Product Market Competition and Analyst Coverage Decisions

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Abstract

We analyze whether product market competition is an important factor in 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 and offers more similar products to the firms already covered by the analyst. We also find that analysts who cover product market competitors are more likely to obtain star status and issue more informative recommendations. Collectively, these results are consistent with the importance of industry and product market knowledge obtained through covering product market competitors to analysts. (*JEL* G24, L20)

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Analysts are important information intermediaries between the firms they cover and the investors in those firms. Prior studies investigate different key roles for analysts, including how they impact firm information environments (Harford, Jiang, Wang and Xi 2019), investment and financing policies (Derrien and Kecske 2013), corporate governance (Chen, Harford, and Lin 2015), and product market outcomes (Billett, Garfinkel, and Yu 2017). A potential key reason for analysts playing such important roles documented by these prior studies is that analysts possess unique industry knowledge that allows them to provide valuable information to investors and other market participants. In annual surveys of institutional fund managers by *Institutional Investor* magazine, industry knowledge consistently ranks as the most important quality for an analyst. In a survey of sell-side analysts by Brown et al. (2015), industry knowledge is also the most important determinant of analyst compensation. These survey findings suggest that industry knowledge is a first-order determinant of analyst coverage and career outcomes. However, there is little empirical evidence on the importance of industry knowledge for analyst coverage choices.

If analysts seek to deepen their industry knowledge through their coverage, they may seek to cover firms that make competing products. We suggest two reasons for this behavior. First, covering competing firms will help analysts enhance their knowledge about industry competition and thus improve their understanding of firm performance.[1] This 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 more firms in an efficient manner. Competitors likely produce similar products, which have similar factor inputs / suppliers,

[1] 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…"

production technologies, markets / customers, 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 2006; Loh and Stulz 2011). Covering competitors also improves 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, Garfinkel and Yu (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 why analysts may cover competing firms. We note, however, although product market competition may intuitively affect analysts' coverage decisions, the net impact of competition on coverage decisions may not be clear. Through different channels, competition may have different effects on firms' information environment, performance, and survivability, making firms more or less attractive for analysts to cover.[2]

We study how product market competition affects analyst coverage decisions and career outcomes. Coverage can be the analyst's decision or assigned by the brokerage house. If covering competing firms deepens industry and product knowledge, and the benefits dominate the costs of covering a new firm for an analyst, analysts and brokers should have similar incentives to cover

[2] For example, competition also has ambiguous effects on firms' voluntary disclosure, which affects analysts' information environment (e.g., Grossman 1981; Milgrom 1981). 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; Haskel, Pereira, and Slaughter 2007; Aghion, Dewatripont, and Stein 2008), while lowering the profitability of firms and increase the bankruptcy risks (e.g., Bolton and Scharfstein 1990; Mazzeo 2002; Seim 2006). Competition has ambiguous effects on managerial incentives, which affect firm performance (e.g., Hermalin 1992; Schmidt 1997; Raith 2003; Dasgupta, Li, and Wang 2018).

such firms. Similar logic would apply to career outcomes such as star rankings, as industry knowledge is rated as a top factor for star rankings, which are crucial to both brokers' status and reputation and analysts' compensation.

We examine whether the firms that analysts add to (drop from) coverage are affected by two aspects of product market 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 identification of whether a firm competes with other firms that the analyst covers and the degree of product similarity among competitors. 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 similar the firm's products are to those of 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 products more (less) similar to the other firms it covers. 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.

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. Our results for acquiring firms 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 firms covered (Hong and Kacperczyk 2010; Chen, Harford, and Lin 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 product market 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&A are exogenous shocks to analyst coverage decisions.

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; 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 product similarity with each other are more likely to be nominated *Institutional Investor* stars and are less likely to be fired.

As an extension of our main analysis, we investigate whether product market competition improves the informativeness of analysts' research reports. Our empirical results show that analysts issue more informative forecasts and recommendations for a firm if this firm has more product peers and has products more similar to those of its peers that the analyst covers.

Our paper makes several contributions to the literature. First, our paper contributes to the literature on analyst behavior by providing a direct explanation for the importance of industry and product knowledge to an analyst. Although it is well observed that analysts are industry specialists (e.g. Boni and Womack 2006), little empirical evidence exists for the underlying reasons. Our evidence suggests that analysts are motivated by the prospect of enhanced industry knowledge through covering firms that offer competing products. Our large-sample empirical evidence complements the survey-based evidence (*Institutional Investor* and Brown et al. 2015) on the importance of industry knowledge to analysts and sheds new light on analysts' decision processes. Our results also show that text-based measures of competitors and product similarity better explain analyst coverage decisions than traditional SIC based measures.

Studies beginning with Lang and Lundholm (1996) examine how analyst coverage relates to firms' financial disclosures using correlation analyses. Our analysis shows how exogenous product market competition influences analyst coverage decisions. While firms might change, say, disclosure practices to cater to analysts and other capital market players, firms are unlikely to change product strategies (e.g., product composition and consequent product market competition) to influence analysts' coverage decisions. Several studies examine how 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, and thus industry and product knowledge, on analyst coverage decisions and career outcomes.

Our paper also contributes to the analyst coverage literature by directly examining 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 et al. (2010, p329): "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 paper sheds light on the importance of industry knowledge for analysts' career outcomes and their ability to influence capital markets. Our findings on career outcomes extend the survey-based evidence in *Institutional Investor* magazine and Brown et al. (2015) that analysts view industry knowledge as the most important attribute related to their career outcomes. Our finding of industry product market knowledge contributing to star selection adds to prior research on star rankings (Stickel 1992; Michaely and Womack 1999; Hong et al. 2000; Emery and Li 2009). Our findings showing analysts' analyst coverage influences stock informativeness complement the evidence in Bradley, Gokkaya, and Liu (2017) on how industry knowledge affect covered firms' information environments.[3]

1. Data and Sample

We obtain and calculate measures of industry competitors and industry product similarity using data downloaded from the Hoberg and Phillips (HP) industry database available at http://hobergphillips.tuck.dartmouth.edu/. Our sample period is from 1996 to 2015 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.[4]

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

[3] Bradley et al. (2017) show that industry expertise enables analysts to make more accurate earnings forecasts. Our untabulated results show that analysts' forecasts are more accurate for a firm when this firm has more product competitors and when its products are more similar to those of its competitors in the analyst portfolio.
[4] 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.

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 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. We also include the number of firm operating segments. Lastly, we only include analysts covering at least three firms in the analysis.

2. Analyst Coverage Decisions

2.1 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. This allows us to capture how industry and product knowledge comes both from the firm itself and from its competitors, thus focusing on product market competition at the individual analyst firm level. We estimate the following analyst-firm coverage decision logit model:

$$\text{Prob}(Add_{ijt+1}{=}1) = \alpha + \beta_1 \times \mathit{TNIC\ Competitor\ Coverage\ Ratio}_{ijt} + \beta_2 \times \mathit{SIC\ Coverage\ Ratio}_{ijt} + \beta_k \times \mathit{Firm\ Level\ Controls}_{it} + \beta_n \times \mathit{Analyst\ Level\ Controls}_{jt} + \varepsilon_{ijt}, \quad (1)$$

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. We also estimate the impact of product similarity among competitors on the analyst add decision by replacing *TNIC Competitor Coverage Ratio* with *TNIC Competitor Product Similarity* in the above equation. We expect β_1 to be positive in Equation (1) if adding industry competitors or covering competitors with high product similarity 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 *TNIC Competitor Coverage Ratio* $_{ijt}$ 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 firms (other than firm *i*) shown both in the analyst *j*'s portfolio and focal firm *i*'s total similarity calculation. Since the database also provides detailed scores for the pairwise similarity index, we create an additional measure, *TNIC Competitor Product Similarity,* as the natural log of the sum of pairwise score of all firms shown both in the analyst *j*'s portfolio and firm *i*'s total similarity calculation plus one.

As discussed earlier, whether firms compete against each other (competitor coverage) and product similarity among competitors (competitor product similarity) are the two dynamic aspects of product market competition that may influence analyst coverage decisions. *TNIC Competitor Coverage Ratio* and *TNIC Competitor Product Similarity* capture these two aspects of product competition. A larger number for *TNIC Competitor Coverage Ratio* or *TNIC Competitor Product Similarity* indicates that firm *i* is competing more with other firms within 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 Ratio* and *TNIC Competitor Product Similarity* 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.[5]

[5] Note that this choice (i.e., reduce the *Add*=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

Our text-based measures of competition are designed to capture how industry knowledge relates to product market competition. For comparison, we also create a measure based on three-digit SIC industry named *SIC Coverage Ratio.* Specifically, *SIC Coverage Ratio* 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 Ratio* or *TNIC Competitor Product Similarity* in capturing the effect of product market 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.

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 (*Ln (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, *Ln(#Segments),* the natural logarithm of the number of business segments reported in the Compustat Segment File, *R&D Intensity* and *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

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.

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 similarity in products among competitors in an analyst's portfolio on their decision to drop a firm from their portfolio, we use the following analyst-firm level logit model:

$$\text{Prob}(Drop_{ijt+1}=1) = \alpha + \beta_1 \times TNIC\ Competitor\ Coverage\ Ratio_{ijt} + \beta_2 \times SIC\ Coverage\ Ratio_{ijt} + \beta_k \times Firm\ Level\ Controls_{it} + \beta_m \times Analyst\text{-}Firm\ Level\ Controls_{ijt} + \beta_n \times Analyst\ Level\ Controls_{jt} + \varepsilon_{ijt}, \quad (2)$$

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 replace *TNIC Competitor Coverage Ratio* with *TNIC Competitor Product Similarity* in the above equation to examine the impact of product similarity 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*.[6] In Equation (2), *TNIC Competitor Coverage Ratio* and *TNIC Competitor Product Similarity* 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 product market competition dominates the cost, we expect β_1 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 also include forecast accuracy (*Accuracy*) because forecast accuracy has been shown to improve career outcomes (Hong and Kubik 2003). We thus expect that analysts are less likely to drop the firm with high forecast accuracy.

We include forecast frequency (*Frequency*) given this variable may capture analyst effort. Analysts who issue more frequent forecasts are less likely to drop a firm from their portfolios, given

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

they have already expanded significant effort on it. Forecast frequency has been shown to be positively associated with forecast accuracy (Jacob et al. 1999; Clement and Tse 2005) and could conceivably affect analysts' drop decisions. We also 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 analyst career outcomes.[7] 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

[7] 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.

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. $Accuracy_{ijt}$ is a relative accuracy rank of the analysts following a firm. 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) / (# $of\ Analysts_{it}$ - 1), where # $of\ Analysts_{it}$ 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 analyst-firm variables (*Frequency, Horizon, Boldness, Experience, Portfolio Size and Brokerage Size*) are similarly defined using relative ranks, with a larger rank number corresponding to a larger raw number for easy interpretation.

In both Equations (1) and (2), we include year and industry fixed effects based on the 48 industry classifications of Fama and French (1997) to account for inter-temporal and cross-industry differences beyond the controls.[8] We also adjust the standard errors for heteroskedasticity and clustering by analyst, industry, and year (Cameron, Gelbach, and Miller 2011).[9]

2.2 Summary Statistics

Table 1 Panel A shows summary statistics for the key variables at the analyst-firm level. For

[8] Our results are not affected if we add other industry fixed effects (two- or four-digit SIC, GICS, or HP FIC industry) or if we do not add any industry fixed effects.
[9] Our results are robust to analyst, firm and year clustering and other clustering methods (firm and year, industry and year, or analyst and year).

add decisions, about 1% of firms competing in products not covered by an analyst in a given year are covered the next year (=134,784 / (134,784+18,500,892)). For drop decisions, about 26% of firms covered by an analyst in one year are dropped from coverage the next year (=166,043 / (166,043 + 461,647)). 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 25% 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 Ratio* (*TNIC Competitor Product Similarity*) is 0.14 (0.09) for the *Add* sample, and is 0.50 (0.50) for the *Drop* sample.

[Insert Table 1 Here]

The descriptive statistics on the other variables are as follows: The mean of *SIC Coverage Ratio* is 0.38 for the *Add* sample, and is 0.50 for the *Drop* sample. About 12% of the samples are covered by star analysts. All other rank variables have a mean and median of 0.50. The mean natural log of market value of equity is 7.64. The average book-to-market value and institutional ownership are both about 50%, and the average monthly return standard deviation is about 12%. The mean natural log of number of business segments is 0.58. The mean ratio of R&D and advertising expenses to operating expense are 0.07 and 0.01, respectively. About 22% of firms report a loss in the sample period.

2.3 Add/drop Decision Main Results

Table 2 presents the results of the logit model in Equation (1) for analysts' add decisions.

The coefficients on *TNIC Competitor Coverage Ratio* (Column 1) and *TNIC Competitor Product Similarity* (Column 2) are both positive and significant, suggesting that analysts are more likely to add firms that are competitors of the existing firms in their portfolios. We find that a one standard deviation increase in *TNIC Competitor Coverage Ratio* (*TNIC Competitor Product Similarity*) increases a firm's probability of being added by 0.12% (0.15%). Given that Table 1 shows that the unconditional probability of being added to analyst portfolios is 0.83%, a one standard deviation increase in *TNIC Competitor Coverage Ratio* (*TNIC Competitor Product Similarity*) increases a firm's probability of being added to coverage by 14.5% (= 0.12% divided by 0.83%) (18.1% (= 0.15% divided by 0.83%)).

[Insert Table 2 Here]

Table 3 presents the results of the logit model in Equation (2) for analysts' drop decisions. The coefficient estimates on *TNIC Competitor Coverage Ratio* (*TNIC Competitor Product Similarity*) are negative and significant, suggesting that analysts are less likely to drop firms that compete more in products with the other firms in their portfolios. Given that Table 1 shows that the unconditional probability of being dropped from analyst portfolios is 26%, the result here means a one standard deviation increase in *TNIC Competitor Coverage Ratio* (*TNIC Competitor Product Similarity*) decreases a firm's probability of being dropped by 2.3% (3.2%), which is equivalent to approximately 8.8% (= 2.3% divided by 26%) (12.3% (= 3.2% divided by 26%)) of the unconditional probability of being dropped. Overall, the results from the coverage decision regressions suggest that analysts actively adapt to the product market 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.

[Insert Table 3 Here]

The coefficient estimate of *SIC Coverage Ratio* is significant but weaker in analysts' add decisions, and is insignificant in analysts' 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 variables are mostly consistent with our expectations. 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 less likely to drop firms from their coverage when their forecasts for these firms are more accurate, while analysts who issue forecasts less frequently or analysts who issue long-horizon forecasts (i.e., do not issue new forecasts) are more likely to drop a firm. 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.

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 product similarity among competitors.

2.4 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 product market competition) to influence analysts' coverage decisions. Thus, our focus on product market competition allows us to draw more powerful inferences about factors driving coverage decisions. To further reinforce our inferences regarding the impact of product market 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 product market 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) one year after the M&A event to examine whether analysts' decision to cover the acquiring firm is positively associated with the product market competition between this firm and other existing firms within an analyst portfolio. For the drop decision, we rerun the Equation (2) during the M&A year to examine whether analysts' decision to drop the acquiring firm is negatively associated with the product market competition between this firm and other existing firms within an analyst portfolio. Note that in these analyses, the sample size in substantially smaller because we focus on analysts' decisions to add or drop an acquiring firm around the M&A event.

[Insert Table 4 Here]

Table 4 reports the estimation results for analysts' decisions to add (drop) an acquiring firm one year after (during) the M&A event year. These results are similar in sign and significance to our main results reported in Table 2 and Table 3, reinforcing our conclusion that product market 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 industries (based on two-digit SIC code).

2.5 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, Harford, and Lin 2015; and Billett, Garfinkel and Yu 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 13 brokerage house merger events from 1994 to 2005 and we examine analysts' decisions to add (drop) a firm one year after brokerage house merger events.

[Insert Table 5 Here]

Table 5 reports the estimation results for analysts' decisions to add (drop) a certain firm one year after the broker M&A event year. These results show that product market competition as measured by *TNIC Competitor Coverage Ratio* and *TNIC Competitor Product Similarity* are both positively and significantly related to analyst add decisions and negatively related to drop decisions. The results reinforce our previous conclusions that industry and product knowledge is important to coverage decisions.

2.6 Firm-level Analysis

We next examine the effect of product market 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 has products more similar to 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 product market competition affects the number of analysts covering a firm, we estimate the firm-level regression:

$$Coverage_{it} = \alpha + \beta_1 \times TNIC\ HHI_{it} + \beta_2 \times SIC\ HHI_{it} + \beta_k \times Controls_{it} + \varepsilon_{it}, \quad (3)$$

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 product similarity among competitors on analyst coverage, we also replace *TNIC HHI* with *TNIC Competitor Product Similarity* for a given TNIC industry where *TNIC Competitor Product Similarity* is the sum of product similarity scores for a given industry based on the text-based methods of Hoberg and Phillips (2016). In our firm-level analysis, we include only firm-years observations with analyst coverage since this test works as an aggregation of our analyst-firm level analysis at the firm level.[10] Note that the Herfindahls (*TNIC HHI* and *SIC HHI*) are higher the more concentrated and less competitive an industry is, and *TNIC Competitor Product Similarity* increases the more similar the firm's products are with its competitors and thus 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. Ali, Klassa and Yeung 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.*

We also include a measure of competition from Li et al. (2013) which we label *LLM Competition.* This measure is straightforward, as it captures competition among firms based on the

[10] We get similar results when we include these firms without analyst coverage in the analysis.

number of references to competition in the firm's 10-K filing. *LLM Competition* is capable of capturing competition beyond the fixed industry boundary and allows within-industry variation in the firm competitive environment.[11] However unlike our first two primary measures discussed above, this measure does not take into account the number of competitors or the identity of competitors, nor the similarity of products among competitors, thus we cannot include this measure in our analyst-firm level or analyst level analyses.

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 fixed affects based on the Fama and French (1997) 48 industry classification 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 6 Here]

Table 6 reports results from estimating the effect of firm-level competition on the number of analysts covering the firm (i.e., Equation (3)). We have different sample sizes for these tests due to varying data availability of the *Census HHI* and *LLM Competition* measures.

The coefficient estimates on *TNIC HHI* and *Competitor Similarity* in Columns 1 and 2 have the predicted signs and are significant, which suggests that analyst coverage is greater for firms with more competitors or greater product similarity. The results suggest that there is a net benefit for analysts to follow firms with more competitors or high competitor product similarity. The

[11] *LLM Competition* is similar to our measure *TNIC HHI* but has a different focus. Since *LLM Competition* measures the number of references to competition in the firm's 10-K filing, this measure is more about managers' perceptions of competition.

coefficient estimate on *SIC HHI* is weakly significant and negative in Column 1, again consistent with the SIC-based measure performing relatively poor as SIC industry membership updates are less timely and thus less informative.

Our results are not affected by adding additional firm- or industry-level competition measures. The coefficients estimate on *LLM Competition* in Columns 3 and 4 are also significant when added to the regressions but of a smaller magnitude than the coefficients of the text-based TNIC method, suggesting that the LLM competition measure does capture an additional aspect of competition but with a weaker signal. Untabulated results show that other industry-level competition measures generate either smaller coefficients or insignificant results.[12] These results are not surprising, as traditional fixed industry classifications capture less nuance given they are fixed 0 or 1 based (i.e., belong or don't belong to an industry), and change infrequently. They do not easily 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 control variables are consistent with prior research. 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.

3. 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 product market competition at the analyst level, we average the analyst-

[12] 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.

firm-level competition indexes *TNIC Competitor Ratio* and *TNIC Competitor Product Similarity* 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 Ratio* and *TNIC Competitor Product Similarity*, the more competitor firms with similar products are within analyst *j*'s portfolio.

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

$$\text{Prob}\ (Star_{jt+1} = 1) = \alpha + \gamma_1 \times TNIC\ Competitor\ Coverage\ Ratio_{jt} + \gamma_2 \times SIC\ Coverage\ Ratio_{jt} + \gamma_n \times Analyst\ Level\ Controls_{it} + \varepsilon_{jt}; \quad (4)$$

$$\text{Prob}\ (Fire_{jt+1} = 1) = \alpha + \gamma_1 \times TNIC\ Competitor\ Coverage\ Ratio_{jt} + \gamma_2 \times SIC\ Coverage\ Ratio_{jt} + \gamma_n \times Analyst\ Level\ Controls_{it} + \varepsilon_{jt}. \quad (5)$$

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 product similarity among competitors on analyst career outcomes using the above equation and replacing *TNIC Competitor Coverage Ratio* with *TNIC Competitor Product Similarity.* If industry product market knowledge 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; Hilary and Hsu 2013), we control for *Accuracy, Frequency*, *Horizon Boldness*, *Experience*, *Portfolio Size,* and *Broker Size*. The first five variables (*Accuracy, Boldness, Experience, Accuracy, Horizon* and *Frequency*) 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 7 Here]

Table 7 presents summary statistics for the sample of 61,093 analyst-year observations used in the analyst-level regressions. The mean (median) *Fire* and *Star* are 0.18 (0.00) and 0.09 (0.00), respectively. The mean of *TNIC Competitor Coverage Ratio* and *TNIC Competitor Product Similarity* are 0.50 and 0.42.

Table 8 presents results on star status (i.e., Equation (4)). The coefficients on *TNIC Competitor Coverage Ratio* and *TNIC Competitor Product Similarity* are positive and significant, which means that analysts covering firms whose products compete with each other are more likely to be voted stars. In untabulated results, we find that a one standard deviation increase in *TNIC Competitor Coverage Ratio* (*TNIC Competitor Product Similarity)* increases an analyst's probability of being a star by approximately 0.22% (0.48%). Given that Table 7 shows that the unconditional probability of being a star is 9%, a one standard deviation increase in *TNIC Competitor Coverage Ratio* (*TNIC Competitor Product Similarity)* increases the unconditional probability of being a star by approximately 2.4% (= 0.22% / 9%) (5.3% (= 0.48% / 9%)).

[Insert Table 8 Here]

Table 9 presents results of estimating firing outcomes (i.e., Equation (5)). The coefficients on *TNIC Competitor Coverage Ratio* and *TNIC Competitor Product Similarity* in Columns 1 and 2 are negative and significant, which suggests that analysts whose portfolios consist of firms 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 a one standard deviation increase in *TNIC Competitor Coverage Ratio* (*TNIC Competitor Product Similarity)* decreases an analyst's probability of being fired by approximately 0.48% (1.8%). Given that Table 7 shows that the unconditional probability of being fired is 18%, a one standard deviation increase in *TNIC Competitor Coverage Ratio* (*TNIC Competitor Product Similarity)* decrease the unconditional probability of being fired by approximately 2.7% (= 0.48% / 18%) (10%=1.8%/18%).

[Insert Table 9 Here]

Similar to what we have found in analyst-firm level tests, the coefficient estimates on *SIC Coverage Ratio* 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, analysts with higher relative forecast accuracy, more frequent forecasts, and 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 13 brokerage house merger events from 1994 to 2005 and 853 analyst-level observations (including bidder and target brokerage houses analysts) in this analysis.

Columns 3 and 4 of Table 9 presents the results of estimating the *Fire* decision around brokerage house mergers. The coefficients on *TNIC Competitor Coverage Ratio* and *TNIC Competitor Product Similarity* are negative and significant. These coefficients are a bit larger in magnitude than those reported in the first two columns, likely because in the last two columns we focus on a setting where brokerage houses may need to fire redundant analysts. Overall, the results reported in Table 9 suggest that analysts whose portfolios consist of firms that compete more in products with each other are less likely to be fired.

Our analyst-level estimation results are robust to excluding relative accuracy from 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. 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 have more similar product offerings.

4. Informativeness Tests

We extend our analysis to examine the relation between the product market competition among firms in an analyst's portfolio and the informativeness of the analyst's forecasts and recommendations. As argued earlier, analysts are motivated to follow product market competitors by an interest in deepening their industry knowledge. Understanding competition and following competitors as well thus helps the analyst make informative forecasts and recommendations. According to the Brown et al. (2015) survey results, analysts have strong incentives to issue informative recommendations and earnings forecasts to meet information demand from investors.

We examine the impact of product competitor coverage and product similarity among competitors on analyst performance at the analyst-firm level. Following prior research (e.g., Green, Jame, Markov and Subasi 2014), we consider the absolute value of market reactions to both analyst forecasts and recommendations as measures of analyst informativeness. We estimate the following regression:

$$\begin{aligned} ReturnForecast_{ijt}\ (ReturnRecom_{ijt}) = \alpha &+ \delta_1 \times \textit{TNIC Competitor Coverage Ratio}_{ijt} \\ &+ \delta_2 \times \textit{SIC Coverage Ratio}_{ijt} + \delta_k \times \textit{Firm Level Controls}_{it} \\ &+ \delta_m \times \textit{Analyst–Firm Level Controls}_{ijt} + \delta_n \times \textit{Analyst Level Controls}_{it} + \varepsilon_{ijt}. \quad (6) \end{aligned}$$

$ReturnForecast_{ijt}$ and $ReturnRecom_{ijt}$ are the two-day (day 0 and day +1) absolute market-adjusted abnormal return around the issuance of analyst forecasts and analyst recommendations, respectively. 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). We also estimate the impact of product similarity among competitors on analyst informativeness using the above equation and replacing *TNIC Competitor Coverage Ratio* with *TNIC Competitor Product Similarity.*

We conduct both analyses (forecast issuance and recommendation revisions) at the individual issuance level. We include the same set of firm-level variables and analyst-firm (or analyst) level variables as defined earlier. Prior studies (e.g., Jacob et al. 1999; Hong and Kubik 2003; Hilary and Hsu 2013) have identified several analyst-firm (or analyst) variables as factors that influence analyst informativeness or performance (e.g., *Accuracy*, *Frequency*, *Horizon*, *Boldness*, *Experience*, *Portfolio Size* and *Broker Size*). We also include year and firm fixed effects in Equations (6) since we compare analysts covering the same firm. Other variables are defined the same as in Equation (2). We expect δ_1 in Equation (6) to be positive for analyst forecast revisions and recommendation revisions.

[Insert Table 10 Here]

Columns 1 and 2 of Table 10 report the results from estimating Equation (6), where we focus on the informativeness of analyst forecast issuance (i.e., the dependent variable is *ReturnForecast*). We find that the coefficients on both *TNIC Competitor Coverage Ratio* and *TNIC Competitor Product Similarity* are both positive and significant, which suggests that the informativeness of analyst forecasts increases with both (1) whether firms compete with other firms and (2) the degree of similarity in product offerings among competitors in analysts' portfolios. This is consistent with the market reacting stronger to analysts with greater industry product market knowledge. Our results on analyst-firm-level or analyst-level variables are largely consistent with our expectations. For example, forecasts with greater accuracy, forecast with greater frequency, forecasts issued by more experienced analysts, and forecasts issued by analysts working for larger brokers have greater impact on market prices. Early forecasts (i.e., forecasts with long horizon) have a greater impact on prices as early forecasts tend to resolve greater information uncertainty, consistent with the finding in Hilary and Hsu (2013).

Columns 3 and 4 of Table 10 report the results from estimating Equation (6), where we focus on the informativeness of recommendation revisions (i.e., the dependent variable is

ReturnRecom). We have fewer observations in Columns 3 and 4 since the number of recommendation revisions is less than the number of forecast revisions. The coefficients on both *TNIC Competitor Coverage Ratio* and *TNIC Competitor Product Similarity* are both positive and significant, suggesting that investors consider analysts recommendation revisions for a firm as more useful when analysts also cover this firm's competitors and when this firm's products are more similar to those of competitors in the analysts' portfolios.

The coefficients on *SIC Coverage Ratio* are insignificant in Table 10, 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-estimate Equation (6) 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). Overall, our evidence is consistent with our hypothesis that covering firms with competing products enhances analysts' industry knowledge.

5. Conclusions

We examine the impact of product market competition on sell-side analysts' coverage decisions. We find that analysts adjust their portfolios to account for product market 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's products are more similar to those of its competitors in the analyst's portfolios. These results suggest that analysts consider industry knowledge, in particular the knowledge about product market competition and product similarity among competitors, in their portfolio management decisions.

We find that an analyst's coverage decisions based on product market competition are also positively associated with their career outcomes. Finally, we find that an analyst makes more informative forecasts on a firm relative to other analysts covering the same firm when the analyst covers competitor firms and when these firms produce similar products.

Overall, our results at the analyst-firm and analyst levels support the proposition that product market competition is a key factor that influences analysts' coverage decisions. Our findings are consistent with the importance of industry knowledge and understanding industry competitions to analysts when making coverage decisions. Analysts covering close competitors and similar products among competitors in their portfolios provide more informative forecasts and recommendations and 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. Our results shed new light on the impact of industry knowledge on analysts and provide a direct explanation for the well-observed industry specialization of analysts.

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Appendix A
Competition Measures at the Analyst-firm Level

Definitions of *TNIC Competitor Coverage Ratio* and *TNIC Competitor Product Similarity*

TNIC Competitor Coverage Ratio: 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 firms (other than firm *i*) shown both in the analyst *j*'s portfolio and focal firm *i*'s total similarity calculation.

TNIC Competitor Product Similarity: the natural log of the sum of pairwise product similarity scores of all firms (other than firm *i*) shown both in the analyst *j*'s portfolio and firm *i*'s total similarity calculation plus one.

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.[13] Suppose the following seven firms (including IBM) enter IBM's HP index calculation in 2000:

$$\{\text{IBM}, \boxed{\text{firm a, firm b, firm c}}, \text{firm d, firm e, firm f}\},$$

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.

[13] 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.

{IBM, $\boxed{\text{firm a, firm b, firm c}}$, firm 5, firm 6, firm 7, firm 8, firm 9, firm 10}.

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*,

TNIC Competitor Coverage Ratio$_{IBMj2000}$ = N_{ijt} /M_{jt} = 3/10;

TNIC Competitor Product Similarity $_{IBMj2000}$ = log (Sum (pairwise product similarity score $_{\text{IBM and firm a}}$ + pairwise product similarity score $_{\text{IBM and firm b}}$ + pairwise product similarity score $_{\text{IBM and firm c}}$) + 1).

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 Ratio	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 firms shown both in the analyst *j*'s portfolio and firm *i*'s total similarity calculation (see Appendix A for an illustration).
TNIC Competitor Product Similarity	The natural log of the sum of pairwise score of all firms shown both in the analyst *j*'s portfolio and firm *i*'s total similarity calculation plus one (see Appendix A for an illustration).
SIC Coverage Ratio	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.
Frequency	Number of forecasts made by the analyst, based on rank 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.
ReturnForecast	Two-day (day 0 to day +1) absolute market-adjusted abnormal return around the issuance of analyst forecasts.
ReturnRecom	Two-day (day 0 to day +1) absolute market-adjusted abnormal return around the issuance of analyst recommendations.

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.
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 rim 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 *Institutional Investor* magazine's All American Team, and zero otherwise.
Portfolio Size	Number of firms coved 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

Variable	N	Mean	StdDev	25%	Median	75%
Add	18,635,676	0.01	0.08	0.00	0.00	0.00
Drop	627,690	0.26	0.44	0.00	0.00	1.00
TNIC Competitor Coverage Ratio (Add Sample)	18,635,676	0.14	0.25	0.00	0.00	0.15
TNIC Competitor Product Similarity (Add Sample)	18,635,676	0.09	0.21	0.00	0.00	0.06
TNIC Competitor Coverage Ratio (Drop Sample)	627,690	0.50	0.30	0.25	0.50	0.75
TNIC Competitor Product Similarity (Drop	627,690	0.50	0.30	0.25	0.50	0.75
SIC Coverage Ratio (Add Sample)	18,635,676	0.38	0.33	0.10	0.24	0.67
SIC Coverage Ratio (Drop Sample)	627,690	0.50	0.32	0.23	0.50	0.78
Ln (Market Cap)	627,690	7.64	1.71	6.43	7.64	8.95
Book-to-Market	627,690	0.50	0.54	0.24	0.41	0.65
Inst. Holdings	627,690	0.57	0.33	0.34	0.66	0.83
Return Volatility	627,690	0.12	0.08	0.07	0.10	0.15
Ln (#Segments)	627,690	0.58	0.72	0.00	0.00	1.39
R&D Intensity	627,690	0.07	0.14	0.00	0.00	0.08
Advertising Intensity	627,690	0.01	0.03	0.00	0.00	0.01
Trading Volume	627,690	361.0	417.32	56.94	168.41	510.3
Loss Firms	627,690	0.22	0.41	0.00	0.00	0.00
Accuracy	627,690	0.50	0.31	0.24	0.50	0.75
Frequency	627,690	0.50	0.30	0.25	0.50	0.77
Horizon	627,690	0.50	0.31	0.25	0.50	0.75
Boldness	627,690	0.50	0.31	0.23	0.50	0.77
Experience	627,690	0.50	0.30	0.24	0.50	0.75
ReturnForecast	639,729	0.02	0.03	0.01	0.01	0.03
ReturnRecom	145,610	0.04	0.05	0.01	0.02	0.04

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

Table 2
Analyst-firm Level Regressions of Add Decisions

	Add	
Variable	(1)	(2)
TNIC Competitor Coverage Ratio	**1.49***** **(5.14)**	
TNIC Competitor Product Similarity		**2.11***** **(7.11)**
SIC Coverage Ratio	0.89*** (6.70)	0.94*** (6.51)
Ln (Market Cap)	0.35*** (17.46)	0.35*** (18.54)
Book-to-Market	0.09*** (2.93)	0.08*** (2.66)
Inst. Holdings	0.65*** (9.29)	0.65*** (9.46)
Return Volatility	0.79** (2.19)	0.78** (2.17)
Ln (# of Segments)	-0.04 (-1.49)	-0.02 (-0.73)
R&D Intensity	-0.15 (-0.70)	-0.28 (-1.40)
Advertising Intensity	0.81 (1.34)	1.06* (1.84)
Trading Volume	0.00 (0.69)	0.00 (0.83)
Loss Firms	0.10*** (3.10)	0.09*** (3.24)
Portfolio Size	0.03*** (7.74)	0.01*** (3.26)
Broker Size	-0.00 (-1.20)	-0.00 (-1.02)
Industry Effects	Yes	Yes
Year Effects	Yes	Yes
Constant	-6.23*** (-32.42)	-5.92*** (-31.43)
Observations	18,635,676	18,635,676
Pseudo R^2	0.142	0.147

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

$$Prob(Add_{ijt+1} = 1) = \alpha + \beta_1 \times \textit{TNIC Competitor Coverage Ratio}_{ijt}\ (\textit{TNIC Competitor Product Similarity}_{ijt}) + \beta_2 \times \textit{SIC Coverage Ratio}_{ijt} + \beta_k \times \textit{Firm Level Controls}_{it} + \beta_n \times \textit{Analyst Level Controls}_{jt} + \varepsilon_{ijt.}$$

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. We include year fixed effects and industry fixed affects based on the Fama and French (1997) 48 industry classification. *z*-statistics reported in parentheses are robust to analyst, industry, and year clustering. ∗∗∗, ∗∗, ∗ denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3
Analyst-firm Level Regressions of Drop Decisions

	Drop	
Variable	(1)	(2)
TNIC Competitor Coverage Ratio	**-0.44***** **(-19.92)**	
TNIC Competitor Product Similarity		**-0.62***** **(-18.89)**
SIC Coverage Ratio	-0.01 (-0.22)	-0.01 (-0.33)
Ln (Market Cap)	-0.25*** (-11.54)	-0.25*** (-11.57)
Book-to-Market	0.08** (2.42)	0.08** (2.42)
Inst. Holdings	0.16*** (2.97)	0.16*** (2.97)
Return Volatility	0.40 (1.44)	0.40 (1.44)
Ln (# of Segments)	-0.02* (-1.67)	-0.02 (-1.62)
R&D Intensity	-0.37 (-1.63)	-0.37* (-1.65)
Advertising Intensity	0.33 (1.38)	0.33 (1.37)
Trading Volume	0.00*** (4.39)	0.00*** (4.36)
Loss Firms	0.21*** (4.52)	0.21*** (4.53)
Accuracy	-0.84*** (-21.90)	-0.84*** (-22.27)
Frequency	-0.94*** (-16.97)	-0.92*** (-17.11)
Horizon	2.36*** (18.38)	2.36*** (18.34)
Boldness	-0.06*** (-4.75)	-0.06*** (-4.93)
Experience	-0.05 (-1.06)	-0.03 (-0.55)
Portfolio Size	-0.53*** (-10.99)	-0.27*** (-5.54)
Broker Size	-0.02 (-0.51)	-0.02 (-0.40)
Industry Effects	Yes	Yes
Year Effects	Yes	Yes
Constant	0.24** (2.01)	0.21* (1.72)
Observations	627,690	627,690
Pseudo R^2	0.181	0.183

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

$$\text{Prob}(Drop_{ijt+1}=1) = \alpha + \beta_1 \times \textit{TNIC Competitor Coverage Ratio}_{ijt} \textit{ (TNIC Competitor Product Similarity}_{ijt}\textit{)}$$
$$+ \beta_2 \times \textit{SIC Coverage Ratio}_{ijt} + \beta_k \times \textit{Firm Level Controls}_{it} + \beta_m \times \textit{Analyst -Firm Level Controls}_{ijt}$$
$$+ \beta_n \times \textit{Analyst Level Controls}_{jt} + \varepsilon_{ijt}.$$

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. We include year and industry fixed affects in our estimation. *z*-statistics reported in parentheses are robust to analyst, industry, and year clustering. ∗∗∗, ∗∗, ∗ denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4
Analyst-firm Level Regressions of Add/Drop Decisions after Firm M&A

	Add		*Drop*	
Variable	(1)	(2)	(3)	(4)
TNIC Competitor Coverage Ratio	**1.30****		**-0.43*****	
	(2.18)		**(-14.35)**	
TNIC Competitor Product Similarity		**1.94*****		**-0.62*****
		(2.96)		**(-17.32)**
SIC Coverage Ratio	1.09***	1.16***	-0.01	-0.01
	(4.19)	(10.58)	(-0.16)	(-0.13)
Ln (Market Cap)	0.28***	0.27***	-0.19***	-0.19***
	(18.95)	(17.71)	(-5.56)	(-5.58)
Book-to-Market	-0.01	-0.04	0.11***	0.11***
	(-0.18)	(-0.53)	(2.70)	(2.68)
Inst. Holdings	0.41***	0.43***	0.13*	0.13*
	(3.75)	(4.04)	(1.76)	(1.77)
Return Volatility	1.72***	1.76***	0.42	0.43
	(3.63)	(3.93)	(0.85)	(0.85)
Ln (# of Segments)	-0.03	-0.02	-0.09***	-0.09***
	(-0.66)	(-0.32)	(-3.44)	(-3.41)
R&D Intensity	-0.62	-0.64	-0.44***	-0.44***
	(-1.23)	(-1.57)	(-4.37)	(-4.29)
Advertising Intensity	0.87	1.11*	1.12	1.13
	(1.32)	(1.73)	(1.56)	(1.57)
Trading Volume	0.00	0.00	0.00	0.00
	(0.83)	(0.89)	(1.41)	(1.41)
Loss Firms	0.02	0.03	0.26***	0.26***
	(0.46)	(0.63)	(3.96)	(3.96)
Accuracy			-0.85***	-0.85***
			(-20.37)	(-20.65)
Frequency			0.96***	0.94***
			(12.27)	(12.21)
Horizon			2.41***	2.40***
			(16.83)	(16.75)
Boldness			-0.05*	-0.06*
			(-1.69)	(-1.82)
Experience			-0.00	0.02
			(-0.11)	(0.53)
Portfolio Size	0.43***	-0.00	-0.57***	-0.30***
	(4.76)	(-0.01)	(-10.63)	(-5.47)
Broker Size	-0.09**	-0.09**	0.09*	0.08*
	(-2.36)	(-2.44)	(1.89)	(1.76)
Industry Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Constant	-5.51***	-5.25***	-0.76***	-0.78***
	(-29.77)	(-26.83)	(-2.63)	(-2.67)
Observations	2,779,338	2,779,338	124,548	124,548
Pseudo R^2	0.157	0.159	0.180	0.182

This table presents the results of estimating analysts' decision to add/drop an acquiring firm to/from their portfolios one year after the firm M&A event, based on the following analyst-firm level logit model:

$$Prob(Add_{ijt+1} / Drop_{ijt+1} = 1) = \alpha + \beta_1 \times TNIC\ Competitor\ Coverage\ Ratio_{ijt}\ (TNIC\ Competitor\ Product\ Similarity_{ijt}) + \beta_2 \times SIC\ Coverage\ Ratio_{ijt} + \beta_k \times Firm\ Level\ Controls_{it} + \beta_n \times Analyst\ Level\ Controls_{jt} + \varepsilon_{ijt}.$$

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. We include year and industry fixed affects in our estimation. *z*-statistics reported in parentheses are robust to analyst, industry, and year clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5
Analyst-firm Level Regressions of Add/Drop Decisions after Brokerage House M&A

	Add		*Drop*	
Variable	(1)	(2)	(3)	(4)
TNIC Competitor Coverage Ratio	**1.38*****		**-0.62*****	
	(7.77)		**(-4.82)**	
TNIC Competitor Product Similarity		**2.46*****		**-0.82*****
		(10.71)		**(-3.84)**
SIC Coverage Ratio	0.76***	0.67***	-0.11	-0.13
	(5.42)	(5.26)	(-1.15)	(-1.55)
Ln (Market Cap)	0.58***	0.58***	-0.40***	-0.40***
	(25.92)	(26.09)	(-9.09)	(-8.74)
Book-to-Market	0.08	0.07	0.06	0.06
	(1.45)	(1.29)	(0.85)	(0.99)
Inst. Holdings	0.47***	0.47***	0.21	0.21
	(5.38)	(5.35)	(0.89)	(0.88)
Return Volatility	1.93***	1.97***	0.96**	0.95***
	(5.34)	(5.51)	(2.54)	(2.95)
Ln (# of Segments)	-0.14***	-0.12***	0.09	0.09
	(-3.40)	(-2.98)	(1.26)	(1.28)
R&D Intensity	-0.39	-0.53	-0.13	-0.11
	(-1.09)	(-1.58)	(-0.49)	(-0.42)
Advertising Intensity	-1.25	-0.90	-0.89	-0.97
	(-0.96)	(-0.69)	(-1.22)	(-1.36)
Trading Volume	-0.00***	-0.00***	0.00***	0.00***
	(-3.78)	(-3.73)	(7.41)	(7.38)
Loss Firms	0.14*	0.12*	0.13	0.13
	(1.94)	(1.72)	(1.23)	(1.22)
Accuracy			-0.78***	-0.77***
			(-8.44)	(-8.13)
Frequency			0.73***	0.69***
			(4.47)	(4.55)
Horizon			1.77***	1.76***
			(6.86)	(6.93)
Boldness			-0.03	-0.02
			(-0.81)	(-0.51)
Experience			0.61***	0.63***
			(3.10)	(3.35)
Portfolio Size	0.28*	-0.27*	-0.84***	-0.52*
	(1.72)	(-1.68)	(-3.89)	(-1.73)
Broker Size	-0.42*	-0.41*	0.41	0.37
	(-1.90)	(-1.92)	(1.44)	(1.27)
Industry Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Constant	-19.93***	-19.50***	0.13	0.02
	(-28.25)	(-31.34)	(0.30)	(0.04)
Observations	259,319	259,319	6,779	6,779
Pseudo R^2	0.186	0.195	0.181	0.183

This table presents the results of estimating analysts' decision to add/drop a certain firm to/from their portfolios one year after brokerage house M&A events, based on the following analyst-firm level logit model:

$$Prob(Add_{ijt+1} \,/\, Drop_{ijt+1} = 1) = \alpha + \beta_1 \times \textit{TNIC Competitor Coverage Ratio}_{ijt} \,(\textit{TNIC Competitor Product Similarity}_{ijt}) + \beta_2 \times \textit{SIC Coverage Ratio}_{ijt} + \beta_k \times \textit{Firm Level Controls}_{it} + \beta_n \times \textit{Analyst Level Controls}_{jt} + \varepsilon_{ijt}.$$

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. We include year and industry fixed affects in our estimation. *z*-statistics reported in parentheses are robust to analyst, industry, and year clustering. ∗∗∗, ∗∗, ∗ denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6
Industry Competition and Firm-level Analyst Coverage

Variable	Predicted sign	Coverage			
		(1)	(2)	(3)	(4)
TNIC HHI	**-**	**-0.70*****		**-1.17*****	
		(-4.75)		**(-5.64)**	
TNIC Competitor Product Similarity	+		**1.78*****		**2.39*****
			(6.58)		**(7.24)**
SIC HHI	-	-0.41*	-0.18	-1.02***	-0.88***
		(-1.72)	(-0.73)	(-3.40)	(-2.92)
Census HHI	-			0.14	0.21
				(0.61)	(0.93)
LLM Competition	+			0.53**	0.47**
				(2.20)	(1.97)
Ln (Market Cap)		2.47***	2.46***	2.66***	2.65***
		(25.26)	(25.16)	(25.62)	(25.24)
Book-to-Market		0.70***	0.68***	1.09***	1.07***
		(7.20)	(7.02)	(8.39)	(8.46)
Institutional Holdings		1.19***	1.19***	0.86***	0.85***
		(6.74)	(6.78)	(3.14)	(3.14)
Return Volatility		-2.54*	-2.75**	-2.54	-3.06*
		(-1.82)	(-1.96)	(-1.55)	(-1.84)
Ln (# of Segments)		-0.49***	-0.44***	-0.51***	-0.46***
		(-5.29)	(-4.94)	(-4.51)	(-4.16)
R&D Intensity		2.15***	1.30**	3.28***	1.89
		(3.00)	(1.96)	(2.59)	(1.61)
Advertising Intensity		9.88***	10.25***	7.08**	7.34**
		(4.15)	(4.22)	(2.23)	(2.29)
Trading Volume		0.01***	0.01***	0.01***	0.01***
		(14.10)	(14.06)	(7.25)	(7.71)
Loss Firms		0.54***	0.52***	0.56***	0.54***
		(4.45)	(4.30)	(3.57)	(3.51)
Industry Effects		Yes	Yes	Yes	Yes
Year Effects		Yes	Yes	Yes	Yes
Observations		70,192	70,192	22,739	22,739
R^2		0.675	0.676	0.684	0.686

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

$$Coverage_{it} = \alpha + \beta_1 \times TNIC\ HHI_{it}\ (TNIC\ Competitor\ Product\ Market_{it}) + \beta_2 \times SIC\ HHI_{it} + \beta_k \times Control\ Variables_{it} + \varepsilon_{it},$$

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 (2015). *TNIC Competitor Product Similarity* is the competitor product similarity measure (TNIC3TSIMM) from Hoberg and Phillips (2015). *SIC HHI* is HHI measure based on Compustat three-digit SIC industry classification. *Census HHI* is HHI considering both public and private firms in census data. We use decile ranks (minus one and divided by nine) for all competition measures. *LLM Competition* is the competition measure from Li, Lundholm and Minnis (2013). See Appendix B for other variable definitions. We include year fixed effects and industry fixed affects based on the Fama and French (1997) 48 industry classification. *z*-statistics reported in parentheses are robust to firm, and year clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Analyst Level Descriptive Statistics

Variable	N	Mean	StdDev	25%	Median	75%
Star	61,093	0.09	0.29	0.00	0.00	0.00
Fire	61,093	0.18	0.39	0.00	0.00	0.00
TNIC Competitor Coverage Ratio	61,093	0.50	0.22	0.34	0.49	0.66
TNIC Competitor Product Similarity	61,093	0.42	0.21	0.27	0.42	0.57
SIC Coverage Ratio	61,093	0.50	0.22	0.33	0.48	0.64
Accuracy	61,093	0.49	0.16	0.40	0.51	0.60
Frequency	61,093	0.53	0.20	0.38	0.51	0.68
Horizon	61,093	0.51	0.21	0.37	0.48	0.62
Boldness	61,093	0.51	0.14	0.42	0.50	0.58
Experience	61,093	0.46	0.22	0.28	0.46	0.63
Portfolio Size	61,093	0.37	0.27	0.13	0.32	0.57
Broker Size	61,093	0.52	0.29	0.27	0.52	0.76

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

Table 8
Analyst Level Regressions of Star Status

	$Star_{t+1}$	
Variable	(1)	(2)
TNIC Competitor Coverage Ratio	**0.36*****	
	(2.89)	
TNIC Competitor Product Similarity		**1.55*****
		(7.79)
SIC Coverage Ratio	0.13	-0.22*
	(1.11)	(-1.71)
Accuracy	1.50***	1.46***
	(7.38)	(7.09)
Frequency	2.41***	2.29***
	(12.15)	(11.57)
Horizon	-1.22***	-1.20***
	(-8.31)	(-8.46)
Boldness	-0.06	-0.07
	(-0.37)	(-0.44)
Experience	1.47***	1.41***
	(6.44)	(6.34)
Portfolio Size	1.71***	0.96***
	(12.89)	(6.06)
Broker Size	-0.28	-0.22
	(-1.04)	(-0.82)
Star	3.88***	3.88***
	(43.65)	(42.97)
Broker Effects	Yes	Yes
Year Effects	Yes	Yes
Observations	61,093	61,093
Pseudo R^2	0.619	0.620

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

$$Prob\ (Star_{jt+1} = 1) = \alpha + \gamma_1 \times TNIC\ Competitor\ Coverage\ Ratio_{jt}\ (TNIC\ Competitor\ Product\ Similarity_{jt}) + \gamma_2 \times SIC\ Coverage\ Ratio_{jt} + \gamma_n \times Analyst\ Level\ Controls_{it} + \varepsilon_{jt},$$

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. *z*-statistics reported in parentheses are robust to analyst and year clustering. $***$, $**$, $*$ denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9
Analyst Level Regressions of Analyst Firing

	Fire $_{t+1}$			
	Total Sample		Broker M&A Sample	
Variable	(1)	(2)	(3)	(4)
TNIC Competitor Coverage Ratio	**-0.16****		**-0.39*****	
	(-2.11)		**(-5.85)**	
TNIC Competitor Product Similarity		**-0.66*****		**-0.84*****
		(-6.05)		**(-4.19)**
SIC Coverage Ratio	-0.08	0.05	0.34	0.41
	(-1.09)	(0.63)	(0.88)	(1.00)
Accuracy	-1.39***	-1.37***	-0.84	-0.85
	(-17.35)	(-17.30)	(-1.06)	(-1.07)
Frequency	-0.67***	-0.61***	0.82***	0.80***
	(-7.04)	(-6.59)	(3.50)	(3.39)
Horizon	4.75***	4.73***	4.50***	4.50***
	(25.14)	(25.20)	(10.22)	(10.63)
Boldness	-0.22***	-0.23***	-0.40	-0.42
	(-3.03)	(-3.16)	(-0.94)	(-1.03)
Experience	0.28***	0.31***	0.21	0.23
	(2.72)	(3.00)	(0.57)	(0.64)
Portfolio Size	-1.06***	-0.77***	-1.44***	-1.36***
	(-7.36)	(-5.07)	(-4.01)	(-3.97)
Broker Size	0.58***	0.59***	0.77	0.78
	(4.97)	(5.05)	(1.15)	(1.17)
Star	-0.18*	-0.16	-0.24**	-0.23**
	(-1.80)	(-1.59)	(-2.23)	(-1.97)
Broker Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Observations	61,093	61,093	853	853
Pseudo R^2	0.281	0.282	0.231	0.232

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

$$Prob\ (Fire_{jt+1} = 1) = \alpha + \gamma_1 \times TNIC\ Competitor\ Coverage\ Ratio_{jt}\ (TNIC\ Competitor\ Product\ Similarity_{jt}) + \gamma_2 \times SIC\ Coverage\ Ratio_{jt} + \gamma_n \times Analyst\ Level\ Controls_{jt} + \varepsilon_{jt},$$

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. We have 13 brokerage house merger events from 1994 to 2005 and 853 analyst-level observations (including bidder and target brokerage houses analysts) in the brokerage house M&A sample. See Appendix B for other variable definitions. We include year fixed effects and broker fixed effects. *z*-statistics reported in parentheses are robust to analyst and year clustering. ∗∗∗, ∗∗, ∗ denote significance at the 1%, 5%, and 10% levels, respectively.

Table 10
Analyst-firm Level Regressions of Analyst Forecast and Recommendation Informativeness

	ReturnForecast		*ReturnRecom*	
Variable	(1)	(2)	(3)	(4)
TNIC Competitor Coverage Ratio	**0.08*** **		**0.16*** **	
	(6.40)		**(3.64)**	
TNIC Competitor Product Similarity		**0.08*** **		**0.16*** **
		(5.60)		**(3.47)**
SIC Coverage Ratio	0.01	0.01	0.02	0.03
	(0.38)	(1.13)	(0.34)	(0.67)
Ln (Market Cap)	-0.22***	-0.22***	-0.44***	-0.44***
	(-17.84)	(-17.84)	(-12.72)	(-12.72)
Book-to-Market	0.01	0.01	0.06	0.06
	(0.44)	(0.46)	(0.98)	(0.99)
Inst. Holdings	-0.17***	-0.17***	-0.16	-0.16
	(-3.80)	(-3.81)	(-1.19)	(-1.19)
Return Volatility	7.17***	7.17***	10.96***	10.96***
	(51.93)	(51.92)	(29.77)	(29.77)
Ln (# of Segments)	-0.03**	-0.03**	-0.01	-0.01
	(-2.05)	(-2.05)	(-0.20)	(-0.19)
R&D Intensity	-0.90***	-0.90***	-1.94***	-1.94***
	(-5.51)	(-5.51)	(-3.72)	(-3.72)
Advertising Intensity	-0.14	-0.14	-0.85	-0.84
	(-0.26)	(-0.26)	(-0.64)	(-0.63)
Trading Volume	0.00***	0.00***	0.00***	0.00***
	(3.73)	(3.73)	(3.55)	(3.55)
Loss Firms	0.13***	0.13***	0.27***	0.27***
	(7.49)	(7.50)	(5.36)	(5.34)
Accuracy	0.49***	0.49***	1.07***	1.08***
	(16.12)	(16.28)	(10.04)	(10.09)
Frequency	0.22***	0.22***	0.51***	0.51***
	(10.17)	(10.12)	(6.68)	(6.65)
Horizon	0.50***	0.50***	0.84***	0.84***
	(19.74)	(19.73)	(9.20)	(9.19)
Boldness	-0.01	-0.01	-0.33***	-0.33***
	(-0.22)	(-0.25)	(-3.36)	(-3.37)
Experience	0.16***	0.16***	0.17***	0.17***
	(8.73)	(8.56)	(2.80)	(2.71)
Portfolio Size	0.05***	0.01	0.09*	0.00
	(3.57)	(0.61)	(1.88)	(0.06)
Broker Size	0.25***	0.25***	0.91***	0.91***
	(20.04)	(20.03)	(21.62)	(21.60)
Firm Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Constant	2.51***	2.53***	4.78***	4.82***
	(26.80)	(26.96)	(16.82)	(16.95)
Observations	639,729	639,729	145,610	145,610
R^2	0.058	0.058	0.050	0.050

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

$$ReturnForecast_{ijt}\,(ReturnRecom_{ijt}) = \alpha + \delta_1 \times TNIC\ Competitor\ Coverage\ Ratio_{ijt}\,(TNIC\ Competitor\ Product\ Similarity_{ijt}) + \delta_2 \times SIC\ Coverage\ Ratio_{ijt} + \delta_k \times Firm\ Level\ Controls_{it} + \delta_m \times Analyst\ –Firm\ Level\ Controls_{ijt} + \delta_n \times Analyst\ Level\ Controls_{jt} + \varepsilon_{ijt},$$

where *ReturnForecast* is two-day (day 0 to day +1) absolute abnormal return relative to the value-weighted market return around the issuance of analyst forecasts and *ReturnRecom* is two-day (day 0 to day +1) absolute market-adjusted abnormal return around stock recommendation revisions. See Appendix B for other variable definitions. All coefficients are multiplied by 100 for readability. We include year and firm fixed effects. *z*-statistics reported in parentheses are robust to firm and year clustering. ∗∗∗, ∗∗, ∗ denote significance at the 1%, 5%, and 10% levels, respectively.