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 LinkedIn, we find that 40% 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 or more biased forecasts than analysts who remain in the sell-side industry. In fact, those with superior forecasting ability ended up at a hedge fund or a private equity firm. We find that analysts with specialized education related to the industry they cover are more likely to switch to the buy-side. Relatedly, buy-side funds hire a sell-side analyst for her expertise on stocks that the fund already holds relatively 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. For those leaving for the buy-side, their job turnover depends less on career-concern determinants.

Keywords: Career outcomes; Analyst forecasts; Sell-side; Buy-side
JEL Classification: 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 IBES database, i.e., career termination driven by 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 so-called "Queen of the Net" since the late 1990's and a long-time internet industry analyst, 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].

Using the novel dataset of sell-side analysts job turnovers, we show that a significant fraction of equity analysts that disappear from IBES (about 40%) 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 the IBES 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 IBES leave their job for a career at buy-side institutions, and importantly, these analysts are not underperformers. That is, prospective buy-side analysts do not make less accurate earnings forecasts than their colleagues who remain or make career moves within the sell-side industry captured by IBES. 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 to address this problem by using the LinkedIn dataset to identify leaving analysts by their prospective job categories. Consistent with Hong, Kubik, and Solomon (2000), Hong and Kubik (2003), we find that analysts who make less accurate earnings forecasts, in general, are

[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."

more likely to disappear from the IBES — regardless of the reason. Nevertheless, the relationship between forecast accuracy and job turnover is not monotonic and the result mostly comes from analysts whose accuracy lies in the bottom fifth percentile of the population. On the other hand, we find the results linking poor forecasting performance to job turnovers are stronger and become monotonically clear once we exclude analysts who leave for a buy-side career. 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 the career termination of sell-side analysts, we do not observe such association between boldness and moves to buy-side career. We also find that buy-side career turnover moves have little to do with analysts' forecast optimism and 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 stock and industry, 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 LinkedIn profile. 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*), but declines with postgraduate education. 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 IBES 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 IBES, 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

We use the IBES Stopped Estimation File to identify analysts whose forecasts are terminated during the period between January 2007 and December 2013. Our sample period starts from 2007 because LinkedIn does not have a good coverage of career information in earlier period. We only focus on analysts covering U.S. listed firms. For an analyst to be included in the sample, we require that she must have made earnings forecasts for at least one year in IBES before her forecast is terminated. This filter allows us to compute analyst characteristics prior to their forecast terminations.

We obtain characteristics of analysts, their brokerage houses, as well as firms' earnings announcements data from IBES. Following Hong and Kubik (2003) and Clement and Tse (2005), we focus on one-year-ahead forecasts. We retain the last forecast that an analyst issues for a particular fiscal year. 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.

We retrieve data from Thomson-Reuters Institutional Holding (13F) to compute stock holdings of buy-side institutions. This database contains ownership information by financial institutions with $100 million or more in assets under management (AUM). Stock trading information, such as stock prices, trading volume, and the number of shares outstanding are obtained from CRSP.

2.2 Analyst Career Transitions

In order to identify analysts' career history before and after their forecast terminations in IBES, we search analysts' career profiles in LinkedIn. Their profile pages contain self-reported information including education, past and current employers, employment positions, and the start time and end time of each employment. This information allows us to identify the first job an analyst obtains after her forecast is terminated in IBES. Based on earning forecasts made by all analysts in IBES from 2007 to 2013, we are able to identify $20,846$ analyst-broker terminations that meet our requirements.

Figure 1 provides a flow-chart structure of our sample. As shown here, forecast terminations in IBES can be characterized in the following three situations. First, an analyst changes her job from one IBES brokerage to another IBES brokerage. In this case, IBES assigns a new analyst ID to the moving analyst. As indicated by Hong and Kubik (2003), this situation reflects either a "promotion" or a "demotion" of an analyst's career, depending on whether she is moving to a larger or a smaller brokerage firm relative to her existing employer. As shown in Figure 1, we find that $2,129$ of them are classified as within-IBES job turnovers.

In the second situation, an analyst changes her job within the same brokerage firm and her new position no longer requires her to issue earnings forecasts, e.g., an analyst moves from the research department to an investment banking division or an analyst is promoted as the head of the research department. This situation represents about three-quarter of analyst-broker terminations reported in IBES. Figure 1 shows that $15,544$ of these analysts-broker terminations in IBES do not lead to changes in the analysts' affiliations. In this case, the forecast termination in IBES is due to a change of responsibilities within the same firm.

In the third situation, an analyst leaves an IBES brokerage to join a non-IBES brokerage/organization, which is the focus of our study. Figure 1 shows that $3,173$ of them are classified as leaving IBES. We collect information about analysts who left IBES as follows. We first eliminate leaving sell-side analysts from very small brokerage firms. Specifically, we identify all major brokerage firms following the procedure used in Nolte, Nolte, and Vasios (2014). We are able to identify 98 brokerage firms that have at least 20 analysts leaving IBES during our sample period. Analysts from these 98 brokerage firms account for 82% (i.e., $2,592$ observations) of all analysts that left IBES.

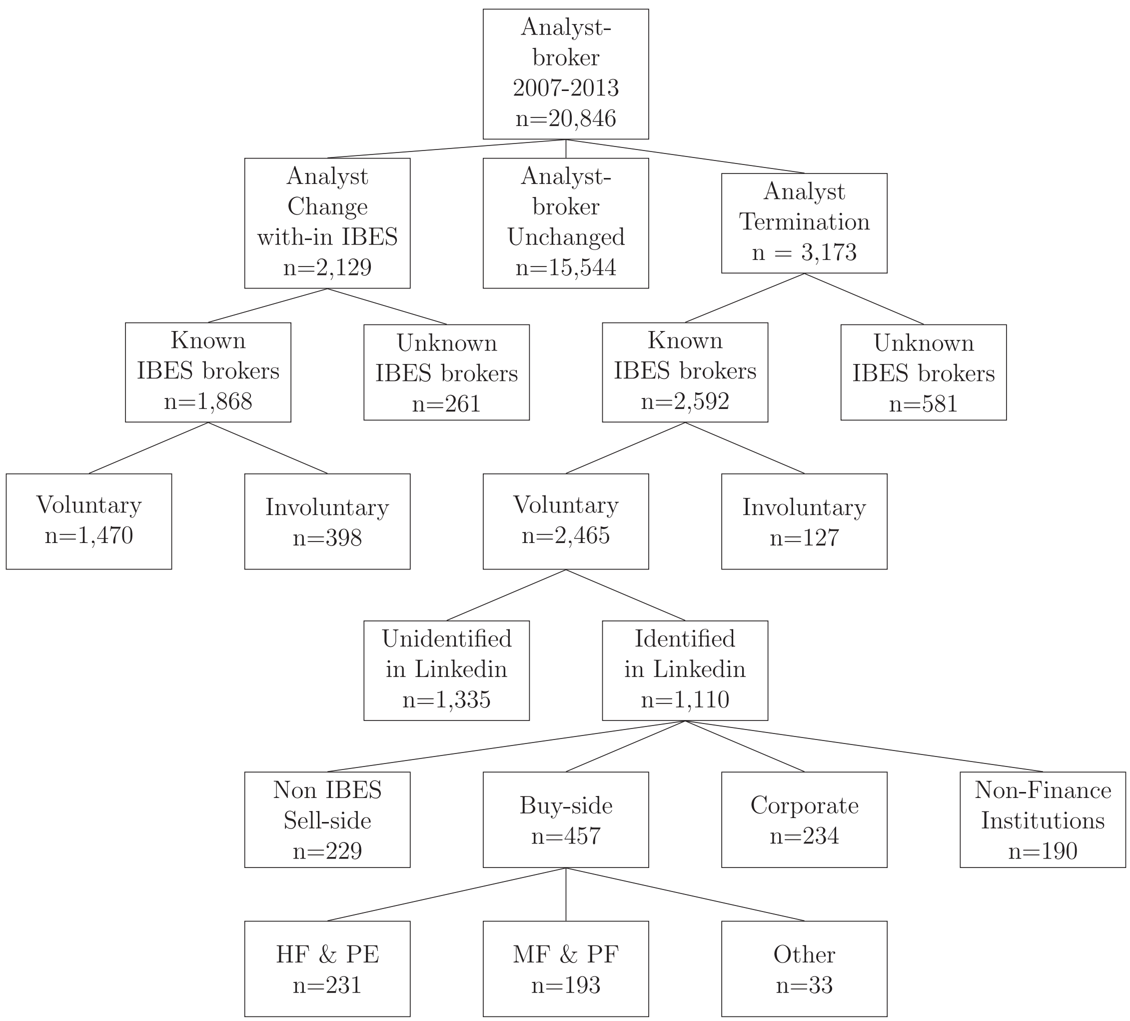
Among IBES-exiting analysts, their job turnover can be voluntary as well as involuntary. For instance, the analyst is headhunted by an external firm, the analyst self-initiates a new job search, or the analyst leaves her current brokerage firm to establishes a new firm. In these cases, the job turnover is likely a voluntary decision. On the other hand, an analyst can be forced to find a new job because her brokerage firm closes down for reasons that are plausibly unrelated to her performance. These involuntary job turnovers are studied in Cen, Chen, Dasgupta, and Ragunathan (2016). In this paper, we focus on job turnovers of analysts from IBES brokerages to non-IBES firms that are not forced by brokerage closure. There are $2,465$ analysts that fall into this category in our sample period.

For these remaining $2,465$ analysts whom we have verified as having left IBES, we search for their complete career history in LinkedIn. A typical LinkedIn profile contains a person's full name, a brief employment history with all their employers' names, the start and end date of each job, affiliated departments/divisions, and job titles. To avoid potential mismatches, we require the above four pieces of information on the LinkedIn page are consistent with those of analysts who are leaving IBES. We also require that the LinkedIn 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 IBES. Importantly, we only consider analysts' new employment that is obtained within one year after their last forecasts were reported in IBES. We impose this maximum one-year transition gap to ensure a meaningful economic association between analyst characteristics before their forecast termination and their new employment. This conservative criteria for matching records in LinkedIn reduces the sample of IBES-exiting analysts by about half, resulting in the final sample of $1,110$ LinkedIn-verified job turnovers.

As shown in Figure 1, we classify new employments of analysts leaving IBES into four categories: (1) sell-side firms that are not captured in the IBES, e.g., independent boutique research firms; (2) buy-side financial institutions; (3) corporate employers; and (4) other jobs, e.g., government agencies, universities and other non-profitable organizations. Analysts moving to buy-side firms are the focus of this paper. Therefore, we further partition analysts captured by group (2) into three subgroups. The 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 buy-side firms in the first 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, and insurance companies.

In our final sample of all $1,110$ identified job turnovers, we find that 229 analysts move

Figure 1: IBES Analysts Identified by Linkedin: Sample Structure
This figure shows how we track sell-side analysts with at least one year IBES experience to identify their job transitions. The number in each node indicates the number of job transitions 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.



into non-IBES sell-side firms, 457 analysts become buy-side analysts or managers, 234 analysts find corporate jobs, and 190 analysts join other non-financial organizations[2]. Overall, the LinkedIn search results show that moving to the buy-side is the most popular career choice for sell-side analysts after they exit the sell-side industry. More precisely, we find that 41% of these IBES-exiting analysts join buy-side institutions within a one-year period after their last forecasts were reported in IBES.[3]

2.3 Sample Description

Panel A of Table 1 presents a time-series descriptive of our dataset. The full sample consists of 20,846 analyst-year job-turnover observations from 2007 to 2013. During this period, 3,173 analysts have their forecasts terminated in IBES, which is equivalent to 14.9% of our sample. Among these 3173 analysts with stopped forecasts, 457 of them find jobs at buy-side financial institutions within one year after their last forecasts appeared in IBES.

We observe some interesting time-series patterns of analyst career turnovers in Panel A. The percentage of total analysts with stopped forecasts (i.e., leaving IBES) peaks in 2008 amid the financial crisis. Further, the percentage of analysts moving to buy-side institutions reaches its trough in 2009. This suggests that it is more difficult for sell-side analysts to keep their jobs or move to buy-side institutions during financial crises. To ensure that our main results are not affected by these time-series patterns in analyst career turnovers, we control for year-fixed effects in all test specifications.

Panel B of Table 1 summarizes analyst characteristics for the full sample, while Panel

[2]In the end, the found and search ratio is close to 50%, which is consistent with Bradley, Gokkaya, and Liu (2017).

[3]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).

C summarizes analyst characteristics for the subsample of analysts who move to buy-side firms. We report 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 similar ways.

Panel B of Table 1 shows that the ranks of a typical analyst in our sample, in terms of accuracy, boldness and optimism, are all close to the 50th percentile. This is expected because we apply a percentile-ranking measure to these variables. The median numbers of stocks and industries followed by an analyst in a given year are 11 and 3, respectively. *Seniority* indicates the number of years that an analyst has been issuing forecasts as reported in IBES. An analyst spends 6.83 years on average in IBES, but the distribution is skewed. The 10th percentile of *Seniority* is 0.76 and the 90th percentile is 15.05. We find that 10% of all analysts in our sample are affiliated with brokerage firms that provide investment banking services to the firms they cover. An analyst is considered to be affiliated 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 the firm that she covers. 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 17.03 analysts in a year, and has 72% of its stocks held by institutional investors.

Panel C of Table 1 reports similar characteristics for analysts who exit the sell-side industry for employment at buy-side firms. Comparing mean statistics in Panels B and C, we do not find that analysts moving to buy-side firms are significantly different from a typical analyst in IBES in terms of accuracy, boldness, optimism, and breadth of coverage. However, they are more junior and less likely to attain the All-star status than a typical analyst in IBES.

[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 IBES increases by 48.6%, whereas the number of financial institutions in the 13F database increases by 82.1% during the same period. The increase in the proportion of buy-side institutions in the financial industry offers increasingly more job opportunities for sell-side analysts to transition 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 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 exiting their industry to establish buy-side institutions themselves.[4].

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 turnover 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 IBES sample is remote." Given the changing landscape of the financial industry, such an assumption may no longer apply to sell-side analysts in the recent sample. 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 IBES may be related to other factors rather than career-concern determinants as documented in prior studies.

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

3 Career Concerns and Forecasting Performance

3.1 Likelihood of Analysts' Career Turnover

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

$$\begin{aligned}\text{Leaving IBES}_{i,t+1} = \alpha + \beta \text{ Forecast Accuracy Indicator}_{i,t} + \text{Control Variable}_{i,t} + \\ + \text{Fixed Effect}_{i,t} + \epsilon_{i,t+1}.\end{aligned} \tag{1}$$

In Equation (1) above, the dependent variable, *Leaving IBES*$_{i,t+1}$, is a dummy variable that is equal to one if the analyst leaves the IBES sample in year $t+1$ and zero otherwise.[5]. All control variables are constructed identically as in Hong, Kubik, and Solomon (2000) and their detailed definitions are included in Appendix A.

Columns (1) and (2) of Table 2 report baseline results. *Forecast Accuracy Indicator*$_{i,t}$ is an indicator variable that is equal to 1 if the analyst's *Accuracy* score falls within the designated percentile range. For instance, in column (1), this variable is equal to 1 if the analyst i's forecasting accuracy falls within 0 through 5 percentiles of the entire sell-side analyst population in IBES in year t.

Consistent with Hong, Kubik, and Solomon (2000), we find that the most inaccurate analysts are the mostly likely ones to leave IBES sample in year $t+1$. Results in column (1) of Table 2 show that an analyst whose forecasts rank in bottom of the accuracy score

[5]This variable is defined identically as the *Job Separation* measure in Hong, Kubik, and Solomon (2000). Our objective is to identify and isolate a sub-sample of sell-side analysts who move to the buy-side voluntarily, and thus, we name the dependent variable differently to avoid potential confusions.

distribution in year t is 5.0% more likely to leave the IBES sample than other analysts in year $t+1$. This economic magnitude, i.e., 5.0%, is higher than that (i.e., 3.8%) reported in Hong, Kubik, and Solomon (2000). One possible explanation is that the career in sell-side analyst research has become more competitive in the recent years and, therefore, the results became more sensitive to analysts' performance. In column (3), we replace the percentile indicator variables with the continuous score measure. Consistent with our results in column (1), the coefficient on the continuous score measure is negative and statistically significant at the 1% level, indicating that lower forecast accuracy is associated with analysts termination in IBES.

Although we find a negative relationship between forecast accuracy and the probability of analysts termination in IBES, such relationship is not monotonic. This important observation is illustrated in column (2) of Table 2. Here, we estimate the probability of analysts' termination in IBES against their forecast accuracy at various percentile-range groups. In column (2), the coefficient estimates on *Forecast Accuracy Indicator* represent the difference in the probability of exiting IBES between analysts in various forecast accuracy groups relative to analysts in the most accurate group (i.e., the benchmark group). For example, as reported in column (2), analysts in the "25-through-50" group have a higher probability of exiting IBES than analysts in both the "10-through-25" and "50-through-75" groups. This finding starkly contrasts the main results in Hong, Kubik, and Solomon (2000), which estimate a similar model using analysts' job turnover records in IBES before 2000.

We also statistically test for the difference in probabilities of exiting IBES between various pairs of analyst forecasting-accuracy groups (untabulated). We find that the difference is only significant when comparing 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. In other words, we find that the negative relationship between IBES termination and forecasting skill mostly derives from analysts whose forecast accuracies are ranked in both extreme ends (i.e., best or worst) of the population.

[**Insert Table 2 Here**]

Overall, using a more recent IBES termination sample, we reach two conclusions. First, results in Table 2 indicate a *stronger* link between analysts whose forecast accuracy are in the lowest group ("0-through-5") and their probability of being terminated in IBES. This suggests that analysts with the least forecasting accuracy face greater termination risk in the recent period. Second, results in Table 2 show that the sensitivity between forecast accuracy and the probability of exiting IBES no longer holds for analysts in the middle-accuracy groups, i.e., those in neither the most accurate nor the least accurate group. In other words, different from Hong, Kubik, and Solomon (2000), we find that for most sell-side analysts, their forecasting skill no longer appears to affect their likelihood of termination in IBES. A natural conjecture that can explain these seemingly inconsistent conclusions is the growth in external career opportunities for sell-side analysts over the recent decade. As a result, several sell-side analysts, particularly those in the middle groups, may have left their industry for other reasons instead of poor performance. We examine this conjecture next.

3.2 Likelihood of Career Turnover to Buy-Side Firms

We repeat our tests reported in Table 2 by isolating analysts moving to the buy-side from the rest of analysts whose forecasts are terminated in IBES. Specifically, we first repeat the same linear probability model in Equation (1) in a subsample that captures only two types of analysts, i.e., the dependent variable is equal to one if a sell-side analyst leaves IBES and subsequently joins a buy-side firm in year $t+1$ (the treatment group), and zero if an analyst stays with IBES in year $t+1$ (the control group). The result is reported in columns (1) to (3) of Table 3. The results in columns (1) and (2) suggest that forecast accuracy does not predict whether an analyst is likely to move to buy-side firms or not, relative to her likelihood of staying with IBES in year $t+1$. Furthermore, the coefficient of the continuous score measure in column (3) is positive but statistically insignificant. These results imply that analysts moving to buy-side firms do not underperform their peers who stay within IBES in terms of forecast accuracy.

Our results above suggest that forecast accuracy is not related to the likelihood of sell-side analysts moving to the buy-side, relative to their likelihood of staying with IBES. If we mix these analysts moving from the sell-side to the buy-side with analysts who lose their jobs in IBES firms because of poor performance, 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 to the buy-side from other leaving analysts in the treatment group. Specifically, we only include two subgroups of analysts in this test, i.e., analysts moving to non-buy-side firms (the treatment group) and analysts staying with IBES (the control 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 for the bottom five percentile is 0.003% more positive than that in column (1) of Table 2. Except for the second most accurate group ("50-through-75"), all other groups have stronger magnitude of regression coefficients than those presented in Table 2. Furthermore, the relationship between accuracy and the likelihood of leaving IBES becomes monotonic and statistically significant in Table 3, while the middle groups in Table 2 exhibit a mixed pattern. Further, the continuous score measure in column (6) of Table 3 confirms that the remaining leaving analysts are indeed less accurate as the coefficient is 0.0001% more negative than that of column (3) of Table 2. In conclusion, after isolating analysts hired by the buy-side from the other leaving analysts, 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 firms 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 firms 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 *t+1* (the treated group) and the group of analysts who stay in IBES (the benchmark group) are exhibited in columns (1) and (2) of Table 4. In columns (3) and (4) we replace the treated 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 all other percentiles and analysts in the most accurate percentile is negative, although none of these coefficients is statistically significant. Moreover, column (2) reports that the continuous measure of forecast accuracy has a positive and statistically significant coefficient. These results suggest that sell-side analysts leaving for hedge funds and private equities were more accurate in earnings forecasts than those staying with IBES before their job turnovers. On the other hand, the regression results in columns (3) and (4) suggests that there is no difference in forecast accuracy between analysts leaving for mutual funds and pension funds and analysts staying with IBES.

The group partition of buy-side firms has interesting implications for our study. First, we identify a special subgroup of IBES-exit analysts who are more accurate in earnings forecasts than those analysts who stay with IBES. Second, our results are consistent with our conjecture that HF&PEs often 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 reply on fundamental analysis of particular stocks. Therefore, in the labor market of finance industry, the ability in making accurate earnings forecasts is valued more highly among HF&PEs than 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, earnings forecasts of analysts moving to hedge funds and private equities are actually more accurate than those made by their peers staying with IBES. This result gives rise to a natural question: if forecast accuracy is not a major determinant of career transition from the sell-side to the buy-side, what are the sell-side characteristics that 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 A.

4.1 Determinants of Sell-Side Job Turnovers in the Existing 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)).

While we inherit from the sell-side analyst literature to investigate portfolio breadth on the firm level, we now incorporate breadth on the industry level as a determinant to capture the difference between the sell-side and buy-side. One analyst in the survey conducted by Brown, Call, Clement, and Sharp (2015) describes this difference, "if the sell-side is 'a foot wide and a mile deep', the buy-side is 'a mile wide and a foot deep'". It is evident that buy-side analysts have a broader focus, whereas sell-side analysts are more specialized.

Seniority, which is defined as the number of years in the analyst profession, often represents three aspects of analyst characteristics. 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[6]. 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. According to Hong, Kubik, and Solomon (2000), broker size is typically correlated with broker reputation. It can also serve as a proxy for the connection with both buy-side investors and corporate managers.

Affiliated analysts and *All-Star* analysts are another two known measures of an analyst's importance to the sell-side firms. Previous studies argue that affiliated analysts are more likely to be optimistic (e.g., O'Brien, McNichols, and Hsiou-Wei (2005) and Malmendier and Shanthikumar (2014)). All-Star analysts, on the other hand, are very influential with institutional investors in generating trade ideas and bringing market-making business to the brokerage. Affiliated analysts and All-Star statues have a high correlation of 18% (Table A1).

We also compute the institutional ownership to proxy for the information demand from institutional investors (see Bozcuk and Lasfer (2005), Boehmer and Kelley (2009)). Stocks with higher institutional ownership also are covered by a larger number of analysts (a correlation of 28%, Table A1).

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

4.2 Other Determinants for Job Turnovers to the Buy-Side

In addition to the above factors, we also include a list of variables observed for the LinkedIn sample, such as the analyst's educational background and the analyst's previous work experience, in our analysis. Brown, Call, Clement, and Sharp (2015) illustrate the importance of the 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 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 transitions.

4.3 Empirical Specifications

Our main empirical specification is provided in Equation (2a). 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, we report results based on different benchmark groups. We adopt two specifications for tests under each benchmark group. We also incorporate year fixed effects and industry fixed effects to control for common trends over time and within each industry.

The first specification is:

$$\mathbf{1}(\text{in treatment group})_{i,t+1} = \alpha + \beta \text{ Factor } 1_{i,t} + \text{Fixed Effect}_{i,t} + \epsilon_{i,t+1}, \tag{2}$$

where the *Factor 1* includes all candidate determinants that we have discussed in Section 4.1.1. The second specification is of the following form:

$$\mathbf{1}(\text{in treatment group})_{i,t+1} = \alpha + \beta \text{ Factor } 1_{i,t} + \gamma \text{ Factor } 2_{i,t} + \text{Fixed Effect}_{i,t} + \epsilon_{i,t+1}, \tag{3}$$

where the *Factor 1* is the same as (2a), and *Factor 2* includes the additional variables that we have discussed in Section 4.1.2.

4.4 Empirical Results

Column (1) of Panel A shows the result based on specification in Equation (2a). This benchmark group (i.e., no job change) 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, however, that their predictability disappears for career transitions from the sell-side to the buy-side. This is perhaps not surprising, given that buy-side firms are looking for a different set of skills from sell-side firms, as we have discussed in Section 2.

However, determinants like *Seniority*, brokerage house reputation (*Broker Size*), *All-Star* statue and demand for information by institutional investors (*Institutional Ownership*) remain effective predictors for buy-side transition according to our result. The estimated coefficients show that *Seniority* and *All-Star* statue are negatively correlated with the probability of transitioning to the buy-side. This is probably caused by the lack of availability of comparable senior positions in buy-side firms. On the other hand, our results suggest that brokerage house reputation and network resources, as well as the information demands of institutional investors can help a sell-side analyst land a buy-side job.

Columns (2) and (3) in Panel A of Table 5 show the results for the second benchmark group (i.e., with-in IBES sell-side change). The determinants (*Seniority*, *Broker Size*, *All-Star*, and *Institutional Ownership*) with statistical significance in column (1) are also significant in column (2), and yet the magnitudes are much stronger in column (2). The estimated coefficients imply that an increase in, for example, *Seniority* by one standard deviation would lead to 0.7% 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 IBES sell-side is 4.8%. The evidence seems to suggest that career transition is rare relative to no change so that the economic significance is small. However, conditional on career transition, those indicators are highly powerful predictors in distinguishing transition to buy-side from that to sell-side.

Results in column (2) exhibit an interesting contrast: the breadth variable at the firm-level is negatively significant, but at the industry-level the breadth variable is positively significant. As discussed in Section 4.1.1, the sell-side prefers analysts who follow more companies so that they can service more clients. Analysts with a broader industry coverage but narrower company coverage can be valuable for buy-side firms because portfolio management focuses on understanding different industries rather than a list of single firms in one industry. Therefore, the statistical significance of breadth variables at firm-level and industry-level in column (2) is reflective of such differences and is consistent with our expectation.

In addition, our result in column (3) shows that the set of education-related variables obtained from LinkedIn profile are significant predictors for buy-side turnovers. They 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 does not hold a post-graduate degree, or if the analyst's educational background matches the covered industry sector. We will see when we discuss the result of Table 6 that the first and second variables predict both buy-side turnovers and also specific types of buy-side. The last variable, in particular, is largely in line with our expectation that a specialty education as a proxy for superior fundamental knowledge is a highly desired characteristic by the buy-side.

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 loadings on both *Accuracy* and *Institutional Ownership* are significant. In particular, an increase by one standard deviation in accuracy rank suggests that an analyst is 6.7% more likely to go to a buy-side firm in t+1 than to a boutique brokerage house not covered by IBES.

The results in columns (6) and (7) (corporate move) shows that previous corporate experience is a negative indicator for transition to a buy-side job relative to transitioning to a corporate job. This is in line with our expectation. The analysts in this benchmark are also less accurate. The last benchmark group (non-finance move) in columns (8) and (9) in general has large variations within the group. Therefore, it makes sense that analysts in this group have different sector knowledge that can be useful to non-financial sectors such as consulting, government and education. Our regression result seems to support this conjecture as this is the only group of analysts that exhibit more industry coverage than the group of analysts moving to the buy-side.

[Insert Table 5 Here]

In the same spirit of 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. Using the same benchmark groups and specifications as in columns (1) - (3) of Table 5, 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.

Note that for the HF&PE type of buy-side, forecast accuracy and brokerage house prestige are positive indicators. In addition, we see in Table 5 that the All-Star analysts are reluctant to leave IBES sell-side for an average buy-side. However, this effect disappears for a typical HF&PE fund but not for a typical MF&PF fund. This difference is consistent with a conjecture that the All-Star analysts enjoy the generous performance-based compensations available at the sell-side due to their All-Star statue and are reluctant to move to a MF&PF where the upside of compensation is relatively limited. It is also interesting to note that having a postgraduate degree is less popular for analysts in HF&PE. One possible explanation could be that a research-oriented HF&PE is more interested in an analyst's practical experience to help generate Alpha than MF&PF. 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 seem to suggest that analysts with higher ability are more desirable by HF&PE whereas MF&PF is less likely to attract such talents.

[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 motived 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.

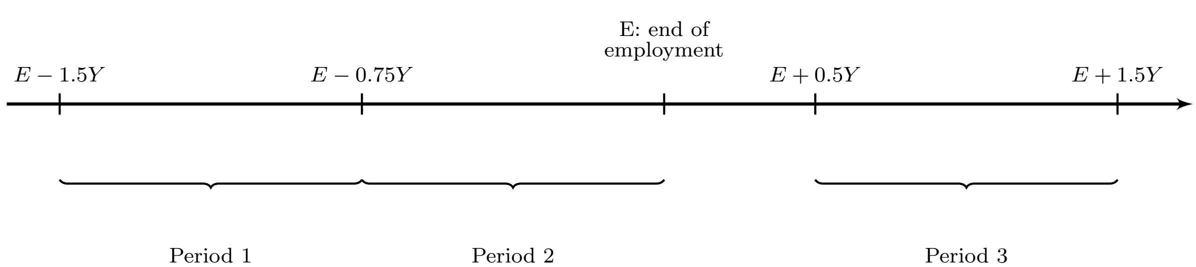
Using the 13F holding data, we are able to observe the number of shares of all stocks held at the quarter end, as long as the buy-side firm AUM exceeds $100 million during the reporting period. There are four limitations of this dataset. First, the reported position is aggregated at the firm level (i.e., 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 (3) below and the timeline for this research setup is illustrated in Figure 2.

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

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.

Figure 2: This figure describes the timeline of our empirical setup (Table 7).



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.

References

Boehmer, E., and E. K. Kelley, 2009, "Institutional Investors and the Informational Efficiency of Prices," *Review of Financial Studies*.

Bozcuk, A., and M. A. Lasfer, 2005, "The Information Content of Institutional Trades on the London Stock Exchange," *Journal of Financial and Quantitative Analysis*.

Bradley, D., S. Gokkaya, and X. Liu, 2017, "Before an Analyst Becomes an Analyst: Does Industry Experience Matter?," *The Journal of Finance*, 72(2), 751–792.

Brown, L. D., A. C. Call, M. B. Clement, and N. Y. Sharp, 2015, "Skin in the Game: The Incentives and Inputs that Shape Buy-Side Analysts' Stock Recommendations," Working Paper.

Cen, L., J. Chen, S. Dasgupta, and V. Ragunathan, 2016, "It's Showtime! Conference Call Participation and Analysts' Career Outcomes," Working Paper.

Cheng, Y., M. H. Liu, and J. Qian, 2006, "Buy-Aide Analysts, Sell-Side Analysts, and Investment Decisions of Money Managers," *Journal of Financial and Quantitative Analysis*.

Clement, M. B., and S. Y. Tse, 2005, "Financial Analyst Characteristics and Herding Behavior in Forecasting," *The Journal of Finance*.

Cornaggia, J., K. J. Cornaggia, and H. Xia, 2016, "Revolving Doors on Wall Street," *Journal of Financial Economics*.

DeChesare, B., 2016, "Investment Banking Exit Opportunities: The Myth of the Buy-Side Job," `http://www.mergersandinquisitions.com/investment-banking-exit-opportunities`.

Guan, Y., H. Lu, and M. F. Wong, 2013, "Regulations and Brain Drain: Evidence from the Wall Street Star Analysts' Career Choices," *Review of Accounting Studies*.

Holmstrom, B., 1982, "Moral Hazard in Teams," *The Bell Journal of Economics*.

Hong, H., and J. D. Kubik, 2003, "Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts," *The Journal of Finance*.

Hong, H., J. D. Kubik, and A. Solomon, 2000, "Security Analysts' Career Concerns and Herding of Earnings Forecasts," *The Rand Journal of Economics*.

Jiang, J. X., I. Y. Wang, and K. P. Wang, 2015, "Former Rating Analysts and the Ratings of MBS and ABS: Evidence from LinkedIn," Working Paper.

Kempf, E., 2015, "The Job Rating Game: The Effects of Revolving Doors on Analyst Incentives," Working Paper.

Lourie, B., 2014, "The Revolving-Door of Sell-Side Analysts: A Threat to Analysts' Independence?," Working Paper.

Malmendier, U., and D. Shanthikumar, 2014, "Do Security Analysts Speak in Two Tongues?," *Review of Financial Studies.*

Michaely, R., and K. L. Womack, 1999, "Conflict of Interest and the Credibility of Underwriter Analyst Recommendations," *Review of Financial Studies*, 12(4), 653–686.

Mirsky, R., A. Cowell, and A. Baker, 2012, "The Value of the Hedge Fund Industry to Investors, Markets, and the Broader Economy," *Financials Analyst Journal.*

Nolte, I., S. Nolte, and M. Vasios, 2014, "Sell-Side Analysts' Career Concerns during Banking Stresses," *Journal of Banking and Finance.*

O'Brien, P. C., M. F. McNichols, and L. Hsiou-Wei, 2005, "Analyst Impartiality and Investment Banking Relationships," *Journal of Accounting Research.*

Prendergast, C., and L. Stole, 1996, "Impetuous Youngsters and Jaded Old-timers: Acquiring a Reputation for Learning," *Journal of Political Economy.*

Scharfstein, D. S., and J. C. Stein, 1990, "Herd Behavior and Investment," *The American Economic Review.*

Siming, L., 2013, "Your Former Employees Matter: Private Equity Firms and Their Financial Advisors," *Review of Finance.*

Spangler, T., 2016, *One Step Ahead: Private Equity and Hedge Funds After the Global Financial Crisis.* Oneworld Publications, London, United Kingdom.

Table 1: Summary Statistics

This table reports the summary statistics of analysts with at least one year IBES experience for period 2007 to 2013. Panel A presents the year by year distribution of analysts' career turnovers. Panel B reports the summary statistics of analysts' characteristics in the full sample. Panel C reports the summary statistics of analysts' characteristics in the sample of analysts moving from the IBES to the buy-side.

Panel A: General Description

Year	Total Number of Analysts	Number of Analysts Leaving IBES	Number of Analysts Found on Linkedin	Number of Analysts Moving to Buy-side
2007	3,066	535	167	89
2008	2,967	595	210	88
2009	2,624	340	104	30
2010	2,783	314	112	43
2011	3,123	445	168	75
2012	3,164	509	196	65
2013	3,119	435	153	68
Total	20,846	3,173	1,110	457

Panel B: Characteristics of All Analysts in the IBES

Variables	Mean	Median	S.D.	Observation
Accuracy	53.02	54.25	15.06	20,846
Boldness	47.46	46.25	14.86	20,846
Optimism	49.72	49.90	15.01	20,846
Breadth - Firm	11.81	11	8.14	20,846
Breadth - Industry	3.20	3	2.37	20,846
Seniority	6.83	5.23	6.10	20,846
Affiliated Analyst	0.10	0	0.29	20,846
All-Star	0.11	0	0.31	20,846
Analysts Following	17.03	16.61	8.20	20,846
Institutional Ownership	0.72	0.76	0.18	17,836

Panel C: Characteristics of Analysts Leaving for Buy-side

Variables	Mean	Median	S.D.	Observation
Accuracy	54.08	54.95	15.71	457
Boldness	47.59	46.04	14.61	457
Optimism	49.92	50.79	15.33	457
Breadth - Firm	11.13	11	7.43	457
Breadth - Industry	3.19	3	2.35	457
Seniority	4.93	3.21	5.10	457
Affiliated Analyst	0.11	0	0.26	457
All-Star	0.07	0	0.26	457
Analysts Following	16.61	15.57	8.15	457
Institutional Ownership	0.74	0.77	0.19	393

Table 2: Analysts Forecast Accuracy and Leaving IBES

This table reports coefficients of OLS regression of Equation (1) with Leaving IBES as the dependent variable. Leaving IBES is defined as a binary variable that equals to 1 if the analyst is not found in IBES in year t+1. 0-through-5 is an indicator variables that equals to 1 if analyst's relative accuracy rank is in the 0 to 5% percentile in year t, whereas 5-through-10, 10-through-25, 25-through-50, 50-through-75 are defined in the same way. Score is the the percentile of analyst's accuracy rank and is defined continuously. Standard errors (in parentheses) are clustered at broker level. ***, **, and * mark significance at the 1%, 5%, and 10% levels respectively. The sample period is from January 2007 to December 2013.

	(1) Probability of Leaving	(2) Probability of Leaving	(3) Probability of Leaving
Percentile Dummy:			
0-through-5	0.0499***	0.0617***	
	(0.015)	(0.017)	
5-through-10		0.0200	
		(0.016)	
10-through-25		0.0164*	
		(0.008)	
25-through-50		0.0176***	
		(0.006)	
50-through-75		0.0160**	
		(0.007)	
Continuous Measure:			
Score			-0.0006***
			(0.000)
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes
Observations	20,846	20,846	20,846
R^2	0.456	0.456	0.456

Table 3: Forecast Accuracy and Buy-side Transitions
This table presents results from OLS regressions of Equation (1) to examine if past forecasting accuracy affects the likelihood of two possible job outcomes. In columns (1)-(3), the dependent variable, Leaving IBES, is defined as a binary variable that equals to 1 if analyst is going to a buy-side institution in year t+1, and 0 if analyst stays in IBES. In columns (4)-(6), the dependent variable, Leaving IBES, is defined as a binary variable that equals to 1 if analyst is in IBES and is not going to a buy-side institution in year t+1, and 0 if analyst stays in IBES. 0-through-5 is an indicator variables that equals to 1 if analyst's relative accuracy rank is in the 0 to 5% percentile in year t, whereas 5-through-10, 10-through-25, 25-through-50, 50-through-75 are defined in the same way. Score is the percentile of analyst's accuracy rank and is defined continuously. Standard errors (in parentheses) are are clustered at broker level. ***, **, and * mark significance at the 1%, 5%, and 10% levels respectively. The sample period is from January 2007 to December 2013.

	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	0.0033	0.0022		0.0519***	0.0647***	
	(0.008)	(0.009)		(0.015)	(0.016)	
5-through-10		-0.0091			0.0262*	
		(0.008)			(0.015)	
10-through-25		-0.0048			0.0200**	
		(0.004)			(0.009)	
25-through-50		-0.0002			0.0182***	
		(0.003)			(0.006)	
50-through-75		0.0050			0.0129*	
		(0.004)			(0.007)	
Continuous Measure:						
Score			0.0001			-0.0007***
			(0.000)			(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,130	18,130	18,130	20,389	20,389	20,389
R^2	0.074	0.074	0.074	0.488	0.489	0.488

Table 4: Forecast Accuracy and Buy-side Transitions by Institutional Type
This table presents results from OLS regressions of Equation (1) to examine if past forecasting accuracy affects the likelihood of job outcomes of two general types of buy-side. In columns (1)-(2), the dependent variable, Leaving IBES, is defined as a binary variable that equals to 1 if analyst is going to a buy-side institution that is classified as a hedge fund, private equity or venture capital (HF & PE) in year t+1, and 0 if analyst stays in IBES. In columns (3)-(4), the dependent variable, Leaving IBES, is defined as a binary variable that equals to 1 if analyst is going to a buy-side institution that is classified as a mutual fund and pension fund (MF & PF) in year t+1, and 0 if analyst stays in IBES. 0-through-5 is an indicator variable that equals to 1 if analyst's relative accuracy rank is in the 0 to 5% percentile in year t, whereas 5-through-10, 10-through-25, 25-through-50, 50-through-75 are defined in the same way. Score is the percentile of analyst's accuracy rank and is defined continuously. Standard errors (in parentheses) are clustered at broker level. ***, **, and * mark significance at the 1%, 5%, and 10% levels respectively. The sample period is from January 2007 to December 2013.

	Probability of Leaving to HF & PE		Probability of Leaving to MF & PF	
	(1)	(2)	(3)	(4)
Percentile Dummy:				
0-through-5	-0.0035		0.0064	
	(0.005)		(0.007)	
5-through-10	-0.0052		-0.0063	
	(0.006)		(0.005)	
10-through-25	-0.0032		-0.0030	
	(0.003)		(0.003)	
25-through-50	-0.0029		0.0009	
	(0.002)		(0.003)	
50-through-75	-0.0001		0.0030	
	(0.003)		(0.002)	
Continuous Measure:				
Score		0.0002**		-0.0000
		(0.000)		(0.000)
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Broker Fixed Effects	Yes	Yes	Yes	Yes
Observations	17,904	17,904	17,866	17,866
R^2	0.044	0.044	0.053	0.053

Table 5: Analysts Characteristics and Job Seperation

This table reports results from OLS regressions of Equation (2a) and (2b) to examine what determines the likelihood of an analyst transitioning to buy-side. The dependent variable is defined as a binary variable that equals to 1 if analyst is in the treatment group(going to a buy-side firm in year t+1), and 0 if in the benchmark groups: columns (1) includes analysts with no job transition, column(2)-(3) includes analysts with transition to a IBES sell-side, column(4)-(5) includes analysts with transition to non IBES sell-side, column(6)-(7) includes analysts with transition to a company, column(8)-(9) includes analysts with transition to non-finance industry. Detailed definitions of independent variables are provided in Appendix. Standard errors are in parentheses. ***, **, and * mark significance at the 1%, 5%, and 10% levels respectively. The sample period is from January 2007 to December 2013.

	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	0.0002	0.0007	0.0005	0.0043***	0.0045***	0.0024	0.0035**	0.0015	0.0008
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Boldness	0.0002	0.0007	0.0003	0.0015	0.0011	0.0019	0.0013	0.0008	-0.0008
	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Optimism	0.0001	0.0002	0.0016	-0.0009	-0.0003	0.0003	-0.0000	0.0005	-0.0000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Breadth-Firm	-0.0004	-0.0052***	-0.0097***	-0.0011	-0.0009	-0.0015	-0.0031	0.0046	0.0026
	(0.000)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Breadth-Industry	0.0005	0.0128**	0.0219**	0.0147	0.0195*	0.0110	0.0219*	-0.0218**	-0.0146
	(0.001)	(0.005)	(0.009)	(0.011)	(0.011)	(0.013)	(0.012)	(0.011)	(0.011)
Seniority	-0.0012***	-0.0079***	-0.0079**	-0.0053	-0.0070	-0.0015	-0.0043	-0.0098**	-0.0114***
	(0.000)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Broker Size	0.0172***	0.1244***	0.0696*	0.0558	0.1049**	0.0796*	0.0823*	0.1097**	0.0972*
	(0.004)	(0.024)	(0.037)	(0.045)	(0.047)	(0.048)	(0.049)	(0.048)	(0.050)
Affiliated Analyst	0.0003	0.0311	0.0332	0.0026	-0.0353	-0.0370	-0.0413	0.0368	0.0367
	(0.005)	(0.032)	(0.052)	(0.066)	(0.069)	(0.069)	(0.070)	(0.069)	(0.073)
All-Star	-0.0135***	-0.0813**	-0.0877	-0.0903	-0.1621**	-0.0741	-0.0941	0.0277	-0.0080
	(0.005)	(0.033)	(0.056)	(0.077)	(0.079)	(0.080)	(0.083)	(0.086)	(0.088)
Institution Ownership	0.0170*	0.1314**	0.0713	0.2873**	0.3078***	0.0934	0.1124	0.1096	0.1250
	(0.010)	(0.061)	(0.105)	(0.122)	(0.116)	(0.127)	(0.125)	(0.128)	(0.129)
Postgraduate			-0.2235**		-0.2860**		-0.0845		-0.2538**
			(0.090)		(0.121)		(0.140)		(0.125)
Corporate Experience			-0.0557		-0.0346		-0.1047*		-0.0234
			(0.043)		(0.058)		(0.057)		(0.061)
Buy-side Experience			0.0967**		0.1244**		0.1314**		0.1183**
			(0.045)		(0.058)		(0.061)		(0.059)
Specialty Major			0.1410**		0.1807**		0.1726**		0.1921**
			(0.067)		(0.084)		(0.085)		(0.087)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,730	1,821	922	643	550	599	511	558	478
R^2	0.138	0.080	0.110	0.181	0.152	0.135	0.094	0.152	0.117

Table 6: Analysts Characteristic and Buy-Side Transition

This table reports results from OLS regressions of Equation (2a) and (2b) to examine what determines the likelihood of an analyst transitioning to different types of buy-side. The dependent variable is defined as a binary variable that equals to 1 if analyst is in the treatment group (analysts going to HF&PE in column (1)-(3) and analysts going to MF&PF in column(4)-(6)) and 0 if in the benchmark groups (columns (1) includes analysts with no job transition, column(2)-(3) includes analysts with transition to a IBES sell-side). Detailed definition of independent variables are provided in Appendix. Standard errors are in parentheses. ***, **, 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 Sell-side=0 HF & PE=1		No Change=0 MF & PF=1	IBES Sell-side=0 MF & PF=1	
	(1)	(2)	(3)	(4)	(5)	(6)
Accuracy	0.0002**	0.0011	0.0017	0.0000	0.0001	-0.0002
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Boldness	0.0001	0.0006	0.0008	0.0001	0.0003	-0.0001
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Optimism	0.0001	0.0007	0.0023*	-0.0000	-0.0005	-0.0005
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Breadth	-0.0000	-0.0014	-0.0033	-0.0003*	-0.0048***	-0.0110***
	(0.000)	(0.001)	(0.003)	(0.000)	(0.001)	(0.003)
Breadth-Industry	0.0001	0.0075*	0.0098	0.0002	0.0067*	0.0207**
	(0.001)	(0.004)	(0.009)	(0.001)	(0.004)	(0.008)
Seniority	-0.0007***	-0.0052***	-0.0055*	-0.0004**	-0.0039***	-0.0056*
	(0.000)	(0.002)	(0.003)	(0.000)	(0.001)	(0.003)
Broker Size	0.0149***	0.1274***	0.1042***	0.0040	0.0411**	0.0030
	(0.003)	(0.021)	(0.037)	(0.003)	(0.019)	(0.035)
Affiliated Analyst	-0.0037	-0.0093	-0.0403	0.0019	0.0392	0.0794*
	(0.004)	(0.028)	(0.052)	(0.003)	(0.026)	(0.047)
All-Star	-0.0054	-0.0468*	-0.0409	-0.0088***	-0.0627**	-0.0738
	(0.004)	(0.028)	(0.053)	(0.003)	(0.026)	(0.050)
Institution Ownership	0.0086	0.0843	0.0548	0.0049	0.0601	0.0341
	(0.008)	(0.053)	(0.107)	(0.006)	(0.048)	(0.099)
Postgraduate			-0.2649***			-0.0639
			(0.089)			(0.077)
Corporate Experience			-0.0621			-0.0153
			(0.042)			(0.038)
Buy-side Experience			0.0491			0.1237***
			(0.046)			(0.041)
Specialty Major			0.1017			0.0873
			(0.068)			(0.065)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,547	1,638	767	11,490	1,581	715
R^2	0.126	0.066	0.093	0.136	0.058	0.120

Table 7: Changes in 13F Holding: Before and After Buy-side Transition
This table reports the results from OLS regressions of Equation (3) 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 to 1 if the stock positions are computed after the analyst's transition, and zero otherwise. *Cover Dummy* is a binary variable that equals to 1 if the stocks are followed by the former sell-side analyst, and zero otherwise. Standard errors are in parentheses. ***, **, and * mark significance at the 1%, 5%, and 10% levels respectively. The sample period is from January 2007 to December 2013.

	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 Fixed Effects	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.

- *Breadth-Industry* is the number of industries 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	Institutional Ownership	Analysts 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