

Does Industry Competition Influence Analyst Coverage Decisions and Career Outcomes?

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Abstract

We analyze whether industry competition influences analyst coverage decisions and whether analysts benefit from covering product market competitors. We find that analysts are more likely to cover a firm when this firm competes with more firms already covered by the analyst. We also find that the intensity of competition among these competitors is additionally important to the coverage decision. Moreover, we find that analysts who cover product market competitors are more likely to obtain analyst star status. These results are consistent with the importance to analysts of industry competition and product market knowledge accumulated through covering product market competitors.

I. Introduction

Analysts are important information intermediaries between the firms they cover and the investors in those firms. They play key roles in firm information environments (Harford, Jiang, Wang, and Xi (2019)), investment and financing policies (Derrien and Kecskes (2013)), corporate governance (Chen, Harford, and Lin (2015)), and product market outcomes (Billett, Garfinkel, and Yu (2017)). The most valuable factor of analysts to investors, according to annual surveys of institutional fund managers by *Institutional Investor* magazine since the 1990s, is their industry knowledge. Recent research also indicates that analysts' industry knowledge can affect their performance and their compensation (Brown, Call, Clement, and Sharp (2015), Bradley, Gokkaya, and Liu (2017)).¹ However, little is known about how competition and the relationships among firms in an industry influence analyst coverage decisions and how analysts gain industry knowledge. In this study, we argue that analysts can accumulate their industry knowledge by covering firms with competing products, and investigate how competition among firms influences analysts' coverage decisions. We also provide quantitative estimates of the importance of industry competition to analyst coverage decisions and their career outcomes. Specifically, we show that analysts manage their portfolios at the analyst-firm level (i.e., add/drop a firm to/from their portfolios) by increasing the likelihood of coverage of a given firm in response to the increased competition of that firm with other firms in analysts' portfolios.

We suggest two reasons why covering firms with competing products can enhance analysts' industry knowledge. First, covering competing firms will help analysts enhance their knowledge about industry competition and thus improve their understanding of firm performance.² This

¹ In a survey of sell-side analysts by Brown et al. (2015), industry knowledge is the most important determinant of analyst compensation.

² For example, Bradshaw (2012) emphasizes the importance of industry competition as part of industry knowledge: "industry knowledge is a firm analyst's understanding of the set of firms competing within an industry, the primary value drivers within that industry, the different strategies adopted by the different firms within the industry..."

knowledge will help an analyst forecast how a competing firm's pricing and product offering strategies may impact the other firms the analyst is following. Second, covering competing firms will help analysts obtain in-depth knowledge about these firms' products and help analysts cover different firms in an efficient manner. Competitors likely produce similar products, which have similar factor inputs/suppliers, production technologies, markets/customers, professional networks, or organizational structures, and thus correlated costs and revenues. Therefore, covering competitors with similar product offerings could help analysts develop expertise about these products.

We posit that increasing knowledge about competitors should help analysts better predict specific industry and product market dynamics adding value to analyst reports (Womack (1996), Loh and Stulz (2011)). Covering competitors should also improve analysts' ability to rank firm performance among competitors, a key area of expertise for high-performing analysts (Boni and Womack (2006)). Furthermore, covering competitors may have real economic implications for the firms covered. Billett et al. (2017) show that the loss of analyst coverage results in negative product market consequences for firms and especially for high competition firms consistent with a decrease in information available for these firms. Their findings thus provide additional motivation for analysts to cover competing firms.

We note, however, although industry competition may intuitively affect analysts' coverage decisions, the net impact of competition on coverage decisions may not be clear. For example, competition may stimulate innovation and total factor productivity and thus affect long term performance and survivability of firms (e.g., Nickell (1996), Olley and Pakes (1996)), while lowering the profitability of firms and increase the bankruptcy risks (e.g., Bolton and Scharfstein (1990)). Competition has ambiguous effects on managerial incentives, which affect firm

performance (e.g., Raith (2003), Dasgupta, Li, and Wang (2018)). Through other different channels, competition may have different effects on firms' performance and survivability, making firms more or less attractive for analysts to cover. In sum, the effect of product competition on analysts' coverage decisions is ultimately an empirical question.

We examine whether the firms that analysts add to (drop from) coverage are affected by two aspects of industry competition based on the text-based firm-level measures of Hoberg and Phillips (2010, 2016) obtained from parsing firms' product descriptions. We examine whether industry competition influences analyst coverage decisions using both the number of product competitors in an analyst's portfolio and the degree of product competition among these firms. These measures of competitors are at the firm level and expand upon traditional fixed industry classifications, since each firm has a unique set of peers. Within the set of industry competitors, product similarity scores measure the extent of overlapping product competition between firm pairs, a nuanced feature infeasible with typical competition measures based on fixed industries such as SIC codes. The unique set of product competitors for each firm allows us to investigate analysts' decisions to add/drop a firm to/from their portfolios, conditional on whether the firm is a product market competitor with other firms in analysts' portfolios and how intensively the firm competes in product markets with its competitors in analysts' portfolios.

We find that analysts are more likely to add a firm to (drop a firm from) coverage if the firm has more (fewer) product competitors in the analyst's portfolio and has more intense product market competition with the other firms the analyst covers. The economic significance is large. A one standard deviation increase in our measure of product competitors (competition intensity) increases a firm's unconditional probability of being added by 31% (41%), and decreases a firm's unconditional probability of being dropped by 8.1% (6.0%). We find our measures of competition

outperform traditional SIC codes in explaining analyst coverage decisions over time. This result is perhaps unsurprising. For example, SIC codes still group Dell, IBM, and Apple as competitors in the computer industry, despite IBM selling its PC business and Apple getting most of its profits from the cell phone business. Given that these measures of competition are updated each year based on the evolving products firms offer, these results support the conclusion that analysts adjust their coverage portfolios to cover evolving industry competitors. Our results further indicate that given the number of product competitors in the analyst's portfolio, the intensity with which they compete (the degree of product similarity among competitors) is additionally important to the coverage decision.³

We also examine analysts' decisions to add or drop an acquiring firm around firm mergers and acquisitions (M&A). Since M&A are an effective way to help acquiring firms generate new products (Hoberg and Phillips (2010)), they create a change in the product market competition between acquiring firms and other firms in analysts' portfolios exogenous to analysts. As highlighted earlier, analyst have incentives to cover firms with greater competition. Covering product market competitors thus helps analysts better understand key aspects of an industry and enables them to deepen industry knowledge. We therefore expect that an exogenous change in the product market competition due to M&A will motivate analysts to adjust their portfolios, i.e., add (drop) acquiring firms to (from) their coverage when acquiring firms have stronger (weaker) competition relationships with other firms in analysts' portfolios after an M&A. Our results confirm this prediction, which are consistent with our main findings on coverage decisions.

We further examine analysts' decisions to add or drop a firm around brokerage house M&A, as coverage decisions are likely to change at these times for reasons exogenous to the underlying

³ Our main inferences are unaffected when we use additional competition intensity measures. Section III provides the details.

firms covered (Hong and Kacperczyk (2010), Chen et al. (2015)). For example, a brokerage house after an M&A may adjust its business and operation strategies (e.g., strengthen its operation in a new market, diversify its lines of business geographically, or strengthen its research department, see, e.g., Hong and Kacperczyk (2010)) and subsequently assign new firms for its analysts to cover. Given such assignment decisions already bear the costs of acquiring and processing new information for new firms, we conjecture that brokerage houses and analysts will look for offsetting benefits such as the ones that may arise from covering product market competitors. We find that industry competition is positively and significantly related to analyst add decisions and negatively related to drop decisions around brokerage house M&A. These results further reinforce our initial findings, given brokerage house M&As are exogenous shocks to analyst coverage decisions.

In addition to investigating analysts' coverage decisions, we also examine how analysts' choices of how many competitor firms to follow and the degree of competition among these firms influence analysts' career outcomes. Note that our earlier discussion about how product competition may affect analysts' coverage decisions may apply to career outcomes such as star rankings. For example, industry knowledge is rated as a top factor for star rankings, which are crucial to both brokers' status and reputation and analysts' compensation. To measure analyst career outcomes, we consider two dimensions of analyst career outcomes: (i) being nominated *Institutional Investor* All-American Research Team stars, and (ii) moving to a smaller brokerage house or leaving the analyst profession. Being named to the All-American Research Team has a significant effect on analyst compensation and their brokerage house reputation (Stickel (1992), Michaely and Womack (1999), Hong, Kubik, and Solomon (2000), and Emery and Li (2009)). Moving to a smaller brokerage house, which generally confers a lower status, or leaving the analyst profession, tend to result in lower compensation (Hong and Kubik (2003)). We find that analysts with portfolios of firms having

greater product competitor overlap and higher competition intensity with each other are more likely to be nominated *Institutional Investor* stars and are less likely to be fired. While we document the benefits of covering competing firms to financial analysts, we should note that because analysts' coverage decisions are determined by various factors as discussed earlier, not all analysts or their brokerage houses may find it optimal to cover firms with strong competition. We also find that given the number of product competitors in the analyst's portfolio, the extent with which these rivals compete is additionally important to the career outcomes.

As an extension of our main analysis, we investigate whether product market competition improves the accuracy of analysts' forecasts and the informativeness of analysts' research reports. Our empirical results show that analysts issue more accurate forecasts, and their forecasts and recommendations are more informative for a firm if this firm has more product peers and competes more intensively with its peers that the analyst covers. These results are consistent with the notion that covering product market competitors enhances analysts' industry knowledge.

Our paper contributes to the literature on analyst behavior by providing insights about how analysts accumulate industry knowledge. Although earlier research suggests that analysts are industry specialists (e.g., Boni and Womack (2006)) and survey evidence indicates that industry knowledge is important to analysts (surveys by *Institutional Investor* and Brown et al. (2015)), little empirical evidence exists to explain how analysts develop or accumulate their industry knowledge and the importance of industry competition to analysts' industry knowledge and coverage decisions. Our empirical evidence confirms the importance of industry competition and competition intensity in analysts' coverage decisions. Our results also provide estimates of the economic significance of covering product market competitors and competition intensity to analysts' decisions.

Our paper also contributes to the analyst coverage literature. Existing studies document that

firm characteristics such as firm size, trading volume, and institutional ownership affect analyst coverage (e.g., Bhushan (1989), Harford et al. (2019)). Our paper extends these studies by documenting the importance of product competition between a firm and its peers on analyst coverage decisions and career outcomes.⁴ Our results also show that text-based measures of competitors and product similarity better explain analyst coverage decisions at the analyst-firm level than traditional SIC based measures. Importantly, we examine how analysts manage their coverage portfolios at the analyst-firm level. We observe an approximate 25% annual turnover rate in the average analyst portfolio, consistent with analysts actively adjusting coverage. Our evidence helps this literature obtain a more granular understanding of the coverage decision and fill the gap noted by Beyer, Cohen, Lys, and Walther ((2010), p.329): “Despite the numerous empirical studies documenting the association between the degree of analyst following and firm characteristics, we still do not know the factors that analysts consider when making this decision, and how the incentives faced by the analyst and/or the composition of the analyst’s portfolio of followed firms shape this decision.”

Finally, our finding of how product market competition influences star selection adds to prior research on star rankings (Stickel (1992), Michaely and Womack (1999), Hong et al. (2000), and Emery and Li (2009)). Our findings regarding analyst forecast accuracy and analyst informativeness complement the evidence in Bradley et al. (2017) on how industry knowledge affect covered firms’ information environments.⁵

⁴ Studies beginning with Lang and Lundholm (1996) examine how analyst coverage relates to firms’ financial disclosures using correlation analyses. Our analysis shows how exogenous industry competition influences analyst coverage decisions. As mentioned above, similar product strategies (e.g., product composition and consequent industry competition) determines similarity in many other aspects among firms, not the other way around. While firms might change, for example, disclosure practices to cater to analysts and other capital market players, firms are unlikely to change product strategies to influence analysts’ coverage decisions.

⁵ Our results regarding analyst coverage and forecast accuracy are robust to including analyst or analyst-year fixed effects, which help control for analysts’ prior work experience in certain industries (Bradley et al. (2017)).

II. Data and Sample

We obtain and calculate measures of industry competitors and competition intensity using data downloaded from the Hoberg and Phillips (HP) industry database available at <http://hobergphillips.tuck.dartmouth.edu/>. Our sample period is from 1988 to 2019 and is based on text-based analysis of product descriptions downloaded from electronically filed 10 – K documents. We provide a brief description of the product text-based method here.⁶

The product text-based method begins by calculating firm pairwise similarity scores from text analysis of firm product descriptions using Section IA of the 10-K filed each year with the SEC. Analysis of the product description sections of the 10-K begins with parsing each word in Section IA and then excluding common words, adjectives, and adverbs, so only product words remain in the pairwise similarity calculation. Using these product words for each firm, a pairwise similarity score is calculated as the pairwise cosine similarity of each two firms' word vectors. The pairwise similarity scores are numerically calculated using word vectors for each firm, with each element of the word vector being a zero-one indicator, indicating that a product word appears in an individual firm's product description.

Once the product-similarity scores are calculated, competitors are identified and grouped into industries by imposing a minimum similarity score, with the minimum score chosen such that the number of related competitors overall across all industry groupings is at the same percentage as that obtained were one to use the SIC code at the three-digit level.

A large difference between this method and competitors available using SIC codes is that in the text-based industry methods each firm has its own distinct set of competitors, and industries thus have non-transitive membership. This feature helps in our identification of whether to add or

⁶ Interested readers can go to Hoberg and Phillips (2016) for more extensive development of the text-based method and for comparisons of this method versus the standard method of identifying industry competitors using SIC codes.

drop specific firms in the analyst coverage decision. Specifically, if firm A is a competitor of firm B and B is a competitor of Firm C, Firm A does not have to be a competitor of Firm C. This relaxation of transitivity is important for multi-product firms. Thus, in the product text-based method, competitors are firm centric with each firm having its own distinct set of competitors— analogous to networks or a "Facebook" circle of friends. Competitor sets are non-overlapping and are measured with respect to each firm—an important feature for our tests of adding and subtracting firms to an analyst's coverage.

Additionally, these new industry classifications are updated annually, which allows us to better track changes in analyst firm industry coverage. By contrast, SIC codes are updated only every five years in the Census Data and do not change very often in COMPUSTAT. Lastly, the SIC codes impose a transitive zero-one industry competitor identification. Firms are either competitors or they are not. In many of our tests, we use the text-based continuous measure of product similarity allowing within industry analysis of add and drop coverage decisions.

We retrieve stock price and return data from CRSP; financial and segment data from COMPUTSTAT; actual earnings, analyst forecast and recommendation data from the I/B/E/S; and institutional holdings from Thomson Reuters. We collect *Institutional Investor's* rankings of All-American Research Team analysts for our sample period. The All-American rankings are published each year in the October issue of the magazine. For our analysis, we require the availability of all the variables except for institutional holdings, R&D intensity, and advertising intensity. We replace these variables with zero if the values are missing. Lastly, we only include analysts covering at least three firms in the analysis.

III. Analyst Coverage Decisions

A. Research Design

We now investigate how analysts make coverage decisions (adding or dropping firms) based on whether a firm competes with the existing firms they cover. These tests allow us to examine the effect of industry competition at the individual analyst firm level. We estimate the analyst-firm coverage decision using the following linear probability model:

$$(1) \text{Prob}(\text{ADD}_{ijt+1}=1) = \alpha + \beta_1 \times \text{TNIC_COMPETITOR_COVERAGE}_{ijt} \\ + (\text{TNIC_COMPETITION_INTENSITY}_{ijt}) + \beta_2 \times \text{SIC_COVERAGE}_{ijt} + \\ \beta_k \times \text{Firm Level Controls}_{it} + \beta_n \times \text{Analyst Level Controls}_{jt} + \varepsilon_{ijt},$$

where ADD_{ijt+1} is equal to one if firm i was not covered by analyst j in year t but is covered in year $t+1$, and zero if firm i was not covered by analyst j in either year t or year $t+1$.⁷ We also estimate the impact of competition intensity among competitors on the analyst add decision by (i) replacing $\text{TNIC_COMPETITOR_COVERAGE}$ with a measure of competition intensity ($\text{TNIC_COMPETITION_INTENSITY}$) in the above equation and (ii) including both $\text{TNIC_COMPETITOR_COVERAGE}$ and $\text{TNIC_COMPETITION_INTENSITY}$ in equation (1). We expect β_1 to be positive in equation (1) if adding industry competitors or covering competitors with high competition intensity has a benefit to analysts.

In these tests, we use the localized measure of how similar a firm's products are to those of the other firms covered by the analyst at the analyst-firm level. This measure allows us to see how each firm is related to the existing competitor firms in an analyst's portfolio. For firm i , we define $\text{TNIC_COMPETITOR_COVERAGE}_{ijt}$ as N_{ijt} / M_{jt} , where M_{jt} is the total number of firms in the analyst's j 's portfolio while N_{ijt} is the number of the firm's TNIC peers (i.e., the number of firms, other than firm i , shown both in the analyst j 's portfolio and focal firm i 's total similarity

⁷ We use a linear probability model instead of a logit model because the coefficient estimates of fixed effect logit models are inconsistent (e.g., Greene (1997), Greene (2004)), although our results are not affected by using a logit or probit model.

calculation). Since the database also provides detailed scores for the pairwise similarity index, we create a second measure, `TNIC_COMPETITION_INTENSITY`, to capture the competitive intensity between firms in the analyst's portfolio. This measure is calculated as the average of pairwise product similarity scores between firm i and all of the firm's TNIC peers within the analyst j 's portfolio.

As discussed earlier, whether firms compete against each other (competitor coverage) and competition intensity among competitors are the two dynamic aspects of industry competition that may influence analyst coverage decisions. `TNIC_COMPETITOR_COVERAGE` and `TNIC_COMPETITION_INTENSITY` capture these two aspects of product competition. A larger number for `TNIC_COMPETITOR_COVERAGE` (`TNIC_COMPETITION_INTENSITY`) indicates that firm i has more competitive peers (competition intensity between firm i and these peers is greater) within the analyst j 's portfolio, given that for another firm to enter the calculation of firm i 's HP similarity score, the score between them has to be larger than the minimum similarity threshold, according to the design of the HP index. We provide a specific example of how we construct the `TNIC_COMPETITOR_COVERAGE` and `TNIC_COMPETITION_INTENSITY` in Appendix A.

If analysts randomly choose firms to follow, any firm from the overall population not covered by analyst j in year t can be in our `ADD=0` sample. However, since the number of firms in this sample pool (Pool A) is very large, the number of observations for regressions at the firm-analyst-year level would be huge. To ensure that any significant result is not caused by too large a number of observations, we use a restricted benchmark sample, which we call Pool B, whereby we include only the firms from Pool A that appear in the same three-digit SIC industry with any other

firms already in the analyst's portfolio.⁸

Our text-based measures of competition are designed to capture firm-specific dynamic changes to industry competition in each year. For comparison, we also create a measure based on three-digit SIC industry named SIC_COVERAGE. Specifically, SIC_COVERAGE is K_{ijt} / M_{jt} , where M_{jt} is the total number of firms in the analyst's j 's portfolio while K_{ijt} is the number of firms shown both in the analyst j 's portfolio and focal firm i 's three-digit SIC industry. Note that this measure does not change as frequently as either the TNIC_COMPETITOR_COVERAGE or TNIC_COMPETITION_INTENSITY in capturing the effect of industry competition on analyst coverage decisions as the fixed SIC industry relationship between firms seldom changes from year to year and is either zero or one.

To strengthen our inferences regarding the role of competition intensity in analyst coverage decisions, we create three additional measures of TNIC_COMPETITION_INTENSITY that capture the intensity of competition by close competitors: TOP4_COMPETITORS_COMP_INTENSITY, COMPETITIVE_FLUIDITY and TOP4_COMPETITIVE_FLUIDITY. Specifically, TOP4_COMPETITORS_COMP_INTENSITY is the average of similarity scores of firm i 's four TNIC competitors with the highest similarity scores within the analyst j 's portfolio. COMPETITIVE_FLUIDITY is natural logarithm of the average fluidity value (Hoberg, Phillips, and Prabhala (2014)) over all of the firm's TNIC peers within the analyst j 's portfolio.⁹ TOP4_COMPETITIVE_FLUIDITY is natural logarithm of the average fluidity value over the firm's four TNIC peers with the largest fluidity scores within the

⁸ Note that this choice (i.e., reducing the $ADD_{ijt}=0$ sample from Pool A to Pool B) works against finding the expected results since benchmark firms (i.e., $ADD_{ijt}=0$ firms) in Pool B already compete with the existing firms in the analyst's portfolio. Our results are not affected if we set Pool B as these either in the same industry (two- or four-digit SIC, GICS or HP TNIC industry) to existing firms in the portfolio.

⁹ According to Hoberg, Phillips and Prabhala (2014), product fluidity is a measure of "the competitive threats faced by a firm in its product market, that captures changes in rival firms' products relative to the firm." The fluidity data is available at <http://hobergphillips.tuck.dartmouth.edu/>.

analyst j 's portfolio.

We also control for firm variables that have been shown to affect analyst coverage decisions (e.g., Bhushan (1989), Beyer et al. (2010), Harford et al. (2019)). Specifically, we include the logarithm of the market value of equity ($\text{Ln}(\text{MARKET_CAP})$) the book-to-market ratio (BOOK_TO_MARKET) and institutional holdings (INST_HOLDINGS), measured as the percentage ownership by institutions obtained from 13-F disclosures in the most recent year. We also include RETURN_VOLATILITY , the standard deviation of firm monthly stock returns for the fiscal year, $\text{Ln}(\#\text{SEGMENTS})$, the natural logarithm of the number of business segments reported in the Compustat Segment File, R\&D_INTENSITY and $\text{ADVERTISING_INTENSITY}$, the ratio of research and development and advertising expenses, respectively, to operating expense. Finally, we include trading volume (TRADING_VOLUME) for the current fiscal year in millions of shares and an indicator for loss firms (LOSS_FIRMS).

We further control for two analyst/broker characteristics that may affect analysts' tendency to add a firm in general. PORTFOLIO_SIZE is the number of firms covered by the analyst in the current year. Prior literature suggests that brokerage houses assign larger number of companies to more capable or talented analysts (Jacob, Lys, and Neal (1999)). If a larger PORTFOLIO_SIZE reflects stronger analyst ability, we expect that analysts with larger portfolios are more likely to expand their coverage. Jacob et al. (1999) suggest that although additional coverage may dilute these analysts' attention to each firm, the revenues generated by the analyst covering additional firms may outweigh the costs of diluted attention. BROKER_SIZE is the number of analysts employed by the brokerage house of the analyst in the current year. Prior studies find that larger brokerage houses have better research resources, better connections with the companies they follow, and attract higher quality analysts (Jacob et al. (1999)). These advantages would imply that analysts

from larger brokerage houses may be more likely to expand coverage. However, large brokerage houses may also decide to expand coverage by hiring more analysts due to the strong research support in these firms (Jacob et al. (1999)). Thus, the impact on brokerage size on individual analysts' coverage decisions is indeterminate.

To investigate the impact of competitor coverage among firms and the competition intensity among competitors in an analyst's portfolio on the analyst's decision to drop a firm from the coverage portfolio, we use the following analyst-firm level linear probability model:

$$(2) \text{Prob}(\text{DROP}_{ijt+1}=1) = \alpha + \beta_1 \times \text{TNIC_COMPETITOR_COVERAGE}_{ijt} \\ + \beta_2 \times \text{TNIC_COMPETITION_INTENSITY}_{ijt} + \beta_3 \times \text{SIC_COVERAGE}_{ijt} + \\ \beta_k \times \text{Firm Level Controls}_{it} + \beta_m \times \text{Analyst-Firm Level Controls}_{ijt} + \beta_n \times \text{Analyst} \\ \text{Level Controls}_{jt} + \varepsilon_{ijt},$$

where DROP_{ijt+1} is equal to one if firm i was covered by analyst j in year t but not in year $t+1$, and zero if firm i was covered by analyst j in both years. In this test our sample consists of firms covered by analysts in year t and we examine whether an analyst drops a firm from coverage in the next year. As in our previous tests, we (i) replace $\text{TNIC_COMPETITOR_COVERAGE}$ with $\text{TNIC_COMPETITION_INTENSITY}$ and (ii) include both $\text{TNIC_COMPETITOR_COVERAGE}$ and $\text{TNIC_COMPETITION_INTENSITY}$ in the above equation to examine the impact of competition intensity among competitors on the drop decision.

In this and all subsequent analyses (except for the firm level analysis), we calculate the relative rank of product competition following Hong and Kubik (2003), given our focus on firms that are covered by analysts in year t . Using a relative (rank) measure instead of a raw measure mitigates the effects of common shocks that affect all analysts covering a firm at a given point in time. Using relative ranks also facilitates the comparison across analysts who cover different firms

and industries in year t .¹⁰ In equation (2), `TNIC_COMPETITOR_COVERAGE` and `TNIC_COMPETITION_INTENSITY` are defined as above but relative to analysts following firm i in year t . The relative measures thus capture the degree of competition between a given firm (firm i) and existing firms in analyst j 's portfolio in year t , with a larger number indicating high potential competition given high product overlaps. We control for firm-level variables in equation (2). If the benefit from industry competition dominates the cost, we expect β_I to be negative in equation (2).

In addition, we control for a number of analyst-firm level variables in equation (2). Note that we cannot include these analyst-firm variables in the ADD regression (equation (1)) because firms added in year $t+1$ have not yet been covered by an analyst in year t . We include these analyst-firm variables in equation (2) where the DROP regression is based on *existing* firms that have been covered by analysts in year t (they may or may not be dropped in year $t+1$).

We include forecast horizon (`HORIZON`), which is a measure of staleness of analyst's *last* forecast for a firm. This variable can measure the level of interest an analyst has in a firm, or the effort they expend covering it. Forecast horizon has been shown to be negatively associated with forecast accuracy (Jacob et al. (1999), Clement and Tse (2005)). We thus expect that analysts are more likely to drop those firms for which they have not issued forecasts for a long time (potentially due to lack of interest or effort).

We also include forecast boldness (`BOLDNESS`). A bold forecast can be a signal of the quality of the agent's private information (Hong et al. (2000), Clement and Tse (2005)). Clement and Tse (2005) show that bold forecasts provide more relevant information to investors than herding forecasts. However, prior studies have shown mixed evidence regarding the effect of boldness on

¹⁰ Our results hold when we use the raw measures of product competition.

analyst career outcomes.¹¹ We thus do not provide signed prediction for this variable. Finally, we include an analyst's firm-specific experience (EXPERIENCE). Prior research finds that forecast accuracy increases with firm-specific experience. If analysts have a longer experience with a firm they cover, they may be less likely to drop this firm from coverage. However, there is a debate about the net effect. Experienced analysts may care less about forecast accuracy as Hong et al. (2000) show that poor forecast performance has little effect on experienced analysts' career outcomes. Thus, we make no prediction on the sign of this variable. Finally, consistent with the ADD regression, we include the number of firms covered by the analyst (PORTFOLIO_SIZE) and the number of analysts employed by the brokerage house of the analyst (BROKER_SIZE) to control for the potential impact of these analyst/broker characteristics (analyst ability and resources) on analysts' drop decisions. We define all of these control variables in Appendix B.

To be consistent with prior analyst studies (e.g., Hong and Kubik (2003)), we define these analyst-firm control variables using relative ranks among analysts following a firm. As mentioned earlier, using relative ranks facilitates the comparison across analysts that might otherwise be difficult due to differences in the firms and industries they cover. We first calculate the raw values for all analyst-firm variables (HORIZON, BOLDNESS, EXPERIENCE, PORTFOLIO_SIZE and BROKERAGE SIZE). For each of these variables, we then rank all of the analysts that cover firm j in year t based on the raw values, and define the relative value as $1 - (\text{RANK}_{ijt} - 1) / (\# \text{ of ANALYSTS}_{it} - 1)$, where $\# \text{ of ANALYSTS}_{it}$ is the total number of analysts covering firm i . If more than one analyst has the same raw value and thus rank as firm i , we assign each of these analysts the average of their ranks, with a larger rank number corresponding to a larger raw number for easy

¹¹ For example, Hong et al. (2000) find that being bold and inaccurate leads to poor career outcomes; however, being bold and accurate does not significantly improve an analyst's career prospects. Clement and Tse (2005), on the other hand, show that bold analysts who follow large numbers of firms appear to enjoy greater job security than other bold analysts.

interpretation.

In both equations (1) and (2), we include year and industry (or firm) fixed effects. The industry fixed effects are based on the 50 fixed industry classifications (FIC) available at the Hoberg-Phillips Data Library.¹² We also adjust the standard errors for heteroskedasticity and clustering by analyst, industry, and year (Cameron, Gelbach, and Miller (2011)).¹³

B. Summary Statistics

Table 1 Panel A shows summary statistics for the key variables at the analyst-firm level. For add decisions, about 1% of firms competing in products not covered by an analyst in a given year are covered the next year. For drop decisions, about 29% of firms covered by an analyst in one year are dropped from coverage the next year. These percentages are essentially the unconditional probability of firms being added to or dropped from an analyst's coverage, respectively. Given that analysts generally cover a similar number of firms across years, these probabilities imply a turnover rate of about 30% of firms each year in the average analyst's portfolio. By comparing observations within three subportfolios: newly covered firms ($ADD_{ijt+1}=1$), firms with continued coverage ($DROP_{ijt+1}=0$), and firms dropped from coverage ($DROP_{ijt+1}=1$), we can see that analysts change a large proportion of their portfolios every year. Panel A also shows that the mean of `TNIC_COMPETITOR_COVERAGE` (`TNIC_COMPETITION_INTENSITY`) is 0.13 (0.02) for the ADD sample, and is 0.50 (0.50) for the DROP sample.¹⁴ We also present summary statistics for additional competition intensity variables that we explore for robustness in later tables. These measures are `TOP4_COMPETITORS_COMP_INTENSITY`, `COMPETITIVE_FLUIDITY` and

¹² Our results are robust to including SIC (two or three digits) or GICS (six or eight digits) industry fixed effects instead.

¹³ Our results are robust to analyst, firm and year clustering and other clustering methods (firm and year, industry and year, or analyst and year).

¹⁴ As mentioned earlier, we standardize our competition measures using relative ranks among analysts following a firm) in the DROP regressions. Since we focus on firms that are not covered by analysts in year t in the ADD regressions, we cannot rank competition measures among analysts following a firm in ADD regressions.

TOP4_COMPETITIVE_FLUIDITY. They capture the intensity of competition by close competitors, as defined earlier.¹⁵

[Insert Table 1 Here]

The descriptive statistics on the other variables are as follows: The mean of SIC_COVERAGE is 0.45 for the *Add* sample, and is 0.50 for the *DROP* sample. All other rank variables have a mean and median of 0.50. The mean natural logarithm of market value of equity is 7.59. The average book-to-market value and institutional ownership are both about 50%, and the average monthly return standard deviation is about 0.04. The mean natural logarithm of number of business segments is 1.08. The mean ratio of R&D and advertising expenses to operating expense are 0.07 and 0.01, respectively. About 21% of firms report a loss in the sample period.

C. Add/drop Decision Main Results

Table 2 presents the results of the linear probability model in equation (1) for analysts' add decisions. We include year and industry (firm) fixed effects in columns 1-3 (columns 4-6). In column 1 (column 4), the coefficient on TNIC_COMPETITOR_COVERAGE is positive and significant, suggesting that analysts are more likely to add firms that have more competitors in their portfolios. In column 2 (column 5), the coefficient on TNIC_COMPETITION_INTENSITY is positive and significant, suggesting that analysts are more likely to add firms that compete more intensively (i.e., have higher average similarity scores) with the existing firms in their portfolios. In column 1 (column 2), we find that a one standard deviation increase in TNIC_COMPETITOR_COVERAGE (TNIC_COMPETITION_INTENSITY) increases a firm's probability of being added by 0.31% (0.41%). Given that Table 1 shows that the unconditional probability of being added to analyst portfolios is approximately 1%, these results are equivalent to

¹⁵ The sample size for fluidity related measures is smaller since the fluidity data starts from 1989 instead of 1988.

approximately 31% (= 0.31% divided by 1%) (41% (= 0.41% divided by 1%)) of the unconditional probability of being added.

In column 3 (6), when we include both `TNIC_COMPETITOR_COVERAGE` and `TNIC_COMPETITION_INTENSITY` in the same regression, the coefficients on `TNIC_COMPETITOR_COVERAGE` and `TNIC_COMPETITION_INTENSITY` are both positive and significant, suggesting that given the number of competitors, the intensity with which they compete is additionally important to the add decision.

[Insert Table 2 Here]

Table 3 presents the results of the linear probability model in equation (2) for analysts' drop decisions. We include year and industry (firm) fixed effects in columns 1-3 (columns 4-6). The coefficient estimates on `TNIC_COMPETITOR_COVERAGE` (`TNIC_COMPETITION_INTENSITY`) are negative and significant, suggesting that analysts are less likely to drop firms that have more competitors (compete more intensively in products with the other firms) in their portfolios. Economically, based on the results in columns 1 and 2, a one standard deviation increase in `TNIC_COMPETITOR_COVERAGE` (`TNIC_COMPETITION_INTENSITY`) decreases a firm's probability of being dropped by 2.35% (1.73%). Given that Table 1 shows that the unconditional probability of being dropped from analyst portfolios is 29%, these results are equivalent to approximately 8.1% (= 2.35% divided by 29%) (6.0% (= 1.73% divided by 29%)) of the unconditional probability of being dropped. Moreover, when we include both `TNIC_COMPETITOR_COVERAGE` and `TNIC_COMPETITION_INTENSITY` in the same regression in columns 3 and 6, our results indicate that that given the number of competitors, the intensity with which they compete is additionally important to the drop decision.

Overall, the results from the coverage decision regressions suggest that analysts actively adapt to the industry competition of covered firms: analysts are more likely to add firms to their coverage portfolios that compete with the firms they already cover, and are less likely to drop firms that compete with the other firms they cover. These results are consistent with the importance to analysts of industry competition and product market knowledge accumulated through covering product market competitors.

[Insert Table 3 Here]

The coefficient estimate of SIC_COVERAGE is generally weaker in analysts' add and drop decisions. SIC based measures do not perform well here likely because they are less timely, coarse and less informative. For example, SIC based measures have former competitors still listed as having the same SIC as current competitors and fail to quickly recognize new competitors, as shown earlier in several cross-validation tests provided by Hoberg and Phillips (2016).

The other firm-level control variables are mostly consistent with our expectations. We discuss these results but do not report the individual coefficients for firm-level control variables. We find that firms with a large size are less likely to be dropped by analysts, whereas firms with higher return volatility and loss firms are more likely to be dropped by analysts. Analysts are more likely to drop firms from their coverage when they issue long-horizon (i.e., do not issue new forecasts). We also find that analysts are less likely to drop firms from their coverage when their forecasts for these firms are bold, consistent with these analysts using these forecasts as a signal of knowledge (Hong et al. (2000)). Analysts with larger portfolio size are more likely to add a new firm but less likely to drop an old firm from their coverage, consistent with brokerage houses assigning more firms to more capable analysts (Jacob et al. (1999)). The analyst-firm level results are also robust to using firm-level clustering.

We report the results of ADD (DROP) analyses using several additional competition intensity measures that capture the intensity of close competition from competitors in Table 4 (Table 5). Panel A reports the results when we replace `TNIC_COMPETITION_INTENSITY` with `TOP4_COMPETITORS_COMP_INTENSITY`, `COMPETITIVE_FLUIDITY` and `TOP4_COMPETITIVE_FLUIDITY`, respectively. Panel B reports the results when we also include `TNIC_COMPETITOR_COVERAGE`. Our results are similar to the main results based on `TNIC_COMPETITION_INTENSITY`. From the results in Panel A of Table 4, we find that a one standard deviation increase in `TOP4_COMPETITORS_COMP_INTENSITY`, `COMPETITIVE_FLUIDITY` and `TOP4_COMPETITIVE_FLUIDITY` increases a firm's probability of being added by 0.65%, 0.41%, 0.38%, respectively. These results are economically significant given that Table 1 shows that the unconditional probability of being added to analyst portfolios is approximately 1%. Based on the results in Panel A of Table 5, a one standard deviation increase in `TOP4_COMPETITORS_COMP_INTENSITY`, `COMPETITIVE_FLUIDITY` and `TOP4_COMPETITIVE_FLUIDITY` decreases a firm's probability of being dropped by 3.08%, 0.95%, and 2.57%, respectively. Given that Table 1 shows that the unconditional probability of being dropped from analyst portfolios is 29%, these results are equivalent to approximately 10.6% (= 3.08% divided by 29%), 3.3% (= 0.95% divided by 29%), and 8.9% (=2.57% divided by 29%) of the unconditional probability of being dropped.

[Insert Tables 4 and 5 Here]

Bradley et al. (2017) find that analysts with prior work experience in certain industries issue more accurate forecasts for firms in these industry compared to their peers who lack such experience, suggesting the importance of analysts' prior industry knowledge in their coverage decisions. To address the concern that our coverage results are driven by analysts' prior work experience rather

than product market competition, in an additional analysis we further control for analyst or analyst-year fixed effects in our baseline regressions (equations (1) and (2)). Doing so helps control for analysts' characteristics, including their prior work experience. Our results from this additional analysis (untabulated) are similar to our main results.

Finally, as an additional analysis, we examine the effect of the *change* in product competition on analysts' add/drop decisions. Specifically, we re-estimate our baseline add/drop regressions by replacing $TNIC_COMPETITOR_COVERAGE$ ($TNIC_COMPETITION_INTENSITY$) with $\Delta TNIC_COMPETITOR_COVERAGE$ ($\Delta TNIC_COMPETITION_INTENSITY$), which is the change in $TNIC_COMPETITOR_COVERAGE$ ($TNIC_COMPETITION_INTENSITY$) from year $t-1$ to year t . We also replace baseline control variables with the corresponding change variables in our add/drop regressions. Our untabulated results show that the effect of the change in product competition is consistent with that based on the level tests reported in Tables 2 and 3.

Overall, our results confirm that analysts' decisions to add/drop a firm to/from their coverage portfolios are significantly influenced by (1) whether firms are product market competitors and (2) the degree of competition intensity among competitors.

D. Add/drop Decisions around Firm Mergers & Acquisitions

As discussed earlier, prior studies on the determinants of analyst coverage decisions face a challenge in establishing causality from their focal variables (e.g., disclosures) to coverage decisions. This is because firm managers might have various motives to change, say, disclosure practices to cater to analysts' preferences. However, it is less likely that firms would change product strategies (e.g., product composition and consequent industry competition) to influence analysts' coverage decisions. Thus, our focus on industry competition allows us to draw more powerful

inferences about factors driving coverage decisions. To further reinforce our inferences regarding the impact of industry competition on analyst coverage decisions, we examine analysts' decisions to add or drop a firm subsequent to its merger with another firm. Since mergers are an effective way to help acquiring firms to develop new products (Hoberg and Phillips (2010)), they can substantially change the industry competition between an acquiring firm and other existing firms within an analyst portfolio. We would expect analysts to be more likely to cover a firm if it makes an acquisition that competes in products with firms in the analyst's portfolio, but we would not expect a firm to make an acquisition decision in order to increase analyst coverage. Thus, M&A activity creates a shock exogenous to the analysts.

We identify mergers and acquisitions (M&A) from the SDC database and require the deals be greater than \$10 million to have a significant impact on product relations and the analyst coverage decisions. To estimate analysts' add decision in our M&A setting, we rerun equation (1) two years after the M&A event to examine whether analysts' decision to cover the acquiring firm is positively associated with the industry competition between this firm and other existing firms within an analyst portfolio. For the drop decision, we rerun the equation (2) two years after the M&A event to examine whether analysts' decision to drop the acquiring firm is negatively associated with the industry competition between this firm and other existing firms within an analyst portfolio. Note that in these analyses, the sample size is substantially smaller because we focus on analysts' decisions to add or drop an acquiring firm after the M&A event.

[Insert Table 6 Here]

Table 6 reports the estimation results for analysts' decisions to add (drop) an acquiring firm two years after the M&A event. Panel A (Panel B) shows the results for add (drop) decisions. These results are similar in sign and significance to our main results reported in Table 2 and Table 3,

reinforcing our conclusion that industry competition with an analyst's portfolio influences their coverage decisions. Our results are unaffected if we require the M&A target to be a public firm. The results also hold regardless of whether acquirers and their targets are in the same or different SIC two-digit industries.

E. Add/drop Decisions around Brokerage House Mergers & Acquisitions

We further implement the tests for a subsample in a quasi-experimental research design and examine how analysts adjust their portfolios after the brokerage house mergers. These brokerage house mergers are most likely exogenous to competition and industry relatedness of the underlying firms the brokerage houses cover. The central idea is that following brokerage house mergers, brokerage houses will make new assignment decisions. For example, a brokerage house after an M&A may adjust its business and operation strategies (e.g., strengthen its operation in a new market, diversify its lines of business geographically, or strengthen its research department, see, e.g., Hong and Kacperczyk (2010)) and subsequently assign new firms for its analysts to cover. We conjecture that given such assignment decisions already bear costs of acquiring and processing new information, brokerage houses will look for offsetting benefits such as the ones that may arise from analysts following competing firms in similar industries.

We build our sample of brokerage house mergers following prior studies (e.g., Hong and Kacperczyk (2010), Chen et al. (2015), and Billett et al. (2017)). Specifically, we keep mergers that have earnings estimates in I/B/E/S for both the bidder and target brokerage houses and retain merging houses that have overlapping coverage (bidder and target brokerage houses cover at least one same company). Following this sampling requirement, we have 19 brokerage house merger events from 1994 to 2008 and we examine analysts' decisions to add (drop) a firm two years after brokerage house merger events.

[Insert Table 7 Here]

Table 7 reports the estimation results for analysts' decisions to add (drop) a certain firm two years after the broker M&A event. Panel A (Panel B) shows the results for add (drop) decisions. These results show that industry competition as measured by `TNIC_COMPETITOR_COVERAGE` and `TNIC_COMPETITION_INTENSITY` are both positively and significantly related to analyst add decisions and negatively related to drop decisions. The results reinforce our previous conclusions that industry competition is important to coverage decisions.

F. Firm-level Analysis

We next examine the effect of industry competition on analyst coverage decisions at the firm level. Note that the competition measures at the firm level reflect the relation between a firm and all other firms in the industry or economy. The firm-level analysis of analyst coverage does not consider the competitor overlapping coverage among firms in analysts' portfolios. However, when a firm competes more intensively with other firms or faces more competitors in general, this firm is more likely to attract greater analyst coverage because this firm is more likely to compete with firms within the analyst's portfolio. This is consistent with our earlier prediction in the analyst-firm level analysis, because such a firm is more (less) likely to be added (dropped) to (from) the analyst's portfolio.

To examine how industry competition affects the number of analysts covering a firm, we estimate the firm-level regression:

$$(3) \text{COVERAGE}_{it} = \alpha + \beta_1 \times \text{TNIC_HHI}_{it} (\text{TNIC_COMPETITION_INTENSITY}_{it}) \\ + \beta_2 \times \text{SIC_HHI}_{it} + \beta_k \times \text{Controls}_{it} + \varepsilon_{it},$$

where COVERAGE_{it} is the number of analysts who issue annual earnings forecasts for firm i in year t . We use both industry and localized firm-level measures of competition. Our competition

measures in equation (3) are TNIC_HHI and SIC_HHI, which are the Herfindahl Indices (sum of squared market shares) based on industry competitors identified either with the TNIC method or for SIC, the traditional three-digit SIC code classification method. To test the effect of competition intensity among competitors on analyst coverage, we also (i) replace TNIC_HHI with TNIC_COMPETITION_INTENSITY for a given TNIC industry and (ii) include both TNIC_HHI with TNIC_COMPETITION_INTENSITY in equation (3), where TNIC_COMPETITION_INTENSITY is the average of product similarity scores between a firm and its competitors for a given TNIC industry based on the text-based methods of Hoberg and Phillips (2016). Note that the Herfindahls (TNIC_HHI and SIC_HHI) are higher the more concentrated and less competitive an industry is, and TNIC_COMPETITION_INTENSITY increases with a more competitive industry environment. We thus predict opposite signs on the HHI measures versus the similarity measures.

Ali, Klassa and Yeung (2009) argue that Census-based Herfindahl measures are more accurate than measures based on public firms as the Census measures also include private firms. They find that using Compustat-based public firms to construct the SIC Herfindahl produce different results from those using Census-based private and public firms. Thus, as a further robustness check, we include the Census-based additional measure of competition: CENSUS_HHI.

Many of these firm-level competition measures are skewed. To correct for the possible impact of skewness and facilitate comparison across different measures, we standardize these competition measures using deciles of each measure. The standardized decile ranks are zero to nine based on the industry or firm measure in year t divided by nine. We include year fixed effects and industry (firm) fixed effects based on the Hoberg-Phillips 50 fixed industry classifications (FIC) and adjust for heteroskedasticity and clustering by both firm and year in the regression. We control

for a number of firm variables that have been shown to affect analyst coverage as in equation (1).

[Insert Table 8 Here]

Table 8 reports the results from estimating the effect of firm-level competition on the number of analysts covering the firm (i.e., equation (3)).¹⁶ Panel A shows the results with year and industry fixed effects while Panel B presents the results with year and firm fixed effects. The coefficient estimates on TNIC_HHI (TNIC_COMPETITION_INTENSITY) are negative (positive) and are significant, which suggests that analyst coverage is greater for firms with more competitors (greater competition intensity). The economic significance is such that a change from the smallest decile to the largest decile in TNIC_HHI and TNIC_COMPETITION_INTENSITY increases the analyst coverage by 3.25 and 1.53, respectively, which are equivalent to 54% and 26% increases relative to the mean analyst coverage (6) in our sample. The results suggest that there is a net benefit for analysts to follow firms with more competitors or high competition intensity. Furthermore, when we include both TNIC_HHI and TNIC_COMPETITION_INTENSITY in the same regression (columns 3 and 6), our results indicate that given the number of competitors, competition intensity is additionally important to analyst coverage decisions.

The coefficient estimates on SIC_HHI are largely insignificant, again consistent with the SIC-based measure performing relatively poor as SIC industry membership updates are less timely and thus less informative. Untabulated results show that other industry-level competition measures generate either smaller coefficients or insignificant results.¹⁷ These results are not surprising, as traditional fixed industry classifications capture less nuance given they are fixed zero or one based (i.e., belong or don't belong to an industry), and change infrequently. They do not easily

¹⁶ We have a smaller sample size in columns 3 and 4 of Table 8 (both Panels A and B) due to fewer data availability of the CENSUS_HHI.

¹⁷ We observe similar results when we use other industry classifications (two- or four-digit SIC, GICS, or HP TNIC industry) to calculate the industry level competition measures.

accommodate entire new product markets, nor can they continuously measure the within- or between-industry distance of firm-specific pairwise product similarity, as they classify firms to industries on a zero-one basis.

The results for the firm-level control variables are consistent with prior research (e.g., Bhushan (1989), Barth, Kasznik, and McNichols (2001), and Harford et al. (2019)). Larger firms, firms with greater institutional holdings, firms with greater uncertainty, less complex firms, value stocks and higher trade volume stocks are associated with a higher analyst following. Firms with higher R&D intensity, advertising intensity, and return volatility are also associated with a higher analyst following, reflecting higher demand for analyst coverage of those firms.

We also re-estimate equation (3) by replacing `TNIC_COMPETITION_INTENSITY` with the additional competition intensity measures that capture the competition from each firm's closest competitors: `TOP4_COMPETITORS_COMP_INTENSITY`, `COMPETITIVE_FLUIDITY`, and `TOP4_COMPETITIVE_FLUIDITY`. Table 9 shows the results, which are similar to those reported in Table 8.

[Insert Table 9 Here]

IV. Analyst-Level Analysis of Career Outcomes

We next assess the effect of covering product market competitors on career outcomes at the analyst level. To measure industry competition at the analyst level, we average the analyst-firm-level competition indexes `TNIC_COMPETITOR_COVERAGE` and `TNIC_COMPETITION_INTENSITY` across firms within analyst j 's portfolio. The measures are a proxy for the degree of competition among firms within analyst j 's portfolio. The larger the `TNIC_COMPETITOR_COVERAGE` and `TNIC_COMPETITION_INTENSITY`, the more competitor firms with greater competition intensity are within analyst j 's portfolio.

We use the following analyst-level linear probability regressions to examine the impact of covering product market competitors on the career outcomes of analysts:

$$(4) \text{Prob}(\text{STAR}_{jt+1}=1) = \alpha + \gamma_1 \times \text{TNIC_COMPETITOR_COVERAGE}_{jt} \\ (\text{TNIC_COMPETITION_INTENSITY}_{jt}) + \gamma_2 \times \text{SIC_COVERAGE}_{jt} + \\ \gamma_n \times \text{Analyst Level Controls}_{it} + \varepsilon_{jt};$$

$$(5) \text{Prob}(\text{FIRE}_{jt+1}=1) = \alpha + \gamma_1 \times \text{TNIC_COMPETITOR_COVERAGE}_{jt} \\ (\text{TNIC_COMPETITION_INTENSITY}_{jt}) + \gamma_2 \times \text{SIC_COVERAGE}_{jt} + \\ \gamma_n \times \text{Analyst Level Controls}_{it} + \varepsilon_{jt}.$$

Following Hong et al. (2000), we define FIRE_{jt+1} as an indicator variable equal to one if analyst j moves to a small brokerage house (less than 25 analysts) or permanently leaves the I/B/E/S database in the following year (i.e., between July 1 of year $t+1$ and June 30 of year $t+2$), and zero otherwise. STAR_{jt+1} is an indicator variable that equals one if the analyst is on *Institutional Investor* magazine's star list in the following year, and zero otherwise. We also estimate the impact of competition intensity on analyst career outcomes by (i) replacing $\text{TNIC_COMPETITOR_COVERAGE}$ with $\text{TNIC_COMPETITION_INTENSITY}$ and (ii) including both $\text{TNIC_COMPETITOR_COVERAGE}$ and $\text{TNIC_COMPETITION_INTENSITY}$ in the above equation. If covering industry competitors benefits analysts' career outcomes, we expect γ_1 to be positive and negative in equations (4) and (5), respectively.

We include several analyst-level variables to control for other factors that might affect analyst career outcomes. Consistent with prior studies (e.g., Hong and Kubik (2003), Emery and Li (2009), and Hilary and Hsu (2013)), we control for HORIZON , BOLDNESS , EXPERIENCE , PORTFOLIO_SIZE , and BROKER_SIZE . The first three variables (BOLDNESS , EXPERIENCE , and HORIZON) are analyst-firm variables defined previously, averaged across firms within analyst

j's portfolio to get the corresponding analyst-level counterparts. PORTFOLIO_SIZE and BROKER_SIZE are analyst/broker characteristics defined previously and ranked among analysts following the firm. We also control for the current year's star status (STAR) because this variable may capture analysts' visibility, which affects their career outcomes (Emery and Li (2009)). We adjust standard errors for heteroskedasticity and clustering by both analyst and year. Finally, we include broker fixed effects and year fixed effects.

[Insert Table 10 Here]

Table 10 presents summary statistics for the sample of 92,734 analyst-year observations used in the analyst-level regressions. The mean (median) STAR and FIRE are 0.08 (0.00) and 0.20 (0.00), respectively. The mean of TNIC_COMPETITOR_COVERAGE and TNIC_COMPETITION_INTENSITY are 0.46 and 0.46.

Table 11 presents results on star status (i.e., equation (4)). The coefficients on TNIC_COMPETITOR_COVERAGE (TNIC_COMPETITION_INTENSITY) are positive and significant, which means that analysts covering more competitors (covering firms whose products compete more with each other) are more likely to be voted stars. We find that a one standard deviation increase in TNIC_COMPETITOR_COVERAGE (TNIC_COMPETITION_INTENSITY) increases an analyst's probability of being a star by approximately 0.28% (0.19%). Given that Table 10 shows that the unconditional probability of being a star is 8%, a one standard deviation increase in TNIC_COMPETITOR_COVERAGE (TNIC_COMPETITION_INTENSITY) increases the unconditional probability of being a star by approximately 2.5% (= 0.28% / 8%) (2.4% (= 0.19% / 8%)). When we include both TNIC_COMPETITOR_COVERAGE and TNIC_COMPETITION_INTENSITY in the same regression, we find that given the number of rivals, competition intensity among rivals is additionally important to analysts' star status.

[Insert Table 11 Here]

Table 12 presents results of estimating firing outcomes (i.e., equation (5)). The coefficient on `TNIC_COMPETITOR_COVERAGE` (`TNIC_COMPETITION_INTENSITY`) in column 1 (column 2) is negative and significant, which suggests that analysts whose portfolios consist of more rivals (rivals that compete more in products with each other) are less likely to be fired. With respect to the magnitude of our results, we find that one standard deviation increase in `TNIC_COMPETITOR_COVERAGE` (`TNIC_COMPETITION_INTENSITY`) decreases an analyst's probability of being fired by approximately 3.26% (2.63%). Given that Table 10 shows that the unconditional probability of being fired is 20%, a zero to one increase in `TNIC_COMPETITOR_COVERAGE` (`TNIC_COMPETITION_INTENSITY`) decreases the unconditional probability of being fired by approximately 16.3% ($= 3.26\% / 20\%$) ($13.2\% = 2.63\% / 20\%$). The results in column 3 show that given the number of rivals (`TNIC_COMPETITOR_COVERAGE`), competition intensity among rivals (`TNIC_COMPETITION_INTENSITY`) is additionally important to analysts' likelihood of being fired.

[Insert Table 12 Here]

Similar to what we have found in analyst-firm level tests, the coefficient estimates on `SIC_COVERAGE` are either much weaker or insignificant in these two tests. The signs for the control variables are largely consistent with expectations. Star analysts in the previous year and analysts with larger coverage are more likely to be a star this year and less likely to be fired. Analysts whose forecasts are relatively old (i.e., longer in horizon) are less likely to be a star and more likely to be fired. The results overall suggest that high competition as captured by how intensively firms compete in products with each other within analysts' portfolios improves analysts' career outcomes.

We also conduct the career test (*Fire* decision) after brokerage house mergers since the combined brokerage houses usually have redundant analysts (due to overlapping coverage) and thus lay off some analysts (Hong and Kacperczyk (2010)). Similar to the analyst-firm add/drop decision analysis in the previous section, we keep mergers that have earnings estimates in I/B/E/S for both the bidder and target brokerage houses and retain merging houses that have overlapping coverage (bidder and target brokerage houses cover at least one same company). This requirement ensures that the brokerage house after an M&A may have to fire analysts. We have 19 brokerage house merger events from 1994 to 2008 and 2,139 analyst-level observations (including bidder and target brokerage houses analysts in two years after broker M&A events) in this analysis.

Columns 4-6 of Table 12 present the results of estimating the *Fire* decision around brokerage house mergers. The coefficients on `TNIC_COMPETITOR_COVERAGE` and `TNIC_COMPETITION_INTENSITY` are negative and significant. These coefficients are slightly larger in magnitude than those reported in the first two columns, likely because in the last three columns we focus on a setting where brokerage houses may need to fire redundant analysts. Overall, the results reported in Table 12 suggest that analysts whose portfolios consist of more rivals or of rivals that compete more in products with each other are less likely to be fired.

Our analyst-level estimation results are robust to including relative accuracy (Hong and Kubik (2003)) in equations (4) and (5). They are also robust to including the analyst-level relative consistency (Hilary and Hsu (2013)), even though our sample size decreases. We get similar results if we exclude those analysts who permanently leave the profession in the *Fire* definition. We get similar results when we use other competition intensity measures at analyst level (results untabulated). Furthermore, our analyst-level results are robust to including analyst fixed effects, which help control for analysts' prior work experience (Bradley et al. (2017)). Finally, our

untabulated results are robust when we replace TNIC_COMPETITION_INTENSITY with the alternative competition intensity measures: TOP4_COMPETITORS_COMP_INTENSITY, COMPETITIVE_FLUIDITY, and TOP4_COMPETITIVE_FLUIDITY. Overall, our results are consistent with our hypothesis that analysts achieve better career outcomes when they cover more product competitors in their portfolios and when these competitors compete with each other more intensively.

V. Additional Analyses

We extend our analysis to examine the effects of product market competition on analyst forecast accuracy and analyst informativeness. As argued earlier, analysts are motivated to follow product market competitors by an interest in deepening their industry knowledge. Understanding competition and following competitors thus should help analysts issue forecasts that are more accurate and make their forecasts and recommendations more informative to investors. As additional analyses, we examine the impact of product market competition on the accuracy of analysts' forecasts and the informativeness of analysts' research reports at the analyst-firm level.

A. Analyst Forecast Accuracy

To examine the effect of product market competition on analyst forecast accuracy, we estimate the following regression:

$$(6) \text{ ACCURACY}_{ijt} = \alpha + \beta_1 \times \text{TNIC_COMPETITOR_COVERAGE}_{ijt} + \beta_2 \times \text{TNIC_COMPETITION_INTENSITY}_{ijt} + \beta_3 \times \text{SIC_COVERAGE}_{ijt} + \beta_4 \times \text{Firm Level Controls}_{it} + \beta_5 \times \text{Analyst -Firm Level Controls}_{ijt} + \beta_6 \times \text{Analyst Level Controls}_{jt} + \varepsilon_{ijt}.$$

ACCURACY_{ijt} is a relative accuracy rank of the analysts following a firm (Hong and Kubik (2003)). To obtain this variable, we first calculate the absolute value of analyst *i*'s forecast error for firm *j* in year *t*. We then rank all of the analysts that cover firm *j* in year *t* based on absolute

forecast error, and define $ACCURACY_{ijt}$, as $1 - (Rank_{ijt} - 1) / (\# \text{ of } Analysts_{it} - 1)$, where $\# \text{ of } Analysts_{it}$ is the total number of analysts covering firm i . If more than one analyst has the same accuracy and thus rank as firm i , we assign each of these analysts the average of their ranks. Other variables are defined the same as in equation (2). If competition increases analysts' forecast accuracy, we expect β_1 to be positive.

Table 13 shows the results. The coefficient estimates on $TNIC_COMPETITOR_COVERAGE$ and $TNIC_COMPETITION_INTENSITY$ in columns 1 and 2 are positive and significant, which suggests that an analyst issues more accurate forecasts on a firm relative to other analysts covering the same firm when (1) more firms compete with other firms in the analyst's portfolio and (2) the competition intensity among competitors in the analyst's portfolio is greater.¹⁸ The results in column 3 show that given the number of rivals ($TNIC_COMPETITOR_COVERAGE$), competition intensity among rivals ($TNIC_COMPETITION_INTENSITY$) is additionally important to analysts' forecast accuracy.

[Insert Table 13 Here]

B. Analyst Informativeness

Finally, we examine the impact of product competitor coverage and competition intensity among competitors on analyst informativeness. We expect to observe a stronger stock market reaction to the forecasts and recommendations for analysts who cover more competitors (whose portfolio firms compete more intensively with each other) because these analysts have higher credibility with investors due to their industry expertise. Following prior research (e.g., Green, Jame, Markov, and Subasi (2014)), we consider the absolute value of market reactions to both analyst

¹⁸ To help differentiate the effect of product market competition from that of analysts' prior work experience on analyst forecast accuracy (Bradley et al. (2017)), we further control for analyst or analyst-year fixed effects in equation (6). Our untabulated results remain unaffected.

forecasts and recommendations as measures of analyst informativeness. Specifically, we construct $RETURN_FORECAST_{ijt}$ and $RETURN_RECOM_{ijt}$, which are the two-day (day 0 and day +1) absolute market-adjusted abnormal return around the issuance of analyst forecasts and the revisions of analyst recommendations, respectively.¹⁹ We re-estimate equation (6) by replacing $ACCURACY_{ijt}$ with $RETURN_FORECAST_{ijt}$ and $RETURN_RECOM_{ijt}$, respectively. We conduct both analyses (forecast issuance and recommendation revisions) at the individual issuance level. The results from both analyses, untabulated, show that the coefficients on both $TNIC_COMPETITOR_COVERAGE$ and $TNIC_COMPETITION_INTENSITY$ are both positive and significant, which suggests that the informativeness of analyst forecasts and analyst recommendations increases with both (1) whether firms compete with other firms and (2) the degree of competition intensity among competitors in analysts' portfolios. This is consistent with the market reacting stronger to analysts with greater industry product market knowledge. The untabulated results also indicate that given $TNIC_COMPETITOR_COVERAGE$, $TNIC_COMPETITION_INTENSITY$ is additionally important to analysts' informativeness.²⁰

Overall, our evidence from the additional analyses regarding analysts' forecast performance and their market influences supports our hypothesis that covering firms with competing products enhances analysts' industry knowledge.²¹

¹⁹ The market benchmark is the value-weighted market index. We require non-overlapping of event window and drop those observations that cannot be attributed to certain analysts (e.g., when multiple analysts issue forecasts or recommendations on the same day).

²⁰ Our untabulated results also show that the coefficients on $SIC_COVERAGE$ are insignificant, in line with our previous results that suggest overall SIC industry coverage is less timely and informative. We get similar results (i.e., larger magnitude of market reactions) if we re-run our regressions by using signed returns and separating the forecast issuance (recommendation) sample into upward revision and downward revision (upgrade and downgrade) subsamples (Green et al. (2014)).

²¹ Our results regarding analyst forecast accuracy and analyst informativeness are unaffected when we replace $TNIC_COMPETITION_INTENSITY$ with the alternative competition intensity measures: $TOP4_COMPETITORS_COMP_INTENSITY$, $COMPETITIVE_FLUIDITY$ and $TOP4_COMPETITIVE_FLUIDITY$.

VI. Conclusions

We examine the impact of industry competition on sell-side analysts' coverage decisions. We find that analysts adjust their portfolios to account for industry competition among firms covered. We show that analysts are more (less) likely add a firm to (drop a firm from) their portfolios if the firm is a competitor of other firms in their portfolios and if the firm competes more intensively with its competitors in the analyst's portfolios. These results suggest that analysts consider industry knowledge and gain industry knowledge, in particular the knowledge about industry competition and product competition intensity among competitors, in and through their portfolio management decisions.

We also find that an analyst's coverage decisions based on industry competition are also positively associated with their career outcomes and that they are more likely to obtain analyst "star" status if they cover more industry competitors. Finally, we find that analysts' forecasts are more accurate and their forecasts and recommendations are more informative when they cover more competing firms and when these firms they cover compete with each other more intensively.

Overall, our results at the analyst-firm and analyst levels support the proposition that industry competition is a key factor that influences analysts' coverage decisions. Our results also provide estimates of the magnitude of the importance of covering product market competitors and competition intensity to analysts' decisions. Analysts covering close competitors with more intensive competition among competitors in their portfolios enjoy better career outcomes. Our results are consistent with benefits to analysts from following competing firms within similar industries and enhancing their understanding of the competitive environment in which the firms exist. We shed light on how analysts can accumulate their industry knowledge through their coverage decisions and provide a direct explanation for the industry specialization of analysts.

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Appendix A

Main Competition Measures at the Analyst-firm Level

Definitions of main competition measures

TNIC_COMPETITOR_COVERAGE: N_{ijt} / M_{jt} , where M_{jt} is the total number of firms in the analyst's j 's portfolio while N_{ijt} is the number of the firm's TNIC peers shown in the analyst j 's portfolio.

TNIC_COMPETITION_INTENSITY: the average of pairwise product similarity scores between firm i and all of the firm's TNIC peers within the analyst j 's portfolio.

Example

The publicly available data from Hoberg and Phillips indicate that six firms are TNIC product competitors of IBM (with pairwise similarity scores greater than the minimum threshold) in year 2000.²² Suppose the following seven firms (including IBM) enter IBM's HP index calculation in 2000:

{ IBM, firm a, firm b, firm c, firm d, firm e, firm f },

where firm a, firm b, and firm c also appear in analyst j 's portfolio which consists of the following ten firms, including IBM and nine other firms, in year 2000.

{ IBM, firm a, firm b, firm c, firm 5, firm 6, firm 7, firm 8, firm 9, firm 10 }.

²² In the actual database from Hoberg and Phillips, 12 firms are TNIC product competitors of IBM (with pairwise similarity scores greater than the minimum threshold) in year 2000. We use six firms in this example to simplify the illustration.

Because three firms (other than IBM) in analyst j 's portfolio appear in IBM's HP index calculation in 2000, for analyst j , firm *IBM*, year t ,

$$\text{TNIC_COMPETITOR_COVERAGE}_{IBMj2000} = N_{ijt} / M_{jt} = 3/10;$$

$$\text{TNIC_COMPETITION_INTENSITY}_{IBMj2000} = \text{Mean (pairwise product similarity score}_{IBM \text{ and firm a} + \text{pairwise product similarity score}_{IBM \text{ and firm b} + \text{pairwise product similarity score}_{IBM \text{ and firm c}}).$$

Appendix B

Variable Definitions

Variable name	Definition
Analyst-Firm Level	
ADD	An indicator variable that is one if firm i was not covered by analyst j in year t but is covered in year $t+1$, and zero if firm i was not covered by analyst j in either year t or $t+1$.
DROP	An indicator variable that is one if firm i was covered by analyst j in year t but not in year $t+1$, and zero if firm i was covered by analyst j in both years t and $t+1$.
TNIC_COMPETITOR_COVERAGE	N_{ijt} / M_{jt} , where M_{jt} is the total number of firms in the analyst's j 's portfolio while N_{ijt} is the number of the firm's TNIC peers shown in the analyst j 's portfolio (see Appendix A for an illustration).
TNIC_COMPETITION_INTENSITY	The average of pairwise product similarity scores between firm i and all of the firm's TNIC peers within the analyst j 's portfolio (see Appendix A for an illustration).
TOP4_COMPETITORS_COMP_INTENSITY	The average of pairwise product similarity scores between firm i and the four TNIC peers with the highest similarity scores within the analyst j 's portfolio.
COMPETITIVE_FLUIDITY	Natural logarithm of the average fluidity value over all of the firm's TNIC peers within the analyst j 's portfolio.
TOP4_COMPETITIVE_FLUIDITY	Natural logarithm of the average fluidity value over the firm's four TNIC peers with the largest fluidity scores within the analyst j 's portfolio.
SIC_COVERAGE	K_{ijt} / M_{jt} , where M_{jt} is the total number of firms in the analyst's j 's portfolio while K_{ijt} is the number of firms shown both in the analyst j 's portfolio and firm i 's three-digit SIC industry.
ACCURACY	Hong and Kubik's (2003) measure of relative accuracy based on the rank of accuracy among analysts following a firm.
HORIZON	Number of days between the forecast and earnings announcement dates, based on rank among analysts following a firm.
BOLDNESS	Hong and Kubik's (2003) measure of boldness in earnings forecasts, based on rank among analysts following a firm.
EXPERIENCE	Number of years an analyst covering the firm, based on rank among analysts following a firm.

Firm Level	
Ln(MARKET_CAP)	Natural logarithm of market value of equity.
BOOK_TO_MARKET	The ratio of book value of equity over market value of equity.
INST_HOLDINGS	The percentage of institutional ownership at the prior fiscal year end.
RETURN_VOLATILITY	Standard deviation of a firm's monthly stock returns in the prior fiscal year.
Ln(#SEGMENTS)	Natural logarithm of the number of reported business segments in the Compustat segment file at the prior fiscal year end.
R&D_INTENSITY	The research and development expense over operating expense at the prior fiscal year end.
ADVERTISING_INTENSITY	The advertising expense over operating expense at the prior fiscal year end.
TRADING_VOLUME	TRADING_VOLUME in millions of shares in the fiscal year.
LOSS_FIRMS	An indicator variable that is one if firm earnings per share are negative, and zero otherwise.
COVERAGE	Number of analysts who issue annual earnings forecasts for firm i in year t .
Analyst Level	
FIRE	An indicator variable that is one if analyst j is demoted (moves to a different and smaller brokerage house) or permanently leaves the I/B/E/S database in the following year (i.e., between July 1 of year $t+1$ and June 30 of year $t+2$), and zero otherwise.
STAR	An indicator variable that is one if the analyst is in <i>Institutional Investor</i> magazine's All American Team, and zero otherwise.
PORTFOLIO_SIZE	Number of firms covered by the analyst in the current year.
BROKER_SIZE	Number of analysts employed by a brokerage house in the current year.

TABLE 1
Analyst-firm Level Descriptive Statistics

This table presents descriptive statistics for variables at the analyst-firm level regressions. See Appendix B for variable definitions.

Variable	N	Mean	StdDev	25%	Median	75%
ADD	30,423,367	0.01	0.10	0.00	0.00	0.00
DROP	949,049	0.29	0.45	0.00	0.00	1.00
TNIC_COMPETITOR_COVERAGE (Add Sample)	30,423,367	0.13	0.26	0.00	0.00	0.10
TNIC_COMPETITION_INTENSITY (Add Sample)	30,423,367	0.02	0.04	0.00	0.00	0.02
TNIC_COMPETITOR_COVERAGE (Drop Sample)	949,049	0.50	0.29	0.28	0.50	0.72
TNIC_COMPETITION_INTENSITY (Drop Sample)	949,049	0.50	0.29	0.29	0.50	0.71
TOP4_COMPETITORS_COMP_INTENSITY (Add Sample)	30,423,367	0.02	0.05	0.00	0.00	0.02
TOP4_COMPETITORS_COMP_INTENSITY(Drop Sample)	949,049	0.50	0.29	0.29	0.50	0.71
COMPETITIVE_FLUIDITY (Add Sample)	30,038,843	0.73	1.10	0.00	0.00	2.09
COMPETITIVE_FLUIDITY(Drop Sample)	930,915	0.50	0.29	0.29	0.50	0.72
TOP4_COMPETITIVE_FLUIDITY (Add Sample)	30,038,843	0.68	1.04	0.00	0.00	1.66
TOP4_COMPETITIVE_FLUIDITY(Drop Sample)	930,915	0.50	0.29	0.29	0.50	0.71
SIC_COVERAGE (Add Sample)	30,423,367	0.45	0.36	0.12	0.33	0.83
SIC_COVERAGE (Drop Sample)	949,049	0.50	0.32	0.22	0.50	0.78
Ln(MARKET_CAP)	949,049	7.59	1.82	6.31	7.60	8.95
BOOK_TO_MARKET	949,049	0.52	0.54	0.24	0.42	0.68
INST_HOLDINGS	949,049	0.49	0.36	0.00	0.56	0.81
RETURN_VOLATILITY	949,049	0.04	0.02	0.03	0.03	0.05
Ln(#SEGMENTS)	949,049	1.08	0.93	0.00	1.10	1.79
R&D_INTENSITY	949,049	0.07	0.14	0.00	0.00	0.08
ADVERTISING_INTENSITY	949,049	0.01	0.03	0.00	0.00	0.01
TRADING_VOLUME	949,049	326.83	439.98	37.80	125.27	409.99
LOSS_FIRMS	949,049	0.21	0.41	0.00	0.00	0.00
ACCURACY	949,049	0.50	0.32	0.23	0.50	0.77
HORIZON	949,049	0.50	0.32	0.23	0.50	0.77
BOLDNESS	949,049	0.50	0.32	0.23	0.50	0.77
EXPERIENCE	949,049	0.50	0.30	0.24	0.50	0.75

TABLE 2
Industry Competition and Analyst Add Decisions

This table represents the results of the following analyst-firm level linear probability model:

$$\text{Prob}(\text{ADD}_{ijt+1} = 1) = \alpha + \beta_1 \times \text{TNIC_COMPETITOR_COVERAGE}_{ijt} (\text{TNIC_COMPETITION_INTENSITY}_{ijt}) + \beta_2 \times \text{SIC_COVERAGE}_{ijt} + \beta_k \times \text{Firm Level Controls}_{it} + \beta_n \times \text{Analyst Level Controls}_{jt} + \varepsilon_{ijt}.$$

ADD equals one if firm i was not covered by analyst j in year t but is covered in year $t+1$, and zero if firm i was not covered by analyst j in either year t or $t+1$. See Appendix B for other variable definitions. Firm-level control variables are included but not reported. We include year fixed effects, industry fixed effects or firm fixed effects in the estimation. We multiple the coefficients by 100 for readability. t -statistics reported in parentheses are robust to analyst, industry, and year clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	ADD					
	1	2	3	4	5	6
TNIC_COMPETITOR_COVERAGE	1.20*** (20.37)		0.53*** (8.53)	0.84*** (11.58)		0.39*** (6.65)
TNIC_COMPETITION_INTENSITY		10.37*** (13.87)	8.37*** (10.77)		7.86*** (9.14)	6.08*** (6.94)
SIC_COVERAGE	0.44*** (7.77)	0.70*** (12.23)	0.55*** (9.33)	1.03*** (15.46)	1.19*** (18.58)	1.09*** (16.54)
PORTFOLIO_SIZE	0.03*** (9.66)	0.03*** (9.92)	0.03*** (9.57)	0.03*** (10.20)	0.03*** (10.33)	0.03*** (10.13)
BROKER_SIZE	0.00*** (4.76)	0.00*** (5.64)	0.00*** (5.90)	0.00 (1.59)	0.00* (2.00)	0.00** (2.20)
Firm-level Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	No	No	No
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effects	No	No	No	Yes	Yes	Yes
Observations	30,423,367	30,423,367	30,423,367	30,423,367	30,423,367	30,423,367
R ²	0.011	0.011	0.012	0.048	0.048	0.048

TABLE 3
Industry Competition and Analyst Drop Decisions

This table presents the results of the following analyst-firm level linear probability model:

$$\text{Prob}(\text{DROP}_{ijt+1}=1) = \alpha + \beta_1 \times \text{TNIC_COMPETITOR_COVERAGE}_{ijt} (\text{TNIC_COMPETITION_INTENSITY}_{ijt}) \\ + \beta_2 \times \text{SIC_COVERAGE}_{ijt} + \beta_k \times \text{Firm Level Controls}_{it} + \beta_m \times \text{Analyst-Firm Level Controls}_{ijt} \\ + \beta_n \times \text{Analyst Level Controls}_{jt} + \varepsilon_{ijt}.$$

DROP equals one if firm i was covered by analyst j in year t but not in year $t+1$, and zero if firm i was covered by analyst j in both years t and $t+1$. See Appendix B for other variable definitions. Firm-level control variables are included but not reported. We include year fixed effects, industry fixed effects or firm fixed effects in the estimation. We multiply the coefficients by 100 for readability. t -statistics reported in parentheses are robust to analyst, industry, and year clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	DROP					
	1	2	3	4	5	6
TNIC_COMPETITOR_COVERAGE	-8.11*** (-17.19)		-7.28*** (-17.27)	-8.11*** (-17.32)		-7.38*** (-17.15)
TNIC_COMPETITION_INTENSITY		-5.98*** (-13.89)	-4.91*** (-13.11)		-5.49*** (-14.17)	-4.28*** (-12.90)
SIC_COVERAGE	-0.74* (-1.76)	-2.53*** (-5.83)	-0.47 (-1.14)	-0.74* (-1.79)	-2.58*** (-5.91)	-0.51 (-1.23)
HORIZON	45.06*** (26.07)	45.23*** (26.11)	44.96*** (26.03)	45.06*** (26.07)	45.24*** (26.12)	44.97*** (26.03)
BOLDNESS	0.46*** (3.51)	0.52*** (3.99)	0.44*** (3.39)	0.46*** (3.52)	0.52*** (4.01)	0.44*** (3.41)
EXPERIENCE	-4.58*** (-7.65)	-4.92*** (-8.06)	-4.52*** (-7.52)	-4.58*** (-7.69)	-4.93*** (-8.10)	-4.52*** (-7.56)
PORTFOLIO_SIZE	-9.83*** (-18.97)	-10.56*** (-21.74)	-9.98*** (-19.04)	-9.83*** (-19.36)	-10.55*** (-22.26)	-9.96*** (-19.39)
BROKER_SIZE	1.98*** (3.08)	2.25*** (3.42)	1.97*** (3.07)	1.98*** (3.13)	2.25*** (3.47)	1.97*** (3.12)
Firm-level Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effects	No	No	No	Yes	Yes	Yes
Observations	949,049	949,049	949,049	949,049	949,049	949,049
R ²	0.213	0.212	0.214	0.262	0.261	0.263

TABLE 4
Close Competition Intensity Measures and Analyst Add Decisions

This table presents the results of the following analyst-firm level linear probability model:

$$\text{Prob}(\text{ADD}_{ijt+1}=1) = \alpha + \beta_1 \times \text{Competition Intensity}_{ijt} + \beta_2 \times \text{SIC_COVERAGE}_{ijt} + \beta_k \times \text{Firm Level Controls}_{it} + \beta_m \times \text{Analyst-Firm Level Controls}_{ijt} + \beta_n \times \text{Analyst Level Controls}_{jt} + \varepsilon_{ijt}.$$

ADD equals one if firm i was not covered by analyst j in year t but is covered in year $t+1$, and zero if firm i was not covered by analyst j in either year t or $t+1$. See Appendix B of the manuscript for other variable definitions. Control variables are included but not reported. We include year fixed effects, industry fixed effects or firm fixed effects in the estimation. We multiply the coefficients by 100 for readability. t -statistics reported in parentheses are robust to analyst, industry, and year clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Without TNIC_COMPETITOR_COVERAGE

Variable	ADD					
	1	2	3	4	5	6
TOP4_COMPETITORS_COMP_INTENSITY	12.97*** (15.69)			12.85*** (15.23)		
COMPETITIVE_FLUIDITY		0.37*** (15.62)			0.26*** (11.15)	
TOP4_COMPETITIVE_FLUIDITY			0.37*** (15.96)			0.25*** (9.82)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	No	No	No
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effects	No	No	No	Yes	Yes	Yes
Observations	30,423,367	30,038,843	30,038,843	30,423,367	30,038,843	30,038,843
R-squared	0.013	0.012	0.011	0.049	0.047	0.047

Panel B: With TNIC_COMPETITOR_COVERAGE

Variable	ADD					
	1	2	3	4	5	6
TOP4_COMPETITORS_COMP_INTENSITY	13.82*** (13.60)			15.34*** (14.86)		
COMPETITIVE_FLUIDITY		0.33*** (12.01)			0.22*** (9.30)	
TOP4_COMPETITIVE_FLUIDITY			0.34*** (10.81)			0.19*** (6.72)
TNIC_COMPETITOR_COVERAGE	0.85*** (11.81)	0.28*** (4.14)	0.20** (2.41)	0.49*** (5.60)	0.26*** (3.88)	0.31*** (4.25)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	No	No	No
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effects	No	No	No	Yes	Yes	Yes
Observations	30,423,367	30,038,843	30,038,843	30,423,367	30,038,843	30,038,843
R-squared	0.013	0.012	0.011	0.049	0.047	0.047

TABLE 5
Close Competition Intensity Measures and Analyst Drop Decisions

This table presents the results of the following analyst-firm level linear probability model:

$$\text{Prob}(\text{DROP}_{ijt+1}=1) = \alpha + \beta_1 \times \text{Competition Intensity}_{ijt} + \beta_2 \times \text{SIC_COVERAGE}_{ijt} + \beta_k \times \text{Firm Level Controls}_{it} + \beta_m \times \text{Analyst-Firm Level Controls}_{ijt} + \beta_n \times \text{Analyst Level Controls}_{jt} + \varepsilon_{ijt}.$$

DROP equals one if firm i was covered by analyst j in year t but not in year $t+1$, and zero if firm i was covered by analyst j in both years t and $t+1$. See Appendix B of the manuscript for other variable definitions. Control variables are included but not reported. We include year fixed effects, industry fixed effects or firm fixed effects in the estimation. We multiply the coefficients by 100 for readability. t -statistics reported in parentheses are robust to analyst, industry, and year clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Without TNIC_COMPETITOR_COVERAGE

Variable	DROP					
	1	2	3	4	5	6
TOP4_COMPETITORS_COMP_INTENSITY	-10.62*** (-17.50)			-10.62*** (-17.60)		
COMPETITIVE_FLUIDITY		-3.28*** (-6.32)			-3.28*** (-6.36)	
TOP4_COMPETITIVE_FLUIDITY			-8.85*** (-18.39)			-8.63*** (-19.71)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	No	No	No
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effects	No	No	No	Yes	Yes	Yes
Observations	949,049	930,915	930,915	949,049	930,915	930,915
R-squared	0.214	0.213	0.215	0.267	0.263	0.265

Panel B: With TNIC_COMPETITOR_COVERAGE

Variable	DROP					
	1	2	3	4	5	6
TOP4_COMPETITORS_COMP_INTENSITY	-8.57*** (-15.06)			-8.57*** (-15.13)		
COMPETITIVE_FLUIDITY		-2.11*** (-4.45)			-2.11*** (-4.49)	
TOP4_COMPETITIVE_FLUIDITY			-6.01*** (-14.91)			-5.57*** (-17.27)
TNIC_COMPETITOR_COVERAGE	-3.39*** (-9.74)	-7.89*** (-17.97)	-5.27*** (-12.89)	-3.39*** (-9.86)	-7.89*** (-18.14)	-5.48*** (-13.65)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	No	No	No
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effects	No	No	No	Yes	Yes	Yes
Observations	949,049	930,915	930,915	949,049	930,915	930,915
R-squared	0.214	0.215	0.216	0.264	0.265	0.266

TABLE 6
Analyst-firm Level Regressions of Add/Drop Decisions after Firm M&A

This table presents the results of estimating analysts' decision to add/drop an acquiring firm to/from their portfolios two years after the firm M&A event, based on the following analyst-firm level linear probability models:

$$\text{Prob}(\text{ADD}_{ijt+1} = 1) = \alpha + \beta_1 \times \text{TNIC_COMPETITOR_COVERAGE}_{ijt} + \beta_2 \times \text{TNIC_COMPETITION_INTENSITY}_{ijt} + \beta_3 \times \text{SIC_COVERAGE}_{ijt} + \beta_k \times \text{Firm Level Controls}_{it} + \beta_n \times \text{Analyst Level Controls}_{jt} + \varepsilon_{ijt}.$$

ADD equals one if an acquiring firm (i.e., firm i) was not covered by analyst j in year t but is covered in year $t+1$, and zero if firm i was not covered by analyst j in either year t or $t+1$. DROP equals one if an acquiring firm (i.e., firm i) was covered by analyst j in year t but not in year $t+1$, and zero if firm i was covered by analyst j in both years t and $t+1$. See Appendix B for other variable definitions. Firm-level control variables are included but not reported. We multiply the coefficients by 100 for readability. t -statistics reported in parentheses are robust to analyst, industry, and year clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Add Decision

Variable	ADD					
	1	2	3	4	5	6
TNIC_COMPETITOR_COVERAGE	1.58*** (17.24)		0.91*** (9.44)	1.21*** (11.09)		0.71*** (7.06)
TNIC_COMPETITION_INTENSITY		12.59*** (9.93)	9.48*** (7.81)		10.64*** (7.88)	7.56*** (5.67)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	No	No	No
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effects	No	No	No	Yes	Yes	Yes
Observations	4,868,031	4,868,031	4,868,031	4,868,031	4,868,031	4,868,031
R ²	0.014	0.014	0.014	0.053	0.053	0.053

Panel B: Drop Decision

Variable	DROP					
	1	2	3	4	5	6
TNIC_COMPETITOR_COVERAGE	-8.83*** (-17.48)		-7.93*** (-17.61)	-8.83*** (-17.46)		-8.04*** (-17.31)
TNIC_COMPETITION_INTENSITY		-6.37*** (-10.76)	-5.16*** (-9.56)		-5.92*** (-11.08)	-4.52*** (-9.40)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	No	No	No
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effects	No	No	No	Yes	Yes	Yes
Observations	186,863	186,863	186,863	186,863	186,863	186,863
R ²	0.171	0.170	0.172	0.275	0.273	0.276

TABLE 7

Analyst-firm Level Regressions of Add/Drop Decisions after Brokerage House M&A

This table presents the results of estimating analysts' decision to add/drop a certain firm to/from their portfolios two years after brokerage house M&A events, based on the following analyst-firm level linear probability models:

$$\text{Prob}(\text{ADD}_{ijt+1} = 1) = \alpha + \beta_1 \times \text{TNIC_COMPETITOR_COVERAGE}_{ijt} + \beta_2 \times \text{TNIC_COMPETITION_INTENSITY}_{ijt} + \beta_3 \times \text{SIC_COVERAGE}_{ijt} + \beta_k \times \text{Firm Level Controls}_{it} + \beta_n \times \text{Analyst Level Controls}_{jt} + \varepsilon_{ijt}$$

ADD equals one if a certain firm (i.e., firm i) was not covered by analyst j in year t but is covered in year $t+1$, and zero if firm i was not covered by analyst j in either year t or $t+1$. DROP equals one if a firm (i.e., firm i) was covered by analyst j in year t but not in year $t+1$, and zero if firm i was covered by analyst j in both years t and $t+1$. See Appendix B for other variable definitions. Firm-level control variables are included but not reported. We multiply the coefficients by 100 for readability. t -statistics reported in parentheses are robust to analyst, industry, and year clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Add Decision

Variable	ADD					
	1	2	3	4	5	6
TNIC_COMPETITOR_COVERAGE	1.19*** (9.47)		0.60*** (3.56)	0.79*** (6.82)		0.33*** (2.41)
TNIC_COMPETITION_INTENSITY		11.27*** (6.68)	9.03*** (5.12)		9.03 *** (7.53)	7.37*** (5.78)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	No	No	No
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effects	No	No	No	Yes	Yes	Yes
Observations	649,217	649,217	649,217	649,217	649,217	649,217
R ²	0.011	0.012	0.012	0.094	0.095	0.095

Panel B: Drop Decision

Variable	DROP					
	1	2	3	4	5	6
TNIC_COMPETITOR_COVERAGE	-10.12*** (-3.37)		-4.93* (-1.84)	-12.11*** (-4.21)		-6.01** (-2.03)
TNIC_COMPETITION_INTENSITY		-12.58*** (-4.35)	-9.06*** (-4.93)		-15.10*** (-5.22)	-10.71*** (-4.13)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	No	No	No
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effects	No	No	No	Yes	Yes	Yes
Observations	17,608	17,608	17,608	17,608	17,608	17,608
R ²	0.209	0.210	0.210	0.387	0.388	0.388

TABLE 8
Industry Competition and Firm-level Analyst Coverage

This table presents the results of the following firm level regression:

$$\text{COVERAGE}_{it} = \alpha + \beta_1 \times \text{TNIC_HHI}_{it} + \beta_2 \times \text{TNIC_COMPETITION_INTENSITY}_{it} + \beta_3 \times \text{SIC_HHI}_{it} + \beta_4 \times \text{CENSUS_HHI}_{it} + \beta_5 \times \text{Ln(MARKET_CAP)}_{it} + \beta_6 \times \text{BOOK_TO_MARKET}_{it} + \beta_7 \times \text{INST_HOLDINGS}_{it} + \beta_8 \times \text{RETURN_VOLATILITY}_{it} + \beta_9 \times \text{Ln(\#SEGMENTS)}_{it} + \beta_{10} \times \text{R\&D_INTENSITY}_{it} + \beta_{11} \times \text{ADVERTISING_INTENSITY}_{it} + \beta_{12} \times \text{TRADING_VOLUME}_{it} + \beta_{13} \times \text{LOSS_FIRMS}_{it} + \beta_{14} \times \text{Industry Effects}_{it} + \beta_{15} \times \text{Year Effects}_{it} + \varepsilon_{it}$$

where COVERAGE is the number of analysts providing annual earnings forecasts for the firm. TNIC_HHI is the HP HHI index from Hoberg and Phillips (2016). TNIC_COMPETITION_INTENSITY is the average value of competitor product similarity among all competitors of the firm, i.e., the total product similarity measure (TNIC3TSIMM) from Hoberg and Phillips (2016) divided by the number of TNIC competitors of the firm. SIC_HHI is HHI measure based on Compustat three-digit SIC industry classification. CENSUS_HHI is HHI measure based on both public and private firms in census data. We use decile ranks (minus one and divided by nine) for all competition measures. See Appendix B for other variable definitions. We include year fixed effects and industry (firm) fixed effects in Panel A (Panel B). *t*-statistics reported in parentheses are robust to firm, and year clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Industry and Year Fixed Effects

Variable	COVERAGE					
	1	2	3	4	5	6
TNIC_HHI	-3.25*** (-13.59)		-3.01*** (-13.04)	-3.68*** (-12.50)		-3.51*** (-11.83)
TNIC_COMPETITION_INTENSITY		1.53*** (10.60)	0.77*** (5.96)		1.28*** (8.38)	0.70*** (4.80)
SIC_HHI	-0.05 (-0.31)	-0.04 (-0.22)	-0.05 (-0.27)	-0.00 (-0.01)	-0.01 (-0.04)	0.01 (0.04)
CENSUS_HHI				2.94 (0.88)	2.72 (0.80)	3.20 (0.96)
Ln(MARKET_CAP)	0.00*** (12.38)	0.00*** (12.33)	0.00*** (12.39)	0.00*** (7.62)	0.00*** (7.51)	0.00*** (7.66)
BOOK_TO_MARKET	-0.34*** (-8.10)	-0.36*** (-8.41)	-0.34*** (-8.15)	-0.32*** (-5.78)	-0.34*** (-5.65)	-0.32*** (-5.74)
INST_HOLDINGS	6.17*** (22.24)	6.38*** (22.27)	6.18*** (22.27)	7.05*** (16.83)	7.35*** (16.43)	7.06*** (16.81)
RETURN_VOLATILITY	-5.53 (-0.44)	-4.68 (-0.38)	-5.65 (-0.45)	-16.36 (-0.90)	-12.24 (-0.71)	-16.77 (-0.92)
Ln(#SEGMENTS)	0.36*** (3.41)	0.37*** (3.46)	0.38*** (3.54)	0.62*** (3.45)	0.62*** (3.40)	0.63*** (3.48)
R&D_INTENSITY	2.37*** (6.15)	2.45*** (6.23)	2.10*** (5.65)	1.89*** (3.81)	2.07*** (3.99)	1.63*** (3.39)
ADVERTISING_INTENSITY	7.72*** (4.45)	7.67*** (4.28)	7.69*** (4.41)	6.94*** (3.24)	6.60*** (2.94)	6.89*** (3.20)
TRADING_VOLUME	0.01*** (16.31)	0.01*** (16.73)	0.01*** (16.35)	0.01*** (14.14)	0.01*** (14.35)	0.01*** (14.06)
LOSS_FIRMS	-1.14*** (-10.55)	-1.19*** (-10.49)	-1.14*** (-10.54)	-1.28*** (-8.28)	-1.31*** (-8.12)	-1.28*** (-8.28)
Industry Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	142,506	142,506	142,506	60,823	60,823	60,823
R ²	0.561	0.556	0.562	0.557	0.549	0.558

Panel B: Firm and Year Fixed Effects

Variable	COVERAGE					
	1	2	3	4	5	6
TNIC_HHI	-0.95*** (-6.64)		-0.87*** (-6.39)	-0.97*** (-5.28)		-0.94*** (-5.16)
TNIC_COMPETITION_INTENSITY		0.55*** (5.28)	0.45*** (4.56)		0.38*** (3.52)	0.32*** (3.09)
SIC_HHI	0.09 (1.07)	0.08 (0.97)	0.09 (1.04)	0.17* (2.04)	0.17* (1.96)	0.17* (2.02)
CENSUS_HHI				-8.65 (-1.48)	-8.56 (-1.45)	-8.56 (-1.46)
Ln(MARKET_CAP)	0.00*** (5.87)	0.00*** (5.87)	0.00*** (5.86)	-0.00 (-0.89)	-0.00 (-0.92)	-0.00 (-0.89)
BOOK_TO_MARKET	0.02 (0.94)	0.02 (0.89)	0.02 (0.94)	0.06 (1.74)	0.06 (1.70)	0.06 (1.73)
INST_HOLDINGS	3.87*** (10.65)	3.89*** (10.62)	3.87*** (10.66)	5.81*** (19.68)	5.84*** (19.74)	5.80*** (19.76)
RETURN_VOLATILITY	-5.59 (-0.37)	-5.37 (-0.36)	-5.63 (-0.37)	-34.62** (-2.26)	-33.98** (-2.22)	-34.72** (-2.26)
Ln(#SEGMENTS)	0.08 (1.22)	0.08 (1.31)	0.08 (1.22)	0.31*** (3.24)	0.31*** (3.26)	0.31*** (3.24)
R&D_INTENSITY	0.73 (1.37)	0.73 (1.37)	0.69 (1.30)	0.98** (2.40)	1.00** (2.46)	0.95** (2.35)
ADVERTISING_INTENSITY	6.17*** (3.18)	6.32*** (3.27)	6.11*** (3.15)	3.20 (1.33)	3.45 (1.43)	3.15 (1.31)
TRADING_VOLUME	0.00*** (6.99)	0.00*** (7.03)	0.00*** (7.00)	0.01*** (9.28)	0.01*** (9.33)	0.01*** (9.28)
LOSS_FIRMS	-0.50*** (-8.81)	-0.51*** (-8.86)	-0.50*** (-8.82)	-0.42*** (-5.31)	-0.43*** (-5.40)	-0.42*** (-5.33)
Firm Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	142,506	142,506	142,506	60,823	60,823	60,823
R ²	0.831	0.831	0.831	0.843	0.843	0.843

TABLE 9
Close Competition Intensity Measures and Firm-level Analyst Coverage

This table presents the results of the following firm level regression:

$$\text{COVERAGE}_{it} = \alpha + \beta_1 \times \text{Competition Intensity}_{it} + \beta_2 \times \text{SIC_HHI}_{it} + \beta_k \times \text{Control Variables}_{it} + \varepsilon_{it},$$

where COVERAGE is the number of analysts providing annual earnings forecasts for the firm. TOP4_COMPETITORS_COMP_INTENSITY is the average of similarity scores of the four competitors with the highest similarity scores. COMPETITIVE_FLUIDITY is the average the fluidity values over all of the firm's TNIC peers and TOP4_COMPETITIVE_FLUIDITY is the average over four peers with the largest fluidity scores. See Appendix B of the manuscript for other variable definitions. We include year fixed effects and industry (firm) fixed effects in Panel A (Panel B). *t*-statistics reported in parentheses are robust to firm, and year clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Without TNIC HHI

Variable	COVERAGE					
	1	2	3	4	5	6
TOP4_COMPETITORS_COMP_INTENSITY	3.99*** (17.61)			1.85*** (9.31)		
COMPETITIVE_FLUIDITY		2.03*** (8.13)			0.95*** (5.08)	
TOP4_COMPETITIVE_FLUIDITY			3.17*** (12.10)			1.24*** (6.15)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	No	No	No
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effects	No	No	No	Yes	Yes	Yes
Observations	142,506	139,920	139,920	142,506	139,920	139,920
R-squared	0.565	0.563	0.566	0.832	0.834	0.834

Panel B: With TNIC HHI

Variable	COVERAGE					
	1	2	3	4	5	6
TOP4_COMPETITORS_COMP_INTENSITY	3.20*** (13.16)			1.70*** (8.16)		
COMPETITIVE_FLUIDITY		0.69*** (3.11)			0.71*** (3.80)	
TOP4_COMPETITIVE_FLUIDITY			1.44*** (5.71)			0.96*** (4.51)
TNIC HHI	-1.25*** (-5.33)	-2.94*** (-13.86)	-2.43*** (-10.87)	-0.25* (-1.81)	-0.69*** (-5.22)	-0.51*** (-3.74)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	No	No	No
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effects	No	No	No	Yes	Yes	Yes
Observations	142,506	139,920	139,920	142,506	139,920	139,920
R-squared	0.565	0.568	0.569	0.832	0.834	0.834

TABLE 10
Analyst Level Descriptive Statistics

This table presents descriptive statistics for variables at the analyst level regressions. See Appendix B for variable definitions.

Variable	N	Mean	StdDev	25%	Median	75%
STAR	92,734	0.08	0.27	0.00	0.00	0.00
FIRE	92,734	0.20	0.40	0.00	0.00	0.00
TNIC_COMPETITOR_COVERAGE	92,734	0.46	0.24	0.29	0.46	0.62
TNIC_COMPETITION_INTENSITY	92,734	0.46	0.22	0.34	0.48	0.60
SIC_COVERAGE	92,734	0.31	0.29	0.05	0.22	0.50
HORIZON	92,734	0.52	0.24	0.36	0.49	0.66
BOLDNESS	92,734	0.51	0.19	0.41	0.50	0.61
EXPERIENCE	92,734	0.44	0.23	0.25	0.45	0.62
PORTFOLIO_SIZE	92,734	0.32	0.28	0.07	0.26	0.52
BROKER_SIZE	92,734	0.51	0.30	0.26	0.52	0.77

TABLE 11
Industry Competition and Analyst Star Status

This table presents the results of the following analyst level linear probability model:

$$\text{Prob}(\text{STAR}_{jt+1} = 1) = \alpha + \gamma_1 \times \text{TNIC_COMPETITOR_COVERAGE}_{jt} (\text{TNIC_COMPETITION_INTENSITY}_{jt}) \\ + \gamma_2 \times \text{SIC_COVERAGE}_{jt} + \gamma_n \times \text{Analyst Level Controls}_{it} + \varepsilon_{jt},$$

where STAR is an indicator variable that is one if the analyst is in *Institutional Investor* magazine's All American Team, and zero otherwise. See Appendix B for other variable definitions. We include year fixed effects and broker fixed effects. We multiply the coefficients by 100 for readability. *t*-statistics reported in parentheses are robust to analyst and year clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	STAR _{t+1}		
	1	2	3
TNIC_COMPETITOR_COVERAGE	1.16*** (4.50)		0.98*** (3.72)
TNIC_COMPETITION_INTENSITY		0.86*** (5.34)	0.61*** (3.78)
SIC_COVERAGE	0.20 (0.66)	0.20 (0.67)	0.03 (0.11)
HORIZON	-3.20*** (-12.88)	-3.26*** (-12.90)	-3.20*** (-12.88)
BOLDNESS	-0.84*** (-3.48)	-0.85*** (-3.62)	-0.84*** (-3.56)
EXPERIENCE	1.37*** (3.82)	1.41*** (3.95)	1.37*** (3.81)
PORTFOLIO_SIZE	4.17*** (13.28)	4.21*** (13.78)	4.15*** (13.17)
BROKER_SIZE	0.20 (0.39)	0.15 (0.31)	0.16 (0.32)
STAR	71.86*** (67.25)	71.86*** (67.26)	71.85*** (67.22)
Broker Effects	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes
Observations	92,734	92,734	92,734
R ²	0.640	0.640	0.640

TABLE 12
Analyst Level Regressions of Analyst Firing

This table presents the results of the following analyst level linear probability model:

$$\text{Prob}(\text{FIRE}_{jt+1} = 1) = \alpha + \gamma_1 \times \text{TNIC_COMPETITOR_COVERAGE}_{jt} (\text{TNIC_COMPETITION_INTENSITY}_{jt}) + \gamma_2 \times \text{SIC_COVERAGE}_{jt} + \gamma_n \times \text{Analyst Level Controls}_{jt} + \varepsilon_{jt},$$

where FIRE is an indicator variable that is one if analyst j is demoted (i.e., moves to a different and smaller brokerage house) or permanently leaves the I/B/E/S database in the following year (i.e., between July 1 of year $t+1$ and June 30 of year $t+2$), and zero otherwise. The first two columns report results based on the total sample, while the last two columns report results based on the brokerage house M&A sample. See Appendix B for other variable definitions. We include year fixed effects and broker fixed effects. We multiply the coefficients by 100 for readability. t -statistics reported in parentheses are robust to analyst and year clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	FIRE _{<i>t+1</i>}					
	Total Sample			Broker M&A Sample		
	1	2	3	4	5	6
TNIC_COMPETITOR_COVERAGE	-13.60*** (-14.69)		-10.93*** (-14.33)	-15.20*** (-5.86)		-12.35*** (-4.81)
TNIC_COMPETITION_INTENSITY		-11.95*** (-12.39)	-9.15*** (-10.70)		-12.63*** (-4.16)	-9.12** (-2.94)
SIC_COVERAGE	-4.81*** (-6.39)	-4.20*** (-5.50)	-2.29*** (-3.09)	-3.00 (-1.27)	-2.94 (-1.06)	-0.75 (-0.29)
HORIZON	82.67*** (43.57)	83.31*** (44.41)	82.58*** (43.43)	82.43*** (21.80)	84.04*** (22.78)	82.50*** (21.89)
BOLDNESS	0.82 (1.03)	0.95 (1.20)	0.77 (0.98)	1.59 (0.33)	2.05 (0.40)	1.41 (0.29)
EXPERIENCE	3.20*** (2.82)	2.64** (2.31)	3.15*** (2.76)	9.70** (3.05)	8.87** (3.01)	9.28** (2.89)
PORTFOLIO_SIZE	-29.09*** (-27.01)	-29.52*** (-26.16)	-28.84*** (-27.93)	-33.57*** (-8.32)	-34.23*** (-8.55)	-33.54*** (-8.21)
BROKER_SIZE	-0.79 (-0.53)	0.00 (0.00)	-0.07 (-0.05)	5.17 (0.67)	4.72 (0.60)	5.54 (0.71)
STAR	-5.14*** (-6.05)	-5.11*** (-5.93)	-4.96*** (-5.88)	-3.11 (-1.37)	-3.05 (-1.31)	-2.71 (-1.16)
Broker Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92,734	92,734	92,734	2,139	2,139	2,139
R ²	0.374	0.374	0.377	0.406	0.405	0.408

TABLE 13
Industry Competition and Analyst Forecast Accuracy

This table presents the results of the following analyst-firm level model:

$$\begin{aligned} \text{ACCURACY}_{ijt} = & \alpha + \beta_1 \times \text{TNIC_COMPETITOR_COVERAGE}_{ijt} + \beta_2 \times \text{TNIC_COMPETITION_INTENSITY}_{ijt} \\ & + \beta_3 \times \text{SIC_COVERAGE}_{ijt} + \beta_4 \times \text{Firm Level Controls}_{it} + \beta_5 \times \text{Analyst -Firm Level Controls}_{ijt} \\ & + \beta_6 \times \text{Analyst Level Controls}_{jt} + \varepsilon_{ijt}. \end{aligned}$$

ACCURACY is a relative accuracy rank among analysts following a firm (Hong and Kubik (2003)). See Appendix B for other variable definitions. Firm-level control variables are included but not reported. We include year and industry fixed effects in our estimation. We multiply the coefficients by 100 for readability. *t*-statistics reported in parentheses are robust to analyst, industry, and year clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	ACCURACY		
	1	2	3
TNIC_COMPETITOR_COVERAGE	3.65*** (16.75)		3.47*** (15.99)
TNIC_COMPETITION_INTENSITY		1.59*** (11.24)	1.08*** (7.86)
SIC_COVERAGE	0.01 (0.09)	0.93*** (5.91)	-0.05 (-0.28)
STAR	1.18*** (4.72)	1.17*** (4.56)	1.16*** (4.71)
HORIZON	-26.94*** (-28.55)	-27.04*** (-28.41)	-26.91*** (-28.57)
BOLDNESS	-3.82*** (-16.07)	-3.86*** (-16.37)	-3.82*** (-16.14)
EXPERIENCE	1.87*** (6.38)	2.05*** (6.94)	1.86*** (6.38)
PORTFOLIO_SIZE	1.77*** (5.04)	2.07*** (6.18)	1.80*** (5.13)
BROKER_SIZE	-1.68*** (-3.58)	-1.81*** (-3.76)	-1.68*** (-3.60)
Firm-level Control Variables	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes
Observations	949,049	949,049	949,049
R ²	0.078	0.077	0.078