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The heterogeneous impact of industry concentration on analyst performance

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ABSTRACT

We examine the impact that industry concentration has on superior and inferior analysts' performance by utilizing a Herfindahl-Hirschman index of analyst specialization. Using broker M&As as a plausibly exogenous shock to analyst workloads, we find that superior analysts' forecast accuracy improves when their coverage is more concentrated within a few industries. However, there is no evidence of an equivalent improvement for inferior analysts. We argue that this is due to superior analysts having a comparative advantage in utilizing intra-industry relevant information and, therefore, the more concentrated their portfolio, the better they can extract this type of information for pricing stocks. We also find that investors who trade according to the buy-sell recommendations of superior analysts who have recently experienced increased industry concentration can gain extra returns on their stock portfolio.

1. Introduction

Dating back to Clement (1999) and Jacob, Lys, and Neale (1999), industry concentration has been identified as one of the key factors explaining analysts' forecasting performance. While the aforementioned research finds that analysts benefit when their coverage of stocks is not spread too widely across multiple industries, other research finds no systematic relationship between analyst forecast accuracy and the number of industries they cover (Bradley, Gokkaya, & Liu, 2017; Clement, Koonce, & Lopez, 2007; Kim, Lobo, & Song, 2011; Mikhail, Walther, & Willis, 1997). Rather, these papers argue that other factors, such as superior analysts' ability (Clement et al., 2007), can explain differences in analyst performance.

While the above papers highlight characteristics that explain differences in analyst performance, a separate stream of literature, examining the types of information analysts impound into markets, finds that analysts play a crucial role in incorporating industry-specific information into stock prices (Chan & Hameed, 2006; Piotroski & Roulstone, 2004). The literature finds that analysts can identify each firm-specific news event's common industry component, which they then utilize to make inferences about other stocks within the same industry. An implication is that the more concentrated an analyst's portfolio is to a limited number of industries, the more opportunity there is to focus on digesting intra-industry information.

Given that analysts are an important conduit in disseminating industry-relevant information to the market, we attempt to examine whether analysts with different forecasting abilities can benefit differently from industry concentration. Specifically, we hypothesize that the benefit of concentrating coverage to a limited number of industries will be pronounced for superior analysts. This will lead to a heterogeneous impact that industry concentration has on analyst performance. It can also potentially explain the mixed results obtained in the prior literature. While superior analysts benefit from specialization, there is no expectation that inferior analysts will benefit to the same degree.

Our hypothesis requires us to capture how concentrated an analyst's workload is across different industries. While prior studies utilize a count variable to capture industry coverage, we utilize the Herfindahl-Hirschman Index (*HHI*) to measure the analyst's industry concentration. While a naïve industry count could show, for example, that an analyst's stock coverage crosses three industries, it could be that all of the individual stocks covered, except for two, are in just one industry, implying that the analyst's overall workload is still highly specialized to a single industry. This would allow the analyst to concentrate on analyzing this industry and take advantage of intra-industry information, similar to the case of an analyst following only one industry. Our *HHI* accounts for this and allows us to capture the degree of industry

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concentration within an analyst's portfolio.

To test our hypothesis, we utilize data of U.S. analyst earnings forecasts obtained from the Institutional Brokers' Estimate System (I/B/E/S) database from 2005 to 2016. To deal with endogeneity concerns, we follow Hong and Kacperczyk (2010) and use M&As between brokerage firms as a pseudo-natural experiment to capture changes to the industry concentration of those analysts who continue to work in the merged firms after an M&A. Hong and Kacperczyk (2010) adopt brokerage M&A as a shock to analyst coverage of an individual stock. Other studies by Irani and Oesch (2013), Derrien and Kecskés (2013), and Chen, Harford, and Lin (2015) also utilize brokerage M&A as natural experiments. However, these papers focus exclusively on the impact of analyst coverage on corporate finance issues, including corporate disclosure, cost of capital and corporate governance. None of them examines a change to an analyst-level variable, such as industry concentration, that is caused by a brokerage M&A.

Using a difference-in-differences (DiD) regression approach, we compare the change in forecasting performance of analysts that have experienced a change in their industry concentration through an M&A (our treatment group) with those that have not gone through an M&A (our control group), and then between superior and inferior analysts within the treatment group. In addition, to ensure we have accounted for analyst fixed effects, stock fixed effects and year fixed effects, we repeat the above procedure for treatment forecasts that are then matched with a comparable portfolio of control forecasts, leaving changes in analysts' industry concentration due to M&As as the only primary factor that can affect analysts' performance.

The regression results from both the unmatched and matched samples provide similar outcomes. When comparing our M&A treatment sample with the matched control sample, we show that an increase of one standard deviation in analyst industry concentration (equivalent to an approximate 29% rise in the industry concentration of an analyst's portfolio) leads to superior analysts becoming 45% more accurate. In contrast, we find no significant impact of industry concentration on inferior analysts. Similarly, we find that investors who follow the buy-sell recommendations of superior analysts who experience an increase in industry concentration can earn 25% extra in one-year stock returns compared to those who follow inferior analysts. Overall, these findings suggest that investors and researchers should no longer treat all analysts the same when assessing how their performance is affected by industry concentration.

We also conduct several robustness tests in recognition that changes to analysts' industry concentration caused by brokerage M&As may not be completely exogenous in eliminating all the confounding factors that can affect both analysts' industry concentration and forecasting performance. Our robustness tests include sub-sampling our data, similar to Wu and Zang (2009), which examines what type of analysts are more or less likely to remain following an M&A. In addition, we conduct tests utilizing alternative measures of analyst forecasting performance and industry concentration, as well as using alternative cut-offs to classify superior and inferior analysts. The results from the above tests as well as additional robustness tests all support our baseline results.

To the best of our knowledge, our study is the first to examine the differential impact that industry concentration has on the performance of superior and inferior analysts. By doing so, we complement the studies of Clement (1999), Jacob et al. (1999) and Clement et al. (2007) which focus on one specific aspect of the work complexity of analysts (i.e., workload).

Our findings may help explain the mixed results in the literature studying the average effect of industry concentration on analysts' performance, as we show it is a specific cohort of analysts that primarily benefits from industry concentration. By introducing the Herfindahl-Hirschman Index (*HHI*) to measure industry concentration, we also provide a more refined measure to capture the extent to which an analyst specializes in a limited number of industries.

Based on our findings, brokerage firms should consider allocating different types of work to align with superior and inferior analysts' skill-sets to enhance their forecasting performance. In particular, we provide evidence supporting the view that superior analysts should specialize, whereas there is no evidence suggesting inferior analysts benefit from concentrating their coverage to fewer industries.

Finally, our contributions include the use of brokerage firm M&As as a pseudo-natural experiment to examine a shock to analyst industry concentration. This research design allows us to mitigate (but not fully eliminate) the endogeneity issue in which the level of industry concentration can be decided based on analyst forecasting performance. This issue, however, becomes less severe in our study since, after a brokerage M&A, most analysts will see a rearrangement of their workload due to the restructuring of the newly merged firm. Therefore, our research design provides a methodology framework for future studies to examine how shocks to other analyst-level characteristics affect analyst forecasting performance.

The remainder of this study is structured into five sections. Section 2 contains the hypotheses development. Section 3 presents our data and methodology. Section 4 reports our primary results and Section 5 contains robustness tests. Finally, Section 6 provides a conclusion to the study.

2. Hypotheses development

Prior analyst literature has suggested that analysts are important intermediaries for industry/market-wide information, as opposed to firm-specific information, to both the domestic U.S. market (Piotroski & Roulstone, 2004) and international markets (Chan & Hameed, 2006; Fernandes & Ferreira, 2008; Kim & Shi, 2012). In fact, industry knowledge is an important input for analyst forecasts and recommendations (Boni & Womack, 2006; Kadan, Madureira, Wang, & Zach, 2012). According to Boni and Womack (2006), analysts have the ability to extract core industry information from public news events to make meaningful inferences about the value of other firms within the same industry. In relation to this, previous studies (i.e., Boni & Womack, 2006; Clement, 1999; Kadan et al., 2012) also emphasize the role of industry specialization on analyst performance. Such specialization of tracking portfolios allows analysts to reduce information gathering costs (Clement, 1999) and assists in the extraction of the common components of news from firm-specific news, which can then be used to make forecasts and recommendations for other stocks in their tracking portfolio (Boni & Womack, 2006; Kadan et al., 2012).

However, the literature on the aggregate impact of industry specialization on analysts' performance provides mixed results. On one hand, Clement (1999) and Jacob et al. (1999) find that the number of industries in an analyst's portfolio is negatively associated with analysts' forecast accuracy. Accordingly, knowing the number of firms and industries an analyst follows may provide sufficient information to investors to predict economically meaningful differences in analyst forecast accuracy. As indicated by Clement (1999), identifying a small systematic difference in forecast accuracy among analysts can provide significant benefits to large institutional investors.

On the other hand, while research continues to find other factors that can explain analyst performance, including the advantage of being a local analyst (Bae, Stulz, & Tan, 2008) and the type of work experience analysts have before joining the brokerage industry (Bradley et al., 2017), further evidence of the impact that industry coverage has on performance is weak. Specifically, Mikhail et al. (1997) finds little support for the positive relationship between forecast accuracy and industry concentration. Also, Kim et al. (2011) shows that there is no relationship after controlling for the timing of analyst forecasts, and Bolliger (2004) finds no evidence that the relationship holds for European analysts. Additionally, Clement et al. (2007) finds that the number of covered industries' impact on analysts' forecast accuracy disappears after controlling for analysts' ability. Therefore, we posit that the disagreement in prior research can be explained by the different ability of analysts to generalize, analyze, and incorporate the component of industry information into their forecasts to improve forecast accuracy.

Complimentary to the above findings, prior analyst literature also documents that analysts are not equal in ability. Specifically, some analysts are better than others in interpreting publicly available news and incorporating it into their forecasts. For example, Jacob et al. (1999) documents an innate component of analysts' ability, which explains why forecast accuracy varies across different analysts. Similarly, Clement et al. (2007) finds that analysts with better ability can apply task-specific knowledge to improve their current forecasting performance, whereas analysts with low ability cannot.

We expect this is also true when applied to processing industry information to price different stocks in the same sector. The superior analysts will have an advantage in utilizing this information relative to inferior analysts. We, therefore, hypothesize that if there is an increase in the level of industry concentration, it is the superior analysts who should experience an improvement in their forecasting accuracy. The fewer industries they follow, the more time they can invest in gathering information relating to those industries:

H1. An increase in the level of industry concentration leads to a positive impact on the performance of superior analysts.

Prior studies have also established a link between analyst earnings forecasts and recommendations. For example, Bradshaw (2004) shows that analysts use their earnings forecasts as inputs of their valuation models, which are then used to make recommendations. Loh and Mian (2006) extends this stream of literature by showing that analysts' forecast accuracy can affect their ability to issue profitable recommendations. This conclusion is further supported by Ertimur, Sunder, and Sunder (2007), which confirms the positive relationship between analysts' forecast accuracy and recommendations, even after controlling for analyst expertise. Therefore, contingent on *H1* being true, superior analysts should improve the profitability of their recommendations when they become more specialized in their tracking portfolio. This leads to our second hypothesis:

H2. An increase in analyst industry concentration leads to a positive impact on the profitability of following superior analysts' recommendations.

3. Data and methodology

3.1. Sample selection

We collect annual earnings per share forecasts from analysts between 2005 and 2016 from the Institutional Brokers' Estimate System (I/B/E/S) database. Our analysis period starts from 2005 so that we only examine analyst forecasts after Global Settlement was introduced, which could have affected analyst forecasting behavior.[1] Also, we limit our analyzes to one-year ahead annual EPS forecasts. In addition, to avoid the effects of reiteration, we follow Hong and Kacperczyk (2010) to only use the most recent analyst forecast for each stock in their tracking portfolio prior to the end of a forecast period. This leads to a sample of 535,203 forecasts.

We calculate *HHI* to capture analyst industry concentration as follows:

$$HHI_{i,j,t} = \sum_{k=1}^{n} S_k^{\,2} \tag{1}$$

where *n* is the number of industries (identified by two-digit SIC codes)[2] that analyst *j* covers, and S_k is the proportion of stocks in analyst *j*'s portfolio that belong to industry *k*. The Herfindahl-Hirschman Index was originally used to measure market concentration to capture whether market share is concentrated within a small number of firms within one industry (Herfindahl, 1950; Hirschman, 1945).[3] Here, we use *HHI* to measure industry concentration. For example, consider two analysts covering the same number of industries, but one has a large proportion of stocks in their portfolio belonging to one industry whereas the other has an equal stock allocation across industries. Clearly, the first analyst's level of industry concentration will be higher than the second analyst, which cannot be captured if we look only at the number of industries they cover. However, since *HHI* accounts for both the number of industries assigned to the analyst and the proportion of stocks in the analyst portfolio that belongs to each industry, it can efficiently measure the differing levels of specialization between these two analysts.

While the largest cluster of analysts, representing 44% of our sample, follow only one industry with an $HHI = 1$, another 34% of analysts cover two to three industries, with their *HHI* varying between 0.3333 and 0.9524. This range also incorporates our entire sample's mean and median HHI (0.7114 and 0.7734, respectively). The remaining 22% of analysts cover a dispersed range of stocks across four to twelve industries. This latter group has an average *HHI* of 0.4. The number of industries covered by analysts in our sample ranges from one to 12, with the median value being three industries. Therefore, we believe that our results are not biased to those analysts who only cover one industry in their portfolio.

One issue that needs to be considered when associating analyst forecast performance with industry concentration is endogeneity. One can argue, for instance, that superior analysts have more power to negotiate for a higher level of specialization in their work. Therefore, it is uncertain whether industry concentration results in better performance for superior analysts, or whether superior performance allows analysts to negotiate for more industry concentration. This reverse causality problem can lead to an estimation bias.

To reduce endogeneity concerns, we focus our empirical analysis on forecasts issued by analysts who experience a change to their industry concentration after their brokerage firm has gone through an M&A. We posit that when the two brokerage firms are merged, there can be substantial changes to the work arrangement among analysts from the two pre-merger firms, leading to changes to the level of industry concentration for all analysts. Since an M&A between two brokerage firms is neither within the control of individual analysts nor easily anticipated by the analysts, our research design can help remove potential endogeneity problems. Moreover, we consider some further endogeneity issues that arise from using M&As later in the paper.

We collect data on broker M&As between 2005 and 2016 from the SDC Mergers and Acquisition database. Following Wu and Zang (2009), we identify broker M&As by restricting our sample to M&As in which the targets' four-digit Standard Industrial Classification (SIC) codes are either 6282 (including investment banks and brokerage firms) or 6211 (including independent research firms). We also require that the

[1] This is an enforcement agreement reached in 2003 that requires the physical and operational separation between the investment banking and research departments of brokerage firms to mitigate the potential of biased forecasts for investment banking clients.

[2] Our main conclusions do not change if we utilize the two-digit North American Industry Classification System (NAICS) code to calculate *HHI*.

[3] Other uses of *HHI* include measuring competition in elections (Stigler, 1972), product market competition (Leroy, 2014), the level of industry specialization (Gompers, Kovner, & Lerner, 2009) and corporate diversification (Atanasova & Li, 2019), individual task specialization (Narayanan, Balasubramanian, & Swaminathan, 2009), and attention diversification (Boydstun et al., 2014).

acquirers belong to one of the following three two-digit SIC codes: 60 (commercial banks), 62 (securities firms), or 63 (insurance companies). In addition, we only examine completed M&As for which the target is 100% owned by the acquirer after the transaction. This is to make sure that the two counterpart firms entirely merged into one entity after the M&A.

We then manually match target and acquirer names with brokerage house abbreviations (IDs) from the Institutional Brokers' Estimate System (I/B/E/S) Database. This is also the source of our analysts' earnings forecasts. To ensure that the names are correctly matched, we require the targets' IDs to disappear from the database after the M&A effective date. In addition, we require that analysts from the targets change their broker IDs to the acquirers' IDs after the merger. This results in a sample of 21 M&As with 806 retained analysts (approximately 66% of all analysts involved in the M&A).[4] Table 1 documents our process of M&A sample selection with the number of M&As dropped after each filter.

We follow Hong and Kacperczyk (2010) and use a 2-year window around the M&A dates. However, we differ from the earlier paper by excluding the event window from 6 months before to 6 months after the merger to avoid any changes to analyst forecasting abilities caused by M&A news and to account for the fact that some analysts can depart from the merged firm during this period. To observe the change in the accuracy of forecasts for individual stocks across the event window, we look only at forecasts for stocks that appear in the retained analysts' portfolio both before and after the M&A. Also, we require that the forecasts are issued on the closest date to the 6-month event window before and after the merger. This results in our reduced sample of 585 analysts from 21 M&As, with 5816 forecasts before and 5816 forecasts after the M&As.

3.2. Methodology

For our quantitative analyzes, we first adopt a change analysis (i.e., first difference analysis) to examine the change in industry concentration and forecast accuracy of analysts in our treatment sample. We then utilize a benchmark difference-in-differences (BDiD) regression approach in which we compare changes to our treatment sample with changes to a control sample of analyst forecasts.

Our treatment sample includes forecasts issued by analysts involved in the M&As and are retained in the merged entities. Our control sample contains all forecasts issued by analysts who are not involved in the M&As. However, we exclude forecasts issued by analysts who change their broker IDs during the event window from the control sample to ensure that any changes in forecast accuracy observed in the control sample are not due to analysts' job departure. This results in our final control sample of 156,179 earnings forecasts from 24,404 analyst-year observations (1946 firm-year observations).

Table 1
Sample selection procedure.

Data from CRSP	*Number of M&A*
All M&As between U.S. targets and U.S. acquirers between 1st Jan 2005 and 31st Dec 2016	109,789
Less uncompleted M&As	17,489
Less M&As in which the target is not 100% owned by the acquirer after the transactions	14,108
Less M&As with targets' primary SIC not being 6282 (including investment banks and brokerage firms) and 6211 (including independent research firms)	76,955
Less M&As with acquirers' primary SIC not being 60 (commercial banks), 62 (securities firms), and 63 (insurance companies)	394
Less M&As not matched with the I/B/E/S database	822
Final sample	21

This table describes the sample selection procedure with the number of M&As dropped after each filter.

For our economic model, we follow Clement (1999) and Bradley et al. (2017) to use the proportional mean absolute forecast error ($PMAFE_{i,j,t}$) to capture analyst performance. Specifically:

$$\mathrm{PMAFE}_{i,j,t} = \frac{\mathrm{AFE}_{i,j,t} - \overline{\mathrm{AFE}_{i,t}}}{\overline{\mathrm{AFE}_{i,t}}} \tag{2}$$

where $AFE_{i,j,t}$ is the absolute forecast error for analyst j's forecast for stock i within forecast period t. $\overline{AFE_{i,t}}$ is the mean absolute forecast error across all analysts issuing forecasts for stock i in forecast period t. To ensure that the estimation of $\overline{AFE_{i,t}}$ is meaningful, we require that there are at least three analysts covering stock i to construct this variable. A negative value of PMAFE suggests the forecast is more accurate than the firm average, whereas a positive value of PMAFE suggests the opposite.[5]

Our main independent variables of interest are *HHI* and two 'ability' dummies to classify analysts into superior and inferior analysts. We define $Superior_{j,t}$ to be equal to one if analyst j is ranked within the top 20% of all analysts within the brokerage industry prior to the M&A, and zero otherwise. We also utilize $Inferior_{j,t}$, which equals one if analyst j is ranked within the bottom 20% prior to the M&A, and zero otherwise.[6] We calculate an average value for each analyst for *PMAFE* across all stocks in their portfolio and use this as the ranking criteria. Therefore, our classification of analysts is not directly related to the dependent variable, which measures forecast error for a single stock in an analyst portfolio.

Based on prior literature, we utilize several measures that can affect analyst forecasting performance to either form part of our control variable set or match our treatment and control groups. These include brokerage firm size ($Size_{j,t}$) to control for analyst resources and $Experience_{j,t}$ to control for analyst years of general experience (Clement, 1999). We also control for analyst workload measured by the number of stocks the analyst covers in year t ($Workload_{j,t}$), the number of industries, identified by two-digit SIC codes that the analyst covers in year t ($Industries_{j,t}$), the number of stocks that are new to the analyst portfolio in year t ($New\ stocks_{j,t}$), and whether the stock belongs to the S&P500 index in year t ($SP500_{i,t}$). These four variables account for the complexity of an analyst's tracking portfolio with respect to the analyst total workload, the difficulty experienced when forecasting new stocks, and the availability of stock information, respectively. Next, we control for the number of days from when the analyst makes a forecast until the end of the forecast period ($Horizon_{i,j,t}$). We use this measure to account for the fact that the closer a forecast is to the forecast period end date, the more information is available to analysts to base the forecast on (Kim et al., 2011). Finally, based on Kim et al.'s (2011) work, we account for the number of forecast revisions an analyst issues for a stock within a year ($Revisions_{i,j,t}$).[7] Appendix I outlines how each of these variables is calculated in detail.

We start our empirical investigation with change analyses by utilizing a first differences regression model. We estimate the change for each

[4] The 21 M&As include 5 M&As in 2005, 3 M&As in 2006, 3 M&As in 2007, 3 M&As in 2008, 1 M&A in 2010, 1 M&A in 2011, 2 M&As in 2012, 1 M&A in 2013, and 2 M&As in 2014.

[5] We follow Hong and Kacperczyk (2010) to winsorize this variable by 2.5% in each tail to address the outlier issue caused by I/B/E/S coding errors. Accordingly, we apply the same winsorization to all continuous variables in our model.

[6] Our main conclusions remain the same if we adjust the cut-off point to 10% or 30%.

[7] We do not include a variable to account for the number of industries the analyst covers as it is captured by our *HHI* variable (with which it is also highly correlated with, $p = 0.82$).

variable observed for the treatment sample alone. The change is calculated for our treatment sample as the difference between the variable value before (*pre-M&A*) and after (*post-M&A*).

$$\Delta_{i,j} = T_{post-M\&A} - T_{pre-M\&A} \tag{3}$$

The first difference regression model is:

$$\Delta PMAFE = \alpha + \beta_1 \Delta HHI + \beta_2 \Delta HHI \times Superior + \beta_3 \Delta HHI \times Inferior + \gamma' \Delta X + \mu \tag{4}$$

In this model, we regress the change in analyst performance (*ΔPMAFE*) against the change in analyst industry concentration (*ΔHHI*), its interactions with *Superior/Inferior*, and a vector ΔX of control variables. These variables are all those that we previously discussed except for the variables that do not change between the pre- and post- periods. This will be the case with the two 'ability' dummies and the variable *Experience*. We also include year, M&A deal, and analyst fixed effects. The coefficients β_2 and β_3 indicate the differential impact that a shock to *HHI* has on superior and inferior analysts, respectively.

We then utilize benchmark DiD regressions for our subsequent analyses. First, to account for the possibility that our treatment and control samples may not share the same characteristics, which can affect the results of our regressions, we construct a matched control sample comparable to our treatment sample of analyst forecasts. We follow the method used by Hong and Kacperckyk (2010) and match each treatment forecast with one benchmark portfolio of control forecasts based on pre-M&A characteristics. We rank all forecasts within each event window into terciles according to the average forecast error of analysts who issue the forecasts ($\overline{PMAFE}$). Then, we repeat the ranking process using *HHI*, *Size*, and *Experience*. All forecasts belonging to the same tercile for all the ranking criteria forms one benchmark portfolio. This process results in 81 (3^4) benchmark portfolios for each M&A event. We proceed to match each treatment forecast with one benchmark portfolio that the treatment forecast belongs to.

Once the matching process is complete, we estimate the benchmark DiD for each variable by contrasting the change in the observed variable from a treatment sample (*T*), before (*pre-M&A*) and after (*post-M&A*) an event, with the average change observed in the matched benchmark portfolio of control forecasts (*BC*).

$$BDiD_{i,j} = \left(T_{post-M\&A} - T_{pre-M\&A}\right) - \left(BC_{post-M\&A} - BC_{pre-M\&A}\right) \tag{5}$$

Fig. 1 illustrates how we measure our variables before and after each M&A. Specifically, we measure the pre-M&A value of each variable using the period from 18 months to 6 months before the M&A, while the post-M&A value is measured from 6 months to 18 months after the M&A.

The regression model is expressed in Eq. (6):

$$BDiD.PMAFE = \alpha + \beta_1 BDiD.HHI + \beta_2 BDiD.HHI \times Superior + \beta_3 BDiD.HHI \times Inferior + \gamma' BDiD.X + \varepsilon \tag{6}$$

In this model, we regress the benchmark DiD estimation of analyst performance (*BDiD.PMAFE*) on the benchmark DiD estimation of industry concentration (*BDiD.HHI*) plus its interactions with *Superior/Inferior*, and a vector *BDiD.X* of control variables. Similar to the first difference model, in our DiD model, the Superior and Inferior dummy variables and the variable *Experience* are all differenced away. We also include year, M&A deal, and analyst fixed effects in our DiD regression. The coefficients β_2 and β_3 indicate the differential impact that a shock to *HHI* has on superior and inferior analysts, respectively.

One possible concern with our regression model is that the dependent variable (*PMAFE*) and the independent variables (*Superior/Inferior*) are measured based on analyst forecasting performance, potentially resulting in unreliable conclusions. However, we ascertain that this is not the case with our model for the following reasons. First, *Superior/Inferior* are identified based on the ranking of analysts in terms of the average *PMAFE* across their stock portfolio 1 year before the event window, whereas the dependent variable measures forecast error for a single stock in an analyst portfolio during the event window. Second, the dependent variable in our model is the change in *PMAFE* or Diff-in-diffs measure of *PMAFE*. Therefore, this change in *PMAFE* is also less likely to be related to the dummy variable *Superior/Inferior*. Finally, since *Superior/Inferior* are dummy variables, they have a low correlation with the dependent variable.[8]

4. Baseline results

4.1. Summary statistics

Panel A of Table 2 reports the summary statistics for all the variables across our treatment and control samples of analyst forecasts prior to the M&As. The statistics show that compared to the control forecasts, our treatment forecasts are more accurate (*PMAFE*), are issued closer to the financial year end date (*Horizon*), and are less likely to cover an S&P500 stock (*SP500*). We also find analysts issuing the treatment forecasts have a higher level of industry concentration (*HHI*), work for larger brokerage firms (*Size*), cover more stocks (*Workload*), have more new stocks in their portfolio (*New stocks*), and are more experienced (*Experience*).

Panel B of Table 2 shows the summary statistics of all the variables across the two samples during the period after the M&As. We find that the two samples are significantly different in all the examined variables. It is worth noting that the average number of industries (*Industries*) followed by the treatment analysts increases at a slower pace compared to that of the control analysts. This also explains the smaller decrease in the average *HHI* of our treatment sample, compared to the control sample.

One potential concern with our research design is that the merged firms may adjust the level of industry concentration for the retained analysts based on their past performance, implying that changes in industry concentration is still endogenous to the outcomes of the M&A. However, this is something that we can check. The statistics in Panel C of Table 2 show that 274 analysts in our M&A sample experience an increase in *HHI*, with an average increase of 0.0990. This is compared to 283 analysts who see a decline in *HHI*, with an average reduction of −0.1126. Importantly, our test results show that there is no significant difference between the average forecast error ($\overline{PMAFE}$) among analysts who experience an increase in *HHI* and those who see a decrease in *HHI* (−0.0278 and − 0.0398, respectively). This means analysts who see an increase or a decrease in *HHI* following an M&A are equally accurate.

In addition, there is no significant difference in the proportion of superior analysts among the two groups of analysts that experience an increase or a decrease in *HHI* (i.e., 15.9% of analysts who see an increase in *HHI* are superior analysts; and 16.8% of analysts who have a decrease in *HHI* are superior analysts). Likewise, this is also true of inferior analysts (35.7% and 30.1%, respectively). Overall, Panel C shows no evidence that the change to analyst industry concentration after an M&A is

[8] The correlation between *BDiD.PMAFE* with *Superior/Inferior* is −0.0105 and 0.0663, respectively.

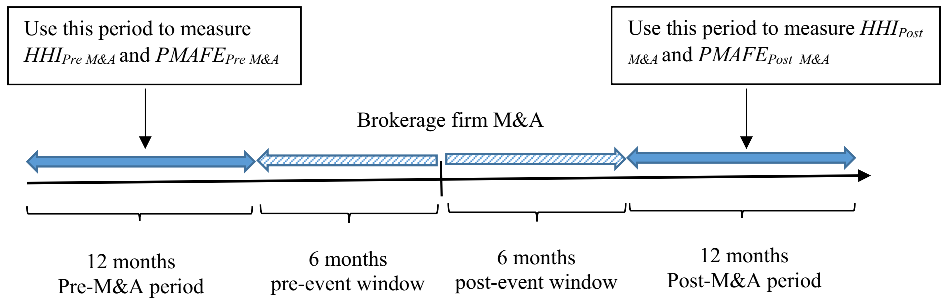

Fig. 1. Timeline for capturing pre- and post-periods.
This figure illustrates the timeline surrounding M&A brokerage events. The pre-M&A event period is from 18 months to 6 months before an M&A, while the post-M&A period is from 6 months to 18 months after the M&A.

Table 2
Summary statistics of the M&A sample.

Panel A: Summary statistics of the treatment and control sample of forecasts prior to the M&As

	Treatment sample			*Control sample*			*Diff. in means*
	Mean	*Median*	*Std.*	*Mean*	*Median*	*Std.*	
PMAFE	0.6031	−0.1007	2.4933	0.7527	−0.0698	2.7180	−0.1496***
HHI	0.6723	0.6676	0.2919	0.6457	0.6235	0.2939	0.02676**
Size	112.5426	67	99.7793	56.4441	32	56.9813	56.0985***
Workload	15.3353	16	7.7007	13.3115	13	8.3194	2.0238***
Industries	3.9583	3	2.3679	3.2583	3	2.0631	0.7000
New stocks	3.8765	3	3.9060	3.5533	3	3.8121	0.3232**
SP500	0.2860	0	0.4519	0.2990	0	0.4578	−0.0130**
Horizon	45.4001	56	56.6442	47.7708	56	59.2703	−2.3702***
Experience	13.7044	14	7.9943	12.1897	11	8.7340	1.5147***
Revisions	3.5871	3	2.4811	3.5501	3	4.1788	0.0370

Panel B: Summary statistics of the treatment and control sample of forecasts after the M&As

	Treatment sample			*Control sample*			*Diff. in means*
	Mean	*Median*	*Std.*	*Mean*	*Median*	*Std.*	
PMAFE	0.8980	−0.0695	3.1850	1.0058	−0.0287	3.2282	−0.1078**
HHI	0.6227	0.5938	0.2847	0.5802	0.5250	0.2849	0.0425***
Size	124.8551	91	89.3640	67.3863	45	57.3427	57.4688***
Workload	18.1780	18	6.6611	18.8303	18	9.1893	−0.6523***
Industries	4.1319	4	2.0309	4.4602	4	2.4074	−0.3283***
New stocks	4.4140	3	4.1010	4.5483	4	4.0901	−0.1343 **
SP500	4.7178	4	3.7644	5.0783	4	4.5230	−0.3605***
Horizon	47.2072	56	61.9334	53.1305	56	70.8439	−5.9233***
Experience	14.7044	15	7.9943	13.1897	12	8.7340	1.5147***
Revisions	4.3556	4	2.5730	4.1318	4	2.8507	0.2238***

Panel C: The decision of firms to increase or decrease analysts' industry concentration (HHI) after M&As

	Increase in HHI	*Decrease in HHI*	*Difference*
Number of analysts	274	283	−9
Average change in HHI post-M&A ($\overline{\Delta HHI}$)	0.0990	−0.1126	0.2117***
Mean forecast errors pre-M&A ($\overline{PMAFE}$)	−0.0278	−0.0398	0.0120
% of analysts as Superior	15.8845	16.7832	−0.8987
% of analysts as Inferior	35.7401	30.0699	5.6701

PMAFE is the measure of analyst forecast error, *HHI* measures industry concentration, *Size* is brokerage firm size, *Workload/Industries* is the number of stocks/industries covered by an analyst, *New stocks* is the number of new stocks that is assigned to an analyst in a given year, *SP500* shows whether the stock belongs to the S&P500 index, *Horizon* is the number of days from the forecast date to the end of the forecasting period, *Experience* represents analysts' years of experience, *Revisions* is the number of forecast revisions an analyst issues in a given year. Appendix I provides a detailed description of the variables. This table shows the summary statistics of the M&A sample. Panels A and B compare the statistics of forecasts in the M&A sample and a control sample during the period prior to and after the M&A, respectively. Our M&A sample contains 5816 forecasts before and 5816 forecasts after the M&As from 585 analysts in 21 M&As. The control sample contains of 156,179 earnings forecasts from 24,404 analyst-year observations (1946 firm-year observations). In Panel C, we report a summary of the change to analyst industry concentration after the M&As, then perform tests for the difference in the *ex-ante* performance of analysts who see an increase versus a decrease in industry concentration following an M&A. ***, **, and * represent significance levels of 1%, 5%, and 10% based on two-tailed tests, respectively.

Table 3
Change analysis and Benchmark DiD analyzes using the M&A sample and a matched control sample.

Panel A: Change analysis using first difference regressions

Variables	(1)	(2)	(3)
	BDiD.PMAFE	*BDiD.PMAFE*	*BDiD.PMAFE*
ΔHHI	0.2507	0.0214	0.3903
	(0.5369)	(0.4573)	(0.5137)
ΔHHI×Superior	−1.9975*		−2.1699**
	(1.0680)		(1.0577)
ΔHHI×Inferior		−0.7717	−1.1844
		(2.2193)	(2.2343)
ΔSize	−0.0030	−0.0029	−0.0030
	(0.0063)	(0.0063)	(0.0063)
ΔWorkload	0.0068	0.0079	0.0065
	(0.0186)	(0.0186)	(0.0186)
ΔIndustries	−0.1037	−0.1149	−0.1028
	(0.0861)	(0.0858)	(0.0860)
ΔNew Stocks	−0.0071	−0.0085	−0.0079
	(0.0130)	(0.0131)	(0.0131)
ΔHorizon	0.0035***	0.0035***	0.0035***
	(0.0009)	(0.0009)	(0.0009)
ΔSP500	−0.0261	−0.0271	−0.0262
	(0.0352)	(0.0351)	(0.0351)
ΔRevisions	−0.0032	−0.0025	−0.0031
	(0.0226)	(0.0226)	(0.0226)
Year FE	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes
Observations	5816	5816	5816
R-squared	0.0268	0.0264	0.0269

Panel B: DiD analysis using the M&A sample and a matched control sample

Variables	(1)	(2)	(3)
	BDiD.PMAFE	*BDiD.PMAFE*	*BDiD.PMAFE*
BDiD.HHI	0.2050	−0.1583	0.2324
	(0.5767)	(0.4961)	(0.5596)
BDiD.HHI×Superior	−1.9214**		−1.9506**
	(0.9806)		(0.9726)
BDiD.HHI×Inferior		0.1622	−0.2013
		(2.0393)	(2.0547)
BDiD.Size	−0.0014	−0.0017	−0.0014
	(0.0055)	(0.0055)	(0.0055)
BDiD.Workload	0.0030	0.0038	0.0030
	(0.0170)	(0.0170)	(0.0170)
BDiD.Industries	−0.1212	−0.1310	−0.1212
	(0.0850)	(0.0849)	(0.0851)
BDiD.New Stocks	−0.0013	−0.0023	−0.0015
	(0.0122)	(0.0122)	(0.0123)
BDiD.Horizon	0.0035***	0.0036***	0.0035***
	(0.0008)	(0.0008)	(0.0008)
BDiD.SP500	−0.0231	−0.0235	−0.0231
	(0.0331)	(0.0331)	(0.0331)
BDiD.Revisions	−0.0060	−0.0054	−0.0060
	(0.0215)	(0.0215)	(0.0215)
Year FE	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes
Observations	5816	5816	5816
R-squared	0.0272	0.0267	0.0272

PMAFE is the measure of analyst forecast error, *HHI* measures industry concentration, *Superior* and *Inferior* are dummy variables that show whether an analyst is superior or inferior in forecasting performance. *Size* is brokerage firm size, *Workload/Industries* is the number of stocks/industries covered by an analyst, *New stocks* is the number of new stocks that is assigned to an analyst in a given year, *SP500* shows whether the stock belongs to the S&P500 index, *Horizon* is the number of days from the forecast date to the end of the forecasting period, *Experience* represents analysts' years of experience, *Revisions* is the number of forecast revisions an analyst issue in a given year. Appendix I provides a detailed description of the variables. This table reports the test results when examining the M&A sample and a matched control sample. Panel A reports the first difference regression results (Eq. 4) for our treatment sample. In Panel B, each treatment forecast is matched with one portfolio of control forecasts issued by analysts having similar *PMAFE, HHI, Size,* and *Experience* characteristics. The results are from DiD regressions (Eq. 6). Robust standard errors are reported in parentheses for all regressions. ***, **, and * represent significance levels of 1%, 5%, and 10% based on two-tailed tests, respectively.

dependent on analyst prior performance. This is most likely due to the firms not controlling the substantial shock M&As cause to analyst workload. This arises from the reallocation of workload from analysts who have left the firm (which is unlikely to be planned) and the drop of workload that the counterpart brokerage firm might already cover.

4.2. Analyzes of the impact of industry concentration on analyst forecast accuracy

We first utilize a first difference regression model to examine the impact of a change in industry concentration on analyst forecasting performance for the treatment sample alone by utilizing Eq. (4). The results are reported in Panel A of Table 3. Column (1) reports the results when we only include the interaction of *ΔHHI* with *Superior* in the model. In Column (2), we only include the interaction of *ΔHHI* with *Inferior*. Then in Column (3), we include the interactions of *ΔHHI* with both 'ability' dummies. The results show that only superior analysts can benefit from industry concentration, whereas the impact is not significant for inferior analysts.

Next, in Panel B of Table 3, we utilize our DiD model to examine the impact of a change in industry concentration on analyst forecasting performance by utilizing Eq. (6). Column (1) reports the results when we only include the interaction of *BDiD.HHI* with *Superior* in the model. In Column (2), we only include the interaction of *BDiD.HHI* with *Inferior*. Then in Column (3), we include the interactions of *BDiD.HHI* with both 'ability' dummies.

Focusing on Column (3), we find that the coefficient for *BDiD.HHI×Superior* is negative and significant at a 5 % level, indicating that superior analysts show more improvement than an average analyst when there is an increase in industry concentration. The coefficient for *BDiD.HHI×Inferior* is, however, not significant. When we consider the total impact of a change to *HHI* on the two groups of analysts, we find the sum of the coefficients for *DiD.HHI* and *DiD.HHI×Superior* is −1.7182 (F-stat = 3.95, p-value = 0.047). This is equivalent to a reduction of 0.51 in the *PMAFE* of a superior analyst when they experience an increase of one standard deviation in *HHI* (0.2947). In economic terms, a one standard deviation rise in industry concentration is equivalent to an approximate 29% increase in the industry concentration of an analyst's portfolio. This means that for a 29% rise in industry concentration, forecasting performance improves by approximately 45% for superior analysts.[9] In contrast, the total impact is not significant for inferior analysts. Overall, the results in Table 3 support our hypothesis that superior analysts benefit more from increased industry concentration than inferior analysts.[10]

4.3. Analyzes of the impact of industry concentration on analyst recommendation profitability

We next test our second hypothesis by examining whether a change in *HHI* can affect analyst performance from the perspective of the profitability of following analyst recommendations. We measure analyst recommendation profitability ($Profitability_{i,j,t}$) as the one-year market-adjusted return (i.e., stock return adjusted for value-weighted market

[9] This is based on the untabulated average *PMAFE* for the sample of 1.1229.

[10] Our main findings still hold when we cluster standard errors by analyst, or analyst and M&A deals, or analyst and year. Our results are also robust when we employ a DiD regression model utilizing an unmatched control sample. These results are reported in Appendix 0.

Table 4
Summary statistics and benchmark DiD analyzes of analyst recommendation profitability.

Panel A: Summary statistics of the profitability of the treatment and control recommendations prior to an M&A

	Treatment sample			*Control sample*		
	Mean	*Median*	*Std.*	*Mean*	*Median*	*Std.*
Profitability	0.0497	0.0525	0.3216	0.0478	0.0959	0.3944

Panel B: Benchmark DiD analysis using analyst recommendation profitability

Variables	(1)	(2)	(3)
	BDiD.Profitability	*BDiD.Profitability*	*BDiD.Profitability*
BDiD.HHI	−4.3001**	−2.0083	−4.4916**
	(1.7172)	(1.3983)	(1.9116)
BDiD.HHI×Superior	10.0254**		10.2427**
	(4.8083)		(5.0257)
BDiD.HHI×Inferior		−0.1297	1.0303
		(2.0104)	(2.0725)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes
Observations	75	75	75
R-squared	0.4291	0.3674	0.4303

Profitability is the one-year market-adjusted return of analyst buy-sell recommendation, *HHI* measures industry concentration, *Superior* and *Inferior* are dummy variables that show whether an analyst is superior or inferior in forecasting performance. Control variables include *Size*, *Workload*, *Industries*, *New stocks*, *SP500*, *Horizon*, *Experience*, and *Revisions*. Appendix I provides a detailed description of the variables. This table documents the summary statistics of *Profitability* and the results of DiD regressions (Eq. 6) with the dependent variable being the benchmark DiD of recommendation profitability. Robust standard errors are reported in parentheses for all regressions. ***, **, and * represent significance levels of 1%, 5%, and 10% based on two-tailed tests, respectively.

returns) of a stock position recommended by analyst *j* for stock *i* in year *t*. The stock position is long if the analyst recommendation is either buy or strong buy; short if the analyst recommendation is hold, sell, or strong sell.[11] The summary statistics for *Profitability* are reported in Panel A of Table 4. We then re-run our DiD regression, utilizing Eq. (6), but replace the dependent variable by the benchmark DiD of *Profitability,* and report the results in Panel B of Table 4. Focusing on the regression results in Column (3), we find that the profitability of the stock positions recommended by superior analysts can be improved when the analysts have more industry concentration. Specifically, the coefficient for the interaction of *BDiD.HHI* and *Superior* is 10.2427, significant at the 5 % level. Given the untabulated average increase of BDiD.HHI of superior analysts in our sample is 0.0440, we can predict that the one-year market-adjusted return of the stock portfolio recommended by superior analysts improves, on average, by 25% (i.e., 25% = 0.0440 × (10.2427–4.4916)). However, we find no similar improvement for inferior analysts who also have a change in industry concentration.

Overall, the results in Table 4 suggest that investors can enhance their investment return by following the recommendations of superior analysts who experience increased industry concentration. This benefit, however, does not exist if investors follow the recommendations of inferior analysts having a similar increase in industry concentration. The results in Table 4, therefore, provide support for our second hypothesis.

5. Robustness tests

5.1. Analysis to control for the chance of analysts being retained after the M&As

While we find no evidence that the re-assignment of industry concentration following an M&A is related to past analyst performance (Panel C of Table 2), we nevertheless conduct a robustness test to further limit the impact that past performance can have on determining who is retained. Wu and Zang (2009) examines the characteristics of those analysts who are more/less likely to depart. The paper finds that several factors are associated with the retention of an analyst that are unrelated to analyst performance. In particular, analysts from the acquiring firms are more likely to stay in the merged firms. Also, analysts who have no direct competitor have a higher chance to be retained. Wu and Zang

Table 5
Regression results using a treatment sample of forecasts from analysts who are more likely to be retained in the merged firm.

Panel A: Probability of retention across different analyst groups

	(1) First group		*(2) Second group*		*Diff. in prob.*
	Obs.	*Average prob. of retention*	Obs.	*Average prob. of retention*	
(1) From acquirer vs. *(2) From target*	815	0.9780	231	0.5108	0.3972***
(1) Have no competitor vs. *(2) Having at least one competitor*	969	0.8369	77	0.6104	0.2203***
(1) From acquirer & having no competitor vs. *(2) From target & having at least one competitor*	778	0.9087	40	0.3500	0.5587***

Panel B: Regression results using a sample of forecasts from analysts who have a higher probability of retention after an M&A.

Variables	(1)	(2)	(3)
	BDiD.PMAFE	*BDiD.PMAFE*	*BDiD.PMAFE*
BDiD.HHI	0.5968	0.2373	0.7716
	(0.6020)	(0.5183)	(0.5829)
BDiD.HHI×Superior	−2.9686**		−3.1507**
	(1.2434)		(1.2328)
BDiD.HHI×Inferior		−0.6095	−1.1554
		(2.3177)	(2.3331)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes
Observations	4683	4683	4683
R-squared	0.0301	0.0292	0.0302

PMAFE is the measure of analyst forecast error, *HHI* measures industry concentration, *Superior* and *Inferior* are dummy variables that show whether an analyst is superior or inferior in forecasting performance. Control variables include *Size*, *Workload*, *Industries*, *New stocks*, *SP500*, *Horizon*, *Experience*, and *Revisions*. Appendix I provides a detailed description of the variables. This table reports results from a sample of forecasts issued by analysts who are more likely to be retained in the merged firm following an M&A. In Panel A, we examine the probability of retention across different groups of analysts. Panel B reports the results of DiD regressions (Eq. 6) when examining a treatment sample of forecasts issued by analysts who are from the acquirer firm and have no direct competitor in the target firm compared to a matched control sample. A direct competitor is another analyst whose portfolio is at least 50% similar to the studied analyst. The Robust standard errors are reported in parentheses for all regressions. ***, **, and * represent significance levels of 1%, 5%, and 10% based on two-tailed tests, respectively.

[11] Our results remain consistent if we use raw returns and classify hold recommendations as to not hold a position in the portfolio. The results are qualitatively similar when we examine a 9-month return window; however, the impact disappears when we examine a 6-month return window. As analyst recommendations are generally made for the forthcoming year, these results suggest the recommendations are not profitable if one only focuses on a short-term horizon.

(2009) defines a direct competitor as another analyst employed by the counterpart firm who owns a portfolio with at least 50% of stocks similar to the stocks covered by the focal analyst. For example, analyst A from the target firm covers 20 stocks and analyst B from the acquirer firm covers 10 stocks. Together, they share five stocks in common. Under this situation, Analyst A will be considered a direct competitor of analyst B, but analyst B will not be classified as a direct competitor of analyst A.

Based on this, we redo our analysis on a subset of forecasts that are (i) issued by analysts from the acquirer firms, and (ii) do not have a direct competitor. This group of analysts will have a higher chance of being retained for reasons unrelated to past performance. The statistics in Panel A of Table 5 confirm this. We find that analysts from the acquirer firms are 39.72% more likely to be retained in the merged entity following an M&A. We also find that the probability of retention for analysts who have no direct competitor are 22.03% higher compared to those having at least one competitor. For analysts coming from the acquiring firm with no competitor, the chance of being retained is 55.87% higher than target analysts having competitors.

Panel B of Table 5 shows the results from repeating our DiD regressions (Eq. 6) using this subsample of treatment forecasts. The results are consistent with our main findings. For example, in Column (3), the coefficient for *BDiD.HHI*×*Superior* is negative and significant at a 5 % level, suggesting that superior analysts show more improvement than other analysts when their industry concentration increases. At the same time, we document the total impact of a change in *HHI* on superior analyst forecast errors is −2.3791 (i.e., the sum of the coefficients for *BDiD.HHI* and *BDiD.HHI*×*Superior*: −2.3791 = 0.7716 + (−3.1507), *F*-stat = 5.20, *p*-value = 0.02). This is equivalent to a reduction of 0.59 in forecast error given an increase of one standard deviation in industry concentration. In contrast, we find that the impact of *HHI* on inferior analyst performance remains insignificant.

5.2. Analyzes using alternative measures of forecast accuracy and industry concentration

One issue with using *PMAFE* to measure analyst performance is that this variable's standard deviation is high. This is potentially caused by low values of $\overline{AFE_{ijt}}$ in the denominator of the equation. Therefore, our results may be driven by outliers. To address this problem, we employ an alternative measure of analyst forecasting performance (*FA*) as suggested by Hong and Kubik (2003) and Clement and Tse (2005).

$$\mathrm{FA} = 100 - \left[\frac{\mathrm{Rank} - 1}{\mathrm{Number\ of\ analysts} - 1}\right] \times 100 \tag{7}$$

We first sort all analyst forecasts covering one stock within one forecast period using their *PMAFE* to obtain a *Rank*. The most accurate forecast (lowest *PMAFE*) receives the lowest rank. *Number of analysts* is the number of analysts who issue forecasts for the same stock in one forecast period. *FA* is therefore a measure of forecast accuracy as the more accurate forecast receives a higher value.

We then rerun our DiD regression, utilizing Eq. (6), with the benchmark DiD estimation of *FA* (*BDiD.FA*) across the event window as our new dependent variable. The results in Panel A of Table 6 are consistent with our main results. We find, as we expect, that the coefficient for *BDiD.HHI*×*Superior* is positive and marginally significant at the 10 % level, whereas the coefficient for *BDiD.HHI*×*Inferior* remains insignificant. The total impact of a change in *HHI* on analyst accuracy (the sum of the coefficient for *BDiD.HHI* and *BDiD.HHI*×*Superior*) is 16.0449 (i.e., 16.0449 = −7.8558 + 23.9007, *F*-stat = 3.94, *p*-value = 0.05). Given a one standard deviation increase in *HHI*, this is equivalent to a jump of almost one place in the ranking if we consider that there are, on average, 17 analysts covering one stock. Whereas for inferior analysts, the total impact is not significant.

Next, we utilize an alternative measure for analyst industry concentration (*Entropy*) to make sure that our results are not biased by one

Table 6
Regression results using alternative measures for the variables of interest.

Panel A: Regression results using an alternative measure for analyst forecast error

Variables	(1)	(2)	(3)
	BDiD.FA	*BDiD.FA*	*BDiD.FA*
BDiD.HHI	−7.2057	−3.2965	−7.8558
	(5.5524)	(5.2733)	(5.8920)
BDiD.HHI×*Superior*	23.2103*		23.9007*
	(12.1918)		(12.3571)
BDiD.HHI×*Inferior*		0.2128	4.8021
		(15.7581)	(15.9659)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes
Observations	5962	5962	5962
R-squared	0.0330	0.0325	0.0330

Panel B: Regression results using an alternative measure for analyst industry concentration

Variables	(1)	(2)	(3)
	BDiD.PMAFE	*BDiD.PMAFE*	*BDiD.PMAFE*
BDiD.Entropy	−0.3584	−0.1245	−0.2905
	(0.2543)	(0.2223)	(0.2512)
BDiD.Entropy×*Superior*	1.0402**		0.9657**
	(0.4861)		(0.4847)
BDiD.Entropy×*Inferior*		−0.6093	−0.4350
		(0.9010)	(0.9103)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes
Observations	5816	5816	5816
R-squared	0.0273	0.0270	0.0274

PMAFE is the measure of analyst forecast error, *FA* is an alternative measure of analyst forecast accuracy, *HHI* measures industry concentration, *Entropy* is an alternative measure of industry concentration, *Superior* and *Inferior* are dummy variables that show whether an analyst is superior or inferior in forecasting performance. Control variables include *Size*, *Workload*, *Industries*, *New stocks*, *SP500*, *Horizon*, *Experience*, and *Revisions*. Appendix I provides a detailed description of the variables. This table reports the regression results (Eq. 6) when using alternative measures of forecast accuracy (Panel A) and industry concentration (Panel B). Robust standard errors are reported in parentheses for all regressions. ***, **, and * represent significance levels of 1%, 5%, and 10% based on two-tailed tests, respectively.

measurement of our variable of interest:

$$\mathrm{Entropy} = -\sum_{k=1}^{n} \mathrm{S_k} \times ln\mathrm{S_k} \tag{8}$$

where n is the number of industries (identified by two-digit SIC code) that analyst j cover, S_k is the proportion of stocks in the analyst portfolio allocated to industry k. *Entropy* is a measure of dispersion and has been previously used to measure industrial diversification within a firm (Jacquemin & Berry, 1979; Palepu, 1985; Raghunathan, 1995), geographic diversification (Vachani, 1991) and market competition (Horowitz & Horowitz, 1968; Nawrocki & Carter, 2010). In our study, higher values of *Entropy* indicate less industry concentration. As *HHI* is a normalized measurement (taking values from 0 to 1), it is insensitive to any change near the maximum and minimum values of specialization (Boydstun, Bevan, & Thomas, 2014). The value of *Entropy*, however, moves in a wider range and therefore minimizes this problem. At the same time, the use of *Entropy* allows us to test the impact of industry concentration on analyst performance in both directions, when specialization increases or decreases.

We rerun our DiD regression, utilizing Eq. (6), with the benchmark DiD estimation of *Entropy* (*BDiD.Entropy*) as the variable of interest. The

Table 7
The importance of industry concentration for firms with more firm-level information.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	BDiD.PMAFE	*BDiD.PMAFE*	*BDiD.PMAFE*	*BDiD.PMAFE*	*BDiD.PMAFE*	*BDiD.PMAFE*
Subsample	10% highest coverage	Exclude 10% highest coverage	10% lowest synchronicity	Exclude 10% lowest synchronicity	10% largest firms	Exclude 10% largest firms
BDiD.HHI	0.3069	0.5224	5.4440	0.3713	−0.9727	0.7159
	(1.2386)	(0.5668)	(4.0205)	(0.7559)	(2.3793)	(0.5305)
BDiD.	1.9922	−2.7686**	−7.4651	−2.2512**	7.0552	−2.0918**
HHI×Superior	(2.1815)	(1.0899)	(5.3531)	(1.1434)	(4.4839)	(1.0120)
BDiD.	−0.3522	−0.2553	−15.0804	4.8192*	7.1395	−1.0743
HHI×Inferior	(4.5263)	(2.3411)	(10.2205)	(2.7532)	(5.9408)	(2.2166)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1074	4736	255	2916	569	5241
R-squared	0.1165	0.0334	0.4147	0.0620	0.1515	0.0290

PMAFE is the measure of analyst forecast error, *HHI* measures industry concentration, *Superior* and *Inferior* are dummy variables that show whether an analyst is superior or inferior in forecasting performance. *Coverage* is the number of analysts following a stock. *Synchronicity* is the R-squared statistics of the market model. *Firm size* is the natural logarithm of the forecasted firm's total asset. Control variables include *Size*, *Workload*, *Industries*, *New stocks*, *SP500*, *Horizon*, *Experience*, and *Revisions*.Appendix I provides a detailed description of the variables. This table reports the results when we rerun our DiD on different subsamples. Regression 1 reports the results of DiD regressions (Eq. 6) when we use a subsample of forecasts for firms belonging to the top 10% of firms with highest analyst coverage, while Regression 2 shows the results for a subsample of forecasts for firms that exclude the top 10% of firms having highest analyst coverage. Regression 3 shows the results when we utilize a subsample of forecasts for the 10% of stocks with lowest synchronicity, and Regression 4 reports the results when we use a subsample that exclude those stocks. Regression 5 show the results when we use a subsample of forecasts for firms belonging to the top 10% largest firms. Regression 6 documents the results when we utilize a subsample of forecasts for firms that exclude the top 10% largest firms. Robust standard errors are reported in parentheses for all regressions. ***, **, and * represent significance levels of 1%, 5%, and 10% based on two-tailed tests, respectively.

results in Panel B of Table 6 show that with an increase in *Entropy*, there is a significant increase in the forecast error of superior analysts, while there is no significant impact on inferior analysts' performance. These results are consistent with our main findings showing that industry concentration affects superior, but not inferior, analysts.

5.3. Analysis for cases where industry-level information is less important

Next, in Table 7, we examine whether industry concentration is equally beneficial for analysts in situations where industry-level information is less important. For example, stocks of firms that have high information opacity and/or low stock return synchronicity (i.e., the co-movement of stock returns with market and industry returns) require analysts to have more knowledge of firm-level information, and stocks of large firms require analysts to analyze more complicated firm-level information. Thus, the role of industry-level information in forecasting the earnings of those stocks can be less significant; in other words, industry concentration can be of less benefit for analysts.

First, we perform subsample analyses, in which our subsamples are segregated using analyst coverage (i.e., the number of analysts covering one stock). According to Jiraporn, Liu, and Kim (2014), for firms with higher information opacity, analyst reports are more useful for investors so there is higher demand for analyst coverage. Thus, analyst coverage can be used as a proxy for firm-level information opacity. In Columns (1) and (2), we utilize a subsample that comprises forecasts for the top 10% of high coverage firms and another subsample that excludes those firms' forecasts. The results show that superior analysts gain no benefit from industry concentration when forecasting stocks with high analyst coverage (Column 1). However, there is a benefit when we exclude those stocks with highest analyst coverage from our sample (Column 2).

Next, in Column (3) and (4), we rerun our DiD regression on two subsamples. The first subsample includes forecasts for the 10% of stocks with the lowest stock return synchronicity and the second subsample contains the remaining forecasts. We measure stock return synchronicity using the R-squared statistics from the market model. The results show that industry concentration is no longer beneficial for superior analysts when forecasting stocks with low stock return synchronicity (Column 3), while the benefit remains qualitatively the same as our baseline results for the second subsample when we exclude those stocks (Column 4). In the second subsample, we document that the coefficient of *BDiD.HHI*-×*Inferior* is positive and significant at the 10% level. This means inferior analysts who provide forecasts for stocks with higher return synchronicity tend to issue less accurate forecasts when they have more industry concentration. We, however, should not infer too much from this result since the coefficient is only marginally significant.

In Columns (5) and (6) of Table 7, we rerun our DiD regression on two subsamples. One subsample comprises forecasts for the top 10% of largest firms and the other subsample excludes forecasts for those largest firms. The results show that superior analysts do not benefit from industry concentration when forecasting large firms' stocks (Column 5), while the benefit persists when excluding those largest firms. In both cases, inferior analysts do not benefit from industry concentration (Column 6).

Overall, Table 7 shows that the benefit of industry concentration disappears when analysts provide forecasts for stocks where industry-level information is relatively less important.

5.4. Other robustness tests

In Table 8, we perform four additional robustness tests to control for other potential confounding factors affecting our results. In Panel A, we include the DiD measures of fundamental control variables in our regression to ensure that our results are not driven by the change in the fundamental characteristics of the forecasted stocks. We follow Hong and Kacperczyk (2010) and include the log of the total asset value of the firm ($Lnsize_{it}$), stock returns ($Retann_{it}$), stock return volatility ($Sigma_{it}$), log of the book to market value of the firm ($Lnbm_{it}$), return on equity of the firm (ROE_{it}), volatility of return on equity using the past ten-year return series ($Var\ ROE_{it}$), and operating income scaled by asset value of the firm ($Profit_{it}$).

In Panel B, we try to account for forecasts by teams of analysts since we cannot observe the change to individual analysts' performance in a team. We identify analysts' teams as analyst codes that cover more than

Table 8
Further robustness tests.

Panel A: Regression results when controlling for the change in the forecasted firm's fundamentals

Variables	(1)	(2)	(3)
	BDiD.PMAFE	*BDiD.PMAFE*	*BDiD.PMAFE*
BDiD.HHI	0.6846	0.1196	0.5367
	(0.5640)	(0.4749)	(0.5441)
BDiD.HHI×Superior	−2.2199**		−2.0626**
	(1.0477)		(1.0366)
BDiD.HHI×Inferior		1.4857	1.0629
		(2.2981)	(2.3170)
Control variables	Yes	Yes	Yes
Fundamental controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes
Observations	4840	4840	4840
R-squared	0.0370	0.0366	0.0371

Panel B: Regression results when forecasts by teams of analysts are excluded

Variables	(1)	(2)	(3)
	BDiD.PMAFE	*BDiD.PMAFE*	*BDiD.PMAFE*
BDiD.HHI	0.3963	0.0680	0.4235
	(0.5518)	(0.4637)	(0.5289)
BDiD.HHI×Superior	−1.8039*		−1.8335*
	(1.0389)		(1.0282)
BDiD.HHI×Inferior		0.1605	−0.1917
		(2.1372)	(2.1540)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes
Observations	5115	5115	5115
R-squared	0.0288	0.0284	0.0288

Panel C: Regression results when including analysts who move to another brokerage firm after the M&As

Variables	(1)	(2)	(3)
	BDiD.PMAFE	*BDiD.PMAFE*	*BDiD.PMAFE*
BDiD.HHI	0.4746	0.2189	0.6331
	(0.4745)	(0.4192)	(0.4590)
BDiD.HHI×Superior	−2.0052**		−2.1589**
	(0.8726)		(0.8682)
BDiD.HHI×Inferior		−0.7305	−1.1110
		(1.6502)	(1.6606)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes
Observations	11,920	11,920	11,920
R-squared	0.0715	0.0711	0.0715

Panel D: Regression results when all variables are measured at the analyst-level

Variables	(1)	(2)	(3)
	$BDiD.\overline{PMAFE}$	$BDiD.\overline{PMAFE}$	$BDiD.\overline{PMAFE}$
BDiD.HHI	0.6727	0.1580	0.4427
	(0.4358)	(0.4770)	(0.4942)
BDiD.HHI×Superior	−2.8249***		−2.6350**
	(1.0683)		(1.0826)
BDiD.HHI×Inferior		1.6340	1.3552
		(1.2047)	(1.2044)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes
Observations	585	585	585
R-squared	0.2742	0.2681	0.2775

PMAFE is the measure of analyst forecast error, *HHI* measures industry concentration, *Superior* and *Inferior* are dummy variables that show whether an analyst is superior or inferior in forecasting performance. Control variables include *Size*, *Workload*, *Industries*, *New stocks*, *SP500*, *Horizon*, *Experience*, and *Revisions*. Fundamental controls include *LnSize, Retann, Sigma, Lnbm, ROE, Var ROE, Profit*. Appendix I provides a detailed description of the variables. Panel A reports the results of DiD regressions (Eq. 6) when we also control for the change in the forecasted firms' fundamentals. Panel B documents the results when excluding forecasts issued by teams of analysts from the sample. We identify teams of analysts from analyst codes that cover more than 25 stocks in their portfolios. Panel C shows the results when we supplement our treatment sample with forecasts by analysts who move to a new firm after the M&A. Panel D shows the regression results when all variables are measured at the analyst-level. Robust standard errors are reported in parentheses for all regressions. ***, **, and * represent significance levels of 1%, 5%, and 10% based on two-tailed tests, respectively.

25 stocks, then remove forecasts by those analyst codes from our treatment sample and re-estimate the regressions.[12]

In Panel C, we supplement our treatment sample with forecasts by analysts who belong to either the target or acquirer firms of the M&A, but move to another brokerage firm after the M&A. After moving to a new firm, those analysts would experience substantial changes in their new working environment, including a change in their industry concentration. Although it is much harder to control for the impact of other confounding factors on those departing analysts' forecasting performance, we want to examine whether our conclusion about the impact of industry concentration on analysts' performance still holds for that subset of analysts. The regression results in Panel C confirm that our conclusion remains consistent when we include departing analysts' forecasts in our treatment sample.

In Panel D, we report the regression results when examining the analyst level's aggregated forecast error. Our main analyses only focus on forecasts for stocks that appear in an analyst portfolio both before and after the M&A. This means we do not account for any stocks that the analyst drops after the M&A, and new stocks that are assigned by the merged firm. To address this issue, we aggregate forecast errors across all stocks in an analyst portfolio to obtain a forecast error score for each analyst, before and after the M&A. The benchmark DiD estimation of the aggregated forecast error ($BDiD.\overline{PMAFE}$) is used as the dependent variable for our regressions. We utilize Eq. (6) for our regressions but exclude all forecast-level control variables. In all four tests, the results align with our main findings.

6. Conclusion

Using broker M&As as a pseudo-natural experiment, we examine the impact of industry concentration (how concentrated the stocks an analyst tracks are across industries) on superior and inferior analysts' forecasting performance. Our main findings suggest that the impact of industry concentration on forecast accuracy is significantly different between these two analyst groups. We find superior analysts can benefit from increased specialization in their portfolio, while we do not find evidence of inferior analysts significantly benefiting. Our findings are consistent across several robustness tests.

We contribute to the literature on financial analysts by showing a heterogeneous impact of industry concentration on analysts. While the prior literature has provided mixed results from examining the average effect that industry concentration has on analyst performance, we show that it is necessary to consider how the impact may vary across analysts with differing abilities. Specifically, superior analysts can take advantage of concentrating the portfolio of stocks that they track.

Our study also has an important practical implication for capital market participants as we find that, on average, investors can earn 25%

[12] The results are also robust if we use a cut-off of 20 stocks or 30 stocks.

extra in annualized returns if they construct their portfolio according to the buy-sell recommendations of superior analysts who experience an increase in industry concentration relative to a portfolio constructed from following all superior analysts. This is due to superior analysts' unique ability to benefit from concentrating their work to a smaller number of industries.

We acknowledge, however, that our study suffers from a limitation regarding our measure of industry concentration (i.e., *HHI*). Given that we use two-digit SIC codes to compute HHI, it captures the horizontal information spillover across firms within the same industries. However, it only indirectly and partially captures the vertical information transfer across related sub-sectors under the same two-digit SIC code. Therefore, future research should address this issue by devising a more efficient measure of industry concentration.

Declaration of Competing Interest

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

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Appendix I: Variable definitions

This appendix provides a detailed description of the construction of all the variables used in the tables.

Variable	Definition
Dependent variables	
$FA_{i,j,t}$	A measure of analyst forecast accuracy following the below formula: $FA = 100 - \left[\frac{Rank - 1}{Number\ of\ analysts - 1}\right] \times 100$ To obtain analyst ranking, we sort all analyst forecasts covering one stock within one forecast period using their *PMAFE* to obtain a *Rank*. The most accurate forecast (lowest *PMAFE*) receives the lowest rank. *Number of analysts* is the number of analysts who issue forecasts for the same stock in one forecast period.
$PMAFE_{i,j,t}$	A measure of analyst forecast error. It is the difference between analyst *j*'s absolute forecast error for stock *i* in year *t* and the mean absolute forecast error across all analysts following stock *i* in the same year, divided by the mean absolute forecast error. We require that there are at least three analysts covering stock *i* in year *t* to construct this variable.
$Profitability_{i,j,t}$	A measure of analyst recommendation profitability. It is the one-year stock return adjusted for value weighted market return by investing in a stock position as recommended by analyst *j* for stock *i.* in year *t*. The stock position is long if analyst recommendation is either buy or strong buy; short if analyst recommendation is hold, sell, strong sell.
Independent variables of interest	
$Entropy_{j,t}$	A measure of work diversification following the below formula: $Entropy = -\sum_{k=1}^{n} S_k \times lnS_k$ where *n* is the number of industries (identified by two-digit SIC code) that analyst *j* cover, S_k is the proportion of stocks in the analyst portfolio allocated to industry *k*.
$HHI_{j,t}$	A measure of industry concentration that is equal to the sum of the squared proportion of stocks within each industry that analyst *j* covers in year *t*.
$Inferior_{j,t}$	A dummy variable that is equal to one if analyst *j* is ranked in the bottom 20% of all analysts within the brokerage industry in year *t* based on forecast accuracy, and zero otherwise. For the M&A sample, this variable is identified using the analyst performance in the year prior to the M&A.
$Experienced_{j,t}$	A dummy variable that is equal to one if analyst *j* is ranked within the top 20% of all analysts within the brokerage industry in year *t* based on years of experience, and zero otherwise. For the M&A sample, this variable is identified using the analyst performance in the year prior to the M&A.
$Inexperienced_{j,t}$	A dummy variable that is equal to one if analyst *j* is ranked within the bottom 20% of all analysts within the brokerage industry in year *t* based on years of experience, and zero otherwise. For the M&A sample, this variable is identified using the analyst performance in the year prior to the M&A.
$Superior_{j,t}$	A dummy variable that is equal to one if analyst *j* is ranked in the top 20% of all analysts within the brokerage industry in year *t* based on forecast accuracy, and zero otherwise. For the M&A sample, this variable is identified using the analyst performance in the year prior to the M&A.
Analyst and brokerage firm control variables	
$Experience_{j,t}$	The number of years analyst *j* worked in the brokerage industry until year *t*.
$Horizon_{i,j,t}$	The number of days from analyst *j* forecast for stock *i* in year *t* until the end of the forecast period.
$Industries_{j,t}$	The number of industries followed by analyst *j* in year *t*, using two-digit SIC codes.
$New\ stocks_{j,t}$	The number of stocks for which analyst *j* issues forecasts for the first time in year *t*.
$Revisions_{i,j,t}$	The number of forecast revisions that analyst *j* issues for stock *i* in year *t*.
$Size_{j,t}$	The number of analysts employed by the brokerage firm that analyst *j* works for in year *t*.
$SP500_{i,t}$	A dummy variable that is equal to one if stock *i* in year *t* belongs to the S&P500 index, and zero otherwise.
$Workload_{j,t}$	The number of stocks followed by analyst *j* in year *t*.
Fundamental control variables	
$Lnbm_{it}$	Log of the book to market value of firm *i* in forecast period *t*.
$Lnsize_{it}$	Log of total assets of firm *i* in forecast period *t*.
$Profit_{it}$	Operating income over book value of assets of firm *i* in year *t*.
$Retann_{it}$	Annualized average monthly returns of stock *i* in year *t*.
ROE_{it}	Annual return on equity (ROE) of firm *i* in year *t*.
$Sigma_{it}$	Annualized daily return volatility of stock *i* in year *t*.
$Var\ ROE_{it}$	The variance of the residuals from an AR(1) model for stock *i*'s ROE using the past ten-year series of the company's annual ROEs.

Appendix II

This Appendix reports the results of DiD regressions to compare a treatment sample of forecasts issued by analysts who experience an M&A and are retained in the merged firm with an unmatched control sample of forecasts issued by analysts who do not experience an M&A. Results indicate only superior analysts show a significant improvement in forecasting accuracy.

DiD analysis using the M&A sample and an unmatched control sample.

Variables	(1)	(2)	(3)
	DiD.PMAFE	*DiD.PMAFE*	*DiD.PMAFE*
DiD.HHI	0.5770	0.3066	0.7280
	(0.5506)	(0.4699)	(0.5332)
DiD.HHI×Superior	−2.1186**		−2.2804**
	(1.0531)		(1.0463)
DiD.HHI×Inferior		−0.6734	−1.1103
		(2.2063)	(2.2242)
Year FE	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes
Observations	5816	5816	5816
R-squared	0.0265	0.0261	0.0266

PMAFE is the measure of analyst forecast error, *HHI* measures industry concentration, *Superior* and *Inferior* are dummy variables that show whether an analyst is superior or inferior in forecasting performance. Control variables include *Size*, *Workload*, *Industries*, *New stocks*, *SP500*, *Horizon*, *Experience*, and *Revisions*. Appendix I provides a detailed description of the variables. Robust standard errors are reported in parentheses for all regressions. ***, **, and * represent significance levels of 1%, 5%, and 10% based on two-tailed tests, respectively.

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