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Brokerage M&As and the peer effect on analyst forecast accuracy

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ABSTRACT

We examine whether the impact of a change in the number of analysts a brokerage firm employs has an asymmetric effect on the forecasting ability of superior and inferior analysts. Specifically, we show that following brokerage M&As only superior analysts benefit from a rise in having a larger number of peers. In addition, we find that the market does not account for the improved performance among superior analysts, and argue that this creates an opportunity for investors to capitalize on this.

1. Introduction

Mergers and acquisitions, in general, result in substantial changes in the working environment, which likely affect the performance of the surviving employees (Conyon, Girma, Thompson, & Wright, 2002; Siegel & Simons, 2006 2010). One notable change is the restructure of human resources where the retained employees from the two counterpart firms are assigned to work together under a single entity and the redundant personnel are let go. This can result in a 'peer effect' as the change of colleagues one is working with will likely affect their performance (Chiaburu & Harrison, 2008Mas & Moretti, 2009Zimmer & Toma, 2000).

One important dimension of the peer effect is related to changes in the actual number of peers an individual finds themselves exposed to within the work environment. For example, Bandiera, Barankay, and Rasul (2005) find that when workers' payment depends on their relative productivity compared to their peers, workers' productivity improves when they have more coworkers. This is because when the team size increases, workers find it harder to know the average effort of the whole team and tend to compensate for this by exerting more effort in their work. Mas and Moretti (2009) also document that by adding a new worker to the team, the performance of the incumbent workers can improve due to the peer monitoring effect. From the financial analyst literature, Clement (1999) uses the number of analysts working in the same firm as a proxy for the resources available to an analyst and documents a positive relationship between the number of coworkers and analyst forecasting performance.

Differences also exist in how peers interact with colleagues based on their own ability. Hambrick (1994) find that top performers are unwilling to share information and cooperate with their peers. However, Hwang, Liberti, and Sturgess (2019) show evidence that star analysts are more likely to receive information sharing from their colleagues.

These above findings motivate us to consider the impact that these factors have on analysts who undergo a brokerage M&A, since an M&A between two brokerage firms likely results in a change in the peers an analyst works with. In particular, we question if analyst forecasting performance is affected not only by the change in the number of their peers following an M&A but, in particular, whether an individual analyst's ability will moderate the impact this peer effect has. In combining the above two related streams of literature, we hypothesize that the impact on analyst performance of a change in the number of analysts will vary depending on the incumbent analyst's own performance. In addition, if we find that analyst forecast accuracy is altered then it is subsequently worth examining if it has a direct market impact because analysts, as financial information intermediaries, influence market prices (Brennan & Subrahmanyam, 1995, Chung & Jo, 1996Hong et al., 2000).

To examine the impact that the peer effect caused from M&As has on analyst performance, we utilize a sample of 21 M&As, involving 837 analysts with 6999 forecasts between 2005 and 2016. These analysts all experience, to a greater or lesser degree, a change in the number of colleagues within the firm that track the same industry as they do. To

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measure the change in analyst performance following an M&A, we use a difference-in-difference (DiD) approach to match and compare the performance of each forecast from analysts that have gone through an M&A (our treatment group) with those that have not (our control group) to examine their post-M&A performance.

Our empirical results from running a number of multivariate regressions of forecast errors against our measures for a change in peer effect find that it is superior analysts who benefit the most from an increase in the number of peers. Specifically, an average increase in the number of peers working in the firm results in an 11.5% improvement in superior analysts' forecast accuracy. Our analyses also reveal that the market does not differentiate the impact that the peer effect has on analysts with varying abilities. Rather, it reacts as if a change in the number of peers will have a homogeneous impact on all affected analysts. This, potentially, provides scope to develop a profitable trading rule. We find when there is an increase in the number of peers, a portfolio constructed based on superior analysts' recommendations tends to achieve a stronger improvement in returns relative to a comparable inferior analysts' portfolio. As a result, the difference between the superior and inferior analyst portfolio returns considerably widens and becomes statistically significant (the difference is 34% in annualized returns when the analysts experience an increase in the number of peers they work with).

Further analyses also document that the benefit of a change in peers on analyst performance is restricted to acquirer analysts. There is no observable impact on target analysts. Our empirical analysis concludes with several robustness tests which include accounting for outliers, making sure the results are not driven by a small number of analysts, and accounting for the sudden change in resources analysts have at their disposal as a result of an M&A.

Our study makes several contributions to the existing literature. First, we contribute to the literature that examine the impact of brokerage M&As. For example, Wu and Zang (2009) study how several factors, including past performance, affect analyst career outcomes (whether they are retained or depart from the merged entity) after an M&A. Hong and Kacperczyk (2010) show how a change in analyst coverage following an M&A affects the forecasting behavior of analysts from the other firms. Similarly, Derrien and Kecskés (2013), Irani and Oesch (2013, 2016), Chen, Harford, and Lin (2015) examine how this change in analyst coverage matters for the affected firm. To our knowledge, we are the first to examine how the survivors of brokerage M&A see a change in their performance due to the restructure of the colleagues they work with in the merged entity. Our study, therefore, provides practical implications for human resource management of brokerage firms after M&As to further enhance the performance of their retained employees.

Second, we also contribute to the analyst literature by showing the heterogeneous performance outcomes of analysts caused from an M&A, with the differences being economically significant. We show that there are significant response differences between analysts from a change in the number of peers and that the noted improvement in performance of analysts following an M&A is mostly driven by the positive reaction superior analysts have to peer changes. Our study, therefore, lends support to Hwang et al. (2019), who find that information sharing among peer analysts is stronger when one of the analysts is a star analyst.

Third, we contribute to the debate on the efficiency of the capital markets by lending support to Clement and Tse (2003), who argue the market sometimes fails to recognize all the characteristics of analysts which will explain their forecasting performance. This contrasts to the views of Stickel (1992), Park and Stice (2000), and Gleason and Lee (2003) who argue the market can recognize forecasts that are more accurate and react accordingly. Our findings suggest the market does not, although it should, realize it is primarily the superior analysts that benefit from a change in peer numbers following an M&A and that they are the principle drivers behind the improved forecasts of the newly merged brokerage firm.

Last but not least, we contribute to the literature that examines post-M&A performance. While most of the previous studies in this field focuses on the impact M&As has on productivity at the brokerage-level (Cummins & Xie, 2008Harrison, Hitt, Hoskisson, & Duane Ireland, 1991Hoskisson, Johnson, & Moesel, 1994Weber, 1996), we examine the impact that an M&A has on individual performance. To our knowledge, Siegel and Simons (2010) is the only study that investigates the impact that M&As have on analyst-level performance. They utilize worker earnings as the measure of performance. We, however, examine a sample of financial analyst forecasts, which allows us to objectively measure individual performance by comparing analyst forecasts against actual earnings per share (EPS).

The remainder of this study is structured into five sections. Section two contains our hypotheses development. Section three describes the data and methodology we employ and in section four we present our empirical results and discuss our main findings. In section five, we provide our robustness tests. Section six contains our conclusion.

2. Hypotheses development

It is well known that peer analysts tracking stocks of the same industry tend to work as a team (Hwang et al., 2019). Therefore, a change in this team due to a human resource restructure, such as following a brokerage M&A, will likely affect their forecasting performance. The literature recognizes several channels through which peers can affect individual performance. For example, Beersma et al. (2003) document that a competitive structure within a team can enhance the speed of work, whereas a cooperative structure can promote accuracy via the sharing of knowledge among team members. Chiaburu and Harrison (2008), in a meta-analysis, find that supportive coworkers can have a positive impact on an individual performance. In contrast, antagonism from co-workers can negatively affect work performance. Mas and Moretti (2009), while studying the productivity of cashiers, find that a worker experiences disutility when they work not as hard as their peers, which motivates them to work harder and consequently enhances their own productivity. Similarly, Hwang et al. (2019) document that there is information sharing among peer analysts within the same brokerage firm, which ultimately enhances their forecasting performance.

One other important aspect of the peer effect, which is easily observable, is related to the number of peer colleagues one is working with. For example, Clement (1999) uses the number of analysts working in the same firm as a proxy for the resources available to an analyst and documents that the more colleagues an analyst has, the better their forecasting performance is. In studying fruit picking workers Bandiera et al. (2005) find that their productivity increases when they have more coworkers as it becomes harder to work out how hard they are working relative to the average. Mas and Moretti (2009) also document that an increase in the number of workers in the team can improve the performance of the incumbent workers due to the peer monitoring effect.

The previous literature also provides evidence that the impact peers have on performance is moderated by the ability of the worker themselves. For example, Beersma et al. (2003) conclude that the poorest performers in a team receive the stronger benefit from the reward structure of a team compared to the top performers. In contrast, a study by Hwang et al. (2019) supplements these studies by showing that star analysts are more likely to receive information sharing from their peers compared to non-star analysts, thereby improving their own performance. Following Hwang et al.'s (2019) work, we conjecture that a rise in the number of analysts will more likely benefit superior analysts more so than inferior analysts, leading us to our first hypothesis:

Hypothesis 1. *An increase in the number of peer analysts after a brokerage M&A will have a stronger, positive impact on the forecast accuracy of superior analysts than inferior analysts.*

Secondly, we examine whether the market can differentiate the impact that the peer effect has on analysts with differing abilities. Stickel (1992), Park and Stice (2000), and Gleason and Lee (2003) argue that the market's response to analyst forecasts always increases with forecast accuracy. If this is the case, then if we find evidence supporting the second hypothesis, the market should react more positively to forecasts issued by superior analysts and less to inferior analysts' forecasts. However, an opposing view, proposed by Clement and Tse (2003), states that the market may fail to recognize all relevant characteristics of analysts that can explain their forecasting ability. If this is the case then it would subsequently lead to the market under-reacting to the improved forecasts of the superior analyst, and over-reacting to inferior analyst forecasts. Conditional on the second hypothesis being true, and assuming the market can determine the relevant features that makes an analyst's forecast accurate, we express our second hypothesis as:

Hypothesis 2. *Given an increase in the number of peer analysts after a brokerage M&A, the equity market will show a stronger reaction to superior analysts' forecasts.*

3. Data and methodology

3.1. Data

We collect data on broker M&As between 2005 and 2016 from the SDC Mergers and Acquisition database. This implies our sample period is post-Global Settlement to avoid any changes to analysts' forecast accuracy this may cause.[1] 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 6211 (including investment banks and brokerage firms) or 6282 (including independent research firms). We also require that the acquirers belong to the three two-digit SIC codes including 60 (commercial banks), 62 (securities firms), and 63 (insurance companies). In addition, we only examine completed M&As of which the targets are 100% owned by the acquirers after the transaction. This is to make sure that the two counterparty firms entirely merge into one entity after the M&As.

We then proceed to 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 make sure 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 our final sample containing 837 analysts with 6999 forecasts from 21 M&As.

Panel A of Table 1 provides the distribution of M&As based on the acquirers' and targets' SIC codes. For most of the M&As (19 deals), the targets' SIC code is 6211 (investment banks or brokerage firms), while only 2 deals have the targets' SIC code of 6282 (independent research firms). Most acquirers in our sample have the SIC code of 62 (securities firm) and only two of them belong to the SIC code of 60 (commercial banks). Panel B shows how M&As affect the working environment, particularly the colleagues an analyst works with. We find that the number of peers generally rises as the merged firms tend to have more analysts employed than either the target or acquirer firms. However, most M&As do lead to substantive changes in the analyst cohort. There are, for example, nearly as many departing analysts (an average of 39) as there are retained analysts (an average of 47) after an M&A.

To ensure that we can treat the M&As as being independent of the decision of firms to retain (remove) superior (inferior) analysts, Panel A of Table 2 examines whether the decision to retain analysts in the newly merged firms are associated with analysts' forecasting performance. The number of superior analysts, as a proportion of the total number of analysts that are retained or depart is approximately the same (8.8% and 7.8%, respectively). Likewise, this is also true of inferior analysts (4.9% and 5.8%, respectively). Similarly, Panel B reveals that the change in the number of peers is not associated with analysts' forecasting performance. We document no significant difference between the proportions of superior/inferior analysts among those who see an increase versus those experiencing a decrease in the number of peers.

Table 1
Final M&A sample description.

Panel A: Distribution of final M&A sample by acquirers' and targets' SIC codes

Acquirers' two-digit SIC codes	Number of deals	Targets' four-digit SIC codes	Number of deals
60	2	6211	19
62	19	6282	2
63	0		
Total	21	Total	21

Panel B: Descriptive statistics for M&As included in the final sample

	N	Mean	Median	StDev	Min	Max
Number of employed analysts						
Target	481	22.9	11	30.0	1	129
Acquirer	1280	64.0	28	80.8	2	278
Merged firm	1491	74.6	55	80.1	4	276
Employment structure of the merged firms after M&As						
Retained analysts	935	46.8	37	50.7	1	174
Departing analysts	826	39.3	23	45.2	2	174
New analysts	556	27.8	15	31.7	2	104
Number of stocks covered						
Target	4605	242.4	129	252.7	7	947
Acquirer	10,758	566.2	330	506.2	12	1501
Overlap	1542	81.2	37	145.3	0	617
Merged firm	12,551	660.6	675	481.0	36	1525

This table presents the description of the final M&A sample. Panel A shows the distribution of M&As included in the sample by the acquirers' and targets' SIC codes. Panel B presents the descriptive statistics of M&As included in the final sample regarding the number of employed analysts, employment structure of the merged firms after M&As, and the summary of stocks involved in the M&As.

Table 2
Changes occurring after the M&As and analysts' forecasting performance.

Panel A: The decision of firms to retain analysts after the M&As and analysts' forecasting performance

	Retained	Depart	Difference	p-value of test for diff. in means
% of analysts as Superior	8.80	7.84	0.96	0.47
% of analysts as Inferior	4.94	5.76	−0.82	0.44

Panel B: Changes to the number of peers after the M&As and analysts' forecasting performance

	Increase in no. of peers	Decrease in no. of peers	Difference	p-value of test for diff. in means
% of analysts as Superior	7.94	8.67	−0.73	0.73
% of analysts as Inferior	5.46	4.33	1.13	0.50

The table shows how the changes caused by broker M&As are not associated with analysts' ability. We test for the difference in the *ex-ante* forecasting performance of analysts who are retained and who depart from the merged firms (Panel A), of those who see an increase versus a decrease in the number of peers (Panel B).

[1] Global Settlement requires the physical and operational separation between the investment banking and research departments of brokerage firms to mitigate the potential of biased forecasts for a brokerage's investment bank customers.

3.2. Research design

Our dependent variable is the EPS forecast error for stock *i* issued by analyst *j* in year *t* (FE_{ijt}), which is measured as the absolute difference between analyst *j*'s EPS forecast for stock *i* in year *t* and stock *i*'s actual EPS in the same year, divided by the actual EPS.

$$FE_{ijt} = \left| \frac{Forecast_j(EPS_{it}) - EPS_{it}}{EPS_{it}} \right| \tag{1}$$

Hwang et al. (2019) posit that analysts within the same brokerage firm following the same sector are more interdependent than those tracking different sectors. Therefore, we employ our measure of the peer effect, $Peer_{it}$, as the number of analysts in the same brokerage firm who track stocks having the same two-digit SIC code as stock *i* in year *t*.

We classify superior and inferior analysts using two 'ability' dummies. These are $Superior_{ij}$, which is equal to one if analyst *j* tracking stock *i* in year *t* is consistently ranked within the top 30% of other analysts that undergo the same M&A for the duration of two years before the M&A, and zero otherwise; and $Inferior_{ij}$, which is equal to one if analyst *j* is consistently ranked within the bottom 30% during the same period, and zero otherwise. We use this classification schema to ensure we can compare the performance of analysts relative to their peers within the brokerage firm and, importantly, how consistent they are in being superior/inferior (i.e., over a two year period). The reason for adopting a cut-off percentile of 30% is so that the percentage of superior and inferior analysts in our sample, who are consistently ranked in the top/bottom 30% in two consecutive years, matches closely with the percentage of All-Star analysts in the whole industry, which is around 11% (Hwang et al., 2019).

We also include in our regressions seven control variables. First, $Coverage_{it}$, is the number of analysts in the whole industry following stock *i* in year *t*, which measures the competition among analysts covering the same stock. Second, $Size_{kt}$ is the firm size of brokerage firm *k* in year *t*, measured by the number of analysts employed by the firm. This accounts for the resources offered by brokerage firms. Third, $New\ Analyst_{kt}$ is the proportion of newly recruited analysts to the total number of analysts employed by brokerage firm *k* in year *t*. This controls for the effect on the forecast accuracy of incumbent analysts caused by the recruitment of new analysts who are not yet familiar with the working procedure of the firm.

The last four control variables account for the complexity of the analysts' tracking portfolio. This includes $Workload_{jt}$ as the number of stocks followed by analyst *j* in year *t*. We also include $Spec_{jt}$ as the number of industries classified by two-digit SIC codes analyst *j* followed in year *t*. $New\ Stock_{jkt}$ is the proportion of new stocks in the tracking portfolio assigned to analyst *i* employed by brokerage firm *k* in year *t*. Finally, $SP500_{jkt}$, is the proportion of stocks that belong to the S&P500 in the tracking portfolio assigned to analyst *i* employed by brokerage firm *k* in year *t*.

As there can be a number of confounding factors that can affect both the peer effect and analysts' ability (Alford & Berger, 1999), we adopt a Difference-in-Differences (DiD) regression approach which involves estimating DiD for stock *i*, issued by analyst *j*, from brokerage firm *k*. This is done by contrasting the change in the observed forecasts (pre and post M&A) from a treatment sample of analysts (*T*) that experience an M&A, with the changes observed from a control sample of forecasts (*C*) from analysts that do not experience the M&A:

$$DiD_{ijk} = \left(T_{post-M\&A} - T_{pre-M\&A}\right) - \left(C_{post-M\&A} - C_{pre-M\&A}\right) \tag{2}$$

The DiD approach allows us to difference away the fixed effects associated with the analysts, stocks, brokerage firms and years of the forecasts, leaving the change in the number of peers due to M&As as the only primary factor that can affect analyst forecast accuracy. To enable this, we start by focusing on forecasts that surround the event window to form our initial treatment sample. We take our lead from Hong and Kacperczyk (2010) and study a two-year window around the M&A dates. However, we only utilize forecasts that are issued on the closest date to a cooling-off period of six months directly before and after the event to avoid any changes to analyst performance caused by M&A news and the instability of the firm's employment structure. We also only look at forecasts for stocks that appear in the retained analysts' portfolio both before and after an M&A to be able to observe the change in forecast accuracy across the M&A. This results in a treatment group of 6999 forecasts before and after the M&As.

We then proceed, using the pre-M&A period, to pair our treatment group forecasts with forecasts from our control group. We use 6 criteria to match each pair. The first three (brokerage size ranking, stock firm size ranking, and forecast timeliness) are forced / hard matches. This implies that each treatment and control must match each of these factors within a set range. For the forced matches, we first require that the matched treatment and control analysts work for brokerage firms within the same quartile ranking of firm size. We also require that stocks being forecasted by the matched analysts are similar in size (by quartile). These matches ensure that the matched analysts receive similar resources from their employers and issue forecasts for stocks with a similar level of complexity (Clement, 1999Hong & Kacperczyk, 2010). The third forced match requires that the control forecast is issued within 30 days around the date of the treatment forecast to avoid any time effect on forecast accuracy (Shroff, Venkataraman, & Xin, 2014). The reason for this is to strictly ensure we are comparing forecasts are within the same period and from similar resourced brokers so we can be confident that we are comparing like-for-like forecasts.

On top of this we then use PSM to generate propensity scores for three other variables that are also important, but we do not require hard matches.[2] The first two covariates are the number of stocks followed by an analyst and the analyst's years of experience within the brokerage industry. This is to ensure the matched forecasts are issued by analysts with comparable workload and forecasting ability, which are proven to be the key factors that affect analyst performance (Clement, 1999). The third covariate is the analyst coverage of the stocks, which allows matching forecasts for stocks with similar information environments (Lys & Soo, 1995; Hong & Kacperczyk, 2010).

Altogether, this procedure results in 6336 pairs of matched observations. This means we can retain most of the initial sample (6999 observations) while ensuring the comparability of our matched samples.

Our regression model utilizing DiD estimations to explain the variation in the changes of analysts' forecast accuracy in our treatment group in response to changes in the peer effect is:

$$\begin{aligned} DiD.FE_{ij} = & \alpha + \beta_1 \times DiD.Peer_i + \beta_2 \times DiD.Peer_{ijk} \times Superior_{ij} \\ & + \beta_3 \times DiD.Peer_i \times Inferior_{ij} + \gamma' \times X_{ijk} + \varepsilon_{ij} \end{aligned} \tag{3}$$

To test our two hypotheses, the dependent variable, $DiD.FE_{ij}$, is regressed against the DiD estimation of $Peer_i$, plus its interaction with the two ability dummy variables. The DiD estimations of our six control variables, M&A deal fixed effects, year fixed effects, stock fixed effects and broker fixed effects are incorporated into the vector X_{ijk}.[3] The coefficient for $DiD.Peer_i$ indicates the peer effect on the performance of all analysts, whilst the coefficients for $DiD.Peer_i \times Superior_{ij}$ and $DiD.Peer_i \times Inferior_{ij}$ indicates whether there is a heterogeneous impact of the change in the number of peers on the performance of analysts with different levels of ability.

[2] We use a caliper of 0.1 in our matching procedure to avoid losing a large number of observations. However, our results remain qualitatively the same if we reduce the caliper by tenfold to 0.01.

[3] We do not control for the 'ability' dummies as these time-invariant variables will be differenced away due to the DiD approach.

4. Main results and discussion

4.1. PSM and DiD summary statistics

Panel A of Table 3 presents the descriptive statistics for the variables used in the PSM procedure. Indicative that the propensity score matching was successful, we find that the *p*-values for the difference in mean tests for each covariate between the treatment and control groups are insignificant. It is also worth highlighting that these two samples are also statistically comparable in terms of analysts' forecast errors for the three year period prior to the M&As. This implies that the matching process has produced two sets of comparable forecasts with only one primary difference – analysts who contribute to the forecasts in the treatment group will undergo an M&A, while analysts in the control group will not.

Panel B of Table 3 reports the summary statistics for the DiD estimations of our main variables. The mean and median values for the DiD estimation of forecast errors ($DiD.FE_{ij}$) are 0.65% and 0.46%, respectively. This indicates, relative to the control sample, the forecast errors in the treatment sample increase slightly after the M&As. The M&As also lead to a large variation in our peer effect measure. While the median value for $DiD.Peer_i$ suggests that there has been a slight rise in peer analysts (by one analyst), a quarter of the treatment forecasts are provided by analysts that see a rise in at least four peers and a quarter experience a decline of at least one peer.

4.2. The peer effect on analysts' forecast accuracy

In Panel A of Table 4, we report univariate tests to examine whether the change in forecast errors between those analysts who experience a rise in the number of peers is different to those who experience a decline. We find that only superior analysts can significantly benefit from an increase in the number of peer analysts. Specifically, superior analysts who experience an increase in the number of peers see an improvement of 17.78% in their forecast accuracy compared to those who see a reduction.

To confirm the results of our univariate test, in Panel B of Table 4, we report the multivariate results for the test of the impact of a change in the number of peers following broker M&As on analysts' performance. Regression (1) shows the basic relationship that a change in the number of peer analysts within the firm ($DiD.Peer_i$) has on the forecast accuracy of incumbent analysts ($DiD.FE_{ij}$). In Regression (2) and (3), we add the interaction terms of $DiD.Peer_i$ with our 'ability' dummy variables $Superior_{ij}$ and $Inferior_{ij}$ to the model, respectively, to examine the peer effect on analysts with different abilities. In Regression (4), we include both interactions in the model.

The results from Regressions (1) show that, on average, a change in the number of peers do not have a significant impact on analysts who undergo an M&A. However, in Regressions (2) to (5), we find that superior analysts can benefit from an increase in the number of peer analysts in the team. Specifically, the results in Regression (5) show that the coefficient for $DiD.Peer_i \times Superior_{ij}$ is -2.2919, significant at the 5% level (i.e., for every peer joining the team, the forecast accuracy of superior analysts improves by 2.29). When considering that analysts in our treatment sample see an average increase of five peers after the mergers, these results imply an improvement of almost 11.5% in the accuracy of superior analyst forecasts. We, however, find that inferior analysts show no significant improvement when there is an increase in the number of peers they work with following a brokerage M&A.

The results in Table 4 support our first hypothesis by showing that superior analysts tend to benefit the most from the peer effect, which is in line with the findings by Hwang et al. (2019) who show that star analysts are more likely to benefit from sharing information with their peers. We can therefore conclude that the peer effect among financial analysts is mostly driven by the benefit that superior analysts receive from their coworkers.

In this paper, we classify superior/inferior analysts as those who are consistently ranked within the top 30% of other analysts, that undergo the same M&A, for two consecutive years before the M&A. We use this classification schema to ensure we can compare the performance of analysts relative to their peers within the brokerage firm and, importantly, how consistent they are in being superior/inferior (i.e., over a two-year period). This results in the proportion of superior/inferior analysts being around 8% of our sample. This matches closely with the percentage of superior analysts in the whole industry as indicated in Hwang et al. (2019), which is around 11%.

We also perform a sensitivity analysis by adjusting the cutoff point of 30% and report the regression results in Appendix II. First, by tightening the classification using a cutoff of 20%, we find that the proportion of superior/inferior analysts reduces to around 3% of our sample. In this case, our findings remain unchanged as we still find that only superior analysts can benefit from an increase in the number of peers (Regression 1). However, when we change the cutoff to 40%, we find no significant benefit of the peer effect on the new group of superior analysts (Regression 2). This result is reasonable since this new group of superior analysts accounts for more than 14% of our sample and it no longer captures those who are truly "superior". Altogether, these results further strengthen our conclusion that only analysts with distinctly superior performance can benefit from the peer effect.

4.3. Market reaction to analyst forecasts following a change in the number of peers

To measure the market reaction of analyst forecasts, we use the absolute value of the two-day cumulative market-adjusted daily returns, CAR_{ijt}. It is the absolute value of the sum of the abnormal returns of stock *i* from the day of, to the day after, the analyst forecast date of stock *i* for forecast period *t*. To calculate abnormal returns, we follow Clement and Tse (2003) and Truong (2011) in subtracting the buy-and-hold value-weighted market returns (i.e. SP500 index) from the buy-and-hold returns of stock *i*.[4] Therefore, CAR_{ijt} can be expressed as:

$$CAR_{ijt} = |(Stock\,return_{it0} - Market\,return_{t0}) + (Stock\,return_{it1} - Market\,return_{t1})| \tag{4}$$

With the DiD estimation of CAR_{ij} being the dependent variable, we run regressions using Eq. (3) to determine if the market can tell the different impact that superior and inferior analysts have when they experience a change in the number of peers. We focus on the first forecast an analyst makes after an annual earnings announcement for a stock in the year of the M&A, and a year after the M&A. This is to avoid any effect that timeliness has on the price impact of the forecasts (Clement & Tse, 2003). To create a control group, we use an identical process to our previous PSM methodology, except that our selection of covariates are different.[5] The first covariate we employ is the past forecast errors of analysts to ensure that the matched forecasts have similar levels of accuracy and therefore should receive similar market reactions. The second covariate is the number of analysts following the stock as Gleason and Lee (2003) argue that the market reacts more strongly to forecasts for stocks with greater analyst coverage.

Table 5 presents the test for the market reaction to analysts' forecasts when there is a change in the number of peers. The results reveal that none of the coefficients for the interaction terms of $DiD.Peer_i$ with the two 'ability' dummy variables are significant. This result does not support our second hypothesis, which predicts that the market will adjust their reaction to superior analysts' forecasts upward when there is an increase in the number of peers they work with following a brokerage M&A. In contrast, this result lends support to Clement and Tse's (2003) view that the market cannot necessarily recognize all the characteristics

[4] Stock returns and S&P500 returns are obtained from the CRSP database.

[5] Our results also hold if we use the original set of covariates.

Table 3
Summary statistics for the variables of interest.

Panel A: Descriptive statistics for the variables used for the Propensity Score Match for forecast accuracy

Variables	Unit	Treatment sample			Control sample			p-value diff. in means test
		Mean	Median	StDev	Mean	Median	*StDev*	
Broker Rank	Quartile	1.02	1	0.15	1.02	1	0.15	1.00
Coverage	Analyst	17.46	15	11.03	17.53	15	10.67	0.71
Exper	Year	13.51	14	8.07	13.51	14	8.01	0.97
FE (t-1)	%	35.27	6.58	212.38	42.61	7.63	308.90	0.11
FE (t-2)	%	31.59	6.70	183.44	32.97	6.77	127.05	0.71
FE (t-3)	%	33.34	6.15	150.89	30.40	6.32	164.17	0.52
Stock Rank	Quartile	1.49	1	1.10	1.49	1	1.10	1.00
Workload	Stock	16.84	17	7.22	16.96	17	6.48	0.33

Panel B: Summary statistics for the Difference-in-Differences estimations of the variables of interest

Variables	Unit	Mean	P_{25}	Median	P_{75}	StDev
DiD.Coverage	Analyst	−0.07	−3	0	3	5.29
DiD.FE	%	0.65	−17.15	0.46	20.11	118.20
DiD.New Analyst	%	18.64	6.00	16.40	27.52	20.18
DiD.New Stock	%	1.25	−15.48	0.99	22.29	43.49
DiD.Peer	Analyst	−0.86	−1	1	4	14.75
DiD.Size	Analyst	15.33	−6	9	36	29.48
DiD.SP500	%	−1.24	−7.36	0.00	5.71	19.45
DiD.Spec	Industry	0.05	−1	0	1	1.51
DiD.Workload	Stock	−0.09	−3	0	3	5.65

This table presents the summary statistics of the variables of interest. Appendix I provides a detailed description of the variables. Panel A shows the descriptive statistics for the covariates employed for the PSM process. The reported values are associated with the treatment and control forecasts during the pre-M&A period. Panel B is the summary statistics for the DiD estimations of our variables of interest.

Table 4
The impact of a change in the number of peers on analysts' forecast accuracy.

Panel A: Univariate test for the impact of peers on analyst's forecast accuracy

		(1) Mean *DiD.FE* if the number of peers increases	(2) Mean *DiD.FE* if the number of peers decreases	(3) Difference in *DiD.FE*
DiD.Peer	***All analysts***	0.80	−3.15	3.95
	Superior	−1.61	16.16**	−17.78**
	Inferior	−15.27	5.58	−20.85

Panel B: Regression results for the impact of peers on analyst's forecast accuracy

Regression:	(1)	(2)	(3)	(4)	(5)
Dependent:	*DID.FE*	*DID.FE*	*DID.FE*	*DID.FE*	*DID.FE*
DID.Peer	0.1581	0.2062	0.1899	0.2728	0.2402
	(0.2279)	(0.2295)	(0.2321)	(0.2333)	(0.2339)
DID.Peer × Superior		−2.2580**		−2.3320**	−2.2919**
		(0.9897)		(0.9887)	(0.9906)
DID.Peer × Inferior			−0.6659	−0.6458	−0.7088
			(0.7088)	(0.7085)	(0.7049)
DiD.Coverage	−1.0268***	−1.0147***	−1.0438***		−1.0220***
	(0.3756)	(0.3759)	(0.3759)		(0.3762)
DID.Size	0.2846	0.2756	0.2884		0.2796
	(0.1792)	(0.1794)	(0.1792)		(0.1794)
DiD.New Analyst	0.4088**	0.4088**	0.4041*		0.4083**
	(0.2071)	(0.2069)	(0.2071)		(0.2070)
DID.Workload	−0.2251	−0.1904	−0.2250		−0.1870
	(0.3766)	(0.3776)	(0.3767)		(0.3777)
DiD.Spec	0.1133	0.0949	0.1307		0.1091
	(1.4957)	(1.4918)	(1.4962)		(1.4920)
DiD.New Stock	0.0374	0.0393	0.0374		0.0395
	(0.0525)	(0.0526)	(0.0525)		(0.0526)
DiD.SP500	0.1023	0.1109	0.1034		0.1117
	(0.0963)	(0.0967)	(0.0963)		(0.0967)
Observations	6336	6336	6336	6336	6336
Robust	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	No	Yes
Deal FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes	Yes	Yes

This table presents test results for the impact of a change in the number of peers on analyst's forecast accuracy. Panel A reports the univariate tests for the impact of each variable of interest on the DiD estimation of forecast accuracy for all analysts, superior analysts, and inferior analysts in the treatment sample. The panel reports the mean DiD of forecast errors (*DiD.FE*) when the analysts experience an increase or a decrease in the number of peers (Columns 1 and 2); then the difference between the two means (Column 3). Panel B presents the regression results utilizing Eq. (3), with the use of the DiD estimations of the variables. Appendix I provides a detailed description of the variables. Robust standard errors are reported in parentheses. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Table 5
Market reaction to changes in the number of peer analysts following a brokerage M&A.

Regression	(1)	(2)	(3)	(4)
Dependent	*DiD.CAR*	*DiD.CAR*	*DiD.CAR*	*DiD.CAR*
DiD.Peer	−0.0066	−0.0075	−0.0067	−0.0075
	(0.0068)	(0.0069)	(0.0068)	(0.0069)
DiD.Peer × Superior		0.0199		0.0200
		(0.0291)		(0.0291)
DiD.Peer × Inferior			0.0016	0.0023
			(0.0364)	(0.0364)
Robust	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes	Yes
Observations	6001	6001	6001	6001

This table shows market reactions to analysts' forecasts given a change in the number of peer analysts. The regressions utilize Eq. (3), with the use of the DiD estimations of the variables. Appendix I provides a detailed description of the variables. Robust standard errors are reported in parentheses. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

of analysts that would explain their forecast accuracy. In our case, we find no evidence that the market recognizes it is the superior analysts that benefit, in terms of their forecasting ability, from an increase in peer numbers.

To examine whether there is a monetary benefit from differentiating the impact that a change in peer numbers has on forecasting ability between inferior and superior analysts, we construct investment portfolios based on the buy-sell recommendations of superior and inferior analysts in our treatment sample for the stocks where EPS forecasts exist. We buy the stocks if the recommendation is 'buy' or 'strong buy', and sell if it is 'underperform' or 'sell'. We then estimate the mean market-adjusted return of each portfolio as the average one-year return of all the trades adjusted for the one-year return on the S&P 500.

The results, reported in Table 6, show that before an M&A the portfolio of superior analysts outperform the inferior analysts' portfolio by an annualized return of 19%. This difference, however, is only significant at the 10% level when we conduct a one-tail *t*-test. The reason for this is likely partially because of sample size has been reduced to a fifth of what it previously was due to the fact that only 20% of analyst forecasts are accompanied by a buy/sell recommendation. From the table, we notice that when analysts are faced with an increase in the number of peers proceeding the M&As, the difference between the two portfolios' returns increases to 34% and becomes significant at the 5% level. This is due to the returns from the superior analysts' portfolio improving more than the inferior analysts' portfolio. These results provide additional support to our main finding as it implies that superior analysts' recommendations improve the most when the number of peers increases. This, combined with the results in Panel A, suggests that investors can capitalize on the market underreaction to superior analysts' forecasts when they experience an increase in the number of peers after the merger of their brokerage firms.

5. Robustness tests

We now examine whether our main findings are driven by different characteristics related to the M&As. First, according to Szücs (2014), M&A events can have an asymmetric impact on the target and acquirer firms. We thus expect that the peer effect on analyst performance after a broker M&A may not be the same for analysts from different sides of the M&A. To test for this, we employ a dummy variable, *Acquirer*, which equals 1 if the focal analyst is from the acquirer firm, and zero if the analyst is from the target firm. We add *Acquirer* to our model (Eq. (3)), together with its interaction with *DiD.Peer*, and its three-way interactions with *DiD.Peer* and the two 'ability' dummies. We rerun the regression and report the results in Regression 1 of Table 7. We find that the coefficient for the interactions *DiD.Peer*×*Superior*, *DiD.Peer*×*Inferior*, and the three-way interaction *DiD.Peer*×*Inferior*×*Acquirer* are all insignificant. Instead, we find that the coefficient for *DiD.Peer*×*Superior*×*Acquirer* is −4.2719, significant at the 5% level. This indicates that the benefit of having more peers is primarily observable for analysts from the acquirer firm. This result can be partly explained by the fact that target analysts account for less than 15% of our sample and therefore likely to be impacted from the M&A in having to become familiar with a new workplace environment that the acquiring firm adopts. Huckman and Pisano (2006) find that this can affect performance.

We also consider that our sample includes M&As during the Global Financial Crisis (GFC), which can affect analyst forecasting behavior (Durand, Limkriangkrai, & Fung, 2014) and possibly bias our main results. To control for this, we utilize a dummy variable, *GFC*, which equals 1 if the focal analyst undergoes an M&A during the GFC period (i.e., from the third quarter of 2007 to the end of 2010), and zero otherwise. We then add *GFC* to our model (Eq. (3)), together with its interaction with *DiD.Peer*, and its three-way interactions with *DiD.Peer* and the two 'ability' dummies. The results from rerunning the regression are reported in Regression 2 of Table 7. We find that only the coefficient for *DiD.Peer*×*Superior* is significantly different from zero, whereas none of the coefficients for the three-way interactions is significant. This finding confirms that the peer effect on analyst performance following an M&A is not driven by the GFC.

Given there is a large variation of analyst forecast errors among our treatment sample (see Table 3), it is possible that our results are driven by outliers. We notice that our sample contains forecasts of stocks with stock prices lower than $10, of which the forecast errors tend to be higher than the forecast errors of stocks with a higher price (the mean and median of forecast errors are 62.31% and 19.23% for low-priced stocks compared to 31.74% and 5.81% of stocks with higher prices). Hence, to address the potential problem of outliers unduly influencing our results, we choose to drop forecasts for stocks having prices below

Table 6
The benefit of being aware of the heterogeneous peer effects on analyst's forecast accuracy.

		(1) Mean market-adjusted return of superior analysts' portfolio (%)	(2) Mean market-adjusted return of inferior analysts' portfolio (%)	(3) Difference in mean returns (%)
Pre-M&A		4.20	−14.89	19.09
Post-M&A	Peer increase	14.77	−19.22	33.99**
	Peer decrease	−5.26	−8.46	3.19

This table reports the returns on the stock portfolios constructed based on the recommendation of superior and inferior analysts both before and after the M&A. Columns (1) and (2) report the mean market-adjusted one year returns on superior and inferior analysts' portfolios, respectively. Column (3) shows the difference in mean returns. Appendix I provides a detailed description of the variables. Robust standard errors are reported in parentheses. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

Table 7
M&A characteristics and the impact of peers on analyst forecast accuracy.

Regression:	(1)	(2)
Dependent:	*DiD.FE*	*DiD.FE*
DiD.Peer	−0.0796	0.1543
	(0.4667)	(0.2484)
DiD.Peer × Superior	0.9825	−2.8822**
	(1.7539)	(1.3356)
DiD.Peer × Inferior	−1.6340	−0.3848
	(2.3077)	(0.6633)
Acquirer	27.2981	
	(19.6587)	
DiD.Peer × Acquirer	0.4824	
	(0.6283)	
DiD.Peer × Superior × Acquirer	−4.2719**	
	(2.1484)	
DiD.Peer × Inferior × Acquirer	1.0794	
	(2.3993)	
GFC		2.5859
		(15.6378)
DiD.Peer × GFC		0.8246
		(2.1431)
DiD.Peer × Superior × GFC		0.4910
		(0.6198)
DiD.Peer × Inferior × GFC		−1.5939
		(2.3614)
Robust	Yes	Yes
Control	Yes	Yes
Deal FE	Yes	Yes
Year FE	Yes	Yes
Stock FE	Yes	Yes
Broker FE	Yes	Yes
Observations	6336	6336

This table presents regression results utilizing Eq. (3) for the impact of a change in the number of peers on analyst's forecast accuracy with the consideration of two M&A characteristics. Column (1) reports the results when we consider the peer impact on analysts from the acquirer or the target firms. Column (2) reports the results when we consider the peer impact during or out of the GFC period. Appendix I provides a detailed description of the variables. Robust standard errors are reported in parentheses. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

$10 from the treatment sample (733 observations) and re-run the regressions. The results, reported in Regression (1) in Table 8, are consistent with our main findings that the peer effect tends to have the strongest positive impact on superior analysts. Specifically, the results in Regression (1) suggest that with an increase in the number of peers, superior analysts' forecast accuracy improves significantly, whereas the peer effect on inferior analysts is insignificant.

Another approach to address the outlier problem is to exclude forecasts for stocks with low coverage from the sample. We find that the forecast errors for stocks followed by less than three analysts are higher than the forecast errors for stocks with more analysts following (the mean and median of forecast errors are 59.42% and 13.16% for low coverage stocks compared to 34.33% and 6.38% for high coverage stocks). This can be explained by the instability in the information environment surrounding those stocks with low coverage. We proceed to exclude forecasts for stocks with less than three analysts following (236 observations) and re-run our regressions. We report the results in Regression (2) in Table 8 and it also supports our main findings by showing that superior analysts see the strongest improvement in their forecast accuracy in response to an increase in the number of peers.

We next consider whether a sudden change in forecasting resources following an M&A could affect our results. We posit that analysts going through an M&A may experience a large change in forecasting resources provided by the brokerage firm, especially those who work for a small firm before the M&A, and then are taken over by a much larger firm. This potentially creates a shock to their working environment and consequently affects their forecasting performance. To make sure that this issue does not affect our results, we re-run the regressions with a

Table 8
Robustness tests for the heterogeneous impact of a change in peer effect on forecast errors.

Regression:	(1)	(2)	(3)	(4)
Dependent:	*DiD.FE*	*DiD.FE*	*DiD.FE*	*DiD.FE*
Sub-sample:	Sub-sample (I)	Sub-sample (II)	Sub-sample (III)	Sub-sample (IV)
DiD.Peer	0.0514	0.3592	0.2343	0.3573
	(0.2267)	(0.2246)	(0.2443)	(0.2953)
DiD.Peer × Superior	−2.5467**	−2.2580**	−2.2001**	−2.3359**
	(0.9973)	(0.9793)	(1.0029)	(1.1547)
DiD.Peer × Inferior	0.2940	−0.6943	−0.6834	−1.3934
	(0.7040)	(0.7266)	(0.7211)	(0.9017)
Robust	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes	Yes
Observations	5603	6100	5573	4584

This Table reports the results for the robustness tests to confirm that a change in the number of peers has different impacts on the forecast accuracy of superior and inferior analysts. The regressions utilized Eq. (3) with the use of the DiD estimations of the variables. Appendix I provides a detailed description of the variables. Robust standard errors are reported in parentheses. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively. The regressions in each panel utilize the following sub-samples, respectively.

- Sub-sample (I) excludes forecasts for low price stocks from our final sample. We define low price stocks as those having prices below $10.
- Sub-sample (II) excludes forecasts for stocks with low coverage from our final sample. We define stocks with low coverage as those followed by less than 3 analysts.
- Sub-sample (III) only includes forecasts issued by analysts working for a brokerage firm that belongs to the top 10% of largest firms in the brokerage industry before the M&A.
- Sub-sample (IV) excludes forecasts issued by analysts who belong to the top 25% of analysts with the highest workload (following more than or equal to 21 stocks).

subsample of forecasts issued by analysts who already work for a large brokerage firm (belong to the top 10% of largest firms) before the M&As and, thus, should not experience a shock in forecasting resources after the M&As. The results, shown in Regression (3) in Table 8, are consistent with our main results. This indicates our main findings are not affected by the sudden change in forecasting resources that analysts may experience after an M&A.

Finally, we consider whether our results might be biased due to the behavior of a small group of analysts. Nine percent of analysts in the treatment sample track large portfolios of more than 21 stocks (belonging to the top quartile of our treatment observations having the highest workload). Their forecasts for different stocks can appear many times in our analysis. This gives rise to the concern that the responses of these few analysts to a change in the number of peers may drive our results. To address this issue, we exclude all forecasts issued by analysts following more than 21 stocks (1459 observations) and re-run the regressions. Again, the results, reported in Regression (4) of Table 8, are similar to our main results.

6. Implications and conclusion

In this paper, we examine the variation in the reactions that financial analysts with different forecasting ability display when faced with a change in the number of peers they work with following an M&A of their brokerage firms. We find evidence that superior analysts respond more positively to an increase in the number of peer analysts and this benefit is only observable for analysts from the acquiring firm. We also confirm that our results are not driven by the GFC period or outliers in our data as well as any possible change in the forecasting resources an analyst has at their disposal following an M&A.

We add to the literature that examine brokerage M&As by showing how the survivors of brokerage M&As see a change in their performance due to the restructure of the colleagues they work with in the merged entity. In particular, we show that there are significant differences between analysts in how a change in the number of peers they work with after an M&A improves their performance, which is mostly driven by the positive reaction of superior analysts to this peer effect. Our study, therefore, provides practical implications for human resource management of brokerage firms after M&As to further enhance the performance of their retained employees. Specifically, while a merged entity can simply enhance superior analysts' performance through increasing the number of peers that work in the firm after an M&A, it needs to think of another solution to support inferior analysts. This can be a worthwhile avenue for future study.

We also contribute to the debate on the efficiency of the capital markets by showing evidence that the market sometimes fails to recognize all the characteristics of analysts which can affect their forecasting performance. This finding lends support to Clement and Tse (2003), but contrasts to the views of Stickel (1992), Park and Stice (2000), and Gleason and Lee (2003) who argue that the market can recognize forecasts that are more accurate and react accordingly. Our study shows that the market fails to recognize the difference between superior and inferior analysts when considering the benefit from a change in peer numbers on analyst forecasting performance following an M&A. This leads to an opportunity for investors to capitalize on the market underreaction to superior analysts' forecasts. Specifically, a profitable trading strategy may be to go long a portfolio recommended by superior analysts and simultaneously short a portfolio by inferior analysts when there is an increase in the number of peers they are working with.

Last but not least, our study provides a good setting to examine the performance of individuals following an M&A. While most of the previous studies in this field focuses on the impact M&As have on productivity at the firm level (Cummins & Xie, 2008Harrison et al., 1991Hoskisson et al., 1994Weber, 1996), we examine the impact that an M&A has on individual performance. To our knowledge, Siegel and Simons (2010) is the only study that investigates the impact that M&As have on individual worker performance, measured by worker earnings. We, however, examine a sample of financial analyst forecasts, which allows us to objectively measure individual performance by comparing analyst forecasts against actual earnings per share (EPS). This research design, therefore, offers an interesting and efficient setting for future research that investigates the impact of special firm events on individual performance.

CRediT authorship contribution statement

Lan Thi Mai Nguyen: Conceptualization; Data curation; Formal analysis; Writing - original draft. Chee Seng Cheong: Investigation; Supervision; Writing - review and editing. Ralf Zurbruegg: Investigation; Supervision; Writing - review and editing

Declaration of Competing Interest

None.

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Appendix A. Variable definitions

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

Variable	Unit	Definition
Dependent variables		
CAR_{ijt}	%	The absolute value of the two-day cumulative market-adjusted daily returns from the day of, to the day after, the analyst forecast date for stock *i* for forecast period (year) *t*.
FE_{ijt}	%	The absolute difference between analyst *j*'s EPS forecast for stock *i* in year *t* and stock *i*'s actual EPS in the same year, divided by the actual EPS.
Classification variables		
$Acquire_{ij}$	NA	A dummy variable that is equal to one if analyst *j* tracking stock *i* is from the acquirer firm, and zero otherwise.
GFC_{it}	NA	A dummy variable that is equal to one if the forecast for stock *i* at time *t* is during the GFC period, and zero otherwise. * GFC period is defined as the period from September 2007 to the end of 2010.
$Inferior_{ij}$	NA	A dummy variable that is equal to one if analyst *j* tracking stock *i* is consistently ranked in the bottom 30% of the most accurate analysts across both firms involved in an M&A (or across the whole treatment sample) for two consecutive years before the M&A, and zero otherwise.
$Superior_{ij}$	NA	A dummy variable that is equal to one if analyst *j* tracking stock *i* is consistently ranked in the top 30% of the most accurate analysts across both firms involved in an M&A (or across the whole treatment sample) for two consecutive years before the M&A, and zero otherwise.
Control variables		
$Coverage_{it}$	Analyst	The number of analysts in the whole industry tracking stock *i* in year *t*.
$Exper_{jt}$	Year	The number of years analyst *j* works in the brokerage industry till year *t*.
$Logat_{it}$	NA	Natural logarithm of total assets value of stock *i* in year *t*
$New\ Analyst_{kt}$	%	The proportion of newly recruited analysts in the total number of analysts employed by brokerage firm *k* in year *t*.
$New\ Stock_{jkt}$	%	The proportion of new stocks in the tracking portfolio assigned to analyst *i* employed by brokerage firm *k* in year *t*.
$Peer_{it}$	Analyst	The number of analysts working in the same brokerage firm who track stocks belonging to the same two-digit SIC code as stock *i* in year *t*.
$Broker\ Rank_{kt}$	Quartile	The firm size quartile ranking, based on the number of analysts a firm employs, of brokerage firm *k* in year *t*. The first decile represents top 25% largest firms.
$Size_{kt}$	Analyst	The firm size of brokerage firm *k* in year *t*, measured by the number of analysts employed by the firm.
$SP500_{jkt}$	%	The proportion stocks belong to the S&P500 in the tracking portfolio assigned to analyst *i* employed by brokerage firm *k* in year *t*.
$Spec_{jt}$	Industry	The number of industries followed by analyst *j* in year *t*.
$Stock\ Rank_{it}$	Quartile	The firm size quartile ranking based on total assets value of stock *i* in year *t*. The first decile represents top 25% largest firms.
$Workload_{jt}$	Stock	The number of stocks followed by analyst *j* in year *t*.

Appendix B. Baseline regression results using different cutoff points to classify superior/inferior analysts

	(1)	(2)
Variables	*DID.FE*	*DID.FE*
DID.Peer	0.1832	0.2186
	(0.2274)	(0.2331)
DID.Peer×Superior20	−3.9679**	
	(1.7604)	
DID.Peer×Inferior20	−0.6688	
	(1.3451)	
DID.Peer×Superior40		−1.1960
		(1.2790)
DID.Peer×Inferior40		−0.2273
		(0.5095)
DiD.Coverage	−1.0225***	−1.0244***
	(0.3749)	(0.3765)
DID.Size	0.2832	0.2818
	(0.1793)	(0.1799)
DiD.New Analyst	0.3972*	0.4125**
	(0.2071)	(0.2071)
DID.Workload	−0.1885	−0.1995
	(0.3767)	(0.3778)
DiD.Spec	0.0737	0.0537
	(1.4930)	(1.4973)
DiD.New Stock	0.0384	0.0378
	(0.0525)	(0.0525)
DiD.SP500	0.1138	0.1027
	(0.0971)	(0.0963)
Observations	6336	6336
Robust	Yes	Yes
Control variables	Yes	Yes
Deal FE	Yes	Yes
Year FE	Yes	Yes
Stock FE	Yes	Yes
Broker FE	Yes	Yes

This table presents test results for the impact of a change in the number of peers on analyst's forecast accuracy, using Eq. (3), with different criteria to classify superior/inferior analyst. Regression (1) show the results when we define superior/inferior analysts as those who are consistently ranked within the top 20% of other analysts that undergo the same M&A for two consecutive years before the M&A. In Regression (2), we report the results when the cutoff point is changed to 40%. Appendix I provides a detailed description of the variables. Robust standard errors are reported in parentheses. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

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