Measuring the Career Concerns of Security Analysts: Job Separations, Stock Coverage Assignments and Brokerage House Status

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Abstract

This paper examines the career concerns of security analysts using long histories of their earnings forecasts, job separations and stock coverage assignments. Our findings include the following. Relatively good (accurate) past forecast performance increases the probability that an analyst moves from a low status to a high status (large, prestigious) brokerage house, while relatively poor past forecast performance leads to movements down the brokerage house hierarchy. High status brokerage houses are more likely to discharge an analyst for poor past forecast performance than other houses. In addition, analysts with poor past forecast performances but who do not change employers are more likely to be removed from following stocks with large market capitalization or significant analyst following. This effect is also more pronounced for analysts who work for high status brokerage houses. These findings suggest that the labor market for security analysts provides important implicit incentives for analysts to produce good forecast track records.

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1. Introduction

Security analysts play an increasingly important role in disseminating information and opinions in financial markets. Investors, both individual and institutional (the buy-side), look to them to provide earnings forecasts and stock recommendations. Believing that analysts can raise their visibility on Wall Street, many firms actively court analyst coverage and spend significant resources managing analysts' expectations (see, e.g., Brennan and Tamarowski (1999)).

The growing prominence of security analysts in financial markets has led to heightened scrutiny of the workings of the labor market for and the careers of security analysts. For instance, regulatory bodies are concerned that sell-side analysts might be beholden to other wings of their brokerage houses such as investment bankers. The SEC strongly endorses a code of ethics that emphasizes a separation between the research and investment banking branches of brokerage houses. An academic literature has focused on to what extent this separation is breached and how analyst recommendations become biased by this conflict of interest (see, e.g., Lin and McNichols (1998), Michaely and Womack (1999)).

Also, the financial press frequently reports on the hirings of up-and-coming analysts by prestigious investment banks and the firings of once-prominent analysts. For example, the *Wall Street Journal* recently reported on the fall of a well-known large-cap tech analyst at Merrill Lynch whose bad calls on a key tech stock led to an erosion of his influence among his buy-side clients and his subsequent departure (see Pulliam (2000)). This public scrutiny into the careers of analysts indicates that analysts work in an environment where their actions and performances greatly affect their future career prospects.

Other descriptions of the labor market for security analysts confirm this impression. Nocera (1997) describes how analysts strive to be influential among their buy-side clients so as to be lured away by (if not already employed at) a top-tier brokerage house. Top-tier brokerage houses such as Goldman Sachs or Merrill Lynch are willing to pay top dollar (substantially more than lower-tier brokerage houses) for these influential analysts.¹ According to these descriptions, an analyst's place in this brokerage house

¹ Security analysts' wages at such top brokerage houses are highly skewed and can exceed \$12 million per year (see, e.g., Nocera (1997)). Krigman, Shaw and Womack (2000) describe one reason why prestigious brokerage houses

hierarchy depends critically on an annual poll conducted by *Institutional Investor* (I.I.) magazine of the buy-side.² Generally, the top three vote getters in each industry are deemed I.I. All-American analysts. One of the two most important criteria for a high ranking in this poll is perceived forecasting expertise, loosely defined as knowledge of the industry and timeliness and accuracy of forecasts (see Stickel (1992) for other criteria).

Additionally, analysts also strive to represent their brokerage houses on important stocks with large market capitalization (e.g., Intel or Microsoft). These stocks are highly visible in the investment community and bring analysts covering them substantial media attention. The informal descriptions of the labor market for analysts also suggest that perceived forecast expertise is important for determining who covers these firms.

More formally, such anecdotal evidence indicates that analyst career concerns of the sort described by Fama (1980) and Holmstrom (1999) may provide an important source of implicit incentives for analysts to produce good forecast track records. Put another way, analysts need to not only appease other wings of their brokerage houses but they also need to cultivate or maintain a reputation for forecasting expertise among the buy-side. This reputation allows them to move up to or to keep their jobs at top-tier brokerage houses and also allows them to cover the high-profile stocks. Few studies, however, have attempted to examine such analyst career concerns.

In this paper, we measure these career concerns using long histories of analysts' earnings forecasts, job separations (movements across brokerage houses or out of the profession) and the stocks that they follow.³ Among brokerage houses, there is a well-defined hierarchy of prestige, with traditional

might value influential analysts. They find that firms that switch underwriters after their IPO's do so in part because they want to graduate to higher reputation analysts. They strategically buy additional and influential analyst coverage from the new lead underwriter.

² A turning point in the history of this labor market is the move by Don Regan in the late 1970s, then chairman of Merrill Lynch and soon to be treasury secretary under Ronald Reagan, to raid other brokerage houses by paying top dollar for analysts at the top of the *Institutional Investor* Poll.

³ This approach of measuring career concerns by estimating the relationship between performance and job turnover is similar to the large literature on the effect of performance on career outcomes in various labor markets such as CEOs, lawyers, accountants, baseball players. We will compare our paper to this literature below.

banking powerhouses such as Goldman Sachs or Merrill Lynch considered high status and more regional, specialized brokerage houses considered lower status.⁴ We explore the effect of this hierarchy in our empirical work by examining the movements of security analysts across brokerage houses of different status and the hiring/firing practices of these different brokerage houses.

We begin our empirical investigation by documenting some characteristics of analyst job mobility along the brokerage house hierarchy. First, when an analyst changes brokerage houses, the portfolio of firms that she covers does not substantially change. Apparently, analysts are hired for some of the specific expertise that they have developed at their previous brokerage house. Second, by tracking the past employment status of all analysts who have been in the profession for at least a fixed number of years (say 6 years), we find that the fraction of these analysts who work for high status brokerage houses increases over time. That is, there is a funnelling of analysts up the brokerage house hierarchy as they gain experience. This suggests that prestigious brokerage houses value seasoned analysts more than less prestigious ones.

To better understand the determinants of these movements, we examine the effect of forecast performance on job separations. We find that extremely good (accurate) relative forecast performance leads to movements up the brokerage house hierarchy, and extremely poor (inaccurate) relative performance leads to movements down the hierarchy. The sensitivity of this relationship between past performances and job termination varies by the status of the brokerage house. High status brokerage houses are more likely to discharge analysts for poor performances than other brokerage houses. In other words, these empirical findings strongly support the informal descriptions in the financial press that the external labor market for security analysts provides important implicit incentives for analysts to produce good forecasting track records.

Finally, we attempt to measure analyst career concerns arising not only from job separations but also from changes in who, within a brokerage house, covers high-profile stocks that have large market

⁴ We will measure brokerage house status in a number of ways (see Section 3.2). For concreteness, whenever we allude to high status houses, one should think of the well-known houses such as Goldman Sachs and Merrill Lynch.

capitalization or large analyst following. We find that, after extreme poor (overall) relative performances, analysts covering high-profile stocks are more likely to move off of those stocks. This effect is most dramatic for analysts working for high status brokerage houses. While analysts have some discretion on the stocks that they follow, it is not likely that an analyst would willingly give up coverage of high-profile stocks voluntarily. Therefore, these findings suggest that internal labor markets (within brokerage houses) also provide some implicit incentives for forecasting expertise.

Our paper proceeds as follows. In section 2, we review the related literature and highlight the contributions of our paper in light of existing work. Section 3 describes our data and constructs measures of the brokerage house hierarchy. We develop our job separation measures and provide a preliminary analysis of movements along the brokerage house hierarchy in section 4. In section 5, we gauge the effects of forecast performance on movements along this hierarchy, and section 6 measures career concerns from changes in who covers high-profile stocks. We conclude in section 7.

2. Related Literature

Our paper is related to the literature studying security analysts. An important branch of this research is motivated by ideas related to efficient markets. For example, many studies have examined whether analysts' forecasts are more accurate than forecasts from simple time-series models (see, e.g., Elton and Gruber (1972), Brown and Rozeff (1978), Crichfield, Dyckman and Lakonishok (1978) and O'Brien (1990)). Other work examines the rationality of analysts' forecasts, testing for unbiasedness and efficiency (e.g., De Bondt and Thaler (1990), Abarbanell and Bernard (1992) and Keane and Runkle (1998)). There are also studies on whether analyst stock recommendations help forecast stock returns (see, e.g., Stickel (1995), Womack (1996)).

Despite the voluminous literature on these analysts, there are few papers that measure the career concerns of security analysts. Two exceptions are Mikhail, Walther and Willis (1999) and Hong, Kubik and Solomon (2000). Mikhail et al. (1999) find that poor relative and not absolute performance leads to job turnover. However, they do not distinguish between job separations related to movements up or down

the brokerage hierarchy or movements out of the profession. Hong et al. (2000) find that young analysts are more likely than their older counterparts to leave the profession for poor relative forecast performance and bold forecasts. However, their paper is focused on testing herding models along the lines of Scharfstein and Stein (1990), Trueman (1994), Zwiebel (1995) and Prendergast and Stole (1996).

Our paper differs from these studies in a number of ways. First, we focus exclusively on measuring the career concerns of security analysts. In particular, we document the career concerns arising from movements up and down the brokerage house hierarchy. In the context of security analysts, this provides a better measure of implicit incentives than merely looking at how performance affects movements out of the profession because it is difficult to track what happens to an analyst when she leaves the profession. Also, we document the differential hiring/firing practices of brokerage houses of different status to better measure the career concerns that analysts face. Finally, we measure analyst career concerns arising from internal labor markets by focusing on the relationship between forecast performance and who gets to cover high-profile stocks within a brokerage house. Few studies have simultaneously studied implicit incentives from both external and internal labor markets.

Our paper is also broadly related to the empirical literature on career concerns in a number of other labor markets. A large literature focuses on the career concerns of top management (see, e.g., Coughlan and Schmidt (1985), Warner, Watts and Wruck (1988), Gibbons and Murphy (1990), Jensen and Murphy (1990), Murphy and Zimmerman (1993), Brickley et al. (1999)). Many of these studies analyze the relationship between changes of top managers of large corporations and firm performance. Generally, these studies find that poor relative performance leads to management changes. In the labor market for mutual fund managers, Khorana (1996) and Chevalier and Ellison (1999) document an inverse relationship between managerial replacement and fund performance. A similar relationship has been documented in other labor markets such as baseball players (see Spurr and Barber (1994)).

Our paper also contributes to this broader literature on career concerns. We use long histories of forecast performances, job separations and stock coverage assignments of individual analysts to

simultaneously measure career concerns arising from both external and internal labor markets. Such panel data are simply not available for most other labor markets.

3. Data and Measures of Brokerage House Status

3.1. The Sample

Our primary data come from the Institutional Brokers Estimate System (I/B/E/S) database. I/B/E/S gathers the earnings forecasts of companies throughout the world from thousands of individual security analysts. We use the I/B/E/S Detail Earnings Estimate History File, which contains earnings forecasts of U.S. companies between 1983 and 1996. During this period, the data consist of the estimates of 8,421 analysts, working for 378 different brokerage houses and covering 4,527 firms.

We can track the behavior of individual analysts in the I/B/E/S sample. At each point in time, we can identify the stocks that these analysts follow (*i.e.* the firms they issue earnings forecasts on) and the brokerage houses that employ the analysts. Generally, analysts tend to specialize and cover firms in the same industry. On average, an analyst in I/B/E/S follows about 9.5 firms in a year, with a standard deviation of about 4.7 firms. In addition, we have a comprehensive record of their forecast histories, allowing us to construct past forecast performance measures (see Section 5 below).

Because we know where an analyst is employed when she issues an earnings forecast, we can measure how many analysts a particular brokerage house employs at each point in time (*i.e.*, the size of the brokerage house). Table 1 provides some summary statistics (for each year in the sample) of the size of brokerage houses. The number of brokerage houses in existence has increased over time, from a low of 90 in 1983 to a high of 223 in 1996. Also, the average size of brokerage houses has fallen over time. In 1983, the average size of a brokerage house was 20.71 analysts, compared to 12.66 in 1996. This decrease in size over time is also apparent by looking at the other percentiles of the size distribution. In 1983, the 25th percentile was 7, the median 12 and the 75th percentile 25 analysts. In 1996, these numbers become 3, 7 and 15 respectively. These numbers reflect the increasing numbers of smaller brokerage houses that specialize on certain industries as opposed to the traditional full service brokerage houses.

The I/B/E/S database does not explicitly record the number of years that an analyst has been working. Because we are interested in how the forecasts and job separations of analysts vary with their experience, we only examine analysts for whom we can calculate the number of years they have been working as analysts. Because our I/B/E/S sample begins in 1983, we know the experience level of all analysts who begin their career after 1983. Therefore, we exclude all left-censored analysts from our subsequent analysis (the samples for Tables 2-11 below exclude all left-censored analysts).

In this sample, an analyst remains in our I/B/E/S sample for almost six years on average, with a standard deviation of about 3.7 years. Some are in the database only one year (the 10th percentile of the distribution), either because they quickly left the profession, they switched to a brokerage houses not covered by I/B/E/S (though this is very unlikely since the vast majority of brokerage houses submit the forecasts of their analysts to I/B/E/S), or they began their career in 1996. However, a number of analysts are in the sample for the entire thirteen-year period between 1984 and 1996. The 90th percentile of the distribution is eleven years.

3.2. Measures of Brokerage House Status

With these basic facts about security analysts in mind, we next construct measures of the brokerage house hierarchy. There is a discernible ladder of prestige in brokerage houses. At the top of this hierarchy are well-known names such as Goldman Sachs and Merrill Lynch. Such brokerage houses include many of the traditional powerhouses of Wall Street and have large investment banking businesses. They tend to employ many analysts because they do business in all types of industries. At the other end of the spectrum are brokerage houses that specialize in covering specific industries (e.g. high-tech) or types of stocks (e.g. small cap). Such brokerage houses tend to be more regional in nature and cater to institutional investors, providing research in exchange for trading commissions from those investors. They tend to be smaller and hire fewer analysts.

Measures of prestige are somewhat arbitrary, although market participants can readily agree that certain traditional banking powerhouses such as Goldman Sachs or Merrill Lynch belong in the top tier.

In this paper, we use two measures of this brokerage house hierarchy. One measure is derived from a brokerage house prestige ranking published by *Institutional Investor*. Each year in the October issue of I.I., the brokerage houses with the most All-Americans are listed as “The Leaders.” Similar to Phillips and Zuckerman (1999), a sociological study of status among brokerage houses, we classify the top ten brokerage houses in this annual poll as high status and other brokerage houses as low status for that year. Not surprisingly, well-known brokerage houses such as Goldman Sachs and Merrill Lynch are invariably categorized as high status using this measure.

Our second method of classifying brokerage houses involves sorting them by their size, measured by the number of analysts they employ. As mentioned above, the traditional investment banks tend to hire more analysts than smaller, specialized brokerage houses; however, prestige is likely not linear in house size. That is, a brokerage house with 30 analysts is not likely to be significantly more prestigious than one with 25 analysts. Therefore, in this second measure of brokerage house status, we classify the ten biggest brokerage houses each year as the high-status houses and the rest as low-status houses for that year.

Table 2 provides some summary statistics for these two status measures by year. The first column shows the percentage of analysts who work for the top 10 houses using the I.I. rankings. On average, about 23% of analysts work for these high status brokerage houses. This percentage is stable for the fourteen-year period of our sample. Using the size measure, about 28% of analysts work for the 10 largest houses. There is a slight decrease over time in this magnitude, indicating that the largest houses are employing a smaller fraction of analysts over time. Finally, we look at the percentage of brokerage houses classified as high status using one of the measures in each year that qualify as high-status under both measures. It ranges from a low of 30% in 1985 to a high of 80% in 1993, averaging about 60% over the fourteen periods. Although these two measures of the brokerage house hierarchy are highly correlated, the level of the correlation suggests that they may still contain different information; therefore, we will use both measures in our analysis.

4. Movements along the Brokerage House Hierarchy

In this section, we begin our analysis of analyst career concerns by documenting several systematic patterns in the movements of analysts along the brokerage house hierarchy. These patterns provide insight into the nature of brokerage house hiring of analysts and set the stage for our analysis of the relationship between forecast performance and job separations in section 5.

4.1. Measures of Job Separation

We are concerned with movements of analysts between brokerage houses of different status, measured by the I.I. rankings and size. We create four job separation measures. First, an analyst in the I/B/E/S data is said to have changed brokerage houses in year t if she worked for one brokerage house at the beginning of year t and at some point during the year moved to a different brokerage house. Second, an analyst is defined as moving to a higher status brokerage house in year t if she was working for a low status brokerage house at the beginning of year t and moves at some point during that year to a high status brokerage house. Third, an analyst is described as moving to a lower status brokerage house in year t if she was working for a high-status brokerage house at the beginning of year t and moves at some point during t to a low-status brokerage house.

A final measure of job separation that we will briefly consider in conjunction with our other separation measures is movements of analysts out of the profession. We do not actually observe in the I/B/E/S database whether a security analyst has been fired; however, we can determine whether an analyst stops producing earnings forecasts. Because an important component of being a security analyst is producing earnings forecasts and virtually all analysts submit their forecasts to I/B/E/S, we infer that most analysts who stop producing forecasts have left the profession. As we mentioned above, our analysis will focus on movements along the hierarchy as opposed to out of the profession since we do not necessarily know for sure what job analysts take after they leave the I/B/E/S sample and the profession. However, since sell-side analysts generally aspire to be I.I. All-Americans (see, e.g., Stickel (1992), Nocera (1997) and Pulliam (2000)), an observation of an analyst leaving the profession is likely an adverse career

outcome. Therefore, we will classify an analyst as terminated in year t if she made forecasts in year t but stopped producing forecasts before year $t+1$.

4.2. Some Characteristics of Job Separations

We provide summary statistics of the various job separation measures for all analysts in I/B/E/S in Table 3. We are most interested in the analysts who leave their brokerage house but stay in the profession. About 7.3% of analysts each year change brokerage houses, indicating that there is substantial job mobility across brokerage houses. Using the I.I. ranking of brokerage house status, only about 1.26% of analysts that started the year at a low status brokerage house move up to a high status brokerage house in any given year. In contrast, nearly 24% of analysts who started the year at a high status brokerage house move down to a lower status brokerage house in a given year. Similar numbers are found when we consider size as the measure of status. These numbers suggests that moving up the brokerage house hierarchy or staying at the top is very competitive.

As an initial characterization of the job matching process, we examine in Table 4 whether analysts cover the same firms when they change brokerage houses. The question here is whether brokerage houses hire analysts for their general knowledge and then allocate them to different tasks or whether they hire analysts to have them perform the same task they were performing for their previous brokerage house. For all analysts, we calculate the percentage of an analyst's portfolio in year t that consists of firms that she was not following in year $t-1$. We then examine whether analysts that change brokerage houses have a bigger change in the firms they follow than analysts that stay with their brokerage house. The findings suggest that there is little difference between the change of the stock portfolios of analysts who leave and those who stay. In the entire sample, the percentage of an analyst's stock portfolio that consists of new firms each year is about 28%; these percentages are almost identical for analysts who stay with their brokerage house and analysts who move to another brokerage house. If we break these numbers down by movements across brokerage houses of different status, we see some small differences. Analysts who move up the brokerage house hierarchy tend to have smaller changes in

their portfolio of stocks that they follow than other analysts. When a prestigious brokerage house hires an analyst, she is perhaps expected to keep her focus on those stocks that got her to the top; however, the differences between these groups of analysts are not large.

4.3. Job Separations and Experience

We next look at the relationship between movements along the brokerage house hierarchy and the experience of analysts. We pursue this analysis in Table 5, where using a sample of all analysts who are in the I/B/E/S sample for n years, we calculate the percentage of those analysts who worked for a high status brokerage house (as measured using the I.I. ranking) their first year, their second year and all the way to their n -th year as analysts.⁵ For example, column (4) includes in the sample all analysts who are in the I/B/E/S sample at least five years. In their first year, only 17% of this sub-set of analysts worked for high status brokerage houses. As these analysts moved to their second year, this percentage rises to 20%. This percentage rises monotonically each year up to year 5 in which the percentage is about 23%. Therefore, we see a funnelling up of analysts from low-status to high-status firms as they age; the same pattern holds for cohorts with different minimum number of years in the sample.⁶ In other words, for analysts who have been in the profession for a given number of years, they were more likely to move to high status brokerage houses as they aged.

Table 5 also indicates that a substantial portion of this funnelling of analysts up the hierarchy occurs between the analyst's first and the second year in the profession or soon thereafter. The change in the percentage of analysts who work for a high status brokerage house is the largest between the first and second year, ranging around 1.5 to 2% across the nine columns. However, the changes in the remaining years are still important. For example, in column (5) (analysts with a minimum of six years in the

⁵ We examine this subset of analysts to avoid the possibility that differential attrition rates between analysts who work for high and low status brokerage houses drive our results. All of the analysts are in the sub-sample the entire period being examined.

⁶ The results of this table are very similar if we use the brokerage house size status measure instead of the I.I. status measure. We omit these results for brevity.

sample), the change in percentage of analysts working for high status brokerage houses is around 2% between years 1 and 2 (18.33% - 16.36%). At year six, about 21.5% of the analysts are working for high-status brokerage houses. So, between year 2 and year 6, another 3% of these analysts moved to high status brokerage houses.⁷

Having established the funnelling of analysts to high-status brokerage houses with age, we examine how movements down the brokerage house hierarchy vary with experience in Table 6. To capture this relationship, we estimate the following simple regression specification that we will use throughout the paper:

$$Job\ Separation_{i,t} = \alpha + Experience\ Dummies_{i,t} + YearEffects + \varepsilon_{i,t} \quad (1)$$

where $Job\ Separation_{i,t}$ is an analyst's career outcome in year t , $Experience\ Dummies_{i,t}$ is a full set of dummies for different years of tenure for the analyst, $YearEffects$ is a full set of year effects, and $\varepsilon_{i,t}$ is an error term. The effect of the first year of experience is omitted; therefore, the coefficients in Table 6 measure how more likely an analyst with two to ten years of experience is to separate from her job than an analyst in her first year.

The job separation dependent variable that we consider throughout the table is an indicator that the analyst moves from a high status to a low status brokerage house. In column (1), we look at the effect of experience on the movements from high status to low status brokerage houses using the I.I. status measure. We find a substantial decline in the probability of moving to a low status brokerage house as an analyst gains experience. In column (2), we look at the effect of experience on movements down the

⁷ Because the number of brokerage houses is increasing over time (as shown in Table 1), if analysts just randomly move across brokerage houses, then we would expect that the percentage of analysts who work for high status brokerage houses to decline as they age. Given that we find the opposite, there appears to be strong evidence that analysts on average move up the brokerage house hierarchy as they gain experience. As an additional robustness check, we also made the calculations of Table 5 applying the 1995 definitions of high status to all years instead of using different definitions of status for each year we examine. We find similar results; therefore, strange movements of status rankings over time do not drive the findings in Table 5.

hierarchy using the size status measure. Similar results hold except that the probability of separation increases in the second year relative to the first and then declines during subsequent years.

These results are similar to findings on the relationship between experience and job turnover documented in other labor markets (see, e.g., Lazear (1995)). Generally, this work finds that there is a small increase in the probability that an analyst leaves an employer in the second year before a pronounced decline in subsequent years. The usual explanation for the small increase early is that it takes time for an employer to evaluate personnel. The subsequent decline reflects better and better matching between employee and employer. This non-linearity is often interpreted along the lines of a model of job matching like Boyanovic (1979). Our findings in Table 6 using the size status measure are similar to this non-linear job separation pattern; however, our findings using the I.I. ranking status measure are different to the extent that there is not much of an initial increase in the probability of job separation with tenure.

In summary, we have established that there are interesting movements up and down the brokerage house hierarchy by analysts. First, we show that moving up or staying at top-tier brokerage houses is quite competitive. Only a small percentage of analysts who start at lower tier houses are able to move up to the top houses, while a large number of those that start at high status brokerage houses move down the ladder. Brokerage houses appear to value the expertise that analysts have cultivated with their previous employers. Also, as analysts become more seasoned, they are more likely to move up this hierarchy. Collectively, these findings suggest that the brokerage house hierarchy may value analysts with good forecasting track records. We next turn to examining how forecast performance (accuracy) affects movements along this hierarchy.

5. Forecast Performance and Movements along the Brokerage House Hierarchy

In this section, we examine the relationship between forecast performance, job separations and brokerage house status. We focus primarily on the effect of forecasting performance on movements up

and down the brokerage house hierarchy and the employment practices of brokerage houses of different status.

5.1. Measures of Forecast Performance

5.1.1. Absolute Performance

We begin by constructing a measure of the absolute forecast performance of an analyst. We use the I/B/E/S data to construct a yearly performance measure based on an analyst's forecast accuracy. We define $F_{i,j,t}$ as the most recent (dollar) earnings per share (EPS) forecast of year-end earnings issued by analyst i on stock j between January 1st and July 1st of year t .⁸ Our measure of analyst i 's accuracy for firm j in year t is the absolute difference between her forecast and the actual EPS of the firm, $A_{j,t}$:

$$\text{Forecast Error}_{i,j,t} = |F_{i,j,t} - A_{j,t}|. \quad (2)$$

Because an analyst generally covers more than one firm in a year, we need to aggregate this forecasting accuracy measure across all the firms that she covers. The simplest way to do this is to just compute the average forecast error of an analyst. We could just take the average of the analyst's scores for the year; however, this measure would be very noisy for analysts that only follow a couple of firms in a year. Hence we construct:

$$\text{Absolute Forecast Performance}_{i,t} = \frac{1}{n} \sum_{j \in J} \text{Forecast Error}_{i,j,t} \quad (3)$$

where n is the number of different firms that an analyst follows in year t and the two previous years and J is the set of firms the analyst covers. That is, the absolute performance measure is an average of the analyst's forecast errors on all the firms she covered over the three previous years. Such a longer averaging period will increase the signal-to-noise ratio of our performance measure.

⁸ We use the most recent forecasts before the cut-off date of July 1st to evaluate the analysts because we need a common time frame to compare different analysts' forecasts (see, e.g., Crichfield, Dyckman and Lakonishok (1978)). Our results are robust to alternative cut-off dates.

5.1.2. Relative Performance

The average absolute forecast error measure is the simplest way of comparing the forecast performances of different analysts; however, because analysts cover different firms, even analysts that cover the same industries, this performance measure is problematic. Some firms are more difficult to accurately predict than other firms. An analyst might have a higher absolute forecast error than another analyst either because the analyst did not perform as well as the other analyst or the firms the analyst follows were more difficult to forecast than the firms of the other analyst.

We construct a relative performance measure that accounts for these issues. We first sort the analysts that cover a particular stock in a year based on their forecast error given in equation (2). We then assign a ranking based on this sorting; the best analyst (the one with the lowest forecast error) receives the first rank for that stock, the second best analyst receives the second rank and onward until the worst analyst receives the highest rank. If more than one analyst was equally accurate, we assign all those analysts the midpoint value of the ranks they take up.⁹ Under this relative ranking system, the analyst that produces the most accurate estimate of Firm A performs as well as the analyst that produces the best estimate of Firm B, regardless of the actual forecast errors of the analysts for the two firms.

We could just use the average rank of an analyst across all the firms she follows as a measure of her overall accuracy for the year. Analysts with a lower average rank would perform better than other analysts. However, this average rank measure might be problematic because the maximum rank an analyst can receive for a firm depends on the number of analysts that cover the firm. Analysts that cover firms that are thinly followed are more likely to have lower average ranks than analysts that follow firms with high coverage regardless of their forecast accuracy. Therefore, we want to scale an analyst's rank for a firm by the number of analysts that cover that firm. We develop a score measure that adjusts for these differences in coverage. The formula for this score is:

⁹ This means that the ranks need not be integers.

$$Score_{i,j,t} = 100 - \left[\frac{Rank - 1}{Number\ of\ Analysts_{j,t} - 1} \right] \times 100 \quad (3)$$

where $Number\ of\ Analysts_{j,t}$ is the number of analysts who cover the firm in a year.¹⁰ An analyst with the rank of one receives a score of 100; an analyst who is the least accurate (and the only one who is least accurate) receives a score of zero. The median and mean score for a firm in a year is 50. This score measure might be easier to understand with an example. Table 7 presents the forecast errors of eight hypothetical analysts for a given firm in a year and their scores based on their ranks. The best and worst analysts receive a score of 100 and 0 respectively. The second through fourth analyst have the same forecast error (as does the sixth and seventh analyst); therefore, they all receive the same rank of 3, the midpoint of the second through fourth slot (6.5 for the sixth and seventh analyst).

After we calculate scores for every firm covered by the analyst, we need to compute an overall score that reflects the analyst's recent forecast accuracy. We could just take the average of the analyst's scores for the year; however, as with the absolute accuracy measure, this relative measure would be very noisy for analysts that only follow a couple of firms in a year. Therefore, we create the measure *Relative Forecast Performance_{i,t}*, which is the average of the analyst's forecast scores in year t and the two previous years.¹¹ Higher overall scores correspond to better analyst performance.

Although we believe both the absolute and relative performance measures are reasonable, we need to keep in mind some of their peculiarities. First, certain types of analysts are likely to have extreme average accuracy measures (both good and bad). For instance, analysts that cover few firms over the three-year period are more likely to be in the extremes. One very good or poor performance on a firm will greatly affect their average score. Also, for the relative measure, analysts that cover thinly followed firms are more likely to be in the extremes. For a given firm, it is easier for an analyst to earn a score near

¹⁰ If only one analyst follows a firm in a given year, a score is not calculated for that firm.

¹¹ Therefore, an analyst must be in at least her third year as an analyst to have a forecast performance measure. We use these three-year averages primarily because they are less noisy proxies of forecasting expertise.

100 or 0 on their relative performance measures if there are few other analysts covering the firm in a year. We need to keep these things in mind when we move to our empirical work because we want to make sure that we are capturing an analyst's accuracy with this score measure and not the types of firms that she follows.

5.2. Sensitivity of Job Separation to Forecast Performance

We begin our analysis of job separation and forecast accuracy by focusing on the effect of analyst forecast accuracy on movements along the brokerage house hierarchy. In this analysis, at any year t , we only include those analysts that have at least three years of forecast history, the number of years necessary to allow us to calculate our forecast performance scores defined in the previous section.¹²

In Table 8, we report summary statistics for the various job separation measures in Table 3 using this sub-sample of analysts with at least three years of experience and the forecast performance measures defined in Section 5.1. In any given year, the probability that an analyst moves from a low status to a high status firm is 1.5%, from a high status to a low status firm is 20% (using the I.I. ranking measure). Similar numbers hold for the size ranking measure. Finally, notice that by construction, the average forecast accuracy and boldness measures have means close to 50, with a standard deviation of 7.4.

To capture the relationship between job separation and forecast performance, we begin with the following simple regression specification:

$$Job\ Separation_{i,t+1} = \alpha + \beta_1 Forecast\ Performance\ Indicator_{i,t} + \varepsilon_{i,t+1} \quad (4)$$

where $Job\ Separation_{i,t+1}$ is an analyst's career outcome, (e.g. whether analyst i moves from a low status to a high status brokerage house in year $t+1$), $Forecast\ Performance\ Indicator_{i,t}$ is some function of the analyst's past forecast accuracy measured as of year t , and $\varepsilon_{i,t+1}$ is an error term. β_1 measures

¹² For instance, at the beginning of 1987, our analysis only includes those analysts that are also in the sample in 1986, 1985 and 1984.

how an analyst's past forecast accuracy affects the probability that she experiences a particular career outcome.

This simple regression specification is incomplete because there are possible biases in the estimation that need to be controlled for carefully. When we described the construction of our analyst forecast performance measures, we noted that analysts who cover firms with thin coverage and analysts that cover few firms are more likely to be in the extremes of forecast performance. If analysts that follow few or thinly covered firms during this window are more or less likely to separate from their jobs for reasons other than their performance, then we might find a spurious relationship between forecast performance and job separation.

Therefore, we need to control for the type and number of firms that analysts follow during the three-year window that is used to calculate the forecast accuracy measure. First, we condition on the average coverage of the portfolio of firms that the analyst follows those three years to control for the fact that an analyst might be following thinly covered firms (*Average Coverage Dummies*_{*i,t*}).¹³ We also add dummy variables for the number of firms the analyst follows during the three-year window (*Number of Firms Covered Dummies*_{*i,t*}). Additionally, we also include indicators for the years of experience of the analyst (*Experience Effects*_{*i,t*}), and a full set of year dummies (*Year Effects*_{*t*}). Our final regression specification is then:

$$\begin{aligned} \text{Job Separation}_{i,t+1} = & \alpha + \beta_1 \text{Forecast Performance Indicator}_{i,t} + \text{Average Coverage Dummies}_{i,t} \\ & + \text{Number of Firms Covered Dummies}_{i,t} + \text{Experience Effects}_{i,t} \\ & + \text{Year Effects}_{t+1} + \varepsilon_{i,t+1} \end{aligned} \quad (5)$$

For all of the job separation estimates, we present only results from linear probability models. Results from logit and probit models are qualitatively similar.

¹³ We could just add this variable linearly to the regression specification, but we are concerned that there might be a more complicated relationship between this average coverage measure and the job separation. Because the values of this variable fall roughly between 0 and 40, we create a series of 40 dummy variables that correspond to increments of one of this value and include those dummies in the regression specification.

Table 9 presents the results of these regressions for the various job separation measures involving movements along the brokerage house hierarchy. Column (1) shows the estimate of the effect of being in the top 10 percent of the distribution of the relative forecasting performance measure on moving from a lower to a higher status brokerage house. The coefficient on past forecast performance is positive and significantly different than zero, suggesting that extreme good relative performance increases the probability of moving from a low status to a high status brokerage house by about 1.5 percentage points. In any given year, about 1.5% of analysts experience such a positive career outcome; therefore, good past relative forecasting performance doubles an analyst's chances of moving up the brokerage prestige hierarchy.

In column (2), we look at the effect of poor relative forecasting performance on the probability of moving from a high status to a low status brokerage house. The coefficient on an indicator of whether the analyst scores in the bottom 10% of the score distribution is positive and statistically different than zero. The size of the coefficient indicates that scoring in the bottom 10% of the performance distribution increases an analyst's chances of moving down the brokerage house hierarchy by about 15 percentage points. In any given year, about 20% of analysts experience such a negative career outcome; therefore, poor past forecasting performance increases an analyst's chances of experiencing such an unfavorable outcome by about 75%.

In columns (3) and (4), we re-estimate effect of forecasting performance on job separations using the measure of absolute forecasting performance instead of the measure of relative forecasting performance. We find that the various job separation measures do not appear to be as sensitive to the absolute performance measure as to the relative performance measure. In column (4), we find that extreme good performance (scoring in the top 10% of absolute performance distribution) has a very small effect (of the wrong sign) and not statistically significant from zero effect on moving from a low to a high status brokerage house. In column (5), we consider the effect of poor absolute forecasting performance on movements down the brokerage house hierarchy. The effect is of the right sign but imprecisely estimated. This difference between the estimates using the relative and absolute performance measures is

similar to Mikhail, Walther and Willis (1999), who find that absolute performance has little effect on job movements. They do not, however, consider the direction of the job movements (i.e. up or down the hierarchy or out of the profession). These findings are also similar to those in the CEO literature, which finds that relative performance matters much more than absolute performance for job separations (see, e.g., Gibbons and Murphy (1990)). Therefore, in the remaining analysis, we will only use the relative performance measure.

5.3. Sensitivity of Job Separation to Forecast Accuracy by Brokerage House Status

After examining how job separations are affected by forecasting performance, we now look at how this sensitivity varies across brokerage houses of different status. One motivation for this decomposition is that prestigious brokerage houses really value analysts with perceived forecasting expertise because their clientele is picky about having such acumen in the research departments of the brokerage houses that they do business with---at least more so than the clientele of lower status brokerage houses (see footnote 1). In this scenario, revelations of a lack of expertise among the analysts of high status brokerage will lead to more rapid dismissal than if an analyst at a lower status brokerage house performs poorly. Moreover, high status brokerage houses can afford to be more impatient with a lack of forecast performance if they have many more analysts who want to work for them than do houses with lower prestige. Hence, we would expect larger and more prestigious firms to fire more quickly for poor performance than other firms.

We measure the firing probabilities across brokerage houses of different status in Table 10. We estimate a regression specification that allows the effect of poor performance on job separations to differ for analysts that work for low versus high status brokerage houses. The specification is similar to equation (5):

$$\begin{aligned}
\text{Job Separation}_{i,t+1} = & \alpha + \beta_1 \text{Forecast Performance}_{i,t} + \beta_2 \text{High Status Indicator}_{i,t} \\
& + \beta_3 \text{Forecast Performance}_{i,t} \times \text{High Status Indicator}_{i,t} \\
& + \text{Average Coverage Dummies}_{i,t} \\
& + \text{Number of Firms Covered Dummies}_{i,t} + \text{Year Effects}_{t+1} \\
& + \text{Experience Effects}_{i,t} + \varepsilon_{i,t+1}
\end{aligned} \tag{6}$$

where *High Status Indicator*_{*i,t*} is a dummy variable for whether the analyst works for a top-tier brokerage house and the other variables are defined as above. The coefficient of interest is β_3 , which measures how much more likely poor performing analysts who work for high status brokerage houses are to leave their job than other poor performing analysts.

In column (1) of Table 10, we estimate the effect of poor performance on the probability that an analyst changes employers by brokerage house status, using the I.I. ranking status measure. The coefficient on the interaction term is positive but not significantly different than zero, suggesting that analysts who work for high status brokerage houses and perform poorly might be more likely to leave to change employers than other poorly performing analysts but the effect is imprecisely estimated. The coefficient on *Forecast Performance*_{*i,t*} $\times$ *High Status Indicator*_{*i,t*} indicates that these poor performing analysts who work for high status firms are 3.5 percentage points more likely to leave their job than other poor performing analysts or about a 43% increase.

In column (2) of Table 10, we examine the effect of past performance and brokerage house status on the probability that an analyst leaves the profession. The positive coefficients on the indicator for poor performance and the interaction term imply that poor performance increases the likelihood that analysts who work for any status brokerage house will leave the industry; however, the positive interaction term suggests that poor performing analysts who work for top-tier brokerage houses are more likely to leave the profession than other poor performing analysts. The size of the coefficient on the interaction term suggests that poor performing analysts working for top houses are about 10 percentage points more likely to leave the profession than other poor performing analysts, indicating that poor performers at top-tier brokerage houses are about 60% more likely to exit the profession than other poor performers.

Columns (3) through (4) display the same regression estimates using the size status measure instead of the I.I. rankings. The results of these regressions are very similar to the I.I. estimates. Job separations again are more likely for poor performing analysts who work for top-tier firms compared to other analysts and these job separations are more likely to be exits from the profession rather than movements to other brokerage houses.

The accumulated evidence above suggests that top brokerage houses value more experienced analysts, that good relative forecast performance leads to movements up the brokerage house hierarchy and that more prestigious brokerage houses are more discriminating about forecasting performance. In other words, there is a well functioning external labor market that rewards forecasting expertise.

6. Forecast Performance and Stock Coverage Assignments

Having measured analyst career concerns using job separations, we next look at implicit incentives that may arise within the brokerage house. Since our data set allows us to track the particular stocks that an analyst follows at any point in time, we can examine whether forecast performance affects the type of firms that an analyst follows for a brokerage house.

The idea is that there are certain firms that receive substantial attention from the investment community (e.g., Intel and Microsoft). Not surprisingly, these stocks are very large firms as measured both by market capitalization and the number of analysts that follow them. To the extent that the buy-side cares about forecasting expertise, it would be reasonable to assume that brokerage houses might replace poor performing analysts on these stocks with analysts who have better performance; anecdotal evidence (see, e.g., Nocera (1997)) suggests that this might be the case. In this section, we attempt to measure whether such implicit incentives indeed exist within brokerage houses.

6.1. Empirical Strategy

Our empirical strategy involves tracking the firms that a brokerage house covers and determining whether the performance of the analyst covering the firm affects whether the brokerage house replaces the

analyst with another analyst. For each stock that an analyst in a given brokerage house is following in a given year, we examine whether the brokerage house has an analyst (any analyst) following that firm the subsequent year. If no one is following the firm, then the brokerage house has dropped the stock. If someone is following the firm, then the brokerage house is continuing to follow the stock. We only look at instances where a brokerage house continues to follow the stock and ask who is following the stock the subsequent year.

If it is a new person, then the brokerage house has rotated a new person onto the stock. This can happen a couple of ways. One, the analyst previously covering the stock could have left the brokerage house (fired or left voluntarily), and therefore the brokerage house had to find a new analyst to follow the stock. Or, the analyst previously covering the stock could have stayed with the brokerage house but for some reason was replaced by another analyst covering this stock.

We are most interested in the rotations in which the analyst who leaves the stock stays with the brokerage house. Therefore, our sample is all stocks that a brokerage house follows in year t and also year $t+1$ in which the analyst who was covering the stock for the brokerage house in year t is also working for that brokerage house (but not necessarily covering that stock) in year $t+1$. Then, we construct a variable that is an indicator of whether that analyst (the one that was covering the stock in year t) is following the stock for the brokerage house in year $t+1$. We include in this sample only stocks that are followed in year t by an analyst who we have a relative performance score for, where the score is as defined in Section 5.1.2. This leaves us with a sample of 85,966 observations for analysis. The unit of observation is a brokerage house/stock/year cell. In this sample, about 89.5% of the time, the analyst who was covering the firm in year t also covered the firm for the brokerage house in year $t+1$.

We want to relate the probability that an analyst continues to follow a given stock for the brokerage house to the analyst's past performance. The regression specification we will use is the following:

$$\begin{aligned} \text{Analyst Stops Covering Stock}_{i,j,k,t} = & \alpha + \beta_1 \text{Analyst Performs Poorly}_{i,t} + \text{Average Coverage Effects}_{i,t} \\ & + \text{Number of Firms Covered Effects}_{i,t} + \text{Year Effects}_t + \varepsilon_{i,j,k,t} \end{aligned} \quad (7)$$

Subscript i is for the analyst who covers the stock in year t . Subscript j is for the stock, and subscript k is for the brokerage house. $\text{Analyst Stops Covering Stock}_{i,j,k,t}$ is an indicator whether analyst i , who was covering stock j for brokerage house k in year t , does not follow the stock in year $t+1$. $\text{Analyst Performs Poorly}_{i,t}$ is an indicator that the analyst scored in the bottom 10% of the relative performance distribution. This variable is measured using all stocks that an analyst followed in the past three years and therefore measures the general forecasting performance over all stocks of the analyst as opposed to performance for just stock j . We also add in the usual controls to account for the number and type of firms that an analyst follows when determining his score measure, $\text{Average Coverage Effects}_{i,t}$ and $\text{Number of Firms Covered Effects}_{i,t}$. We also add Year Effects_t . The coefficient of interest is β_1 , which measures whether analysts who perform poorly are more likely to move off a stock than other analysts.

We are most interested in estimating the regression in equation (7) for a sub-sample of only high-profile stocks. We will classify a stock as high-profile in two ways. First, we define a stock as being high profile if 30 or more analysts follow the firm. Second, we classify a stock as being high-profile if it has a value greater than \$15 billion. About ten percent of firms are classified as high-profile using both classifications.

However, we first run the regression in equation (7) using all stocks as a benchmark. There are a couple of reasons for doing so. Because analysts tend to cover more than one stock at any point in time, it might be the case that poor performance will lead to movements out of a stock, regardless of size, because brokerage houses want to curtail the responsibilities of the analyst by decreasing the number of stocks that the analyst follows. Also, it might be that analysts have some discretion over which stocks they cover and for some reason, after poor performances, they might want to drop some stocks from their coverage.

Since the high profile stocks are always covered by brokerage houses and are what analysts strive to cover, if we find analysts moving off of high profile stocks after poor performances, then it is likely not to be done voluntarily by analysts. In some sense, what interests us is the difference in magnitudes between β_1 for the sub-sample of high profile stocks and the sample comprising of all stocks.

6.2. Results

The results of the regression in equation (7) are presented in Table 11. The first three columns show the effect of poor performance on whether an analyst stops following a stock for all brokerage houses. The first column includes all stocks and is the benchmark case. The coefficient on the poor performance indicator is essentially zero, suggesting that analysts who perform poorly (and do not leave their brokerage house) are not more likely to stop following a given stock than any other analyst. In column (2), we present the regression results only including the analysts who follow the stocks with high analyst coverage. The effect of performing poorly is positive and statistically significant for this group of stocks compared to the entire sample. The size of the coefficient suggests that poor performance increases the probability that an analyst leaves a high-profile stock by over three percentage points, an increase of about 30%. In column (3), we present the regression result only including the analysts who follows stocks with high market caps. Again, the coefficient is positive and statistically significant from zero for this sub-sample, again suggesting that analysts who are following high-profile stocks are more likely to move off of high-profile stocks following extreme poor forecasting performances.

In columns (4)-(6) of Table 11, we replicate the estimates of the first three columns using only high status brokerage houses (using the I.I. ranking measure). Column (4) presents the effect of poor performance on an analyst moving off of any stock. The coefficient indicates that an analyst working for a high status brokerage house who performs poorly is more likely than other analysts to stop following a given stock. This result suggests that, after poor performances, a high status brokerage house curtails an analyst's responsibility or the analyst simply chooses to drop coverage of some stocks. Columns (5) and

(6) present the regression results using only high-profile stocks. For both measures of high-profile firms, poor performing analysts are much more likely to leave a stock. For such high-profile stocks, it is not likely that an analyst would voluntarily drop coverage since they are rather important ones. Hence, it is probably the case that they were dropped from these stocks by their brokerage houses.

In other words, these findings strongly suggest that the internal labor markets within brokerage houses may provide some implicit incentives for security analysts to produce forecast track records by rationing high-profile or “plum” stocks to analysts with better track records.

7. Conclusions

In this paper, we attempt to measure the career concerns of security analysts. We find that higher status brokerage houses tend to value more seasoned security analysts than other houses. Good relative forecast performances lead to movements up the brokerage house hierarchy, while poor relative performances lead to movements down the hierarchy. Higher status brokerage houses are more likely to terminate an analyst for poor forecasting performance. Furthermore, analysts with poor past forecast performances are more likely to be removed by their brokerage houses from following high-profile stocks. This effect is more significant among high status brokerage houses. Overall, these findings paint a consistent picture of a labor market that provides implicit incentives for analysts to produce good forecast track records.

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Table 1: Characteristics of Brokerage Houses over Time

The entries are descriptive statistics on brokerage houses that employ security analysts in the I/B/E/S database between 1983 and 1996. For each year in the sample, we report the total number of such houses and sample statistics on the size of these houses (number of analysts employed).

Year	Number of Houses	Number of Analysts Working for Brokerage House			
		Average	25 th Percentile	Median	75 th Percentile
1983	90	20.71	7	12	25
1984	108	18.26	7	11	25
1985	126	16.56	5	10	22
1986	136	15.02	4	9	16
1987	142	15.07	5	9	17
1988	153	13.46	5	9	16
1989	171	12.67	4	8	15
1990	174	11.91	4	7	15
1991	178	10.76	4	7	14
1992	166	11.83	4	7	15
1993	196	11.41	3	7	15
1994	196	11.57	3	7	14
1995	211	12.48	3	7	15
1996	223	12.66	3	7	15

Table 2: Characteristics of High Status Brokerage Houses

Security analysts in the I/B/E/S database between 1983 and 1996 are categorized as working for a high or low status brokerage house using two measures. The first measure classifies an analyst as working for a high status brokerage house if the house is one of the ten brokerage houses that employed the most *Institutional Investor* (I.I.) All-Americans that year. The second measure classifies an analyst as working for a high status brokerage house if the house is one of the ten largest (in terms of size) brokerage houses that year. The entries are the percentage of all analysts who are categorized as working for high status firms based on these two definitions in a year and the percentage of brokerage houses that are classified as high status that are high status using both measures.

Year	Percentage of Analysts Working for Top 10 Brokerage Houses by I.I. Ranking	Percentage of Analysts Working for Top 10 Brokerage Houses by Size Ranking	Percentage of High Status Brokerage Houses that are High Status in Both Rankings
1983	22.87	39.13	40%
1984	23.66	33.44	60%
1985	21.34	29.76	30%
1986	24.91	31.94	60%
1987	20.99	28.12	50%
1988	26.44	28.69	70%
1989	26.35	28.11	70%
1990	21.78	25.07	70%
1991	23.19	25.03	70%
1992	20.66	25.68	60%
1993	24.84	25.97	80%
1994	24.74	24.88	70%
1995	22.78	25.20	70%
1996	22.81	25.92	60%

Table 3: Characteristics of Analyst Job Separations

Security analysts in the I/B/E/S database in a year are tracked to see if they separate from their employer during the next year. The entries contain the percentage of analysts who experience various types of job separations. For those who move to a new brokerage house, we categorize some of these job changes as movements up or down the brokerage house hierarchy. We calculate the percentage of analysts who work for low status brokerage houses that move to a high status brokerage house (moving up the hierarchy) and the percentage of analysts who work for high status brokerage house that move to a low status brokerage house (moving down the hierarchy). These percentages are calculated using both the *Institutional Investor* (I.I.) rankings and the brokerage house size measures to determine brokerage house status.

Analysts who Change Brokerage House	7.30%
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I.I. Ranking Measure

Analysts who Move to a High Status Brokerage House From a Low Status Brokerage House	1.26%
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Analysts who Move to Low Status Brokerage House From a High Status Brokerage House	23.98%
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Size Ranking Measure

Analysts who Move to a High Status Brokerage House From a Low Status Brokerage House	1.36%
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Analysts who Move to Low Status Brokerage House From a High Status Brokerage House	30.31%
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Table 4: The Percentage of an Analyst's Portfolio in a Year that Consist of New Firms

Security analysts in the I/B/E/S database in a year are tracked to see what percentage of firms they cover in the following year are not firms they are covering this year. The entries contain the percentage of an analyst's portfolio the following year that are new firms. Analysts are separated into different samples depending on whether they separated from their firm the subsequent year. For those who move to a new brokerage house, we categorize some of these job changes as movements up or down the brokerage house hierarchy. We calculate the percentage of analysts who work for low status brokerage houses that move to a high status brokerage house (moving up the hierarchy) and the percentage of analysts who work for high status brokerage house that move to a low status brokerage house (moving down the hierarchy). These percentages are calculated using both the *Institutional Investor* (I.I.) rankings and the brokerage house size measures to determine brokerage house status.

Entire Sample	28.26%
Analysts who Leave Brokerage House	29.17%
Analysts who Stay with Brokerage House	27.96%

I.I. Ranking Measure

Analysts who Move to High Status Brokerage House From Low Status Brokerage House	23.85%
Analysts who Move to Low Status Brokerage House From High Status Brokerage House	26.34%

Size Ranking Measure

Analysts who Move to High Status Brokerage House From Low Status Brokerage House	22.62%
Analysts who Move to Low Status Brokerage House From High Status Brokerage House	27.92%

Table 5: The Percentage of Analysts Who Work for High Status Brokerage Houses by Experience

Security analysts in the I/B/E/S database who start their career between 1983 and 1996 are partitioned into different samples based upon the number of years they are in the I/B/E/S database. The samples include all analysts who are in the I/B/E/S database a minimum number of years. The entries are the percentage of analysts in these samples that work for high status brokerage houses by their experience.

Years of Experience	Minimum Number of Years Analyst is in Sample								
	2 Years	3 Years	4 Years	5 Years	6 Years	7 Years	8 Years	9 Years	10 Years
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1	18.32	19.24	18.00	17.42	16.36	15.91	16.51	14.91	15.26
2	19.72	21.12	20.33	20.08	18.33	18.10	18.23	17.34	17.67
3		21.20	20.56	21.00	19.32	17.23	17.85	16.80	17.67
4			20.73	21.08	20.20	17.96	18.43	18.70	20.08
5				22.83	21.95	20.58	21.31	18.97	20.88
6					21.51	20.58	21.11	18.16	18.47
7						21.46	21.50	19.51	20.48
8							22.07	20.33	21.69
9								19.24	20.88
10									21.69
Number of Analysts	4083	2557	1722	1200	911	685	521	369	249

Table 6: The Effect of Experience on the Probability of Moving Down the Brokerage House Hierarchy

Security analysts in the I/B/E/S database in a year who begin their career between 1983 and 1996 are tracked to see if they move down the brokerage house hierarchy during the next year. Two regression models are estimated to predict the probability that an analyst moves from a high status to a low status brokerage house based upon the number of years of experience of the analyst. Year effects are also included in the regression specifications. The entries are the coefficients on the indicators of experience and should be interpreted as the probability that an analyst with that many years of job experience is likely to change brokerage houses compared to an analyst in her first year as an analyst. Regression (1) uses the I.I. ranking measure, and regression (2) uses the size ranking measure. Standard errors are in parentheses.

	I.I. Ranking Measure	Size Ranking Measure
	(1)	(2)
Second Year	-.0006 (.0222)	.0480 (.0202)
Third Year	.0164 (.0251)	.0098 (.0237)
Fourth Year	-.0244 (.0290)	-.0887 (.0280)
Fifth Year	-.0813 (.0328)	-.0925 (.0314)
Sixth Year	-.0302 (.0368)	-.0486 (.0358)
Seventh Year	-.0761 (.0415)	-.0800 (.0401)
Eighth Year	-.0111 (.0486)	-.0542 (.0463)
Ninth Year	-.1011 (.0593)	-.1180 (.0564)
Tenth Year	-.0800 (.0709)	-.1574 (.0694)
Observations	3053	3948

Table 7: A Hypothetical Example of a Score Calculation for a Group of Analysts Following a Firm

The entries are an example of the forecasts of eight analysts covering a hypothetical firm. The analysts are ranked based on the size of the error of their forecasts, and the relative performance score measure of each analyst, described in Section 5.1.2, is calculated.

Analyst	Forecast Error	Rank	Score
1	0.12	1	100
2	0.25	3	71.4
3	0.25	3	71.4
4	0.25	3	71.4
5	0.38	5	42.9
6	0.67	6.5	21.4
7	0.67	6.5	21.4
8	0.80	8	0

Table 8: Summary Statistics of Data Set

The entries are the descriptive statistics on the sample of security analysts in the I/B/E/S database that begin their career between 1983 and 1996 and have at least three prior years of forecasting experience. The first rows are the percentage of these analysts that experience some sort of job separation the subsequent year. For those who move to a new brokerage house, we categorize some of these job changes as movements up or down the brokerage house hierarchy. We calculate the percentage of analysts who work for low status brokerage houses that move to a high status brokerage house (moving up the hierarchy) and the percentage of analysts who work for high status brokerage house that move to a low status brokerage house (moving down the hierarchy). These percentages are calculated using both the *Institutional Investor* (I.I.) rankings and the brokerage house size measures to determine brokerage house status. The final row is the average relative performance score of this sample of analysts. The standard deviation is in brackets

Analysts who Change Brokerage House	8.14%
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I.I. Ranking Measure

Analysts who Move to a High Status Brokerage House From a Low Status Brokerage House	1.52%
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Analysts who Move to Low Status Brokerage House From a High Status Brokerage House	19.86%
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Size Ranking Measure

Analysts who Move to a High Status Brokerage House From a Low Status Brokerage House	1.03%
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Analysts who Move to Low Status Brokerage House From a High Status Brokerage House	21.08%
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Relative Performance Score	51.28 [7.38]
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Table 9: The Effect of Past Performance on Analyst Job Turnover

Security analysts in the I/B/E/S database who begin their careers between 1983 and 1996 and have at least three prior years of forecasting experience are tracked to examine if prior forecasting performance affects the likelihood that they change employers. The regression specification is equation (5). The entries are the coefficients on indicators that the analyst forecasted very well or poorly the previous three years and should be interpreted as the probability that analysts with these extreme performances experience a job change compared to other analysts. Regressions (1) and (2) use the relative performance measure described in Section 5.1.2. The regression in (1) measures the effect of an analyst scoring in the top 10% of the relative score distribution on the probability that the analyst moves from a low status brokerage house to a high status brokerage house. The regression in (2) measures the effect of an analyst scoring in the bottom 10% of the relative score distribution on the probability that the analyst moves from a high status brokerage house to a low status brokerage house. The regression in (3) is similar to (1) except that the absolute performance measure is used instead of the relative performance measure. Also, regression (4) is similar to (2) except that the absolute performance measure is used instead of the relative measure. Standard errors are in parentheses.

	Relative Performance Measure		Absolute Performance Measure	
	Analyst Moves to Higher Status House	Analyst Moves to Lower Status House	Analyst Moves to Higher Status House	Analyst Moves to Lower Status House
	(1)	(2)	(3)	(4)
Indicator for Good Past Performance (Top 10% of Distribution)	.0149 (.0068)		-.0023 (.0070)	
Indicator for Poor Past Performance (Bottom 10% of Distribution)		.1522 (.0554)		.0455 (.0350)
Experience Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Average Coverage Effects	Yes	Yes	Yes	Yes
Number of Firms Covered Effects	Yes	Yes	Yes	Yes
Observations	4282	1133	4282	1133

**Table 10: The Effect of Poor Past Performance on Analyst Job Turnover
by Brokerage House Status**

Security analysts in the I/B/E/S database who begin their careers between 1983 and 1996 and have at least three prior years of forecasting experience are tracked to examine if the effect of prior forecast performance on job separations is different for analysts who work for high and low status brokerage houses. The regression specification is equation (6). The entries are coefficients on an indicator that the analyst scored in the bottom 10% of the relative performance distribution the previous three years, an indicator that the analyst works for a high status brokerage house, and the interaction of performing poorly and working for a high status brokerage house. The coefficient on the indicator should be interpreted as the effect of poor forecasting performance on the probability of job separation of analysts who work for high status brokerage houses compared to other analysts. Regressions (1) and (2) use the *Institutional Investor* (I.I.) ranking of brokerage houses. Regression (1) measures the effect of performance and brokerage house status on the probability that an analyst changes brokerage houses the following year. Regression (2) measures the effect of performance and status on the probability that an analyst leaves the profession the following year. Regressions (3) and (4) are identical to regressions (1) through (3) except that the size ranking of brokerage houses is used instead of the I.I. ranking. Standard errors are in parentheses.

	I.I. Ranking Measure		Size Ranking Measure	
	Changes House	Leaves Profession	Changes House	Leaves Profession
	(1)	(2)	(3)	(4)
Indicator for Poor Past Performance (Bottom 10% of Distribution)	-.0349 (.0143)	.0277 (.0191)	-.0316 (.0145)	.0239 (.0194)
Works for High Status Brokerage House	-.0475 (.0153)	-.0465 (.0204)	-.0062 (.0134)	-.0462 (.0179)
Poor Performance $\times$ High Status House	.0350 (.0404)	.0971 (.0540)	.0061 (.0365)	.0981 (.0486)
Experience Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Average Coverage Effects	Yes	Yes	Yes	Yes
Number of Firms Covered Effects	Yes	Yes	Yes	Yes
Observations	5415	5415	5415	5415

Table 11: The Effect of Past Performance on the Probability that a Brokerage House Removes an Analyst from Following a Firm

Brokerage houses in the I/B/E/S database that cover a firm for more than one year are tracked to examine whether the past performance of the analyst following the firm influences whether the brokerage house replaces that analyst with another analyst. The regression specification is equation (7). The entries are coefficients on an indicator that the analyst following the firm for the brokerage house forecasted poorly and should be interpreted as the probability that analysts with a poor forecast history are removed from following a firm compared to other analysts. The regression in (1) measures the effect of an analyst scoring in the bottom 10% of the relative score distribution on the probability that the analyst is removed from following the firm. The regression in (2) measures the same effect only for analysts that follow firms that are covered by 30 or more other analysts. The regression in (3) again measures the same effect for analysts covering firms valued at more than \$15 billion. The regressions in (4) through (6) are identical to the first three regressions except that only analysts that work for high status brokerage houses, using the I.I. status measure, are included.

	All Brokerage Houses			High Status Brokerage Houses		
	All Firms	High Coverage Firms	High Value Firms	All Firms	High Coverage Firms	High Value Firms
	(1)	(2)	(3)	(4)	(5)	(6)
Indicator for Poor Past Performance (Bottom 10% of Distribution)	.0027 (.0035)	.0326 (.0131)	.0186 (.0093)	.0212 (.0098)	.0730 (.0323)	.0961 (.0337)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Average Coverage Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Firms Covered Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	76,859	7503	10,137	26,299	2737	2212