The importance of sell-side analysts' specialised education in technical sectors: Evidence from the chemical manufacturing industry

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Abstract

This paper studies how sell-side analysts' educational background affects their forecasting behaviour and career outcomes. Focusing on the chemical manufacturing industry and analysts' university education, I find that analysts with a matching relevant technological degree provide more accurate earnings and sales forecasts than analysts without one. The matching degree effect on forecast accuracy is more pronounced among firms with high R&D intensity and among analysts in their early career stages. In addition, I find that the market reacts more strongly to forecasts revised and recommendations issued by analysts with a matching degree. Finally, I find that analysts with a matching degree have more favourable career outcomes than analysts who cover the same industry but lack a matching degree.

Keywords: Financial analysts, Industry knowledge, Education, Career outcome

JEL Classifications: G24, I21, D83

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1. Introduction

This paper studies how sell-side analysts' university degrees affect their forecasting behaviour and career prospects in an industry with a high level of technological complexity. Sell-side analysts play an important role in the capital market by gathering and disseminating information to market participants. Prior literature finds that both analysts' personal traits and the characteristics of the companies they cover affect their forecasting quality and career path. Analysts' earnings forecasts are a function of (1) the information on, and the predictability of, the underlying firm and (2) the skills and incentives of the analyst providing the forecast (Pope 2003). On the firm side, the extant literature documents that information disclosure and business complexity are associated with analyst forecast accuracy (Gu and Wang 2005; Amir et al. 2003). In particular, Gu and Wang (2005) and Amir et al. (2003) use R&D intensity and the amount of balance-sheet intangible assets to measure firms' complexity, and find that analysts' forecast accuracy is negatively associated with each. On the analyst side, analysts' skills and incentives are important factors that affect their forecasting behaviour. Controlling for firm characteristics, an array of research documents how forecast accuracy is affected by analysts' personal characteristics, including general and firm-specific experience (Clement 1999), career concerns (Hong et al. 2000; Hong and Kubik 2003), reputation (Scharfstein and Stein 1990), and industry knowledge (Kadan et al. 2012; Bradley et al. 2017), with the latter being crucial to analysts' performance (Brown et al. 2015).

Analysts can obtain industry knowledge from relevant work experience before they become analysts (Bradley et al. 2017), their university education, or both. In this paper, after controlling for relevant pre-analyst work experience, I investigate the impact of analysts' industry knowledge obtained from their university education. Specifically, I explore the implications of having a matching university degree for analysts' forecasting behaviour and career outcomes. I focus on companies in the chemical manufacturing industry and on the analysts who cover them. I consider a university degree related to chemistry, biology, pharmaceuticals, or medicine as matching the technologies in the chemical manufacturing industry. I expect that analysts who possess such a degree have more relevant technological skills, which improves their forecasting ability and leads to favourable career outcomes.

I focus on the chemical manufacturing industry and analysts' university degree for two reasons. First, firms in this industry use a high level of specialised technology, such that analysts without relevant knowledge will find it difficult to understand their business models and operations, as well as the market demands. For example, the new drug development stage in a pharmaceutical company may influence the firm's financial performance. To evaluate the stages of new drug development or the likelihood of a drug's success, an analyst most likely needs relevant technological knowledge, which arguably may come from the analyst's university studies. Analysts could also obtain such knowledge from work experience such as employment in a pharmaceutical company, but this too could require relevant university degrees. Second, firms' technological complexity can be quantified by measuring their R&D amount, and firms in the chemical manufacturing industry exhibit rich cross-sectional variation in these amounts, relative to their industry peers. These factors allow for effective differentiation of technological complexity across the firms.

I use a sample with 1,170 US companies in the chemical manufacturing industry (SIC 2800–2899) from 2003 to 2021 and the university qualifications (as well as their pre-analyst employment history) of 1,485 sell-side analysts covering those companies during the sample period. I define a matching or relevant degree as one whose title includes any of the following words: chemical, chemistry, biology, biochemistry, medical, medicine, pharmaceutical, or pharmacy. Analysts with a matching degree are classified as matching analysts; others are classified as non-matching. Of the 1,485 analysts, 370 are matching and 1,115 are non-matching.

First, I test whether matching analysts provide more accurate earnings forecasts than non-matching analysts. Analysts with a matching degree should better understand chemical technological knowledge, so I predict that they will generate more accurate earnings forecasts. My results support this hypothesis. I find that matching analysts generate 1.9% more accurate earnings forecasts than non-matching analysts. The economic magnitude of analysts' having a matching university degree is similar to the effect of analysts' relevant pre-analyst work experience documented in Bradley et al. (2017).[1] I include relevant pre-analyst work experience to control for the analyst's industry experience from prior employment, but I do not find a significant effect. A possible reason for this is that, in the sector I study, industry knowledge from a technological university degree is more relevant than industry knowledge from the pre-analyst work experience. In addition, I also test whether analysts' matching degrees improve their sales forecast accuracy. Analysts with a matching degree should understand better the products from the companies they cover, such as their chemical ingredients. They should therefore have a better prediction of products' popularity and demands among the customers, which leads to more accurate sales forecasts. Consistent with my prediction, I find that matching analysts generate 0.9% more accurate in forecasting sales than non-matching analysts. The sales forecast tests also corroborate findings from the earnings forecast tests as sales forecast accuracy is closely related to earnings forecast accuracy.

Second, I explore the impact of the firm's forecasting difficulty on the matching degree effect. Gu and Wang (2005) combine amount of R&D, balance-sheet intangible assets, and advertising

[1] Bradley et al. (2017) find that analysts with relevant pre-analyst work experience issue 1.55% more accurate earnings forecasts than analysts without it.

expenditure as “intangible assets” to measure forecasting difficulty, they find that analysts’ earnings forecast accuracy is negatively associated with firms’ intangible assets. I expect that the effect of a matching university degree on forecasting accuracy will vary with firms’ R&D amount but not with firms’ balance-sheet intangible assets. since the former is more likely to be associated with technological complexity (Gu and Wang 2005). Consistent with this, I find that when I partition the sample by firms’ R&D amount, the magnitude of the increase in earnings forecast accuracy among matching analysts (relative to non-matching analysts) is 61.5% higher when the firm has a high level of R&D. When I partition by firms’ balance-sheet intangible assets, I do not find a significant difference in the matching effect between firms with high and firms with low balance-sheet intangible assets.

Third, I investigate whether the matching effect varies with analysts’ career stages. I predict that the effect should be greater when the analyst is in her early career, as analyst-specific work experience will gradually compensate for the lack of a matching degree. I use analysts’ general experience – their number of years working as an analyst – as a proxy for their career stages, and partition the sample by high or low general experience. Consistent with my prediction, I find that the matching degree effect is only significant among analysts with low general experience. As opposed to the general experience partition, I also partition the sample by analysts’ firm-specific experience and do not find significant difference on the matching effect between two groups with high and low level of firm-specific experience.

Fourth, investors can obtain the information of sell-side analysts’ educational background and their working experience either from the websites of their employing brokerage houses or from their personal *LinkdedIn* profiles. To investigate whether investors value analysts’ matching degrees, I compare the market reactions to matching analysts’ and non-matching analysts’ forecast revisions and recommendation issuance. Using three-day absolute cumulative abnormal return as the measure of market reaction, I find that matching analysts' earnings forecast revisions elicit a 0.691% higher market reaction than non-matching analysts' after controlling the analyst- and the firm-level variables. However, the result holds only for upward forecast revisions. As forecast revisions are the interim product of analyst research, I also explore the market reaction to analysts' recommendations and find similar results: the market reacts more strongly to matching analysts' recommendation issuance, and the effect is only significant for positive (i.e., buy or strong buy) recommendations.

Finally, I study whether a matching degree leads to favourable career outcomes for analysts covering the chemical manufacturing sector. Forecast accuracy is an important measure of analysts' ability that affects analysts' career prospects. Mikhail et al. (1999) document that analysts are more likely to be terminated if they make less accurate earnings forecasts. If, as I have argued, matching analysts provide more accurate earnings forecasts than non-matching analysts, then they should also have more favourable career outcomes. To explore career outcomes, I use analysts' employment turnover and likelihood of being selected as *Institutional Investor All-American Star* analyst (*II-Star* analysts). I find that matching analysts are less likely to move from a top brokerage house to a non-top brokerage house and more likely to receive an *II-Star* analyst award.

My paper contributes to the literature regarding the impact of analysts' industry knowledge on their forecast behaviour and career. Survey evidence shows that institutional investors value analysts' industry knowledge as the most important trait (Brown et al. 2015; Bradshaw 2011). However, there is a paucity of empirical evidence specific to such knowledge. Bradley et al. (2017) provide evidence on how analysts' relevant pre-analyst work experience – the authors' proxy for industry knowledge – impacts analysts' performance. However, I propose that highly technological knowledge is more likely to be obtained through education, as people without such knowledge are less likely to work in highly technological industries in the first place. I find evidence consistent with this intuition. In addition, my paper provides insights into how the effect of analysts' matching technological knowledge varies with firms' technological complexity and with analysts' career stages.

Next, my paper contributes to research examining the value of education in the realm of the capital market. Some of the papers on this subject touch on the level or the quality of the educational degrees, treating the degrees as proxies for individuals' unobservable ability. For example, Li et al. (2011) and Chevalier and Ellison (1999) find that hedge fund and mutual fund managers who attended high-SAT undergraduate institutions have higher risk-adjusted excess returns; Falato et al. (2015) find that CEOs who graduated from prestige institutions receive a pay premium; and King et al. (2016) find that CEO educational attainment matters for bank performance. Additionally, several papers examine the type of educational degrees. Tyler and Steensma (1998) and Barker and Mueller (2002) find that CEO degree type (science- or engineering-related degrees versus business degrees) influences firms' R&D funding, and Chu et al. (2021) find that auditors with accounting degrees are associated with higher accruals quality and increased audit fees relative to auditors with qualitative university degrees. My paper adds to this research by investigating the effect of education on sell-side analysts' behaviour; specifically, I shed light on how degree-level knowledge is transferred into forecasting performance.

My paper also contributes to the literature about how people's education – particularly in areas that match their job demands – impacts their career prospects (Schultz 1961; Becker 1975; Mincer 1974). Shaw (1984, 1987) shows the importance of occupation-specific knowledge for career prospects. My paper contributes to this line of research by providing evidence that analysts' matching technological knowledge improves their career outcomes.

The remainder of this paper is organised as follows. In the next section, I discuss the related literature and develop the hypotheses. In Section 3, I outline the research design and variables. Section 4 describes the sources of data collection and the general sample. Section 5 reports the primary results and findings. Section 6 concludes.

2. Literature review and hypotheses

2.1. *Human capital effects in financial markets*

There has been a long debate about the role of the human capital theory and signalling theory in explaining the career outcomes from education (Weiss 1995; Riley 1979). From the perspective of human capital theory, the general knowledge and skills people acquire from education can improve their productivity, resulting in better career outcomes (Schultz 1961; Becker 1975; Mincer 1974). In contrast, signalling theory predicts that better educations signal higher innate ability, leading to better performance (Miller et al. 2004). Regardless of which theory dominates, the amount of education a person has is positively associated with their productivity and performance. In line with this stream of literature, some papers focus on the level or the quality of the degrees, such as comparing bachelor degrees to master degrees or the reputations of different degree-awarding institutions. Chevalier and Ellison (1999) provide evidence that mutual fund managers who attended higher-SAT schools have higher risk-adjusted excess returns. Falato et al. (2015) find that CEOs who graduated from prestige institutions receive a pay premium. Miller et al. (2015) find that the differences in CEOs' skill sets can be attributed to the levels and the quality of the awarding institutions. These studies all use educational degrees as a proxy of the person's underlying unobservable ability. Having a higher-level or higher-quality degree is indicative of better ability, which results in better productivity and performance.

Labour economists distinguish between general knowledge from education and specific knowledge from education (Becker 1962). Shaw (1984, 1987) shows that occupation-specific knowledge dominates the human capital in career development. Therefore, if one is to analyse the effect of education on employees' productivity and performance, it is essential to consider occupation-specific knowledge. Relatedly, one stream of the education literature in the capital market considers the type or the content of educational degrees. Chu et al. (2021) find that auditors with accounting degrees are associated with higher quality of companies' accruals assessment and increased audit fees relative to auditors with unrelated university degrees. Hitt and Tyler (1991) document that, among CEOs, the type of educational background (liberal arts versus engineering) is related to the information they use in evaluating strategic decisions. Tyler and Steensma (1998) find that CEOs with a technical educational degree more strongly emphasise the opportunities provided by strategic alliance, relative to CEOs with a non-technical degree. And Barker and Mueller (2002) find that CEOs with a technical degree spend significantly more on R&D. In line with this stream of literature, I study how matching technological knowledge from a university degree affects analysts' performance.

Being a financial analyst calls for a certain level of financial knowledge. Thus, matching analysts who do not gain financial knowledge from their first university degrees would normally undertake an MBA program, or business-related master's degrees, or obtain a CFA or CPA certification to make up the difference. Therefore, I expect that all the analysts, regardless of what degrees they hold, possess a certain level of financial knowledge.[2] A similar pattern does not necessarily hold for the non-matching analysts who have a degree in business, liberal arts, or social science but lack technological knowledge. Unlike matching analysts who earn an MBA or CFA to obtain financial knowledge, non-matching analysts rarely complete a second degree in technology or science, because the entry requirements for a science master's degree pose a significant hurdle. Therefore, I expect that all the sell-side analysts have obtained the requisite financial knowledge before becoming analysts, whereas technological knowledge is possessed solely by analysts with a matching technological degree. In highly technological industries, the technological complexity increases the forecasting difficulty, which lowers analysts' performance. Analysts' matching technological university degrees should reduce this negative impact. Thus, the matching analysts should be more adept at analysing the performance of companies with intensive technology.

2.2. *The influence of analysts' characteristics*

A substantial amount of literature explores the influence of analyst-related characteristics on analysts' behaviour. One stream focuses on analyst earnings forecast accuracy. Earnings forecast is the input to the valuation process which affects the final stock recommendations directly, and forecast accuracy is a straightforward way to measure analysts' performance. Analyst forecast accuracy is associated with the analysts' number of firms followed, general and firm-specific experience (Clement 1999; Mikhail et al. 1997), innate ability (Clement et al. 2007), geographical proximity (Malloy 2005), social connection with the executives of the firms they cover (Cohen et al. 2010; Bae et al. 2008), and industry experience (Bradley et al. 2017). Bradshaw (2011) and

[2] Section 4 will discuss the collection of analysts' educational background for the sample. All the identified analysts have reported the source of their financial knowledge (either university degrees in a business-related subject or certificates like a CFA or CPA). I do not see any analysts without financial knowledge.

Brown et al. (2015) show the importance of analysts' industry knowledge. Brown et al. (2015) conduct a comprehensive survey of 365 sell-side analysts and find that the analysts themselves believe that industry knowledge is the most important skill. Brown et al. (2016) conduct a similar survey of buy-side analysts and find that industry knowledge ranks as the top response to the survey question "How useful to you (buy-side analysts) are the following services provided by sell-side analysts?"

Two papers explore analysts' industry knowledge in specific: Kadan et al. (2012) find that analysts have superior ability to select and rank individual stocks within an industry in which they have expertise, and Bradley et al. (2017), using pre-analyst employment history as a proxy of industry knowledge, find that an analyst with previous relevant experience in the industry that matches her coverage portfolio tends to generate more accurate forecasts. Note that, across studies, there is no consensus definition of industry knowledge. The term may refer to pre-analyst employment history (i.e., industry knowledge obtained from work experience) or to technological knowledge (i.e., industry knowledge obtained from analysts' university studies). In a highly technological industry, where technological innovation is imperative to companies' performance, analysts with a matching technological degree should be more capable of analysing companies' operations and should thus provide more accurate earnings forecasts.[3] In this paper, I focus on the companies in the chemical manufacturing industry and analysts who cover them. Analysts with university degrees related to chemistry, biology, pharmaceuticals, or medicine are labelled

[3] Anecdotal evidence supports this assumption: "When you're looking at life science companies, both large and small, the big questions are, will the drug or device they're working on be successful in pivotal or phase three clinical trials? Is the FDA going to approve it? Is there enough clinical utility that the payers will reimburse? Those are the three big things that determine whether a bio-pharmaceutical investment will be successful, and that's where the finance world really wants doctors." Available at: http://www.leaddoc.org/Stories/2013/story1-0523.html#.Vyxg3vkrLIU [Accessed 16 August 2016].

"matching analysts". Analysts with other degrees are labelled "non-matching analysts". My first hypothesis is as follows:

Hypothesis 1: Analysts with a matching degree provide more accurate forecasts than analysts without a matching degree.

Frankel et al. (2006) find that the primary role of financial analysts is to provide private information to their clients. Analysts collect and process public information, as well as generate and disseminate private information to the market, contributing to the price discovery process (Kim and Verrecchia 1997, 1994; Barron et al. 2002). Prior literature documents cross-sectional differences in the market reactions to forecasts and recommendations by analysts with different characteristics. Gleason and Lee (2003), for example, find that analysts' forecast revisions are informative and that the market reacts more strongly to revisions by celebrity analysts. Stickel (1995) and Ivković and Jegadeesh (2004) observe that the market reacts differently to recommendations by analysts with different abilities. Bradley et al. (2017) find that forecasts by analysts with pre-employment industry experience receive stronger market reactions. And De Franco and Zhou (2009) document a stronger market reaction to forecast revisions by analysts with a CFA certification. The underlying theory of these papers is that the market perceives analysts with certain characteristics (celebrity, industry experience, CFA certification) as having a greater ability to provide valuable and informative forecasts and recommendations. In a highly technological industry, a matching degree should improve analysts' ability to analyse the companies they cover. Therefore, I anticipate a stronger market reaction to forecast revisions and recommendations by analysts with a matching degree.

Hypothesis 2: The market reaction is greater for forecasts revised or recommendations issued by analysts with a matching degree than for forecasts revised or recommendations issued by analysts without a matching degree.

Prior literature documents that analysts' poor performance leads to negative labour market consequences. Mikhail et al. (1999) document that analysts are more likely to be terminated if they make less accurate earnings forecasts. *Institutional Investor* magazine measures analyst quality and reputation each year, and analysts who are chosen as *Institutional Investor All-American Star* analysts (*II-Star* analysts) – which is likely to due to their superior ability (Leone and Wu 2007) – experience a favourable career outcome in the next year (Stickel 1992; Groysberg et al. 2011). Bradley et al. (2017) document that analysts with pre-employment industry experience are more likely to be awarded *II-Star* status. Leone and Wu (2007) explore analysts' turnover during mergers and acquisitions involving the analysts' employing brokerage houses and find that experienced analysts – especially experienced stars – are more likely to become executives. I therefore propose that, for an analyst covering a highly technological industry, a degree with matching technological knowledge will improve analysts' performance and lead to favourable career outcomes.

Hypothesis 3: Analysts with a matching degree have more favourable career outcomes than analysts without a matching degree.

3. Research design

3.1. *Analyst forecast accuracy*

I exploit analysts' one-quarter-ahead earnings per share (EPS) forecasts to explore the impact of a matching university degree on analysts' forecast accuracy. I keep one forecast by each analyst for each company for each quarter end in the sample. If there are multiple forecasts by the same analyst for the same quarter end, I keep the most recent one before the quarterly earnings announcement. Using one-quarter-ahead EPS forecasts instead of one-year-ahead forecasts improves my sample size, as I keep one forecast for each company-analyst-quarter, rather than for each company-analyst-year. The regression model is as follows:

$$\begin{aligned} AFE_{ijqt} = {} & \alpha + \beta MATCH_j + \gamma_1 WORKEXP_j + \gamma_2 BROSIZE_{jt} + \gamma_3 ANCOVSIZE_{jt} \\ & + \gamma_4 PAC_{jt} + \gamma_5 HOR_{ijqt} + \gamma_6 GEXP_{jt} + \gamma_7 FEXP_{ijt} + \gamma_8 NUMFIRM_{jt} \\ & + \gamma_9 MV_{it} + \gamma_{10} RD_{it} + \gamma_{11} INTA_{it} + \gamma_{12} MB_{it} + \gamma_{13} ROE_{it} \\ & + \gamma_{14} INSTOWN_{it} + FE + \varepsilon_{ijqt} \end{aligned} \tag{1}$$

The dependent variable is analysts' absolute earnings forecast error (*AFE*), defined as the absolute value of the difference between the one-quarter-ahead EPS forecast and the actual EPS value and then standardised as in Clement and Tse (2005) and De Franco and Zhou (2009). Specifically, I adjust the raw variables from 0 to 1 through a process that maintains the relative distances within each variable for firm *i* in a fiscal quarter *q*. The process is as follows:

$$Standardised\ Variable_{ijqt} = \frac{Raw\ Variable_{ijqt} - Raw\ Variable\ Min_{iq}}{Raw\ Variable\ Max_{iq} - Raw\ Variable\ Min_{iq}}$$

where

- $Raw\ Variable_{ijqt}$ is the forecast variable made by analyst *j* for the firm *i* for the end of the quarter *q* on the day *t*;
- $Raw\ Variable\ Min_{iq}$ is the minimum value of the variable among all the analysts for firm *i* for the end of the quarter *q*;
- and $Raw\ Variable\ Max_{iq}$ is the maximum value of the variable among all the analysts for firm *i* for the end of the quarter *q*.

The standardisation controls for the systematic difference of the variable within the firm-quarters. Greater forecast error suggests lower forecast accuracy. AFE_{ijqt} is the earnings forecast accuracy for analyst *j* for firm *i* for the end of the quarter *q* on day *t*. I create an indicator variable, *MATCH*, that is equal to one for analysts who have university degrees related to chemistry, biology, medicine, or pharmaceuticals (matching analysts) and zero for analysts who have other degrees (non-matching analysts).

To control for analysts' industry experience from their pre-analyst employment, I create an indicator variable, *WORKEXP*, that takes a value of one if the analysts once worked in a related industry (chemical manufacturing, pharmaceutical, medical, or biological science) and zero otherwise. I include a set of analyst-related control variables documented in the prior literature: brokerage portfolio size (*BROSIZE*), defined as the total market value of all companies covered by the analysts in a brokerage house; analysts' coverage size (*ANCOVSIZE*), defined as the total market value of all companies that the analyst covers; analysts' past forecast accuracy (*PAC*), defined as in Hong and Kubik (2003); forecast horizon (*HOR*), measured as the number of days from when the forecast is provided to when the firm's earnings are released; analysts' firm-specific experience (*FEXP*), defined as the number of years since the analyst provided her first forecast for the firm; general experience (*GEXP*), defined as the number of years since the analyst provided her first forecast ever (Clement 1999; Mikhail et al. 1997); and the number of firms the analyst covers (*NUMFIRM*) (Clement 1999). These analyst-related variables (except *MATCH* and *WORKEXP*) are standardised the same way as *AFE*. The firm-related control variables are the market value of equity in the natural logarithm form (*MV*), market-to-book ratio (*MB*), return-on-equity ratio (*ROE*), R&D expenditure scaled by annual sales (*RD*) (to control for the firm's technological complexity), and intangible assets scaled by total assets (*INTA*) (to control for the firm's non-technological complexity). The firm-related variables are one-quarter lagged and winsorised at the 1% and 99% levels. I cluster standard errors at the analyst level.

I also use Model (1) to test analysts' sales forecast accuracy after replacing the dependent variable with analysts' sales forecast accuracy (*AFE_SALES*). The sales forecast accuracy is calculated in the same way as in the calculation of earnings forecast accuracy where I firstly take the absolute value of the difference between the one-quarter-ahead sales forecast and the actual sales value, and then standardized as in Clement and Tse (2005) and De Franco and Zhou (2009).

3.2. *Market reactions to analysts' forecast revisions and recommendation issuance*

This section details my research design for examining the market reaction to forecast revisions and recommendation issuance. I use three-day cumulative abnormal *CRSP* value-weighted adjusted returns ([0, +2]-day) as the measure of the market reaction (*CAR*). In addition, I calculate the absolute value of cumulative abnormal returns (*ABSCAR*) by taking the absolute value of *CAR* for the tests that do not distinguish upward or downward revisions. Following Gleason and Lee (2003), I calculate forecast revision (*REV*) as the difference between the forecast for the same quarter end by analyst *j* for firm *i* at time *t* and the previous forecast by the same analyst for the same firm. I also calculate the absolute value of forecast revision (*ABSREV*) by taking the absolute value of *REV* and scaling it by the absolute value of the previous forecast by analyst *j* for firm *i* for the end of the quarter *q*. The variable of interest is still *MATCH*. I delete forecasts made by multiple analysts on the same day for the same company, as they duplicate the observations of the dependent variable and make *MATCH* hard to code (if matching and non-matching analysts made forecasts for the same companies on the same day). I include *WORKEXP* to control for analysts' relevant pre-analyst industry experience. I also include unstandardised forecast error (*AFE_U*). The other analyst-level control variables are all unstandardised, including the forecast horizon (*lnHOR*), analysts' firm-specific experience (*lnFEXP*), general experience (*lnGEXP*), and the numbers of firms covered (*lnNUMFIRM*). These variables are all in the natural logarithm form to reduce the concern of data skewness. I also control for firm size (*MV*), market-to-book ratio (*MB*), return-on-equity ratio (*ROE*), R&D (*RD*), and the intangible assets (*INTA*), and the institutional investor ownership (*INSTOWN*). The firm-related variables are again one-quarter lagged. All control variables are winsorised at 1% and 99% levels. Quarter-year fixed effects are included. I adjust standard errors for two-way clustering at the firm and quarter levels. Analysts' upward (downward) forecast revisions indicate analysts' positive (negative) opinions of the firms they cover. Because the market may react differently to different types of forecast revisions, I first use absolute cumulative abnormal return (*ABSCAR*) as the dependent variable and run the regression; then, I run the regressions separately in subsamples with upward and downward forecast revisions, with signed cumulative abnormal return (*CAR*) as the dependent variable. The model is as follows:

$$\begin{aligned} ABSCAR_{ijt}&(or\ CAR_{ijt}) \\ &= \alpha + \beta MATCH_j + \gamma_1 WORKEXP_j + \gamma_2 ABSREV_{ijt}(or\ REV_{ijt}) \\ &+ \gamma_3 AFE\_U_{ijt} + \gamma_4 lnHOR_{ijt} + \gamma_5 lnGEXP_{jt} + \gamma_6 lnFEXP_{ijt} \\ &+ \gamma_7 lnNUMFIRM_{jt} + \gamma_8 lnPAC_{jt} + \gamma_9 lnANCOVSIZE_{jt} \\ &+ \gamma_{10} lnBROSIZE_{jt} + \gamma_{11} MV_{it} + \gamma_{12} MB_{it} + \gamma_{13} RD_{it} + \gamma_{14} ROE_{it} \\ &+ \gamma_{15} INTA_{it} + \gamma_{16} INSTOWN_{it} + FE + \varepsilon_{ijt} \end{aligned} \tag{2}$$

Earnings forecast is the interim product provided by analysts. Analysts apply earnings forecasts for the valuation process and then calculate the target stock price, eventually giving investors their recommendations on whether to buy, sell, or hold the stock. Thus, I also test the market reaction to analysts' recommendations. In line with Palmon and Yezegel (2012), I keep all the positive (buy and strong buy) and negative (sell and strong sell) recommendation issuance and delete the hold recommendations. As in the forecast revision tests, I delete recommendations by multiple analysts on the same day for the same company. I first use absolute cumulative abnormal return (*ABSCAR*) as the dependent variable to run the regression in the full sample. I then run the regressions separately in the subsamples with positive and negative recommendations. The variable of interest is still *MATCH*. The analyst-level control variables are the same except that forecast horizon, revisions, and error are not included. The firm-related control variables are the same as in the forecast revision test. The model is as follows:

$$\begin{aligned}
ABSCAR_{ijt}(or\ CAR_{ijt}) \\
&= \alpha + \beta MATCH_j + \gamma_1 WORKEXP_j + \gamma_2 lnGEXP_{jt} + \gamma_3 lnFEXP_{ijt} \\
&+ \gamma_4 lnNUMFIRM_{jt} + \gamma_5 lnPAC_{jt} + \gamma_6 lnANCOVSIZE_{jt} \\
&+ \gamma_7 lnBROSIZE_{jt} + \gamma_8 MV_{it} + \gamma_9 MB_{it} + \gamma_{10} RD_{it} + \gamma_{11} ROE_{it} \\
&+ \gamma_{12} INTA_{it} + \gamma_{13} INSTOWN_{it} + FE + \varepsilon_{ijt} \qquad (3)
\end{aligned}$$

3.3. *Analysts' career outcomes: employment turnover*

In this section, I present the research design in which I assess analysts' career outcome by exploring their employment turnover. The test considers analysts' career movement per se, so the regression is at the analyst-year level. The dependent variable is either *MOVEUP* or *MOVEDOWN*. *MOVEUP* is a dummy variable that takes a value of one if the analyst moves from a non-top brokerage house to a top brokerage house, whilst *MOVEDOWN* is a dummy variable that takes a value of one if the analyst moves from a top brokerage house to a non-top brokerage house. I define a top brokerage house as one where the number of analysts is above the 90th percentile of all brokerage houses in a year. The typical top brokerage houses are J.P. Morgan, Morgan Stanley, Merrill Lynch, and Deutsche Bank. The variable of interest is still *MATCH*. The control variables are all unstandardised, including analysts' general experience (*lnGEXP*), numbers of firms and industries covered (*lnNUMFIRM* and *lnNUMIND*), and analysts' past forecast accuracy (*lnPAC*), as well as the portfolio size of analysts' employing brokerage houses (*lnBROSIZE*), and analysts' portfolio size (*lnANCOVSIZE*). These variables are again all in the natural logarithm form. Year fixed effect is included to account for the time-varying factors. All control variables are one-year lagged and winsorised at the 1% and 99% levels. I use a probit model and cluster the standard error by analysts.

$$\begin{aligned}\Pr\,(MOVEUP = 1)_{jt}\ or\ \Pr\,(MOVEDOWN = 1)_{jt} \\ &= \alpha + \beta MATCH_j + \gamma_1 WORKEXP_j + \gamma_2 lnNUMFIRM_{jt} \\ &+ \gamma_3 lnNUMIND_{jt} + \gamma_4 lnGEXP_{jt} + \gamma_5 lnPAC_{jt} + \gamma_6 lnBROSIZE_{jt} \\ &+ \gamma_7 lnANCOVSIZE_{jt} + Year\ FE + \varepsilon_{jt} \qquad (4)\end{aligned}$$

3.4. *Analysts' career outcomes: awarded II-Star analyst status by Institutional Investor*

This section describes the research design for testing the likelihood of analysts receiving the *II-Star* award from *Institutional Investor.* Following Bradley et al. (2017), I define the dependent variable *STAR* as a dummy variable that takes a value of one if the analyst is recognised as an *Institutional Investor All-American Star* analyst. Similar to the employment turnover test, I use a probit model to test the difference between the likelihood of analysts with and analysts without a matching degree receiving the award for their coverage of the chemical manufacturing industry.[4] The variable of interest is still *MATCH*. The control variables are the natural logarithm form of analysts' general experience (*lnGEXP*), numbers of firms and industries covered (*lnNUMFIRM* and *lnNUMIND*), past forecast accuracy (*lnPAC*), and portfolio size (*lnANCOVSIZE*). In addition, I also control for analysts' previous *II-Star* status (*lagSTAR*). Year fixed effect is included as well.

[4] *Institutional Investor* classifies the chemical manufacturing industry into the following sectors: Biotechnology, Chemicals, Health Care Facilities, Health Care Technology & Distribution, Pharmaceuticals/Major, and Pharmaceuticals/Specialty.

All control variables are one-year lagged (except the already lagged *lagSTAR*) and winsorised at the 1% and 99% levels. I cluster the standard error by analysts.

$$
\begin{aligned}
\Pr\,(STAR = 1)_{jt} & \\
&= \alpha + \beta MATCH_j + \gamma_1 WORKEXP_j + \gamma_2 lnNUMFIRM_{jt} \\
&+ \gamma_3 lnNUMIND_{jt} + \gamma_4 lnGEXP_{jt} + \gamma_5 lnPAC_{jt} + \gamma_6 lnBROSIZE_{jt} \\
&+ \gamma_7 lnANCOVSIZE_{jt} + \gamma_8 lagSTAR_{jt} + Year\ FE + \varepsilon_{jt} \qquad (5)
\end{aligned}
$$

4. Data and sample

4.1. *Data collection*

The key variable in this paper is analysts' university background. To identify the biographical information of analysts who cover the chemical manufacturing industry, I first merge the recommendation file in the Institutional Broker Estimate System (I/B/E/S) with CRSP/COMPUSTAT Merged (CCM). I/B/E/S provides analysts' surnames, first-name initials, and employment history in the recommendation file. CCM provides SIC codes. I keep firms in the chemical manufacturing industry only (SIC 2800 to 2899) for the period from 2003 to 2021. Then, I obtain 1,170 companies and 2,127 analyst ID codes to be identified (Table 1, Panels A and B). Next, I search the analysts' surnames, initials of first names, and brokerage houses in *Bloomberg* and manually match analysts' coverage portfolio in I/B/E/S with the portfolio of company coverage of analysts in *Bloomberg* who have the same surname, first-name initial, and brokerage house.[5] Once the match is successful, I have the full name. Lastly, following the methodology in

[5] This step is essential in the identifying process, as I only have partial information on analysts' names. Bloomberg returns multiple results quite often when I use surnames and first-name initials only, especially for widely used surnames like "Brown", "Williams", or "Li". Bloomberg provides analysts' coverage list, which presents the names of the firms they follow. Matching the coverage lists from Bloomberg and I/B/E/S would, to the largest extent, reduce the errors in the identification process.

Bradley et al. (2017), I use the full name (identified in the previous step) and the name of the employing brokerage house to search each analyst's *LinkedIn* profile for their university background and employment history. If the analysts' full name and employing brokerage houses from *LinkedIn* match the information in *Bloomberg*, the biographical identification is successful. Using this technique, I obtain the majority of analysts' university information and employment history from *LinkedIn*. In cases when *LinkedIn* fails to provide the analyst's degree, or does not provide analysts' complete employment history, I cannot identify whether the analyst has obtained relevant university degree or work experience from their pre-analyst employment, so I drop the analyst.

Other variables are collected from various sources. I obtain the accounting fundamental variables from COMPUSTAT, the analyst-related variables from I/B/E/S, the stock price from CSRP, and institutional ownership from Thomson Reuters 13f.

4.2. *Sample description*

Table 1 Panel A presents the sample collection of firms. I start from firms on COMPUSTAT during the sample period of 2003 to 2021, then drop non-US firms, firms in non-chemical manufacturing industries, and firms not covered by any analysts on I/B/E/S. My final sample contains 1,170 firms from the chemical manufacturing industry (SIC: 2800–2899). Panel B of Table 1 reports the result of the analyst identification. Starting with 2,127 I/B/E/S ID codes of analysts who cover the chemical manufacturing industry over the sample period, I identify 1,485 analysts with complete university information and pre-analyst employment history – a success rate of 69.8%. Panel C presents analysts' classification by degree type. Reading the titles of all identified analysts' degrees, I find that 370 analysts – 24.9% of all identified analysts – have a university degree with a major related to chemistry, biology, medicine, or pharmaceuticals. I label them as the matching analysts. The other 1,115 analysts do not have a matching degree but cover at least one company from the chemical manufacturing industry. The non-matching analysts include 137 who have a science degree that is not related to chemistry, biology, medicine, or pharmaceuticals; 636 whose major is related to business studies such as accounting, finance, management, and economics; and 342 who have other degree types (such as social science).

Table 2 compares the numbers of matching and non-matching analysts to the analysts with and without relevant pre-analyst work experience (*WorkExp*) by four-digit SIC and by year. Specifically, in Panel A, the first two columns show that the chemical manufacturing industry is dominated by firms with an SIC of 2834, 2835, or 2836. These firms, together with firms in 2833, are the medical, pharmaceutical, or biological product manufacturers (Appendix 1 reports the names of industries in detail).[6] Firms whose SIC starts with "283", which account for over 80% of all chemical manufacturing companies, have the highest percentage of analysts following who have a matching degree (32% to 49%) or relevant work experience (39% to 48%). In the last two columns, I report the number and percentage of analysts who have both types of industry knowledge (the matching degree and relevant work experience), and the "283" industries again have the largest portion (18% to 31%). Turning to Panel B, the total number of analysts covering the chemical manufacturing industry is stable during the sample period, but the number of matching analysts has decreased in recent years. A similar trend is seen for analysts with relevant work experience.

[6] Firms in 2833 manufacture medicinal chemicals and botanical products. Firms in 2834 manufacture pharmaceutical preparations. Firms in 2835 manufacture in vitro and in vivo diagnostic substances. Firms in 2836 manufacture biological products.

5. Empirical results

5.1. *Analyst forecast accuracy*

This section presents the results for testing analyst forecast accuracy. I use forecast error as the proxy of forecast accuracy, with larger error indicating lower accuracy. Panels A, B and C of Table 3 report the standardised and unstandardised summary statistics for the test between analysts with and analysts without a matching degree separately. The observations for the forecasts provided by analysts with (without) a matching degree is 46,169 (41,787). Then the mean of *MATCH* is 0.525, indicating that 52.5% of analysts in the forecast sample have a matching degree.[7] *WORKEXP* is the dummy variable for analysts who used to work in the chemical manufacturing or pharmaceutical industries. The mean of *WORKEXP* among analysts with a matching degree is 0.444, suggesting that 44.4% of forecasts are by matching analysts who used to work in those industries. This compares to 0.237, the mean of *WORKEXP* among analysts without a matching degree, indicating only 23.7% of analysts used to work in those industries without a matching degree. Panel D of Table 3 reports the correlation matrix. The correlation between *MATCH* and *WORKEXP* is 0.22 and significant at the 5% level.

Panel E of Table 3 presents the regression results. Column (i) reports the result without including any control variables, while column (ii) reports the result after controlling for the analyst-level factors. Column (iii) of the Panel E further controls for firms' accounting fundamental variables. The results are consistent with Hypothesis 1. Specifically, in column (i), the coefficient estimate of *MATCH* is -0.017 and significant at the 1% level. This suggests that, for matching analysts, forecast error is around 1.7% lower (in the standardised forecast error) than for non-matching analysts, indicating the matching analysts are, on average, 1.7% more accurate in

[7] The mean of *MATCH* is equal to the number of observations for the forecasts provided by analysts with matching degrees (46,169) divided by the total number of observations (46,169 plus 41,787).

forecasting earnings. The economic magnitude of the coefficient on matching analysts (*MATCH*) is similar to the Bradley et al. (2017) finding that analysts with relevant pre-analyst industry experience issue earnings forecasts that are, on average, 1.55% more accurate. My result remains similar after I control for analyst-related variables in column (ii) and further control for firm-level variables in column (iii). Contradicting Bradley et al. (2017), I do not find that analysts' relevant work experience explains forecast error, as the coefficients of *WORKEXP* in columns (ii) and (iii) are not significant at any conventional level. A possible reason for this is that companies in the chemical manufacturing industry are technologically complex and difficult to forecast, so matching technological knowledge becomes more important than relevant pre-analyst work experience. Regarding other analyst-related variables, the coefficient estimates are largely consistent with the previous literature. I find that forecast horizon is positively associated with forecast error. Analysts' firm-specific experience (*FEXP*) and previous forecast accuracy (*PAC*) are negatively associated with the forecast error. In addition, the proxy for analysts' workload (*NUMFIRM*) is positively significantly associated with the forecast error, suggesting that busyness is negatively associated with forecast accuracy.

Table 4 presents the results of additional tests for forecast accuracy where I use sales forecast error as the dependent variable. Analysts with a matching degree should understand better the market demand and are expected to provide more accurate sales forecasts. In column (i) of Table 4, the coefficient estimate of *MATCH* is -0.013 and significant at the 5% level. This suggests that analysts with a matching university degree have sales forecast error around 1.3% lower in the standardised sales forecast error, relative to analysts without a matching degree. The coefficient estimate of *MATCH* is still significant at least at 10% level after adding analyst-level and/or firm-level control variables in columns (ii) and (iii).

Overall, I find evidence that supports Hypothesis 1 that analysts provide more accurate forecasts, in both earnings and sales, when they have a matching degree.

5.2. *Matching analysts' forecast accuracy with firms' R&D and balance-sheet intangible assets*

Forecasting difficulty may stem from the complexity in processing firms' information. One proxy for information-processing complexity is the amount of firms' intangible assets. Amir et al. (2003) and Gu and Wang (2005) find that analyst forecast accuracy is negatively associated with firms' intangible assets. Specifically, using R&D intensity as a proxy of technology-related intangible assets, Amir et al. (2003) find that analysts' forecast error is positively associated with firms' R&D intensity, indicating that analysts fail to fully understand the impact of R&D on firms' future profitability. Gu and Wang (2005) find that firms' R&D intensity increases the difficulty of information processing, leading to a decrease in analysts' forecast accuracy. If matching analysts' understanding of technology allows them to better analyse operating performance and forecast future earnings, then the effect should be strongest when firms' technological complexity is high. Following Amir et al. (2003) and Gu and Wang (2005), I use firms' R&D amount as a proxy of technological complexity and partition the sample into two groups by firms' R&D amount. I expect the increase in the earnings forecast accuracy of matching analysts to be greater within the high R&D group.

Gu and Wang (2005) use balance-sheet (BS) intangible assets as another type of intangible asset and find that higher BS intangible assets are associated with lower analysts' forecast accuracy. Balance-sheet intangible assets are not related to technology, so the matching analysts' university knowledge should have little impact on processing information about them. I partition the sample into firms with high and firms with low balance-sheet intangible assets and expect no significant difference in the matching degree effect on the earnings forecast accuracy between the two groups.

Table 5 presents the results. Panel A reports the partition by firms' R&D amount, and panel B reports the partition by firms' BS intangible assets amount. Panel A shows the coefficient on *MATCH* is -0.013 in the low R&D group and -0.021 in the high R&D group. Both coefficients are significant at least at 5% level. The last two columns show the t-test statistics and p-value of coefficient estimates between two groups. The difference of the coefficients on *MATCH* is -0.008 and the p-value is less than 0.05, indicating that the matching degree has 61.5% greater impact in the high R&D group.[8] The coefficient on *WORKEXP* is again not significant in either group, which suggests that relevant work experience has little impact on forecast accuracy regardless of the technological complexity. The results in the BS intangible assets partition are reported in Panel B of Table 5. The coefficients on *MATCH* between the high BS intangibles and low BS intangibles are similar, and the t-test comparing the *MATCH* coefficient in the last two columns shows no significant difference between the two coefficients. These findings are consistent with the notion that matching analysts' technological knowledge is less helpful in processing information related to firms' BS intangible assets, which are not technology related.

In sum, I find that matching analysts' technological degree plays an important role in analysing and forecasting firms with a high level of technology; however, it does not impact the analysis of firms' BS intangible assets.

[8] Dividing the difference value of 0.008 by the *MATCH* coefficient of 0.013 in the low R&D group, I obtain the difference in percentage of 61.5%.

5.3. *Matching analyst' forecast accuracy with analysts' career stages*

I also expect that the impact of a matching degree on forecast accuracy is likely to vary with analysts' career stages, with the effect being greatest early in the analyst's career. Over time, the accumulated analyst-specific work experience should eliminate the knowledge difference for analysts who lack a matching degree. This is in line with Clement (1999), who finds that forecasting accuracy is positively associated with analysts' general experience. To test my argument, I use analysts' general experience as a proxy of their career stages, and partition the sample by analysts with high and analysts with low general experience. I expect that the effect of the matching degree to be greater among analysts in their early career (the low general experience group). In addition, Clement (1999) documents a positive association between analysts' forecast accuracy and firm-specific experience. However, firm-specific experience measures how well the analyst knows a specific firm, which is not directly related to analysts' career stages. (A senior analyst who starts to cover a new company will have rich general experience but little firm-specific experience.) Thus, the effect of a matching degree on forecast accuracy should not differ significantly among analysts with different levels of firm-specific experience. I partition the sample by analysts' firm-specific experience to test this.

Table 6 reports the results partitioned by analysts' general and firm-specific experience. Panel A reports the general experience partition and panel B reports the firm-specific experience partition. Consistent with my expectation, the estimate of the coefficient on *MATCH* in panel A is significant at the 1% level in the low general experience group and not significant at any conventional level in the high general experience group. The t-test for the difference of *MATCH* is also significant at 5% level. This indicates that, as expected, the effect of a matching degree is greater among analysts who are in their early career. In contrast, the *MATCH* coefficients with the firm-specific experience partition, reported in Panel B of Table 6, are similar between two groups. The difference test for the coefficients is also insignificant. Therefore the effect of matching degree remains the same with analysts' firm-specific experience.

In sum, I find that the effect of a matching university degree on forecasting accuracy is greater when analysts are early in their careers and have less general experience.

5.4. *The market reaction to forecast revisions and recommendation issuance*

This section reports the results for the test of the market reaction to analysts' forecast revisions and recommendation issuance. Table 7 presents the data description and results for the forecast revision test, and Table 8 reports the recommendation test. In the forecast revision test, I initially do not distinguish upward or downward revisions. I use three-day absolute cumulative abnormal return (*ABSCAR*) as the dependent variable and control for the absolute forecast revision (*ABSREV*). The results, reported in columns (i) to (iii) in Panel C of Table 7, are as predicted. In column (i), the *MATCH* coefficient is 0.694 and significant at the 1% level, indicating that the market reaction is 0.694% stronger when an analyst with a matching degree revises her earnings forecast. This amounts to 14% of the mean cumulative abnormal return (0.694/4.99). The results are similar when I add the controls. When I control for analyst-level variables in column (ii), the *MATCH* coefficient is 0.700; and when I further control for firm-level variables in column (iii), the *MATCH* coefficient is 0.689. Columns (iv) and (v) report the test results after I partition the sample into upward forecast revisions and downward forecast revisions. The dependent variable is three-day signed cumulative abnormal return (*CAR*), and I control for the signed forecast revisions (*REV*). In column (iv), where I test the market reaction to the upward forecast revisions, the *MATCH* coefficient is 0.588 and significant at the 5% level, which suggests that investors particularly value analysts' matching technological degrees when analysts reveal good news about the company and revise the forecasts upward. However, in column (v), where I test the market reaction to downward forecast revisions, I fail to find any significance on *MATCH*, which suggests that investors do not value analysts' matching degrees when analysts reveal bad news about the company and revise the forecasts downward.

Earnings forecast is analysts' interim product in their research report. Analysts use their forecasts as the input for the valuation process, then estimate companies' target price and eventually make buy, hold, or sell recommendations. The recommendation is the analysts' final product and is based on a well-rounded analysis of the company. I also test the market reaction to analysts' recommendations, as I expect that the market reacts more strongly to recommendations by analysts with a matching degree. Table 8 reports the results. In line with Palmon and Yezegel (2012), I keep all positive (buy and strong buy) and negative (sell and strong sell) recommendations and delete the hold recommendations. I use three different samples, based on the direction of the recommendation. In the first sample, I do not distinguish positive or negative recommendations, and use three-day absolute cumulative abnormal return (*ABSCAR*) as the dependent variable. Column (i) in Panel B of Table 8 reports the result. I find a positively significant coefficient of 0.807 on *MATCH*, indicating that the market reaction is 0.807% higher when matching analysts issue a buy or sell recommendation (relative to other analysts). The second and third samples (reported in columns (ii) and (iii)) are subsamples which consist of positive (buy and strong buy) and negative (sell and strong sell) recommendations, respectively, with the signed cumulative abnormal return (*CAR*) as the dependent variable. In column (ii), the *MATCH* coefficient is positively significant, suggesting the market reacts more positively to matching analysts' positive recommendations. In column (iii), the *MATCH* coefficient is not significant (despite the sign being in the expected direction), indicating that the market does not distinguish between negative recommendations issued by matching or non-matching analysts (which is similar to my above finding for downward forecast revisions).

Overall, I find evidence that supports Hypothesis 2 – that the market reacts more strongly to analysts' forecast revisions and recommendations when the analyst has a matching degree. I find that the effect is strongest for upward forecast revisions and positive recommendations.

5.5. *Analysts' career outcome*

In this section, I present the results for analysts' career outcomes, including the analysts' employment turnover and likelihood of receiving an *Institutional Investor All-American Star* analyst award. The two sets of tests are on the analyst-year level. Analysts who specialise in different industries may have different incentives for employment by brokerage houses or criteria for being recognised as an *II-Star* analyst. To ensure that the analysts are mainly covering the same industry, I restrict the sample to those whose portfolio coverage consists of more than 50% chemical manufacturing companies.[9]

Table 9 reports the results for analysts' employment turnover. I test the likelihood of matching and non-matching analysts moving from a top brokerage house to a non-top brokerage house, and vice versa. I use the probit model. The dependent variable is either *MOVEUP* (a dummy variable that takes the value of one if the analyst moves from a non-top brokerage house to a top brokerage house) or *MOVEDOWN* (a dummy variable that takes the value of one if the analyst moves from a top brokerage house to a non-top brokerage house). I define a top brokerage house as one where the number of analysts is above the 90th percentile of all brokerage houses within a year. The

[9] I also tried increase the threshold to 80% or 90%. The results remain the same, but the sample size shrinks.

sample only includes the analyst-years where the analysts' employing brokerage houses change from the previous analyst-year. Panel A of Table 9 reports the data description. Among the 370 analyst-years, 19.7% involve a move from a non-top brokerage house to a top brokerage house, and 14.3% involve a move the other way. The remaining 66% move within the same type of the brokerage houses. Panel B of Table 9 presents the result. I find that analysts with a matching degree are less likely to move from a top brokerage house to a non-top brokerage house, as the coefficient on *MATCH* in column (ii) is negatively significant. However, the *MATCH* coefficient in column (i) is insignificant, indicating that matching analysts do not differ significantly from non-matching analysts in the likelihood of moving up.

Table 10 presents the results for the likelihood of being recognised as an *II-Star* analyst. I use the probit model again. The dependent variable is *STAR*, which takes the value of one if the analyst is recognised as an *II-Star* analyst by *Institutional Investor* within a given year, and zero otherwise. *II-Star* analysts are ranked by industries. As I study chemical manufacturing industry in this paper, I focus on *II-Star* rankings in the Biotechnology, Chemicals, Health Care Facilities, Health Care Technology & Distribution, Pharmaceuticals/Major, and Pharmaceuticals/Specialty sectors. The sample period is from 2003 to 2015.[10] In Panel A of Table 10, the mean of *STAR* is 0.071, indicating that only 7.1% of analysts earn the *II-Star* ranking in the chemical manufacturing industry. Panel B of Table 10 reports the results for matching and non-matching analysts. Consistent with my expectation, the coefficient estimate on *MATCH* is positively significant, suggesting that matching analysts are more likely to be awarded *II-Star* status. I also control for the lagged *STAR* dummy (*lagSTAR*), which is highly significant. This suggests that the *II-Star* awarding is sticky and persistent. Having that said, the matching degree still plays an important

[10] I do not have the access to the data after 2015, so my sample period ends in 2015.

role in the *II-Star* award competition after controlling for the stickiness of the *II-Star* award competition.

Overall, I find evidence supporting Hypothesis 3 – that the matching degree impacts the career outcomes of analysts mainly covering the chemical manufacturing industry. Matching analysts are less likely to move from a top brokerage house to a non-top brokerage house and more likely to be recognised as an *II-Star* analyst, compared to other analysts covering the chemical manufacturing industry.

6. Conclusion

This paper studies how sell-side analysts' university degrees affect their forecasting behaviour and career outcomes. I focus on chemical manufacturing companies and analysts' specific university degrees. Using hand-collected data on 1,485 analysts who cover US chemical manufacturing companies, I find 370 analysts whose university degrees are related to majors in chemistry, biology, medicine, or pharmaceuticals – subjects that match the industries they cover. After controlling for relevant pre-analyst work experience, I find that analysts with a matching university degree provide more accurate earnings and sales forecasts than analysts without one. This effect on the earnings forecast accuracy is more pronounced in firms with high R&D intensity and among analysts who are in their early career. The market values the matching analysts' technological knowledge and reacts more strongly to their forecast revisions and recommendations. Lastly, matching analysts covering the chemical manufacturing industry have more favourable career outcomes than non-matching analysts.

My paper contributes to the analyst literature regarding the impact of analysts' industry knowledge on their forecast behaviour and career. Industry knowledge is one of the most valuable traits for individuals providing research services (Brown et al. 2015). My paper studies a new type of industry knowledge – one from the university degrees – which adds to the Bradley et al. (2017) study of relevant pre-analyst work experience. I expect that high technological knowledge is more likely to come from education, as those without matching technological knowledge are less likely to be employed in a highly technological industry. I find evidence consistent with this argument. My paper also provides insights into how the effect of analysts' matching technological knowledge varies with the level of firms' technological complexity and analysts' career stages.

My paper also contributes to research examining the value of education in the business domain. Some papers on the impact of educational background touch on the level or quality of the education and treat university degrees as a proxy for individuals' unobservable ability. Others examine the type of degree, such as engineering-related versus business, or accounting versus non-accounting. My paper adds to this research by investigating the effect of education on sell-side analysts' behaviour, which sheds light on how technological knowledge is transferred into forecasting performance.

Lastly, my paper contributes to the literature about the impact of education on career prospects – specifically, how knowledge that matches the job requirements affects career outcomes. I provide evidence that analysts' matching technological knowledge allows for better career outcomes.

I acknowledge two caveats in this paper. First, the generalisability of the study is limited as I only focus on one industry. My findings may shed light on other industries with high technological complexity, such as high-tech (using computer science as a matching relevant degree) and oil & gas (using geography-related degrees as a matching relevant degree). However, they may not extend to industries with low technological complexity (such as retail) and those without much technological knowledge. Second, I do not consider team analysts. Analysts may work in teams but only one analyst's biographical information is recorded in I/B/E/S (Fang and Hope 2021). The treatment group in my paper is analysts with a matching degree. These analysts are verified with *LinkedIn* information. The control group is analysts without a matching degree. The control group may contain member analysts (in a team) with a matching degree but the member analyst is not recorded in I/B/E/S. However, any such noise in the control group would bias my results towards a null result.

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Appendix 1. Description of 4-digit SIC industries

SIC	Name
2800	Chemicals & allied products
2810	Industrial inorganic chemicals
2820	Plastic material, synth resin/rubber, cellulose (no glass)
2821	Plastic materials, synth resins & non-Vulcan elastomers
2833	Medicinal chemicals & botanical products
2834	Pharmaceutical preparations
2835	In vitro & in vivo diagnostic substances
2836	Biological products, (no diagnostic substances)
2840	Soap, detergents, cleaning preparations, perfumes, cosmetics
2842	Specialty cleaning, polishing and sanitation preparations
2844	Perfumes, cosmetics & other toilet preparations
2851	Paints, varnishes, lacquers, enamels & allied prods
2860	Industrial organic chemicals
2870	Agricultural chemicals
2890	Miscellaneous chemical products
2891	Adhesives & sealants

Note. This table describes the four-digit SIC industries from the U.S. Securities and Exchange Commission (SEC) official website: https://www.sec.gov/info/edgar/siccodes.htm

Appendix 2. Definition of variables

Panel A: Standardised analyst-level variables		

I follow the standardisation method in Clement and Tse (2005) and De Franco and Zhou (2009) to standardise the analyst-level variables. Specifically, I adjust the raw variables from 0 to 1 through a process that maintains the relative distances among each variable for firm *i* in the fiscal quarter q. The process is as follows:

$$Standardised\ Variable_{ijqt} = \frac{Raw\ Variable_{ijqt} - Raw\ Variable\ Min_{iq}}{Raw\ Variable\ Max_{iq} - Raw\ Variable\ Min_{iq}}$$

Variable	Description	Source
AFE	Analysts' earnings forecast error. Take the absolute value of the difference between the one-quarter-ahead EPS forecast and actual EPS, then standardised.	I/B/E/S
AFE_SALES	Analysts' sales forecast error. Take the absolute value of the difference between the one-quarter-ahead sales forecast and actual sales, then standardised.	I/B/E/S
ANCOVSIZE	Analyst coverage portfolio size, defined as the sum of the market value of all companies covered by an analyst, then standardised.	I/B/E/S
BROSIZE	Brokerage house portfolio size, defined as the sum of the market value of all companies covered by a brokerage house, then standardised.	I/B/E/S
FEXP	Firm-specific experience, measured as the number of years from the analyst's first opinion for the specific firm to the present, then standardised.	I/B/E/S
GEXP	Analyst general experience, measured as the number of years from the analyst's first opinion for any firms to the present, then standardised.	I/B/E/S
HOR	Forecast horizon, defined as the number of days between the date when the forecast is provided and the date when the actual EPS is announced, then standardised.	I/B/E/S
NUMFIRM	Total number of firms covered by an analyst in a year, then standardised.	I/B/E/S
PAC	Analysts' relative accuracy score in the previous year. Analyst's relative accuracy score is calculated in line with the method in Hong and Kubik (2003), then standardised.	I/B/E/S

Appendix 2. Continued.

Panel B: Unstandardised analyst-level variables		
Variable	Description	Source
ABSREV	Absolute value of earnings forecast revision calculated by taking the absolute value of *REV*, scaled by the absolute value of the previous forecast.	I/B/E/S
AFE_U	Earnings forecast error, defined as the absolute value of analysts' earnings forecasts minus the actual earnings value.	I/B/E/S
lnANCOVSIZE	Analyst coverage portfolio size in the natural logarithm form, defined as the sum of the market value of all companies covered by an analyst in a year.	I/B/E/S
lnBROSIZE	Brokerage portfolio size in the natural logarithm form. Brokerage portfolio size is measured as the sum of the market value of all companies covered by a brokerage house in a year.	I/B/E/S
lnFEXP	Firm-specific experience in the natural logarithm form. Firm-specific experience is measured as the number of years from the analyst's first opinion for the specific firm to the present.	I/B/E/S
lnGEXP	General experience in the natural logarithm form. Analyst general experience is measured as the number of years from the analyst's first opinion for any firm to the present.	I/B/E/S
lnHOR	Forecast horizon in the natural logarithm form, defined as the number of days between the date when the forecast is provided and the date when the actual EPS is announced.	I/B/E/S
lnNUMFIRM	Total number of firms covered by an analyst in the natural logarithm form.	I/B/E/S
lnNUMIND	Total number of 4-digit industries covered by an analyst in the natural logarithm form.	I/B/E/S
lnPAC	Analysts' relative accuracy score in the previous year in the natural logarithm form. Analyst's relative accuracy score is calculated in line with the method in Hong and Kubik (2003).	I/B/E/S
MATCH	Dummy variable, equals one if an analyst has a matching degree (chemistry, biology, medicine, and pharmacy), and zero otherwise.	LinkedIn
MOVEDOWN	Dummy variable, with the value of one when analyst move from the top brokerage house to a lower tier brokerage house. A top brokerage house is defined the one where the number of analysts is above the 90^{th} percentile of all brokerage houses within a year.	I/B/E/S

Appendix 2. Continued.

MOVEUP	Dummy variable, with the value of one when analyst move from the lower tier brokerage house to a top brokerage house. A top brokerage house is defined the one where the number of analysts is above the 90th percentile of all brokerage houses within a year.	I/B/E/S
REV	Earnings forecast revision, defined as the difference of the forecast made by an analyst for the firm at the time and the previous forecast made by the same analyst for the same firm for the same fiscal quarter.	I/B/E/S
STAR	Dummy variable, with value of one when the analyst is awarded as the star analyst by *Institutional Investor*.	Institutional Investor
WORKEXP	Dummy variable, equal to one if the analyst has pre-analyst relevant working experience, and zero otherwise.	LinkedIn

Panel C: Firm-level variables

Variable	Description	Source
ABSCAR	Absolute value of CAR.	CRSP
CAR	3-day [0, 2] cumulative abnormal CRSP value-weighted adjusted return in the percentage form.	CRSP
INSTOWN	Institutional investor ownership in the percentage form.	Thomson Reuter 13f
INTA	Intangible assets scaled by total assets in the percentage form.	Compustat
MB	Market value of equity divided by book value of equity.	Compustat
MV	Market value of equity in the natural logarithm form.	Compustat
RD	R&D expense scaled by total sales.	Compustat
ROE	Return on equity.	Compustat

Note: This tables report the definitions of all variables used in this paper.

Table 1. Data collection

Panel A: Sample creation		
		No. of firms
COMPUSTAT 2003 – 2021		13,132
Less non-US companies	*2,194*	
Less non-chemical manufacturing industry	*9,581*	
Less companies not covered by analysts	*187*	
Final Sample (chemical manufacturing industry, SIC 2800 – 2899)		1,170

Panel B: Analysts' educational degree identification		
		No. of analysts
IBES forecast history 2003 – 2021		46,799
Less analysts not covering any companies from the chemical manufacturing industry	*44,672*	
Analysts covering chemical manufacturing industry		2,127
Less analysts' university degree unspecified	*375*	
Less analysts' pre-analyst employment unspecified	*267*	
Analysts with *university degree* and *pre-analyst employment* identified in the final sample		1,485

Panel C: Number of analysts have a matching degree or have relevant working experience

Degree types	No. of analysts	Percent
Analysts with a degree related to chemistry, biology, medicine, and pharmacy (matching degree)	370	24.9%
Analysts with a science degree unrelated to chemistry etc.	137	9.2%
Analysts with a business-related degree (finance, accounting, management, economics)	636	42.8%
Analysts with other degree (e.g. social science degree)	342	23.0%
Analysts with a matching degree	**370**	24.9%
Analysts without a matching degree	**1,115**	75.1%
Analysts with pre-analyst relevant working experience	505	34.0%
Analysts without pre-analyst relevant working experience	980	66.0%
Analysts with a matching degree and relevant working experience	225	15.2%

Note. This table presents the result of the identification process of analysts' educational degrees and pre-analyst relevant working experience within the sample period from 2003 to 2021. Panel A shows the sample creation. Panel B reports analysts' degree identification. Panel C reports the numbers of matching and non-matching analysts respectively.

Table 2. Sample description

Panel A: Matching analysts and analysts with pre-analyst relevant working experience by covering companies' four-digit SIC

Firms		Analysts						
SIC	No. of Firms	Total No. of Analysts	No. of Match	Match / Total %	No. of WorkExp	WorkExp / Total %	No. of Both	Both / Total %
2800	5	53	10	18.9%	9	17.0%	5	9.4%
2810	22	140	24	17.1%	26	18.6%	12	8.6%
2820	8	63	15	23.8%	13	20.6%	8	12.7%
2821	14	93	17	18.3%	17	18.3%	7	7.5%
2833	10	71	23	32.4%	28	39.4%	13	18.3%
2834	309	685	269	39.3%	316	46.1%	165	24.1%
2835	64	319	156	48.9%	153	48.0%	98	30.7%
2836	646	655	267	40.8%	316	48.2%	161	24.6%
2840	5	73	3	4.1%	1	1.4%	0	0.0%
2842	3	86	6	7.0%	6	7.0%	0	0.0%
2844	17	96	5	5.2%	8	8.3%	1	1.0%
2851	5	80	17	21.3%	16	20.0%	9	11.3%
2860	29	181	22	12.2%	28	15.5%	9	5.0%
2870	14	107	13	12.1%	11	10.3%	6	5.6%
2890	16	104	16	15.4%	21	20.2%	8	7.7%
2891	3	43	4	9.3%	9	20.9%	2	4.7%
Total	1,170							

Table 2. Continued.

Panel B: Matching analysts and analysts with pre-analyst relevant working experience by years								
Firms		Analysts						
Year	No. of firms	Total No. of Analysts	No. of Match	Match / Total %	No. of WorkExp	WorkExp / Total %	No. of Both	Both / Total %
2003	212	219	89	40.64%	86	39.3%	57	26.0%
2004	241	285	117	41.05%	115	40.4%	71	24.9%
2005	260	300	129	43.00%	115	38.3%	76	25.3%
2006	276	343	145	42.27%	134	39.1%	88	25.7%
2007	297	358	146	40.78%	138	38.5%	90	25.1%
2008	285	373	148	39.68%	148	39.7%	95	25.5%
2009	249	330	127	38.48%	132	40.0%	80	24.2%
2010	236	359	132	36.77%	130	36.2%	76	21.2%
2011	239	371	136	36.66%	132	35.6%	81	21.8%
2012	248	360	133	36.94%	131	36.4%	79	21.9%
2013	273	353	129	36.54%	121	34.3%	72	20.4%
2014	324	359	134	37.33%	124	34.5%	77	21.4%
2015	366	375	147	39.20%	128	34.1%	79	21.1%
2016	378	382	132	34.55%	129	33.8%	68	17.8%
2017	395	382	117	30.63%	125	32.7%	58	15.2%
2018	457	403	112	27.79%	124	30.8%	51	12.7%
2019	524	416	106	25.48%	141	33.9%	52	12.5%
2020	600	445	95	21.35%	138	31.0%	42	9.4%
2021	710	503	89	17.69%	144	28.6%	36	7.2%

Note. This table presents the final sample description. Panel A reports the number and the percentage of matching analysts and analysts with pre-analyst relevant working experience by four-digit SIC. Panel B shows the number and the percentage of matching analysts and analysts with pre-analyst relevant working experience by years.

Table 3. Forecast accuracy

Panel A: Descriptive statistics for the standardised dependent variable and the standardised analyst-level variables

	Analysts with a matching degree					Analysts without a matching degree				
Variable	MEAN	SD	P25	MEDIAN	P75	MEAN	SD	P25	MEDIAN	P75
AFE	0.415	0.343	0.105	0.338	0.667	0.431	0.346	0.118	0.381	0.700
BROSIZE	0.502	0.345	0.191	0.491	0.829	0.515	0.340	0.235	0.517	0.827
ANCOVSIZE	0.530	0.328	0.261	0.557	0.803	0.489	0.336	0.199	0.490	0.776
PAC	0.480	0.323	0.221	0.463	0.734	0.492	0.335	0.208	0.479	0.773
HOR	0.657	0.414	0.179	0.962	1.000	0.660	0.409	0.200	0.952	1.000
GEXP	0.438	0.329	0.156	0.369	0.726	0.441	0.365	0.096	0.363	0.824
FEXP	0.440	0.360	0.109	0.357	0.777	0.387	0.354	0.070	0.273	0.683
NUMFIRM	0.473	0.317	0.222	0.435	0.714	0.426	0.317	0.171	0.381	0.647
No. of Observations			46,169					41,787		

Panel B: Descriptive statistics for the unstandardised dependent variable and the unstandardised analyst-level variables

	Analysts with a matching degree					Analysts without a matching degree				
Variable	MEAN	SD	P25	MEDIAN	P75	MEAN	SD	P25	MEDIAN	P75
AFE	0.150	0.243	0.030	0.070	0.160	0.126	0.216	0.020	0.057	0.130
WORKEXP	0.444	0.497	0.000	0.000	1.000	0.237	0.425	0.000	0.000	0.000
BROSIZE	3.839	1.218	2.944	3.738	4.868	3.842	1.182	2.996	3.807	4.682
ANCOVSIZE	3.612	1.590	2.444	3.694	4.781	3.664	1.610	2.418	3.644	4.877
PAC	50.540	6.368	47.338	50.219	53.455	50.911	6.545	47.811	50.756	53.661
HOR	67.868	33.643	40.000	81.000	91.000	67.492	33.191	38.000	82.000	91.000
GEXP	11.601	8.009	5.140	9.858	16.474	12.680	9.441	4.238	10.364	19.888
FEXP	3.747	4.120	0.923	2.348	5.047	4.161	4.941	0.904	2.353	5.381
NUMFIRM	21.509	9.683	15.000	20.000	26.000	19.493	7.988	14.000	19.000	24.000
No. of Observations			46,169					41,787		

Table 3. Continued.

Panel C: Descriptive statistics for variable of interest and firm-level variables										
	Analysts with a matching degree					Analysts without a matching degree				
Variable	MEAN	SD	P25	MEDIAN	P75	MEAN	SD	P25	MEDIAN	P75
MV	1.657	1.387	0.532	1.184	2.487	1.823	1.415	0.630	1.428	2.682
RD	8.088	36.968	0.095	0.311	1.703	4.527	28.613	0.017	0.062	0.281
INTA	0.138	0.183	0.000	0.037	0.249	0.208	0.202	0.008	0.161	0.344
MB	6.303	13.192	2.784	4.530	7.838	5.542	13.157	2.468	3.979	6.435
ROE	-0.057	0.392	-0.141	-0.011	0.053	-0.012	0.356	-0.069	0.027	0.064
INSTOWN	0.542	0.408	0.000	0.685	0.900	0.570	0.389	0.000	0.718	0.888
No. of Observations			46,169					41,787		

Table 3. Continued.

Panel D: Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	*AFE*	1.00															
(2)	*MATCH*	**-0.02**	1.00														
(3)	*WORKEXP*	-0.00	**0.22**	1.00													
(4)	*BROSIZE*	**-0.02**	**-0.02**	**-0.06**	1.00												
(5)	*ANCOVSIZE*	-0.00	**0.06**	**0.07**	**0.17**	1.00											
(6)	*PAC*	**-0.03**	**-0.02**	**-0.02**	0.00	**-0.05**	1.00										
(7)	*HOR*	**0.05**	-0.00	**-0.02**	**-0.03**	**-0.05**	0.00	1.00									
(8)	*GEXP*	**0.01**	-0.00	**-0.06**	**0.04**	**0.12**	**-0.07**	**0.03**	1.00								
(9)	*FEXP*	0.00	**0.07**	**-0.02**	**0.01**	**0.02**	**-0.05**	**0.06**	**0.31**	1.00							
(10)	*NUMFIRM*	**0.03**	**0.07**	**0.01**	**0.07**	**0.17**	**-0.09**	**0.08**	**0.21**	**0.19**	1.00						
(11)	*MV*	**-0.04**	**-0.06**	**-0.03**	**0.10**	**0.10**	**-0.01**	**-0.08**	**0.06**	**-0.11**	**-0.07**	1.00					
(12)	*RD*	**0.01**	**0.05**	**0.02**	**-0.02**	**-0.02**	0.00	**0.03**	**-0.01**	**0.02**	**0.02**	**-0.13**	1.00				
(13)	*INTA*	-0.01	**-0.18**	**-0.08**	**0.07**	**0.06**	0.01	**-0.06**	**0.04**	**-0.06**	**-0.04**	**0.46**	**-0.15**	1.00			
(14)	*MB*	-0.00	**0.03**	**0.01**	0.00	0.00	**-0.01**	**-0.00**	**-0.02**	**-0.02**	**0.01**	**0.08**	0.01	**-0.03**	1.00		
(15)	*ROE*	-0.00	**-0.06**	**-0.04**	**0.02**	**0.01**	-0.00	-0.02	**0.02**	**-0.02**	**-0.02**	**0.17**	**-0.10**	**0.13**	**-0.30**	1.00	
(16)	*INSTOWN*	-0.00	**-0.03**	**-0.07**	**-0.04**	**-0.04**	**0.01**	**0.02**	**-0.04**	**0.04**	**-0.03**	**0.04**	**0.01**	**0.04**	**0.04**	0.00	1.00

Table 3. Continued.

Panel E: Regression Results			
DEPVAR = AFE	i	ii	iii
MATCH	-0.017***	-0.019***	-0.019***
	(0.006)	(0.005)	(0.005)
WORKEXP	0.002	0.002	0.002
	(0.006)	(0.005)	(0.005)
BROSIZE		-0.017***	-0.015**
		(0.006)	(0.006)
ANCOVSIZE		-0.000	0.002
		(0.005)	(0.005)
PAC		-0.032***	-0.032***
		(0.005)	(0.005)
HOR		0.035***	0.039***
		(0.004)	(0.004)
GEXP		0.007	0.010
		(0.006)	(0.006)
FEXP		-0.005	-0.008*
		(0.005)	(0.005)
NUMFIRM		0.025***	0.022***
		(0.006)	(0.006)
MV			-0.011***
			(0.002)
RD			0.000
			(0.000)
INTA			0.026***
			(0.010)
MB			0.000
			(0.000)
ROE			0.002
			(0.003)
INSTOWN			-0.028***
			(0.009)
Observations	87,956	87,956	87,956
Adjusted R^2	0.001	0.007	0.008
Month-year FE	No	Yes	Yes

Note. This table reports the tests for analysts' earnings forecast accuracy. Panels A and B present descriptive statistics for standardised and unstandardised analyst-level variables. Panel C presents descriptive statistics for the firm-level control variables and the variable of interest. *AFE* is the dependent variable, which is analysts' absolute earnings forecast error, calculated by taking the absolute value of the difference between the one-quarter-ahead EPS forecast and the actual EPS, and then standardised as in Clement and Tse (2005) and De Franco and Zhou (2009). *MATCH* is an indicator variable, equal to one if the analyst has a matching degree, and zero otherwise. *WORKEXP* is indicator variable, equal to one if the analyst has pre-analyst relevant working experience, and zero otherwise. Analyst-level control variables are as follows. *BROSIZE* is brokerage house portfolio size, defined as the sum of the market value of all companies covered by a brokerage house. *ANCOVSIZE* is analyst coverage portfolio size, defined as the sum of the market value of all companies covered by an analyst. *PAC* denotes the relative accuracy score of an analyst in the previous year, which is calculated in line with Hong and Kubik (2003). *HOR* denotes forecast horizon, which is the number of days between the date when the forecast is provided and the date when the actual EPS is announced. *GEXP* is analysts' general experience, measured as the number of years from when the analyst issued her first forecast for any firms to present. *FEXP* is analysts' firm-specific experience, measured as the number of years since the analyst provided her first forecast for the specific firm to present. *NUMFIRM* denotes the number of firms followed by each analyst. All the analyst-level control variables are standardised as in Clement and Tse (2005) and De Franco and Zhou (2009). Firm-level control variables are as follows. *MV* represents the market value of equity in the natural logarithm form. *RD* denotes the R&D expense scaled by total sales. *INTA* indicates the percentage of intangible assets scaled by total assets. *MB* is the market-to-book ratio and measured by dividing the market value of equity by the book value of equity. *ROE* is return on equity. *INSTOWN* is the institutional investor ownership. All firm-level variables are lagged by one quarter. Panel D reports the correlation matrix for all variables. The correlations significant at the 5 percent level are shown in bold. Panel E outlines the results. All the regressions are clustered at the analyst level. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Table 4. Additional test: Sales forecast accuracy

DEPVAR = AFE_SALES	i	ii	iii
MATCH	-0.013**	-0.012**	-0.009*
	(0.006)	(0.006)	(0.006)
WORKEXP	0.000	0.003	0.003
	(0.007)	(0.007)	(0.007)
BROSIZE		-0.008	-0.008
		(0.007)	(0.007)
ANCOVSIZE		0.009*	0.009*
		(0.005)	(0.005)
PAC		-0.017***	-0.017***
		(0.005)	(0.005)
HOR		0.059***	0.060***
		(0.004)	(0.004)
GEXP		0.012*	0.012*
		(0.007)	(0.007)
FEXP		-0.012**	-0.013**
		(0.005)	(0.005)
NUMFIRM		0.015**	0.015**
		(0.007)	(0.007)
MV			-0.005***
			(0.002)
RD			-0.000***
			(0.000)
INTA			0.033***
			(0.010)
MB			0.000**
			(0.000)
ROE			-0.002
			(0.004)
INSTOWN			-0.023**
			(0.010)
Observations	63,131	63,131	63,131
Adjusted R^2	0.006	0.011	0.012
Month-year FE	No	Yes	Yes

Note. This table reports tests for analysts' sales forecast accuracy. *AFE_SALES* is the dependent variable, which is analysts' absolute sales forecast error, calculated by taking the absolute value of the difference between the one-quarter-ahead sales forecast and the actual sales value, and then standardised as in Clement and Tse (2005) and De Franco and Zhou (2009). *MATCH* is an indicator variable, equal to one if the analyst has a matching degree, and zero otherwise. *WORKEXP* is indicator variable, equal to one if the analyst has pre-analyst relevant working experience, and zero otherwise. Analyst-level control variables are as follows. *BROSIZE* is brokerage house portfolio size, defined as the sum of the market value of all companies covered by a brokerage house. *ANCOVSIZE* is analyst coverage portfolio size, defined as the sum of the market value of all companies covered by an analyst. *PAC* denotes the relative accuracy score of an analyst in the previous year, which is calculated in line with Hong and Kubik (2003). *HOR* denotes forecast horizon, which is the number of days between the date when the forecast is provided and the date when the actual EPS is announced. *GEXP* is analysts' general experience, measured as the number of years from when the analyst issued her first forecast for any firms to present. *FEXP* is analysts' firm-specific experience, measured as the number of years since the analyst provided her first forecast for the specific firm to present. *NUMFIRM* denotes the number of firms followed by each analyst. All the analyst-level control variables are standardised as in Clement and Tse (2005) and De Franco and Zhou (2009). Firm-level control variables are as follows. *MV* represents the market value of equity in the natural logarithm form. *RD* denotes the R&D expense scaled by total sales. *INTA* indicates the percentage of intangible assets scaled by total assets. *MB* is the market-to-book ratio and measured by dividing the market value of equity by the book value of equity. *ROE* is return on equity. *INSTOWN* is the institutional investor ownership. All the regressions are clustered at the analyst level. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Table 5. Earnings forecast accuracy test partitioned by firm-level variables

Panel A: Partitioned by high/low level of firms' R&D amount

DEPVAR = AFE	R&D PARTITION			
	LOW	HIGH	HIGH - LOW	*p-value*
MATCH	-0.013**	-0.021***	-0.008**	*0.050*
	(0.006)	(0.006)		
WORKEXP	0.001	0.003	0.002	*0.34*
	(0.006)	(0.006)		
Observations	41,438	46,518		
Adjusted R^2	0.011	0.009		
Analyst control	Yes	Yes		
Firm control	Yes	Yes		
Month-year FE	Yes	Yes		

Panel B: Partitioned by high/low level of firms' balance-sheet intangible assets

DEPVAR = AFE	BS INTANGIBLE ASSETS PARTITION			
	LOW	HIGH	HIGH - LOW	*p-value*
MATCH	-0.015***	-0.018***	-0.003	*0.330*
	(0.006)	(0.006)		
WORKEXP	0.006	0.002	-0.004	*0.260*
	(0.006)	(0.007)		
Observations	38,361	49,595		
Adjusted R^2	0.005	0.015		
Analyst control	Yes	Yes		
Firm control	Yes	Yes		
Month-year FE	Yes	Yes		

Note. This table reports the test results for analyst earnings forecast accuracy partitioned by firms' R&D and balance-sheet intangible assets. Panel A presents the results partitioned by high/low level of firms' R&D amount. Panel B presents the results partitioned by high/low level of firms' balance-sheet intangible assets. *AFE* is the dependent variable, which is analysts' absolute earnings forecast error, calculated by taking the absolute value of the difference between the one-quarter-ahead EPS forecast and the actual EPS value, and then standardised as in Clement and Tse (2005) and De Franco and Zhou (2009). *MATCH* is an indicator variable, equal to one if the analyst has a matching degree, and zero otherwise. *WORKEXP* is indicator variable, equal to one if the analyst has pre-analyst relevant working experience, and zero otherwise. Analyst-level and firm-level control variables are included. All the regressions are clustered at the analyst level. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Table 6. Earnings forecast accuracy test partitioned by analyst-level variables

Panel A: Partitioned by high/low level of analysts' general experience

DEPVAR = AFE	GENERAL EXPERIENCE PARTITION			
	LOW	HIGH	HIGH - LOW	*p-value*
MATCH	-0.022***	-0.010	0.011**	*0.010*
	(0.006)	(0.006)		
WORKEXP	-0.001	0.006	0.007*	*0.090*
	(0.006)	(0.007)		
Observations	47,314	40,642		
Adjusted R^2	0.008	0.009		
Analyst control	Yes	Yes		
Firm control	Yes	Yes		
Month-year FE	Yes	Yes		

Panel B: Partitioned by high/low level of analysts' firm-specific experience

DEPVAR = AFE	FIRM-SPECIFIC EXPERIENCE PARTITION			
	LOW	HIGH	HIGH - LOW	*p-value*
MATCH	-0.016***	-0.020***	-0.004	*0.190*
	(0.005)	(0.006)		
WORKEXP	0.001	0.004	-0.003	*0.370*
	(0.006)	(0.006)		
Observations	47,648	40,308		
Adjusted R^2	0.008	0.009		
Analyst control	Yes	Yes		
Firm control	Yes	Yes		
Month-year FE	Yes	Yes		

Note. This table reports the test results for analyst earnings forecast accuracy partitioned analysts' general and firm-specific experience. Panel A presents the results partitioned by high/low level of analysts' general experience. Panel B presents the results partitioned by high/low level of analysts' firm-specific experience. *AFE* is the dependent variable, which is analysts' absolute earnings forecast error, calculated by taking the absolute value of the difference between the one-quarter-ahead EPS forecast and the actual EPS value, and then standardised as in Clement and Tse (2005) and De Franco and Zhou (2009). *MATCH* is an indicator variable, equal to one if the analyst has a matching degree, and zero otherwise. *WORKEXP* is indicator variable, equal to one if the analyst has pre-analyst relevant working experience, and zero otherwise. Analyst-level and firm-level control variables are included. All the regressions are clustered at the analyst level. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Table 7. Market reaction to analysts' earnings forecast revisions

Panel A: Descriptive statistics

Variable	#Obs	MEAN	SD	P25	MEDIAN	P75
ABSCAR	6,464	4.988	6.813	1.095	2.676	5.991
ABSREV	6,464	0.290	0.663	0.029	0.079	0.220
CAR (RevUp)	3,106	0.962	7.922	-2.087	0.382	3.465
REV (RevUp)	3,106	0.099	0.181	0.010	0.030	0.096
CAR (RevDown)	3,290	-0.084	7.378	-2.698	-0.169	2.558
REV (RevDown)	3,290	-0.105	0.170	-0.110	-0.040	-0.015
MATCH	6,464	0.505	0.500	0.000	1.000	1.000
WORKEXP	6,464	0.177	0.382	0.000	0.000	0.000
AFE_U	6,464	0.196	0.370	0.030	0.080	0.200
lnHOR	6,464	4.177	0.964	3.611	4.466	4.779
lnGEXP	6,464	2.250	0.918	1.710	2.409	2.927
lnFEXP	6,464	0.874	1.189	0.124	0.923	1.742
lnNUMFIRM	6,464	2.991	0.434	2.773	2.996	3.258
lnPAC	6,464	3.940	0.126	3.887	3.941	3.999
lnANCOVSIZE	6,464	3.646	1.700	2.330	3.617	4.911
lnBROSIZE	6,464	3.795	1.236	2.890	3.638	4.828
MV	6,464	1.680	1.501	0.472	1.148	2.567
MB	6,464	6.043	13.714	2.390	4.125	7.146
ROE	6,464	-0.162	0.405	-0.379	0.015	0.098
INTA	6,464	0.176	0.201	0.000	0.100	0.309
RD	6,464	6.210	29.550	0.020	0.170	0.849
INSTOWN	6,464	0.749	0.237	0.623	0.797	0.923

Table 7. Continued.

Panel B: Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1)	*ABSCAR*	1.00																			
(2)	*CAR*	**-0.06**	1.00																		
(3)	*MATCH*	**0.05**	0.00	1.00																	
(4)	*WORKEXP*	**-0.01**	0.00	**0.14**	1.00																
(5)	*ABSREV*	**0.10**	**-0.01**	**0.05**	**0.01**	1.00															
(6)	*REV*	-0.00	**0.09**	**0.03**	**0.01**	**-0.04**	1.00														
(7)	*AFE_U*	**0.03**	**-0.01**	**0.04**	**-0.02**	**0.10**	**0.06**	1.00													
(8)	*lnHOR*	**0.05**	**-0.01**	**-0.03**	**-0.01**	**-0.02**	**0.01**	**0.10**	1.00												
(9)	*lnGEXP*	**-0.05**	0.00	**0.11**	**0.06**	**-0.04**	-0.00	**-0.01**	**-0.01**	1.00											
(10)	*lnFEXP*	**-0.11**	**0.00**	**0.06**	**0.05**	**-0.04**	0.00	**0.01**	**-0.04**	**0.42**	1.00										
(11)	*lnNUMFIRM*	**0.09**	-0.00	**0.20**	**0.05**	**0.05**	**0.01**	**0.09**	**0.04**	**0.25**	**0.09**	1.00									
(12)	*lnPAC*	**-0.02**	0.00	**-0.05**	**-0.02**	**-0.01**	-0.00	**-0.02**	**-0.01**	**-0.07**	**-0.02**	**-0.11**	1.00								
(13)	*lnANCOVSIZE*	**-0.16**	0.00	**-0.03**	**-0.02**	**-0.10**	0.00	0.00	**-0.05**	**0.20**	**0.16**	**0.05**	**-0.02**	1.00							
(14)	*lnBROSIZE*	**-0.08**	**-0.01**	**-0.03**	**0.02**	**-0.06**	0.00	**-0.01**	**-0.02**	**0.04**	**0.08**	**0.05**	**0.02**	**0.30**	1.00						
(15)	*MV*	**-0.29**	0.00	**-0.04**	**-0.02**	**-0.18**	**0.01**	**0.04**	**-0.08**	**0.16**	**0.30**	**-0.11**	**0.02**	**0.45**	**0.26**	1.00					
(16)	*MB*	**-0.02**	0.00	**0.03**	**-0.02**	**0.02**	**-0.01**	-0.00	-0.00	**-0.01**	0.00	**0.01**	-0.00	**0.04**	**0.03**	**0.11**	1.00				
(17)	*ROE*	**-0.07**	**0.01**	**-0.06**	-0.00	**-0.03**	**0.01**	**0.01**	**-0.02**	**0.05**	**0.10**	**-0.05**	0.00	**0.10**	**0.06**	**0.18**	**-0.22**	1.00			
(18)	*INTA*	**-0.18**	**0.01**	**-0.17**	**-0.02**	**-0.11**	**-0.02**	**-0.11**	**-0.05**	**0.11**	**0.19**	**-0.16**	**0.02**	**0.28**	**0.14**	**0.50**	0.00	**0.14**	1.00		
(19)	*RD*	**0.05**	-0.00	**0.05**	**-0.01**	**-0.01**	0.00	0.00	**0.02**	**-0.02**	**-0.08**	**0.06**	**-0.01**	**-0.09**	**-0.04**	**-0.14**	**-0.01**	**-0.09**	**-0.15**	1.00	
(20)	*INSTOWN*	**-0.06**	**-0.01**	**0.04**	**-0.00**	**0.03**	**-0.04**	**0.09**	-0.00	**-0.04**	**0.08**	**-0.03**	**-0.01**	**0.03**	**0.08**	**0.01**	**0.03**	**0.03**	**0.03**	**-0.05**	1.00

Table 7. Continued.

Panel C: Regression results					
DEPVAR	ABSCAR			CAR	
	i	ii	iii	iv	v
MATCH	0.694***	0.700***	0.689***	0.588**	0.162
	(0.213)	(0.154)	(0.149)	(0.235)	(0.275)
WORKEXP	0.186	0.139	0.100	-0.158	0.325
	(0.264)	(0.246)	(0.209)	(0.465)	(0.380)
ABSREV		0.463**	0.198		
		(0.181)	(0.178)		
REV				1.586*	-0.317
				(0.910)	(0.831)
AFE_U		0.220	0.527*	0.303	0.456
		(0.289)	(0.272)	(0.517)	(0.284)
lnHOR		0.915***	0.533***	0.120	0.203
		(0.119)	(0.109)	(0.134)	(0.153)
lnGEXP		0.188	0.211*	0.080	0.129
		(0.120)	(0.122)	(0.235)	(0.180)
lnFEXP		-0.552***	-0.225**	0.004	0.145
		(0.091)	(0.085)	(0.188)	(0.137)
lnNUMFIRM		1.223***	0.403*	0.014	0.004
		(0.197)	(0.215)	(0.013)	(0.013)
lnPAC		0.275	0.672	-0.288	2.289**
		(0.587)	(0.587)	(1.084)	(0.991)
lnANCOVSIZE		-0.609***	-0.193***	0.125	-0.021
		(0.057)	(0.058)	(0.099)	(0.115)
lnBROSIZE		-0.183**	0.008	-0.069	-0.043
		(0.070)	(0.072)	(0.094)	(0.112)
MV			-0.974***	-0.477***	0.016
			(0.082)	(0.144)	(0.116)
MB			-0.005	-0.007	-0.014
			(0.005)	(0.014)	(0.012)
ROE			0.156	0.526	0.331
			(0.304)	(0.362)	(0.453)
INTA			-1.264**	0.374	-0.316
			(0.572)	(0.862)	(0.696)
RD			0.008	0.001	0.010
			(0.005)	(0.006)	(0.009)
INSTOWN			-2.224***	-0.628	-0.126
			(0.508)	(0.948)	(0.824)
Observations	6,464	6,464	6,464	3,106	3,290
Adjusted R^2	0.024	0.093	0.133	0.018	0.007
Quarter-year FE	Yes	Yes	Yes	Yes	Yes

Note. This table reports the test of market reaction to analyst earnings forecast revisions. Panel A presents descriptive statistics. The dependent variable is 3-day [0, 2] cumulative abnormal *CRSP* value-weighted adjusted return in the percentage form (*CAR*), or the absolute value of *CAR* (*ABSCAR*). *MATCH* is an indicator variable, equal to one if the analyst has a matching degree, and zero otherwise. *WORKEXP* is indicator variable, equal to one if the analyst has pre-analyst relevant working experience, and zero otherwise. *REV* is earnings forecast revision, defined as the difference of the earnings forecast made by an analyst for the firm at the time and the previous forecast made by the same analyst for the same firm for the same fiscal quarter. *ABSREV* is the absolute value of forecast revision calculated by taking the absolute value of *REV*, scaled by the absolute value of the previous forecast. *AFE_U* is unstandardised forecast error, defined as the absolute value of analysts' earnings forecasts minus the actual earnings value. *lnHOR* denotes forecast horizon in the natural logarithm form, which is the number of days in the natural logarithm form between the date when the forecast is provided and the date when the actual EPS is announced. *lnFEXP* is analysts' firm-specific experience for a specific firm in the natural logarithm form. Firm-specific experience is measured as the number of years since the analyst provided her first forecast for the specific firm to present. *lnGEXP* is analysts' general experience of being an analyst in the natural logarithm form. Analysts' general experience is measured as the number of years from when the analyst issued her first forecast for any firms to present. *lnNUMFIRM* denotes unstandardised number of firms followed by each analyst in the natural logarithm form. *lnPAC* denotes unstandardised relative accuracy score of an analyst in the previous year in the natural logarithm form, which is calculated in line with Hong and Kubik (2003). *lnBROSIZE* is brokerage house portfolio size, defined as the sum of the market value in the natural logarithm form of all companies covered by a brokerage house. *lnANCOVSIZE* is analyst coverage portfolio size, defined as the sum of the market value in the natural logarithm form of all companies covered by an analyst. *MV* represents the market value of equity in the natural logarithm form. *RD* denotes the R&D expense scaled by total sales. *INTA* indicates the percentage of intangible assets scaled by total assets. *MB* is the market-to-book ratio and measured by dividing the market value of equity by the book value of equity. *ROE* is return on equity. *INSTOWN* is the institutional investor ownership. All firm-level variables are lagged by one quarter. Panel B reports the correlation matrix for all variables. The correlations significant at the 5 percent level are shown in bold. Panel C outlines the regression results All the regressions are clustered at the firm and quarter level. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Table 8. Market reaction to analysts' recommendation issuance

Panel A: Descriptive statistics						
Variable	#Obs	MEAN	SD	P25	MEDIAN	P75
ABSCAR	7,041	6.070	9.065	1.391	3.323	7.256
CAR (Pos Rec)	6,387	3.0281	9.937	-1.043	1.614	5.540
CAR (Neg Rec)	654	-3.7804	11.650	-6.323	-2.179	0.450
MATCH	7,041	0.506	0.500	0.000	1.000	1.000
WORKEXP	7,041	0.182	0.386	0.000	0.000	0.000
lnGEXP	7,041	2.079	1.019	1.423	2.260	2.862
lnFEXP	7,041	0.515	1.008	0.000	0.000	1.165
lnNUMFIRM	7,041	2.874	0.557	2.565	2.944	3.219
lnPAC	7,041	3.915	0.255	3.860	3.932	4.001
lnBROSIZE	7,041	3.603	1.242	2.773	3.497	4.564
lnANCOVSIZE	7,041	3.901	1.723	2.641	3.932	5.151
MV	7,041	1.401	1.332	0.378	0.904	2.066
MB	7,041	6.076	11.893	2.553	4.366	7.527
ROE	7,041	-0.059	0.397	-0.143	-0.032	0.049
INTA	7,041	0.151	0.194	0.000	0.047	0.266
RD	7,041	7.484	33.126	0.012	0.160	1.304
INSTOWN	7,041	0.713	0.265	0.554	0.771	0.911

Table 8. Continued.

Panel B: Regression results			
DEPVAR	ABSCAR	CAR	
	i	ii	iii
	ABS	POS	NEG
MATCH	0.807***	0.879***	-0.489
	(0.219)	(0.251)	(1.044)
WORKEXP	0.191	0.123	-0.505
	(0.345)	(0.336)	(1.202)
lnGEXP	-0.279**	-0.052	-0.466
	(0.133)	(0.166)	(0.503)
lnFEXP	0.224*	0.499***	-0.198
	(0.119)	(0.152)	(0.528)
lnNUMFIRM	0.828***	0.316	-0.456
	(0.243)	(0.256)	(0.777)
lnPAC	-0.047	0.208	-1.886
	(0.279)	(0.380)	(2.197)
lnANCOVSIZE	0.324***	0.438***	0.201
	(0.078)	(0.113)	(0.317)
lnBROSIZE	0.012	-0.053	0.355
	(0.105)	(0.099)	(0.386)
MV	-1.544***	-1.035***	1.454***
	(0.126)	(0.134)	(0.444)
MB	0.000	-0.026***	-0.022
	(0.008)	(0.009)	(0.027)
ROE	-0.394	-0.246	0.331
	(0.340)	(0.381)	(1.409)
INTA	-0.720	-0.023	1.232
	(0.693)	(0.814)	(2.207)
RD	0.005	0.007	-0.027
	(0.004)	(0.004)	(0.033)
INSTOWN	-2.947***	-1.940***	6.375**
	(0.550)	(0.572)	(2.855)
Observations	7,041	6,387	654
Adjusted R^2	0.088	0.030	0.076
Quarter-year FE	Yes	Yes	Yes

Note. This table reports the results for the test of the market reaction to analysts' recommendations. Panel A presents descriptive statistics. The dependent variable is 3-day [0, 2] cumulative abnormal *CRSP* value-weighted adjusted return in the percentage form (*CAR*), or the absolute value of *CAR* (*ABSCAR*). *MATCH* is an indicator variable, equal to one if the analyst has a matching degree, and zero otherwise. *WORKEXP* is indicator variable, equal to one if the analyst has pre-analyst relevant working experience, and zero otherwise. *lnFEXP* is analysts' firm-specific experience for a specific firm in the natural logarithm form. Firm-specific experience is measured as the number of years since the analyst provided her first forecast for the specific firm to present. *lnGEXP* is analysts' general experience of being an analyst in the natural logarithm form. Analysts' general experience is measured as the number of years from when the analyst issued her first forecast for any firms to present. *lnNUMFIRM* denotes unstandardised number of firms followed by each analyst in the natural logarithm form. *lnPAC* denotes unstandardised relative accuracy score of an analyst in the previous year in the natural logarithm form, which is calculated in line with Hong and Kubik (2003). *lnBROSIZE* is brokerage house portfolio size, defined as the sum of the market value in the natural logarithm form of all companies covered by a brokerage house. *lnANCOVSIZE* is analyst coverage portfolio size, defined as the sum of the market value in the natural logarithm form of all companies covered by an analyst. *MV* represents the market value of equity in the logarithm form. *RD* denotes the R&D expense scaled by total sales. *INTA* indicates the percentage of intangible assets scaled by total assets. *MB* is the market-to-book ratio and measured by dividing the market value of equity by the book value of equity. *ROE* is return on equity. *INSTOWN* is the institutional investor ownership. All firm-level variables are lagged by one quarter. Panel B outlines the regression results All the regressions are clustered at the firm and quarter level. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Table 9. Analysts' employment turnover

Panel A: Descriptive statistics

Variable	MEAN	SD	P25	MEDIAN	P75
MOVEUP	0.197	0.399	0.000	0.000	1.000
MOVEDOWN	0.143	0.351	0.000	0.000	1.000
MATCH	0.586	0.493	0.000	1.000	1.000
WORKEXP	0.489	0.501	0.000	0.000	1.000
lnNUMFIRM	2.548	0.607	2.303	2.639	2.944
lnNUMIND	1.042	0.445	0.693	1.099	1.099
lnGEXP	1.675	1.121	0.693	1.792	2.708
lnPAC	3.917	0.206	3.85	3.93	4.01
lnANCOVSIZE	3.328	1.236	2.64	3.33	4.17
No. of Observations			370		

Panel B: Regression results

DEPVAR	Pr(MOVEUP=1)	Pr(MOVEDOWN=1)
	(i)	(ii)
MATCH	0.051	-0.405**
	(0.147)	(0.169)
WORKEXP	-0.027	0.106
	(0.146)	(0.180)
lnNUMFIRM	0.404**	0.258
	(0.183)	(0.202)
lnNUMIND	-0.352*	0.020
	(0.208)	(0.223)
lnGEXP	-0.130*	-0.081
	(0.078)	(0.090)
lnPAC	0.277	-0.562
	(0.440)	(0.356)
lnANCOVSIZE	0.001	0.113*
	(0.054)	(0.060)
Observations	370	328
Pseudo R^2	0.122	0.125
Year FE	0.088	0.115

Note. This table reports analysts' employment turnover. Panel A presents descriptive statistics. The dependent variable is either *MOVEUP*, which is a dummy variable with the value of one if the analyst moves from a non-top brokerage house to a top brokerage house in a year; or *MOVEDOWN*, which is a dummy variable with the value of one if the analyst moves from a top brokerage house to a non-top brokerage house in a year. A top brokerage house is defined as the one with the number of analysts above 90^{th} percentile of all brokerage houses within a year. In order to make the candidate analysts in my sample are mainly covering chemical and pharmaceutical industry. I restrict the sample to analysts whose coverage has more than 50% of companies belonging to chemical manufacturing industry (SIC 2800 – 2899). *MATCH* is an indicator variable, equal to one if the analyst has a matching degree, and zero otherwise. *WORKEXP* is indicator variable, equal to one if the analyst has pre-analyst relevant working experience, and zero otherwise. *lnGEXP* is analysts' general experience of being an analyst in the natural logarithm form. Analysts' general experience is measured as the number of years from when the analyst issued her first forecast for any firms to present. *lnNUMFIRM* denotes unstandardised number of firms followed by each analyst in the natural logarithm form. *lnNUMIND* denotes the number of 4-digit SIC industries followed by each analyst in the natural logarithm form. *lnPAC* denotes unstandardised relative accuracy score of an analyst in the previous year in the natural logarithm form, which is calculated in line with Hong and Kubik (2003). *lnANCOVSIZE* is the natural logarithm form of the total market value of equity of all the companies covered by an analyst. All independent variables (expect *MATCH* and *WORKEXP*) are lagged by one year. Panel B outlines the results. All the regressions are clustered at the analyst level. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Table 10. Analysts rewarded as Star analysts by *Institutional Investor*

Panel A: Descriptive statistics

Variable	MEAN	SD	P25	MEDIAN	P75
STAR	0.071	0.257	0.000	0.000	0.000
MATCH	0.622	0.485	0.000	1.000	1.000
WORKEXP	0.466	0.499	0.000	0.000	1.000
lnANCOVSIZE	3.240	1.774	1.753	3.312	4.595
lnBROSIZE	3.616	1.294	2.708	3.526	4.585
lnGEXP	1.856	0.991	1.099	1.946	2.708
lnPAC	3.934	0.229	3.875	3.944	4.014
lnNUMFIRM	2.528	0.590	2.303	2.639	2.890
lnNUMIND	1.076	0.539	0.693	1.099	1.386
No. Observations			1,564		

Panel B: Regression results

DEPVAR:	Pr(STAR=1)
MATCH	0.320**
	(0.144)
WORKEXP	0.140
	(0.148)
lnANCOVSIZE	0.115**
	(0.046)
lnBROSIZE	0.342***
	(0.080)
lnGEXP	0.121
	(0.128)
lnPAC	0.285
	(0.426)
lnNUMFIRM	-0.143
	(0.179)
lnNUMIND	0.157
	(0.168)
lagSTAR	2.329***
	(0.247)
Observations	1,442
Pseudo R^2	0.578
Year FE	Yes

Note. This table reports the likelihood of analysts being rewarded as *Institutional Investor All-American Star* (*II Star*) analysts. Panel A presents descriptive statistics. The dependent variable is *STAR*, which is a dummy variable with the value of one if the analyst is awarded as *Institutional Investor All-American Star* *analyst* in a given year, and zero otherwise. *II Star* analysts are ranked by industries. I focus on the *II* rankings in sectors of Biotechnology, Chemicals, Health Care Facilities, Health Care Technology & Distribution, Pharmaceuticals/Major and Pharmaceuticals/Specialty. In order to make the candidate analysts in my sample are mainly covering chemical and pharmaceutical industry. I restrict the sample to analysts whose coverage has more than 50% of companies belong to chemical and pharmaceutical industry (SIC 2800 – 2899). *MATCH* is an indicator variable, equal to one if the analyst has a matching degree, and zero otherwise. *WORKEXP* is indicator variable, equal to one if the analyst has pre-analyst relevant working experience, and zero otherwise. *lnGEXP* is analysts' general experience of being an analyst in the natural logarithm form. Analysts' general experience is measured as the number of years from when the analyst issued her first forecast for any firms to present. . *lnNUMFIRM* denotes unstandardised number of firms followed by each analyst in the natural logarithm form. *lnNUMIND* denotes the number of 4-digit SIC industries followed by each analyst in the natural logarithm form. *lnPAC* denotes unstandardised relative accuracy score of an analyst in the previous year in the natural logarithm form, which is calculated in line with Hong and Kubik (2003). *lnANCOVSIZE* is the natural logarithm form of the total market value of equity of all the companies covered by an analyst. *lnBROSIZE* is the natural logarithm form of the total market value of equity of all the companies covered all analysts employed in a brokerage house in a year. *lagSTAR* is the lagged *STAR*. All independent variables (expect *MATCH* and *WORKEXP*) are lagged by one year. Panel B outlines the results. All the regressions are clustered at the analyst level. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.