Navigating Wall Street: Career Concerns and Analyst Transitions from Sell-Side to Buy-Side*

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Abstract

Existing studies find that sell-side analysts who make less accurate and less optimistic forecasts are more likely to be terminated, suggesting that career concerns affect their forecasting decisions. Using employment data collected from career-related websites (e.g., LinkedIn), we find that 32% of equity analysts that exited the sell-side industry find immediate employment at buy-side institutions. These prospective buy-side analysts do not make less accurate forecasts than analysts who remain in the sell-side industry. In fact, those with superior forecasting ability end up at a hedge fund, a private equity, or a venture capital firm. We find that analysts with prior buy-side experience and specialized education related to the industry they cover are more likely to switch to the buy-side. Buy-side institutions hire a sell-side analyst for her expertise on stocks on which the fund has already held large positions. Our findings suggest that analysts' exit from the sell-side industry is often a voluntary decision resulting from a worker-employer skill matching.

Keywords: Career outcomes; Analyst forecasts; Sell-side; Buy-side

JEL Codes: G11; G23; G24; J40

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1 Introduction

For most institutional investors, sell-side equity analysts are the "go-to" people for expert knowledge and new insight into stocks and industries. This role empowers the sell-side analysts to be major information providers and monitors in financial markets. To understand their economic incentives, it is important to study both the internal reward system in place and the potential external career opportunities for financial analysts. While the lack of analyst compensation data makes it difficult to investigate the first aspect, we focus on the second aspect — career-exit opportunities for sell-side analysts, where evidence is limited.

Early studies on analysts' career concerns generally equate bad career outcome with their disappearance from the I/B/E/S database, i.e., forecast terminations are driven by job losses because of poor performance in earnings forecasts, (e.g., Hong, Kubik, and Solomon, 2000; Hong and Kubik, 2003). However, recent anecdotal evidence indicates that talented sell-side analysts often set their sights on buy-side careers, thereby leaving the sell-side industry voluntarily. For instance, Mary Meeker, the "Queen of the Net" since the late 1990's and a long-time analyst specializing in the internet industry, announced her departure from Morgan Stanley to become a venture capitalist at Kleiner Perkins in the fall of 2010. According to a survey on *eFinancialCareer.com* by the recruitment firm Odyssey Search Partners, the most desired career path for sell-side analysts is a move to a private equity investment firm, followed by a hedge fund and then a possible move to a start-up company. These examples indicate that our understanding of an analyst's career path is far from being complete. Despite some recent work on "revolving-door" analysts who leave to work for companies that they follow, there are little to no academic studies on other career outcomes of equity analysts after they exit the sell-side industry.[1]

We obtain analyst profiles and career histories from various online sources, including career and professional relationship websites (e.g., LinkedIn and ZoomInfo), network/relationship

[1] For instance, Cornaggia, Cornaggia, and Xia (2016), Jiang, Wang, and Wang (2015), and Kempf (2015) examine rating biases and performance of "revolving-door credit analysts."

websites (e.g., RelationshipScience), regulator's background check websites (e.g., BrokerCheck by FINRA), and other general financial information websites (e.g., Bloomberg and Reuters). Using these novel resources, we show that a significant fraction of equity analysts that disappear from I/B/E/S (about 32%) leave sell-side industry to join buy-side institutions. We then examine the determinants of analysts' career transitions, in particular, whether past forecasting performance and biases affect their career changes. Given our new evidence that analysts who leave I/B/E/S often find subsequent buy-side employment, this question is particularly important because prior literature associates analysts' poor forecasting performance with their likelihood of leaving the sell-side industry. Therefore, we ask whether prospective buy-side analysts are less skilled than their peers who remain in the sell-side industry. Relatedly, our empirical setup allows us to examine characteristics that buy-side employers look for when they make hiring decisions, e.g., are they hiring talents? Such findings, we believe, have a far-reaching implication because buy-side firms are delegated professionals specializing in making superior investment decisions on behalf of individual investors.

We first present evidence that a significant fraction of the analysts who disappear from the I/B/E/S database leave their job for a career at buy-side institutions, and importantly, these analysts do not underperform their peers in terms of forecast accuracy. That is, prospective buy-side analysts do not make less accurate earnings forecasts than their colleagues who stay with the same sell-side employer or those who make career moves within the sell-side industry. This finding offers new insights into the prior literature that equates a bad analyst career outcome with her sell-side-industry exit. Our method helps address this problem by using analysts' online career profiles to identify leaving analysts by their prospective job categories. Consistent with Hong, Kubik, and Solomon (2000) and Hong and Kubik (2003), we find that analysts who make less accurate earnings forecasts, in general, are more likely to disappear from I/B/E/S — regardless of the reason. Nevertheless, the relationship between forecast accuracy and job turnover is not monotonic. On the other hand, we find the results linking poor forecasting performance to job turnovers are stronger and become more monotonically clear once we exclude analysts who leave the sell-side for buy-side institutions. Interestingly, we find that among the sell-side analysts who leave to join buy-side institutions, those that make more accurate forecasts are likely to find employment at hedge funds, private equity firms, or venture capital funds, while those with less accurate forecasts find employment at individual firms (i.e., "revolving-door" analysts).

In light of the above findings, we turn to explore other analyst characteristics besides accuracy that affect the probability of a buy-side move. We borrow insights from the career concern literature to lead our analysis. The reputation-based herding model of Scharfstein and Stein (1990) depicts that bold forecasting behaviour affects agent's reputations and leads to an unfavorable career outcome of sell-side analysts as measured by their disappearance from I/B/E/S. We observe a positive association between analysts' boldness and their career transition to a buy-side when using analysts that experience no job changes as the benchmark group. We also find that analysts' career transition to buy-side institutions has little to do with their brokerage house's investment banking relationships with firms that the analysts cover (i.e., affiliated analyst). These findings suggest that conventional career-concern incentives such as the pressure to generate investment banking business (the "strategic distortion" view) do not explain the behaviour of prospective buy-side analysts.

Using buy-side job turnovers as the treatment group, we estimate a linear probability model comparing the characteristics of analysts that make buy-side career moves against those that make career moves to new sell-side brokerage firms, to a corporate firm ("revolving-door" analysts), or to a non-financial institution. We examine various characteristics (e.g. brokerage size, forecast breadth in stocks, institutional ownership, and All-Star statue) in relations to analysts' buy-side career outcomes. We find that some of these factors are informative about analysts' buy-side career moves. In addition, we explore some unconventional factors. We are able to retrieve the education background and previous work experience for a subset of analysts from their online career profiles. We find that the probability of buy-side turnover increases if the analyst has previous buy-side experience and if the analyst has an undergraduate degree major in a field related to the business sector that the analyst follows (*Specialty Major*) or an MBA degree. Overall, our results suggest that prospective buy-side analysts are primarily hired for their expertise (the "human capital" view).

Finally, we analyze whether the holdings in the buy-side fund's portfolio differ before and after the fund hires the sell-side analyst. Answering this question is helpful for understanding the buy-side hiring decision. We test two non-mutually exclusive reasons. If the buy-side hiring decision is reflective of its focus on stocks from a pre-selected list (the "selection" hypothesis), the buy-side firm will have a greater incentive to choose an analyst with expertise on stocks that the fund already has a large investment in. Alternatively, if the buy-side fund selects an analyst to generate new investment insights (the "impact" hypothesis) on stocks that the fund currently underweights or has no exposure to, we expect the fund's portfolio allocation to change and tilts towards stocks that the analyst previously covered. Using a difference-in-difference regression, we find evidence in support of the "selection" hypothesis.

A closely related paper to ours is Siming (2013), which uses LinkedIn data to identify former investment bankers who subsequently work for private equity firms. Our work differs from his study in that the subjects of our study are sell-side equity analysts and institutional investors who interact mainly in the public and secondary market. On the other hand, Siming (2013) focuses on investment bankers and private equity investors who primarily trade actively in the private market. Another work that is related to ours is Guan, Lu, and Wong (2013). While their study focuses on the incentive of all-star analysts moving to buy-side after the Global Settlement regulation in 2003, our work is more comprehensive. We study all analyst job turnovers identified in the I/B/E/S stopped file and our empirical design is not specific to a regulation change.

Our work is also closely related to the literature focusing on analyst career moves within sell-side firms. Holmstrom (1982) describes a model in which the labor market observes past performance to evaluate an agent's ability. Prendergast and Stole (1996) suggest that forecast boldness may be important in determining analysts' job outcomes. Hong, Kubik, and Solomon (2000) provides evidence in support of these models but the measure of analysts' career outcomes, as proxied by their disappearance from I/B/E/S, is over-simplified in today's view. Hong and Kubik (2003) adopts a similar setup to measure analysts' career outcomes and finds that controlling for forecast accuracy, analysts' optimism positively affects their career outcome. We provide a more complete dataset on career outcomes to fill in missing components in previous theoretical and empirical studies.

There is also an extensive amount of work studying the "revolving-door" phenomenon in the context of equity analysts (Lourie, 2014), and of credit analysts (e.g., Cornaggia, Cornaggia, and Xia, 2016; Jiang, Wang, and Wang, 2015; and Kempf, 2015). While these studies generally focus on the career move from sell-side (the "monitor") to the firms that they cover (the "monitored"), we are concerned with the transition from the sell-side analysts (the "advisor") to the buy-side firms (the "client"), which is a more popular career-exit option for sell-side analysts.

The structure of the paper is organized as follows. Section 2 describes our data sources and summary statistics of our sample. In Section 3, we first replicate the result in Hong, Kubik, and Solomon (2000) with data in our sample period, followed by a separation of prospective buy-side analysts. We then compare the results before and after separation and contrast the difference. We investigate analysts' characteristics and the determinants for buy-side turnovers in Section 4. In Section 5, we analyses whether the change in portfolios of the buy-side is consistent with the analyst's expertise. Section 6 concludes the paper.

2 Data and Sample Characteristics

2.1 Data Sources

In this paper, we only focus on analysts covering U.S. listed companies. Our main dataset is organized at the analyst-year level between 2007 and 2013. For an analyst to be included in our sample for year t, we require that she must make at least one one-year-ahead (i.e., FY1) earnings forecast in year t and she must have made earnings forecasts covering one or more firms for at least one year in I/B/E/S by the end of year t. This filter allows us to have sufficient information to compute analyst characteristics prior to their forecast terminations in I/B/E/S. After applying this preliminary filter, we start with $21,570$ analyst-year observations in our initial sample between 2007 and 2013.

Some analysts change jobs during our sample period. Understanding determinants of analyst career turnovers requires information of their entire career histories. To retrieve this information, we search analyst profiles in all possible information sources, including career and professional relationship websites (e.g., LinkedIn and ZoomInfo), network/relationship websites (e.g., RelationshipScience), regulator's background check websites (e.g., BrokerCheck by FINRA), and other general financial information websites (e.g., Bloomberg and Reuters). Most profile pages of sell-side analysts contain information including education degrees, employers, positions/titles, and the start and the end time of each employment. Our sample period starts from 2007 because information sources above typically do not have a good coverage of career information in earlier period.

We obtain information related to analyst characteristics, their brokerage affiliations, and firms' earnings announcements from I/B/E/S. Following Hong and Kubik (2003) and Clement and Tse (2005), we compute analyst characteristics based on one-year-ahead forecasts (i.e., FY1), which are the most common forecasts made by sell-side analysts. For accuracy, boldness, and optimism, we calculate these measures based on the last forecast that an analyst issues before each fiscal year of a firm.[2] We retrieve institutional ownership and holding data from Thomson-Reuters Institutional Holding Database (13f). Stock trading information, such as stock prices, trading volume, and the number of shares outstanding are obtained from CRSP.

[2] We drop forecasts that were issued 415 days earlier or later than their corresponding earnings announcement dates. This filter eliminates stale forecasts, and forecasts that are revised after the earnings announcements.

2.2 Analyst Career Transitions

As shown in Figure 1, for each analyst we observe in our sample in year *t*, their job outcomes in year *t+1* can be grouped into three scenarios.

In the first and also the most frequently observed scenario, an analyst continues to work for the same I/B/E/S brokerage firm in the following year. This scenario includes analysts who keep the same positions and analysts move within the same brokerage firm, e.g., an analyst of a research department moves to the investment banking division of the same company or an analyst is promoted as the head of the research department. Not surprisingly, this scenario represents about three-quarter of our observations in the full sample. Figure 1 shows that $15,553$ analyst-year observations fall into this scenario.

In the second scenario, an analyst moves from one I/B/E/S brokerage firm to another I/B/E/S brokerage firm, e.g., an analyst moves from Morgan Stanley to Goldman Sachs. In this case, I/B/E/S assigns a new analyst ID to the moving analyst. Hong and Kubik (2003) classify all job turnovers under this scenario as either a "promotion" or a "demotion" depending on whether an analyst is moving to a larger or a smaller brokerage firm relative to her previous employer. As shown in Figure 1, we find that $2,129$ of them are classified as within-IBES job turnovers within our sample period.

In the third scenario, an analyst moves from an I/B/E/S brokerage firm to join a firm, an institution, or an organization that is not covered by I/B/E/S. In this paper, we often refer to this scenario as an analyst "exits" or "leaves" I/B/E/S or the forecasts of this analyst are "terminated" by I/B/E/S. The new employer can be a boutique sell-side firm not covered by I/B/E/S, a buy-side financial institution, a non-financial corporation, a university or a government organization. Figure 1 shows that $3,888$ of analyst-year observations belong to this scenario.

Among all $3,888$ analyst-year observations in the third scenario, we can identify their previous brokerage affiliations from I/B/E/S for $3,345$ of them. Further, job turnovers can be voluntary or involuntary. [3] We identify 110 analyst-years whose job turnovers are driven by brokerage closures.[4] Job turnovers associated with the remaining $3,239$ analyst-year observations are likely to be voluntary.

These $3,239$ analysts who voluntarily left I/B/E/S brokerage firms are the focus of this paper. We search for their complete career history online as mentioned in the previous section. To avoid potential mismatches, we require three pieces of information on the profile pages, including the name of an analyst, her affiliated brokerage firm in year t, and her job title, are consistent with those provided by I/B/E/S. We also require that the profile page provides enough information to indicate both the name of the new employer and the start date of the first job that the analyst obtains after leaving I/B/E/S. We only consider an analyst's new employment that is obtained within one year after their last forecasts were reported in I/B/E/S. We impose this maximum one-year transition gap to ensure a meaningful economic association between analyst characteristics before their forecast terminations and their new employments. These conservative criteria yield a sample of $1,825$ analyst-year observations where the full career history of an analyst that voluntarily moves to a non-IBES institution/firm can be identified.[5]

As shown in Figure 1, we classify new employments of analysts who disappear in I/B/E/S into four categories: (1) sell-side firms that are not covered by I/B/E/S, e.g., independent boutique research firms; (2) buy-side financial institutions, e.g., hedge funds, private equities, or mutual funds; (3) corporate employers; and (4) other jobs, e.g., government agencies, universities and other non-profitable organizations. We further partition new employers in group (2) into three subgroups according to the activeness of their trading strategies. The

[3]When an analyst is headhunted by another firm, self-initiates a new job search, or leaves her current brokerage firm to establishes a new firm herself, the job turnover is likely a voluntary one. On the other hand, an analyst can be forced to find a new job when her brokerage firm shuts down for reasons that are plausibly unrelated to her performance. These job turnovers are likely to be involuntary. These involuntary job turnovers are studied in Cen, Chen, Dasgupta, and Ragunathan (2016).

[4]Similarly, we find 398 forced job turnovers driven by brokerage closures under the second scenario. Cen, Chen, Dasgupta, and Ragunathan (2016) study forced job turnovers under both the second and the third scenarios.

[5]The found and search ratio in our study is close to 56%, which is consistent with Bradley, Gokkaya, and Liu (2017).

first subgroup includes hedge funds, private equities, and venture capital firms (HF&PE), which are traditionally considered as actively managed funds. The second subgroup includes mutual funds and pension funds (HF&PE), which are more passively managed than the previous subgroup. The third subgroup includes all other buy-side firms that do not belong to the first and second subgroups, including investment divisions of commercial banks, trusts (including REITs), and insurance companies.

Among all $1,825$ analysts with verified information of their career histories, we find that 471 analysts move into non-IBES sell-side firms, 587 analysts become buy-side analysts or managers, 347 analysts find corporate jobs, and 420 analysts join other non-financial organizations. Overall, the online search results show that moving to buy-side institutions is the most popular career choice for sell-side analysts after they exit the sell-side industry. Specifically, we find that approximately 32% of these IBES-exiting analysts join buy-side institutions within a one-year period after their last forecasts were reported in I/B/E/S.[6]

2.3 Sample Description

Panel A of Table 1 presents time-series distributions of all analysts in I/B/E/S, analysts whose forecasts are terminated in I/B/E/S, "exiting" analysts whose full career histories can be identified, and analysts that move to buy-side institutions for each year in our sample period.

We observe some interesting patterns of analyst career turnovers in Panel A. The percentage of total analysts with stopped forecasts (i.e., analysts that "exit" I/B/E/S) peaks in 2008 amid the subprime mortgage crisis. Further, the percentage of analysts moving to buy-side institutions reaches its trough in 2009. These observations suggest that it is more difficult for sell-side analysts to keep their jobs or move to the buy-side during financial crises. To ensure that our main results are not affected by major financial crises that affect analyst

[6] Not surprisingly, this percentage is much higher in our sample for voluntary job turnovers, relative to the sample of involuntary job turnovers, e.g., 17% of analysts join buy-side firms after involuntary job turnovers in Cen, Chen, Dasgupta, and Ragunathan (2016).

career turnovers together with all other fundamental aspects in the economy, we control for year-fixed effects in all test specifications.

Panel B of Table 1 summarizes analyst characteristics for the full sample, while Panel C summarizes analyst characteristics for the subsample of analysts who move to buy-side institutions. We report summary statistics of analyst characteristics that are potentially important for their future career outcomes. Appendix A provides detailed definitions of these characteristics. Following Hong, Kubik, and Solomon (2000), we measure the accuracy, the boldness, and the optimism of analyst forecasts using a ranking measure. For instance, to calculate *Accuracy*, we first rank an analyst's forecasting accuracy, on a percentile scale, relative to all other analysts covering the same stock (i.e., 0 being the worst to 100 being the best). We then average accuracy rankings across all analyst-stock pairs to yield the *Accuracy* measure at the analyst level. *Boldness* and *Optimism* are computed in a similar manner.

Panel B of Table 1 shows that the ranks of an average analyst in our sample, in terms of accuracy, boldness and optimism, are all close to the 50th percentile. The median numbers of stocks and industries followed by an analyst in a given year are 11 and 3, respectively. *Seniority IBES* indicates the number of years that an analyst has been issuing forecasts as reported in I/B/E/S. An analyst in our sample spends an average of 9.56 years in I/B/E/S, but the distribution is skewed. In addition, we also compute *Seniority Broker*, which indicates the number of years that an analyst has been issuing forecasts for a brokerage firm as reported in I/B/E/S. An analyst is considered to be an affiliated one if the investment bank that she is affiliated with is a lead underwriter in equity issuance, or a financial advisor in mergers and acquisitions for at least one firm that she covers in year t. We find that 5% of all analysts in our sample are affiliated with brokerage firms that provide investment banking services to one or more firms they cover. Further, we find that 11% of analysts in our sample have been awarded with the All-star status in the annual ranking of the *Institutional Investor* magazine. A typical stock in our sample is followed by 17.02 analysts in a year, and has 67% of its stocks held by institutional investors. Finally, we find that the analyst industry is dominated by male workers. 94% of our observations are associated with male analysts.

Panel C of Table 1 reports similar characteristics for analysts who move from sell-side firms to buy-side institutions. Comparing mean statistics in Panels B and C, we do not find that analysts moving to buy-side institutions are significantly different from an average analyst in I/B/E/S in terms of boldness, optimism, breadth of coverage, and gender. They are slightly more accurate, much more junior, and less likely to attain the All-star status, relative to their peers in I/B/E/S.

[Insert Table 1 Here]

2.4 Career Opportunities: Sell-side vs. Buy-side

In this paper, we focus on sell-side analysts' career transition to the buy-side industry. We are motivated by the following four reasons. First, over the last decade, career opportunities in the buy-side industry have grown much faster than those in the sell-side industry. For example, from 2000 to 2014, the number of brokerage firms in I/B/E/S increases by 48.6%, whereas during the same period the number of financial institutions in the 13F database increases by 82.1%. A faster growth in the buy-side business relative to the sell-side provides job opportunities for financial practitioners to move from the sell-side to the buy-side.

Second, relative to sell-side firms, buy-side institutions tend to offer more diverse opportunities that attract experienced financial practitioners with different skill sets. According to DeChesare (2016) and Cheng, Liu, and Qian (2006), sell-side analysts that switch to the buy-side are likely to enjoy more involvement in the investment decision-making process, better upside on pay compensation, as well as improvement in work-life balance. In particular, unlike sell-side research, buy-side institutions focus on the performance and characteristics of the overall portfolio rather than individual stocks. Therefore, relative to sell-side firms, buy-side institutions may value skills in portfolio management more than firm-specific knowledge or connections (Cen, Chen, Dasgupta, and Ragunathan, 2016).

Third, as investor recognition of buy-side institutions improves (e.g., hedge funds, venture capitals, and private equities), the cost to establish new buy-side firms has become cheaper relative to two decades ago (see Mirsky, Cowell, and Baker, 2012; Spangler, 2016). As a results, it is becoming more common to witness sell-side financial workers leaving their affiliated brokerage firms to establish buy-side institutions themselves.[7].

Finally, we are motivated to examine analysts' career move from the sell-side to the buy-side because empirical evidence in the literature is limited. In fact, existing literature on analysts' job turnovers is largely silent on external-career opportunities of sell-side analysts, and how these opportunities affect their forecasts. For instance, an early study on career concerns among sell-side analysts by Hong, Kubik, and Solomon (2000) assumes that "the possibility that an analyst may have left for a better job such as mutual fund manager after leaving the I/B/E/S sample is remote." Given the changing landscape of the financial industry, such an assumption may no longer apply to sell-side analysts in the more recent sample. More importantly, analysts' career transition from the sell-side to the buy-side could be a voluntary move. As a result, the probability of sell-side analysts' career termination in I/B/E/S may be related to other factors rather than career-concern determinants as documented in prior studies.

3 Career Concerns and Forecasting Performance

3.1 Likelihood of Analysts' Career Turnovers

We begin our analysis by replicating the main results in Hong, Kubik, and Solomon (2000) for our sample period from 2007 to 2013. We closely follow their empirical setup and estimate

[7]For example, Meredith Whitney, who was once the most famous Wall Street analyst, launched her own hedge fund Kenbelle Capital in 2013. Whitney made her name with accurate prediction of losses and write-downs about Citigroup Inc. in 2007, before most saw the financial crisis coming.

the following linear probability model:

$$\mathbb{1}(\text{Leaving IBES})_{i,t+1} = \alpha + \beta \text{ Forecast Accuracy Indicator}_{i,t} + \text{Control Variables}_{i,t} + \delta_{b(i)} + \theta_{s(i)} + \mu_t + \epsilon_{i,t+1}. \tag{1}$$

In Equation (1) above, the dependent variable, $\mathbb{1}(\text{Leaving IBES})_{i,t+1}$, is a dummy variable that is equal to one if an analyst who makes earnings forecasts in year t cannot be identified in I/B/E/S in *t+1*, and zero otherwise.[8]. All control variables, including industry fixed effects ($\theta_{s(i)}$), year fixed effects (μ_t), and broker fixed effects ($\delta_{b(i)}$), are constructed identically as those in Hong, Kubik, and Solomon (2000). Detailed definitions of all control variables are included in Appendix A.

Columns (1) and (2) of Table 2 report our baseline results. *Forecast Accuracy Indicators*$_{i,t}$ are a group of indicator variables that are equal to 1 if an analyst's forecast accuracy falls within the designated percentile range. For instance, *Accuracy Percentile Dummy 0-through-5* is equal to 1 if an analyst's forecast accuracy falls between the 0th and the 5th percentiles of the entire sell-side analyst population covered by I/B/E/S in year *t*.

Consistent with Hong, Kubik, and Solomon (2000), we find that the most inaccurate analysts, e.g., analysts within the *0-through-5* group, are most likely to disappear in the I/B/E/S sample in year $t + 1$. Results in column (1) of Table 2 show that an analyst that belongs to the lowest group in terms of forecast accuracy in year t is 3.6% more likely to disappear in the I/B/E/S sample in year *t+1* relative to other analysts. This economic magnitude, i.e., 3.6%, is slightly lower than that (i.e., 3.8%) reported in Hong, Kubik, and Solomon (2000). In column (3), we replace the percentile indicator variables with the continuous measure of forecast accuracy, i.e., *Score*, which is the percentile of an analyst's forecast accuracy rank. Consistent with our results in column (1), the coefficient of this

[8]This variable is defined identically as the *Job Separation* measure in Hong, Kubik, and Solomon (2000). Since a significant portion of analysts whose forecasts are terminated in I/B/E/S move from the sell-side to the buy-side voluntarily in our sample period, we rename the dependent variable to avoid the potential confusion that all forecast terminations are driven by involuntary job separations

continuous measure is negative and statistically significant at the 1% level, indicating that lower forecast accuracy in t is associated with an higher probability that an analyst's forecasts will be terminated in the I/B/E/S sample in year $t+1$.

Although we find a negative relationship between prior forecast accuracy and the probability of forecast terminations in I/B/E/S, such relationship is no longer monotonic. This important observation is illustrated in column (2) of Table 2. In this test, we estimate the probability of forecast termination in I/B/E/S against analyst forecast accuracy measured by *Accuracy Percentile Dummies*. In column (2), the coefficient estimates of Accuracy Percentile Dummies represent the differences in the probability of forecast termination in I/B/E/S between analysts in various forecast accuracy groups relative to analysts in the most accurate group, i.e., analysts in the "75-through-100" group. As shown in column (2), analysts in the "10-through-25" group have a higher probability of forecast termination in I/B/E/S than analysts in both the "10-through-25" and "50-through-75" groups. This finding starkly contrasts the monotonic pattern between forecast accuracy and the probability of forecast terminations in I/B/E/S in Hong, Kubik, and Solomon (2000), which estimate the same model based on information from I/B/E/S before 2000.

We also statistically test the differences in probabilities of forecast termination in I/B/E/S between analyst forecasting-accuracy groups (untabulated). We find that the difference is only statistically significant between the most accurate group ("75-through-100") and one of the other groups, or between the most inaccurate group ("0-through-5") and one of the other groups. Put differently, we find that the overall negative relationship between forecast termination in I/B/E/S and forecast accuracy is mainly derived from analysts in two extreme groups in terms of forecast accuracy.

Among all control variables, we find that analysts covering more firms, with all-stat status and with higher seniority at their brokerage firms are less likely to disappear in I/B/E/S sample in the following year. We also find that male analysts are more likely to stay in the I/B/E/S sample relative to their female peers.

[Insert Table 2 Here]

Overall, using a more recent I/B/E/S sample, we find that the monotonic relationship between prior forecast accuracy and the probability of forecast termination in I/B/E/S does not hold any more for analysts in the middle-accuracy groups, i.e., those analysts in neither the most accurate nor the least accurate group. In other words, we find that, for most sell-side analysts within our sample period, their prior forecast accuracy is no longer monotonically related to the likelihood of forecast termination in I/B/E/S, which is seemingly inconsistent with what Hong, Kubik, and Solomon (2000) find for an earlier sample. A plausible explanation to reconcile this seemingly inconsistency is the explosive growth of career opportunities provided by buy-side institutions in recent years. Specifically, if sell-side analysts voluntarily move to buy-side institutions, their forecast termination in I/B/E/S is not likely driven by job separations because of poor performance.

3.2 Likelihood of Career Turnover to Buy-Side Firms

As mentioned earlier, our study main focuses on sell-side analysts that move to buy-side institutions. It is important to understand the difference between this type of analysts and other analysts whose forecasts are terminated in I/B/E/S because of forced job separations. Therefore, we repeat our tests reported in Table 2 by isolating sell-side analysts moving to buy-side firms from other analysts that disappear in I/B/E/S in year *t+1*. Specifically, we first repeat the same linear probability model in Equation (1) within a subsample that captures only two types of analysts, i.e., sell-side analysts dropping out from I/B/E/S because they joins a buy-side firm in year $t + 1$ (the treatment group), analysts whose forecasts are still reported in I/B/E/S in year $t + 1$ (the control group). The result is reported in columns (1) to (3) of Table 3. Results in column (1) suggest that analysts with the lowest forecast accuracy, i.e., analysts in the *0-through-5* group, are less likely to join buy-side firms after their sell-side careers, relative to all other analysts in our treated and control groups. When we use percentile dummies for all forecast accuracy groups, we find a non-linear relationship between prior forecast accuracy and the probability of joining buy-side institutions. Our results suggest that analysts with moderate forecast accuracy, e.g., those in the *25-through-75* group and *50-through-75* group, are more likely to join buy-side institutions after their sell-side careers, relative to analysts in both the lowest accuracy group and the highest accuracy group.

Taken results from both columns (1) and (2) together, we observe the following empirical patterns. First, analysts moving to buy-side institutions do not underperform their peers in their previous sell-side jobs. This is again confirmed by our results in column (3), where forecast accuracy is proxied by a continuous measure. In fact, results in column (3) suggest that analysts moving to the buy-side, on average, are more accurate than their peers staying at I/B/E/S in the following year. Second, the relationship between prior forecast accuracy and the probability of joining buy-side institutions is non-linear. Analysts in both the highest and the lowest accuracy groups are less likely to join buy-side institutions relative to an average analyst in terms of forecast accuracy. It is easy to understand why analysts with the lowest forecast accuracy group are less likely to move to buy-side institutions than their peers. Because of their poor performance, they probably have a lower probability to get any jobs. For analysts with the highest level of forecast accuracy, it is plausible that they have already earned (or they are very likely to earn) star analyst status in the sell-side profession. Therefore, their cost of moving into another segment in finance industry is higher than their peers. These empirical patterns lead to a more interesting question pertaining to what determines career transitions from the sell-side to the buy-side and we will formally address this question in the next section.

Our results above suggest that sell-side analysts' prior forecast accuracy is not monotonically related to their likelihood of moving to buy-side institutions. If we test this relationship in a linear regression, we observe that analysts moving to the buy-side are more accurate than their peers. If we mix these analysts moving from the sell-side to the buy-side with analysts who lose their jobs because of poor performance together, the results in Hong, Kubik, and

Solomon (2000) could be significantly weakened and biased. To correct this bias, we repeat the same linear probability model in Equation (1) by excluding analysts moving from the sell-side to the buy-side from other analysts whose forecasts are terminated in I/B/E/S in year t in the treatment group. Specifically, we now only include two subgroups of analysts in this test, i.e., analysts whose forecasts appear in I/B/E/S in both year t and year $t+1$ (the control group) and analysts whose forecasts disappear in year $t+1$ and whose disappearances are not driven by career transitions to buy-side firms (the treatment group). Columns (4) to (6) of Table 3 report the results of this test. After excluding analysts moving to buy-side firms in the treatment group, we resurrect and verify the main message in Hong, Kubik, and Solomon (2000) that less accurate sell-side analysts are more likely to lose their jobs. For example, column (4) of Table 3 shows that the coefficient of *0-through-5 Percentile Dummy* is 0.024% higher than that in column (1) of Table 2. We find a consistent pattern while comparing the coefficients of the continuous measure of forecast accuracy, *Score*, reported in column (3) of Table 2 and column (6) of Table 3. Further, the relationship between prior forecast accuracy and the likelihood of leaving I/B/E/S becomes monotonic in Table 3, while the middle groups in Table 2 exhibit a mixed pattern. Overall, after excluding analysts hired by buy-side institutions from other analysts that drop out from I/B/E/S in year $t+1$, Table 3 exhibits a more comparable and less noisy result that confirms and strengthens the argument in Hong, Kubik, and Solomon (2000).

[Insert Table 3 Here]

While buy-side financial institutions share many characteristics in common, there are distinctive cross-sectional differences among hedge funds, private equities, mutual funds, pension funds and other buy-side institutions. For example, Hedge funds employ more aggressive financial instruments and trading strategies than their mutual fund counterparts. Specifically, hedge funds are able to carry out long-short strategies that take advantage of asset mispricing in the cross section. These differences across various types of buy-side institutions imply that buy-side institutions may value certain skill sets of their employees differently. To shed light on this nature of buy-side labor market, we split analysts moving to buy-side institutions into two subgroups: a subgroup of hedge funds and private equities (HF&PE) and a subgroup of mutual funds and pension funds (MF&PF). This group partition is based on the economic intuition that hedge funds and private equities, which are more actively managed, are likely to be more sensitive to firm-specific information related to asset mispricing (i.e., alphas). Therefore, we expect HF&PEs would value the ability in analyzing firm-specific information, e.g., the ability of forecasting earnings accurately, more highly than their counterparts in the MF&PF group.

To test this conjecture, we run the same linear probability model as in Equation (1) for these two subgroups. For example, tests based on sample consisting of the group of analysts leaving for HF&PE in year *t+1* (the treatment group) and the group of analysts who stay in I/B/E/S in year *t+1* (the benchmark group) are exhibited in columns (1) and (2) of Table 4. In columns (3) and (4) we replace the treatment group by analysts leaving for MF&PFs.

Results in Column (1) of Table 4 suggest that the difference in probability of joining HF&PEs between analysts in the least accurate group and the most accurate group is negative, suggesting that hedge funds and private equities do value analysts' prior forecast accuracy. This is confirmed by the results based on the continuous measure of forecast accuracy in column (2). These results suggest that sell-side analysts leaving for hedge funds and private equities were more accurate in earnings forecasts than those staying with I/B/E/S before their job turnovers. On the other hand, the regression results in columns (3) and (4) suggests that there is no significant difference in forecast accuracy between analysts leaving for mutual funds and pension funds and analysts staying with I/B/E/S. For this sub-group of analysts, the above-median analysts in terms of forecast accuracy, i.e., those in the *50-through-75* group, have a higher chance to join mutual funds and pension funds, relative to those analysts in the highest accuracy group.

The group partition of buy-side firms has interesting implications for our study. First, we identify a special subgroup of analysts who disappear in I/B/E/S but are actually more accurate in earnings forecasts than those analysts who stay with I/B/E/S. Second, our results are consistent with our conjecture that HF&PEs value fundamental analysis that relies on analyst's knowledge and expertise in individual stocks to generate Alphas, but MF&PFs in general emphasize on portfolio properties that do not rely on fundamental analysis of particular stocks. Therefore, in the labor market of finance industry, our results hint that the ability in making accurate earnings forecasts is valued more highly among HF&PEs, relative to MF&PFs.

[Insert Table 4 Here]

4 Who Moves to the Buy-Side?

Our results in Section 3 suggest that analysts moving to buy-side firms do not underperform those who keep their sell-side jobs in terms of forecast accuracy. In particular, before their job turnovers, analysts moving to hedge funds and private equities were actually more accurate than their peers staying with I/B/E/S. This result gives rise to a natural and open question that has not been addressed in the literature: Is forecast accuracy an important determinant for analysts to move from sell-side brokerage firms to buy-side institutions? What are other analysts characteristics that significantly affect this type of job turnover?

This question is of particular importance since buy-side analysts, different from their sell-side counterparts, provides internal advice to fund managers who invest to pursue high returns for clients. The buy-side profession has different career incentives and skill sets, and an analyst's characteristics should vary with job-specific aspects in some predictable ways if the job turnover indeed reflects the appropriate fit between the job requirements and the candidate's skill sets. More importantly, addressing this question will allow us to understand economic incentives of sell-side analysts who prepare to move to the buy-side. Results from our analysis would complement existing studies that exclusively focus on economic incentives of financial analysts within sell-side business.

Based on empirical results in the analyst literature and anecdotal evidence in the financial market, we examine potential determinants leading to job turnovers among sell-side analysts with a focus on the buy-side type turnover (Given the role of forecast accuracy has been extensively discussed above, we will skip this aspect below for parsimony). We provide detailed definitions of these variables and the correlation matrix in Appendix A1.

4.1 Determinants of Sell-Side Job Turnovers in the Literature

We first follow prior literature on sell-side career turnovers and the "revolving-door" phenomenon to investigate whether these known career determinants also affect the probability of job turnovers from the sell-side to the buy-side. Studies on analyst herding behaviours (e.g., Prendergast and Stole, 1996) suggest that bold forecasts can affect analysts' career outcomes.

The literature regarding economic incentives for sell-side analysts argue that sell-side analysts issue optimistic forecasts to please company management for two distinctive incentives. The first economic incentive is to generate investment banking business and trading commissions for the brokerage house they are affiliated with (see Michaely and Womack, 1999; Malmendier and Shanthikumar, 2014); the second incentive is to build and maintain good relationships with their potential future employers, which leads to analyst behaviors documented in the "revolving-door" literature (Lourie, 2014; Cornaggia, Cornaggia, and Xia, 2016; Kempf, 2015).

We incorporate *Seniority Broker*, which is defined as the number of years an analyst has been working for her brokerage firm, within our controls. First, it is an important proxy for an analyst's experience. Second, it proxies for an analyst's connections with both institutional investors and corporate managers. Third, the availability of senior job position is relatively rare. Therefore, to some extent, seniority presents a barrier to find comparable outside job opportunities.

One limitation of our regression analysis is that we do not have broker fixed effects in our specification.[9] Instead, we control for brokerage affiliations by incorporating a dummy variable that equals one if the broker is among the ten largest brokerages based on the number of hired analysts (*Top10 Broker*). According to Hong, Kubik, and Solomon (2000), the size of a brokerage firm is typically correlated with its reputation. It can also serve as a proxy for the connection with both buy-side investors and corporate managers.

We also include *Affiliated Analyst* into control variables since previous studies argue that affiliated analysts are more likely to be optimistic (e.g., O'Brien, McNichols, and Hsiou-Wei, 2005; Malmendier and Shanthikumar, 2014). All-Star analysts, on the other hand, are very important to brokerage firms since their forecasts are influential in generating trading among institutional investors and bringing market-making business to the brokerage. *Affiliated Analyst* and *All-Star* have a high correlation of 18% as shown in Table A1.

We also compute the average institutional ownership of stocks covered by the analyst to proxy for the information demand from institutional investors (see Bozcuk and Lasfer, 2005; Boehmer and Kelley, 2009). Similarly, we also include *Avg. Coverage*, which is the average of analyst coverage for stocks covered by the analyst. Both measures capture whether an analyst covers large and leading stocks.

4.2 Other Determinants for Job Turnovers to the Buy-Side

In addition to the above factors, we also include a list of variables obtained from our online search of analysts' personal history, such as an analyst's educational background and her previous working experience. Brown, Call, Clement, and Sharp (2015) illustrate the importance of an analyst's educational background in equity research for some specialized sectors: "Pharma would be a good example for sell-side analysts covering very few firms but having a very, very special niche. The majority of the pharma analysts are either ex-pharma guys or they are M.D.s or Ph.D.s, etc. in that specialization." Therefore, this provides

[9] In some pair-wise regression specifications, some small size brokers have only one analyst observation.

a foundation for our analysis that a postgraduate degree and a specialty major could be important determinants for career transitions from the sell-side to the buy-side. We also conjecture that related past working experience is helpful in predicting future careers in similar roles. In this section, we formally test whether the above variables can predict sell-side analysts' likelihood of moving to the buy-side in their career turnovers.

4.3 Empirical Specifications

Our main empirical specification is provided in Equations (2) and (3). The dependent variable is equal to 1 when analysts move from the sell-side to the buy-side in year *t+1*, i.e., the treatment group, and zero otherwise. In Table 5, while we keep the treatment group constant (i.e., analysts moving from the sell-side to the buy-side), we report results based on different benchmark groups. We adopt two test specifications under each benchmark group. We also incorporate year fixed effects (μ_t) and industry fixed effects ($\theta_{s(i)}$) to control for common trends over time and within each industry. The first specification is:

$$\mathbb{1}(\text{Treated})_{i,t+1} = \alpha + \beta \text{ Factor } 1_{i,t} + \theta_{s(i)} + \mu_t + \epsilon_{i,t+1}, \tag{2}$$

where the *Factor 1* includes all candidate determinants that we have discussed in Section 4.1. The second specification is of the following form:

$$\mathbb{1}(\text{Treated})_{i,t+1} = \alpha + \beta \text{ Factor } 1_{i,t} + \gamma \text{ Factor } 2_{i,t} + \theta_{s(i)} + \mu_t + \epsilon_{i,t+1}, \tag{3}$$

where the *Factor 1* is the same as equation (2), and *Factor 2* includes the additional variables discussed in Section 4.1.

4.4 Empirical Results

Column (1) of Panel A shows the result based on specification in Equation (2a). The benchmark group (i.e., analysts with no job change in year *t+1*) is of particular importance in the sense that prior literature suggest that *Accuracy*, *Boldness* and *Optimism* are important predictors for within sell-side turnovers and corporate moves. Our result shows, analysts that are bolder and more optimistic in earnings forecasts are more likely to move to buy-side institutions. After controlling for boldness and optimism, forecast accuracy is not a significant predictor of moving to the buy side while the benchmark group comprises analysts that have no job changes in year *t+1*.

Further, we find that the breadth of analyst coverage, all-star status, analyst seniority, broker reputation and average institutional ownership of firms covered by the analyst are significant predictors for analysts moving to buy-side institutions. The estimated coefficients show that *Seniority* and *All-Star* statue are negatively correlated with the probability of moving to the buy-side. This is perhaps not surprising. Relative to their junior peers, senior analysts that have gained sufficient reputation within the sell-side business have a higher cost and a lower benefit of moving to buy-side institutions. On the other hand, broker reputation (*Top10 Broker*) and average institutional ownership of firms covered by the analyst (*Institutional Ownership*) have positive coefficients in this predictive regression. These results suggest that working for a reputable brokerage firm and covering large and reputable companies improve the chance for an analyst to move to a buy-side institution.

Columns (2) and (3) in Panel A of Table 5 show the results for the second benchmark group: analysts that move from one I/B/E/S brokerage firm to another I/B/E/S brokerage firm. The determinants, including *Optimism*, *Breadth-Firm*, *Seniority-Broker*, *All-Star*, *Top10 Broker*, and *Institutional Ownership*, which are statistical significance in column (1), remain statistically significant in column (2). The estimated coefficients imply that an increase in, for example, *Seniority-Broker*, by one standard deviation would lead to 0.6% lower probability of transition from no job change to a buy-side job change, and yet the reduction in the probability of transition to buy-side versus transition to an I/B/E/S sell-side is 3.2%. Our results suggest that, conditional on career transition, those indicators are still highly powerful predictors in distinguishing transitions to the buy-side from those to the sell-side.

In addition, our result in column (3) shows that the set of education-related variables obtained from online profile search are significant predictors for buy-side turnovers. Our results imply that an analyst is more likely to go to the buy-side in year *t+1* if the analyst had worked for the buy-side before, if the analyst holds a MBA degree, or if the analyst's educational background matches the covered industry sector.

The results in columns (4) to (9) in Panel A of Table 5 are also informative based on other benchmark groups. The coefficients in column (4) and (5) seem to imply that these analysts in the third benchmark group (non-IBES sell-side change) are "demoted" to a lower prestigious brokerage house since the coefficient on *Accuracy* is positive and statistically significant. Based on our result reported in column (4), an increase by one standard deviation in accuracy rank suggests that an analyst is 7.5% more likely to go to a buy-side firm in year *t+1* than to a boutique sell-side brokerage house not covered by I/B/E/S.

The results in columns (6) and (7) suggest that previous corporate experience is a negative indicator for transition to a buy-side job relative to transitioning to a corporate job. This is consistent with the notion that analysts with previous corporation experience want to go back to work for corporations, relative to moving to buy-side institutions.

[**Insert Table 5 Here**]

In the same spirit of the buy-side partition as in Table 4, we provide results for the finer separation of the buy-side in this session to further identify the difference of characteristics between HF&PE and MF&PF. We use the same benchmark groups and specifications as in columns (1) - (3) of Table 5. Specifically, columns (1) - (3) of Table 6 show the result for analysts moving to HF&PE as the treatment group and columns (4) - (6) for analysts moving to MF&PF as the treatment group.

Both both groups and under both benchmark groups, analysts that cover more firms, have worked for their brokerage firms longer, and have gained all-star status are more likely to move to the buy-side.

However, for the HF&PE type of buy-side, forecast accuracy is a positive and statistically significant predictors, while it has no effect when the treatment group comprises analysts moving to MF&PF. Also, our results suggest that being affiliated with reputable brokerage firms is more important if one analyst wants to move to a hedge fund or a private equity, relative to moving to a mutual fund or a pension fund. It is also interesting to note that analysts holding MBA degrees and also with a good background of special knowledge of industries they cover are more valued by HF&PE. Furthermore, we find that only MF&PF likes analysts with previous buy-side experience, while it does not seem to matter for HF&PE. All these differences are consistent with our conjecture that HF&PE value general and industry-specific knowledge more than MF&PF.

[**Insert Table 6 Here**]

5 Buy-side Holdings and Sell-Side Analyst's Coverage

In Section 4, we have discussed possible determinants that predict career moves from the sell-side to the buy-side. A natural follow-up question is why do buy-side firms value these characteristics of sell-side analysts? To answer this question, we conduct a preliminary investigation on the relationship between analysts' stock coverage and the equity holdings of prospective buy-side firms that may employ these analysts. Our test is motivated by two non-exclusive hypotheses. Our first hypothesis, the "selection" hypothesis, conjectures that buy-side funds are more likely to hire sell-side analysts who have expertise with stocks of higher exposures in their fund's holdings. Our second hypothesis, the "impact" hypothesis, conjectures that a sell-side analyst, once recruited by a buy-side firm, is more likely to help the buy-side firm to build positions in stocks where the analyst has expertise, or stocks that the analyst is familiar with.

To investigate this, we adopt a difference-in-difference (DID) strategy to identify the causality between the position changes in the buy-side fund and the hiring event of a sell-side analyst. The goal is to compare the difference between the holdings in stocks that were covered by the leaving analyst (covered, treatment group) and those that were not (non-covered, control group), before and after the analyst starts the new job at the buy-side firm. In our setting, the "selection" hypothesis and the "impact" hypothesis would have non-exclusive but slightly different predictions. The "selection" hypothesis suggests that a buy-side firm chooses to hire a sell-side analyst precisely because the analyst has the expertise with the stocks that the buy-side firm is planning to trade. Therefore, the "selection" hypothesis predicts that the holdings of stocks in the treatment group can be higher than those in the control group even before the job turnover actually happens. The "impact" hypothesis focuses on how an analyst's expertise and familiarity with certain stocks would affect future purchase decisions of buy-side firms. Therefore, the "impact" hypothesis predicts the difference between the treatment group and the control group would occur only after the analyst's turnover event.

Using the 13F holding data, we are able to observe the number of shares of all stocks held at the quarter end, as long as the market value of assets held by a financial institution exceeds $100 million during the reporting period. There are four limitations of this dataset. First, the reported position is aggregated at the firm level (i.e., fund house) so it is empirically challenging to identify the position changes of one mutual fund in a big fund house. Therefore, we only conduct this analysis for the group of HF&PE in our sample, which typically manages a small number of portfolios. We manage to identify 128 HF&PE in the 13F database that match with our sample. Second, short-sale positions are not required to disclose, and thus we can not observe any changes in the short portfolios of these investors. The third limitation is that the reported position only provides a snapshot of institutional holdings at each quarter end, while in reality there are many unobservable holding changes taking place during the interval of two quarters; fourth, we do not in fact observe the exact time and price when each share trade is purchased, i.e., we cannot compute the initial weight of capital invested in each stock. Our research design adopts two approximation methods to mitigate the third and the fourth concerns. We first assume no intermediate position turnovers, and use the reported number of shares (scaled in millions) to proxy for the true position. We further assume that the initial capital weight of each stock is based on the closing price on the report day when the stock first appears in the portfolio during the observation period.

The main specification of this test is provided in Equation (4) below and the timeline for this research setup is illustrated in Figure 2.

$$\begin{aligned} Y_{i,j,t} = \alpha_i + \beta \text{ Post Dummy}_{i,t} + \rho \text{ Cover Dummy}_{j,t} + ... \\ + \gamma \text{ Post Dummy}_{i,t} \times \text{Cover Dummy}_{j,t} + \epsilon_{i,j,t}, \end{aligned} \tag{4}$$

where $Y_{i,j,t}$ is the average position of stock j at time t in the buy-side firm that hires analyst i. $Post\,Dummy_{i,t}$ is an indicator variable and equals one if the holding is during period half year (i.e. $E + 0.5Y$ in Figure 2) to one and one-half years (i.e. $E + 1.5Y$ in Figure 2) after analyst i ends IBES employment (i.e., Period 3 in Figure 2), $Cover\,Dummy_{j,t}$ is also an indicator variable and equals one if the stock j is followed by analyst i. To assess the sensitivity of the portfolio's response to the treatment effect, we also specify two pre-event periods. The first is the period during 1.5 years to 0.75 year before the end of employment (i.e., Period 1 in Figure 2), and the second is the period during 0.75 year before and to the end of employment (i.e., Period 2 in Figure 2). Therefore, using the holdings during one pre-period and post period, we apply the Equation (3) respectively for Periods 1 and 2, and the difference in coefficients between these two specifications should reflect how sensitive the buy-side portfolio (i.e., the long side) reacts to the need for hiring the sell-side analysts.

Finally, we use a Pseudo test, in which we assign an event time that is 0.75 year before the actual event time to provide a robustness check to our DID results. The Pseudo test is conducted between Periods 1 and 2, both of which happen before the true event. Therefore, we should not observe any treatment effect in our Pseudo test. We also add analyst turnover fixed effect as control in all specifications.

[Insert Table 7 Here]

Columns (1)–(3) of Table 7 show the result for using adjusted shares number to proxy for the holding position. Column (1) reports the results for the treatment effect between Periods 1 and 3, whereby column (2) reports those between Periods 2 and 3. The variables of interests are the coverage dummy and the interaction dummy between time and coverage. It shows that the average number of shares is 0.159 million to 0.306 million higher in the treatment group, implying that the stocks followed by the analysts have more shares relative to those that are not, even before the career turnovers. This observation is consistent with the "selection" hypothesis. The coefficient in the interaction term is not significant and this suggests the lack of evidence for the "impact" story: there is no significant divergence in the difference of shares between the treatment and control groups after the turnover event. Finally, column (3) shows that the result for the Pseudo test exhibits no treatment effect.

Columns (4) - (6) of Table 7 apply the same specifications as those in columns (1) - (3) but replace the dependent variable by the value-weight proxy. Instead of using the raw number of shares, this proxy specification provides an approximation to the relative dollar position of each stock in the fund's portfolio. We keep the price adjustment constant throughout the comparison period so that this variable reflects the change in position that is not driven by the price. Similarly to the findings in the last paragraph, the empirical evidence seems to support the "selection" hypothesis as the existing portfolios on average have 0.10% to 0.15% more value-weight in each stock in the treatment group, before and after the job turnovers.

6 Conclusions

In this paper we investigates equity analyst's characteristics that affect her likelihood of exit to buy-side institutions. We first document that the implicit assumption that all leaving analysts are bad performers is not supported by our data. Our empirical result distinguishes analysts leaving to buy-side from other sell-side leaving analysts to show that the former do not systematically underperform those who stay in the sell-side. We then provide empirical evidences to uncover the linkage between analyst's characteristic and distinctive features of buy-side career. We find that unlike with-in sell-side movers and "revolving-door" analysts, prospective buy-side analysts do not exhibit strategic behaviours such as herding and optimistic. Instead they are more portfolio-oriented and focus on fundamental analysis. We also show some preliminary evidences that former sell-side analysts are not hired by buy-side to make stock recommendations unrelated to existing portfolios, but rather to improve the research in stocks with relatively high existing positions. While our findings provide some preliminary support for the "selection" hypothesis, it is important to stress that the robustness of this result can be further improved if it is supplemented with data from additional hedge fund databases.

In summary, our study is the first to conducting a comprehensive analysis on the determinants of equity analysts' transition from sell-side to buy-side. Our results have the potential to contribute to the literature on the matching theory, career concern theory and fund performance theory. We have shown that buy-side job turnover seems to be a result of the labor market equilibrium. The buy-side job opportunity, in particular that at active funds, has positive effect on the ex-ante incentive to exert analyst's efforts to perform. In addition, our work contributes to the on-going debate on the cost and benefit of actively managed fund. The need to attract valuable human capital by competing with sell-side provides some justification to the higher fixed cost and variable cost of active fund.

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Tables and Figures

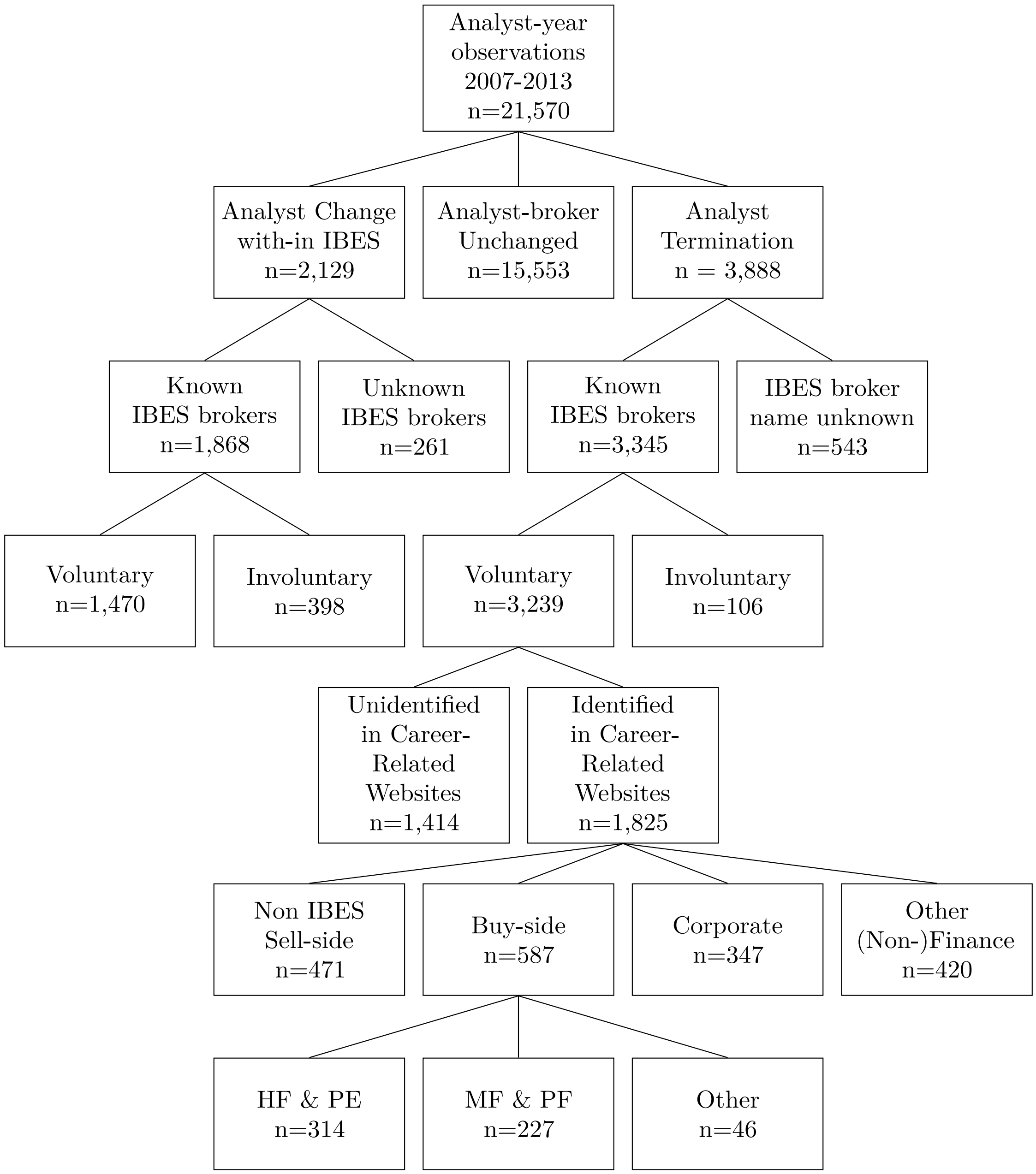

Figure 1: This figure shows how we track sell-side analysts with at least one year I/B/E/S experience to identify their career turnovers. The number in each node indicates the number of job turnovers in this category. HF & PE indicate the number of sell-side analysts transition to hedge funds or private equity firms. MF & PF indicate the number of sell-side analysts transition to mutual funds or pension funds.

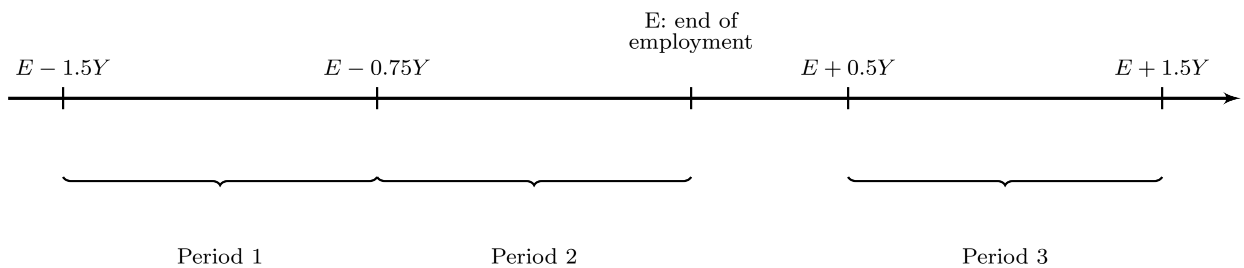

Figure 2: *Notes.* This figure describes the timeline of our empirical setup used to generate the results shown in Table 7.

Table 1: Summary Statistics

Our main dataset is organized at the analyst-year level for the sample period from 2007 to 2013. To be included in our sample for year *t*, an analyst must make at least one one-year-ahead earnings forecast in year *t* and must have made earnings forecasts covering one or more firms for at least one year by the end of year *t*. Panel A presents the time-series distributions of all analysts in I/B/E/S, analysts whose forecasts are terminated in I/B/E/S (i.e., "exiting" analysts), "exiting" analysts whose complete career histories can be identified by online search, and analysts who move from the sell-side to the buy-side in each year within our sample period. Panel B reports the summary statistics of analyst characteristics in the full sample. Panel C reports the summary statistics of analyst characteristics for the sample of analysts moving from the sell-side to the buy-side. Detailed definitions of all variables are provided in Appendix A.

Panel A: General Description

Year	Total Number of Analysts	Number of Analysts Leaving IBES	Number of Analysts Found Online	Number of Analysts Moving to the Buy-Side
2007	3067	535	167	86
2008	3126	754	369	122
2009	2770	484	248	62
2010	2888	416	214	63
2011	3211	532	255	85
2012	3279	625	312	87
2013	3229	542	260	82
Total	21570	3888	1825	587

Panel B: Characteristics of All Analyst-Years in I/B/E/S

	N	**Mean**	**SD**	**p25**	**Median**	**p75**
Accuracy	21570	52.80	15.04	46.16	54.03	60.78
Boldness	21570	47.69	14.86	40.05	46.47	54.05
Optimism	21570	49.76	14.98	42.39	49.93	57.12
Breadth - Firm	21570	11.68	8.12	5.00	11.00	17.00
Avg. Coverage	21570	17.02	8.22	11.00	16.17	21.73
Affiliated Analyst	21570	0.05	0.22	0.00	0.00	0.00
All-Star	21570	0.11	0.31	0.00	0.00	0.00
Seniority IBES	21570	9.56	6.64	4.40	8.37	13.01
Seniority Broker	21570	6.84	6.09	2.11	5.23	9.74
Inst. Ownership	21570	0.67	0.25	0.60	0.75	0.83
Male	21570	0.94	0.23	1.00	1.00	1.00

Panel C: Characteristics of Analysts Leaving for Buy-side

	N	Mean	SD	p25	Median	p75
Accuracy	587	54.69	12.90	46.99	54.03	60.83
Boldness	587	47.60	12.90	40.27	47.04	54.43
Optimism	587	50.92	13.59	43.33	51.00	58.34
Breadth - Firm	587	10.73	7.19	5.00	10.00	15.00
Avg. Coverage	587	16.55	7.99	10.92	15.75	21.00
Affiliated Analyst	587	0.06	0.25	0.00	0.00	0.00
All-Star	587	0.06	0.24	0.00	0.00	0.00
Seniority IBES	587	5.65	5.37	1.97	3.85	7.05
Seniority Broker	587	5.47	5.39	1.71	3.75	7.17
Inst. Ownership	587	0.70	0.25	0.63	0.76	0.86
Male	587	0.95	0.22	1.00	1.00	1.00

Table 2: Prior Forecast Accuracy and The Likelihood of Forecast Termination in I/B/E/S

This table reports the relationship between prior forecast accuracy and the probability of forecast termination in I/B/E/S based on an linear probability model. The dependent variable, *Leaving IBES*, is defined as an indicator variable that equals to 1 if an analyst whose forecasts are reported in I/B/E/S in year t cannot be identified in I/B/E/S in the following year, i.e., year $t+1$. *0-through-5* is an indicator variables that equals to 1 if an analyst's relative accuracy rank is between the 0th and the 5th percentile in year t. *5-through-10, 10-through-25, 25-through-50, 50-through-75* are defined similarly. *Score* is a continuous measure of forecast accuracy proxied by the percentile of an analyst's accuracy rank in year t. Detailed definitions of other control variables are provided in Appendix A. We include year, industry, and broker fixed effects in all specifications. t-statistics (in parentheses) are based on standard errors clustered at the broker level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Probability of Leaving IBES		
	(1)	(2)	(3)
Accuracy Percentile Dummy:			
0-through-5	0.0357**	0.0665***	
	(2.17)	(3.82)	
5-through-10		0.0476**	
		(2.53)	
10-through-25		0.0628***	
		(6.40)	
25-through-50		0.0428***	
		(6.06)	
50-through-75		0.0245***	
		(3.28)	
Accuracy			-0.00125***
			(-5.35)
Breadth - Firm	-0.00724***	-0.00738***	-0.00736***
	(-12.98)	(-13.02)	(-13.17)
Avg. Coverage	-0.00000255	0.0000632	0.0000196
	(-0.01)	(0.14)	(0.04)
Affiliated Analyst	0.0142	0.0120	0.0128
	(1.26)	(1.07)	(1.14)
All-Star	-0.0295**	-0.0270**	-0.0278**
	(-2.32)	(-2.18)	(-2.21)
Seniority Broker	-0.00155**	-0.00170**	-0.00165**
	(-2.30)	(-2.51)	(-2.48)
Top10 Broker	0.0417	0.0426	0.0424
	(1.12)	(1.15)	(1.14)
Male	-0.0359***	-0.0347***	-0.0354***
	(-2.74)	(-2.67)	(-2.71)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes
N	21510	21510	21510
R^2	0.105	0.107	0.107

Table 3: Prior Forecast Accuracy and The Likelihood of Forecast Termination in I/B/E/S: Career Transition to Buy-Side Institutions

This table reports the relationship between prior forecast accuracy and the probability of forecast termination in I/B/E/S conditional on whether the forecast termination is driven by analysts' career transition to buy-side institutions. The dependent variable in columns (1)–(3), *Leaving IBES*, is defined as an indicator variable that equals to 1 if an analyst whose forecasts are reported in I/B/E/S in year t cannot be identified in I/B/E/S in year $t+1$ and the disappearance is driven by the analyst's career transition to a buy-side firm. The dependent variable in columns (4)–(6), *Leaving IBES*, is defined as an indicator variable that equals to 1 if an analyst whose forecasts are reported in I/B/E/S in year t cannot be identified in I/B/E/S in year $t+1$ and the disappearance is not driven by the analyst's career transition to a buy-side firm. *0-through-5* is an indicator variables that equals to 1 if an analyst's relative accuracy rank is between the 0th and the 5th percentile in year t. *5-through-10, 10-through-25, 25-through-50, 50-through-75* are defined similarly. *Score* is a continuous measure of forecast accuracy proxied by the percentile of an analyst's accuracy rank in year t. We include the same set of control variables as those reported in Table 2 in all test specifications. Detailed definitions of these control variables are provided in Appendix A. We include year, industry, and broker fixed effects in all test specifications. t-statistics (in parentheses) are based on standard errors clustered at the broker level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Probability of Leaving to the Buy-Side			Probability of Leaving to the Non-Buy-Side		
	(1)	(2)	(3)	(4)	(5)	(6)
Percentile Dummy:						
0-through-5	−0.0394***	−0.0362***		0.0605***	0.0914***	
	(−9.63)	(−7.12)		(3.63)	(5.20)	
5-through-10		−0.00287			0.0695***	
		(−0.35)			(3.79)	
10-through-25		0.00257			0.0593***	
		(0.55)			(5.98)	
25-through-50		0.00833**			0.0389***	
		(2.46)			(5.88)	
50-through-75		0.00787**			0.0199***	
		(2.14)			(2.95)	
Continuous Measure:						
Score			0.000245**			−0.00148***
			(2.35)			(−6.55)
Analyst Controls	Yes	Yes	Yes	Yes	Yes	Yes
Broker Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes	Yes	Yes	Yes
N	18211	18211	18211	20921	20921	20921
R^2	0.032	0.032	0.031	0.112	0.115	0.114

Table 4: Prior Forecast Accuracy and The Likelihood of Forecast Termination in I/B/E/S: Career Transition to Specific Types of Buy-Side Institutions

This table reports the relationship between prior forecast accuracy and the probability of forecast termination in I/B/E/S conditional on whether the forecast termination is driven by analysts' career transition to specific types of buy-side institutions. The dependent variable in columns (1)–(2), *Leaving IBES*, is defined as an indicator variable that equals to 1 if an analyst whose forecasts are reported in I/B/E/S in year *t* cannot be identified in I/B/E/S in year *t+1* and the disappearance is driven by the analyst's career transition to a hedge fund or a private equity firm. The dependent variable in columns (3)–(4), *Leaving IBES*, is defined as an indicator variable that equals to 1 if an analyst whose forecasts are reported in I/B/E/S in year *t* cannot be identified in I/B/E/S in year *t+1* and the disappearance is driven by the analyst's career transition to a mutual fund or a pension fund. *0-through-5* is an indicator variables that equals to 1 if an analyst's relative accuracy rank is between the 0th and the 5th percentile in year *t*. *5-through-10, 10-through-25, 25-through-50, 50-through-75* are defined similarly. *Score* is a continuous measure of forecast accuracy proxied by the percentile of an analyst's accuracy rank in year *t*. We include the same set of control variables as those reported in Table 2 in all test specifications. Detailed definitions of these control variables are provided in Appendix A. We include year, industry, and broker fixed effects in all test specifications. *t*-statistics (in parentheses) are based on standard errors clustered at the broker level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Probability of Leaving to HF and PE		Probability of Leaving to MF and PF	
	(1)	(2)	(3)	(4)
Percentile Dummy:				
0-through-5	-0.0208***		0.00356	
	(-6.36)		(0.59)	
5-through-10	-0.00693		-0.00341	
	(-1.30)		(-0.63)	
10-through-25	0.00115		-0.000349	
	(0.32)		(-0.12)	
25-through-50	0.00295		0.00275	
	(1.06)		(1.12)	
50-through-75	0.00139		0.00416**	
	(0.46)		(2.27)	
Continuous Measure:				
Score		0.000182**		-0.0000155
		(2.38)		(-0.27)
Analyst Controls	Yes	Yes	Yes	Yes
Broker Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Broker FE	Yes	Yes	Yes	Yes
N	17943	17943	17861	17861
R^2	0.028	0.027	0.023	0.023

Table 5: Analysts Characteristics and Job Turnovers

This table reports the coefficients of linear probability models on the determinants for analysts moving to buy-side institutions. The dependent variable is an indicator variable that equals 1 if an analyst moves to a buy-side institution in year *t+1*, and 0 if she stays within the benchmark group. The benchmark group for the test reported in columns (1) includes analysts with no job transitions; the benchmark group for the tests reported in columns (2) and (3) includes analysts that move to other brokerage firms covered by I/B/E/S; the benchmark group for the tests reported in columns (4) and (5) includes analysts that move to sell-side firms not covered by I/B/E/S; the benchmark group for the tests reported in columns (6)and (7) includes analysts that move to corporations; the benchmark group for tests reported in columns (8) and (9) includes analysts that move to other organizations (e.g., government, universities and non-profitable organizations). Detailed definitions of all variables are provided in Appendix A. We control for year and industry fixed effects in all test specifications. *t*-statistics (in parentheses) are based on standard errors clustered at the broker level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	No Change=0 Buy-side=1	IBES sell-side=0 Buy-side=1		Non-IBES sell-side=0 Buy-side=1		Corporate=0 Buy-side=1		Non-Finance=0 Buy-side=1	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Accuracy	0.000105	-0.000604	-0.00134	0.00501***	0.00350***	0.00317***	0.00187	0.00367***	0.00243*
	(0.94)	(-0.87)	(-1.05)	(5.56)	(3.39)	(2.89)	(1.54)	(3.46)	(1.96)
Boldness	0.000253**	0.00110	0.000639	0.0000815	-0.0000495	0.000291	-0.000463	-0.000905	-0.00107
	(2.21)	(1.56)	(0.63)	(0.07)	(-0.04)	(0.25)	(-0.40)	(-0.76)	(-0.82)
Optimism	0.000214**	0.00148***	0.00266***	0.000804	0.000286	0.000745	0.00101	0.000408	0.000324
	(2.12)	(2.76)	(2.96)	(0.80)	(0.25)	(0.78)	(0.99)	(0.44)	(0.28)
Breadth - Firm	-0.000758***	-0.00461***	-0.00699***	0.00867***	0.00628**	0.00385	0.00202	0.00529**	0.000365
	(-3.80)	(-3.10)	(-2.94)	(4.32)	(2.49)	(1.52)	(0.76)	(2.40)	(0.15)
Avg. Coverage	-0.000255	-0.00229	-0.000453	-0.00244	-0.000971	-0.00348	-0.00144	-0.000850	-0.0000594
	(-1.09)	(-1.40)	(-0.17)	(-1.13)	(-0.37)	(-1.59)	(-0.63)	(-0.42)	(-0.03)
Affiliated Analyst	0.0114	0.00106	-0.0492	0.0320	-0.0169	-0.0167	-0.0591	0.0778	0.0525
	(1.30)	(0.02)	(-0.83)	(0.51)	(-0.25)	(-0.20)	(-0.68)	(1.37)	(0.80)
All-Star	-0.0177***	-0.101***	-0.0987***	-0.131**	-0.116	-0.144*	-0.146*	-0.0319	-0.0232
	(-4.10)	(-4.72)	(-2.82)	(-2.51)	(-1.53)	(-1.94)	(-1.93)	(-0.50)	(-0.36)
Seniority Broker	-0.00108***	-0.00528***	-0.00333	-0.00224	-0.00438	-0.00338	-0.00469	-0.0103***	-0.00950***
	(-4.18)	(-2.93)	(-1.06)	(-0.73)	(-1.22)	(-1.16)	(-1.27)	(-3.41)	(-2.85)
Top10 Broker	0.0172***	0.139***	0.0910*	0.0822**	0.0814**	0.102***	0.0842**	0.119***	0.0923***
	(3.30)	(3.47)	(1.76)	(2.43)	(2.00)	(3.07)	(2.18)	(3.42)	(2.79)
Male	-0.00160	0.0283	0.0379	0.148**	0.156**	0.0546	0.0684	0.171***	0.188**
	(-0.24)	(0.89)	(0.78)	(2.39)	(2.24)	(0.68)	(0.77)	(2.87)	(2.39)
Institutional Ownership	0.0299***	0.133***	-0.00613	0.237***	0.232***	0.123**	0.0909	0.208***	0.138**
	(2.84)	(2.78)	(-0.08)	(3.59)	(2.76)	(2.13)	(1.43)	(3.79)	(2.01)
MBA			0.164***		-0.0305		0.0133		-0.0611
			(2.80)		(-0.51)		(0.20)		(-1.12)
Postgraduate			0.0338		-0.114		-0.0919		-0.0609
			(0.42)		(-1.65)		(-1.40)		(-0.94)
Corporate Experience			-0.0441		-0.0194		-0.162***		-0.0582
			(-1.27)		(-0.43)		(-3.43)		(-1.35)
Buyside Experience			0.128***		0.130***		0.172***		0.115***
			(3.39)		(2.96)		(3.52)		(2.78)
Speciality Major			0.136**		0.0466		0.123*		0.137**
			(2.17)		(0.75)		(1.84)		(2.06)
Year & Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	16222	2334	1132	1059	751	956	717	1028	703
R^2	0.010	0.063	0.098	0.112	0.105	0.070	0.117	0.122	0.125

Table 6: Analysts Characteristics and Job Turnovers: Moving to Buy-Side Institutions

This table reports the coefficients of linear probability models on the determinants for analysts moving to specific typs of buy-side institutions. The dependent variable is an indicator variable that equals 1 if analyst is in the treatment group (analysts moving to HF&PE in columns (1) to (3) and analysts moving to MF&PF in columns (4) to (6)) and 0 if they belong to the benchmark group. The benchmark group for the test reported in column (1) includes analysts with no job turnovers; the benchmark group for the tests reported in columns (2)and (3) includes analysts that move to other brokerage firms covered by I/B/E/S). Detailed definition of all variables are provided in Appendix A. *t*-statistics (in parentheses) are based on standard errors clustered at the broker level. ***, **, and * mark significance at the 1%, 5%, and 10% levels respectively. The sample period is from January 2007 to December 2013.

	No-Change=0 HF & PE=1	IBES-Sellside=0 HF & PE=1		No-Change=0 MF & PF=1	IBES-Sellside=0 MF & PF=1	
	(1)	(2)	(3)	(4)	(5)	(6)
Accuracy	0.000300***	0.00135**	0.00190	-0.0000460	-0.00105*	-0.00226*
	(3.32)	(2.02)	(1.35)	(-0.81)	(-1.91)	(-1.74)
Boldness	0.000127	0.000736	0.000153	0.0000452	0.000226	0.000473
	(1.57)	(1.27)	(0.16)	(0.65)	(0.41)	(0.43)
Optimism	0.0000963	0.000815	0.00230*	0.000101	0.000850*	0.00139
	(1.50)	(1.57)	(1.95)	(1.47)	(1.80)	(1.38)
Breadth - Firm	-0.000297**	-0.00238**	-0.00532**	-0.000402***	-0.00338***	-0.00630**
	(-2.21)	(-1.99)	(-2.57)	(-3.15)	(-2.65)	(-2.61)
Avg. Coverage	-0.0000301	-0.000714	0.00209	-0.000150	-0.00169	-0.00182
	(-0.18)	(-0.59)	(0.83)	(-1.01)	(-1.28)	(-0.64)
Affiliated Analyst	0.00185	-0.0186	-0.0640	0.00682	0.00839	0.00189
	(0.30)	(-0.46)	(-1.10)	(1.46)	(0.28)	(0.04)
All-Star	-0.00956***	-0.0665***	-0.0589	-0.00803***	-0.0697***	-0.0667**
	(-2.62)	(-2.78)	(-1.55)	(-3.71)	(-3.96)	(-2.12)
Seniority Broker	-0.000409**	-0.00225	0.000746	-0.000595***	-0.00418***	-0.00537*
	(-2.19)	(-1.52)	(0.24)	(-3.82)	(-2.99)	(-1.83)
Top10 Broker	0.0132***	0.118***	0.0902	0.00413	0.0687**	0.0375
	(3.24)	(3.30)	(1.62)	(1.48)	(2.42)	(0.98)
Male	0.00115	0.0298	0.0208	-0.000826	0.0159	0.0519
	(0.29)	(1.17)	(0.41)	(-0.20)	(0.65)	(1.25)
Institutional Ownership	0.0180**	0.107**	-0.00863	0.00660	0.0457	-0.0509
	(2.54)	(2.57)	(-0.13)	(1.23)	(1.13)	(-0.59)
MBA			0.192***			0.0777
			(2.98)			(1.33)
Postgraduate			0.000961			0.0760
			(0.01)			(1.05)
Corporate Experience			-0.0206			-0.0531
			(-0.57)			(-1.57)
Buyside Experience			0.0411			0.175***
			(1.01)			(4.14)
Speciality Major			0.138**			0.0623
			(2.09)			(0.76)
Year & Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	15933	2045	906	15852	1964	853
R^2	0.008	0.048	0.090	0.005	0.057	0.119

Table 7: Changes in Institutional Holding Around Analyst Job Turnovers

This table reports the results from OLS regressions of Equation (4) to examine the investment position changes in the buy-side institutions before and after the firm hires the analyst from sell-side. *Post Dummy* is a binary variable that equals 1 if the stock positions are computed after the analyst's transition, and zero otherwise. *Cover Dummy* is a binary variable that equals 1 if the stocks are followed by the former sell-side analyst, and zero otherwise. t-statistics (in parentheses) are based on standard errors clustered at the broker level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable					
	Shares Number			Value Weight		
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.0408**	0.0370**		0.0001	-0.0000	
	(0.017)	(0.016)		(0.000)	(0.000)	
Covered	0.1588	0.3064**	0.1699	0.0014***	0.0010**	0.0015***
	(0.138)	(0.135)	(0.118)	(0.000)	(0.000)	(0.000)
Post × Covered	0.3126	0.1621		-0.0001	0.0003	
	(0.194)	(0.190)		(0.001)	(0.001)	
Pseudo_Post			0.0039			0.0001
			(0.014)			(0.000)
Pseudo_Post × Covered			0.1504			-0.0005
			(0.166)			(0.001)
Analyst-Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,074	124,074	124,074	124,074	124,074	124,074
R^2	0.056	0.059	0.063	0.105	0.106	0.114

Appendix A Variable Definitions

- *Accuracy* is the average value of relative *Accuracy Rank* for all firms followed by analyst i in year t. Similar to Hong, Kubik, and Solomon (2000), we scale it between 0 and 100. The *Accuracy Rank* is given by

$$Accuracy\ Rank = 100 - (\frac{Forecast\ Error\ Rank}{Number\ of\ Analysts\ Following - 1}) \times 100,$$

  where *Forecast Error* is the absolute difference between the forecast and actual earning.

- *Affiliated Analyst* is a dummy variable that equals one if the analyst's investment bank was the lead underwriter of an initial public offering (IPO) in the past five years, and zero otherwise.

- *All-Star* is a dummy variable equals one if the analyst is named to *Institutional Investor*'s All-American team during the past five years, and zero otherwise.

- *Analysts Following* is the number of analysts who follow this stock in a given year.

- *Breadth-Firm* is the number of stocks covered by the analyst in a given year.

- *Avg. Coverage* is the average analyst coverage (i.e., the number of analyst covering a firm) of firms covered by the analyst in a given year.

- *Broker Size* is a dummy variable that is equal to one if broker is among the largest 10 brokers by the number of analysts in a given year.

- *Boldness* is the average value of relative *Boldness Rank* for all firms followed by analyst i in year t. Following Hong, Kubik, and Solomon (2000), we scale it between 0 and 100. The *Boldness Rank* is calculated as

$$Boldness\ Rank = 100 - (\frac{Forecast\ Boldness\ Rank}{Number\ of\ Analysts\ Following - 1}) \times 100,$$

  where *Forecast Boldness* is the absolute difference between forecast of analyst i and the average of forecasts by all analysts other than i.

- *Buy-side Experience* is a dummy variable that is equal to one if the analyst has previously worked at buy-side.

- *Corporate Experience* is a dummy variable that is equal to one if the analyst has a previous corporate working (non-investment banking) experience.

- *Institutional Ownership* is the average of stock ownership held by institutional investors for all firms followed by analyst i in year t.

- *Optimism* is the average value of *Optimism Dummy* for all firms followed by analyst i in year t. *Optimism Dummy* is defined as one if earning forecast is higher than actual earning, and zero otherwise.

- *Postgraduate* is a dummy variable that is equal to one if the analyst indicates that he or she has a master(non-MBA) or Ph.D degrees on LinkedIn profile, and zero otherwise.
- *Seniority* is the number of years an analyst has been in the IBES database.
- *Specialty Major* is a dummy variable that is equal to one if the analyst has an educational degree specializing in the area related to the industry that she covers, and zero otherwise. For instance, if an analyst has undergraduate or post-graduate degree in computer science, and she also covers stocks in the relevant sector such as technology.

Table A1: Cross Correlation Matrix

Variables	Accuracy	Boldness	Optimism	Breadth	Breadth Industry	Seniority	Size	Affiliated Analyst	All-Star	Inst. Own.	Analyst Following
Accuracy	1.000										
Boldness	-0.430*	1.000									
Optimism	0.080*	-0.005	1.000								
Breadth	0.098*	-0.099*	-0.014	1.000							
Breadth-Industry	0.045*	-0.053*	-0.018	0.569*	1.000						
Seniority	0.066*	-0.058*	-0.000	0.336*	0.197*	1.000					
Size	-0.013	0.015	0.000	-0.046*	-0.099*	-0.065*	1.000				
Affiliated Analyst	0.005	-0.006	-0.008	0.197*	0.103*	0.065*	0.230*	1.000			
All-Star	0.043*	-0.038*	-0.006	0.246*	0.109*	0.275*	0.259*	0.180*	1.000		
Institutional Ownership	0.034*	-0.041*	0.027*	0.078*	0.065*	0.081*	0.110*	0.033*	0.110*	1.000	
Analysts Following	0.003	0.007	0.032*	0.085*	-0.073*	0.094*	0.007	0.030*	0.173*	0.286*	1.000