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Does analysts' industrial concentration affect the quality of their forecasts?

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Abstract

We examine the association between financial analysts' industrial concentration and the quality of their earnings forecasts. We find that analysts' forecast quality, measured by forecast accuracy, forecast informativeness, and forecast timeliness, is positively associated with analysts' industrial concentration on firm coverage, suggesting that allocation of effort and resources to the concentrated industries helps promote the quality of earnings forecasts. We also find that the positive relation of analysts' industrial concentration with forecast accuracy and informativeness (forecast timeliness) is more (less) pronounced for firms faced with fiercer industrial product market competition, higher firm-specific risk, and/or higher information opacity. Overall, our results highlight the importance of analysts' industrial concentration in contributing to the quality of their earnings forecasts.

Keywords Industry-specific information · Industrial concentration · Forecast accuracy · Forecast informativeness · Forecast timeliness

JEL Classification G11 · G14 · G24 · M41

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1 Introduction

Financial analysts act as the key information intermediaries between firms and investors in capital markets (e.g. Lang and Lundholm 1996). To this end, they evaluate the future prospects of firms and provide earnings forecasts for investors (Barth and Hutton 2004). As with board directors (Brown et al. 2019) and institutional investors (Kang et al. 2018), analysts may opt to cover firms in more than one industry for various reasons. For instance, analysts might intend to cover industries which are related to their educational backgrounds (Kini et al. 2009; Cao et al. 2022); on which they have prior work experience (Bradley et al. 2017a) and social networks (Cohen et al. 2010; Chen et al. 2021); or for which their forecast accuracy is expected to be higher (Balashov 2017). In the case when competition among analysts in a specific industry is so fierce that it becomes difficult for them to stand out from the crowd, they might diversify their firm coverage across multiple industries to reduce competitive risk and adversities posed to their career prospects and compensation (Merkley et al. 2017). Despite the analysts' multi-industry engagements (e.g. Clement 1999; Jacob et al. 1999; Kini et al. 2009), the literature has paid little attention to the phenomenon that analysts put different emphasis on, and allocate varying time, effort, and resources to, the industries they covered, and thus whether this differential by analysts for their covered industries affects their forecast quality remains unknown. We aim to fill this gap in the literature. To this end, we investigate the impact of analysts' industrial concentration on the quality of their earnings forecasts. We measure the forecast quality by the accuracy, informativeness, and timeliness of analysts' earnings forecasts.

The industrial concentration of analysts pertains to a structural characteristic of their firm coverage. We define analysts' industrial concentration as the extent to which an analyst concentrates her/his research firms on a smaller proportion of industries s/he covers. Analysts who provide forecasts for a large number of firms within a small proportion of industries have a relatively higher level of industrial concentration, and vice versa. Accordingly, we use the Herfindahl–Hirschman Index (HHI) to construct two empirical measures of analysts' industrial concentration. First, for each analyst, we compute the square of the ratio of the number of forecasts of earnings per share (EPS) for each covered industry to the total number of her/his EPS forecasts in a fiscal year, and then take the sum of all the squares as our first measure of analysts' industrial concentration (*HHI*). Second, analysts may follow a few firms, with quite a few forecasts made for each covered firm, in each covered industry. In such a case, compared with the number of EPS forecasts for each sector, the number of covered firms for the sector might be better in reflecting analysts' effort and resources allocated to the analysis of industry information. To account for this case, we compute the square of the ratio of the number of an analyst's covered firms for each covered industry to the total number of her/his covered firms in a fiscal year, and then take the sum of all the squares as our second measure of analysts' industrial concentration (*HHI1*).

The degree of an analyst's industrial concentration is conceptually determined by the proportion of the number of covered firms in each industry to the total number of covered firms. Yet, the industrial concentration has nothing to do with the number of industries covered by the analyst if s/he covers more than one industry. An analyst can be industrially concentrated even if s/he covers a great deal of industries. That said, analysts with higher industrial concentration usually cover a considerable number of firms in each concentrated industry, and are likely to expend more time, effort, and resources in analysing these firms. As a result, their industry analyses tend to be in more depth and breadth for the concentrated industries.

Because of the information commonality of peer firms in the same industry (Frankel et al. 2006; Liu 2011), industrial-concentrated analysts may acquire and accumulate industry knowledge and experience, and thereby become more sophisticated and specialized in analysing industry information. By following a considerable number of firms in few industries, industrial-concentrated analysts can also benefit from economies of scale in the decreased (increased) costs (efficiency) of their information acquisition and/or processing. Indeed, the extant literature (e.g. Ramnath 2002; Piotroski and Roulstone 2004; Boni and Womack 2006; Brown and Mohammad 2010; Hilary and Shen 2013; Dichev et al. 2013; Chen et al. 2021) documents that industry-specific information is important and conducive to earnings forecasting. For instance, Brown et al. (2015) show that analysts, whose equity research attaches importance to industry information, are more likely to detect stock mispricing, thereby providing more accurate forecasts and rendering stock recommendation opinions more informative to investors. Bradley et al. (2017a) find that analysts, who have industry experience before becoming analysts, are more specialized in processing industry information, which increases their forecast accuracy. To the extent that higher industrial concentration enables analysts to acquire and process industry information better, the quality of their earnings forecasts should be higher. On this basis, the association between analysts' industrial concentration and forecast quality is expected to be positive.

On the other hand, as analysts with higher industrial concentration follow more firms in the concentrated industries, they might deem the firm-specific information of industry peers to be of high similarity, and thus under-emphasize analysis of firm-specific information for their forecasting. They might be overconfident in, and over-reliant on, industry information, and take less effort to analyse firm-specific information than they should. As a result, their forecast quality decreases. Thus, whether analysts' industrial concentration is positively or negatively associated with their forecast quality is an open empirical issue to explore in this study.

We also examine how the relation between analysts' industrial concentration and their earnings forecast quality varies with product market competition, firm-specific risk, and the information opacity of firms. In a highly competitive product market, firms tend to reduce information disclosures due to the concern on high proprietary costs of disclosures (Ellis et al. 2012; Mattei and Platikanova 2017). The lack of corporate disclosures would make industry information more important for analysts' earnings forecasts. Furthermore, a firm's prospect in a highly competitive industry depends critically on its competitive advantage over its industrial peer firms rather than on its own performance alone (Gu 2016; Martens and Sextroh 2021). As such, industry information becomes more value-relevant to analysts, who need to make a comparative analysis of the industrial peers to assess the firm's performance and prospect and make forecasts. As industrial-concentrated analysts have a superior capacity to acquire and process industry-specific information, their industrial concentration should be conducive to improving the quality of their earnings forecasts for firms confronted with higher industrial product market competition.

High firm-specific risk and high opacity of corporate information make it difficult for analysts to evaluate the future prospects of firms (Lang and Lundholm 1996; Hope 2003; Dhaliwal et al. 2012). Consequently, analysts might need to refer to the related common information from industrial peer firms to complement the uncertain or opaque firm-specific information so as to maintain their forecast quality. Industrial-concentrated analysts are likely better at exploiting and analysing the information commonality from industry peers. Therefore, the analysts' industrial concentration should help improve their forecast quality when the uncertainty or opacity of firm-specific information is high. In sum, we hypothesize that the association between analysts' industrial concentration and forecast quality is positively moderated by industrial product market competition, firm-specific risk, and firms' information opacity.

Our regression analysis of the three proxies for analysts' forecast quality—the accuracy, informativeness, and timeliness of forecasts, is based on 21,396, 17,804, and 24,873 analyst-year observations, respectively, covering 5561, 4860, and 6107 US listed companies for the period 1995–2017. We find that a higher level of analysts' industrial concentration is associated with higher quality of their earnings forecasts. Furthermore, we find evidence to suggest that analysts tend to compromise their forecast timeliness to provide more accurate and informative forecasts for firms that face intense industrial product market competition, high firm-specific risk, or high information opacity.

To mitigate potential endogeneity concerns, we adopt a two-stage least-squares regression technique. Besides, following Larcker and Rusticus (2010), we analyse the impact threshold for a confounding variable (ITCV) to ensure that our regression estimations are not biased by potential correlated-omitted variable(s). We also follow Oster (2019) to check the sensitivity of our main results to unobservable confounder(s). The results from using these approaches elicit the same inferences in support of our expectation that analysts' industrial concentration promotes the quality of analyst earnings forecasts.[1]

Prior studies provide some evidence on the impact of industry experience on the performance of stock market participants, such as institutional investors (Kang et al. 2018), board directors (Brown et al. 2019), and auditors (Low 2004; Carson 2009; Bills et al. 2015; Petrov and Stocken 2022). Our paper differs from, and adds to, this line of literature in that we look at industrial concentration and analyse its

[1] Our independent variable as to the analysts' industrial concentration (*HHI*, *HHI1*) is sticky, displaying no or little variation over time in our samples. Since the generalized method of moments (GMM), firm-fixed-effects model, or year-on-year change regression analysis requires that the independent variables have sufficient time-series variation, these approaches may not be suited for use in our study to alleviate potential endogeneity concerns.

association with the performance of financial analysts, thereby offering implications for analysts in particular and plausibly for stock market participants in general.

Our study shows that analysts' industrial concentration promotes the quality of earnings forecasts, which is appreciated and favoured by the market. In specific, to the extent that industrial-concentrated analysts are able to provide more accurate and more timely forecasts based on their industry knowledge and experience, their forecasts would likely be valued more by investors. Consistent with this proposition, we find that analysts' industrial concentration is associated with greater forecast accuracy, higher forecast timeliness, and stronger stock market reactions to forecasts, suggesting that analysts with higher industrial concentration are perceived by investors as being better able to decipher the industry-level implications for future earnings in an accurate and timely manner. Thereby, our study lends support to the extant view that analysts are more sophisticated in processing information than investors (e.g. Bradshaw 2012; Kadan et al. 2012; Brown et al. 2015), and that analysts' industry knowledge and expertise are highly valued by investors (Bradley et al. 2017a; Brown et al. 2015).

Last, but not least, our findings hold important implications for practitioners. Specifically, given that analysts with higher industrial concentration tend to make more accurate, more informative, and more timely earnings forecasts, analysts might seek to concentrate on a smaller proportion of covered industries to improve their forecast accuracy, forecast informativeness, and forecast timeliness to investors. When following firms subject to intense product market competition, high risk, and high information opacity, analysts might need to take more effort and resources to analyse industry information as well as peer firms' information for making high-quality earnings forecasts. Investors who refer to analyst research for their investment decision-making may recognize that analysts who focus their firm coverage on a smaller proportion of covered industries tend to provide more accurate earnings forecasts.

The remainder of our paper proceeds as follows. Section 2 reviews the related literature and develops hypotheses. Section 3 describes our data, sample, and variable measurements. Section 4 expounds the research design. Section 5 discusses our results, and Sect. 6 concludes.

2 Literature review and hypothesis development

2.1 The impact of analysts' industrial concentration on the quality of their earnings forecasts

Analysts' industrial concentration helps them acquire and process industry information better for forecasting. Based on the limited-attention argument (e.g. Hirshleifer and Teoh 2003; Dechow and You 2012; Hameed et al. 2015; Harford et al. 2018), analysts who focus on a smaller proportion of covered industries might devote more time, effort, and resources to the analysis of industry information of the concentrated industries. This enables them to foster industry knowledge and experience, thereby becoming more specialized and sophisticated in analysing the value implications of industry information for firms. Peer firms in the same industry share information commonality in corporate fundamentals that drive accounting returns and stock returns (De Franco et al. 2014), and the analysis specific to an industry can be applicable to all companies in that industry (Liu 2011). Hence, industrial-concentrated analysts can benefit from economies of scale in information acquisition and processing (Kini et al. 2009; Kadan et al. 2012; Huang et al. 2022). Moreover, the information spillovers among industrial peer firms make it possible to interpret a firm's performance by the information from its industrial peers (e.g. Piotroski and Roulstone 2004; Frankel et al. 2006; Hilary and Shen 2013). Therefore, an industrial-concentrated analyst, who usually covers a large number of firms in the same industry, can benefit not only from reduced costs of information acquisition and processing but also from improved efficiency in the information analysis.

Extensive research (e.g. Ramnath 2002; Piotroski and Roulstone 2004; Boni and Womack 2006; Brown and Mohammad 2010; Hilary and Shen 2013; Dichev et al. 2013; Brown et al. 2015; Bradley et al. 2017a) provides evidence that industry-specific information is crucial for evaluating firm performance and making earnings forecasts. For instance, Brown et al. (2015) contend that a good understanding of an industry's key development trends as well as its supply chains, technologies, management, and distribution models is conducive to forecasting future earnings. Chen et al. (2021) find that industry information becomes more important for earnings forecasting after the implementation of Regulation Fair Disclosure (Reg FD), because corporate managers shift from private disclosures of firm-specific information to those of industry information, which is a practice belonging to a legal grey area post Reg FD. Dichev et al. (2013) document that a firm's financial reporting choices are largely driven by economic conditions specific to the firm's industry; thus, relevant industry information and knowledge are essential for making valuation judgements from corporate reporting and disclosures. Also, analysts' industry expertise is considered as a research trait that is valued substantially by institutional investors (Brown et al. 2015). Taken together, provided that analysts with higher industrial concentration are better able to acquire and process industry information, and given the importance of industry information in evaluating firms' future prospects, it is reasonable to conjecture that analysts' industrial concentration helps promote the quality of their earnings forecasts.

On the other hand, industrial-concentrated analysts, who usually cover a large number of firms in the same industry, might deem the information analysis of these firms to be overlapping to a substantial degree due to the high similarity of information from the industrial peer firms under the analysts' research portfolios. As a result, they might unconsciously or imperceptibly under-emphasize firm-specific information and associated analysis, and be overconfident in, and over-reliant on, industry information for their earnings forecasts. Therefore, the quality of the analysts' forecasts might be impaired as a result of their high industrial concentration. Based on the above discussion, we propose the following two competing hypotheses for empirical tests:

Hypothesis 1a. Analysts' industrial concentration increases the quality of their earnings forecasts.

Hypothesis 1b. Analysts' industrial concentration decreases the quality of their earnings forecasts.

2.2 Cross-sectional analysis of industrial product market competition

When firms face high industrial product market competition, industry information becomes more important for the evaluation of corporate performance and prospect. On the one hand, there is often a high degree of product homogeneity in competitive industries. As such, disclosures by a firm are likely to reveal information about the demand-side factors affecting the entire industry (Ali et al. 2007). On the other hand, firms in fiercely competitive product markets are often subject to high proprietary costs of disclosures (Verrecchia 1983). They are more likely to deliberately withhold information about their major customers, product innovation, and/or business expansion plans (Ellis et al. 2012; Mattei and Platikanova 2017), leading to higher information opacity and increased difficulty in forecasting earnings. In this case, analysts would rely more on industry information due to the lack of firm-specific information. Moreover, a firm's prospect in a highly competitive industry is largely contingent on its competitive position in the whole industry rather than on its own performance alone (Gu 2016; Martens and Sextroh 2021). As such, industry information becomes more value-relevant to analysts as they need to analyse a firm's competitive advantage over its industrial peer firms to evaluate the firm's future prospect. To the extent that industrial-concentrated analysts have the superior capability to acquire and process industry information, analysts' industrial concentration should help improve the quality of their earnings forecasts for firms confronted with fiercer industrial product market competition. Therefore, we put forth our second hypothesis as follows:

Hypothesis 2. The positive (negative) association between analysts' industrial concentration and the quality of their earnings forecasts, as predicted in Hypothesis 1a (Hypothesis 1b), is more (less) pronounced for firms that face fiercer industrial product market competition.

2.3 Cross-sectional analysis of firm-specific risk and the information opacity of firms

High firm-specific risk and high firm information opacity make firm-specific information itself of greater uncertainty (Barth et al. 2001; Dichev and Tang 2009; Dichev et al. 2013; Dhaliwal et al. 2012). As a result, *ceteris paribus*, it is more difficult for analysts to provide quality earnings forecasts. Analysts may refer to the information of industrial peer firms to compensate for the uncertainty or opacity of firm-specific information so as to maintain their forecast quality. To the extent that industrial-concentrated analysts have the superior ability to acquire and process industrial information and to exploit the information commonality among industry peers, analysts' industrial concentration should be instrumental in improving the quality of their earnings forecasts for the firms that have high risk or high information opacity. Accordingly, we put forward our third hypothesis as follows:

Hypothesis 3. The positive (negative) association between analysts' industrial concentration and the quality of their earnings forecasts, as predicted in Hypothesis 1a (Hypothesis 1b), is more (less) pronounced for firms that have higher risk or higher information opacity.

3 Data and variable measurements

3.1 Data sources and sample

Prior to 1995, the release dates of analyst forecasts were often not precisely reported in the Institutional Brokers Estimate System's (I/B/E/S) detail files (Frankel et al. 2006; Clement et al. 2011), so our sample period starts from 1995. In 2018, I/B/E/S started to anonymize the names of brokers and their analysts in its detail history files, which led to 13.8% of broker identifiers (IDs) and 30.7% of analyst IDs being reshuffled, according to the announcement of Wharton Research Data Services.[2] To maintain the stability and continuation of broker IDs and analyst IDs for our sample period (Law 2023), we end it in 2017.

While data on analyst earnings forecasts are gathered from I/B/E/S, other data are collected from the *Centre for Research in Security Prices* (CRSP) and Compustat. We require that firms have the necessary data available on these databases to construct the variables of interest for our regression analysis. The independent variables and dependent variables used for our regression estimates are measured in the same year.[3] To alleviate the problem of outliers, we winsorize all continuous variables at the 1st and 99th percentiles, respectively. Our multivariate tests of the impact of analysts' industrial concentration on forecast accuracy, forecast informativeness, and forecast timeliness are based on 21,396, 17,804, and 24,873 analyst-year observations, respectively, corresponding with 5,561, 4,860, and 6,107 US listed firms and with 3,225, 3,326, and 3,333 analysts. Panel A (Panel B) of Table 1 reports the distribution of the mean values of analysts' industrial concentration, forecast accuracy, forecast informativeness, and forecast timeliness across years (industries). Firms in the industry of health, energy, and finance have the highest level of analysts' industrial concentration.

[2] In 2021, the Wharton Research Data Services announced the IBES changes (i.e. the anonymization of broker IDs and analyst IDs) at the webpage—https://wrds-www.wharton.upenn.edu/pages/about/data-vendors/vendor-partner-ibes/.

[3] We estimate regressions by lagging the independent variables one-year behind the dependent variables, and get qualitatively unchanged results for our hypothesis tests.

Table 1 Analysts' industrial concentration (*HHI* & *HHI1*), forecast accuracy (*accuracy*), forecast informativeness (*car*), and forecast timeliness (*timeliness*) across years and industries

Year	HHI	HHI1	Accuracy	Car	Imeliness
Panel A: The distribution of mean values of *HHI, HHI1*, *accuracy*, *car*, and *timeliness* across years					
1995	0.4533	0.4333	− 0.0661	0.0717	− 3.5912
1996	0.4491	0.4229	− 0.0550	0.0780	− 3.4524
1997	0.4647	0.4431	− 0.0158	0.0855	− 3.4850
1998	0.4757	0.4574	− 0.0581	0.0958	− 3.2487
1999	0.4942	0.4730	− 0.0513	0.1112	− 3.2402
2000	0.5014	0.4793	− 0.0126	0.1272	− 3.1337
2001	0.5603	0.5357	0.0003	0.1341	− 2.9830
2002	0.5659	0.5444	0.0360	0.1218	− 2.5994
2003	0.5812	0.5596	− 0.0210	0.1022	− 2.9167
2004	0.5986	0.5836	− 0.0399	0.0831	− 2.6080
2005	0.5905	0.5741	− 0.0503	0.0788	− 2.6373
2006	0.5980	0.5863	− 0.1073	0.0779	− 2.4379
2007	0.5950	0.5830	0.0101	0.0834	− 2.3233
2008	0.6036	0.5865	0.0133	0.1240	− 2.2355
2009	0.5889	0.5737	0.0619	0.1329	− 2.2164
2010	0.5786	0.5684	− 0.0063	0.0902	− 2.1575
2011	0.5844	0.5676	− 0.0557	0.0859	− 2.1287
2012	0.5767	0.5672	− 0.0440	0.0897	− 2.2280
2013	0.5903	0.5774	− 0.0755	0.0799	− 2.2049
2014	0.5837	0.5763	0.0021	0.0872	− 2.1854
2015	0.5718	0.5568	− 0.0174	0.0933	− 2.2066
2016	0.5925	0.5827	− 0.0730	0.1015	− 2.3396
2017	0.6382	0.6272	− 0.2221	0.0773	− 3.1769

Table 1 (continued)

Fama–French 12 industries	HHI	HHI1	Accuracy	Car	Timeliness
Panel B: The distribution of mean values of *HHI, HHI1, accuracy*, *car*, and *timeliness* across industries					
Consumer nondurables—food, tobacco, textiles, apparel, leather, toys	0.4519	0.4301	0.0553	0.0854	− 3.1841
Consumer durables—cars, TVs, furniture, household appliances	0.3373	0.3158	0.1283	0.0879	− 3.0117
Manufacturing—machinery, trucks, planes, paper, computer printing	0.3625	0.3409	0.1422	0.0835	− 3.0179
Energy—oil, gas, and coal extraction and products	0.6716	0.6453	0.0019	0.0829	− 2.7261
Chemistry—chemicals and allied products	0.5763	0.5575	0.0423	0.0762	− 2.9867
Business Equipment—computers, software, and electronic equipment	0.5533	0.5364	− 0.0446	0.1291	− 2.4455
Telecommunication—telephone and television transmission	0.5675	0.5503	− 0.0358	0.1000	− 2.9277
Utilities	0.6388	0.6330	0.0972	0.0389	− 3.7115
Shops—wholesale, retail, and some services such as laundries, repair shops	0.3776	0.3525	0.0920	0.0956	− 2.9691
Health—healthcare, medical equipment, and drugs	0.6802	0.6643	− 0.0357	0.1116	− 2.7373
Money—finance	0.7150	0.7046	0.0917	0.0696	− 2.9479
Others—mines, construction, transportations, hotels, bus services, entertainment	0.4487	0.4267	0.0063	0.0991	− 2.9224

Panel A of Table 1 reports the distribution of mean values of analysts' industrial concentration (*HHI & HHI1*), forecast accuracy (*accuracy*), forecast informativeness (*car*), and forecast timeliness (*timeliness*) across years, and Panel B reports these variable distributions by industries. The industry classification is based on the Fama–French 12 codes. The samples used for the regressions of *accuracy*, *car*, and *timeliness* consist of 21,396, 17,804, and 24,873 analyst-year observations, respectively, covering the period 1995–2017. It is worth noting that the distributions of the variables *HHI* and *HHI1* are provided based on the sample of forecast informativeness, which is the largest sample and consists of 24,873 observations for 6,107 US listed firms and 3,333 analysts. All the variables are defined in "Appendix 1"

3.2 Measures of analysts' industrial concentration

We use the Herfindahl–Hirschman Index (HHI), developed by Herfindahl (1950) and Hirschman (1945), to construct two measures of analysts' industrial concentration. Firstly, for each analyst, we compute the square of the ratio of the number of forecasts of earnings per share (EPS) for each covered industry to the total number of her/his EPS forecasts in a fiscal year, and then take the sum of all the squares as our first measure of analysts' industrial concentration. In line with Rhoades (1993) and Sonney (2009), we use the first two digits of standard industrial classification (SIC) codes for industry classification, and measure the analysts' industrial concentration by the following HHI model:

$$HHI_{i,t} = \sum_{j=1}^{J} \left(\frac{Sector_{i,j,t}}{Sum_{i,t}} \right)^2 \tag{1}$$

where $Sector_{i,j,t}$ is the number of earnings forecasts issued by analyst i for all the firms in industry j in year t; $Sum_{i,t}$ is the total number of earnings forecasts issued by analyst i in year t. The value of $HHI_{i,t}$ is greater than 0, and less than or equal to 1. The higher the *HHI* value, the greater the industrial concentration of an analyst. $HHI_{i,t}$ equals 1 in cases when an analyst focuses her/his coverage on firms in a single industry. Secondly, we compute the square of the ratio of the number of an analyst's covered firms for each covered industry to the total number of her/his covered firms in a fiscal year, and then take the sum of all the squares as another measure of analysts' industrial concentration (*HHI1*). For construction of the second measure, $Sector_{i,j,t}$ in Model (1) is re-defined as the number of firms covered by analyst i in industry j and in year t, and $Sum_{i,t}$ is re-defined as the total number of firms covered by analyst i in year t. An analyst is regarded as having a reasonable degree of industrial concentration if the *HHI* or *HHI1* is more than 50%. The proportion of analysts, for whom the value of *HHI* (*HHI1*) is over 0.5, is 51.29% (54.12%). Since the proportion of industrial-concentrated analysts is not significantly higher than the other, it is unclear whether analysts in general appreciate the benefits of industrial concentration to firm coverage.

4 Research design

4.1 Test of Hypothesis 1

Hypothesis 1 concerns the relationship between analysts' industrial concentration and the quality of their earnings forecasts. We measure the quality by the analysts' forecast accuracy, forecast informativeness, and forecast timeliness. To test the association between analysts' industrial concentration and forecast accuracy, we employ the following ordinary least-squares (OLS) regression model:

$$\begin{aligned}accuracy = {} & \alpha_0 + \alpha_1 HHI(orHHI1) + \alpha_2 bsize + \alpha_3 top10 + \alpha_4 gexp + \alpha_5 freq \\ & + \alpha_6 portsize + \alpha_7 horizon + \alpha_8 size + \alpha_9 price \\ & + \alpha_{10} stdearnings + \alpha_{11} competition \\ & + \alpha_{12} insti + \alpha_{13} liquidity + \alpha_{14} salesgrowth \\ & + \alpha_{15} intanratio + \alpha_{16} firmage + \alpha_{17} capx \\ & + \alpha_{18} abtradvol + YearDummies + IndustryDummies + \varepsilon\end{aligned} \tag{2}$$

where *accuracy* is calculated as − 1 times the absolute value of the difference between actual EPS and an analyst's last forecast of annual EPS for a firm for a fiscal year, divided by the firm's actual EPS at the end of the fiscal year. If analysts' industrial concentration increases (decreases) their earnings forecast accuracy, the coefficients for *HHI* and *HHI1* should be positive (negative) and statistically significant at conventional levels.

Following prior literature on the determinants of analyst forecast accuracy, we control for two main categories of variables to alleviate potential correlated-omitted-variable(s) bias. The first category comprises analyst characteristics. Analysts employed by large brokers usually have better access to datasets as well as private information of firm management, which contributes to their forecast accuracy (Stickel 1995; Clement 1999). We therefore use broker size (*bsize*) and top− 10 brokerage (*top10*) to control for the research resources available to analysts. Furthermore, Jacob et al. (1999) find that analysts improve their forecast accuracy through learning-by-doing. Clement (1999) shows that analysts' forecast experience enhances their abilities and skills to make accurate forecasts. Hence, we include analysts' general forecast experience (*gexp*) and firm-specific forecast experience (*freq*) in the regression. Kini et al. (2009) find that the sector diversity in the analysts' portfolios of covered firms adds research complexity and the costs of information processing, making it more difficult to forecast earnings accurately. Therefore, we control for the size of analysts' portfolios (*portsize*). We also control for analyst forecast horizon (*horizon*), because analysts' forecast accuracy decreases with the number of days between their forecast issuance date and the earnings announcement date (Jacob et al. 1999). The second category of the determinant variables for analyst forecast accuracy comprises firm characteristics, which include firm size (*size*), stock price (*price*), earnings volatility (*stdearnings*), product market competition (*competition*), institutional stock ownership (*insti*), stock liquidity (*liquidity*), sales growth (*salesgrowth*), intangible assets (*intanratio*), firm age (*firmage*), capital expenditures (*capx*), and abnormal trading volume (*abtradvol*) (e.g. Lim 2001; Gu and Wang 2005; Dhaliwal et al. 2012; Bradley et al. 2017b; He et al. 2019a).

Next, we test whether analysts' industrial concentration improves their earnings forecast informativeness, using the following OLS regression model:

$$
\begin{aligned}
car = {} & \alpha_0 + \alpha_1 HHI(orHHI1) + \alpha_2 gexp + \alpha_3 freq + \alpha_4 portsize + \alpha_5 bsize \\
& + \alpha_6 top10 + \alpha_7 size + \alpha_8 price + \alpha_9 stdearnings + \alpha_{10} competition \\
& + \alpha_{11} insti + \alpha_{12} liquidity + \alpha_{13} salesgrowth + \alpha_{14} intanratio \\
& + \alpha_{15} beta + \alpha_{16} btm + \alpha_{17} tradingvol + \alpha_{18} changeeps \\
& + \alpha_{19} xrd + \alpha_{20} regulated + \alpha_{21} changeroa + \alpha_{22} abaccruals \\
& + YearDummies + IndustryDummies + \varepsilon
\end{aligned} \tag{3}
$$

Following Frankel et al. (2006), we define analyst earnings forecast informativeness (*car*) as the magnitude of the stock price reaction to analyst earnings forecasts. In particular, *car* equals the three-day [− 1, 1] cumulative unsigned abnormal stock returns surrounding an analyst's last forecast of EPS for a firm for a fiscal year. The abnormal stock returns are estimated using a market model with an estimation period of [− 181, − 2] relative to the forecast date.[4] If analysts' industrial concentration makes their earnings forecasts more (less) informative to investors, the coefficients on *HHI* and *HHI1* should be positive (negative) and statistically significant at conventional levels.

In line with prior studies on analyst forecast informativeness (e.g. Frankel et al. 2006; Arand et al. 2015; He and Marginson 2020; He et al. 2020), we control for analysts' general forecast experience (*gexp*), analysts' firm-specific forecast experience (*freq*), analysts' portfolio size (*portsize*), broker size (*bsize*), top− 10 brokerage (*top10*), firm size (*size*), stock price (*price*), earnings volatility (*stdearnings*), product market competition (*competition*), institutional stock ownership (*insti*), stock liquidity (*liquidity*), sales growth (*salesgrowth*), intangible assets (*intanratio*), firm beta (*beta*), the book-to-market ratio (*btm*), stock trading volume (*tradingvol*), change in EPS (*changeeps*), research and development expenditures (*xrd*), industrial regulatory status (*regulated*), change in pre-tax return on assets (*changeroa*), and abnormal accruals (*abaccruals*).

To test the impact of analysts' industrial concentration on forecast timeliness, we employ the following OLS regression model:

$$
\begin{aligned}
timeliness = {} & \alpha_0 + \alpha_1 HHI(orHHI1) + \alpha_2 gexp + \alpha_3 fexq + \alpha_4 freq \\
& + \alpha_5 portsize + \alpha_6 bsize + \alpha_7 top10 + \alpha_8 size \\
& + \alpha_9 price + \alpha_{10} stdearnings + \alpha_{11} competition \\
& + \alpha_{12} insti + \alpha_{13} liquidity + \alpha_{14} beta + \alpha_{15} btm \\
& + \alpha_{16} horizon + \alpha_{17} firmage + \alpha_{18} capx \\
& + YearDummies + IndustryDummies + \varepsilon
\end{aligned} \tag{4}
$$

Where *timeliness* is measured, in line with previous research (e.g. Zhang 2008), as − 1 times the natural logarithm of the number of days between the date on which a firm announces its earnings for the current fiscal year and the date on which an

[4] Our results for the baseline regressions remain qualitatively unchanged if we use an alternative estimation window, which is [− 91, − 2] relative to the forecast date, to calculate the abnormal stock returns.

analyst issues her/his first earnings forecast since the earnings announcement. Provided that analysts' industrial concentration increases (decreases) the timeliness of their forecasts, *HHI* and *HHI1* should take on a positive (negative) coefficient that is statistically significant at a conventional level.

We control for analysts' general forecast experience (*gexp*), analysts' firm-specific forecast experience (*fexp* and *freq*), analysts' portfolio size (*portsize*), broker size (*bsize*), top− 10 brokerage (*top10*), firm size (*size*), stock price (*price*), earnings volatility (*stdearnings*), industrial product market competition (*competition*), institutional stock ownership (*insti*), stock liquidity (*liquidity*), firm beta (*beta*), the book-to-market ratio (*btm*), analyst forecast horizon (*horizon*), firm age (*firmage*), and capital expenditures (*capx*). All these variables are documented by prior literature (e.g. Louis et al. 2013; Jackson 2005; Guttman 2010) to be related to the timeliness of analyst forecasts.

For the foregoing Models (2), (3), and (4), we include year- and industry-fixed effects; the standard errors of the coefficients are clustered by firms to control for potential correlations of residuals within firms (Petersen 2009).[5] Detailed definitions of all the control variables are provided in "Appendix 1".

To mitigate potential endogeneity concerns, we use a two-stage least-squares regression approach. A brokerage house having more analysts following a specific industry is likely to attach more importance to that industry. As a result, the likelihood of an analyst being industrial-concentrated increases. However, the number of analysts of a brokerage house following a specific industry is unlikely to exert a direct effect on analysts' individual forecast performance.[6] On this basis, we use *bexp* as a plausible instrument for the two-stage least-squares regression. It is calculated as the natural logarithm of the ratio of the number of analysts in a brokerage house, who follow a given industry, to the total number of analysts employed by the same brokerage house in a fiscal year. Except for the instrument, the control variables used in the first-stage regression are the same as those included in the second-stage regression (Wooldridge 2000).

We also perform a test of the impact threshold for a confounding variable (ITCV) as per Larcker and Rusticus (2010) to further check whether or not our baseline regression results are biased by potential correlated-omitted variable(s). Frank (2000) defines ITCV as the threshold of the impact of omitted variable(s), beyond which the regression results would be overturned if the omitted variable(s) were controlled in our regression. The larger the value of ITCV, the less possible that our regression results are driven by correlated-omitted variable(s).

[5] All our regression results are qualitatively the same if we cluster the standard errors by industry.

[6] Huang et al. (2022) document that the cross-industry information sharing among analyst colleagues covering industries in the same supply chain improves their forecast accuracy. Since the performance evaluation for analysts is incomparable across different sectors, the competition among the analysts within the same industry tends to be much fiercer than that for the analysts whose firm coverage is in the industry different from one another (Yin and Zhang 2014). Due to the competition concern, the analysts following the same industry should be less likely to share information with each other. In our sample, for analysts at a brokerage house who cover firms in the same industry in a fiscal year, the standard deviation of their forecast accuracy averages 0.94 among all the brokerage houses, which is significantly larger than does that of all analysts at the same brokerage (0.83). This result further alleviates the concern that analysts' intra-industry information sharing within a brokerage house may affect their forecast performance, and thereby validates the exclusion restriction assumption for the instrumental variable *bexp*.

We further test the sensitivity of our baseline regression results to omitted variable(s) bias by using a method developed by Oster (2019). Under Oster's approach, a coefficient of proportionality δ is proposed to capture the importance of unobservable variable(s) relative to that of observed variables in the regression, and to determine the threshold beyond which the bias induced by unobservable variable(s) would nullify the regression results. A value of δ larger than 1 indicates that the omitted variables need to be more influential than the included variables to explain away the regression results, which is almost impossible provided that the major determinants of the dependent variable are controlled in the regression. In such a case, the regression results are unlikely to be biased by potential omitted variable(s).

4.2 Tests of Hypothesis 2 and Hypothesis 3

Hypothesis 2 concerns whether the association between analysts' industrial concentration and forecast quality is stronger for firms faced with fiercer industrial product market competition. In line with Karuna (2007), we construct a composite measure of industrial product market competition, which is captured by industry-level capital expenditures, industry-level sales, and industry-level operating costs. A high industry-level of capital expenditures or operating costs indicates that firms need to incur high costs in order to maintain a stable supply of competitive products and/or services to the market, suggesting a high level of product market competition. High industry-level sales indicate a high market demand and thus relatively low industrial competition. Hypothesis 3 predicts that firms' risk or information opacity positively moderates the association between analysts' industrial concentration and forecast quality. As with previous studies (e.g. Fink et al. 2010; Cao et al. 2008), we measure firm-specific risk by idiosyncratic return volatility. We follow Hutton et al. (2009) to measure a firm's information opacity as the three-year moving sum of the absolute value of abnormal accruals for the current and previous two fiscal years.

To test Hypotheses 2 and 3, we construct the moderating variables, *dcompetition*, *dfirmrisk*, and *dopacity*, which equal 1 if the moderator variables (i.e. industrial product market competition, firm-specific risk, and firms' information opacity) are larger than their sample medians, and 0 otherwise. We interact the moderating variables with the variables as to the analysts' industrial concentration, and include the interaction terms in Models (2–4) for the regression estimation. If the hypotheses hold, the coefficients on the interaction terms should be positive and statistically significant at conventional levels.

5 Empirical results

5.1 Univariate results

Table 2 reports the descriptive statistics of all variables used for our empirical tests. The mean values of *HHI* (*HHI1*) are 0.5081, 0.5460, and 0.5384 (0.4888, 0.5271, and 0.5201) for the samples of analyst forecast accuracy, forecast informativeness,

Table 2 Summary statistics

Variable	*N*	Mean	Std.dev	10th	25th	Median	75th	90th
Panel A: The sample for analysts' industrial concentration and forecast accuracy								
accuracy	21,396	− 0.0258	1.3738	0.9508	0.1048	− 0.0476	− 0.2182	− 0.6897
HHI	21,396	0.5081	0.2732	0.1811	0.2800	0.4506	0.7259	0.9524
HHI1	21,396	0.4888	0.2730	0.1667	0.2632	0.4259	0.6955	0.9168
gexp	21,396	2.4787	0.6880	1.6094	2.3026	2.6391	2.8904	3.1781
feq	21,396	0.9636	0.6363	0.0000	0.6931	1.0986	1.3863	1.7918
portsize	21,396	2.7750	0.6385	2.0794	2.4849	2.8332	3.1355	3.4657
bsize	21,396	3.3183	1.1891	1.7918	2.5649	3.3673	4.1744	4.7274
top10	21,396	0.4773	0.4995	0.0000	0.0000	0.0000	1.0000	1.0000
size	21,396	5.7503	1.7479	3.5815	4.5234	5.6931	6.8892	8.0299
price	21,396	17.8123	16.8216	2.3700	5.5900	12.7500	24.8750	40.4375
stdearnings	21,396	41.4055	115.3344	1.2112	2.9549	8.2826	26.3433	86.4842
competition	21,396	− 0.2960	0.4989	− 0.7229	− 0.6525	− 0.4566	− 0.1174	0.4215
insti	21,396	0.3227	0.3602	0.0000	0.0000	0.1684	0.6451	0.8851
liquidity	21,396	0.0186	0.0221	0.0011	0.0028	0.0111	0.0256	0.0462
salesgrowth	21,396	0.2099	0.7035	− 0.2338	− 0.0414	0.0877	0.2726	0.6265
intanratio	21,396	0.1498	0.1857	0.0000	0.0000	0.0707	0.2369	0.4416
horizon	21,396	1.6531	0.1858	1.4215	1.6268	1.7296	1.7702	1.7749
firmage	21,396	2.2089	0.9080	1.0986	1.3863	2.1972	2.8904	3.4340
capx	21,396	0.0635	0.0728	0.0091	0.0197	0.0408	0.0772	0.1403
abtradvol	21,396	0.8255	9.6320	− 3.5266	− 0.5922	0.0089	1.1322	5.9182
Variable	*N*	Mean	Std.dev	10th	25th	Median	75th	90th
Panel B: The sample for analysts' industrial concentration and forecast informativeness								

Table 2 (continued)

Variable	*N*	Mean	Std.dev	10th	25th	Median	75th	90th
car	17,804	0.1000	0.0687	0.0315	0.0506	0.0831	0.1300	0.1901
HHI	17,804	0.5460	0.2792	0.2013	0.3067	0.5000	0.7924	1.0000
HHI1	17,804	0.5271	0.2796	0.1852	0.2896	0.4810	0.7600	1.0000
gexp	17,804	2.4274	0.7230	1.3863	2.1972	2.6391	2.8904	3.1781
freq	17,804	0.9470	0.6423	0.0000	0.6931	1.0986	1.3863	1.7918
portsize	17,804	2.7060	0.7223	1.7918	2.3979	2.7726	3.0910	3.4340
bsize	17,804	3.3977	1.2140	1.7918	2.6391	3.4657	4.2767	4.8122
top10	17,804	0.5025	0.5000	0.0000	0.0000	1.0000	1.0000	1.0000
size	17,804	5.8670	1.8340	3.6256	4.5816	5.7799	7.0386	8.2967
price	17,804	17.9431	17.3260	2.1875	5.2600	12.5000	25.2300	41.4000
stdearnings	17,804	52.6393	140.6605	1.3623	3.2389	9.3207	31.2387	114.9514
competition	17,804	− 0.2015	0.5086	− 0.6680	− 0.5753	− 0.3764	0.0084	0.5304
insti	17,804	0.2996	0.3489	0.0000	0.0000	0.1133	0.5929	0.8640
liquidity	17,804	0.0180	0.0209	0.0012	0.0030	0.0109	0.0248	0.0442
salesgrowth	17,804	0.2260	0.7449	− 0.2429	− 0.0437	0.0918	0.2845	0.6518
intanratio	17,804	0.1456	0.1849	0.0000	0.0000	0.0650	0.2274	0.4400
beta	17,804	0.7746	0.6415	0.0516	0.3346	0.7152	1.1500	1.6145
btm	17,804	0.5392	0.9803	0.1054	0.2474	0.4568	0.7563	1.1857
tradingvol	17,804	10.7553	26.4814	0.1215	0.4035	1.6997	7.4257	27.0270
changeeps	17,804	− 0.0596	0.5042	− 0.1883	− 0.0455	− 0.0005	0.0316	0.1318
xrd	17,804	5.1496	23.7615	0.0000	0.0000	0.0000	0.0000	0.0000
regulated	17,804	0.0909	0.2875	0.0000	0.0000	0.0000	0.0000	0.0000
changeroa	17,804	− 0.0258	0.2164	− 0.1871	− 0.0550	− 0.0047	0.0265	0.1124
abaccruals	17,804	12.5047	61.2249	0.0243	0.0622	0.1768	0.7804	5.7300

Table 2 (continued)

Variable	*N*	Mean	Std.dev	10th	25th	Median	75th	90th
Panel C: The sample for analysts' industrial concentration and forecast timeliness								
timeliness	24,873	− 2.8441	1.9588	− 5.1417	− 4.4543	− 3.5264	− 0.6931	0.0000
HHI	24,873	0.5384	0.2806	0.1956	0.2951	0.4911	0.7884	1.0000
HHI1	24,873	0.5201	0.2816	0.1806	0.2798	0.4629	0.7600	1.0000
gexp	24,873	2.5258	0.6425	1.6094	2.3026	2.6391	2.9444	3.1781
freq	24,873	1.0353	0.6196	0.0000	0.6931	1.0986	1.3863	1.7918
portsize	24,873	2.8233	0.5982	2.1972	2.5649	2.8332	3.1355	3.4657
bsize	24,873	3.4315	1.1617	1.9459	2.7081	3.4965	4.2767	4.7958
top10	24,873	0.5177	0.4997	0.0000	0.0000	1.0000	1.0000	1.0000
size	24,873	5.9008	1.8050	3.6506	4.6295	5.8507	7.1134	8.2494
price	24,873	19.0069	17.7537	2.3750	5.8700	13.7500	26.7100	42.8400
stdearnings	24,873	48.6081	127.2529	1.3311	3.2843	9.6930	31.8741	107.1284
competition	24,873	− 0.0901	0.8958	− 0.7179	− 0.6398	− 0.4154	0.0964	0.8401
insti	24,873	0.3386	0.3629	0.0000	0.0000	0.2173	0.6751	0.8896
liquidity	24,873	0.0172	0.0209	0.0010	0.0025	0.0100	0.0235	0.0433
beta	24,873	0.7501	0.6196	0.0460	0.3270	0.7010	1.1114	1.5545
btm	24,873	0.5912	1.0391	0.1255	0.2827	0.5009	0.8205	1.2913
horizon	24,873	1.6685	0.1821	1.4532	1.6567	1.7400	1.7726	1.7763
firmage	24,873	2.2863	0.8949	1.0986	1.6094	2.3026	2.9444	3.4965
capx	24,873	0.0565	0.0674	0.0035	0.0153	0.0365	0.0708	0.1276
fexp	24,873	1.1271	0.8747	0.0000	0.0000	1.0986	1.7918	2.3979

Table 2 presents summary statistics of all variables used in the hypothesis tests. All the continuous variables are winsorized at the 1% and 99% levels, respectively. The samples used for the regressions of *accuracy*, *car*, and *timeliness* comprise 21,396, 17,804, and 24,873 analyst-year observations, respectively, covering the period 1995–2017. All the variables are defined in "Appendix 1" and forecast timeliness, respectively, indicating that analysts have the propensity to concentrate their research firms to a smaller proportion of industries they cover. The mean of *car*, which measures the average abnormal stock returns to the earnings forecasts issued by industrial-concentrated analysts, amounts to 0.1, suggesting that their forecasts are valued significantly by investors. "Appendix 2" presents the Spearman correlations between the variables involved in our baseline regression analyses. *accuracy*, *car*, and *timeliness* are positively correlated with *HHI* (or *HHI1*). The correlations amount to 8.5%, 2.8%, and 5.0% (8.4%, 2.9%, and 5.4%), respectively, and are statistically significant at the 1% level. These results provide preliminary support for the hypothesis that analysts' industrial concentration is conducive to improving forecast quality.

5.2 Multivariate regression results

Tables 3, 4, and 5 report the OLS regression results for the association between analysts' industrial concentration and the accuracy, informativeness, and timeliness of their earnings forecasts, respectively. The coefficients on *HHI* and *HHI1* are both positive and statistically significant at the 1% level.[7] A one-standard-deviation increase in *HHI* (*HHI1*) leads to an increase in *accuracy*, *car*, and *timeliness* by 0.0366, 0.0024, and 0.0508 (0.0337, 0.0025, and 0.0531), which account for 141.86%, 2.40%, and 1.79% (130.62%, 2.5%, and 1.87%) of the sample means of *accuracy*, *car*, and *timeliness*, respectively. These findings support our prediction that analysts' industrial concentration promotes the quality of their earnings forecasts in terms of forecast accuracy, forecast informativeness, and forecast timeliness.

Table 6 presents the two-stage least-squares (2SLS) regression results for Hypothesis 1. In the first-step regression estimations, *bexp*, which indicates the proportion of analysts at a brokerage who follow a given industry, has a positive and statistically significant relationship with *HHI* (*HHI1*). This result is in line with the notion that when a brokerage house has more analysts following a specific industry, the likelihood of an analyst being industrial-concentrated increases. The partial *F*-statistics for the instrument are all much larger than the cut-off point of 10 and statistically significant at the 1% level, suggesting that our models are not subject to weak-instrument problems (Stock et al. 2002; Larcker and Rusticus 2010). For the second-stage regression results, the coefficients on *accuracy*, *car*, and *timeliness* are positive and statistically significant at the conventional level, suggesting that our results reported in Tables 3, 4, and 5 are robust to correcting for endogeneity. These results for the 2SLS regressions are also economically significant. Specifically, in Column (1a) (Column (2a)) of Panels A, B, and C, a one-standard-deviation increase in the instrument *bexp* leads to an increase in *HHI* (*HHI1*) by 0.0433, 0.0462, and 0.0506 (0.0442, 0.0485, and 0.0514), respectively, which account for 8.52%, 8.46%, and 9.40% (9.04%, 9.20%, and 9.88%) of the sample mean of *HHI* (*HHI1*). In Column (1b) (Column (2b)) of Panels A, B, and C, a one-standard-deviation increase

[7] Our results for the baseline regressions remain qualitatively unchanged if we use the Fama–French 48 (or Fama–French 12) industry classification, in lieu of the first 2-digit SIC codes, to re-construct the *HHI* and *HHI1* variables.

Table 3 Test of Hypothesis 1: Analysts' industrial concentration and forecast accuracy

Variables	Dependent Variable = *accuracy* (1)	(2)
HHI	**0.1339***** **(3.17)**	
HHI1		**0.1235***** **(2.92)**
bsize	0.0033 (0.23)	0.0039 (0.27)
top10	0.0064 (0.20)	0.0062 (0.20)
gexp	0.0119 (0.75)	0.0118 (0.74)
freq	− 0.0246 (− 1.56)	− 0.0246 (− 1.55)
portsize	0.0237 (1.34)	0.0225 (1.27)
horizon	− 0.0300 (− 0.78)	− 0.0300 (− 0.78)
size	− 0.0723*** (− 6.46)	− 0.0721*** (− 6.45)
price	− 0.0002 (− 0.30)	− 0.0002 (− 0.33)
stdearnings	0.0003** (2.49)	0.0003** (2.50)
competition	− 0.0188 (− 0.54)	− 0.0187 (− 0.54)
insti	− 0.1010** (− 2.52)	− 0.1005** (− 2.51)
liquidity	1.4246 (1.61)	1.4191 (1.60)
salesgrowth	− 0.0240 (− 1.66)	− 0.0238 (− 1.65)
intanratio	− 0.0538 (− 0.84)	− 0.0551 (− 0.86)
firmage	− 0.0077 (− 0.63)	− 0.0079 (− 0.65)
capx	0.1388 (0.80)	0.1387 (0.79)
abtradvol	− 0.0011 (− 1.30)	− 0.0011 (− 1.31)
Constant	0.0727 (0.41)	0.0820 (0.46)
Industry-fixed effects	Included	Included

Table 3 (continued)

Variables	Dependent Variable = *accuracy*	
	(1)	(2)
Year-fixed effects	Included	Included
No. of observations	21,396	21,396
Adj. R^2	0.0186	0.0185

Bold highlights the results for the testable hypotheses of interest

Table 3 reports the OLS regression results for the test of the association between analysts' industrial concentration and forecast accuracy. The sample period ranges from 1995 to 2017. The key independent variable is *HHI* (*HHI1*), of which the regression results are displayed in Column (1) (Column (2)). The dependent variable, *accuracy*, equals − 1 times the absolute value of the difference between actual EPS and an analyst's last forecast of annual EPS for a firm for a fiscal year, divided by the firm's actual EPS at the end of a fiscal year. Industry- and year-fixed effects are included in the regressions, but their results are not reported for brevity. All the other variables are defined in "Appendix 1". The industry dummies are constructed based on the first two digits of SIC codes. The *t*-statistics in parentheses are based on robust standard errors clustered by firm. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively

in *HHI* (*HHI1*) causes an increase in *accuracy, car*, and *timeliness* by 0.2800, 0.0168, and 0.2575 (0.2935, 0.0160, and 0.2545), respectively, which are equivalent to 1085.27%, 16.8%, and 9.05% (1137.60%, 16%, and 8.95%) of the sample mean of *accuracy*, *car*, and *timeliness*. Despite the use of the 2SLS regression to tackle potential endogeneity concerns, we do not claim that we have established the causality between analysts' industrial concentration and their forecast quality. As with prior research (e.g. Huang et al. 2022; Sonney 2009; Jiang et al. 2016) on the determinants of analyst forecast performance, our study focuses on pointing to the association between the two variables of interest, and provides some inferences based on the association.

Table 7 reports the results of the tests of the impact threshold for a confounding variable (ITCV). Panels A, B, and C present the results of ITCV tests for Hypothesis 1, for which the dependent variables in the regressions are *accuracy*, *car*, and *timeliness*, respectively. None of the control variables included in our baseline models has an *impact* with its absolute value larger than the absolute ITCV values of 0.0084, 0.016, and 0.0083 (0.0067, 0.0176, and 0.0091) for *HHI* (*HHI1*), indicating that our baseline results reported in Column (1) (Column (2)) of Tables 3, 4, and 5 are not biased by potential correlated-omitted variable(s).

Table 8 presents the results of Oster's (2019) estimate of the proportional degree of selection, δ. The values of δ for the regressions of *accuracy*, *car*, and *timeliness* on *HHI* (*HHI1*) are 6.196, 9.872, and 1.527 (5.668, 15.812, and 1.477), respectively, which are all larger than the recommended threshold of 1. Put differently, to attribute our baseline results alternatively to the omission of unobservable variable(s) in the regressions, the unobservable variable(s) would have to be around 6.2, 9.9, and

Table 4 Test of Hypothesis 1: analysts' industrial concentration and forecast informativeness

Variables	Dependent Variable = *car*	
	(1)	(2)
HHI	**0.0085***** **(4.05)**	
HHI1		**0.0090***** **(4.27)**
gexp	− 0.0002 (− 0.22)	− 0.0002 (− 0.22)
freq	0.0084*** (11.10)	0.0084*** (11.10)
portsize	0.0027*** (3.48)	0.0027*** (3.53)
bsize	0.0032*** (4.95)	0.0032*** (4.94)
top10	0.0028* (1.84)	0.0027* (1.82)
size	− 0.0133*** (− 22.58)	− 0.0133*** (− 22.59)
price	− 0.0003*** (− 8.83)	− 0.0003*** (− 8.82)
stdearnings	− 0.000006 (− 1.63)	− 0.000005 (− 1.62)
competition	0.0013 (0.59)	0.0014 (0.60)
insti	− 0.0026 (− 1.28)	− 0.0027 (− 1.30)
liquidity	0.2452*** (5.48)	0.2454*** (5.49)
salesgrowth	0.0046*** (6.25)	0.0046*** (6.27)
intanratio	0.0001 (0.03)	0.0002 (0.06)
beta	0.0190*** (20.36)	0.0190*** (20.35)
btm	− 0.0037*** (− 5.15)	− 0.0037*** (− 5.15)
tradingvol	0.0003*** (11.79)	0.0003*** (11.79)
changeeps	− 0.0007 (− 0.53)	− 0.0007 (− 0.53)
xrd	0.00004** (2.13)	0.00004** (2.15)
regulated	− 0.0230*** (− 3.33)	− 0.0228*** (− 3.29)

Table 4 (continued)

Variables	Dependent Variable = *car*	
	(1)	(2)
changeroa	− 0.0051	− 0.0051
	(− 1.64)	(− 1.64)
abaccruals	0.000007	0.000007
	(0.80)	(0.80)
Constant	0.1167***	0.1164***
	(18.11)	(18.10)
Industry-fixed effects	Included	Included
Year-fixed effects	Included	Included
No. of observations	17,804	17,804
Adj. R^2	0.3050	0.3051

Bold highlights the results for the testable hypotheses of interest

Column (1) (Column (2)) of Tables 4 reports the OLS regression results for the test of the impact of analysts' industrial concentration, proxied by *HHI* (*HHI1*), on forecast informativeness, *car*. The sample period ranges from 1995 to 2017. The industry dummies are constructed based on the first two digits of SIC codes. Industry- and year-fixed effects are included in the regressions, but their results are not reported for brevity. All variables are defined in "Appendix 1". The *t*-statistics in parentheses are based on robust standard errors clustered by firm. ***, **, * represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively

1.53 (5.7, 15.8, and 1.5) times as powerful as the observed variables in explaining the dependent variable. This is unlikely to take place given our control of a comprehensive list of variables as per prior literature. Therefore, we may rest assured that our baseline results are free from potential omitted variable(s) bias.

Table 9 reports the results for the cross-sectional analysis of product market competition. The coefficients on *HHI*dcompetition* (or *HHI1*dcompetition*) are positive and statistically significant for both the regressions of *accuracy* and *car*, but are significantly negative for the regression of *timeliness*. These results imply that, in covering firms faced with fiercer industrial product market competition, analysts tend to compromise their forecast timeliness to achieve more accurate and more informative forecasts for investors. Table 10 displays the results for the cross-sectional analysis of firm-specific risk. The coefficients on *HHI*dfirmrisk* and *HHI1*dfirmrisk* are positive and statistically significant in the regressions of *accuracy* and *car*, but are significantly negative in the regression of *timeliness*. These results suggest that in forecasting firms that confront higher risk, analysts may prioritize provisions of more accurate and informative forecasts over that of more timely forecasts. Table 11 reports the results for the cross-sectional analysis of firms' information opacity. *HHI*dopacity* and *HHI1*dopacity* have positive (negative) and statistically significant coefficients in the regressions of *accuracy* and *car* (the regression of *timeliness*). Thus, analysts' industrial concentration has a larger positive impact on forecast accuracy and forecast informativeness for firms that have a high level of information opacity. Nonetheless, it takes longer for industrial-concentrated analysts to make forecasts

Table 5 Test of Hypothesis 1: analysts' industrial concentration and forecast timeliness

Variables	Dependent variable = *timeliness*	
	(1)	(2)
HHI	**0.1812***** **(3.25)**	
HHI1		**0.1886***** **(3.38)**
gexp	0.0146 (0.66)	0.0145 (0.65)
fexp	0.0126 (0.72)	0.0124 (0.71)
freq	0.6085*** (29.29)	0.6085*** (29.30)
portsize	0.0656*** (3.02)	0.0661*** (3.05)
bsize	0.0997*** (5.67)	0.0997*** (5.67)
top10	0.0036 (0.09)	0.0034 (0.09)
size	− 0.0113 (− 0.83)	− 0.0114 (− 0.83)
price	− 0.0016 (− 1.52)	− 0.0016 (− 1.53)
stdearnings	0.00001 (0.10)	0.00001 (0.11)
competition	− 0.0677* (− 1.69)	− 0.0677* (− 1.69)
insti	0.0278 (0.51)	0.0278 (0.51)
liquidity	− 2.4967*** (− 2.98)	− 2.4886*** (− 2.97)
beta	0.0091 (0.40)	0.0090 (0.40)
btm	− 0.0125 (− 1.07)	− 0.0125 (− 1.07)
horizon	2.2180*** (28.05)	2.2179*** (28.04)
firmage	− 0.0895*** (− 5.11)	− 0.0894*** (− 5.11)
capx	0.0094 (0.05)	0.0100 (0.05)
Constant	− 8.5932*** (− 24.28)	− 8.5946*** (− 24.29)
Industry-Fixed Effects	Included	Included
Year-Fixed Effects	Included	Included

Table 5 (continued)

Variables	Dependent variable = *timeliness*	
	(1)	(2)
No. of observations	24,873	24,873
Adj. R^2	0.1754	0.1754

Bold highlights the results for the testable hypotheses of interest

Table 5 reports the OLS regression results for the test of the impact of analysts' industrial concentration on forecast timeliness. The sample period ranges from 1995 to 2017. The key independent variable is *HHI* (*HHI1*), of which the regression results are displayed in Column (1) (Column (2)). Industry- and year-fixed effects are included in the regressions, but their results are not reported for brevity. All variables are defined in "Appendix 1". Industry dummies are constructed based on the first two digits of SIC codes. The *t*-statistics in parentheses are based on robust standard errors clustered by firm

***, **, * Represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively

for these firms, meaning that they compromise their forecast timeliness to ensure the higher level of forecast accuracy and informativeness for investors.

6 Conclusion

This study examines the association between analysts' industrial concentration and the quality of their earnings forecasts. Our results reveal that analysts' industrial concentration increases their forecast accuracy, forecast informativeness, and forecast timeliness, which lends support to the view that allocation of effort and resources to the analysis of industry-specific information is conducive to making quality forecasts. We further find that the positive association between analysts' industrial concentration and the accuracy and informativeness (the timeliness) of their earnings forecasts is more (less) prominent in cases when firms are subject to fiercer industrial product market competition, higher firm-specific risk, and/or higher information opacity. This suggests that the benefits of industrial concentration are more salient for firms in those cases, but that the analysts need to spend more time making more accurate and more informative forecasts.

Our findings illuminate the benefits and importance of industrial concentration to financial analysts and have important practical implications. In specific, analysts may opt to concentrate their equity research on a smaller proportion of industries they cover in order to make quality forecasts. For firms faced with fiercer industrial product market competition and/or higher firm information opacity, analysts should allocate more effort and resources to the analysis of industry information by industrially concentrating their firm coverage. Also, it is important for analysts to make a great effort to foster industry knowledge and expertise, which are conducive to improving their forecast quality and thus advancing their career developments. For investors who seek analyst reports for their investment decision-making, it would be helpful to refer to the forecasts

Table 6 Two-stage least-squares regression analyses of Hypothesis 1

Variables	(1a) 1st stage *HHI*	(1b) 2nd stage *accuracy*	(2a) 1st stage *HHI1*	(2b) 2nd stage *accuracy*
Panel A: Two-stage least-squares regression on the association between analysts' industrial concentration and forecast accuracy				
HHI		**1.0980****		
		(2.49)		
HHI1				**1.0750**** **(2.49)**
bexp	**0.0437*****		**0.0446*****	
	(10.56)		**(10.75)**	
bsize	0.0653***	− 0.0375	0.0647***	− 0.0354
	(17.71)	(− 1.60)	(17.47)	(− 1.55)
top10	− 0.0075	0.0073	− 0.0061	0.0056
	(− 1.12)	(0.23)	(− 0.91)	(0.18)
gexp	− 0.0002	0.0129	0.0004	0.0123
	(− 0.06)	(0.80)	(0.10)	(0.76)
freq	0.0075**	− 0.0308*	0.0074***	− 0.0306*
	(2.59)	(−1.89)	(2.61)	(− 1.88)
portsize	− 0.1009***	0.1188**	− 0.0995***	0.1150**
	(− 28.21)	(2.57)	(− 27.27)	(2.56)
horizon	− 0.0080	− 0.0223	− 0.0090	− 0.0215
	(− 0.85)	(− 0.56)	(− 0.95)	(− 0.54)
size	0.0158***	− 0.0873***	0.0162***	− 0.0873***
	(5.86)	(− 6.60)	(5.93)	(− 6.61)
price	− 0.0010***	0.0008	− 0.0010***	0.0007
	(− 4.63)	(0.90)	(− 4.34)	(0.81)
stdearnings	0.00003	0.0002**	0.00002	0.0002**

Table 6 (continued)

Variables	(1a) 1st stage *HHI*	(1b) 2nd stage *accuracy*	(2a) 1st stage *HHI1*	(2b) 2nd stage *accuracy*
	(1.19)	(2.13)	(0.96)	(2.18)
competition	0.0215*	− 0.0403	0.0220*	− 0.0403
	(1.94)	(− 1.07)	(1.96)	(− 1.07)
insti	0.0481***	− 0.1474***	0.0483***	− 0.1465***
	(4.54)	(− 3.27)	(4.54)	(− 3.26)
liquidity	− 0.2355	1.6544*	− 0.2106	1.6222*
	(− 1.62)	(1.84)	(− 1.46)	(1.81)
salesgrowth	0.0069***	− 0.0309**	0.0060***	− 0.0298**
	(2.72)	(− 2.07)	(2.39)	(− 2.01)
intanratio	− 0.1373***	0.0824	− 0.1386***	0.0806
	(− 8.46)	(0.90)	(− 8.48)	(0.89)
firmage	− 0.0157***	0.0082	− 0.0153***	0.0075
	(− 4.75)	(0.57)	(− 4.63)	(0.53)
capx	− 0.0326	0.1771	− 0.0344	0.1783
	(− 0.85)	(1.00)	(− 0.89)	(1.01)
abtradvol	− 0.00004	− 0.0010	− 0.0000002	− 0.0011
	(− 0.25)	(− 1.20)	(− 0.00)	(− 1.26)
Constant	0.6919***	− 0.5261	0.6705***	− 0.4871
	(13.97)	(− 1.59)	(14.42)	(− 1.54)
industry-fixed effects	Included	Included	Included	Included
Year-fixed effects	Included	Included	Included	Included
Partial F-statistic	112***		116***	
No. of obs	21,396	21,396	21,396	21,396
Adj. R^2	0.3246	0.0184	0.3353	0.0184

Table 6 (continued)

Variables	(1a) 1st Stage *HHI*	(1b) 2nd Stage *car*	(2a) 1st Stage *HHI1*	(2b) 2nd Stage *car*
Panel B: Two-stage least-squares regression on the association between analysts' industrial concentration and forecast informativeness				
HHI		**0.0600***** **(3.20)**		
HHI1				**0.0572***** **(3.21)**
bexp	**0.0487***** **(10.52)**		**0.0511***** **(10.97)**	
gexp	0.0011 (0.29)	− 0.0002 (− 0.21)	0.0014 (0.37)	− 0.0002 (− 0.23)
freq	0.0093*** (2.87)	0.0080*** (10.17)	0.0082** (2.54)	0.0080*** (10.38)
portsize	− 0.1029*** (− 28.13)	0.0079*** (3.80)	− 0.1021*** (− 27.17)	0.0075*** (3.83)
bsize	0.0638*** (15.57)	0.0011 (1.17)	0.0636*** (15.39)	0.0013 (1.44)
top10	− 0.0011 (− 0.14)	0.0025 (1.59)	0.0005 (0.07)	0.0024 (1.53)
size	0.0094*** (3.25)	−0.0137*** (− 21.78)	0.0102*** (3.47)	− 0.0138*** (− 21.85)
price	− 0.0010*** (− 4.34)	− 0.0003*** (− 6.56)	− 0.0010*** (− 4.29)	− 0.0003*** (− 6.72)

Table 6 (continued)

Variables	(1a) 1st Stage *HHI*	(1b) 2nd Stage *car*	(2a) 1st Stage *HHI1*	(2b) 2nd Stage *car*
stdearnings	− 0.00003	− 0.000004	− 0.00003	0.000004
	(− 1.32)	(− 1.20)	(− 1.44)	(− 1.19)
competition	0.0036	0.0012	0.0010	0.0014
	(0.25)	(0.51)	(0.07)	(0.57)
insti	0.0359***	− 0.0044**	0.0385***	− 0.0045**
	(3.10)	(− 1.98)	(3.32)	(− 2.01)
liquidity	− 0.2233	0.2554***	− 0.2306	0.2552***
	(− 1.37)	(5.65)	(− 1.41)	(5.66)
salesgrowth	0.0095***	0.0041***	0.0078***	0.0043***
	(3.72)	(5.44)	(3.09)	(5.65)
intanratio	− 0.1451***	0.0079*	− 0.1489***	0.0077*
	(− 8.24)	(1.78)	(− 8.35)	(1.76)
beta	0.0120***	0.0182***	0.0115***	0.0183***
	(2.95)	(18.43)	(2.85)	(18.60)
btm	− 0.0035*	− 0.0036***	− 0.0031*	− 0.0036***
	(− 1.73)	(− 4.79)	(− 1.51)	(− 4.86)
tradingvol	0.0004***	0.0003***	0.0004***	0.0003***
	(3.3)	(9.94)	(3.20)	(10.08)
changeeps	− 0.0071	− 0.0003	− 0.0066	− 0.0004
	(− 1.48)	(− 0.25)	(− 1.37)	(− 0.29)
Xrd	− 0.0001	0.00005**	− 0.0001	0.00005**
	(− 0.97)	(2.33)	(− 1.11)	(2.39)
regulated	− 0.1748***	− 0.0145*	− 0.1859***	− 0.0144*

Table 6 (continued)

Variables	(1a) 1st Stage *HHI*	(1b) 2nd Stage *car*	(2a) 1st Stage *HHI1*	(2b) 2nd Stage *car*
	(− 4.32)	(− 1.91)	(− 4.52)	(− 1.87)
changeroa	0.0009	− 0.0051	0.0032	− 0.0052*
	(0.10)	(− 1.63)	(0.35)	(− 1.67)
abaccruals	0.00004	0.000005	0.00004	0.000005
	(1.12)	(0.61)	(1.21)	(0.61)
Constant	0.7794***	0.0787***	0.7679***	0.0816***
	(20.66)	(5.07)	(19.75)	(5.55)
Industry-Fixed Effects	Included	Included	Included	Included
Year-Fixed Effects	Included	Included	Included	Included
Partial F-statistic	111***		120***	
No. of obs	17,804	17,804	17,804	17,804
Adj. R^2	0.3677	0.1683	0.3812	0.1688

Variables	(1a) 1st Stage *HHI*	(1b) 2nd Stage *timeliness*	(2a) 1st Stage *HHI1*	(2b) 2nd Stage *timeliness*
Panel C: Two-stage least-squares regression on the association between analysts' industrial concentration and forecast timeliness				
HHI		**0.9176****		
		(2.03)		
HHI1				**0.9036**** **(2.03)**
Bexp	**0.0507*****		**0.0515*****	

Table 6 (continued)

Variables	(1a) 1st Stage *HHI*	(1b) 2nd Stage *timeliness*	(2a) 1st Stage *HHI1*	(2b) 2nd Stage *timeliness*
	(12.65)		**(12.83)**	
Gexp	− 0.0080**	0.0219	− 0.0072*	0.0210
	(− 2.15)	(0.97)	(− 1.92)	(0.94)
Fexp	0.0134***	0.0024	0.0137***	0.0023
	(4.45)	(0.13)	(4.60)	(0.12)
Freq	0.0057**	0.6050***	0.0052*	0.6056***
	(2.00)	(28.85)	(1.84)	(28.95)
Portsize	− 0.0951***	0.1337***	− 0.0943***	0.1316***
	(− 25.06)	(2.82)	(− 24.29)	(2.83)
bsize	0.0632***	0.0731***	0.0622***	0.0749***
	(17.37)	(3.11)	(17.10)	(3.26)
top10	− 0.0092	0.0049	− 0.0082	0.0039
	(− 1.42)	(0.12)	(− 1.25)	(0.10)
size	0.0063**	− 0.0155	0.0065**	− 0.0156
	(2.35)	(− 1.11)	(2.42)	(− 1.12)
price	− 0.0006***	− 0.0012	− 0.0005**	− 0.0013
	(− 2.69)	(− 1.13)	(− 2.39)	(− 1.19)
stdearnings	0.00003	− 0.000009	0.00002	− 0.000004
	(1.37)	(− 0.07)	(1.11)	(− 0.03)
competition	0.0252***	− 0.0851**	0.0244***	− 0.0840**
	(2.74)	(− 1.99)	(2.62)	(− 1.97)
insti	0.0242** (2.45)	0.0112 (0.20)	0.0230**	0.0125
			(2.32)	(0.23)
liquidity	− 0.2170	− 2.3306***	− 0.2511*	− 2.3027***

Table 6 (continued)

Variables	(1a) 1st Stage *HHI*	(1b) 2nd Stage *timeliness*	(2a) 1st Stage *HHI1*	(2b) 2nd Stage *timeliness*
	(− 1.54)	(− 2.77)	(− 1.79)	(− 2.73)
beta	0.0191***	− 0.0060	0.0186***	− 0.0052
	(5.37)	(− 0.24)	(5.24)	(− 0.21)
btm	− 0.0028*	− 0.0105	− 0.0025	− 0.0107
	(− 1.76)	(− 0.89)	(− 1.62)	(− 0.91)
horizon	− 0.0119	2.2280***	− 0.0110	2.2270***
	(− 1.25)	(28.13)	(− 1.16)	(28.10)
firmage	− 0.0234***	− 0.0713***	− 0.0230***	− 0.0721***
	(− 6.48)	(− 3.43)	(− 6.37)	(− 3.50)
capx	0.0198	0.0003	0.0160	0.0040
	(0.48)	(0.00)	(0.39)	(0.02)
Constant	0.7608***	− 9.0960***	0.7424***	− 9.0687***
	(13.17)	(− 18.99)	(13.10)	(− 19.29)
Industry-Fixed Effects	Included	Included	Included	Included
Year-Fixed Effects	Included	Included	Included	Included
Partial F-statistic	160***		164***	
No. of obs	24,873	24,873	24,873	24,873
Adj. R^2	0.3677	0.1683	0.3812	0.1688

Bold highlights the results for the testable hypotheses of interest

Table 6 reports the results for the two-stage least-squares regression for Hypothesis 1. The sample period is 1995–2017. All the first-stage regressions are run on the determinants of analysts' industrial concentration (*HHI* & *HHI1*). The instrument variable is *bexp*. Industry- and year-fixed effects are included in the regressions, but their results are not reported for brevity. All variables are defined in "Appendix 1". The t/z-statistics in parentheses are based on robust standard errors clustered by firm. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively.

Table 7 Tests of the impact threshold for a confounding variable (ITCV)

Variables	(1) Implied ITCV correlation	Independent variable = *HHI*			Independent variable = *HHI1*		
		(1a) ρ(covariate, *HHI*)	(1b) ρ(covariate, *accuracy*)	(1c) Impact	(2a) ρ (covariate, *HHI1*)	(2b) ρ(covariate, *accuracy*)	(2c) Impact
Panel A: ITCV test for the regression on analysts' industrial concentration and forecast accuracy							
HHI	**0.0084**						
HHI1	**0.0067**						
bsize		0.1195	− 0.0031	− 0.0004	0.1152	− 0.0031	− 0.0004
top10		− 0.0008	− 0.0026	0.0000	0.0021	− 0.0026	− 0.0000
gexp		− 0.0296	− 0.0046	0.0001	− 0.0274	− 0.0046	0.0001
freq		0.012	0.0111	0.0001	0.0112	0.0111	0.0001
portsize		− 0.2143	0.0028	− 0.0006	− 0.2127	0.0028	− 0.0006
horizon		− 0.0065	0.0044	− 0.0000	− 0.0062	0.0044	− 0.0000
size		0.0602	0.0497	0.003	0.0604	0.0497	0.003
price		− 0.0621	0.0115	− 0.0007	− 0.0598	0.0115	− 0.0007
stdearnings		0.0064	− 0.0246	− 0.0002	0.0043	− 0.0246	−0.0001
competition		0.2156	− 0.0116	− 0.0025	0.2272	− 0.0116	− 0.0026
insti		0.0607	− 0.003	− 0.0002	0.0641	− 0.003	− 0.0002
liquidity		− 0.0424	0.0044	− 0.0002	− 0.0452	0.0044	− 0.0002
salesgrowth		0.0386	0.0108	0.0004	0.0364	0.0108	0.0004
intanratio		− 0.1249	0.0008	− 0.0001	− 0.1245	0.0008	− 0.0001
firmage		− 0.0655	0.0085	− 0.0006	− 0.0648	0.0085	− 0.0005
capx		0.0295	− 0.0066	− 0.0002	0.0234	− 0.0066	− 0.0002
abtradvol		0.0004	0.0045	0.0000	0.0021	0.0045	0.0000

Table 7 (continued)

Variables	Implied ITCV correlation	Independent variable = *HHI*			Independent variable = *HHI1*		
		(1a) ρ(covariate, *HHI*)	(1b) ρ(covariate, *car*)	(1c) Impact	(2a) ρ (covariate, *HHI1*)	(2b)ρ(covariate, *car*)	(2c) Impact
Panel B: ITCV test for the regression on analysts' industrial concentration and forecast informativeness							
HHI	**0.016**						
HHI1	**0.0176**						
gexp		− 0.0225	− 0.0057	0.0001	− 0.0219	− 0.0057	0.0001
freq		0.0146	0.0681	0.001	0.0111	0.0681	0.0008
portsize		− 0.2353	− 0.0185	0.0044	− 0.2334	− 0.0185	0.0043
bsize		0.1161	0.0809	0.0094	0.1105	0.0809	0.0089
top10		0.0061	− 0.009	− 0.0001	0.0096	− 0.009	− 0.0001
size		0.0458	− 0.2338	− 0.0107	0.0468	− 0.2338	− 0.0109
price		− 0.0606	− 0.0834	0.0051	− 0.06	− 0.0834	0.005
stdearnings		− 0.0175	− 0.0112	0.0002	− 0.0192	− 0.0112	0.0002
competition		0.1771	− 0.009	− 0.0016	0.1868	− 0.009	− 0.0017
insti		0.0482	0.0455	0.0022	0.0525	0.0455	0.0024
liquidity		− 0.0266	0.0419	− 0.0011	− 0.0304	0.0419	− 0.0013
salesgrowth		0.0537	0.0659	0.0035	0.0488	0.0659	0.0032
intanratio		− 0.1341	0.0273	− 0.0037	− 0.1336	0.0273	− 0.0037
beta		0.0191	0.1907	0.0036	0.0179	0.1907	0.0034
btm		− 0.0406	− 0.0503	0.002	− 0.0406	− 0.0503	0.002
tradingvol		0.0338	0.1286	0.0043	0.034	0.1286	0.0044
changeeps		− 0.0237	− 0.0037	0.0001	− 0.0228	− 0.0037	0.0001
xrd		− 0.0129	0.029	− 0.0004	− 0.0142	0.029	− 0.0004

Table 7 (continued)

Variables	Implied ITCV correlation	Independent variable = *HHI*			Independent variable = *HHI1*		
		(1a) ρ(covariate, *HHI*)	(1b) ρ(covariate, *car*)	(1c) Impact	(2a) ρ (covariate, *HHI1*)	(2b)ρ(covariate, *car*)	(2c) Impact
regulated		0.0015	− 0.0617	− 0.0001	0.0032	− 0.0617	− 0.0002
changeroa		− 0.0013	− 0.0304	0.0000	0.0007	− 0.0304	− 0.0000
abaccruals		0.0413	0.026	0.0011	0.0455	0.026	0.0012

Variables	Implied ITCV correlation	Independent variable = *HHI*			Independent variable = *HHI1*		
		(1a) ρ(covariate, *HHI*)	(1b) ρ(covariate, *timeliness*)	(1c) Impact	(2a) ρ (covariate, *HHI1*)	(2b) ρ(covariate, *timeliness*)	(2c) Impact
Panel C: ITCV test for the regression on analysts' industrial concentration and forecast timeliness							
HHI	**0.0083**						
HHI1	**0.0091**						
gexp		− 0.0404	0.0303	− 0.0012	− 0.0379	0.0303	− 0.0011
fexp		0.0291	− 0.0019	− 0.0001	0.0297	− 0.0019	− 0.0001
freq		0.0062	0.22	0.0014	0.004	0.22	0.0009
portsize		− 0.1856	− 0.0103	0.0019	− 0.1847	− 0.0103	0.0019
bsize		0.0981	0.0335	0.0033	0.0933	0.0335	0.0031
top10		− 0.0009	0.0026	− 0.0000	0.0012	0.0026	0.0000
size		0.0158	− 0.0516	− 0.0008	0.0156	− 0.0516	− 0.0008
price		− 0.0373	− 0.0247	0.0009	− 0.0352	− 0.0247	0.0009
stdearnings		− 0.0065	0.0195	− 0.0001	−0.0089	0.0195	− 0.0002
competition		0.3757	− 0.0173	− 0.0065	0.3868	− 0.0173	− 0.0067
insti		0.015	0.0924	0.0014	0.0159	0.0924	0.0015

Table 7 (continued)

Variables	Implied ITCV correlation	Independent variable = *HHI*			Independent variable = *HHI1*		
		(1a) ρ(covariate, *HHI*)	(1b) ρ(covariate, *timeliness*)	(1c) Impact	(2a) ρ (covariate, *HHI1*)	(2b) ρ(covariate, *timeliness*)	(2c) Impact
liquidity		− 0.0488	− 0.0853	0.0042	− 0.0548	− 0.0853	0.0047
beta		0.0373	0.037	0.0014	0.0354	0.037	0.0013
btm		− 0.0255	− 0.0067	0.0002	− 0.0263	− 0.0067	0.0002
horizon		− 0.0133	0.2131	− 0.0028	− 0.0113	0.2131	− 0.0024
firmage		− 0.0605	− 0.0361	0.0022	− 0.0591	− 0.0361	0.0021
capx		0.0448	− 0.0183	− 0.0008	0.039	− 0.0183	− 0.0007

Bold highlights the results for the testable hypotheses of interest

Panels A, B, and C of Table 7 report the impact threshold for a confounding variable (ITCV) for the regression results of analysts' industrial concentration (*HHI* and *HHI*) on forecast accuracy (*accuracy*), forecast informativeness (*car*), and forecast timeliness (*timeliness*), respectively. The calculation is based on a prior study by Frank (2000). Column (1) represents the minimum correlation a confounding variable must have with both dependent variables and *HHI* (*HHI1*) to make the coefficient on *HHI* (*HHI1*) statistically nonsignificant at the conventional 5% level. Column (1a) (Column (2a)) reports the partial Pearson correlation between *HHI* (*HHI1*) and each control variable. Column (1b) (Column (2b)) reports the partial Pearson correlation between dependent variables and each control variable. Column (1c) (Column (2c)) is the partial impact of each control variable, defined as the product of the correlation between *HHI* (*HHI1*) and the control variable and the correlation between dependent variables and the control variable.

Table 8 Oster's (2019) estimates of the proportional degree of selection

Variables	Coefficient on *HHI* without controls (1)	Coefficient on *HHI* with controls (2)	R^2 without controls (3)	R^2 with controls (4)	$R_{max}=1.3\,\widetilde{R}$ (5)	$\delta\,(\beta=0)$ (6)
Panel A: Oster's (2019) estimate of the proportional degree of selection when the independent variable is *HHI*						
accuracy	0.1347	0.1339	0.001	0.019	0.024	**6.196**
car	0.0078	0.0085	0.001	0.305	0.396	**9.872**
timeliness	0.3655	0.1812	0.003	0.175	0.228	**1.527**
Variables	coefficient on *HHI1* without controls (1)	coefficient on *HHI1* with controls (2)	R^2 without controls (3)	R^2 with controls (4)	$R_{max}=1.3\,\widetilde{R}$ (5)	$\delta\,(\beta=0)$ **(6)**
Panel B: Oster's (2019) estimate of the proportional degree of selection when the independent variable is *HHI1*						
accuracy	0.1261	0.1235	0.001	0.019	0.024	**5.668**
car	0.0074	0.0090	0.001	0.305	0.396	**15.812**
timeliness	0.3812	0.1886	0.003	0.175	0.228	**1.477**

Bold highlights the results for the testable hypotheses of interest

Table 8 reports the results for Oster's estimate of the proportional degree of selection, δ, for the multivariate test of Hypothesis 1. δ reflects the importance of unobservable variables relative to that of observed variables in the regression, and represent a threshold point beyond which the baseline regression results would be attributed alternatively to the omitted variable(s). δ is calculated on the assumption that $R_{max}=1.3\,\widetilde{R}$, where $\widetilde{R}$ is the R-squared value of the baseline OLS regression, and R_{max} indicates the maximum R-square in the case when both theexisting control variables and the omitted variables were included in the hypothetical regression. Columns (1) and (3) of Panel A (Panel B) report the coefficient on *HHI* (*HHI1*) and R^2, respectively, of the univariate regressions that do not have any control variable explaining *accuracy*, *car*, and *timeliness*. Columns (2) and (4) of Panel A (Panel B) report the coefficient on *HHI* (*HHI1*) and R^2, respectively, of the baseline OLS regressions of *accuracy*, *car*, and *timeliness* for Models (2), (3), and (4). Column (5) displays the value of R_{max} which equals 1.3 $\widetilde{R}$. More details about the calculation of δ can be found in Oster (2019).

Table 9 Test of Hypothesis 2 as to the cross-sectional analysis of industrial product market competition

Variables	Dependent Variable = *accuracy*		Dependent Variable = *car*		Dependent Variable = *timeliness*	
	(1)	(2)	(3)	(4)	(5)	(6)
HHI* dcompetition	**0.0906***		**0.0058****		**– 0.1549****	
	(1.90)		**(2.51)**		**(– 2.11)**	
HHI1* dcompetition		**0.0955****		**0.0055****		**– 0.1759****
		(1.97)		**(2.31)**		**(– 2.34)**
HHI	0.1098**		0.0052**		0.2756***	
	(2.01)		(2.11)		(3.61)	
HHI1		0.1017*		0.0058**		0.2981***
		(1.85)		(2.36)		(3.86)
bsize	0.0079	0.0085	0.0032***	0.0032***	0.1222***	0.1222***
	(0.49)	(0.52)	(4.94)	(4.93)	(5.77)	(5.77)
top10	– 0.0457	– 0.0459	0.0029*	0.0028*	– 0.0278	– 0.0285
	(– 1.28)	(– 1.29)	(1.91)	(1.89)	(– 0.59)	(– 0.60)
gexp	0.0115	0.0113	– 0.0001	– 0.0001	0.0102	0.0099
	(0.58)	(0.57)	(– 0.18)	(–0.18)	(0.38)	(0.37)
fexp	0.0106	0.0107			0.0157	0.0154
	(0.69)	(0.70)			(0.74)	(0.73)
portsize	0.0076	0.0065	0.0026***	0.0027***	0.0986***	0.0996***
	(0.36)	(0.31)	(3.44)	(3.49)	(3.82)	(3.85)
horizon	– 0.0420	– 0.0420			2.3177***	2.3184***
	(– 0.95)	(– 0.95)			(25.59)	(25.59)
size	– 0.0355***	– 0.0354***	– 0.0133***	– 0.0133***	0.0064	0.0064
	(– 2.91)	(– 2.89)	(– 22.61)	(– 22.62)	(0.39)	(0.39)
price	0.0003	0.0003	– 0.0003***	– 0.0003***	– 0.0019	– 0.0019
	(0.34)	(0.33)	(– 8.80)	(– 8.79)	(– 1.50)	(– 1.50)
stdearnings	0.0000	0.0000	– 0.0000*	– 0.0000*	– 0.0000	– 0.0000
	(0.16)	(0.17)	(– 1.68)	(– 1.67)	(– 0.22)	(– 0.21)
liquidity	1.6675*	1.6636*	0.2461***	0.2462***	– 5.0272***	– 5.0116***
	(1.81)	(1.80)	(5.50)	(5.50)	(– 5.02)	(– 5.00)
insti	– 0.0691	– 0.0686	– 0.0026	– 0.0026	0.0514	0.0513
	(– 1.48)	(– 1.47)	(– 1.26)	(– 1.29)	(0.78)	(0.77)
freq	– 0.0135	– 0.0137	0.0084***	0.0084***		
	(– 0.74)	(– 0.75)	(11.14)	(11.16)		
salesgrowth	– 0.0345*	– 0.0344*	0.0046***	0.0046***		
	(– 1.79)	(– 1.79)	(6.20)	(6.23)		
beta			0.0189***	0.0189***	– 0.0832***	– 0.0833***
			(20.35)	(20.34)	(– 3.16)	(– 3.17)
btm			– 0.0037***	– 0.0037***	0.0015	0.0016
			(– 5.14)	(– 5.15)	(0.11)	(0.12)
firmage	– 0.0095	– 0.0098			– 0.1020***	– 0.1019***
	(– 0.62)	(– 0.64)			(– 4.93)	(– 4.93)

Table 9 (continued)

Variables	Dependent Variable = *accuracy*		Dependent Variable = *car*		Dependent Variable = *timeliness*	
	(1)	(2)	(3)	(4)	(5)	(6)
capx	0.0780	0.0779			0.4879**	0.4894**
	(0.39)	(0.39)			(1.97)	(1.97)
roa	− 0.6532***	− 0.6542***				
	(− 15.33)	(− 15.35)				
abtradvol	0.0004	0.0004				
	(0.44)	(0.43)				
intanratio			− 0.0002	− 0.0000		
			(− 0.05)	(− 0.01)		
tradingvol			0.0003***	0.0003***		
			(11.81)	(11.81)		
changeeps			− 0.0007	− 0.0007		
			(− 0.53)	(− 0.54)		
xrd			0.0000**	0.0000**		
			(2.12)	(2.13)		
regulated			− 0.0233***	− 0.0230***		
			(− 3.44)	(− 3.40)		
changeroa			− 0.0050	− 0.0051		
			(− 1.61)	(− 1.62)		
abaccruals			0.0000	0.0000		
			(0.44)	(0.47)		
opacity					0.0000	0.0000
					(0.10)	(0.14)
Constant	− 0.1036	− 0.1110	0.1169***	0.1166***	− 8.6254***	− 8.6373***
	(− 0.60)	(− 0.65)	(18.56)	(18.54)	(− 34.93)	(− 34.98)
No. of obs	17,505	17,505	17,804	17,804	18,545	18,545
Adj. R^2	0.024	0.024	0.301	0.301	0.143	0.144

Bold highlights the results for the testable hypotheses of interest

Table 9 shows the results for the moderating effect of industrial product market competition on the association between analysts' industrial concentration and their forecast accuracy (*accuracy*), forecast informativeness (*car*), and forecast timeliness (*timeliness*), respectively. The sample period ranges from 1995 to 2017. Industry- and year-fixed effects are included in the regressions, but their results are not reported for brevity. All variables are defined in "Appendix 1". The *t*-statistics in parentheses are based on the standard errors clustered by firm. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively

issued by industrial-concentrated analysts. Their higher-quality forecasts are beneficial not only to the investors but also for the strategy formation process and monitoring of firms (e.g. zu Knyphausen-Aufseß et al. 2011; He et al. 2019b).

Lastly, prior research (e.g. Huang et al. 2022; Sonney 2009; Jiang et al. 2016; Hirshleifer et al. 2019) which focuses on analysing the association between analyst forecast properties and their determinants does not account for potential

Table 10 Test of Hypothesis 3 as to the cross-sectional analysis of firm-specific risk

Variables	Dependent Variable = *accuracy*		Dependent Variable = *car*		Dependent Variable = *timeliness*	
	(1)	(2)	(3)	(4)	(5)	(6)
HHI* dfirmrisk	**0.2469*** (4.06)**		**0.0515*** (23.23)**		**– 0.2309*** (– 3.05)**	
HHI1* dfirmrisk		**0.2504*** (4.02)**		**0.0524*** (23.13)**		**– 0.2451*** (– 3.18)**
HHI	– 0.0366		– 0.0169***		– 0.0342	
	(– 0.55)		(– 6.39)		(– 0.34)	
HHI1		– 0.0461		– 0.0171***		– 0.0390
		(– 0.69)		(– 6.39)		(– 0.39)
bsize	0.0262	0.0268	0.0039***	0.0039***	– 0.1646***	– 0.1645***
	(1.20)	(1.22)	4.54	(4.55)	(– 5.59)	(– 5.59)
top10	– 0.0389	– 0.0397	0.0012	0.0011	0.0814	0.0822
	(– 0.83)	(– 0.85)	0.61	(0.58)	(1.26)	(1.27)
gexp	0.0013	0.0011	0.0014	0.0014	– 0.0366	– 0.0366
	(0.05)	(0.04)	(1.48)	(1.50)	(– 1.05)	(– 1.05)
fexp	0.0134	0.0136			0.0383	0.0385
	(0.67)	(0.68)			(1.34)	(1.35)
portsize	0.0422	0.0415	0.0025**	0.0025**	– 0.0639*	– 0.0651*
	(1.36)	(1.34)	2.27	(2.31)	(– 1.68)	(– 1.71)
horizon	0.0091	0.0078			– 2.4787***	– 2.4783***
	(0.14)	(0.12)			(– 16.04)	(– 16.04)
size	– 0.0508***	– 0.0509***	– 0.0119***	– 0.0119***	– 0.0228	– 0.0230
	(– 3.10)	(– 3.10)	– 15.28	(– 15.37)	(– 0.99)	(– 1.00)
price	0.0009	0.0008	– 0.0002***	– 0.0002***	0.0042**	0.0042**
	(0.92)	(0.90)	– 4.32	(– 4.31)	(2.36)	(2.35)
stdearnings	0.0001	0.0001	– 0.000005	– 0.000005	0.00002	0.00002
	(0.64)	(0.66)	– 1.28	(– 1.20)	(0.13)	(0.12)
liquidity	– 0.3698	– 0.3760	0.1651**	0.1641**	5.4431***	5.4274***
	(– 0.22)	(– 0.23)	2.17	(2.15)	(2.98)	(2.98)
insti	– 0.0842	– 0.0841	0.0023	0.0022	– 0.1162	– 0.1165
	(– 1.62)	(– 1.62)	1.03	(0.98)	(– 1.46)	(– 1.46)
freq	– 0.0110	– 0.0109	0.0097***	0.0097***		
	(– 0.45)	(– 0.44)	(9.49)	(9.49)		
salesgrowth	– 0.0654**	– 0.0649**	0.0015	0.0016***		
	(– 2.07)	(– 2.06)	(1.48)	(1.55)		
beta			0.0173***	0.0173***	0.1066***	0.1075***
			(13.84)	(13.84)	(2.82)	(2.85)
btm			– 0.0045***	– 0.0045***	– 0.0121	– 0.0121
			(– 4.90)	(– 4.93)	(– 0.68)	(– 0.67)
firmage	– 0.0226	−4 0.0229			0.0886***	0.0880***
	(– 1.14)	(– 1.16)			(2.95)	(2.93)
capx	– 0.1278	– 0.1259			– 1.0158**	– 1.0181***

Table 10 (continued)

Variables	Dependent Variable = *accuracy*		Dependent Variable = *car*		Dependent Variable = *timeliness*	
	(1)	(2)	(3)	(4)	(5)	(6)
	(− 0.47)	(− 0.46)			(− 2.59)	(− 2.60)
roa	− 0.4635***	− 0.4644***				
	(− 8.36)	(− 8.36)				
abtradvol	− 0.0009	− 0.0009				
	(− 0.92)	(− 0.93)				
intanratio			0.0037	0.0039		
			(0.097)	(1.01)		
tradingvol			0.0003***	0.0002***		
			(8.76)	(8.77)		
changeeps			0.0001	0.0001		
			(0.1)	(0.09)		
xrd			0.00005*	0.00005*		
			(1.82)	(1.81)		
regulated			− 0.0145*	− 0.0146*		
			(− 1.82)	(− 1.83)		
changeroa			− 0.0011	− 0.0012		
			(− 0.31)	(−0.33)		
abaccruals			0.00001	0.00001		
			(1.11)	(1.13)		
opacity					0.0001	0.0001
					(0.50)	(0.49)
Constant	− 0.1497	− 0.1420	0.1510***	0.1517***	10.6875***	10.7076***
	(− 0.45)	(− 0.43)	(15.62)	(15.64)	(26.13)	(26.20)
No. of obs	9,072	9,072	9,998	9,998	10,839	10,839
Adj. R^2	0.039	0.038	0.339	0.339	0.114	0.114

Bold highlights the results for the testable hypotheses of interest

Table 10 shows the results for the moderating effect of firm-specific risk on the association between analysts' industrial concentration and their forecast accuracy (*accuracy*), forecast informativeness (*car*), and forecast timeliness (*timeliness*), respectively. The sample period ranges from 1995 to 2017. Industry- and year-fixed effects are included in the regressions, but their results are not reported for brevity. All variables are defined in "Appendix 1". The *t*-statistics in parentheses are based on the standard errors clustered by firm. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively

endogeneity concerns. In contrast, we go to great lengths to address the concerns in our analysis, but we concede that they are not eliminated completely, which remains a limitation of this study.

Table 11 Test of Hypothesis 3 as to the cross-sectional analysis of firms' information opacity

Variables	Dependent Variable = *accuracy*		Dependent Variable = *car*		Dependent Variable = *timeliness*	
	(1)	(2)	(3)	(4)	(5)	(6)
HHI*dopacity	**0.0877****		**0.0058*****		**− 0.0963***	
	(2.11)		**(2.93)**		**(− 1.65)**	
HHI1*dopacity		**0.0920****		**0.0059*****		**− 0.0998***
		(2.16)		**(2.91)**		**(− 1.67)**
HHI	0.1440***		0.0045*		0.2295***	
	(2.58)		(1.78)		(2.99)	
HHI1		0.1328**		0.0054**		0.2383***
		(2.37)		(2.10)		(3.08)
gexp	0.0208	0.0205	0.0013	0.0013	0.0138	0.0136
	(1.06)	(1.05)	(1.38)	(1.39)	(0.49)	(0.49)
portsize	0.0041	0.0030	0.0024***	0.0025***	0.1129***	0.1136***
	(0.19)	(0.14)	(2.74)	(2.83)	(4.14)	(4.17)
bsize	0.0031	0.0036	0.0032***	0.0032***	0.1293***	0.1293***
	(0.19)	(0.23)	(4.43)	(4.40)	(5.69)	(5.68)
top10	− 0.0162	− 0.0162	0.0027	0.0027	− 0.0476	− 0.0477
	(− 0.46)	(− 0.46)	(1.61)	(1.60)	(− 0.94)	(− 0.95)
size	− 0.0385***	− 0.0384***	− 0.0131***	− 0.0131***	0.0130	0.0129
	(− 3.09)	(− 3.08)	(− 20.08)	(− 20.09)	(0.73)	(0.73)
price	− 0.0008	− 0.0008	− 0.0003***	− 0.0003***	− 0.0016	− 0.0016
	(− 1.03)	(− 1.04)	(− 7.42)	(− 7.40)	(− 1.19)	(− 1.19)
stdearnings	0.0001	0.0001	− 0.0000	− 0.0000	− 0.0001	− 0.0001
	(0.58)	(0.58)	(− 1.34)	(− 1.32)	(− 0.34)	(− 0.33)
competition	− 0.0117	− 0.0113	− 0.0019	− 0.0019	− 0.0833	− 0.0832
	(− 0.34)	(− 0.33)	(− 0.79)	(− 0.78)	(− 1.52)	(− 1.52)
liquidity	2.5952***	2.5904***	0.2617***	0.2624***	− 4.9695***	− 4.9580***
	(2.59)	(2.59)	(5.09)	(5.11)	(− 4.72)	(− 4.71)
fexp	0.0126	0.0127	− 0.0055***	− 0.0055***	0.0224	0.0222
	(0.80)	(0.81)	(− 8.42)	(− 8.42)	(1.01)	(1.01)
freq	− 0.0148	− 0.0146	0.0069***	0.0069***		
	(− 0.82)	(− 0.81)	(7.72)	(7.74)		
insti	− 0.0615	− 0.0611	0.0005	0.0004		
	(− 1.31)	(− 1.30)	(0.22)	(0.19)		
beta			0.0206***	0.0206***	− 0.1019***	− 0.1020***
			(18.90)	(18.89)	(− 3.68)	(− 3.68)
btm			− 0.0027***	− 0.0027***	0.0157	0.0157
			(− 3.42)	(− 3.42)	(1.10)	(1.10)
horizon	− 0.0224	− 0.0224			2.3136***	2.3140***
	(− 0.53)	(− 0.53)			(24.08)	(24.08)
roa	− 0.5939***	− 0.5951***			− 0.1486**	− 0.1478**
	(− 14.28)	(− 14.32)			(− 2.21)	(− 2.20)
firmage	0.0034	0.0030			− 0.1071***	− 0.1071***
	(0.22)	(0.19)			(− 4.90)	(− 4.90)
capx	0.1167	0.1177			0.5490**	0.5503**

Table 11 (continued)

Variables	Dependent Variable = *accuracy*		Dependent Variable = *car*		Dependent Variable = *timeliness*	
	(1)	(2)	(3)	(4)	(5)	(6)
	(0.56)	(0.57)			(2.06)	(2.06)
abtradvol	0.0015*	0.0015*				
	(1.66)	(1.66)				
salesgrowth			0.0044***	0.0044***		
			(4.77)	(4.78)		
intanratio			− 0.0010	− 0.0008		
			(− 0.26)	(− 0.21)		
tradingvol			0.0003***	0.0003***		
			(10.38)	(10.37)		
changeeps			− 0.0014	− 0.0014		
			(− 0.86)	(−0.85)		
xrd			0.0001***	0.0001***		
			(2.75)	(2.76)		
regulated			− 0.0190***	− 0.0188***		
			(− 2.89)	(− 2.85)		
changeroa			− 0.0033	− 0.0034		
			(− 0.87)	(− 0.88)		
abaccruals			0.0000	0.0000		
			(0.54)	(0.54)		
Constant	− 0.1973	− 0.2093	0.1162***	0.1156***	− 8.8070***	− 8.8121***
	(− 0.94)	(− 1.00)	(15.80)	(15.73)	(− 32.82)	(− 32.83)
No. of obs	16,657	16,657	13,487	13,487	16,623	16,623
Adj. R^2	0.025	0.025	0.33	0.33	0.146	0.146

Bold highlights the results for the testable hypotheses of interest

Table 11 shows the results of the moderating effect of firms' information opacity on the association between analysts' industrial concentration and their forecast accuracy (*accuracy*), forecast informativeness (*car*), and forecast timeliness (*timeliness*), respectively. The sample period ranges from 1995 to 2017. Industry- and year-fixed effects are included in the regressions but their results are not reported for the sake of brevity. All variables are defined in "Appendix 1". The *t*-statistics in parentheses are based on the standard errors clustered by firm. ***, **, * represent the 1%, 5%, and 10% statistical significance levels (two-tailed), respectively

Appendix 1: Variable definitions

Variables	Definitions
Key variables	
HHI	For each analyst, we compute the square of the ratio of the number of EPS forecasts for each covered industry to the total number of her/his EPS forecasts in a fiscal year, and then take the sum of all the squares as the measure of the analysts' industrial concentration (*HHI*). The first 2-digit SIC codes are used for the industry classification

Variables	Definitions
HHI1	For each analyst, we compute the square of the ratio of the number of firms in each covered industry to the total number of her/his covered firms in a fiscal year, and then take the sum of all the squares as the measure of the analysts' industrial concentration (*HHI1*). The first 2-digit SIC codes are used for the industry classification
accuracy	− 1 times the absolute value of the difference between actual EPS and an analyst's last forecast of annual EPS for a firm for a fiscal year, divided by the firm's actual EPS at the end of a fiscal year
car	The three-day [− 1, 1] cumulative unsigned abnormal stock returns surrounding an analyst's last forecast of EPS for a firm for a fiscal year. The abnormal stock returns are calculated using market model with an estimation period of [− 181, − 2] relative to the forecast date
Timeliness	− 1 times the natural logarithm of the number of days an analyst takes to issue her/his first forecast for the current fiscal year since a firm announces its earnings for the previous fiscal year
Other variables	
Analyst characteristics	
gexp	The natural logarithm of the number of years since an analyst makes her/his first earnings forecast that appeared in I/B/E/S
freq	The natural logarithm of the number of earnings forecasts by an analyst for a firm in a fiscal year
portsize	The natural logarithm of the number of firms followed by an analyst in a fiscal year
bsize	The natural logarithm of the number of analysts employed by a brokerage house in a fiscal year
top10	1 if an analyst works for a brokerage house which is ranked within the top decile based on the number of analysts employed in year *t*, and 0 otherwise
horizon	The natural logarithm of the number of days between a firm's earnings announcement date and analyst earnings forecast date
fexp	The natural logarithm of the number of years since an analyst's first earnings forecast for a firm
bexp	The natural logarithm of the ratio of the number of analysts in a brokerage house, who follow an industry involving analyst-year observations, to the total number of analysts employed by the same brokerage house in a fiscal year
Firm characteristics	
size	The natural logarithm of the market value of a firm's equity at the end of a fiscal year
price	Stock price of a firm at the fiscal-year-end date
salesgrowth	Sales for the current fiscal year minus sales for the previous fiscal year, divided by sales for the previous fiscal year
stdearnings	The standard deviation of income before extraordinary items for the previous five fiscal years
competition	A composite measure of product market competition, which is constructed by three proxies (*mktsize*, *substitution*, and *entrycost*) for proprietary costs of disclosures using common factor analysis. *mktsize* equals the sum of sales of all firms in an industry for a fiscal year. *substitution* equals the sum of operating costs of each firm in an industry for a fiscal year, divided by the sum of the sales of all firms in the same industry. *entrycost* equals the average gross PPE for all firms in an industry for a fiscal year, weighted by each firm's sales in the same industry. The first 2-digit SIC codes are used for the industry classification

Variables	Definitions
firmrisk	The standard deviation of the residuals from the following market model over the 52-week window before the end of a fiscal year: $r_{i,t} = \alpha_i + \beta_{1i} r_{m,t-1} + \beta_{2i} r_{m,t-2} + \alpha_{3i} r_{m,t} + \alpha_{4i} r_{m,t+1} + \alpha_{5i} r_{m,t+2} + \varepsilon_{i,t}$, where $r_{i,t}$ is the weekly return on firm i, and $r_{m,t}$ is the value-weighted CRSP index return
opacity	A firm's financial opacity, which is measured as the three-year moving sum of the absolute value of abnormal accruals for the current and previous two fiscal years as per Hutton et al. (2009)
dcompetition	1 if the industrial product market competition degree (*competition*) is larger than the value of its sample median, and 0 otherwise
dfirmrisk	1 of a firm's idiosyncratic risk (*firmrisk*) is larger than its sample median, and 0otherwise
dopacity	1 if a firm's information opacity (*opacity*) is greater than its sample median, and 0 otherwise
intanratio	Intangible assets divided by total assets for a firm at the end of a fiscal year
roa	Income before extraordinary items, divided by total assets, of a firm at the end of a fiscal year
insti	Institutional investors' stock ownership as a percentage of the outstanding shares for a firm at the end of a fiscal year
liquidity	The natural logarithm of annual relative effective spread, which is the arithmetic mean of daily relative effective spreads for a stock. The daily relative effective spread is computed as the absolute difference between the closing transaction price and the midpoint of the prevailing bid-ask quote, scaled by the midpoint of the prevailing bid-ask quote, at a trading date
abtradvol	Abnormal trading volume of a firm for a fiscal year, which is calculated as the daily dollar trading volume (i.e. the closing price at a given date times the number of shares traded at that date) (in millions of US dollars) averaged over a fiscal year for a firm, minus the daily dollar trading volume averaged over the previous year for the firm
firmage	The natural logarithm of the number of months since a firm's IPO. If the IPO date is not available in Compustat, the *firmage* variable is computed as the number of months since CRSP first reported return data for the firm
capx	Capital expenditures divided by sales of a firm at the end of a fiscal year
tradingvol	Daily dollar trading volume (i.e. the closing price at a given date times the number of shares traded at that date) (in millions of US dollars) averaged over a fiscal year for a firm
beta	Equity beta for a firm for a fiscal year
changeeps	Annual EPS of a firm for the current fiscal year minus that for the previous year, divided by stock price at the end of the previous fiscal year
xrd	Research and development expense of a firm divided by sales of a firm for a fiscal year
btm	The book value of firm equity divided by the market value of firm equity at the end of a fiscal year
regulated	1 if a firm belongs to a regulated industry (SIC codes 4900–4999, 6000–6411, or 6500–6999), and 0 otherwise
changeroa	Return on assets of a firm for the current fiscal year minus that for the previous fiscal year. Return on assets is computed as pre-tax income net of special items and divided by total assets at the end of a fiscal year
abaccruals	The absolute value of abnormal accruals, computed per Dechow et al. (1995), for a firm for a fiscal year

Appendix 2: Correlation matrixes

	accuracy	*HHI*	*HHI1*	*gexp*	*freq*	*portsize*	*bsize*	*top10*	*size*	*price*
Panel A: Correlation matrix between analysts' industrial concentration and forecast accuracy										
Accuracy	1									
HHI	0.085***	1								
HHI1	0.084***	0.982***	1							
gexp	− 0.058***	0.015**	0.024**	1						
freq	− 0.091***	0.037***	0.041***	0.155***	1					
portsize	− 0.042***	− 0.122***	− 0.115***	0.117***	0.103***	1				
bsize	− 0.003	0.185***	0.189***	0.130***	0.080***	0.158***	1			
top10	− 0.006	0.140***	0.145***	0.101***	0.057***	0.180***	0.857***	1		
size	− 0.196***	0.114***	0.124***	0.349***	0.144***	0.147***	0.232***	0.207***	1	
price	− 0.264***	− 0.006	0.0002	0.181***	0.071***	0.161***	0.152***	0.137***	0.777***	1
stdearnings	0.001	0.142***	0.148***	0.320***	0.157***	0.088***	0.209***	0.175***	0.601***	0.232***
competition	0.047***	0.299***	0.314***	0.096***	0.026***	0.047***	0.037***	0.027***	0.186***	0.054***
insti	− 0.052***	0.116***	0.127***	0.410***	0.178***	− 0.063***	0.110***	0.082***	0.322***	0.167***
liquidity	0.103***	− 0.158***	− 0.172***	− 0.477***	− 0.229***	− 0.029***	− 0.130***	− 0.127***	− 0.661***	− 0.440***
salesgrowth	− 0.094***	0.018***	0.016**	− 0.064***	− 0.026***	0.009	0.001	0.013*	0.094***	0.192***
intanratio	− 0.058***	− 0.112***	− 0.107***	0.142***	0.022***	− 0.077***	0.082***	0.074***	0.187***	0.103***
horizon	− 0.059***	0.038***	0.042***	0.073***	0.201***	0.041***	0.072***	0.061***	0.025***	− 0.035***
firmage	− 0.102***	− 0.078***	− 0.074***	0.146***	0.039***	0.051***	− 0.080***	− 0.061***	0.257***	0.215***
Capx	− 0.039***	− 0.040***	− 0.048***	− 0.011	0.029***	0.075***	0.040***	0.030***	0.058***	0.098***
Abtradvol	− 0.114***	− 0.005	− 0.002	0.022***	0.005	0.044***	− 0.005	0.005	0.308***	0.388***

	stdearnings	*competition*	*insti*	*liquidity*	*salesgrowth*	*intanratio*	*horizon*	*firmage*	*capx*	*abtradvol*
Panel A: Correlation matrix between analysts' industrial concentration and forecast accuracy										
Accuracy										
HHI										
HHI1										
gexp										
freq										
portsize										
bsize										
top10										
size										
price										
stdearnings	1									
competition	0.199***	1								
insti	0.311***	0.113***	1							
liquidity	− 0.481***	− 0.228***	− 0.654***	1						
salesgrowth	− 0.183***	0.031***	− 0.080***	− 0.016	1					
intanratio	0.123***	− 0.024***	0.233***	− 0.237***	0.054***	1				
horizon	0.076***	0.157***	0.111***	− 0.097***	− 0.055***	0.043***	1			
firmage	0.220***	− 0.040***	0.186***	− 0.229***	− 0.231***	0.033***	− 0.024***	1		
Capx	− 0.001	− 0.038***	− 0.148***	0.092***	0.091***	− 0.222***	− 0.049***	− 0.026***	1	
Abtradvol	0.030***	0.045***	0.011	− 0.173***	0.261***	0.030***	− 0.033***	0.093***	0.048***	1

Variables	*car*	*HHI*	*HHI1*	*gexp*	*Freq*	*portsize*	*bsize*	*top10*	*size*	*price*	*stdearnings*	*competition*
Panel B: Correlation matrix between analysts' industrial concentration and forecast informativeness												
car	1											
HHI	0.028***	1										

Variables	*car*	*HHI*	*HHI1*	*gexp*	*Freq*	*portsize*	*bsize*	*top10*	*size*	*price*	*stdearnings*	*competition*
HHI1	0.029***	0.983***	1									
gexp	–0.034***	− 0.020**	− 0.012	1								
freq	0.098***	0.024***	0.026***	0.150***	1							
portsize	− 0.069***	− 0.161***	− 0.152***	0.173***	0.111***	1						
bsize	− 0.014*	0.203***	0.203***	0.070***	0.072***	0.071***	1					
top10	− 0.024***	0.154***	0.157***	0.060***	0.052***	0.118***	0.858***	1				
size	− 0.372***	0.137***	0.143***	0.263***	0.118***	0.071**	0.269***	0.227***	1			
price	− 0.433***	0.010	0.015*	0.151***	0.063***	0.135***	0.166***	0.147***	0.778***	1		
stdearn-ings	− 0.148***	0.151***	0.154***	0.229***	0.131***	0.009	0.250***	0.197***	0.609***	0.239***	1	
competi-tion	− 0.088***	0.279***	0.292***	0.083***	0.017**	0.028***	0.042***	0.023***	0.188***	0.057***	0.211***	1
insti	0.067***	0.099***	0.110***	0.387***	0.169***	− 0.035***	0.069***	0.053***	0.245***	0.126***	0.247***	0.120***
liquidity	0.118***	− 0.148***	− 0.161***	− 0.437***	− 0.222***	− 0.036***	− 0.109***	− 0.108***	− 0.613***	− 0.425***	− 0.427***	− 0.235***
sales-growth	0.018**	0.023***	0.021***	− 0.043***	− 0.018**	0.010	− 0.001	0.015**	0.105***	0.196***	− 0.165***	0.015**
intanratio	− 0.007	− 0.115***	− 0.112***	0.131***	0.024***	− 0.084***	0.072***	0.062***	0.181***	0.106***	0.122***	− 0.015*
beta	0.153***	0.089***	0.092***	0.162***	0.013*	− 0.027***	0.047***	0.044***	0.265***	0.077***	0.271***	0.073***
btm	− 0.018**	− 0.10***	− 0.104***	− 0.016**	0.011	− 0.009	− 0.012	− 0.023***	− 0.275***	− 0.304***	− 0.053***	− 0.061***
tradingvol	− 0.09***	0.124***	0.131***	0.340***	0.182***	0.137***	0.175***	0.154***	0.779***	0.577***	0.529***	0.149***
changeeps	− 0.068***	–0.021***	− 0.023***	0.008	− 0.018**	− 0.002	− 0.001	0.009	0.123***	0.139***	0.079***	0.006
xrd	− 0.069***	0.015**	0.011	− 0.101***	− 0.026***	− 0.087***	0.092***	0.062***	0.155***	0.119***	0.131***	0.005
regulated	− 0.215***	0.037***	0.044***	− 0.001	− 0.095***	0.135***	− 0.026***	− 0.024***	0.081***	0.137***	− 0.020**	0.338***
changeroa	− 0.096***	0.010	0.011	0.021***	− 0.023***	0.006	− 0.007	0.007	0.170***	0.186***	0.078***	0.016**
abaccruals	0.224***	0.117***	0.120***	0.001	− 0.0002	− 0.092***	0.0060	− 0.005	− 0.074***	− 0.120***	− 0.037***	0.127***

Variables	*insti*	*liquidity*	*salesgrowth*	*intanratio*	*beta*	*btm*	*tradingvol*	*changeeps*	*xrd*	*regulated*	*changeroa*	*abaccruals*
Panel B: Correlation matrix between analysts' industrial concentration and forecast informativeness												
car												
HHI												
HHI1												
gexp												
freq												
portsize												
bsize												
top10												
size												
price												
stdearnings												
competition												
insti	1											
liquidity	− 0.620***	1										
salesgrowth	− 0.049***	− 0.046***	1									
intanratio	0.234***	− 0.241***	0.057***	1								
beta	0.240***	− 0.453***	0.047***	0.081***	1							
btm	− 0.020**	0.169***	− 0.180***	− 0.006	− 0.150***	1						
tradingvol	0.363***	− 0.723***	0.129***	0.158***	0.468***	− 0.269***	1					
changeeps	0.065***	− 0.061***	0.204***	0.007	− 0.007	−0.104***	0.032***	1				
xrd	− 0.158***	− 0.054***	0.024***	0.016**	0.009	− 0.043***	0.022***	0.040***	1			
regulated	− 0.104***	0.034***	0.001	− 0.130***	− 0.151***	0.124***	− 0.020***	− 0.006	− 0.077***	1		

Variables	*insti*	*liquidity*	*salesgrowth*	*intanratio*	*beta*	*btm*	*tradingvol*	*changeeps*	*xrd*	*regulated*	*changeroa*	*abaccruals*
changeroa	0.129***	− 0.076***	0.217***	0.014*	0.016**	− 0.112***	0.061***	0.734***	0.031***	0.016**	1	
abaccruals	0.101***	− 0.080***	0.083***	0.082***	0.138***	− 0.202***	0.035***	− 0.003	− 0.052***	− 0.216***	− 0.037***	1

Variables	*timeliness*	*HHI*	*HHI1*	*gexp*	*freq*	*portsize*	*bsize*	*top10*	*size*	*price*
Panel C: Correlation matrix between analysts' industrial concentration and forecast timeliness										
Timeliness	1									
HHI	0.050***	1								
HHI1	0.054***	0.984***	1							
Gexp	0.097***	0.020***	0.029***	1						
Freq	0.280***	0.032***	0.034***	0.137***	1					
portsize	− 0.003	− 0.085***	− 0.079***	0.115***	0.088***	1				
Bsize	0.072***	0.145***	0.148***	0.112***	0.070***	0.108***	1			
top10	0.061***	0.117***	0.120***	0.085***	0.053***	0.140***	0.857***	1		
Size	0.022***	0.076***	0.085***	0.336***	0.138***	0.130***	0.204***	0.178***	1	
Price	− 0.045***	0.006	0.012	0.191***	0.080***	0.157***	0.115***	0.109***	0.782***	1
Stdearnings	0.077***	0.082***	0.087***	0.300***	0.135***	0.062***	0.208***	0.164***	0.610***	0.240***
Competition	0.047***	0.368***	0.381***	0.122***	0.041***	0.094***	0.024***	0.019***	0.176***	0.094***
insti	0.159***	0.109***	0.117***	0.383***	0.159***	− 0.062***	0.103***	0.076***	0.314***	0.190***
liquidity	− 0.180***	− 0.158***	− 0.172***	− 0.458***	− 0.226***	− 0.033***	− 0.110***	− 0.114***	− 0.656***	− 0.464***
Beta	0.090***	0.090***	0.093***	0.174***	0.050**	− 0.022***	0.069***	0.062***	0.307***	0.088***
Btm	− 0.011	− 0.039***	− 0.042***	0.005	− 0.007	0.017***	− 0.037***	− 0.041***	− 0.325***	− 0.323***
Horizon	0.509***	0.053***	0.056***	0.050***	0.153***	0.022***	0.042***	− 0.038***	− 0.005	− 0.047***
Firmage	− 0.038***	− 0.066***	− 0.061***	0.164***	0.010	0.051***	− 0.086***	− 0.069***	0.309***	0.260***
Capx	− 0.043***	− 0.162***	− 0.171***	− 0.058***	0.017***	0.015	0.021***	0.011	0.033***	0.054***
Fexp	− 0.020**	− 0.013**	− 0.010	0.278***	0.034***	0.108***	0.034***	0.014	0.327***	0.227***

Variables	*stdearnings*	*competition*	*insti*	*liquidity*	*beta*	*btm*	*horizon*	*firmage*	*capx*	*fexp*
Panel C: Correlation matrix between analysts' industrial concentration and forecast timeliness										
Timeliness										
HHI										
HHI1										
Gexp										
Freq										
portsize										
Bsize										
top10										
Size										
Price										
Stdearnings	1									
Competition	0.164***	1								
insti	0.275***	0.137***	1							
liquidity	−0.452***	− 0.259***	− 0.618***	1						
Beta	0.337***	0.092***	0.246***	− 0.473***	1					
Btm	− 0.106***	− 0.009	0.003	0.170***	− 0.145***	1				
Horizon	0.004***	0.203***	0.086***	− 0.090***	0.043***	− 0.020***	1			
Firmage	0.245***	− 0.014	0.187***	− 0.244***	0.052***	0.043***	− 0.064***	1		
Capx	− 0.009	− 0.254***	− 0.163***	0.142***	− 0.048***	− 0.138***	− 0.088***	− 0.016***	1	
Fexp	0.313***	− 0.012	0.162***	− 0.215***	0.058***	0.028***	− 0.079***	0.513***	0.007***	1

"Appendix 2" presents the results for the Spearman correlation test. The correlation matrix includes variables used in the main hypothesis tests, where ***, **, * denote the two-tailed significance levels at the 1%, 5%, and 10%, respectively. The samples used for computing the correlation coefficients in Panels A, B, and C comprise 21,396, 17,804, and 24,873 firm-analyst observations, respectively, covering the period 1995–2017. All the variables are defined in "Appendix 1".

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Declarations

Conflict of interest None.

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