*BM*), cashflows from operating activities (*CFO*), operating profit (*OPR*), asset growth rate (*GOA*), operating income (*TAT*), financial leverage (*LEV*), and total non-current asset (*PPE*) as well as corporation governance characteristics such as the largest shareholder ownership (*TOP*), other large shareholder ownership (*CR*), independent director ratio (*INDRATIO*), managerial ownership (*MAOW*), executives, directors, and supervisors' compensation (*COMPEN*), the state-ownership nature of the firm (*SOE*), duality of the CEO and board chairperson (*DUAL*), general and administrative expense (*ADM*), other receivables (*OCCUPY*), board size (*BOARD*), minority interests (*MINO*), institutional investor ownership (*INSTI*), and the number of committees of the board (*COMTE*). We also control for accounting information disclosure quality (*PEER_DACC*) because accounting information quality may influence information asymmetry and then affect investment decisions (Chen & Ma, 2017). Finally, we control for industry and year fixed effects and use standard errors clustered by firm. We divide *PEER_ACCU1, PEER_ACCU2, PEER_DISP,* and *PEER_OPT* by 100 for easier interpretation of the results in Section 4.2 to Section 4.4. We winsorize all continuous variables at the 1% and 99% levels to mitigate the influence of extreme observations. Appendix C presents the detailed definitions of variables.

4. Results

4.1. Descriptive statistics

Table 1 reports the descriptive statistics for the sample. The average *ABSINV* is 0.026, and the median is 0.019, suggesting that most investments by Chinese firms are inefficient. As for analyst earnings forecasts proxies, the averages of *PEER_ACCU1* and *PEER_ACCU2* are −3.155 and − 3.181 with the corresponding standard deviations of 3.986 and 4.000. Hence, there are considerable variations among analysts in earnings forecasts. The average of *PEER_DISP* is 0.951, and the standard deviation is 1.165, showing that compared with individual forecast dispersion, the average and standard deviation are small. The mean of *PEER_OPT* is 3.031, which indicates that analysts, in general, are optimistic about firms' futures. Finally, the mean of *PEER_DACC* is 0.075, showing that the financial reporting quality of peers is low.

4.2. Baseline findings

Table 2 presents the baseline results of Eq. (6). The coefficients of *PEER_ACCU1* and *PEER_ACCU2* are negative and significant at the 5% level while those of *PEER_DISP* and *PEER_OPT* are positive and significant at the 5% or 10% level. The results show that when peers' analyst earnings forecast errors are small (columns (1) and (2)) or the forecast dispersion is small (column (3)), investment efficiency of the focal firm is enhanced.

Similarly, if analyst earnings forecasts of peers are optimistic, the firm's investment efficiency decreases. In terms of economic significance, in column (2), the magnitude of the coefficient is −0.010, which means a one standard deviation increase in *PEER_ACCU2* leads to an approximate decrease of 0.04 percentage points in the firm's investment efficiency (i.e., −0.010*4.000), which is approximately 2.10% better than a median firm's *ABSINV*. Similarly, in column (3), the coefficient of *PEER_DISP* is 0.029. A one standard increase in *PEER_DISP* (1.165) means an increase of 0.034% percentage points, which is approximately 1.78% of a median firm's *ABSINV*.

Table 1
Summary statistics.

Variables	N	Mean	Std. dev.	Min	Median	Max
ABSINV	26,512	0.026	0.026	0	0.019	0.136
PEER_ACCU1	26,512	−3.155	3.986	−26.660	−2.128	−0.389
PEER_ACCU2	26,512	−3.181	4.000	−26.700	−2.158	−0.408
PEER_DISP	26,512	0.951	1.165	0.125	0.634	7.351
PEER_OPT	26,512	3.031	3.997	−0.008	2.038	26.510
SIZE	26,512	22.270	1.284	19.880	22.090	26.180
ROA	26,512	0.033	0.066	−0.290	0.034	0.198
BM	26,512	0.318	0.153	0.040	0.296	0.776
CFO	26,512	0.470	0.885	−2.099	0.321	4.269
OPR	26,512	0.069	0.197	−1.022	0.069	0.598
GOA	26,512	0.154	0.289	−0.317	0.091	1.825
ATT	26,512	0.628	0.428	0.065	0.532	2.509
LEV	26,512	0.453	0.203	0.063	0.451	0.901
TOP	26,512	33.900	14.940	0.286	31.620	89.410
CR	26,512	0.695	0.593	0.024	0.525	2.680
INDRATIO	26,512	0.374	0.054	0.308	0.333	0.571
MAOW	26,512	0.070	0.136	0	0	0.567
COMPEN	26,512	15.240	0.783	13.230	15.240	17.330
SOE	26,512	0.410	0.492	0	0	1
DUAL	26,512	0.253	0.435	0	0	1
ADM	26,512	0.086	0.070	0.008	0.068	0.439
OCCPUY	26,512	0.017	0.025	0	0.008	0.152
BOARD	26,512	2.137	0.202	1.609	2.197	2.708
MINO	26,512	0.066	0.095	−0.017	0.0260	0.477
INSTI	26,512	44.300	23.750	0.350	46.160	89.880
PPE	26,512	0.436	0.201	0.047	0.422	0.909
COMTE	26,512	3.864	0.447	0	4	4
PEER_DACC	26,512	0.075	0.037	0.041	0.067	0.348

Table 1 presents the descriptive statistics for the variables used in the analyses.

4.3. Robustness checks

We conduct several robustness checks and discuss the results below. First, we use an alternative method to gauge investment efficiency. According to Biddle, Hilary, & Verdi (2009), we use the absolute value of residuals from Eq. (7) to measure investment efficiency and denote it as (*ABSINV_B*):

$$INV_{i,t} = \beta_0 + \beta_1 GROWTH_{i,t-1} + \varepsilon_{i,t.} \quad (7)$$

In Eq. (7), we use the lagged growth rate of gross operating income to define *GROWTH*, and the definition of *INV* is the same as in Eq. (5). Then, we estimate Eq. (7) for each industry-year based on the 3-digit industry classification[7] and use the absolute values of residuals to proxy firm-specific investment efficiency. We present the results in Panel A of Table 3. For brevity, we do not include the coefficients of control variables hereafter. The results are qualitatively similar to our baseline findings.

Second, we use stock price at the end of the year to normalize

[7] This 3-digit industry classification is based on the Guidelines of Industry Classification of Listed Companies revised by the CSRC in 2012.

Table 2
The impact of peers' analyst forecasts on investment efficiency.

Variables	(1)	(2)	(3)	(4)
	ABSINV			
PEER_ACCU1	−0.009**			
	(−2.32)			
PEER_ACCU2		−0.010**		
		(−2.39)		
PEER_DISP			0.029*	
			(1.92)	
PEER_OPT				0.009**
				(2.29)
SIZE	−0.003***	−0.003***	−0.003***	−0.003***
	(−11.46)	(−11.46)	(−11.46)	(−11.46)
ROA	−0.007	−0.007	−0.007	−0.007
	(−1.18)	(−1.18)	(−1.19)	(−1.18)
BM	−0.006***	−0.006***	−0.006***	−0.006***
	(−3.66)	(−3.65)	(−3.66)	(−3.66)
CFO	0.001***	0.001***	0.001***	0.001***
	(3.34)	(3.34)	(3.34)	(3.34)
OPR	−0.003*	−0.003*	−0.003*	−0.003*
	(−1.93)	(−1.93)	(−1.92)	(−1.94)
GOA	0.018***	0.018***	0.018***	0.018***
	(20.62)	(20.62)	(20.61)	(20.62)
ATT	−0.002***	−0.002***	−0.002***	−0.002***
	(−3.02)	(−3.02)	(−3.02)	(−3.02)
LEV	−0.003**	−0.003**	−0.003**	−0.003**
	(−2.04)	(−2.04)	(−2.03)	(−2.04)
TOP	−0.000	−0.000	−0.000	−0.000
	(−0.62)	(−0.62)	(−0.63)	(−0.62)
CR	−0.001	−0.001	−0.001	−0.001
	(−1.44)	(−1.44)	(−1.45)	(−1.44)
INDRATIO	0.009**	0.009**	0.009**	0.009**
	(2.22)	(2.22)	(2.23)	(2.22)
MAOW	0.012***	0.012***	0.012***	0.012***
	(6.28)	(6.28)	(6.29)	(6.28)
COMPEN	0.000	0.000	0.000	0.000
	(1.04)	(1.04)	(1.05)	(1.04)
SOE	−0.003***	−0.003***	−0.003***	−0.003***
	(−7.38)	(−7.38)	(−7.37)	(−7.38)
DUAL	0.001	0.001	0.001	0.001
	(1.25)	(1.25)	(1.25)	(1.25)
ADM	0.001	0.001	0.001	0.001
	(0.39)	(0.39)	(0.39)	(0.39)
OCCUPY	0.014*	0.014*	0.014*	0.014*
	(1.87)	(1.87)	(1.86)	(1.87)
BOARD	0.001	0.001	0.001	0.001
	(1.31)	(1.31)	(1.31)	(1.31)
MINO	0.003	0.003	0.003	0.003
	(1.38)	(1.38)	(1.38)	(1.38)
INSTI	0.000***	0.000***	0.000***	0.000***
	(4.45)	(4.45)	(4.45)	(4.45)
PPE	0.029***	0.029***	0.029***	0.029***
	(22.08)	(22.08)	(22.08)	(22.08)
COMTE	−0.000	−0.000	−0.000	−0.000
	(−0.92)	(−0.92)	(−0.91)	(−0.92)
DACC	−0.010**	−0.010**	−0.010**	−0.010**
	(−2.07)	(−2.07)	(−2.13)	(−2.07)
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	26,512	26,512	26,512	26,512
Adjusted R^2	0.129	0.129	0.129	0.129

Columns (1) and (2) present the results that examine the effect of peers' analyst earnings forecasts accuracy on a firm's investment efficiency (*ABSINV*). Columns (3) and (4) present the results that examine the impact of forecast dispersion and analyst optimism on a firm's investment efficiency, respectively. In this table, the dependent variable is investment efficiency (*ABSINV*), and the explanatory variables are peers' analyst earnings forecasts proxies (*PEER_ACCU1, PEER_ACCU2, PEER_DISP,* and *PEER_OPT*). All variables are defined in Section 3 and Appendix C. We report the OLS coefficients and the *t*-statistics in parentheses. Standard errors are clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3
Robustness checks.

Panel A: Alternative metric of investment efficiency

Variables	(1)	(2)	(3)	(4)
	ABSINV_B			
PEER_ACCU1	−0.014***			
	(−2.78)			
PEER_ACCU2		−0.015***		
		(−2.86)		
PEER_DISP			0.055***	
			(2.90)	
PEER_OPT				0.014***
				(2.75)
Controls var.	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	26,528	26,528	26,528	26,528
Adjusted R^2	0.148	0.148	0.148	0.148

Panel B: Alternative metric of explanatory variable: using stock price at the end of the year to normalize earnings forecast

Variables	(1)	(2)	(3)	(4)
	ABSINV			
PEER_ACCU1_SP	−0.020*			
	(−1.85)			
PEER_ACCU2_SP		−0.020*		
		(−1.86)		
PEER_DISP_SP			0.117***	
			(2.68)	
PEER_OPT_SP				0.019**
				(2.09)
Controls var.	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	25,240	25,240	25,240	25,240
Adjusted R^2	0.116	0.116	0.116	0.116

Panel C: Controlling for uncertainties

Variables	(1)	(2)	(3)	(4)
	ABSINV			
PEER_ACCU1	-0.009**			
	(−2.32)			
PEER_ACCU2		−0.010**		
		(−2.38)		
PEER_DISP			0.029*	
			(1.89)	
PEER_OPT				0.009**
				(2.31)
EPU	−0.000	−0.000	−0.000	−0.000
	(−0.69)	(−0.70)	(−0.67)	(−0.69)
UC	0.048**	0.048**	0.047**	0.049**
	(2.02)	(2.01)	(1.98)	(2.05)
Controls var.	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	26,388	26,388	26,388	26,388
Adjusted R^2	0.129	0.129	0.129	0.129

Panel D: Placebo tests

Variables	(1)	(2)	(3)	(4)
	ABSINV			
PEER_ACCU1_PLACEBO	−0.007			
	(−1.35)			
PEER_ACCU2_PLACEBO		−0.006		
		(−1.32)		
PEER_DISP_PLACEBO			−0.000	
			(−0.02)	

(*continued on next page*)

Table 3 (*continued*)

Panel D: Placebo tests				
Variables	(1)	(2)	(3)	(4)
	ABSINV			
PEER_OPT_PLACEBO				0.007
				(1.41)
Controls var.	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	26,466	26,466	26,466	26,466
Adjusted R^2	0.128	0.128	0.128	0.128

Panel A presents the results using an alternative measure of investment efficiency. We use Biddle's method to measure investment efficiency (*ABSINV_B*). Panl B represents the results using alternative metric of explanatory variable. Specifically, we use stock price at the end of year to normalize earning forecasts *(PEER_ACCU1_SP, PEER_ACCU2_SP, PEER_DISP_SP*, and *PEER_OPT_SP*). Panel C represents the results controlling for economic uncertainty (*UC*) and policy uncertainty (*EPU*). Panel D presents the result of a placebo test. We use 3-digit SIC codes to randomly assign firm-years to construct placebo proxies for analyst earnings forecasts (*PEER_ACCU1_PLACEBO, PEER_ACCU2_PLACEBO, PEER_DISP_PLACEBO,* and *PEER_OPT_PLACEBO*). All variables are defined in Sections 3 and 4, and Appendix C. We report the OLS coefficients and the *t*-statistics in parentheses. Standard errors are clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

earnings forecast as an alternative metric to calculate *PEER_ACCU1, PEER_ACCU2, PEER_DISP,* and *PEER_OPT*. The results in Panel B of Table 3 are qualitatively similar to those in Table 2.

Third, according to Wu & Hu (2015), high economic uncertainty causes greater analyst earnings forecast errors and dispersion. Simultaneously, economic uncertainty is a factor that affects investment efficiency. Thus, we control for economic uncertainty proxies that could be associated with investment and analyst earnings forecasts. Specifically, we use two proxies to gauge economic uncertainty. First, following Papanikolaou & Panousi (2012), we use weekly stock returns of a stock ($R_{i\tau}$) and regress it on the weekly market return ($RMKT_\tau$) for every firm *i* and every year *t*. Then, our measure of economic uncertainty is the standard deviation of the regression residuals (UC_{it}). Second, following Baker, Bloom, & Davis (2016), we download the economic policy uncertainty index for China based on the South China Morning Post (SCMP)[8] and use the average value of the index for every year, multiplying by 100, to measure policy uncertainty (*EPU*). We present our findings in Panel C of Table 3. Even after controlling for economic and policy uncertainty, the coefficients on the key proxies for peers' analyst earnings forecasts are consistent with the baseline findings in Table 2, suggesting that our findings are robust.

Last, we conduct a placebo test to ensure that our results are not due to randomness. Specifically, we use 3-digit stock identity codes to randomly assign firm-years to calculate placebo proxies of peers' analyst earnings forecasts (*PEER_ACCU1_PLACEBO, PEER_ACCU2_PLACEBO, PEER_DISP_PLACEBO,* and *PEER_OPT_PLACEBO*). For instance, the stock code of the first observation is 001 and the firm belongs to Industry A. Then, we randomly generate a code, 010, which belongs to Industry B, for the first observation. If our testable hypothesis is valid, the coefficients on the new proxies should be insignificant. Panel D of Table 3 shows the expected results.

4.4. Additional analysis

In this section, we further exploit heterogeneity in our sample to identify factors that affect the association between peers' analyst earnings forecasts and a firm's investment efficiency to complement the evidence on the main findings.

4.4.1. The impact of industry competition

We posit that industry competition affects the relation between peers' analyst earnings forecasts and a firm's investment efficiency. First, in an intensely competitive market, managers who want to excel must pay more attention to their competitors, which includes paying attention to peers' information (He, Chen, & Chan, 2022). Therefore, we conjecture that information from analysts, which is relatively reliable and more objective than information from the peers' financial reporting, is more helpful to managers of a focal firm if the firm belongs a highly competitive industry.

We use the Lerner index and the ratio of a firm's sales to the sales of top-five firms in the same industry (*CR5*) to proxy for competition. Following Peress (2010), we calculate Lerner index as (revenue – cost – sales expense – management expense) / revenue. A small Lerner index value suggests the firm has high competitiveness in its industry. Similarly, a low *CR5* suggests the industry is highly competitive. We use median of Lerner index and *CR5* to classify firms into high and low industry competition. We then run Eq. (6) for each subsample separately.

We present the results in Panel A of Table 4. The coefficients of *PEER_ACCU1, PEER_ACCU2, PEER_DISP,* and *PEER_OPT* are significant at the 10% or 5% level with the expected signs for the low Lerner Index subsample, while the same set of coefficients are insignificant for the high Lerner Index subsample. Hence, the relation between peers' analyst earnings forecasts and a firm's investment efficiency is driven by firms in more-competitive industries (low Lerner Index), which is consistent with our prediction that peers' information (analyst earnings forecasts) is more critical for a focal firm if it operates in a competitive industry.

4.4.2. Based on analysts' prediction of earnings and losses

Ciccone (2005) shows that the loss of firm earnings is more difficult to predict because it is more challenging for analysts to forecast their followed firms having losses. Specifically, we consider an analyst at *t-1* to forecast i^{th} firm's earnings at *t*. We separate a focal firm's peers into two groups based on whether peers have positive earnings or losses. Then, we calculate analyst forecasts for these two groups of peers, getting the variable *PEER_ACCU1_P, PEER_ACCU2_P, PEER_DISP_P*, and *PEER_OPT_P* for the positive earnings group and *PEER_ACCU1_L, PEER_ACCU2_L, PEER_DISP_L,* and *PEER_OPT_L* for the loss group. Table 5 presents the moderating analyses that are based on prediction of earnings and losses. The results suggest that for the subsample of predicting losses, the coefficients of all peer explanatory variables are insignificant while those of predicting positive earnings continue to be significant with the expected signs. We interpret the findings as that, when firms have losses, the peer information from analyst earnings forecasts is less helpful than when firms have positive earnings.

4.4.3. The impact of peers' financial reporting quality

Prior research finds that a focal firm also learns from peers' own disclosures (Durnev & Mangen, 2009; Foucault & Fresard, 2014). However, managers or shareholders sometimes manipulate earnings or other metrics because of earnings-based bonus contracts (Healy, 1985), debt contracts (Smith & Warner, 1979) or asset pricing (Brown, 1968). We argue that as another channel of peers' information, peers' analyst earnings forecasts can be a more important supplement to peers' own disclosures, especially when peers' own disclosures are not credible. This logic is consistent with Shroff et al. (2017), who find that the peer information environment matters only when investors cannot get enough information from a firm. Thus, we predict that the relationship between the focal firm's investment efficiency and peers' analyst earnings forecasts is more salient when the quality of peers' annual reports is low.

We measure a firm's annual report quality using discretionary accruals (*DACC*). Specifically, we use a modified Jones model (Dechow, Sloan, & Hutton, 1995) to calculate $\beta_1, \beta_2, \beta_3$ from Eq. (8) regressed by

[8] The website is http://www.policyuncertainty.com/china_monthly.html.

Table 4
Subsample test based on industry competition.

Panel A: Use Lerner index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low Lerner index				High Lerner index			
	ABSINV				ABSINV			
PEER_ACCU1	−0.013**				−0.006			
	(−2.28)				(−0.98)			
PEER_ACCU2		−0.013**				−0.006		
		(−2.27)				(−1.09)		
PEER_DISP			0.040*				0.020	
			(1.86)				(0.90)	
PEER_OPT				0.014**				0.005
				(2.32)				(0.90)
Controls var.	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	13,250	13,250	13,250	13,250	13,262	13,262	13,262	13,262
Adjusted R^2	0.123	0.123	0.123	0.123	0.132	0.132	0.132	0.132

Panel B: Use top five customer ratio in sales

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low *CR5*				High *CR5*			
	ABSINV				ABSINV			
PEER_ACCU1	−0.019**				−0.007			
	(−2.58)				(−1.24)			
PEER_ACCU2		−0.019***				−0.007		
		(−2.58)				(−1.32)		
PEER_DISP			0.051**				0.007	
			(2.13)				(0.30)	
PEER_OPT				0.019***				0.006
				(2.63)				(1.17)
Controls var.	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	11,634	11,634	11,634	11,634	14,857	14,857	14,857	14,857
Adjusted R^2	0.128	0.128	0.128	0.128	0.132	0.132	0.131	0.132

Table 4 presents the linear probability regression results regarding whether the spillover effect of peers' analyst earnings forecasts is stronger when a firm is in a more concentrated industry. We use the Lerner index and the ratio of a firm's sales to the sales of top-five firms in the same industry (*CR5*) to proxy for competition. we calculate Lerner index as (revenue – cost – sales expense – management expense) / revenue. A small Lerner index value suggests the firm has high competitiveness in its industry. Similarly, a low *CR5* suggests the industry is highly competitive. We use median of Lerner index and *CR5* to classify firms into high and low industry competition. Other variables are defined in Section 3 and Appendix C. We report the OLS coefficients and the *t*-statistics in parentheses. Standard errors are clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

industry and year.[9] Then, we use $\beta_1, \beta_2, \beta_3$ to calculate non-discretionary accruals (*NDAC*) in Eq. (9) and get *DACC* in Eq. (10).

$$\frac{TAC_{i,t}}{A_{i,t-1}} = \beta_1 \frac{1}{A_{i,t-1}} + \beta_2 \frac{\Delta REV_{i,t}}{A_{i,t-1}} + \beta_3 \frac{PPE_{i,t}}{A_{i,t-1}} + \varepsilon_{i,t} \tag{8}$$

$$NDAC_{i,t} = \beta_1 \frac{1}{A_{i,t-1}} + \beta_2 \frac{\left(\Delta REV_{i,t} - \Delta REC_{i,t}\right)}{A_{i,t-1}} + \beta_3 \frac{PPE_{i,t}}{A_{1,t-1}} \tag{9}$$

$$DACC_{i,t} = \frac{TAC_{i,t}}{A_{i,t-1}} - NDAC_{i,t}, \tag{10}$$

where $A_{i,t-1}$ is total assets for a firm at the end of year *t–1*; $TAC_{i,t}$ is total accruals for firm *i* in year *t*, defined as net income from continuing operations minus operating cash flow; $\Delta REV_{i,t}$ is the change in revenues for firm *i* at the end of year *t;* $\Delta REC_{i,t}$ is the change in accounts receivable for firm *i* at the end of year *t*; and $PPE_{i,t}$ is fixed assets at the end of year *t*. Then, we use the average of peers' *DACC* (*PEER_DACC*) to measure peers' financial reporting quality for a focal firm.

We partition the full sample into two groups based on the median value of *PEER_DACC*. The subsample with high (low) *PEER_DACC* means peer firms have low-quality (high-quality) financial reporting.

We present the findings in Table 6. The coefficients of *PEER_ACCU1, PEER_ACCU2, PEER_DISP,* and *PEER_OPT* are significant at the 10% or 5% level with the expected signs for the high *PEER_DACC* subsample. In contrast, the same set of coefficients is insignificant for the low *PEER_DACC* subsample. The results are consistent with our conjecture.

4.4.4. The information asymmetry of the focal firm

In addition to peers, we also consider the focal firm itself. Specifically, we consider the extent of a focal firm's information asymmetry. We contend that if the focal firm has high information asymmetry, investors can alternatively use the peers' earnings forecasts to make decisions.

To gauge a firm's information asymmetry, we follow Amihud (2002) to use a firm's illiquidity metric (*ILL*). *ILL* is the daily ratio of absolute stock return to its dollar volume, averaged over some period.

$$ILL_{it} = \frac{1}{D_{it}} \sum_{k=1}^{Dit} \sqrt{\frac{|r_{it}(k)|}{V_{it}(k)}}, \tag{11}$$

[9] Huang and Xia (2009) demonstrate that the modified Jones model is more powerful for detecting revenue-based manipulation than others in the Chinese context.

Table 5
Moderating analyses that are based on prediction of earnings and losses.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ABSINV							
PEER_ACCU1_L	−0.002 (−1.04)							
PEER_ACCU1_P		−0.008** (−2.02)						
PEER_ACCU2_L			−0.002 (−1.12)					
PEER_ACCU2_P				−0.008** (−2.03)				
PEER_DISP_L					0.001 (0.15)			
PEER_DISP_P						0.032* (1.90)		
PEER_OPT_L							0.001 (0.72)	
PEER_OPT_P								0.008** (2.04)
Controls var.	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	22,982	26,512	22,982	26,512	20,004	26,512	22,982	26,512
Adjusted R^2	0.133	0.129	0.133	0.129	0.127	0.129	0.133	0.129

Table 5 presents the moderating analyses that are based on prediction of earnings and losses The logic follows Ciccone (2005) that it is more challenging for analysts to forecast their followed firms having losses. Specifically, we consider an analyst at *t-1* to forecast i^{th} firm's earnings at *t*. We separate a focal firm's peers into two groups based on whether peers have positive earnings or losses. Then, we calculate analyst forecasts for these two groups of peers, getting the variable *PEER_ACCU1_P, PEER_ACCU2_P, PEER_DISP_P,* and *PEER_OPT_P* for the positive earnings group and *PEER_ACCU1_L, PEER_ACCU2_L, PEER_DISP_L,* and *PEER_OPT_L* for the loss group. Other variables are defined in Section 3 and Appendix C. We report the OLS coefficients and the *t*-statistics in parentheses. Standard errors are clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6
Subsample test based on peers' financial reporting quality.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High *PEER_DACC*				Low *PEER_DACC*			
	ABSINV				*ABSINV*			
PEER_ACCU1	−0.013** (−2.11)				−0.007 (−1.12)			
PEER_ACCU2		−0.013** (−2.19)				−0.007 (−1.11)		
PEER_DISP			0.041* (1.91)				0.011 (0.48)	
PEER_OPT				0.013** (2.09)				0.007 (1.14)
Controls var.	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	13,250	13,250	13,250	13,250	13,262	13,262	13,262	13,262
Adjusted R^2	0.135	0.135	0.135	0.135	0.122	0.122	0.122	0.122

Table 6 presents the linear probability regression results regarding whether the spillover effect of peers' analyst earnings forecasts is stronger when the quality of peers' financial reports is inferior. We use discretionary accruals to measure the quality of information derived from financial reports. We partition the full samples into two groups based on the median value of the average discretionary accruals (*PEER_DACC*). *PEER_DACC* is defined in Section 4.4. Other variables are defined in Section 3 and Appendix C. We report the OLS coefficients and the *t*-statistics in parentheses. Standard errors are clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

where $r_{it}(k)$ is the return in firm *i* on day *k* of year *t*, and $V_{it}(k)$ is the daily volume in dollars. D_{it} is the number of days for which data are available for firm *i* in year *t*. If *ILL* is small, the firm has high liquidity and thus, its information asymmetry is low. Illiquidity reflects the impact of order flow on price—the discount that a seller concedes or the premium that a buyer pays when executing a market order. It captures a firm's adverse selection costs and inventory costs (Amihud & Mendelson, 1986; Glosten & Milgrom, 1985).

We partition the full sample into high *ILL* (high information asymmetry) and low *ILL* (low information asymmetry) subsamples using median and reexamine Eq. (6). The findings in Table 7 show that the coefficients of *PEER_ACCU1, PEER_ACCU2,* and *PEER_DISP* are significant at the 10% or 5% level with the expected signs for high *ILL* subsample. In contrast, the same set of coefficients for the low *ILL* are insignificant. Hence, the impact of peers' analyst earnings forecasts on a focal firm's investment efficiency is more salient when the focal firm has high information asymmetry.

5. Conclusions

Previous studies have shown that firms do not make investment decisions in isolation (Roychowdhury et al., 2019). These studies focus on how peers' own financial reporting rather than information derived from a third party, such as analysts' reports, affect a focal firm. In addition, the literature underexplores the framework of information asymmetry when discussing the impact of the peers' information on a

Table 7
Subsample test based on the focal firm's information asymmetry.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High *ILL*				Low *ILL*			
	ABSINV				*ABSINV*			
PEER_ACCU1	−0.010*				−0.008			
	(−1.69)				(−1.53)			
PEER_ACCU2		−0.011*				−0.008		
		(−1.82)				(−1.50)		
PEER_DISP			0.047**				0.009	
			(2.06)				(0.47)	
PEER_OPT				0.009				0.009
				(1.58)				(1.62)
Controls var.	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	13,145	13,145	13,145	13,145	13,367	13,367	13,367	13,367
Adjusted R^2	0.133	0.133	0.133	0.133	0.122	0.122	0.122	0.122

In Table 7, we partition full samples into two groups based on the firm stock's illiquidity. We use illiquidity to measure the degree of information asymmetry. We partition the full samples into two groups based on the median value of the illiquidity (*ILL*). *ILL* is defined in Section 4.4. Other variables are defined in Section 3 and Appendix C. The high illiquidity means that the extent of information asymmetry is more serious. We predict that the relation between peer's analyst earnings forecasts and a firm's investment efficiency is stronger when the firm faces serious information asymmetry. We report the OLS coefficients and the *t*-statistics in parentheses. Standard errors are clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

firm's investment efficiency. Thus, we investigate the association between peers' analyst earnings forecasts and a focal firm's investment efficiency.

We find that analyst earnings forecast accuracy for peers is positively related to a focal firm's investment efficiency. Analyst dispersion and forecast optimism are negatively related to a focal firm's investment efficiency. The findings are robust to alternative metrics of investment efficiency, alternative mertrics of analyst earnings forecasts, controlling for economic uncertainty, and placebo tests.

Further, we document that the effect is more salient when the focal firm operates in a competitive industry, when analysts are predicting positive earnings, when peers have low-quality annual reports or when the firm has high information asymmetry. These scenarios represent an environment in which a focal firm's managers or investors particularly need more information about its peers or the firm itself. We interpret the information on peers from analyst earnings forecasts to be informative for managers and investors. Our findings suggest that analyst earnings forecasts have spillover effects in the product market, and firms can learn from peers' information gleaned from a third party.

Acknowledgements

Jie He acknowledges the financial support from the National Natural Science Foundation of China (no. 71902189). Bin Wang acknowledges the financial support from the Philosophy and Social Science Planning Project of Shanghai (no. 2020BGL024).

Appendix A. Summary statistics of the analyst earnings forecast by year

Year	N	Mean	Std. dev.	Min	Median	Max
2007	603	4.834	4.537	1	3	29
2008	797	9.004	10.11	1	5	65
2009	953	15.75	18.25	1	8	113
2010	1121	14.91	17.11	1	9	116
2011	1296	16.41	17.66	1	11	111
2012	1670	17.36	20.25	1	10	152
2013	1739	19.82	23.42	1	10	189
2014	1743	19.58	23.16	1	11	168
2015	1849	18.11	20.97	1	10	213
2016	2060	15.03	16.41	1	9	140
2017	2295	18.30	18.98	1	12	155
2018	2294	20.52	25.39	1	10	185
2019	2081	22.22	28.88	1	10	234
2020	2061	22.87	30.92	1	9	273
2021	2094	21.83	28.71	1	10	274

Appendix A presents summary statistics of the mean number of analysts making earnings forecast for a year by year. In the table, N is the number of firms that received earnings forecasts. The mean is the average earnings forecast that analysts follow firms. For example, in 2007 there are 603 firms followed by analysts, and on average a firm is followed by 4.8 analysts.

Appendix B. Frequency distribution (as a percent of N) of the sample by industry

Code	Industry	2007–2009	2010–2012	2013–2015	2016–2018	2019–2021
B06	Coal mining and dressing	0.81%	1.93%	1.45%	1.16%	0.76%
B09	Non-ferrous metal ore mining	0.00%	0.00%	0.00%	0.35%	0.69%
C13	Farm and sideline food processing	1.47%	2.01%	1.77%	1.54%	1.47%

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(*continued*)

Code	Industry	2007–2009	2010–2012	2013–2015	2016–2018	2019–2021
C14	Foodstuff manufacturing	0.00%	0.00%	0.80%	1.54%	1.50%
C15	Wine, beverage and refined tea manufacturing	2.67%	2.12%	1.73%	1.69%	1.22%
C17	Textile	3.67%	2.57%	1.85%	1.41%	1.12%
C18	Textile and garment	0.00%	0.53%	1.41%	1.29%	1.07%
C21	Furniture manufacturing	0.00%	0.00%	0.00%	0.00%	0.73%
C22	Paper making and paper products	1.43%	1.54%	1.22%	0.75%	0.85%
C26	Chemical material and products manufacturing	9.12%	7.60%	8.32%	7.31%	7.29%
C27	Medical manufacturing	8.96%	7.42%	6.95%	7.48%	7.00%
C28	Chemical fibers manufacturing	0.00%	1.56%	0.06%	0.00%	0.70%
C29	Rubber and plastic manufacturing	2.28%	2.17%	2.27%	2.20%	2.37%
C30	Non-metal mineral products	4.40%	3.63%	3.58%	3.05%	2.72%
C31	Ferrous metal foundries and presses	2.98%	2.09%	1.62%	1.24%	0.94%
C32	Non-ferrous metal foundries and presses	2.82%	2.70%	2.59%	2.29%	2.10%
C33	Metal products	0.00%	1.80%	2.11%	1.99%	1.88%
C34	General equipment manufacturing	3.67%	4.03%	4.72%	4.21%	3.87%
C35	Special equipment manufacturing	4.83%	4.93%	6.00%	6.66%	6.55%
C36	Automobile manufacturing	3.67%	3.44%	3.83%	3.81%	3.95%
C37	Railway, shipping, aerospace, and other transportation equipment manufacturing	2.40%	1.91%	1.68%	1.48%	1.52%
C38	Electrical machinery and equipment manufacturing	4.64%	5.67%	7.50%	7.48%	7.13%
C39	Computers, communications, and other electronic equipment manufacturing	8.81%	9.83%	9.92%	10.03%	10.77%
C40	Instrument and meter manufacturing	0.00%	0.00%	0.40%	1.44%	1.44%
D44	Electric power and hot power production and supply	5.76%	4.16%	3.18%	2.90%	2.28%
D45	Gas production and supply	0.00%	0.00%	0.00%	0.00%	0.69%
E48	Civil engineering construction	0.00%	0.87%	2.42%	2.54%	2.06%
E50	Building fitting up and others	0.00%	0.00%	0.00%	0.36%	0.77%
F51	Wholesales	0.00%	1.93%	3.10%	2.77%	2.33%
F52	Retail trade	7.88%	6.07%	4.44%	3.53%	2.71%
G54	Road transport	0.00%	0.74%	1.66%	1.38%	1.15%
G55	Waterway transport	0.00%	0.69%	1.41%	1.11%	0.90%
G58	Air transport	3.63%	1.75%	0.00%	0.00%	0.00%
I64	Internet and related service	0.00%	0.00%	0.00%	1.76%	1.74%
I65	Software and information technology service	1.51%	3.13%	4.78%	5.67%	6.45%
K70	Real estate	7.11%	9.09%	6.86%	5.14%	3.62%
L72	Commercial service	0.00%	0.00%	0.00%	1.43%	1.51%
M74	Professional technical service	0.00%	0.00%	0.00%	0.40%	1.26%
N77	Science and technology extension and application services	0.00%	0.00%	0.00%	0.00%	1.25%
R85	Journalism and publishing	0.00%	0.00%	0.00%	0.00%	0.77%
R86	Radio, television, film and film recording manufacturing	0.00%	0.00%	0.00%	0.00%	0.77%
S90	Comprehensive	5.49%	2.07%	0.36%	0.61%	0.20%
N		2588	3774	5250	6033	8867

Appendix B presents the frequency distribution of the sample. We only keep an industry if it has at least 20 observations to calculate investment efficiency.

Appendix C. Variable definitions

Variable	Definitions
ABSINV	The absolute value of residual from the Richardson model below: $INV_{i,t} = \beta_0 + \beta_1 GROWTH_{i,t-1} + \beta_2 LEV_{i,t-1} + \beta_3 CASH_{i,t-1} + \beta_4 AGE_{i,t-1} + \beta_5 SIZE_{i,t-1} + \beta_6 RETURN_{i,t-1} + \beta_7 INV_{i,t-1} + \varepsilon_{i,t,}$ where *INV* represents new investments, which is the value of the sum of capital expenditure and spending on mergers and acquisitions minus the sum of income from the sales of long-term assets and depreciation deflated by total assets in year *t*. *GROWTH* is measured by the market value deflated by fiscal-year-end total assets. *LEV* is the asset–liability ratio. *CASH* is the net amount of cash and cash equivalents at the end of the fiscal year. *AGE* is the natural logarithm of the number of years a firm has been listed. *SIZE* is the natural logarithm of a firm's total assets at the end of the fiscal year. *RETURN* is the annual stock return.
ACCU1 (*ACCU2*)	We define *ACCU1* (*ACCU2*) as the absolute value of the deviation (the mean of the absolute deviation) of the average forecast from the actual earnings per share (EPS), deflated by the stock price at the end of the year *t*. Then we multiply them by −1 to make it easier to interpret the results. A higher value of *ACCU1* or *ACCU2* represents analyst earnings forecasts that are more accurate.
PEER_ACCU1	The average of peer-firm analyst forecast indicator (*PEER_ACCU1*) excluding firm i's analyst earnings forecasts to measure peers' analyst earnings forecasts.
PEER_ACCU2	The average of peer-firm analyst forecast indicator (*PEER_ACCU1*) excluding firm i's analyst earnings forecasts to measure peers' analyst earnings forecasts.
PEER_DISP	We define *DISP* as the standard deviation of individual forecasts from all analysts that follow the firm scaled by the stock price at the end of year t. We use the average of peer-firm *DISP* excluding firm i's analyst earnings forecasts to measure peers' analyst earnings forecasts.
PEER_OPT	Analyst optimism (*OPT*) is defined as the deviation of the average forecast from the actual EPS, deflated by the stock price at the end of the year t. We use the average of peer-firm *OPT* excluding firm i's analyst earnings forecasts to measure peers' analyst earnings forecasts.
SIZE	The natural logarithm of total assets
ROA	Net income divided by total assets
BM	Equity divided by market value
CFO	Cash flow from operating activities divided by total shares
OPR	Operating profits divided operating income
GOA	The difference in total assets between the current year and previous year divided by total assets in the previous year
TAT	Operating income divided by total assets
LEV	Debt divided by total assets
TOP	The proportion of ownership of the largest stockholder
CR	Sum of ownership proportions held by the second to fifth stockholders divided by the proportion of the first major stockholder
INDRATIO	Percentage of independent directors in a board
MAOW	Share proportion of managers
COMPEN	The natural logarithm of the sum salary of directors, supervisors, and managers

(*continued on next page*)

(*continued*)

Variable	Definitions
SOE	Equals 1 if the firm is state owned, and 0 otherwise
DUAL	Equals 1 if the board chair serves as general manager, and 0 otherwise
ADM	General and administrative expenses divided by operating income
OCCUPY	Other receivables divided by total assets
BOARD	The natural logarithm of the number of board members
MINO	Minority interests divided by equity
INSTI	Share proportion of institutional investors
PPE	Total non-current assets divided by total assets
COMTE	The number of committees including audit committee, strategy committee, nominating committee, and compensation committee
PEER_DACC	We calculate peers' discretionary accruals based on the adjusted Jones model (*DACC*). Then, *PEER_DACC* is the average of peers' *DACC*.
UC	Economic uncertainty based on weekly stock returns. Details are in Section 4.3.
EPU	Economic policy uncertainty based on the South China Morning Post (SCMP). The data are from Baker et al. (2016). We use the average value of the index for every year, multiplying by 100, to measure EPU.
ILL	The illiquidity of the stock market which is $ILL_{it} = \frac{1}{D_{it}} \sum_{k=1}^{Dit} \sqrt{\frac{\lvert r_{it}(k) \rvert}{V_{it}(k)}}$, where $r_{it}(k)$ is the return in firm i on day k of year t, and $V_{it}(k)$ is the daily volume in dollars. D_{it} is the number of days for which data are available for firm i in year t.

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