Resources and workload: heterogeneous impact on analysts' performance

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Preliminary Draft: August 2017

ABSTRACT

We find the impacts resources and workload have on forecast accuracy are significantly different between superior and inferior analysts. Specifically, industry specific resources and workload tend to affect superior analysts significantly more relative to inferior analysts, whilst the latter are more likely affected by a change in generic resources and workload. Our findings imply that it is no longer informative to only study the aggregate effect of resources and/or workload on analysts' performance. It also suggests brokerage firms should consider offering different types of resources and having different workload policy to better enhance the forecasting performance for each group of analysts.

Keywords: analysts' resources, analysts' workload, forecast accuracy, broker M&As, limited attention

JEL Classification: G14, G24, J24, J44

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I. Introduction

Dating back to Clement (1999) and Jacob et al. (1999), brokerage firm size and workload have been examined as the key factors that affect analysts' forecasting performance. This is due to the fact that large brokers tend to provide better resources by offering analysts with more access to information, whereas less workload allows analysts to allocate more time to individual stocks. These subsequently lead to an improvement in analysts' forecast accuracy. These results, however, only show the aggregate impact of resources and workload on the performance of all analysts in general. What left unexamined is whether these two factors can have different impact on individual analysts in particular. On one hand, we can expect superior analysts can make better use of an increase in resources and/or a decrease in workload compared to their inferior colleagues, which in turns translates into their higher forecast accuracy. Alternatively, we can also attribute the higher forecast accuracy of superior analysts to their innate ability, in such case, a change in resources and workload should have less impact on the performance of superior analysts compared to inferior analysts. This study will fill this gap by examining the heterogeneous impact that resources and workload have on the forecast accuracy of superior versus inferior analysts.

There has been inconclusive literature on the impact of resources and workload on analysts' performance. Clement (1999) and Jacob (1999) find a positive link between information resources, proxied by brokerage firm size, and analysts' forecast accuracy. In addition, Jacob et al. (1999) also provide evidence that analyst forecast accuracy can improve if there are more analysts in the brokerage firm covering the same industry. This is because peer analysts within one firm following the same industry tend to work as a team and exchange industry-level information to enhance the accuracy of their forecasts (Hwang et al., 2016). On the other hand, there is also evidence that analysts are not efficient in processing all new information resources when they become available. For example, Plumlee (2003) find analysts choose to include the impact of tax-law changes into their forecasts only when the law change has less complex economics effects on the firm but not when it has more complex impacts. Similarly, Chang et al. (2016) show proof that analysts' forecasts for new derivatives user are less accurate after derivatives initiation.

In terms of analysts' workload, Clement (1999) and Jacob et al. (1999) show that the number of stocks and industries covered by an analyst is negatively associated with the analyst's forecast accuracy. On the contrary, Clement and Tse (2005) find a significantly positive relationship between these two workload measures and the accuracy of analysts' forecasts. A recent paper by Bradley et al. (2017), however, shows workload has no impact on analysts' forecast accuracy when they separately examine analysts with industry experience before they join the brokerage industry, or when they study the period after the Regulation Fair Disclosure[1].

We conjecture that the inconsistent findings in the literature can be due to the fact that the impacts resources and workload have on forecast accuracy are not the same for all analysts. Therefore, the findings can be driven by one group of analysts or the others, which subsequently results in conflicting conclusions.

We perform a test for our conjecture by employing broker M&As as natural experiments which create exogenous changes to the resources and workload of those analysts who are retained to work in the merged firms. We then examine how these changes affect the forecast accuracy of analysts and whether the impacts are the same for superior versus inferior

[1] This is a regulation that was promulgated by the US Securities and Exchange Commission in August 2000, which mandates that all publicly traded companies must disclose material information to all investors at the same time.

analysts. Our sample consists of 21 M&As, involving 837 analysts with 6,999 forecasts during the period between 2005 and 2015. These analysts all experience, to a greater or lesser degree, a change in the number of colleagues within the firm in general and those that track the same industry as they do in particular. In other words, their information resources are affected. Also, the number of firms and industries they follow will likely change. This allows us to examine how analysts manage with a change in their workload.

This research approach is a big improvement in mitigating the concern for a reverse causality relationship between resources/workload and analysts' forecast accuracy that pervades in the traditional research design using panel data of analysts' forecast. Clement (1999) suspects that analysts' forecast accuracy can also drive resources and/or workload since more accurate analysts tend to be attracted by large brokerage firms and have more power to negotiate for less workload. Though we cannot fully address this concern, our research design can mitigate the reverse causality issue by employing broker M&As as our natural experiments. Since the M&A itself can be treated as an exogenous event (see Hong and Kacperczyk, 2010), any change to information resources and/or workload experienced by an involved analyst is less likely to be associated with the analyst's ability. In addition, we also have statistical evidence that there is no significant different between the forecast errors of analysts who experience an increase or a decrease in resources/workload in our sample.

At the same time, another concern is about the selection bias regarding the decision to retain and let go analysts after the M&As. Empirically, we find no significant difference in the forecasting performance of the retained analysts compared to those who depart. Additionally, we also mitigate this second concern by basing our tests on the comparison between two groups of analysts (superior and inferior) among those who stay in the merged firm after the M&As.

We use a difference-in-difference (DiD) approach to compare the forecasting performance of analysts that have experienced a change in their resources and/or workload through an M&A (our treatment group) with those that have not (our control group), then between the superior and inferior analysts within our treatment sample. Specifically, we examine the change in forecast accuracy between these groups from one year before to one year after the M&A. In addition, to make sure our treatment and control samples share the similar characteristics, we also perform propensity score match to pair one treatment observation with one comparable control observation and rerun our tests. This approach allows us to account for analyst fixed effects, stock fixed effects, and natural changes with time, leaving changes in resources and workload due to M&As as the only primary factor that can affect analysts' performance.

Our multivariate regression results utilizing the diffs-in-diffs estimations of the variables show that resources have different impacts on the performance of superior and inferior analysts. Specifically, the accuracy of inferior analysts' forecasts improves by almost 2% and tend to issue 0.2 less forecast revisions within one forecast period for each stock they cover, given an average firm size increase of 31 analysts. We, however, find a significant 8% reduction in forecast errors and 0.3 increase in the number of revisions for the remaining analysts in the firm. In contrast, our evidence shows that superior analysts' forecast accuracy and frequency improve by almost 8% and 0.2 revisions when they have additional industry-level information coming from an average increase of five peers. We, however, find no significant improvement in the performance of other analysts within the same firm.

Our results also show significant difference between the impact workload has on superior and inferior analysts. Specifically, when analysts are assigned to track more stocks, those that are ranked as inferior within the firm see a considerable drop in their performance (forecast accuracy and frequency decrease by almost 12% and 0.5 revisions). In contrast, other analysts' performance sees a slight improvement (forecast accuracy and frequency increase by almost 3% and 0.1 revisions). Interestingly, we find superior analysts are negatively affected by an increase in the number of industries to follow (forecast accuracy and frequency decrease by 12% and 0.3 revisions), whilst other analysts are almost unaffected. This can be explained by superior analysts' ability to benefit from industry specialization. As a results, their forecasts can improve with additional information from covering more stocks but get worse when they have to cover more industries.

The differences in superior and inferior analysts' ability to process information are economically significant if one considers an average analyst in our treatment sample has forecast error of 32% and produces 4.7 revisions per stock per forecast period. Overall, our results imply that superior analysts are more affected by industry specific factors (the number of peer analysts and the number of industries to follow), whereas inferior analysts likely to be affected by more general factors (the number of all analysts in the firm and the number of stock to follow). This highlights the better ability for industry specialization of superior analysts compared to their inferior colleagues.

Our empirical analysis concludes with several robustness tests which include controlling for M&A deal and year fixed effects, accounting for outliers, accounting for M&A deals involving the same firms but having overlapping windows, and using the sample at analyst level. In all cases, our main findings still hold.

Our study makes several contributions to the existing literature. First, we find little evidence that a change in resources and/or workload can have significant impacts on the forecast accuracy of analysts, on average. In fact, we find superior and inferior analysts are affected differently by these changes, and the effects are almost cancelled out when we take the average. We thus complement the studies of Clement (1999), Jacob et al. (1999), and Clement et al. (2007) who show the aggregate effect of resources and/or workload on analysts' performance, as we proceed to focus on the significant differences that exist between individual analysts.

Our findings, therefore, have an important implication to brokerage firms who can then decide which strategy is the most beneficial to enhance the accuracy for each group of analysts. Based on our findings, the firms should offer more industry specific resources and less tracking industries for superior analysts. Whereas, the firms should offer more resources on brokerage firm level and reduce the number of tracking stocks for those that are classified as inferior within the firm.

Our study also shows a big improvement in mitigating the concern that there exists a reverse causality relationship between resources/workload and analysts' forecast accuracy, which causes uncertainty in interpreting the direction of impact. Since the M&A itself can be treated as an exogenous event (see Hong and Kacperczyk, 2010), any change to information resources and/or workload experienced by an involved analyst is less likely to be associated with the analyst's ability. Additionally, by comparing between two groups of analysts among those who stay in the merged firm after the M&As, we can also mitigate the bias regarding the selection of analysts to stay or to let go from the merged firms.

The remainder of this study is structured into four sections. Section Two outlines our data and methodology. In Section Three we present our empirical results and discuss our main findings, and in Section Four we provide additional analyses and robustness tests. Section Five contains our conclusion.

II. Methodology and data

A. Data

We collect data on broker M&As between 2005 and 2015 from the SDC Mergers and Acquisition database. We start from 2005 to exclude the period before the Global Analyst Research Settlement (Global Settlement), which is an enforcement agreement between the US Securities Exchange Commission (SEC), Financial Industry Regulatory Authority (NASD), New York Stock Exchange (NYSE) and the ten largest US investment firms. This agreement requires physical and operational separation between the investment banking and research departments. The purpose is to mitigate the pressure from investment banking departments on analysts to issue biased forecasts in favour of their customers. As we believe that the implementation of the Global Settlement would result in substantial changes in analysts' behaviour and performance, we choose to only look at the post-Global Settlement period to avoid any changes to analysts' forecast accuracy caused by this event.

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 merged 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 6,999 forecasts from 21 M&As.

[Insert Table 1]

Panels A and B of Table 1 present the distribution of our M&A sample. Panel A shows the number of M&As by year, with most transactions (15 out of 21) occurring between 2005 and 2008. Panel B 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), 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). We document no M&A with an insurance company (SIC code 63) as the acquirer.

Panel C provides the key statistics relating to the M&As in our sample that support the premise that broker M&As can create shocks to analysts' resources and/or workload. With regard to resources, the statistics in Panel B suggest that, after the M&As, the merged firms tend to have bigger size than either the targets or acquirers. While, on average, the target and acquirer firms recruit 23 and 64 analysts, respectively, we document a higher average number of analysts recruited by the merged firms (75 analysts). We also observe a large number of analysts departing from the firms (822 analysts) as well as analysts newly recruited by the firms (553 analysts) after the mergers. This could possibly result in a change in the number of peer analysts in the firms that follow the same industry. Overall, analysts involving in a broker M&A likely see a change in their resources. In terms of workload, analysts tend to have a change in both the number of stocks and the number of industries they are assigned to cover. Specifically, an analyst working in a target firm before the M&A occurs will follow, on average, 10.5 stocks and 2.8 industries. The average workload for an analyst in the acquirer firm is 9.3 stocks and 2.7 industries. After the M&A, the workload is adjusted to 9.1 stocks and 2.6 industries per analyst.

[Insert Table 2]

Table 2 provides evidence to support our conjecture that broker M&As can be treated as exogenous events, which means any decisions related to retaining analysts or changing their resources and/or workload are less likely driven by the analysts' ability. First, we try to address the concern that retained analysts could be those who are more superior, thus any change to the resources happened in the merged firm is associated with the analysts' stronger ability. In fact, our statistics in Panel A show there is no difference in the performance between retained and departing analysts. We find no significant difference between the forecast accuracy of those who are retained in the merged firm versus those who depart from the two counterpart firms. In addition, among the group of analysts who stay and those who depart, we find statistically similar proportions of superior and inferior analysts. We apply the same test to see whether the decision to increase/decrease the number of stocks and industries assigned to an analyst is connected with the analyst's forecasting ability (Panel B). Again, the statistics show that there is no significant difference in the performance of those analysts who have an increase in workload and those who have a workload reduction.

B. Research design

We adopt a Difference-in-Differences (DiD) regression approach that is commonly employed in natural experiments by comparing our treatment sample with a control sample.

Our treatment sample includes forecasts issued by analysts involved in the M&As. Our control sample contains all forecasts issued by analysts who are not involved in M&As. However, we do exclude forecasts issued by analysts who change their broker IDs during the event window to make sure that any changes in forecast accuracy observed in the control sample is not due to analysts' job departure.

We follow Hong and Kacperczyk (2010) and use a two-year window around the M&A dates. However, we differ from them by including a cooling-off period from six months before to six months after the event to avoid any changes to analyst forecasting abilities caused by M&A news and the instability of the firm's recruitment policy. To be able to observe the change in the accuracy of forecasts for individual stocks caused by the M&As, we only look at forecasts for stocks that appear in the retained analysts' portfolio both before and after an M&A. Also, we only focus on one-year ahead annual EPS forecasts and require that they are issued on the closest date to the cooling-off period. This results in our final treatment sample of 6,999 forecasts before and after the M&As.

For our econometric model, the main 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[2].

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

[2] Following Hong and Kacperzyx (2010), we winsorize our dependent variable by 2.5% in each tail to account for coding errors in I/B/E/S database. Our results do not change if we employ 1% or 5% for the winsorization.

As for our independent variables, we employ $Treat_{ijk}$ as the dummy that is equal to one if the observation belongs to our treatment sample and zero if it belongs to the control sample. We also employ two dummies to capture analysts' ability when they are compared against other analysts involving in the same M&A, we define $High_{ij}$ to be equal to one if analyst j tracking stock i in year t remains within the top 30% of other analysts that undergo the same M&A over a two-year period prior to the M&A. Low_{ij} is equal to one if analyst j is consistently ranked within the bottom 30% during the same period and zero otherwise.

Our classification of superior and inferior analysts differs from previous papers by Mikhail et al. (1997) and Jacob et al. (1999), who use analysts' years of experience to measure their ability. It is agreeable that longer experience indicates higher ability as good analysts tend to remain longer in the industry. However, short experience does not always refer to poor ability. This is typically true for analysts with innate aptitude who can still achieve good performance without having much experience. In fact, our ranking is a more direct measure of ability.

We also differs from Hong et al. (2000) and Clarke et al. (2007) who identify superior analysts as those who are in the list of Institutional Investor's All America Research Team for each year (All-Star analysts). However, our identification, focusing on relative performance and how consistent it is, allows us to account for good performance attributed to ability, rather than luck and reputation. The reason for adopting a cut-off percentile of 30% is so that the percentage of superior and inferior analysts in our sample is closest to the percentage of All-Star analysts in the whole industry, which is around 11% (Hwang et al., 2016).

We represent our two resource measures in the regressions as $Rank_{kt}$ for the firm size quartile ranking of brokerage firm k in year t; and $Peer_{it}$, for 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. Our two workload measures are $Workload_{jt}$ as the number of stocks followed by analyst *j* in year *t*; and $Spec_{jt}$ as the number of industries followed by analyst *j* in year *t*.

Finally, we also include four control variables. First, $Coverage_{it}$ as the number of analysts in the whole industry following stock *i* in year *t*. This will account for any major change in information disclosure and the competitive environment the analysts tracking stock *i* face before and after the M&A that can influence their forecasting performance. The second control variable, $New\ Analyst_{kt}$, 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 performance of incumbent analysts caused by the recruitment of new analysts who are not yet familiar with the working procedure of the firm. The third control variable, $New\ Stock_{jkt}$, 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 stocks belong to the S&P500 in the tracking portfolio assigned to analyst *i* employed by brokerage firm *k* in year *t*. We employ these two final control variables to control for the change in the complexity of the analysts' tracking portfolio.

Our regression models to explain the variation in the changes of analysts' forecast accuracy in our treatment group in response to changes in the resources and/or workload are:

$$\Delta FE_{ij} = \alpha + \beta_1 \times Treat_{ijk} + \beta_2 \times \Delta Resource_{ijk} + \beta_3 \times Treat_{ijk} \times \Delta Resource_{ijk} + \beta_4 \times Treat_{ijk} \times \Delta Resource_{ijk} \times High_{ij} + \beta_5 \times Treat_{ijk} \times \Delta Resource_{ijk} \times Low_{ij} + \gamma' \times \Delta X_{ijk} + \varepsilon_{ij} \quad (2)$$

$$\Delta FE_{ij} = \alpha + \beta_1 \times Treat_{ijk} + \beta_2 \times \Delta Workload_{ijk} + \beta_3 \times Treat_{ijk} \times \Delta Workload_{ijk} + \beta_4 \times Treat_{ijk} \times \Delta Workload_{ijk} \times High_{ij} + \beta_5 \times Treat_{ijk} \times \Delta Workload_{ijk} \times Low_{ij} + \gamma' \times \Delta X_{ijk} + \varepsilon_{ij} \quad (3)$$

These models use the change in each variable across the event window (first difference) as the inputs. To test how analysts' forecast accuracy is affected by a change in resources and/or workload, the dependent variables are regressed against the change in the resource/workload variable we focus on, its interaction with the $Treat_{ijk}$ dummy, then its three-way interaction with $Treat_{ijk}$ and each of the two 'ability' dummy variables. The changes in the remaining resource and workload variables and four control variables are incorporated into the vector ΔX_{ijk}.[3]

In the next step, we try to address the concern that our treatment and control sample do not share the same characteristics, and to deal with the fact that our variables of interest will also experience a natural change over the observation period apart from the exogenous change. We proceed, using the pre-M&A period, to pair each of our treatment forecasts with one forecast from the control group using propensity score matching (PSM)[4]. Propensity scores are calculated from logit regressions using three covariates plus two enforced matches. As Clement (1999) argues that brokerage firm size is the most important factor that can explain analysts' forecasting performance, our first forced match requires that the treatment and control forecasts are issued by brokerage firms that are ranked within the same size quartile, in terms of the number of employed analysts. The second forced match requires the treatment and control forecasts are for stocks of companies having the same size quartile ranking. We measure firm size of the stocks based on the total assets of each company[5]. We use this forced match to control for the difficulty in forecasting the stocks.

[3] We do not control for the 'ability' dummies as these time-invariant variables will be differenced away due to the DiD approach.
[4] We use a caliper of 0.1 in our matching procedure to avoid losing a large number of observations. However, our results still hold if we reduce the caliper by tenfold to 0.01.
[5] We use the Compustat database to obtain information on company total assets.

The three covariates include two analyst-specific variables, namely, the number of stocks followed by an analyst and the analyst's years of experience within the brokerage industry. These covariates ensure that the matched forecasts are issued by analysts with similar workload and comparable forecasting skills and knowledge accumulated through experience. The last covariate is the number of analysts following the stocks, which allows matching forecasts for stocks with comparable level of information disclosure and ensures that the matched analysts face similar competition level. We also require that the matched forecast in the control sample is issued within 30 days around the date of the treatment forecast to avoid any time effects on forecast accuracy. This procedure results in 6,337 pairs of matched forecasts.

We then calculate the DiD estimation of each variable. DiD for forecast of stock *i*, issued by analyst *j*, from brokerage firm *k*, is estimated by contrasting the changes in the observed variables from a treatment sample (*T*), before (*pre-M&A*) and after (*post-M&A*) an event, with the changes observed in a control sample (*C*):

$$DiD_{ijk} = \left(T_{post-M\&A} - T_{pre-M\&A}\right) - \left(C_{post-M\&A} - C_{pre-M\&A}\right) \tag{4}$$

We posit that since the matched treatment and control observations share the similar characteristics, any change experienced by the control forecast can be considered a natural change that could occur to the treatment forecast if there were no M&A. Thus, by subtracting the change observed for the control forecast from the change occurring to the treatment forecast across the M&As, we can separate the exogenous component of change from natural change. This approach allows us to account for forecast fixed effects, analyst fixed effects, brokerage firm fixed effects leaving changes in resources and/or workload due to M&As as the only primary factor that can affect analyst forecast accuracy.

Our regression models utilizing the DiD estimation of the variables as the input are:

$$DiD.FE_{ij} = \alpha + \beta_1 \times DiD.Resource_{ijk} + \beta_2 \times DiD.Resource_{ijk} \times High_{ij} + \beta_3 \times DiD.Resource_{ijk} \times Low_{ij} + \gamma' \times DiD.X_{ijk} + \varepsilon_{ij} \quad (5)$$

$$DiD.FE_{ij} = \alpha + \beta_1 \times DiD.Workload_{ijk} + \beta_2 \times DiD.Workload_{ijk} \times High_{ij} + \beta_3 \times DiD.Workload_{ijk} \times Low_{ij} + \gamma' \times DiD.X_{ijk} + \varepsilon_{ij} \quad (6)$$

In these models, the DiD estimation of forecast error is regressed against the DiD of the resource/workload variable we focus on, plus its interaction with the two 'ability' dummy variables. To further support our main findings, we also run Equations (5) and (6) again but utilize the change in Rev_{ij} as the dependent variable to test for the impact resources and workload have on analysts' forecast frequency. Rev_{ijt} is the number of annual EPS forecast revisions analyst *j* issue for stock *i* during forecast period *t*. For each stock covered by one analyst, we look at one forecast period before and one after the M&A date. We require these two forecast periods to lie out of the cooling-off period of six months before and six months after the M&A date to ensure any change to the number of revision is not due to the interrupted working period surrounding the M&A[6].

[6] With this requirement, when we examine the number of forecast revisions, the sample size reduces to 5,045 and 5,009 observations before and after PSM process, respectively.

III. Empirical results

A. Summary statistics

[Insert Table 3]

Panel A of Table 3 reports the summary statistics for the change of our main variables observed in the treatment and control samples. We find that, on average, our treatment sample experiences a larger change in firm size and the number of peer analysts compared to the control sample (a change of 11.99 analysts and -0.73 peers versus -4.81 analysts and 0.05 peers, respectively). In contrast, our treatment sample tends to experience a smaller change the number of stocks and industries in the tracking portfolio (a change of 0.52 stocks and 0.12 industries compared to 1.11 stocks and 0.18 industries, respectively).

Panels B presents the descriptive statistics for the variables used in the PSM procedure. We find, as we should, that the *p*-values for the difference in mean tests for each covariate between the treatment and control groups are insignificant. More importantly, we find these two samples are also statistically comparable in terms of analysts' forecast error during the pre-M&A period. This implies the matching process has produced two sets of comparable forecasts with only one difference – analysts who contribute to the forecasts in the treatment group will undergo an M&A, whilst analysts in the control group will not.

Panel C reports the summary statistics for the DiD estimations of our main variables. The mean and median values for the DiD estimation of forecast errors are 0.65% and 0.46%, respectively. This indicates that, relative to the matched control sample, the forecast errors in the treatment sample increase slightly after the M&As. In contrast, the mean and median value for the DiD estimation of the number of forecast revisions are 0.51 and 0, respectively. This suggests, on average, analysts tend to issue more forecast revisions after the M&A. Also, compared to the matched control sample, the treatment sample experiences an average decrease of 15.33 in brokerage firm size (*$Size_{kt}$*), a reduction of 0.07 in the analyst coverage of the stock (*$Coverage_{it}$*), an increase of 0.05 in the number of industries assigned to cover (*$Spec_{jt}$*), and a workload reduction of 0.09 stocks (*$Workload_{jt}$*). As for the control variables, on average and relative to the control sample, the treatment sample experiences a reduction of 0.07 analysts that cover the same stock (*$Coverage_{it}$*), an increase of 18.64% new analysts within the firm (*$New\ Analyst_k$*), an increase of 1.25% of new stocks in the tracking portfolio (*$New\ Stock_{jk}$*), and a reduction of 1.24% as stocks belong to the S&P500 in the tracking portfolio (*$SP500_{jk}$*).

B. The impact of resources and workload on analysts' forecast accuracy

[Insert Table 4]

To test how analysts utilize resources to improve their forecast accuracy, we employ Equation (2) with *$Size_{kt}$* and then *$Peer_{it}$* as the variables of interest. The regression results are shown in Table 4. Regression (4.1) and (4.2) show the baseline results when forecasts errors are regressed against all the resource and workload measures plus four control variables, before and after controlling for M&A deal fixed effects and year fixed effects. We can see that the coefficient estimates for both *$\Delta Size_k$* and *$\Delta Peer_i$* are not significant, which means a change in broker firm size and the number of peers cannot significantly impact analysts' performance in general.

In Regression (4.3), we add the interaction terms of *$\Delta Size_k$* with our 'Treat' and 'ability' dummy variables to the model. The results suggest that an increase of one analyst in firm size can improve the accuracy of inferior analysts' forecasts by almost 0.5%[7], significant at the five percent level. A change in brokerage firm size, however, only results in a slight improvement

[7] This is the sum of the estimated coefficient for the improvement in forecast accuracy of all analysts (-0.1161) and the estimated coefficient for the forecast accuracy of only inferior analysts (-0.3571).

of 0.1% on other analysts' performance. Considering an analyst in the treatment sample experiences an average increase of 31 analysts in firm size, this translates into an improvement of 15% in the accuracy of superior analysts, and only 4% for the rest of the firm. In Regression (4.4), after controlling for fixed effects, we find the positive impact of firm size in inferior analysts still persists but the impact on the other analysts becomes insignificant.

Regressions (4.5) and (4.6) focus on the interaction between $\Delta Peer_i$ and the ability dummy variables, before and after controlling for fixed effects. The results in Regression (4.5) show that whilst superior analysts experience an improvement of 0.4%[8] in their forecasts, all other analysts suffer, with an average decline of 0.26% in forecast accuracy from each, additional peer joining the team. Given the average increase in the number of peers occurring to our treatment sample is 1.6 peer analysts, this causes an improvement of 0.6% in the accuracy of superior analysts and the reduction of 0.4% for their inferior colleagues. In Regression (4.6), after controlling for fixed effects, we also find a positive impact of the number of peers on superior analysts' forecast accuracy but the negative impact on the other analysts become insignificant.

Overall, the results in Table 4 confirm our first hypothesis that the forecast accuracy of superior analysts tend to improve with an increase in the number of peer analysts, providing more industry specific information. Whereas, inferior analysts tend to benefit more from an increase in the number of analysts employed by the firm who can provide more general type of information.

[Insert Table 5]

[8] This is the sum of the estimated coefficient for the improvement in forecast accuracy of all analysts (0.2648) and the estimated coefficient for the forecast accuracy of only superior analysts (-0.6640).

Table 5 presents the regression results when we focus on the impact that a change in workload (*$\Delta Workload_j$* and *$\Delta Spec_j$*) has on the forecast accuracy of analysts. The baseline model in Regressions (5.1) and (5.2) show that a change in workload, either the number of stocks or the number of industries to cover, has no significant impact on analysts' forecast accuracy in general.

In Regression (5.3), after adding the interaction terms of *$\Delta Workload_j$* with the 'treat' and 'ability' dummy variables, we find that a change in workload does affect analysts differently. Specifically, an increase of one stock in the tracking portfolio of an analyst will lead to an improvement of 0.47% in forecast accuracy. However, an increase in workload causes a net reduction of 1.85%[9] in the forecast accuracy of inferior analysts. The negative impact of workload changes on the forecast accuracy of inferior analysts is four times as much as the positive impact that workload changes have on the other analysts. When one considers that the average increase in workload that analysts in the treatment sample face involves tracking 4.5 stocks, inferior analysts will see a considerable reduction of over 8.3% in their accuracy. Meanwhile, other analysts see an improvement of around 2%. The results remain the same when we control for fixed effects in Regression (5.4).

We then look at the interactive relationship between *$\Delta Spec_j$* and the 'ability' dummy variables. In regression (5.6), after controlling for fixed effects, we find that an increase in the number of industries to cover has a more negative impact on the performance of superior analysts. Specifically, an increase of one industry causes a reduction of 2.9%[10] in superior analysts' forecast accuracy. This is a decline of 4.6% when one considers that an analyst in the

[9] This is the sum of the estimated coefficient for the improvement in forecast accuracy of all analysts (-0.4694) and the estimated coefficient for the forecast accuracy of only inferior analysts (2.3204).
[10] This is the sum of the estimated coefficient for the improvement in forecast accuracy of all analysts (-1.4645) and the estimated coefficient for the forecast accuracy of only superior analysts (4.3666).

treatment sample, on average, sees an increase of 1.6 industries. At the same time, the forecast accuracy of other analysts in the firm see an increase of 2.3% given the same industry increase.

Overall, the results in Table 5 support our conjecture that the impacts of workload on forecast accuracy are different between superior and inferior analysts. It also suggests that superior analysts are better at industry specialization. Therefore, by covering more stocks, superior analysts can benefit from a wider range of information, especially when the stocks are from the same industry, whereas they perform worse when assigned to covered more industries. This suggests brokerage firms should employ different strategies to promote the performance of superior and inferior analysts. Superior analysts can perform better when they focus in a small number of industries, regardless of the number of stocks they cover, whilst inferior analysts can improve when being given less stocks to cover, regardless of which industries the stocks come from.[11]

IV. Additional analyses

A. Analyses using the matched control sample

We perform univariate for the DiD estimation of analysts' forecast errors when they experience an increase versus a decrease in resources and/or workload. Again, the DiD of the variables are estimated by comparing the change observed in our treatment sample to the change occurring for the matched control sample. We estimate the mean DiD of analyst forecast errors across two subsamples: when the DiD estimation of resources and/or workload are higher or lower than the median value. We then test for any significant difference between these two means to detect the impact that resources and workload have on forecast accuracy.

[11] Our main findings still hold when we use the clustered standard errors for analyst, analyst and M&A deal, and analyst and year.

The results in Table 6 align with our main findings that resources and workload tend to have different impact on the performance of superior versus inferior analysts. Specifically, we find the forecast accuracy of superior analysts is positively affected by the number of peers while there is no significant impact reported for inferior analysts. The results also show inferior analysts are negatively affected by the number of stocks they cover while there is no impact for superior analysts. In contrast, superior analysts' forecast accuracy is negatively impacted by the number of industries in their portfolio but the impact is insignificant for inferior analysts. We, however, find no significant difference between the impact of brokerage firm size among these two groups of analysts.

The univariate tests, however, cannot control for various change happen at the same time. For example, one analyst can experience both a change in resources and workload after the M&As. To address this concern, we proceed to run our multivariate regression models (Equations 4 and 5) using the DiD estimation of the variables as the inputs. The results, presented in Table 7, are consistent with our main findings. Regression (7.2) shows that, given an increase of 31 analysts in the firm, the forecast accuracy of inferior analysts increases by 1.59%, compared to a reduction of 8% in the forecast accuracy of all other analysts. The results in Regression (7.3) suggest an average increase of five peer analysts can cause an improvement of 7.6% in superior analysts' forecast accuracy while having no impact on other analysts.

As for the impact of workload on forecast accuracy, the results in Regression (7.4) show that with an average increase of 4.5 stocks in the tracking portfolio, the forecast accuracy of inferior analysts drops by 12% compared to an improvement of 2.7% among other analysts. In contrast, superior analysts suffer more from an increase in the number of industries to cover, with a reduction of 16% in forecast accuracy given an average increase of 1.6 industry.

In Table 8, we also rerun the regressions using a subset of our sample that experience a small change in resources or workload. Specifically, for Regressions 8.1 to 8.3, we utilize the subsample with the absolute change in the number of stocks in the tracking portfolio belong to the smallest 30 percent, whereas for Regressions 8.4 to 8.6, we utilize the subsample with the absolute change in brokerage firm size belong to the smallest 30 percent. This method allows us to separate the impact that resources then workload have on analysts' performance. Most of the results support our main findings. The only difference is that we find an increase in the number of peer analysts can have a positive impact on the performance of both superior and inferior analysts. This, however, still align with our conjecture as the effect of peers on inferior analysts is still less significant compared to superior analysts.

B. The impact of resources and workload on analysts' number of forecast revisions

[Insert Table 9]

We also find further evidence to support our conjecture by looking at the impact resources and workload have on the number of forecast revisions analysts issue for a particular stock given a change in resources. The results in Table 9 show that resources and workload also affect the forecast frequency of superior and inferior analysts differently. Regression 9.2 shows that with an average change of 31 analysts in brokerage firm size, inferior analysts issue 0.2 less revisions, significant at the one percent level, whereas other analysts see an increase of 0.3 revisions. With any one peer analyst joining the firm, superior analysts issue 0.05[12] more revisions, whilst number of forecast revisions issued by other analysts reduces by 0.03 (it is an

[12] This is the sum of the estimated coefficient for the decrease in the number of forecast revisions of all analysts (-0.0287) and the estimated coefficient for the number of revisions of only superior analysts (0.0759).

increase of 0.2 revisions and a decrease of 0.14 revisions given an average increase of five peers), significant at the one percent level

Regarding a change in workload, from Regression (9.5), the number of forecast revisions issued by inferior analysts reduces by an additional 0.11 revisions relative to other analysts if they cover less stocks, significant at the ten percent level (it is an 0.5 revisions given an average increase of 4.5 stocks), while the decrease observed for other analysts is only one third of that. From Regression (9.6), superior analysts, who more likely benefit from industry specialization, see a significant reduction of 0.2 in the number of forecast revisions relative to other analysts when the number of industries they cover rises by one industry (it is 0.3 revisions given an average reduction of 1.6 industries). Whereas we find an increase in the number of industry can increase the frequency of forecasts for other analysts.

C. Robustness tests

[Insert Table 10]

Given the large standard deviation of analyst forecast errors among our sample (see Table 3), it is possible that our results when examining analysts' forecast accuracy 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% compared to 31.74% and 5.81%). Hence, to address the potential problem of outliers unduly influencing our results, we rerun the regression for Sub-sample (I), in which we drop forecasts for stocks having prices below $10 from the treatment sample (734 observations). The results are reported in Regressions (10A.1), (10B.1), (10C.1) and (10D.1) of Table 10. These regressions show the models with the interaction terms of the brokerage firm size, number of peers, number of stocks, and number of industries covered by an analyst with the ‘ability’ dummy variables, respectively. The reported results are all consistent with our main results in that they show significant differences in the way superior and inferior analysts respond to a change in resources and/or workload.

We also 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% compared to 34.33% and 6.38%). This is possibly due to the instability in the information environment surrounding stocks with low coverage. Hence, to further address the outlier issue, we rerun our regressions with Sub-sample (II), in which we exclude forecasts for stocks with less than three analysts following (237 observations). We report the results in Regressions (10A.2), (10B.2), (10C.2) and (10D.2) in Table 10 and they are similar to our main results. Altogether, the first two robustness tests confirm that our results are not driven by outliers.

Next, we recognize that there are some M&A deals in our sample involving the same brokerage firms but having overlapping windows (M&A cluster). This can be one source of bias to our main findings as analysts’ forecast accuracy can be affected by different M&As at the same time. To address this issue, we employ Sub-sample (III), which excludes all forecasts involving in three M&As with overlapping windows (3347 observations) and rerun the regressions. The results, reported in Regressions (10A.3), (10B.3), (10C.3) and (10D.3) in Table 10, are consistent with our main results.

Our final robustness test is to rerun the multivariate regression at analyst level. We use the median forecast error across all stocks covered by one analyst as the dependent variables. We then proceed to match one analyst in the treatment sample with one closely matched analysts in the control sample using PSM technique. We employ one forced match (brokerage firm size quartile ranking – Qua_Rank_k) and two covariates (analysts' years of experience – $Exper_j$ and the number of stocks covered by the analysts – $Workload_j$). Our matching process results in two samples with no significant differences regarding the three matching criteria. Our regressions model utilize Equations (4) and (5) but we exclude all stock specific variables from the control variables. We report the results in Regressions (10A.4), (10B.4), (10C.4) and (10D.4). All results also align with our main findings.

V. Conclusion

We utilize broker M&As as natural experiments to examine various measures of resources and workload and the impact on analysts' forecast accuracy. Our main findings suggest that the impacts resources and workload have on forecast accuracy are significantly different between superior and inferior analysts. We find superior are more affected by industry specific factors. Their forecast accuracy improves more when experiencing an increase in the number of peers while decrease more with an increase in the number of industries to follow, relative to inferior analysts. Meanwhile, inferior analysts are likely affected by more general factors. This latter group of analysts become more accurate with an increase in the number of analysts employed by the firm, and become less accurate when given more stocks to follow. Such impacts, however, are not documented for superior analysts. We also confirm that our results are not driven by outliers, are not biased by M&As with overlapping windows, and remain consistent for our analysis at analyst level.

Our study shows a big improvement compared to the traditional research approach using panel data of analyst forecasts, which suffers from a reverse causality relationship between resources/workload and analysts' forecast accuracy. By utilizing broker M&As as natural experiments that create exogenous shocks to analysts' resources and workload, we find that superior and inferior analysts are affected differently by these shock, and the effects are cancelled out when we take the average. This suggests a potential research direction to exam the possible interaction between analysts' characteristics with various other factors that explain analysts' performance. This would include changes in the regulatory environment and changes in competitive environment.

Our findings have an important implication to brokerage firms who can then decide on their strategy to promote analysts' forecasting performance. Based on our results, the firms can consider offering different types of resources and having different workload policy for analysts with different ability levels to better enhance the performance for each individual analysts.

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Appendix 1: Variable definitions

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

Variable		Definition
$Coverage_{it}$	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*.
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.
$High_{ij}$	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 for two consecutive years before the M&A, and zero otherwise.
$Spec_{jt}$	Industry	The number of industries followed by analyst *j* in year *t*.
$Logat_{it}$	NA	Natural logarithm of total assets value of stock *i* in year *t*
Low_{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 for two consecutive years before the M&A, and zero otherwise.
$New\ Analyst_{kt}$	%	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*.
Qua_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.
$Rank_{kt}$	Decile	The firm size decile ranking, based on the number of analysts a firm employs, of brokerage firm *k* in year *t*. The first decile represents top 10% largest firms.
Rev_{ijt}	Revisions	The number of annual EPS forecast revisions analyst *j* issue for stock *i* during forecast period *t*.
$SP500_{jkt}$	%	The proportion stocks belong to the S&P500 in the tracking portfolio assigned to analyst *i* employed by brokerage firm *k* in year *t*.
$Treat_{ijk}$	NA	a dummy variable that is equal to one if the observation belongs to the treatment sample and zero if it belongs to the control sample.
$Workload_{jt}$	Stock	The number of stocks followed by analyst *j* in year *t*.

Table 1: Final M&A sample description

Panel A: Distribution of final M&A sample by year

2005	*2006*	*2007*	*2008*	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*	*Total*
6	3	3	3	0	1	1	2	1	1	0	21

Panel B: 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 C: 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	1,280	64.0	28	80.8	2	278
Merged firm	1,491	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 per analyst (workload)						
Target	NA	10.5	10	7.2	1	32
Acquirer	NA	9.3	6	8.2	1	61
Merged firm	NA	9.1	6	8.0	1	58
Number of industries per analyst (specialization)						
Target	NA	2.8	2	2.0	1	13
Acquirer	NA	2.7	2	2.1	1	12
Merged firm	NA	2.6	2	2.1	1	17

This table presents the description of the final M&A sample. Panels A and B show the distribution of M&As included in the sample by year, and by the acquirers' and targets' four-digit SIC codes, respectively. Panel C 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: The decisions of brokerage firm after the M&As

Panel A: The decision of firms to retain analysts after the M&As

	Retained	*Depart*	*Difference*	*p-value of test for diff. in means*
Mean forecast errors (%)	18.12	22.72	-4.60	0.16
% of analysts as Superior	8.80	7.84	0.06	0.47
% of analysts as Inferior	4.94	5.76	-0.82	0.44

Panel B: The decision of firms to increase or decrease analysts' workload after the M&As

	Increase in no. of stocks	*Decrease in no. of stocks*	*Difference*	*p-value of test for diff. in means*
Mean forecast errors (%)	19.44	15.74	3.71	0.53
% of analysts as Superior	8.61	7.54	1.07	0.63
% of analysts as Inferior	5.06	5.28	-0.22	0.90
	Increase in no. of industries	*Decrease in no. of industries*	*Difference*	*p-value of test for diff. in means*
Mean forecast errors (%)	25.72	17.36	8.35	0.46
% of analysts as Superior	9.86	7.63	2.23	0.49
% of analysts as Inferior	4.23	4.58	-0.35	0.88

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* forecast accuracy 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 stocks or industries to cover (Panel B). ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively, of the two-tail t-test for difference in means.

Table 3: Summary statistics for the variables of interest

Panel A: Summary statistics for the changes of the variables of interest across the M&As

		Treatment sample			*Control sample*		
Variables	*Unit*	*Mean*	*Median*	*StDev*	*Mean*	*Median*	*StDev*
ΔFE_{ij}	%	1.95	-0.03	59.30	3.40	-0.04	51.02
$\Delta Coverage_{i}$	Analyst	0.38	0	4.74	0.67	1	3.60
$\Delta Spec_{j}$	Industry	0.12	0	1.12	0.18	0	1.20
$\Delta New\ Analyst_{k}$	%	24.89	14.06	93.46	-83.08	-1.91	838.75
$\Delta New\ Stock_{jk}$	%	-2.77	0	28.87	-0.99	0	45.16
$\Delta Peer_{i}$	Analyst	-0.73	1	11.62	0.05	0	1.98
$\Delta Size_{k}$	Analyst	11.99	9	22.28	-4.81	1	24.76
$\Delta SP500_{jk}$	%	1.21	0	11.63	5.62	0	20.22
$\Delta Workload_{j}$	Stock	0.52	0	4.81	1.11	1	4.29

Panel B: Descriptive statistics for the covariates used for the Propensity Score Match for analyst-stock level

		Treatment sample			*Matched control sample*			*p-value of test for differences in means*
Variables	*Unit*	*Mean*	*Median*	*StDev*	*Mean*	*Median*	*StDev*	
FE_{ijt}	%	35.27	6.58	212.38	42.61	7.63	308.90	0.11
Qua_Rank_{kt}	Quartile	1.02	1	0.15	1.02	1	0.15	1.00
$Coverage_{it}$	Analyst	17.46	15	11.03	17.53	15	10.67	0.71
$Exper_{jt}$	Year	13.51	14	8.07	13.51	14	8.01	0.97
$Stock\ Rank_{it}$	Quartile	1.49	1	1.10	1.49	1	1.10	1.00
$Workload_{jt}$	Stock	16.84	17	7.22	16.96	17	6.48	0.33

Panel C: Summary statistics for the Difference-in-Differences estimations of the variables of interest after performing Propensity Score Match

Variables	*Unit*	*Mean*	*Median*	*StDev*
$DiD.FE_{ij}$	%	0.65	0.46	118.20
$DiD.Coverage_{i}$	Analyst	-0.07	0	5.29
$DiD.Spec_{j}$	Industry	0.05	0	1.51
$DiD.New\ Analyst_{k}$	%	18.64	16.40	20.18
$DiD.New\ Stock_{jk}$	%	1.25	0.99	43.49
$DiD.Peer_{i}$	Analyst	-0.86	1	14.75
$DiD.Rev_{ij}$	Revision	0.51	0	4.03
$DiD.Size_{k}$	Analyst	15.33	9	29.48
$DiD.SP500_{jk}$	%	-1.24	0	19.45
$DiD.Workload_{j}$	Stock	-0.09	0	5.65

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

Table 4: The impacts of changes in resources on forecast errors – First difference estimation

Regression:	(4.1)	(4.2)	(4.3)	(4.4)	(4.5)	(4.6)
Dependent:	*ΔFE_{ij}*	*ΔFE_{ij}*	*ΔFE_{ij}*	*ΔFE_{ij}*	*ΔFE_{ij}*	*ΔFE_{ij}*
Model:	*Baseline*	*Baseline*	*Size*	*Size*	*Peer*	*Peer*
Treat	-1.7637**	-3.9557***	-0.5338	-3.6303***	-1.7638**	-3.9895***
	(0.7765)	(0.9894)	(0.8633)	(1.2835)	(0.7764)	(0.9909)
$\Delta Size_k$	0.0072	0.0011	0.0215**	0.0029	0.0076	0.0018
	(0.0095)	(0.0105)	(0.0100)	(0.0109)	(0.0095)	(0.0105)
$\Delta Peer_i$	0.0072	0.0327	0.0363	0.0324	-0.1994	-0.0862
	(0.0469)	(0.0502)	(0.0480)	(0.0503)	(0.1246)	(0.1241)
$\Delta Workload_j$	-0.0613	-0.0587	-0.0652	-0.0595	-0.0614	-0.0581
	(0.0761)	(0.0756)	(0.0762)	(0.0756)	(0.0761)	(0.0756)
$\Delta Spec_j$	0.1201	-0.1330	0.1172	-0.1334	0.1240	-0.1309
	(0.2558)	(0.2542)	(0.2558)	(0.2544)	(0.2558)	(0.2542)
$\Delta Coverage_i$	-0.2009***	-0.1473**	-0.2053***	-0.1498**	-0.1981***	-0.1454**
	(0.0605)	(0.0617)	(0.0603)	(0.0616)	(0.0605)	(0.0617)
$\Delta New\ Analyst_k$	0.0006***	0.0005**	0.0008***	0.0005**	0.0006**	0.0005*
	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
$\Delta New\ Stock_{jk}$	0.0028	0.0010	0.0024	0.0012	0.0023	0.0007
	(0.0069)	(0.0072)	(0.0069)	(0.0072)	(0.0069)	(0.0073)
$\Delta SP500_{jk}$	-0.0005	-0.0074	-0.0006	-0.0076	-0.0008	-0.0074
	(0.0112)	(0.0113)	(0.0112)	(0.0113)	(0.0112)	(0.0113)
Treat_ΔSize			-0.1161***	-0.0121		
			(0.0325)	(0.0398)		
Treat_ΔSize_ High			0.0492	0.0400		
			(0.0727)	(0.0723)		
Treat_ΔSize_Low			-0.3571**	-0.3186*		
			(0.1813)	(0.1821)		
Treat_ΔPeer					0.2648**	0.1631
					(0.1349)	(0.1364)
Treat_ΔPeer_High					-0.6640**	-0.6071**
					(0.2758)	(0.2738)
Treat_ΔPeer_ Low					-0.2124	-0.1205
					(0.3012)	(0.2988)
Observations	56,709	56,709	56,709	56,709	56,709	56,709
Robust	Yes	Yes	Yes	Yes	Yes	Yes
Deal FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes

The regressions use the first difference estimations of the variables. The Appendix provides a detailed description of the variables. Robust standard errors are reported in parentheses. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively. Regressions (4.1) and (4.2) are the baseline model without interaction between resources and analysts' ability, before and after control for fixed effects. Regressions (4.3) and (4.4) present the regression results for models with interaction for the change in broker firm size and the ability dummies, before and after controlling for fixed effects. Regressions (4.5) and (4.6) present the regression results for models with interaction for the change in the number of peers and the ability dummies, before and after controlling for fixed effects.

Table 5: The impacts of changes in workload on forecast errors – First difference estimation

Regression:	(5.1)	(5.2)	(5.3)	(5.4)	(5.5)	(5.6)
Dependent:	ΔFE_{ij}	ΔFE_{ij}	ΔFE_{ij}	ΔFE_{ij}	ΔFE_{ij}	ΔFE_{ij}
Model:	*Baseline*	*Baseline*	*Workload*	*Workload*	*Spec.*	*Spec.*
Treat	-1.7637**	-3.9557***	-1.5022*	-3.5972***	-1.6981**	-3.9238***
	(0.7765)	(0.9894)	(0.7850)	(0.9960)	(0.7793)	(0.9911)
$\Delta Size_k$	0.0072	0.0011	0.0069	0.0005	0.0070	0.0009
	(0.0095)	(0.0105)	(0.0095)	(0.0105)	(0.0095)	(0.0105)
$\Delta Peer_i$	0.0072	0.0327	0.0077	0.0304	0.0056	0.0305
	(0.0469)	(0.0502)	(0.0468)	(0.0502)	(0.0469)	(0.0502)
$\Delta Workload_j$	-0.0613	-0.0587	0.0068	0.0131	-0.0615	-0.0587
	(0.0761)	(0.0756)	(0.0822)	(0.0814)	(0.0761)	(0.0755)
$\Delta Spec_j$	0.1201	-0.1330	0.0364	-0.2156	0.2251	-0.0007
	(0.2558)	(0.2542)	(0.2577)	(0.2559)	(0.2652)	(0.2634)
$\Delta Coverage_i$	-0.2009***	-0.1473**	-0.1958***	-0.1433**	-0.1992***	-0.1456**
	(0.0605)	(0.0617)	(0.0606)	(0.0617)	(0.0605)	(0.0617)
$\Delta New\ Analyst_k$	0.0006***	0.0005**	0.0006***	0.0005**	0.0006***	0.0005**
	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
$\Delta New\ Stock_{jk}$	0.0028	0.0010	0.0030	0.0014	0.0028	0.0010
	(0.0069)	(0.0072)	(0.0069)	(0.0072)	(0.0069)	(0.0072)
$\Delta SP500_{jk}$	-0.0005	-0.0074	-0.0004	-0.0070	0.0001	-0.0066
	(0.0112)	(0.0113)	(0.0112)	(0.0113)	(0.0112)	(0.0113)
Treat_ΔWorkload			-0.4694***	-0.4605***		
			(0.1679)	(0.1672)		
Treat_ΔWorkload_ High			-0.0413	-0.1916		
			(0.8474)	(0.8530)		
Treat_ΔWorkload_ Low			2.3204***	1.8301**		
			(0.8505)	(0.8495)		
Treat_ΔSpec					-1.2308*	-1.4645**
					(0.7295)	(0.7291)
Treat_ΔSpec_ High					3.5020	4.3666**
					(2.2189)	(2.2127)
Treat_ΔSpec_ Low					1.2515	0.0007
					(2.8175)	(2.8099)
Observations	56,709	56,709	56,709	56,709	56,709	56,709
Robust	Yes	Yes	Yes	Yes	Yes	Yes
Deal FE	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes

The regressions use the first difference estimations of the variables. The Appendix provides a detailed description of the variables. Robust standard errors are reported in parentheses. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively. Regressions (5.1) and (5.2) are the baseline model without interaction between workload and analysts' ability, before and after control for fixed effects. Regressions (5.3) and (5.4) present the regression results for models with interaction for the change in the number of stocks covered by analysts and the ability dummies, before and after controlling for fixed effects. Regressions (5.5) and (5.6) present the regression results for models with interaction for the change in the number of industry covered by analysts and the ability dummies, before and after controlling for fixed effects.

Table 6: Univariate test for the impact of resources and workload on analysts' forecast accuracy

		(6.1) Mean DiD.FE$_{ij}$ if the change is larger than median change	*(6.2) Mean DiD.FE$_{ij}$ if the change is smaller than median change*	*(6.3) Difference in DiD.FE$_{ij}$*
DiD.Size$_k$	All analysts	1.68	-0.03	1.71
	Superior	4.03	5.99	-1.96
	Inferior	-13.50	-2.85	-10.65
DiD.Peer$_i$	All analysts	2.09	0.29	1.80
	Superior	-1.06	15.77**	-16.83*
	Inferior	-10.94	4.08	-15.02
DiD.Workload$_j$	All analysts	-2.47	2.37	-4.85*
	Superior	5.47	-1.08	6.56
	Inferior	5.29	-17.44*	22.73*
DiD.Spec$_j$	All analysts	-1.35	2.11	-3.46
	Superior	15.88***	-17.94***	33.82***
	Inferior	-9.60	-14.49	4.89

This table presents the univariate test 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 Table reports the mean DiD of forecast errors when the DiD estimation of each variable of interest is larger or smaller than the median value; then the difference between the two means. The Appendix provides a detailed description of the variables. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively, of the one-tail t-test for significance (Columns 6.1 and 6.2) and test for difference in means (Column 6.3).

Table 7: The impacts of changes in resources/workload on forecast errors – DiD estimation

Regression:	(7.1)	(7.2)	(7.3)	(7.4)	(7.5)
Dependent:	*DiD.FE$_{ij}$*	*DiD.FE$_{ij}$*	*DiD.FE$_{ij}$*	*DiD.FE$_{ij}$*	*DiD.FE$_{ij}$*
Model:	*Baseline*	*Size*	*Peer*	*Workload*	*Spec.*
DiD.Size$_k$	0.2099**	0.2661**	0.2373	0.2289**	0.2060**
	(0.1006)	(0.1057)	(0.1725)	(0.1001)	(0.1005)
DiD.Peer$_i$	0.0907	0.0855	0.2050	0.0858	0.0867
	(0.1280)	(0.1284)	(0.2477)	(0.1284)	(0.1283)
DiD.Workload$_j$	-0.3720	-0.4078	-0.3885	-0.5959**	-0.3603
	(0.2915)	(0.2925)	(0.5065)	(0.3036)	(0.2905)
DiD.Spec$_j$	-0.3174	-0.2650	-0.6017	-0.4406	-1.5136
	(1.1438)	(1.1455)	(1.9360)	(1.1451)	(1.2068)
DiD.Size$_k$ × *High$_{ij}$*		-0.0209			
		(0.1462)			
DiD.Size$_k$ × *Low$_{ij}$*		-0.3175*			
		(0.1738)			
DiD.Peer$_i$ × *High$_{ij}$*			-1.5104**		
			(0.6290)		
DiD.Peer$_i$ × *Low$_{ij}$*			-0.9417		
			(0.7832)		
DiD.Workload$_j$ × *High$_{ij}$*				0.8447	
				(0.9418)	
DiD.Workload$_j$ × *Low$_{ij}$*				3.2309**	
				(1.2970)	
DiD.Spec$_j$ × *High$_{ij}$*					9.9729**
					(4.0891)
DiD.Spec$_j$ × *Low$_{ij}$*					6.6608
					(4.5703)
Observations	6,337	6,336	6,336	6,336	6,336
Robust	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

The regressions use the DiD estimations of the variables. The Appendix provides a detailed description of the variables. Robust standard errors are reported in parentheses. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively. Regressions (7.1) is the baseline model without interaction between resources/workload and analysts' ability. Regressions (7.2) and (7.3) present the regression results for models with interaction for the DiD of resources and the ability dummies, controlling for fixed effects. Regressions (7.4) and (7.5) present the regression results for models with interaction for the DiD of workload and the ability dummies, controlling for fixed effects.

Table 8: The impact of changes in resources/workload on forecast errors with small change in the other factor

Regression:	(8.1)	(8.2)	(8.3)	(8.4)	(8.5)	(8.6)
Dependent:	*DiD.FE_{ij}*	*DiD.FE_{ij}*	*DiD.FE_{ij}*	*DiD.FE_{ij}*	*DiD.FE_{ij}*	*DiD.FE_{ij}*
Model:	*Baseline*	*Rank*	*Peer*	*Baseline*	*Workload*	*Spec.*
$DiD.Size_k$	0.2448	0.2722	0.2390	0.1731	0.2135	0.1340
	(0.1795)	(0.1796)	(0.1799)	(0.7427)	(0.7480)	(0.7439)
$DiD.Peer_i$	0.5025**	0.4928**	0.6221***	0.5010**	0.4945**	0.4992**
	(0.2146)	(0.2158)	(0.2247)	(0.2389)	(0.2399)	(0.2400)
$DiD.Workload_j$	-4.5865*	-4.6363**	-4.6438**	-1.1863*	-1.7813***	-1.0448*
	(2.3588)	(2.3546)	(2.3532)	(0.6204)	(0.6642)	(0.6179)
$DiD.Spec_j$	2.3357	2.3985	2.5898	1.8412	1.7240	-0.6412
	(2.2110)	(2.2093)	(2.2052)	(2.1430)	(2.1674)	(2.2732)
$DiD.Size_k \times High_{ij}$		0.1994				
		(0.2556)				
$DiD.Size_k \times Low_{ij}$		-0.8773*				
		(0.4935)				
$DiD.Peer_i \times High_{ij}$			-1.2905**			
			(0.5567)			
$DiD.Peer_i \times Low_{ij}$			-1.7135*			
			(1.0082)			
$DiD.Workload_j \times High_{ij}$					2.7203	
					(1.9675)	
$DiD.Workload_j \times Low_{ij}$					4.8908**	
					(2.1577)	
$DiD.Spec_j \times High_{ij}$						16.6763*
						(9.9328)
$DiD.Spec_j \times Low_{ij}$						7.0028
						(6.3678)
Observations	2,231	2,230	2,230	1,927	1,926	1,926
Robust	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

The regressions use the DiD estimations of the variables. The Appendix provides a detailed description of the variables. Robust standard errors are reported in parentheses. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively. Regressions (8.1), (8.2) and (8.3) present the regression results for the subsample of forecasts issued by analysts with the absolute DiD of the number of stocks they cover belong to the smallest 30%. Regressions (8.4), (8.5) and (8.6) present the regression results for the subsample of forecasts issued by analysts with the absolute DiD of the brokerage firm size belong to the smallest 30%.

Table 9: The impacts of changes in resources/workload on forecast frequency

Regression:	(9.1)	(9.2)	(9.3)	(9.4)	(9.5)
Dependent:	*DiD.FE$_{ij}$*	*DiD.FE$_{ij}$*	*DiD.FE$_{ij}$*	*DiD.FE$_{ij}$*	*DiD.FE$_{ij}$*
Model:	*Baseline*	*Size*	*Peer*	*Workload*	*Spec.*
DiD.Size$_k$	0.0075*	0.0108**	0.0081*	0.0488***	0.0406***
	(0.0042)	(0.0044)	(0.0042)	(0.0124)	(0.0117)
DiD.Peer$_i$	-0.0272***	-0.0276***	-0.0287***	0.0072*	0.0076*
	(0.0063)	(0.0063)	(0.0065)	(0.0043)	(0.0042)
DiD.Workload$_j$	0.0409***	0.0390***	0.0393***	-0.0273***	-0.0274***
	(0.0117)	(0.0118)	(0.0118)	(0.0063)	(0.0063)
DiD.Spec$_j$	0.0762*	0.0800*	0.0772*	0.0799*	0.0843*
	0.0075*	(0.0433)	(0.0434)	(0.0435)	(0.0465)
DiD.Size$_k$ × *High$_{ij}$*		-0.0037			
		(0.0059)			
DiD.Size$_k$ × *Low$_{ij}$*		-0.0179***			
		(0.0056)			
DiD.Peer$_i$ × *High$_{ij}$*			0.0759***		
			(0.0207)		
DiD.Peer$_i$ × *Low$_{ij}$*			-0.0291		
			(0.0248)		
DiD.Workload$_j$ × *High$_{ij}$*				-0.0551	
				(0.0373)	
DiD.Workload$_j$ × *Low$_{ij}$*				-0.0855*	
				(0.0441)	
DiD.Spec$_j$ × *High$_{ij}$*					-0.2470*
					(0.1412)
DiD.Spec$_j$ × *Low$_{ij}$*					0.2126
					(0.1482)
Observations	5,009	5,008	5,008	5,008	5,008
Robust	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

The regressions use the DiD estimations of the variables. The Appendix provides a detailed description of the variables. Robust standard errors are reported in parentheses. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively. Regressions (9.1) is the baseline model without interaction between resources/workload and analysts' ability. Regressions (9.2) and (9.3) present the regression results for models with interaction for the DiD of resources and the ability dummies, controlling for fixed effects. Regressions (9.4) and (9.5) present the regression results for models with interaction for the DiD of workload and the ability dummies, controlling for fixed effects.

Table 10: Robustness tests for the heterogeneous impacts of resources and workload on forecast errors

Panel A: The impacts of changes in broker rankings on forecast errors

Regression:	(10A.1)	(10A.2)	(10A.3)	(10A.4)
Dependent:	$DiD.FE_{ij}$	$DiD.FE_{ij}$	$DiD.FE_{ij}$	$DiD.FE_{ij}$
Sub-sample:	Sub-sample (I)	Sub-sample (II)	Sub-sample (III)	Analyst level
$DiD.Size_k$	0.1565	0.2569**	0.4328**	0.1155
	(0.1118)	(0.1072)	(0.1708)	(0.0740)
$DiD.Size_k \times High_{ij}$	0.0944	-0.0341	-0.2739	-0.1037
	(0.1185)	(0.1468)	(0.2634)	(0.1086)
$DiD.Size_k \times Low_{ij}$	-0.4136**	-0.2947*	-0.3951*	-0.3704*
	(0.1848)	(0.1717)	(0.2079)	(0.1930)
Robust	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	5,603	6,100	2,990	773

Panel B: The impacts of changes in the number of peer analysts on forecast errors

Regression:	(10B.1)	(10B.2)	(10B.3)	(10B.4)
Dependent:	$DiD.FE_{ij}$	$DiD.FE_{ij}$	$DiD.FE_{ij}$	$DiD.FE_{ij}$
Sub-sample:	Sub-sample (I)	Sub-sample (II)	Sub-sample (III)	Analyst level
$DiD.Peer_i$	0.1363	0.0368	0.3065	-0.0785
	(0.1357)	(0.1352)	(0.4184)	(0.0986)
$DiD.Peer_i \times High_{ij}$	-0.9206**	-0.6964*	-3.6305**	-0.4820***
	(0.4202)	(0.3715)	(1.4747)	(0.1514)
$DiD.Peer_i \times Low_{ij}$	-0.6105	-0.7398	-2.2080**	-0.1944
	(0.3914)	(0.5367)	(1.1119)	(0.2083)
Robust	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	5,603	6,100	2,990	773

Table 10 (continued)

Panel C: The impacts of changes in the number of stocks covered by analysts on forecast errors

Regression:	(10C.1)	(10C.2)	(10C.3)	(10C.4)
Dependent:	$DiD.FE_{ij}$	$DiD.FE_{ij}$	$DiD.FE_{ij}$	$DiD.FE_{ij}$
Sub-sample:	Sub-sample (I)	Sub-sample (II)	Sub-sample (III)	Analyst level
$DiD.Workload_j$	-0.7189**	-0.5493*	-0.8206	-0.2454
	(0.3207)	(0.3040)	(0.5042)	(0.2557)
$DiD.Workload_j \times High_{ij}$	0.7843	0.6569	0.7558	0.5592
	(0.9532)	(0.8676)	(1.2561)	(0.4933)
$DiD.Workload_j \times Low_{ij}$	3.6196***	3.2993**	4.5681***	1.0354*
	(1.4042)	(1.2939)	(1.7025)	(0.5516)
Robust	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	5,603	6,100	2,990	773

Panel D: The impacts of changes in the number of industries covered by analysts on forecast errors

Regression:	(10D.1)	(10D.2)	(10D.3)	(10D.4)
Dependent:	$DiD.FE_{ij}$	$DiD.FE_{ij}$	$DiD.FE_{ij}$	$DiD.FE_{ij}$
Sub-sample:	Sub-sample (I)	Sub-sample (II)	Sub-sample (III)	Analyst level
$DiD.Spec_j$	-1.4661	-1.6642	-0.6934	0.2244
	(1.1276)	(1.1226)	(2.1060)	(1.1479)
$DiD.Spec_j \times High_{ij}$	9.9525**	10.7624***	10.4381*	4.9759*
	(4.0418)	(4.1467)	(5.8660)	(2.9325)
$DiD.Spec_j \times Low_{ij}$	7.0509	6.8485	4.1420	-1.4387
	(4.9562)	(4.6216)	(5.6295)	(3.3245)
Robust	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
Deal FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	5,603	6,100	2,990	773

This table reports the results for the robustness tests to confirm that resources and workload have different impact on the forecast accuracy of superior and inferior analysts. Panels A to D relate to changes in broker firm size, the number of peers, workload, and industries assigned to analysts, respectively. The regression uses the DiD estimations of the variables. The Appendix 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 first three regression 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 price 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) excludes forecasts by analysts involved in three M&As with overlapping windows.

The fourth regression in each panel is run at analyst level by aggregating median forecast accuracy of all the stocks covered by one analyst.