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ANALYST PROMOTIONS WITHIN CREDIT RATING AGENCIES: ACCURACY OR BIAS?

Darren J. Kisgen Matthew Osborn Jonathan Reuter

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ABSTRACT

We examine whether credit rating agencies reward accurate or biased analysts. Using data collected from Moody's corporate debt credit reports, we find that Moody's is more likely to promote analysts who are accurate, but less likely to promote analysts who downgrade frequently. Combined, analysts who are accurate but not overly negative are approximately twice as likely to get promoted. Further, analysts whose rating changes are more informative to the market are more likely to get promoted, unless their ratings changes cause large negative market reactions. Moody's balances a desire for accuracy with a desire to cater to its corporate clients.

Darren J. Kisgen Boston College Fulton Hall, Finance Department 140 Commonwealth Av. Chestnut Hill, MA 02467 Kisgen@bc.edu

Matthew Osborn m.g.osborn@gmail.com Jonathan Reuter Carroll School of Management Boston College 224B Fulton Hall 140 Commonwealth Avenue Chestnut Hill, MA 02467 and NBER reuterj@bc.edu

I. Introduction

Potential conflicts of interest in the credit rating process have been well documented.¹ While bond ratings are directed at institutional investors, rating agencies are traditionally paid by bond issuers, calling into question their objectivity. Exacerbating this potential conflict of interest is the widespread integration of credit ratings into rules and regulations on investments by banks, pension funds, and insurance companies. These regulations provide inherent value to ratings regardless of accuracy (Behr, Kisgen, and Taillard (2016)). While there is growing evidence of biased bond ratings, especially with respect to mortgage backed securities (e.g., Ashcraft, Goldsmith-Pinkham, and Vickery (2010)), there is little evidence on the inner workings of credit rating agencies. In particular, we lack direct evidence on how credit rating analysts are incentivized by their employers.

In this paper, we use promotions within Moody's and departures from Moody's to infer whether analysts are rewarded for providing accurate ratings to institutional investors, or for providing optimistic ratings to issuers. Our empirical tests exploit data on analyst names and ranks hand collected from over 40,000 "announcement" and "ratings action" reports on corporate debt between 2002 and 2011. We focus on corporate bond ratings because the incentive to reward accurate ratings are arguably stronger for corporate bonds than for mortgage backed securities (e.g., Frenkel (2015)). Our final sample includes 177 Moody's analysts covering 1,843 firms. The junior most rank is "Analyst" and the senior most rank is "Managing Director." Tracking analysts across reports issued on different dates allows us to identify when they are promoted and when they depart the firm. To the extent that credit ratings agencies internalize the preferences of institutional investors, we expect them to prioritize accuracy when determining whom to promote (although as we discuss later, even institutions might prefer inflated ratings). To the ex-

¹ Recent examples include Cornaggia, Cornaggia, and Xia (2015) and Behr, Kisgen, and Taillard (2016).

tent that conflicts of interest lead credit rating agencies to internalize the preferences of issuers, however, we expect them to punish analysts who rate firms negatively, even when the negative ratings are accurate. Because we recognize that some departures from Moody's may reflect external promotions rather than forced exits, we collect data from LinkedIn.com on the career paths of 79 analysts who stop authoring credit reports during our sample period. We find 16 career changes that we classify as external promotions and 14 rotations into other divisions of Moody's, leaving 49 cases where the departure plausibly reflects an unfavorable assessment within Moody's.

To determine whether Moody's values accurate ratings, we test whether analysts who are more accurate are more likely to be promoted and less likely to depart (after excluding external promotions). Our first measure of accuracy is based on the idea that more informative rating initiations and revisions should generate larger stock price reactions. We find that analysts with above-median stock price reactions in year t-1 (relative to those of other Moody's analysts) are significantly more likely to be promoted within Moody's and significantly less likely to depart in year t. These correlations between analysts accuracy and positive career outcomes are our first piece of evidence that Moody's values accuracy.

Our second measure of accuracy is based on the idea that we can infer the accuracy of Moody's ratings from future revisions to S&P ratings. Specifically, if Moody's and S&P disagree on the rating for firm *i* in year *t-1*, and S&P subsequently moves its rating toward Moody's rating, we classify that rating as accurate (since the S&P movement validates the initial Moody's rating). We then classify an analyst as accurate when he has more accurate ratings than the median Moody's analyst of the same rank in the same calendar year. (We observe disagreement between Moody's and S&P with respect to at least one rating in 77.9% of our analyst-year observa-

tions.) We continue to find that accurate analysts are more likely to experience positive career outcomes at Moody's with this measure, but the magnitudes are smaller (between 28 and 39 percent), and not as reliably statistically significant.²

To begin distinguishing preferences for accuracy from preferences for optimism, we ask whether the downgrades that generate the largest negative announcement returns are rewarded or punished by Moody's. Because these downgrades are arguably the most accurate rating changes in our sample, they allow us to test whether Moody's rewards analysts who identify significant problems with firm creditworthiness. On the other hand, because these downgrades are the most likely to harm relationships with issuers, Moody's may prefer for their analysts to wait to follow downgrades by other credit rating agencies. We limit these tests to the subset of analyst-year observations for which we both observe a downgrade and can calculate a 3-day announcement return. We find that analysts who generate an abnormal equity return of -9.7% or below in year t-1(the bottom quartile of abnormal equity returns within our sample) are approximately half as likely to be promoted in year t as other analysts. This finding strongly suggests that Moody's punishes analysts for downgrades that are harmful to issuers. However, when we include this extreme return measure alongside either of our more-general accuracy measures, we continue to find that accurate analysts are significantly more likely to be promoted and significantly less likely to depart from Moody's. In other words, while Moody's appears to value accuracy, it also appears to fault analysts when their downgrades surprise the market.

Next, we examine whether and how promotions and departures are related to analyst bias. Our findings suggest that Moody's punishes analysts for negative bias. We measure negative bi-

 $^{^2}$ In the appendix, we examine a third measure of accuracy based on changes in bond yields. We find significant bond yield changes for the subset of Moody's ratings that we classify as accurate based on subsequent revisions of S&P ratings, but not for other Moody's ratings. However, between the data filters outlined in Fracassi, Petry, and Tate (2014) with the need to focus on cases where Moody's and S&P's ratings differ, we are left with relatively few firm-year observations. This fact leads us to emphasize the two accuracy measures described above.

as in several ways, but our main approach is to evaluate the frequency that each analyst downgrades away from the S&P rating on a firm (59.1% of analysts downgrade or upgrade at least 10% of their rated assets in a given year). Consider a firm that has a BBB rating from Moody's and an equivalent rating from S&P. We define a Moody's analyst to have a negative bias if the analyst downgrades the rating to BBB-, departing negatively from the current S&P rating. Using S&P as a benchmark implicitly controls for firm fundamentals, reducing concerns about analyst selection bias. Using changes in ratings instead of levels of ratings also reduces concerns about a Moody's fixed effect or industry-analyst fixed effects.³ We find that analysts with negative bias are between 27 and 41 percent less likely to get promoted and more likely to depart the firm. Interestingly, although investment-grade issuers have an obvious preference for remaining investment grade, we do not find any evidence that Moody's punishes analysts for downgrading firms from investment grade to speculative grade. Nor do we find any evidence that Moody's rewards analysts with an upward bias (relative to analysts whose ratings tend to match S&P's ratings).

In separate tests, where the unit of observation is firm *i* in year *t*, we analyze changes in analyst coverage within the rating agency. We find that negative analysts are more likely to be reassigned within Moody's. Specifically, a firm is more likely to receive a new Moody's analyst in year *t* when its rating either was downgraded in year *t*-1 or was below the corresponding S&P rating in year *t*-1. These findings, which hold even when we exclude reassignments associated with analyst departures, reinforce our other findings that Moody's discourages downgrades.

In our final set of tests, we attempt to reconcile our seemingly contradictory findings that Moody's rewards accurate ratings but punishes negative ratings. When we include interactions between our accuracy and downgrader measures in the same predictive regression, we find that both variables continue to explain variation in the likelihood of promotions. Overall, our findings

³ Our findings are similar when we focus on downgrades without the S&P benchmark.

are consistent with Moody's valuing accuracy, but also wanting its analysts to avoid downgrades that are likely to generate significant negative returns and media attention for its issuers. These are precisely the patterns that we would expect to find if Moody's were incentivizing analysts to balance the conflicting preferences of investors and issuers. Our findings are broadly consistent with the findings of Hong and Kubik (2003), who relate movements of equity analysts between brokerage houses to the accuracy and bias of their earnings forecasts, using data between 1983 and 2000. The main difference (beyond the different types of analysts and time periods) is that Hong and Kubik emphasize the effect of external promotions on analyst behavior whereas we emphasize the effect of internal promotions and (less favorable) departures.

Endogeneity is frequently a concern in papers identifying empirical relationships outside a laboratory setting. In our case, the most likely concern would be that analysts are not randomly assigned to firms. For example, if lower quality analysts are assigned to lower quality firms, we might identify a relationship between downgrades and career outcomes that neglects the omitted variable of analyst quality. To address this issue, our empirical design tends to match our analysts of interest (Moody's analysts) with analysts from another rating agency (S&P) rating the same firm, and all of our measures of Moody's analyst activity are measured relative to S&P. For example, when we identify an analyst as downgrading more frequently, we focus only on cases where Moody's downgrades and S&P does not. If lower quality analysts are assigned to lower quality firms, any impact on downgrade frequency should cancel out, since lower quality analysts would be assigned to lower quality firms at both Moody's and S&P. Furthermore, we primarily study changes in ratings. While different quality analysts might be selected for different qualities of firms, it is less likely that different quality analysts would be selected for firms whose ratings are about to change.

II. Hypothesis Development and Related Literature

We test two hypotheses in this paper regarding the incentive systems within rating agencies. The first is that rating agencies internalize the preferences of institutional investors (and the government) for accuracy, leading them to reward analysts whose ratings are more accurate. Rating agencies are primarily information providers and rely on their reputations for accurate information to drive their business.⁴ If the desire for accuracy is paramount to rating agencies, they will reward analysts who provide more accurate ratings on a timely basis. The null hypothesis is that ratings agencies do not value accuracy due to a lack of significant competition in the rating industry plus a payment model in which issuers pay for ratings. Regulations in the rating industry both increase barriers to entry and provide a guaranteed client base since many regulations for institutional bond investment depend on ratings. Kisgen and Strahan (2010) find that regulations based on ratings affect a firm's cost of capital; this implies that firms have a material reason to care about their credit rating absent any information content of those ratings. These regulations might lead rating agencies to place little weight on analyst accuracy in promotion and firing decisions. Consistent with this possibility, Cornaggia and Cornaggia (2013) show that ratings agencies that are paid directly by investors (rather than by issuers) provide ratings that are more timely with regard to default likelihoods. Institutional investors that want to engage in regulatory arbitrage may also place less weight on accurate ratings if bond yields do not fully reflect the published ratings (e.g., Opp, Opp, and Harris (2013)). Of course, a rating agency that places too little weight on accuracy may eventually lose its Nationally Recognized Statistical Ratings Organiza-

⁴ Bouvard and Levy (2013) and Frenkel (2015) both model rating agency profits as a function of accuracy. Bouvard and Levy argue that profitability is eventually decreasing in an agency's reputation for accuracy, because perfectly accurate ratings reduce revenues from lower-quality issuers. They also argue that when issuers are allowed to receive ratings from multiple agencies, competition between agencies weakens the return to developing a reputation for accuracy. Frenkel (2015) argues that biased ratings are more likely to arise when there are a small number of issuers that receive (and pay for) ratings on a large number of issues. The implication is that ratings for corporate bonds should be more accurate than ratings for mortgage backed securities, even within the same agency.

tion (NRSRO) status, resulting in dramatically lower expected revenues.

The second hypothesis is that ratings agencies internalize the preferences of issuers for optimistic ratings, leading them to reward analysts whose ratings are more optimistic. To attract new business (and thereby increase revenue), rating agencies might forgo accuracy and offer positive ratings to encourage a firm to choose that agency. Institutional investors may also push for inflated ratings to give them access to higher yielding bonds that would otherwise be restricted due to regulations. Some contend that optimist ratings on mortgage backed securities contributed to the recent financial crisis (e.g., Griffin and Tang (2012)). With respect to corporate bond ratings, Behr, Kisgen and Taillard (2016) find that entrenchment due to ratings regulations first enacted in 1975 led to ratings inflation. Bongaerts, Cremers and Goetzmann (2006) find that firms shop for the best rating they can get, especially if the already have split ratings from Moody's and S&P around the investment grade rating distinction. Fracassi, Petry and Tate (2015) examine analyst bias and determine that some analysts' ratings are systematically optimistic or pessimistic. They show that this bias affects corporate decision making, which is consistent with the evidence in Kisgen (2006). Blume, Lim, and MacKinlay (1998) and Alp (2013) show that ratings standards have changed over time. Kedia, Rajgopal, and Zhou (2014, 2015) present evidence that Moody's awarded differentially higher ratings to firms from which it was likely to earn more revenues after it became a publicly traded firm, and that it awarded differentially higher ratings to firms held in the portfolios of its two largest post-IPO shareholders (i.e., Berkshire Hathaway and Davis Selected Advisors). While these studies suggest that rating standards have shifted and that rating analyst behavior may have contributed to these shifts, none of them use the career outcomes of analysts to infer the preferences of credit rating agencies. Our paper is closer in spirit to Hong and Kubik (2003), who use movements of equity analysts between brokerage houses between 1983 and 2000 to infer brokerage house preferences for accurate versus biased earnings forecasts.

To test these hypotheses, we focus on promotions and departures. A promotion is an unambiguously positive outcome for an analyst. A departure is likely to be a negative outcome, except when the analyst is leaving to take a higher-paying, more prestigious job. For example, Cornaggia, Cornaggia, and Xia (2015) find that some analysts leave their rating agency to work for banks for which they previously issued a favorable rating. It is important to note, however, that this possibility does not jeopardize the interpretation of our results. Regarding downgrades, if analysts with a positive bias are systematically recruited away from Moody's, we should find that upgrades lead to departures and downgrades do not. We find the opposite to be true. Regarding accuracy, we find accurate analysts are more likely to be promoted and inaccurate analysts are more likely to depart. It is unclear why inaccurate analysts would be differentially recruited away from Moody's. Indeed, Kempf (2015) finds that analysts issuing more accurate ratings for non-agency securitized finance deals are more likely to leave for an investment bank. However, to account for departures that are positive career outcomes, we collect data on career outcomes from LinkedIn. To more cleanly infer Moody's preferences for accuracy and bias from career outcomes, we exclude the small number of external promotions from our tests.

We summarize our empirical predictions in Figure 1. We consider three cases. First, if Moody's internalizes only the preferences of institutional investors (and the government) for accurate ratings, we expect analysts issuing more accurate ratings to be more likely to be promoted. Second, if Moody's internalizes only the preferences of issuers more optimistic ratings, we expect analysts issuing more optimistic ratings to be promoted. Third, if Moody's attempts to internalize both sets of preferences, we expect it to reward analysts for accurate upgrades and punish them for non-accurate downgrades.

III. Data

We analyze hand-collected data on Moody's analyst coverage, ratings, promotions and departures. Our data come from over 40,000 "announcement" and "rating action" reports published on Moody's website between 2002 and 2011. Each report is linked to a firm and typically includes the names and current titles of two credit rating analysts (e.g., "John Smith, Senior Analyst").⁵ Aggregating this analyst information across all firms allows us to infer the timing of promotions within Moody's and departures from Moody's. Our review of all Moody's reports linked to Compustat firms during the sample period yields 342 unique analysts. From this initial list, we limit our sample to analysts with at least one year of tenure at Moody's and at least five analyst reports, where the analyst-rank spell begins in 2001 or later.⁶ We further limit our sample to analysts covering 1,843 firms across 799 analyst-years and 9,557 firm-years.

We assume that an analyst is promoted in the year of the first report in which the analyst lists a new title. We identify 102 promotions. We do not find any instances of apparent analyst demotions within Moody's (i.e., where an analyst assumes a lower rank subsequent to obtaining a higher rank). To identify departures from Moody's, we begin by identifying 79 analysts whose names appear on multiple corporate credit reports in year *t*-1, but on zero corporate credit reports in year *t*. We then attempt to collect data on these 79 analysts' career paths from LinkedIn.com.

⁵ We assume an analyst covers a firm if he signed at least one of the last two analyst reports specific to the firm. We deem a report specific to the firm, as opposed to a broader industry comment, if the same report is linked to fewer than four firms. An analyst's coverage status expires when a new analyst begins covering the firm, when two years pass without the analyst writing a report that references the firm, or when the firm leaves the Compustat database.

⁶ Moody's began publishing analyst reports on their website in 2000. Because we cannot determine the history of analyst-rank spells in effect at the start of the sample, we include only analyst-rank spells that begin in 2001 or later in our sample for analysis. This allows us to condition promotions and departures on time in rank. Our empirical analysis is based on credit reports issued between 2002 and 2011.

Of the 58 analysts with LinkedIn accounts, we find that 16 leave Moody's for arguably more prestigious jobs (e.g., Blackstone Group, Goldman Sachs, or Merrill Lynch), 28 leave Moody's for comparable or less prestigious jobs (e.g., journalist, analyst at a foreign bank, analyst at A.M. Best, consultant at S&P), and 14 rotate to another division within Moody's. The remaining 21 analysts appear on neither LinkedIn nor Moody's website, leading us to conclude that they also represent departures to comparable or less prestigious firms. In the end, we classify 49 departures as "external demotions" and 14 rotations as neither a promotion nor a departure. Three of the 16 "external promotions" occur in the same calendar year as an internal promotion. Because our focus is on Moody's preferences for accuracy and bias, we retain these analyst-year observations as internal promotions, and we exclude the remaining 13 "external promotions" from our tests, reducing the number of analyst-year observations from 799 to 786.

We supplement our hand-collected data with firm- and event-level information from other standard sources. We obtain Moody's credit ratings data from Moody's Default Risk Service database.⁷ We then match each firm to Compustat, where we obtain firm-level financial information and the corresponding S&P ratings for each firm. We compare Moody's rating for each firm to S&P's rating by converting both rating scales to a numeric index, ranging from 1 (Ca/CC or lower) to 20 (Aaa/AAA). For this index, ratings of 11 (Baa3/BBB-) and above are considered investment-grade, whereas ratings of 10 (Ba1/BB+) and below are considered speculative-grade. Finally, using daily stock return data from CRSP, we calculate three-day abnormal stock returns around the dates of ratings actions by analysts in the sample, using a Fama-French three factor model estimated over the prior three years of returns.. Since analysts cover multiple firms simultaneously, we aggregate all firm- and event-level data to the analyst-year level for our main empirical analysis as described in the next section.

⁷ We use Moody's long term issuer rating. If unavailable, we use the Moody's Corporate Family rating.

To understand how Moody's coverage varies across analyst ranks, Table 1 reports analyst-level summary statistics by rank. The five ranks are Analyst, Senior Analyst, Senior Credit Officer, Senior Vice President, and Managing Director. The average Moody's analyst rates 14.7 firms representing \$161 billion in aggregate firm assets. However, the number and average size of firms covered increases significantly with rank. The average Analyst covers 7.4 firms with an average firm size of \$11.6 billion in assets, while the average Managing Director covers 28.5 firms with an average firm size of \$24.7 billion in assets. Aggregate firm assets covered increases from \$34 billion for Analysts to \$387 billion for Managing Directors. These statistics reveal that analysts assume significantly broader firm coverage responsibility as they move up the ranks within Moody's. The average (and median) rating is consistently above the investment-grade cutoff, but also increases slightly with analyst rank. The fact that the average difference in ratings between Moody's and S&P is negative confirms existing evidence that ratings issued by Moody's are slightly lower, on average, than those issued by S&P.

Moody's corporate credit reports are signed by two analysts. Table 2 presents firm-level summary statistics on analyst coverage for our 9,557 firm-year observations. It reveals that larger and more highly rated firms are disproportionately assigned to Moody's more senior analysts. For instance, a Managing Director is the senior most rank assigned to 81.4 percent of firms rated A or higher, but only 55.5 percent of firms rated B or lower. Likewise, a Senior Vice President or higher is the junior most rank for 27.2 percent of firms rated A or higher, but only 14.2 percent of firms rated B or lower. Similar patterns hold for larger versus smaller firms. In other words, Moody's tends to assign its senior analysts to cover potentially valuable relationships with larger, less risky firms (e.g., blue chips) while its junior analysts are assigned to smaller, riskier firms (e.g., junk issuers). Note that if Moody's allocates more assets to the most promising analysts

within each rank, we should find a positive relation between the level of rated assets and subsequent career outcomes. To address this potential concern, we include the (log) level of rated assets in our set of analysts-level control variable. The downside, however, is that if Moody's rewards accurate or biased analysts with additional firms to rate, controlling for the level of rated assets may make it more difficult to detect the effect of accuracy or bias on career outcomes.⁸

The average number of analysts covering each firm is consistently greater than two because we are focusing on the number of distinct analysts who cover firm j during calendar year tand there is some turnover in analyst coverage within each calendar year. The fact that the average number of analysts is slightly higher among lower rated firms (2.4 versus 2.2) implies that analyst turnover rates are also slightly higher among these firms.

Table 3 summarizes the frequency of Moody's analyst promotions and departures. As we describe above, we classify analyst i as having been promoted in year t if the analyst's title changes, for example, from Analyst to Senior Analyst during year t. We classify analyst i as having departed from Moody's in year t if we directly observe the departure on LinkedIn, or if the analyst signs one or more credit reports in year t-1, does not sign any credit reports in year t or later, does not rotate to another division within Moody's, and does not appear on LinkedIn. Across the full sample, we observe promotion and departures in 13.0 percent and 6.6 percent of analyst-years, respectively. Of the 177 unique analysts in the sample, 45.2 percent receive at least one promotion and 28.8 percent depart from Moody's during the sample period.

The rate of both promotion and departures is highest in the two most junior positions, at

⁸ Consistent with the patterns in Table 3, we find that the number of rated firms increases with years in rank. To examine whether accuracy or bias impacts the number of firms that an analyst covers, we estimate logit regressions where the dependent variable equals one if the analyst covers more firms in year *t* than in year *t*-1, and zero otherwise. While we find no evidence in Table A-4 that the number of rated firms responds to either measure of accuracy, we find some evidence that analysts who downgraded in year *t*-1 are less likely to receive additional firms to rate in year *t*. Consequently, controlling for the (log) level of rated assets may reduce our ability to detect the effect of downgrades on promotions and departures.

16.7 percent and 9.7 percent for an Analyst, and at 18.3 percent and 7.9 percent rate for a Senior Analyst. These differences motivate us to include analyst rank fixed effects in specifications that include control variables. Although we do not observe any discernable time-series patterns with respect to either promotions or departures when we sort the data by calendar year (Panel A), we also include calendar year fixed effects as control variables. Finally, when we sort by the number of years in position across all levels (Panel B), we find that the likelihood of promotion is highest in the fourth and fifth years at 24.2 and 21.9 percent compared to 8.8 and 8.3 percent in the first and second years. These differences motivate us to include analyst years in rank fixed effects in our set of control variables.

IV. Results

A. Measures of accuracy and bias

Our goal is to determine how ratings accuracy or bias influences the careers of Moody's analysts. Evaluating these relations empirically requires us to distinguish accurate ratings from inaccurate ratings and positive bias from negative bias. However, studying Moody's analysts' ratings in isolation can raises serious measurement issues. For instance, an analyst's propensity to downgrade or upgrade firms may simply reflect relative performance of the firms and industries that the analyst covers. To address these types of concerns, we tend to compare Moody's analyst ratings to corresponding ratings from S&P.

We construct two measures of Moody's analysts accuracy, one based on stock returns to Moody's rating initiations and revisions and another based on the direction of S&P rating revisions. For the return-based measure, we classify an analyst's rating as being accurate if the rated company's stock reacts significantly to Moody's ratings decision, based on a three factor abnormal return over a three day window around the rating announcement. For each rating event, we calculate an accuracy "score" based on the corresponding abnormal return that accounts for the direction of the ratings changes. Specifically, we use the absolute value of the abnormal return for new ratings, the negative of the abnormal return for downgraded ratings, and the unadjusted abnormal return for upgraded ratings. We consider a higher score to reflect a more accurate ratings decision. Next, we aggregate accuracy measure to a firm-year level by taking the maximum accuracy score within each firm-year. For example, if the Moody's analyst downgrades a firm twice within the same year, we use the downgrade with the highest return impact. We aggregate to analyst-year level by taking the median accuracy score across firms the analyst covered in that year. Finally, we set the "Stock Accurate" dummy variable equal to one for the half of analyst-year observations that have accuracy scores above the median for the full sample.

To construct our second measure of accuracy, we focus on situations where Moody's and S&P publish different ratings for firm *i* in year *t*. When the S&P analyst's next rating change reduces or eliminates this difference in ratings (i.e., S&P follows Moody's), we classify the Moody's analyst's rating of firm *i* in year *t* as being accurate. When S&P's ratings converge to Moody's ratings for at least 15 percent of the analyst's rated firm assets in year *t*, we set the "Accurate" dummy variable equal to one for that Moody's analyst in year *t*. (The 15 percent cutoff was chosen so that approximately half of all analysts who disagree with S&P are coded as accurate.) By this approach, accuracy could reflect one accurate rating for a relatively large firm or several accurate ratings for relatively small firms. On the other hand, we set the accuracy dummy variable equal to zero if S&P's ratings do not converge toward Moody's ratings, or if S&P's and Moody's ratings differ for less than 10 percent of the analyst's rated firm assets. Based on this measure, 313 of the 786 analyst-year observations involve a "Rating Accurate" analyst.⁹

⁹ In Table A-1, we study the correlation between accurate ratings defined using the "Stock Accurate" approach and changes in bond yields. We focus on a sample firm-years where Moody's rating is either optimistic or pessimistic

To measure bias, we focus on the frequency that each analyst upgrades or downgrades relative to the S&P rating on a firm. Consider a firm that has a BBB rating from S&P and a (comparable) Baa2 rating from Moody's. If the Moody's analyst lowers her rating below Baa2 in year *t and* S&P's analyst does not lower her rating in year *t*, we classify the Moody's rating change as a downgrade. Focusing on downgrades relative to S&P effectively controls for firm-level and industry-level shocks. If the analyst downgrades ratings on at least 10 percent of the rated firm assets, we set the "Downgrader" dummy variable equal to one for that analyst in year *t*. Similarly, if the analyst upgrades ratings on at least 10 percent of rated firm assets in year *t*. (The 10 percent cutoff was chosen so that approximately one third of analysts are coded as downgraders, upgraders, and neither.) Based on this approach, 265 of the 786 analyst-year observations involve downgraders and 272 involve upgrader. Note that although a given analyst can be classified as both an "Upgrader" and a "Downgrader" in the same calendar year, this is rarely the case.

Table 4 presents univariate evidence on the link between accuracy or bias and career outcomes. Focusing on the full sample of analysts, we find that accurate analysts are more likely to be promoted and less likely to depart. For our stock return based measure of accuracy, the probability of promotion during the next calendar year increases from 11.7% to 16.6% and the probability of departure decreases from 11.7% to 5.6%. Magnitudes are similar for our ratings change based measure of accuracy: 16.6% versus 12.5% for promotions and 4.5% versus 11.4% for departures. These differences, which we plot in Figure 2 Panel A, suggest that Moody's rewards

relative to S&P in year t and where we possess bond yield date in years t and t+1. Within this sample, average changes in bond yields are an economically and statistically significant 1.43 percentage points for analysts that we classify as accurate (versus -0.01 percentage point for all other analysts). While we conjecture that our measure is also positively correlated with subsequent changes in the likelihood of default, actual defaults in our sample are rare.

accuracy. However, when we shift our focus to Downgraders and Upgraders, we also find suggestive evidence that Moody's rewards positive bias and punishes negative bias. As seen in Figure 2 Panel B, Downgraders are less likely to be promoted (11.1% versus 15.6%) and more likely to depart (10.2% versus 7.9%). The patterns are qualitatively similar for Upgraders, who are more likely to be promoted and less likely to depart, but the differences are smaller in magnitude

When we focus on promotions and departures within a given analyst rank, we tend to find slightly larger effects of accuracy and bias on the career outcomes of more senior analysts, who cover more and larger firms. While we cannot rule out the possibility that downgraders are being hired away from Moody's by other firms, these statistics exclude the 13 departures that we classify as external promotions. More generally, this practice would imply that other firms value downgraders more than Moody's, and it would not explain why downgraders are less likely to be promoted by Moody's.

B. Does accuracy influence analyst career paths?

Table 5 explores the effect of accuracy on promotions and departures. In Panel A, we report the odds ratios from an ordered logit that classifies promotions as positive outcomes and departures as negative outcomes, after excluding the 13 departures that we classify as external promotions. Because we recognize that some of the remaining departures may reflect analyst preferences as well as Moody's preferences, in Panel B, we report the odds ratios from logit regressions that predict whether the analyst is promoted in year t or not. All standard errors are clustered on analyst.

In the univariate specifications that relate our stock return based accuracy measure for year t-1 to outcomes in year t, we find strong evidence that accurate analysts are more likely to be promoted and less likely to depart. The magnitude ranges from 60.1 percent in the ordered

logit specification that analyzes both promotions and departures to 38.6 percent in the logit specification that analyzes only promotions. The odds ratios are virtually identical when we introduce analyst rank fixed effects, calendar year fixed effects, and analyst years in rank fixed effects, but the odds ratio in the specification predicting promotions is no longer statistically significant at conventional levels. When we further control for the (log) level of rated assets, the odds ratios on Stock Accuracy decline slightly in both specifications, but remains an economically (and statistically) significant 50.0 percent in the ordered logit. Recall that if Moody's allocates more assets to the most promising analysts within each rank, we should find a positive relation between the (log) level of rated assets and subsequent career outcomes. Indeed, this is what we find. The odds ratios on the control variable are economically and statistically significant, ranging from 19 percent in the ordered logit predicting promotions and departures to 34 percent in the logit predicting promotions.

When we switch our focus to the ratings-change based measure of accuracy, the patterns are qualitatively similar, but the estimated odds ratios on Rating Accurate are lower and only statistically significant at conventional levels in the univariate specifications and one of the four specifications that include controls. In other words, the evidence that Moody's rewards accuracy is stronger when we define analyst accuracy using ratings announcement returns (Stock Accuracy) rather than using the likelihood that S&P ratings converge towards Moody's ratings (Rating Accuracy).

C. Accuracy versus extreme equity market reactions to rating decisions

To shed more light on how Moody's values accuracy, we examine whether the stock market announcement returns in the three days around a credit report in year t-1 predict analyst

promotions or departures in year t.¹⁰ On the one hand, analysts may be rewarded for reports that convey new information about default risk to market participants, even if that information is negative. On the other hand, analysts may be punished for reports that significantly reduce the market capitalization of Moody's clients. To distinguish between these two possibilities, we focus on the most negative announcement returns.

The dependent variables and specifications in the first two columns of Table 6 mirror those in Tables 5. The independent variable of interest equals one if at least one of the analyst's announcement returns was in the bottom quartile of all announcement returns in our sample (-9.7 percent and below). We find that low abnormal announcement returns are associated with significantly lower probabilities of promotion. In Panel B, the odds ratio is 0.567 without controls and 0.529 with controls. (Both odds ratios are statistically significant from one at the 1-percent level.) These findings suggest that Moody's is reluctant to promote analysts whose recent downgrades generated large negative returns. The odds ratios in the ordered logits are closer to one and not statistical significant, suggesting that these analysts are no more likely to depart than their peers.

The remaining specifications tell a more nuanced story. When we include the low abnormal return dummy variable alongside either of our earlier accuracy measures, we find strong evidence that low abnormal returns are associated with lower probabilities of promotion and higher probabilities of departure. We also continue to find that Moody's rewards accuracy, with odds ratios that are both larger and more consistently significant than in Table 5. In other words, while Moody's appears to value accuracy, it also appears to fault those analysts whose downgrades

¹⁰ Jorion, Liu, and Shi (2005) also focus on a three-day event window centered on the date of the rating change. By including day t-1, we capture any announcement effect that might arise if the rating change leaks one day early.

most surprise the market.¹¹ One interpretation, in the spirit of Opp, Opp, and Harris' (2013) political economy model of rating agencies, is that Moody's is catering to those issuers and investors with a preference for gradual ratings adjustments.

D. Does bias influence analyst career paths?

In this section, we switch our focus from accuracy to bias. Panels A and B of Table 7 mirror those in Table 5 except that the accuracy dummy variable has been replaced with dummy variables that indicate whether analyst *i* was an upgrader or a downgrader in year *t-1*. We find, across all six specifications, that downgraders are significantly less likely to be promoted and significantly more likely to depart than other analysts. In univariate specifications, the odds ratio range between 0.656 and 0.724. When we include the full set of control variables, the odds ratios range between 0.650, and remain statistically significant at the 5-percent level. Interestingly, we find little evidence that upgraders are more likely to be promoted or less likely to depart than the omitted category of analysts who we classified as neither upgraders nor downgraders in year *t-1*.

We refine our measures of upgrades and downgrades in Table 8. Specifically, we distinguish between four types of ratings changes: downgrades that cause Moody's ratings to diverge from S&P's ratings, upgrades that cause Moody's ratings to diverge from S&P's ratings, downgrades that cause Moody's ratings to converge to S&P's ratings, and upgrades that cause Moody's ratings to converge to S&P ratings. We find evidence in both panels that Moody's punishes downgrades that push Moody's below S&P's ratings. The odds ratios are between 0.576 and 0.718, and statistically significant at the 10-percent level or below. We also find weak evidence that Moody's is more likely to promote analysts whose upgrades cause Moody's ratings to

¹¹ Restricting our analysis to analyst-year observations in which the analyst downgraded at least one firm in year t-1 reduces our sample by approximately 25%, but yields similar estimates and inferences. See Table A-3.

converge to S&P's ratings. The odds ratios are economically significant, ranging between 1.366 and 1.412, but only two of the three are statistically significant, and only at the 10-percent level.

In Table 9, we consider another event that may affect analyst promotions: the decision to downgrade a firm from investment grade to speculative grade. This event is rare. Within our sample, only 4.5 percent of analyst-years involve a rating downgrade that crosses this threshold. However, to the extent that Moody's internalizes the preference of issuers to remain investment grade, we predict that these downgrades will reduce the probability of promotion and increase the probability of departure. To test this prediction, we include a dummy variable that is equal to one if analyst *i* downgraded at least one firm from investment grade to speculative grade in year *t-1*. We also include a dummy variable that is equal to one if analyst *i* upgraded to investment grade in year *t-1* (which occurs in 3.6 percent of the analyst year observations). Note that in Table 9 we are not measuring downgrades or upgrades as deviations relative to S&P because doing so would further reduce the fraction of analyst-years for which either dummy variable is non-zero. Perhaps for this reason, none of the odd ratios on either dummy variable is statistically significant at conventional levels.

E. Does bias influence analyst reassignment?

In Table 10, we explore whether Moody's is more likely to reassign analysts when firms have negatively biased ratings. Analyst reassignment is a more common and less extreme outcome than an analyst departure, which still allows us to infer Moody's preferences toward ratings bias. We evaluate analyst reassignment at the firm-year level. Our dependent variable is a binary variable indicating whether Moody's assigned a new analyst to cover the firm in year t, thus replacing an existing analyst covering the firm in year t-1. We expect that if Moody's dislikes negative ratings bias, we should observe more analyst reassignment when Moody's rating is

negatively biased relative to S&P.

Specifically, we evaluate whether the likelihood of observing an analyst reassignment is higher in year *t* when Moody's downgrades the firm relative to S&P in year *t*-*1*, Moody's rating level is pessimistic relative to S&P in year *t*-*1*, or both conditions hold. In univariate specifications estimated on the full sample of firm-years, we find that downgrades increase the likelihood of an analyst reassignment by 18.9 percent and pessimistic ratings increase it by 52.2 percent. Both effects are statistically significant at the 1-percent level. Next, we estimate a specification that includes the downgrade and pessimistic dummy variables, as well as their interaction. The direct effects are very similar to those estimated separately, and firms that were *both* downgraded and pessimistic relative to S&P have an additional 55.9 percent higher likelihood of new analyst assignment in the following year (statistically significant at the 5-percent level). Interestingly, these patterns are not driven by analyst departures. Excluding firm-years where any of the analysts that covered the firm in year *t*-*1* depart from Moody's in year *t* yields similar odds ratios.

In the previous section we show that Moody's is less likely to promote downgraders and that downgraders are more likely to be let go from Moody's. In this section we find that Moody's is more likely to reassign analysts with a negative bias—perhaps in response to demands from issuers. Together these results provide significant evidence that Moody's has an aversion to negative bias by its analysts.¹²

F. Does Moody's value accuracy, bias, or both?

Table 11 investigates whether Moody's values accuracy, bias, or both. We group analysts into four categories, based on whether they were accurate in year t-1 (yes or no) and on whether they were a downgrader in year t-1 (yes or no). Because our findings are quite similar regardless

¹² The evidence gets stronger still when we consider the finding in Table A-4 that downgraders are less likely than their peers to be awarded additional firms to rate.

of whether we define accuracy using Stock Accurate (Panel A) or Rating Accurate (Panel B), we focus our discussion on Panel A. We begin by reporting the probability of analyst promotions and departures for each category of analysts. These statistics reveal that accurate, non-downgraders are significantly more likely to be promoted (20.4 percent) and significantly less likely to depart (3.1 percent) than any of the other categories of analysts. Promotion probabilities are similar across the other three categories (ranging from 11.4 percent to 12.9 percent), but non-accurate, downgraders are the most likely to depart (12.1 percent). These patterns suggest that Moody's values upgrades by accurate analysts significantly more than downgrades by accurate analysts.

The ordered logit regressions confirm that accurate, non-downgraders are approximately twice as likely to be promoted as the omitted category of non-accurate, non-downgraders. The odds ratios range between 1.829 and 1.996 and are statistically significant at the 1-percent level. The patterns are qualitatively similar, but slightly weaker in terms of economic and statistical significance when we focus only on promotions. The odds ratios range between 1.724 and 1.888 and are statistically significant at the 5-percent level, except in the specification that controls for the log of rated assets. None of the odds ratios estimated for the other categories of analysts is statistically significantly different from the omitted category of non-accurate, non-downgraders. In other words, we find that Moody's internal labor market favors accurate analysts who do not downgrade relative to S&P. Overall, the patterns in Table 11 are the most consistent with Scenario 3 of Figure 1, suggesting that Moody's incentivizes analysts to balance the conflicting preferences for accuracy and bias.

G. Robustness: Career Outcomes of Junior Analysts

While credit reports are signed by two analysts, the tests above assume Moody's holds

both analysts responsible for the accuracy or bias of a given rating. It is possible that Moody's tends to reward or punish the senior most analyst on each credit report. It is also possible that Moody's tends to reward or punish the most junior analyst on each credit report, so that they internalize Moody's preferences when they begin covering larger and more highly rated firms. In the appendix, we re-estimate the specifications in Tables 5, 6, 7, and 11 on the sample of junior most analysts ("Analyst," "Senior Analyst," and "Senior Credit Officers). The evidence that Moody's rewards accuracy and punishes downgraders is at least as strong in the sample of junior analysts as it is in the full sample, leading us to conclude that the junior most analyst.

V. Conclusions

To shed new light on the continuing debate regarding the behavior of credit rating agencies, we examine the career paths of corporate credit rating analysts within Moody's. Focusing on outcomes within Moody's internal labor market provides us with a unique opportunity to infer Moody's preferences for accuracy and bias. Focusing on corporate credit ratings provides us with a setting in which accuracy is likely to be valued by institutional investors. Indeed, we find that accurate analysts are more likely to be promoted and less likely to depart. This finding holds for two different measures of accuracy, and is strongest when we estimate specifications that consider the effect of accuracy on the likelihood of both positive and negative outcomes. However, we also find that Moody's is less likely to promote analysts whose downgrades result in large negative equity returns, or whose downgrades cause Moody's ratings to diverge from S&P's ratings. As further evidence that Moody's discourages negative bias, we find that Moody's is more likely to assign new analysts to firms with pessimistic ratings from existing analysts. Because we find that Moody's rewards accurate analysts but also punishes analysts for negative bias, we conclude that Moody's incentivizes analysts to consider the conflicting preferences of investors and issuers. While our findings that Moody's values accuracy are both novel and encouraging, the preference for upwardly biased ratings suggests that there is still room for improvement.

References

- Alp, Aysun (2013). Structural shifts in credit rating standards. *Journal of Finance* 68(6), 2435-2470.
- Ashcraft, Adam, Paul Goldsmith-Pinkham, and James Vickery (2010). MBS Ratings and the Mortgage Credit Boom. SSRN Working paper 1615613.
- Baghai, Ramin, Henri Servaes, and Ane Tamayo (2014). Have rating agencies become more conservative? *Journal of Finance* 69(5), 1961-2005.
- Becker, Bo and Todd Milbourn (2011). How did increased competition affect credit ratings? Journal of Financial Economics 101, 493-514.
- Behr, Patrick, Darren Kisgen, and Jerome Taillard (2016). Did government regulations lower credit rating quality? *Management Science*, forthcoming.
- Bhanot, Karan and Antonio Mello (2006). Should corporate debt include a rating trigger? *Journal of Financial Economics* 79, 69-98.
- Blume, Marshall, Felix Lim and Craig MacKinlay (1998). The declining credit quality of U.S. corporate debt: Myth or reality? *Journal of Finance* 53, 1389-1413.
- Bongaerts, Dion, Martijn Cremers, and William Goetzmann (2012). Tiebreaker: Certification and multiple credit ratings. *Journal of Finance* 67(1), 113-152.
- Boot, Arnoud, Todd Milbourn, and Anjolein Schmeits (2006). Credit ratings as coordination mechanisms. *Review of Financial Studies* 19(1), 81-118.
- Bouvard, Matthieu and Raphael Levy (2015). Two-sided reputation in certification markets. Working paper.
- Cornaggia, Jess and Kimberly Cornaggia (2013). Estimating the costs of issuer-paid credit ratings. *Review of Financial Studies* 26(9), 2229-2269.
- Cornaggia, Jess, Kimberly Cornaggia, and Han Xia (2015). Revolving doors on Wall Street. Working paper.
- Fracassi, Cesare, Stefan Petry, and Geoffrey Tate (2014). Do credit analysts matter? The effect of analysts on ratings, prices, and corporate decisions. Working paper.
- Frenkel (2015). Repeated interaction and rating inflation: A model of double reputation. *Ameri*can Economic Journal: Microeconomics 7(1): 250-280.
- Griffin, John and Dragon Tang (2012). Did subjectivity play a role in CDO credit ratings? *Journal of Finance* 67(4): 1293-1328.

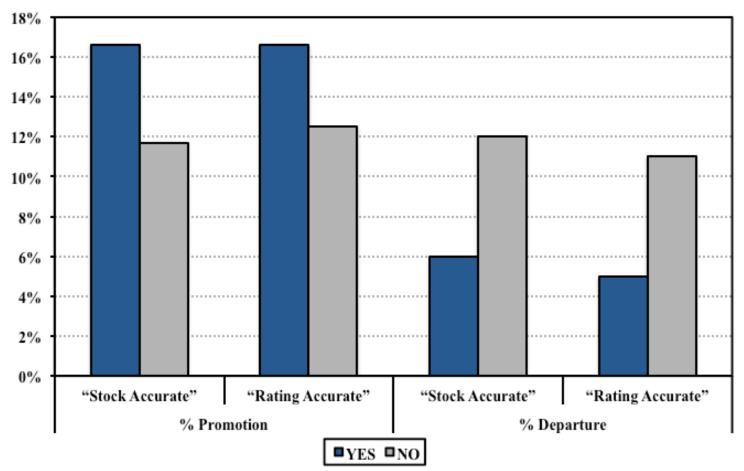
- Hong, Harrison, and Jeffrey Kubik (2003). Analyzing the analysts: Career concerns and biased earnings forecasts. *Journal of Finance* 58(1), 313-351.
- Jorion, Philippe, Zhu Liu, and Charles Shi (2005). Informational effects of regulation FD: Evidence from rating agencies. *Journal of Finance Economics* 76(2), 309-330.
- Kedia, Simi, Shivaram Rajgopal, and Xing Zhou (2014). Did going public impair Moody's credit ratings? *Journal of Finance Economics*, Forthcoming.
- Kedia, Simi, Shivaram Rajgopal and Xing Zhou (2015). Does it matter who owns Moody's? Working Paper.
- Kempf, Elisabeth (2015). The job rating game: The effects of revolving doors on analyst incentives. Working Paper.
- Kisgen, Darren (2006). Credit ratings and capital structure. Journal of Finance 41(3), 1035-1072.
- Kisgen, Darren and Philip Strahan (2010). Do regulations based on credit ratings affect a firm's cost of capital? *Review of Financial Studies* 23(12), 4324-4347.
- Kliger, Doron and Oded Sarig (2000). The information value of bond ratings. *Journal of Finance* 40(6), 2879-2902.
- Opp, Christian, Marcus Opp, and Milton Harris (2013). Rating Agencies in the Face of Regulation. Journal of Financial Economics 108, 46-61.
- Sufi, Amir (2009). The real effects of debt certification: Evidence from the introduction of bank loan ratings. *Review of Financial Studies* 22(4), 1659-1691.
- Tang, Tony (2006). Information asymmetry and firms' credit market access: Evidence from Moody's credit rating format refinement. *Journal of Financial Economics* 93, 325-351.

Analyst Type	Scenario 1: Moody's only internalizes preferences for accuracy	Scenario 2: Moody's only internalizes preferences for bias	Scenario 3: Moody's internalizes preferences for both accuracy and bias
Optimistic & Accurate	Reward	Reward	Reward
Optimistic & Not Accurate	Punish	Reward	Neutral
Pessimistic & Accurate	Reward	Punish	Neutral
Pessimistic & Not Accurate	Punish	Punish	Punish

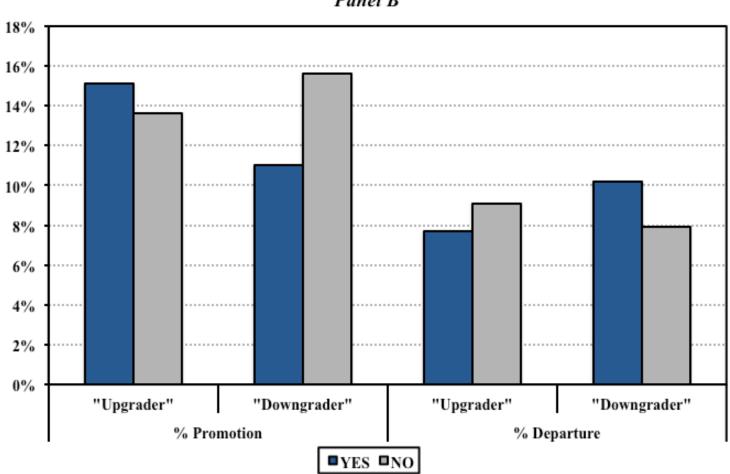
Figure 1. Summary of Empirical Predictions Based on Moody's Preferences

Figure 2. Univariate Evidence on Influence of Accuracy and Bias on Career Outcomes

This Figure plots the fraction of analysts that promoted by Moody's or departing from Moody's in year t. Panel A focuses on "Stock Accuracy" and "Rating Accuracy." Panel B focuses on "Upgraders" and "Downgraders." We define these measures and report the relevant percentages in Table 4.



Panel A



Panel B

Table 1Analyst-Level Summary Statistics

This table summarizes how the number and types of firms that analysts cover varies with analyst rank. We report statistics for all analystyears and separately for each (beginning of year) rank within Moody's. "Analyst" is the junior most rank and "Managing Director" is the senior most rank. The table reports means and medians for the number of firms covered with an issuer-level Moody's credit rating, the average asset size of rated firms, the aggregate asset size of rated firms, as well as the average rating level and ratings notch difference from S&P. Credit rating notch levels range from 1 (Ca or lower) to 20 (Aaa), where 10 is equivalent to a Moody's rating of Ba1.

		Analyst Rank							
Variable		All Levels	Analyst N = 144	Senior Analyst N = 229	Senior Credit Officer N = 158	Senior Vice President N = 170	Managing Director N = 85		
variable		N = 700	11 - 144	N - 229	N = 130	N = 1/0	N - 03		
Number Rated Firms	Mean	14.7	7.4	9.2	9.9	25.8	28.5		
	Median	8.0	7.0	9.0	8.0	13.0	7.0		
Mean Firm Assets [Mill. \$]	Mean	\$20,976	\$11,591	\$17,964	\$30,704	\$22,219	\$24,710		
	Median	\$8,190	\$3,086	\$6,804	\$10,232	\$9,302	\$13,549		
Aggregate Rated Assets [Mill. \$]	Mean	\$161,643	\$34,178	\$92,880	\$119,278	\$293,276	\$386,508		
	Median	\$64,611	\$17,538	\$52,492	\$78,910	\$159,836	\$231,683		
Moody's Credit Rating	Mean	9.2	8.7	8.9	10.1	8.9	9.8		
	Median	8.0	8.0	8.0	9.0	8.0	9.0		
Mean Difference from S&P	Mean	-0.22	-0.17	-0.28	-0.24	-0.15	-0.23		
	Median	-0.20	-0.20	-0.29	-0.20	-0.13	-0.13		

Table 2

Issuer Characteristics and Analyst Ranks

This table reveals that larger and more highly rated firms tend to be covered by more senior analysts. The unit of observation is firm j in year t and the sample is limited to rated issuers covered by Moody's analysts between 2002 and 2011. We report the fraction of firm-years where the "Senior Most Analyst" is a Managing Director, Senior Vice President, or below. We also report the fraction of firm-years where the "Junior Most Analyst" is an Analyst, Senior Credit Officer, or above. In each case, percentages sum to 100. Note that while the typical credit report is signed by two analysts, the average number of analysts is consistently greater than two because we are focusing on the number of distinct analysts who covered firm j in calendar year t and there is some turnover in analyst coverage within each calendar year.

			Firm Crea	dit Rating		Firm Asset Size Quartile			
	All Firm- Years	B or Lower	Baa	Ba	A or Higher	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
	N = 9,557	N = 3,081 N = 2,067		N = 716	N = 523	N = 2,365	N = 2,364	N = 2,364	N = 2,364
Number of Analysts	2.4	2.4	2.4	2.2	2.2	2.3	2.4	2.4	2.4
Senior Most Analyst:									
Managing Director	69.7%	55.5%	66.5%	88.3%	81.4%	49.6%	66.5%	77.9%	84.8%
Senior Vice President	27.5%	39.3%	31.6%	9.6%	16.9%	43.8%	31.3%	20.8%	14.2%
SCO or Lower	2.8%	5.2%	2.0%	2.1%	1.7%	6.6%	2.3%	1.2%	1.0%
Junior Most Analyst:									
SVP or Higher	18.5%	14.2%	17.4%	20.5%	27.2%	12.3%	15.3%	18.5%	27.8%
Senior Credit Officer	24.3%	19.9%	20.4%	25.4%	31.4%	18.0%	22.5%	27.1%	30.0%
Senior Analyst	39.1%	42.0%	43.0%	42.7%	29.5%	39.7%	41.8%	41.5%	33.4%
Analyst	18.1%	23.9%	19.1%	11.3%	11.9%	30.0%	20.5%	12.9%	8.8%

Table 3

Frequency of Analyst Promotion and Departure

This table summarizes the frequency of promotions and departures for Moody's analysts. The column "% Promoted" reports the percentage of analyst-years with a promotion to a higher rank. The column "% Depart" reports the percentage of analyst-years where the analyst departs from Moody's during the year (excluding the 13 observations where we classify the departure as an external promotion). We report promotion and departure percentages for all analyst-years and separately for each (beginning of year) rank within Moody's. "Analyst" is the junior most rank and "Managing Director" is the senior most rank. Panel A reports percentages by calendar year. Panel B reports percentages by the number of years the analyst has remained in the current rank.

		All Levels		Anal	lyst	Senior A	alyst		r Credit Sen fficer Vice Pro			Managing Director
		N = 786		N = 2	144	$\mathbf{N} = 2$	229	N = 1	158	N = 170		N = 85
	Analyst-	%	%	%	%	%	%	%	%	%	%	%
	Years	Promoted	Depart	Promoted	Depart	Promoted	Depart	Promoted	Depart	Promoted	Depart	Depart
					Р	anel A: By Yec	ır					
2002	25	8.0%	8.0%	0.0%	0.0%	0.0%	14.3%	25.0%	12.5%	0.0%	0.0%	0.0%
2003	41	14.6%	2.4%	0.0%	0.0%	27.3%	0.0%	9.1%	0.0%	18.2%	9.1%	0.0%
2004	54	14.8%	13.0%	28.6%	28.6%	21.4%	14.3%	13.3%	20.0%	9.1%	0.0%	0.0%
2005	63	11.1%	4.8%	14.3%	14.3%	16.7%	5.6%	21.4%	7.1%	0.0%	0.0%	0.0%
2006	85	10.6%	3.5%	12.5%	6.3%	10.3%	6.9%	23.1%	0.0%	5.9%	0.0%	0.0%
2007	102	15.7%	8.8%	9.5%	0.0%	25.0%	13.9%	23.1%	7.7%	9.5%	0.0%	27.3%
2008	111	13.5%	7.2%	18.5%	7.4%	18.8%	9.4%	15.8%	5.3%	4.6%	4.6%	9.1%
2009	112	13.4%	6.3%	20.0%	12.0%	16.7%	3.3%	8.7%	4.4%	12.5%	8.3%	0.0%
2010	96	16.7%	6.3%	35.3%	11.8%	19.2%	11.5%	14.3%	4.8%	9.1%	0.0%	0.0%
2011	97	8.3%	6.2%	5.9%	17.7%	19.2%	0.0%	4.8%	4.8%	4.8%	9.5%	0.0%
					Panel	B: By Time In	Level					
1 Year	125	8.8%	4.0%	20.0%	0.0%	5.0%	10.0%	12.2%	6.1%	9.1%	0.0%	0.0%
2 Years	206	8.3%	5.8%	2.2%	8.7%	10.1%	4.4%	20.5%	7.7%	3.1%	6.3%	0.0%
3 Years	156	12.8%	9.0%	8.1%	10.8%	21.8%	12.7%	16.0%	8.0%	3.9%	3.9%	0.0%
4 Years	120	24.2%	7.5%	27.6%	13.8%	43.2%	8.1%	11.1%	5.6%	13.0%	0.0%	7.7%
5 Years	73	21.9%	5.5%	50.0%	0.0%	16.7%	5.6%	20.0%	0.0%	11.8%	0.0%	30.0%
6+ Years	106	8.5%	7.6%	22.2%	22.2%	10.0%	6.7%	5.9%	5.9%	7.7%	7.7%	0.0%
Total Analyst- Years	786	13.0%	6.6%	16.7%	9.7%	18.3%	7.9%	14.6%	6.3%	7.7%	3.5%	4.7%
Total Analysts	177	45.2%	28.8%	46.2%	26.9%	50.6%	21.7%	40.4%	17.5%	31.0%	14.3%	16.7%

Table 4Measures of Accuracy and Bias

This table summarizes the frequency of Moody's analyst promotions and departures for our measures of accuracy and bias. Across the columns, we report statistics for all analyst-years and separately for each (beginning of year) rank within Moody's. "Analyst" is the junior most rank and "Managing Director" is the senior most rank. Panel A reports the percentage of analyst-years in which analysts that we classify as accurate or biased are promoted; it excludes Managing Directors because they are not eligible to be promoted. Panel B reports comparable percentages for departures from Moody's; it includes Managing Directors but excludes the 13 analysts-year observations where we classify the departure as an external promotion. "Stock Accurate" analysts in year t-1 are those analysts whose credit reports generated above-median stock price reactions in year t-1 (relative to other Moody's analysts). "Rating Accurate" analysts in year t-1 are those analysts with more rated assets towards which S&P's ratings subsequently converge. Because it is not possible for an analyst to be Rating Accurate unless some of her ratings differ from those published by S&P, a 15 percent rated asset cutoff was chosen so that approximately half of all analysts who disagree with S&P are coded as Rating Accurate. We classify an analyst as a "Downgrader" ("Upgrader") in year t-1 if he downgraded (upgraded) at least 10 percent of his rated assets that year. The 10 percent cutoff was chosen so that approximately one third of analysts are classified as Downgraders, one third are classified as upgraders, and one third are classified as neither.

		Analyst Rank								
Variable	Value	All Levels	Analyst	Senior Analyst	Senior Credit Officer	Senior Vice President	Managing Director			
		Panel A:	Promotion [N =	= 701]						
Stock Accurate [t-1]	Yes [N = 350] No [N = 351]	16.6% 11.7%	15.4% 15.2%	22.4% 13.3%	18.3% 11.5%	9.2% 5.6%	-			
Rating Accurate [t-1]	Yes [N = 278] No [N = 423]	16.6% 12.5%	18.2% 13.5%	21.7% 15.2%	18.0% 12.4%	6.2% 8.6%	-			
Downgrader [t-1]	Yes [N = 234] No [N = 467]	11.1% 15.6%	14.9% 15.5%	12.4% 21.0%	10.9% 16.1%	6.7% 8.2%	-			
Upgrader [t-1]	Yes [N = 238] No [N = 463]	15.1% 13.6%	8.9% 18.2%	21.8% 15.9%	18.2% 13.2%	9.9% 6.1%	-			
		Panel B:	Departure [N =	= 786]						
Stock Accurate [t-1]	Yes $[N = 393]$ No $[N = 393]$	5.6% 11.7%	6.2% 15.2%	5.2% 14.2%	4.2% 10.3%	5.1% 6.9%	9.3% 9.5%			
Rating Accurate [t-1]	Yes $[N = 313]$ No $[N = 473]$	4.5% 11.4%	5.5% 14.6%	8.3% 10.6%	1.6% 11.3%	0.0% 9.5%	5.7% 12.0%			
Downgrader [t-1]	Yes [N = 265] No [N = 521]	10.2% 7.9%	10.6% 11.3%	12.4% 8.1%	13.0% 5.4%	5.0% 6.4%	9.7% 9.3%			
Upgrader [t-1]	Yes $[N = 272]$ No $[N = 514]$	7.7% 9.1%	8.9% 12.1%	10.3% 9.3%	6.8% 7.9%	4.2% 7.1%	8.8% 9.8%			

Table 5

Does Accuracy Influence Career Paths?

This table reports odds ratios from logistic regressions of Moody's analyst accuracy on career outcomes. Panel A estimates an ordered logit model for promotion and departure outcomes on the full sample of analyst ranks. After dropping the 13 analystyear observations that we classify as external promotions, we code internal promotions as 1 and all other departures from Moody's as -1. Panel B estimates a binary logit model for internal promotion for the subset of analysts below Managing Director (the senior most rank). "Stock Accurate" analysts in year t-1 are those analysts whose credit reports generated abovemedian stock price reactions in year t-1 (relative to other Moody's analysts). "Rating Accurate" analysts in year t-1 are those analysts with more rated assets towards which S&P's ratings subsequently converge. Because it is not possible for an analyst to be Rating Accurate unless some of her ratings differ from those published by S&P, a 15 percent rated asset cutoff was chosen so that approximately half of all analysts who disagree with S&P are coded as Rating Accurate. Most specifications include analyst rank fixed effects, calendar year fixed effects, and years in rank fixed effects. Columns 3, 6, 9, and 12 also control for the log of total rated firm assets in year t-1. Z-statistics are reported below the coefficients, where ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively, based on heteroskedasticity-robust standard errors that are clustered by analyst.

	I	Panel A: Care	er Path								
	Ordered Logit: Career Path [t]										
	{ Promoted = 1, Departed = -1, Otherwise = 0 }										
Explanatory Variables	[1]	[2]	[3]	[4]	[5]	[6]					
Stock Accurate [t-1]	1.601**	1.603**	1.500**								
	(2.555)	(2.531)	(2.166)								
Rating Accurate [t-1]				1.465**	1.410*	1.305					
				(2.146)	(1.825)	(1.366)					
Log of Rated Assets [t-1]			1.187**			1.194***					
			(2.518)			(2.603)					
Analyst Rank Fixed Effects	No	Yes	Yes	No	Yes	Yes					
Year Fixed Effects [2002-2011]	No	Yes	Yes	No	Yes	Yes					
Years in Rank Fixed Effects	No	Yes	Yes	No	Yes	Yes					
Ν	786	786	786	786	786	786					
Pseudo R-Squared	0.007	0.037	0.044	0.005	0.034	0.041					
		Panel B: Pro	motion								
			Logit: Pro	moted [t]							
		{	Promoted $= 1$,	Otherwise $= 0$) }						
Explanatory Variables	[7]	[8]	[9]	[10]	[11]	[12]					
Stock Accurate [t-1]	1.386*	1.378	1.284								
	(1.880)	(1.508)	(1.116)								
Rating Accurate [t-1]				1.299*	1.193	1.122					
				(1.948)	(1.091)	(0.656)					
Log of Rated Assets [t-1]			1.337***			1.346***					
			(3.201)			(3.274)					
Analyst Rank Fixed Effects	No	Yes	Yes	No	Yes	Yes					
Year Fixed Effects [2002-2011]	No	Yes	Yes	No	Yes	Yes					
Years in Rank Fixed Effects	No	Yes	Yes	No	Yes	Yes					
Ν	701	701	701	701	701	701					
Pseudo R-Squared	0.004	0.064	0.080	0.003	0.062	0.079					

Do Accuracy and Extreme Announcement Returns Influence Career Paths?

This table reports odds ratios from logistic regressions of Moody's analyst accuracy and extreme announcement returns on career outcomes. Panel A estimates an ordered logit model for promotion and departure outcomes on the full sample of analyst ranks. After dropping the 13 analyst-year observations that we classify as external promotions, we code internal promotions as 1 and all other departures from Moody's as -1. Panel B estimates a binary logit model for internal promotion for the subset of analysts below Managing Director (the senior most rank). "Low Abnormal Return" is equal to one when the analyst's lowest return around a rating decision in year t-1 falls in the lowest sample quartile (a decline of 9.7 percent), and equal to zero otherwise. Abnormal returns are calculated using a Fama-French three factor model and a three day trading window around the event. "Stock Accurate" analysts in year t-1 are those analysts whose credit reports generated above-median stock price reactions in year t-1 (relative to other Moody's analysts). "Rating Accurate" analysts to be Rating Accurate unless some of her ratings differ from those published by S&P, a 15 percent rated asset cutoff was chosen so that approximately half of all analysts who disagree with S&P are coded as Rating Accurate. Specifications that include analyst are reported below the coefficients, where ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively, based on heteroskedasticity-robust standard errors that are clustered by analyst.

		Panel A: Ca	areer Path			
			Ordered Logit:	Career Path [t]		
		{ Pro	omoted = 1, Resig	gned = -1 , Other	$= 0 \}$	
Explanatory Variables	[1]	[2]	[3]	[4]	[5]	[6]
Low Abnormal Return [t-1]	0.812 (-1.163)	0.729 (-1.535)	0.625 ** (-2.309)	0.589** (-2.382)	0.723* (-1.680)	0.661* (-1.878)
Stock Accurate [t-1]			1.821*** (2.964)	1.699*** (2.672)		
Rating Accurate [t-1]					1.550** (2.344)	1.404* (1.659)
Log of Rated Assets [t-1]		1.228 *** (3.017)		1.205*** (2.723)		1.211** ; (2.791)
Analyst Rank Fixed Effects	No	Yes	No	Yes	No	Yes
Year Fixed Effects [2002-2011]	No	Yes	No	Yes	No	Yes
Years in Rank Fixed Effects	No	Yes	No	Yes	No	Yes
Ν	786	786	786	786	786	786
Pseudo R-Squared	0.001	0.041	0.011	0.048	0.007	0.044

	Logit: Promoted [t] { Promoted = 1, Otherwise = 0 }										
	[7]	[8]	[9]	[10]	[11]	[12]					
Low Abnormal Return [t-1]	0.567*** (-2.756)	0.529*** (-2.885)	0.459*** (-3.280)	0.452*** (-3.213)	0.527 *** (-3.052)	0.502*** (-3.056)					
Stock Accurate [t-1]			1.646*** (2.659)	1.496* (1.796)							
Rating Accurate [t-1]					1.400** (2.423)	1.230 (1.138)					
Log of Rated Assets [t-1]		1.355*** (3.384)		1.337*** (3.220)		1.351*** (3.280)					
Analyst Rank Fixed Effects	No	Yes	No	Yes	No	Yes					
Year Fixed Effects [2002-2011]	No	Yes	No	Yes	No	Yes					
Years in Rank Fixed Effects	No	Yes	No	Yes	No	Yes					
N Pseudo R-Squared	701 0.006	701 0.081	701 0.014	701 0.073	701 0.010	701 0.068					

Does Bias Influence Career Paths?

This table reports odds ratios from logistic regressions of measures of Moody's analyst bias on career outcomes. Panel A estimates an ordered logit model for promotion and departure outcomes on the full sample of analyst ranks. After dropping the 13 analyst-year observations that we classify as external promotions, we code internal promotions as 1 and all other departures from Moody's as -1. Panel B estimates a binary logit model for internal promotion for the subset of analysts below Managing Director (the senior most rank). We classify an analyst as a "Downgrader" ("Upgrader") in year t-1 if he downgraded (upgraded) at least 10 percent of his rated assets that year. The 10 percent cutoff was chosen so that approximately one third of analysts are classified as Downgraders, one third are classified as Upgraders, and one third are classified as neither. Most specifications include analyst rank fixed effects, calendar year fixed effects, and years in rank fixed effects. Columns 3 and 6 also control for the log of total rated firm assets in year t-1. Z-statistics are reported below the coefficients, where ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively, using heteroskedasticity-robust standard errors that are clustered by analyst.

	Pan	el A: Career	Path	Pa	nel B: Promo	tion	
	{ Promo	Logit: <i>Caree</i> ted = 1, Resig Otherwise = 0	gned = -1 ,	Logit: <i>Promoted</i> [t] { Promoted = 1, Otherwise = 0 }			
Explanatory Variables	[1]	[2]	[3]	[4]	[5]	[6]	
Downgrader [t-1]	0.656** (-2.133)	0.630** (-2.229)	0.590** (-2.478)	0.724** (-2.423)	0.679** (-2.422)	0.650*** (-2.624)	
Upgrader [t-1]	1.066 (0.367)	1.148 (0.760)	1.083 (0.445)	1.120 (0.704)	1.227 (1.127)	1.157 (0.725)	
Log of Rated Assets [t-1]			1.231*** (3.152)			1.351*** (3.557)	
Analyst Rank Fixed Effects Year Fixed Effects [2002-2011] Years in Rank Fixed Effects	No No No	Yes Yes Yes	Yes Yes Yes	No No No	Yes Yes Yes	Yes Yes Yes	
N Pseudo R-Squared	786 0.005	786 0.037	786 0.046	701 0.004	701 0.066	701 0.084	

Does Diverging from or Converging to S&P Influence Career Paths?

This table reports odds ratios from logistic regressions of measures of the direction of Moody's analyst bias relative to S&P on career outcomes. Panel A estimates an ordered logit model for promotion and departure outcomes on the full sample of analyst ranks. After dropping the 13 analyst-year observations that we classify as external promotions, we code internal promotions as 1 and all other departures from Moody's as -1. Panel B estimates a binary logit model for internal promotion for the subset of analysts below Managing Director (the senior most rank). "Diverge from S&P" ("Converge to S&P") means the Moody's analyst ratings move away from (toward) the corresponding S&P rating for at least 10 percent of the analyst's rated assets. Most specifications include analyst rank fixed effects, calendar year fixed effects, and years in rank fixed effects. Columns 3 and 6 also control for the log of total rated firm assets in year t-1. Z-statistics are reported below the coefficients, where ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively, using heteroskedasticity-robust standard errors that are clustered by analyst.

	Pan	el A: Career	Path	Pa	nel B: Promo	tion	
	{ Promo	Logit: <i>Caree</i> ted = 1, Resig Otherwise = 0	gned = -1 ,		Logit: <i>Promoted</i> [t] { Promoted = 1, Otherwise = 0 }		
Explanatory Variables	[1]	[2]	[3]	[4]	[5]	[6]	
Downgrades Diverge from S&P [t-1]	0.647* (-1.928)	0.612** (-2.077)	0.576** (-2.265)	0.718** (-2.003)	0.662** (-1.980)	0.645** (-2.103)	
Upgrades Diverge from S&P [t-1]	0.877 (-0.515)	0.912 (-0.353)	0.858 (-0.588)	0.733 (-1.114)	0.804 (-0.739)	0.762 (-0.929)	
Downgrades Converge to S&P [t-1]	0.843 (-0.465)	0.808 (-0.559)	0.787 (-0.625)	0.865 (-0.518)	0.870 (-0.524)	0.835 (-0.645)	
Upgrades Converge to S&P [t-1]	1.295 (1.309)	1.341 (1.401)	1.297 (1.255)	1.386* (1.742)	1.412* (1.664)	1.366 (1.490)	
Log of Rated Assets [t-1]			1.228*** (3.094)			1.351*** (3.470)	
Analyst Rank Fixed Effects	No	Yes	Yes	No	Yes	Yes	
Year Fixed Effects [2002-2011]	No	Yes	Yes	No	Yes	Yes	
Years in Rank Fixed Effects	No	Yes	Yes	No	Yes	Yes	
Ν	786	786	786	701	701	701	
Pseudo R-Squared	0.006	0.038	0.047	0.007	0.068	0.086	

Do Speculative-Grade Downgrades or Investment-Grade Upgrades Influence Analyst Career Paths?

This table reports odds ratios from logistic regressions of speculative-grade downgrades and investment-grade upgrades on analyst career outcomes. Panel A estimates an ordered logit model for promotion and departure outcomes on the full sample of analyst ranks. After dropping the 13 analyst-year observations that we classify as external promotions, we code internal promotions as 1 and all other departures from Moody's as -1. Panel B estimates a binary logit model for internal promotion for the subset of analysts below Managing Director (the senior most rank). "Speculative-Grade Downgrade" equals one when the analyst downgrades at least one firm to speculative grade status in year t-1, and zero otherwise. "Investment-Grade Upgrade" equals one when the analyst downgrades at least one firm to investment grade status in year t-1, and zero otherwise. Most specifications include analyst rank fixed effects, calendar year fixed effects, and years in rank fixed effects. Columns 3 and 6 also control for the log of total rated firm assets in year t-1. Z-statistics are reported below the coefficients, where ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively, using heteroskedasticity-robust standard errors that are clustered by analyst.

	Pan	el A: Career	Path	Pa	nel B: Promo	tion		
	{ Promo	Logit: Caree ted = 1, Resign therwise = 0	gned = -1 ,		Logit: <i>Promoted [t]</i> { Promoted = 1, Otherwise = 0 }			
Explanatory Variables	[1]	[2]	[3]	[4]	[5]	[6]		
Speculative-Grade Downgrade [t-1]	0.640 (-0.915)	0.735 (-0.624)	0.635 (-0.911)	0.920 (-0.112)	0.854 (-0.201)	0.743 (-0.368)		
Investment-Grade Upgrade [t-1]	0.879 (-0.242)	0.881 (-0.259)	0.792 (-0.487)	1.269 (0.253)	0.968 (-0.045)	0.911 (-0.128)		
Log of Rated Assets [t-1]			1.225*** (2.942)			1.353*** (3.235)		
Analyst Rank Fixed Effects	No	Yes	Yes	No	Yes	Yes		
Year Fixed Effects [2002-2011]	No	Yes	Yes	No	Yes	Yes		
Years in Rank Fixed Effects	No	Yes	Yes	No	Yes	Yes		
Ν	786	786	786	701	701	701		
Pseudo R-Squared	0.001	0.031	0.040	0.000	0.061	0.079		

Does Ratings Bias Influence Analyst Reassignment?

This table reports odds ratios from logistic regressions that assess whether firms with negatively biased ratings are more likely to be assigned a new Moody's analyst than other issuers. The unit of observation is firm-year. For each firm-year covered by Moody's analysts in years t and t-1, the dependent variable equals one if one or more of the analysts covering the firm in year t was not covering the firm in year t-1. The independent variables include two indicator variables and their interaction. "Downgrade" equals one if Moody's downgraded the firm relative to S&P in year t-1. "Pessimistic" equals one if Moody's rating level was lower than S&P's rating level in year t-1. Columns 1-3 report odds ratios using all firm-years and columns 4-6 report odds ratios estimated for the subset of firm-years for which the analysts covering firms in year t-1 are still covering firms for Moody's in year t-1. Z-statistics are reported below the coefficients, where ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively, using heteroskedasticity-robust standard errors that are clustered by firm.

	Logit Dependent Var: New Analyst [t] { New Analyst Assigned to Firm = 1, Otherwise = 0 }								
Explanatory Variables	[1]	[2]	[3]	[4]	[5]	[6]			
Downgrade [t-1]	1.189*** (3.546)		1.214*** (3.701)	1.198*** (3.311)		1.212*** (3.311)			
Pessimistic [t-1]		1.522*** (5.302)	1.466*** (4.199)		1.525*** (4.838)	1.443*** (3.639)			
Downgrade x Pessimistic [t-1]			1.559** (2.368)			1.712*** (2.593)			
Excluding Analyst Departures	No	No	No	Yes	Yes	Yes			
Ν	5,440	5,440	5,440	4,545	4,545	4,545			
Pseudo R-Squared	0.001	0.004	0.007	0.001	0.004	0.008			

Does Accuracy or Bias Influence Career Paths?

This table reports raw incidence of promotion and departure for subgroups of analysts based on interactions of our accuracy and bias measures, and then estimates ordered logit and logit regressions similar to those estimated in earlier tables. Panel A defines accuracy using "Stock Accurate" and Panel B defines accuracy using "Rating Accurate". "Stock Accurate" analysts in year t-1 are those analysts whose credit reports generated above-median stock price reactions in year t-1 (relative to other Moody's analysts). "Rating Accurate" analysts in year t-1 are those analysts with more rated assets towards which S&P's ratings subsequently converge. Because it is not possible for an analyst to be Rating Accurate unless some of her ratings differ from those published by S&P, a 15 percent rated asset cutoff was chosen so that approximately half of all analysts who disagree with S&P are coded as Rating Accurate. We classify an analyst as a "Downgrader" in year t-1 if he downgraded at least 10 percent of his rated assets that year. The 10 percent cutoff was chosen so that approximately one third of analysts are classified as Downgraders. Most columns include analyst rank fixed effects, calendar year fixed effects, and years in rank fixed effects. Columns 5, 8, 13, and 16 control for log rated assets in year t-1. Z-statistics are reported below the coefficients, where ***, **, and * denote statistical significance at the 1 percent, 5 percent levels, respectively, based on heteroskedasticity-robust standard errors that are clustered by analyst.

				L	Panel A				
Stock Accurate	Downgrader	% Promoted [N=701]	% Depart [N=786]		ed Logit: <i>Career I</i> , Departure = -1,		Logit: <i>Promoted</i> [t] { Promoted = 1, Otherwise = 0 }		
[t-1]	[t-1]	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Yes	Yes	11.4%	6.0%	1.000 (0.001)	0.949 (-0.206)	0.858 (-0.589)	0.909 1.809**	0.838 1.888**	0.773 1.724
No	Yes	12.9%	12.1%	0.685 (-1.045)	0.712 (-0.906)	0.653 (-1.108)	1.050 (0.142)	1.055 (0.151)	0.984 (-0.043)
Yes	No	20.4%	3.1%	1.901*** (2.986)	1.996*** (3.228)	1.829*** (2.826)	1.809** (2.043)	1.888** (2.071)	1.724 (1.643)
No	No	12.4%	7.8%	-	-	-	-	-	-
	or Log of Rated A ank, Year, and Y	Assets [t-1]? ears in Rank Fixe	d Effects?	No No	No Yes	Yes Yes	No No	No Yes	Yes Yes
N Pseudo R-	-Squared			786 0.015	786 0.047	786 0.054	701 0.013	701 0.075	701 0.091
					Panel B				
Stock Accurate	Downgrader	% Promoted [N=7011	% Depart [N=786]		ed Logit: <i>Career I</i>			Logit: <i>Promoted</i> [oted = 1_Otherwi	5

Stock	Downgrader	% Promoted	% Depart	Ordere	ed Logit: Career I	Path [t]	I	ogit: Promoted [t]
Accurate	[t-1]	[N=701]	[N=786]	{ Promoted = 1	, Departure = -1 ,	Otherwise = 0 }	{ Prom	oted = 1, Otherwi	$se = 0$ }
[t-1]	[1-1]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]
Yes	Yes	10.4%	5.9%	0.884 (-0.504)	0.827 (-0.753)	0.748 (-1.117)	0.777 (-1.009)	0.696 (-1.332)	0.646 (-1.593)
No	Yes	12.1%	15.9%	0.729 (-0.962)	0.708 (-1.010)	0.659 (-1.202)	1.106 (0.573)	1.021 (0.090)	0.957 (-0.191)
Yes	No	22.4%	3.1%	1.984 *** (3.125)	1.952*** (2.951)	1.775** (2.453)	1.936*** (4.577)	1.763*** (2.578)	1.619** (2.156)
No	No	12.7%	10.0%	-	-	-	-	-	
	or Log of Rated A Cank, Year, and Ye	Assets [t-1]? ears in Rank Fixe	d Effects?	No No	No Yes	Yes Yes	No No	No Yes	Yes Yes
N Pseudo R-	-Squared			786 0.014	786 0.045	786 0.052	701 0.015	701 0.074	701 0.090

Internet Appendix

"Analyst Promotions within Credit Rating Agencies: Accuracy or Bias?"

In this appendix, we examine whether our measure of accuracy based on future changes in ratings ("Rating Accuracy") is positively correlated with changes in bond yields. One key advantage of our ratings-based accuracy measure is that the only necessary inputs are future changes in Moody's and S&P ratings. Because these inputs are standardized and widely available across our sample of covered firms, we are able to calculate a consistent and comprehensive measurement of accuracy across analysts. Market-based measures, in contrast, require observations of market prices that are often unavailable, difficult to compare across debt instruments, or unreliable for illiquid debt issues. Nevertheless, where we can measure and compare bond market prices for firms in our sample, we test for a relationship between our ratings-based accuracy measure and an alternative accuracy measure based on bond market yields.

There are 1,843 firms in our sample. Before applying any data filters, we find that 1,564 of these firms (84.9%) have at least one bond listed in FISD. When we limited the sample to fixed-rate coupon bonds (i.e., by excluding bonds that exchangeable, putable, convertible, payin-kind, sub guarantee, senior secured, subordinated, or bonds for which the maturity date is missing), we are left with 17,706 bonds, of which 5,373 bonds match to 1,036 firms (56.2% of the 1,843 firms in the full sample). These 5,373 bonds correspond to 23,556 bond-years. When we further limit the sample to bond-years that have market prices in TRACE, at least one remaining payment, and a duration of at least one year, we are left with 15,123 bond-years. To calculate bond yield spreads, we compute bond yield to maturity based on trade-weighted average bond prices in the last month of the year and subtract the duration-matched treasury yield. We interpolate the treasury yield curve to match the duration of each bond using the 1, 2, 5, 7, 10, 20, and 30 year rates. We aggregate bond yield spreads to a firm level by taking the principal-weighted average bond yield spread. When we collapse the data to the firm-year level, we are left with 3,202 firm-years for which we can calculate yield spreads between year t and t+1. Finally, when we limit the data to firm years for which Moody's and S&P have split bond ratings, we are left with 798 firm-years.

Table A-1 summarizes the relationship between our ratings-based accuracy measure ("*Accurate*") and a measure for accuracy based on changes in bond yields (" Δ *Bond Yield*"). If Moody's is pessimistic in year *t*, we calculate Δ *Bond Yield* by taking the one-year change in yields from year *t* to year *t*+1. If Moody's is optimistic relative to S&P in year *t*, we perform the same calculation and then multiply by -1. That is, the measure is constructed such that positive (negative) values for the Δ *Bond Yield* correspond to "more accurate" ("less accurate") ratings.

We test for a correlation between *Accurate* and Δ *Bond Yield* using both non-parametric and parametric tests. For the non-parametric test, we evaluate whether *Accurate* ratings more often predict the correct direction in bond yields (i.e., Δ *Bond Yield* > 0). We find that *Accurate* ratings are indeed more likely predict the correct direction in bond yields at a 12.7 percent higher rate than ratings that do not qualify as accurate. This differential is statistically significant based on a chi-squared test for equal proportions. For the parametric test, we test for a difference in means for Δ *Bond Yield* between *Accurate* ratings and ratings that do not qualify as accurate. We again find that ratings-based accuracy is associated with larger average bond yield changes in the correct direction (i.e., *Accurate* is associated with higher values of Δ *Bond Yield*). The difference in means of 1.43 percentage points is statistically significant at the 1-percent level. We conclude from these tests that our ratings-based measure of accuracy is indeed related to accuracy as measured with market prices.

List of Appendix Tables

- Table A-1: Correlation between Rating Accuracy and changes in bond yields
- Table A-2: Issuer–level summary statistics
- **Table A-3:** Alternative version of Table 3 that is restricted to the sample of analysts that downgraded at least one firm in year *t*-1
- **Table A-4:** Specifications predicting whether accuracy or bias is associated with an increase in the number of rated firms between year *t* and year *t*-1
- Table A-5: Alternative version of Table 5 that is restricted to junior analyst ranks
- Table A-6: Alternative version of Table 6 that is restricted to junior analyst ranks
- Table A-7: Alternative version of Table 7 that is restricted to junior analyst ranks
- Table A-8: Alternative version of Table 11 that is restricted to junior analyst ranks

Table A-1 Correlation Between Accuracy and Bond Yields

This table summarizes the correlation between the Rating Accuracy measure used throughout our analysis and a third measure of accuracy based on changes in bond yield spreads. In this analysis, we focus on 798 firm-years in our sample where the Moody's rating is either optimistic or pessimistic relative to S&P and where bond yield data are available for the issuer in years t and t+1. If Moody's is pessimistic in year t, we calculate the Δ Bond Yield Measure by taking the one-year change in spreads from year t to year t+1. If Moody's is optimistic relative to S&P in year t, we perform the same calculation and then multiply by -1. Positive (negative) values for the Δ Bond Yield Measure correspond to "accurate" ("inaccurate") ratings. To calculate bond yield spreads, we compute bond yield to maturity based on trade-weighted average bond prices in the last month of the year and subtract the duration-matched treasury yield. We include all bonds for sample firms where TRACE and Mergent FISD bond data are available, excluding bonds that are exchangeable, putable, convertible, PIK, subordinated, secured, guaranteed, zero coupon, variable coupon, missing maturity dates, and with duration less than one year. We interpolate the treasury yield curve to match the duration of each bond using the 1, 2, 5, 7, 10, 20, and 30 year rates. We aggregate bond yield spreads to a firm level by taking the principal-weighted average bond yield spread.

				Incidence	Δ Bond Yie	eld Measure	
Rating Accurate	Δ Bond Yield Measure > 0	Number of Firm- Years	% of Firm-Years	% Within Accurate	% Within Measure	Mean	Median
Yes	Yes	125	15.7%	60.7%	30.6%	4.148	1.615
Yes	No	81	10.2%	39.3%	20.8%	-2.775	-1.108
No	Yes	284	35.6%	48.0%	69.4%	2.610	1.014
No	No	308	38.6%	52.0%	79.2%	-2.427	-1.039
Tot	tal	798	100.0%			0.360	0.039
Test for Equal H	Proportion of Δ B	ond Yield Measure >	> 0	Test for Equal 1	Means of Δ Bond Yie	eld Measure	
% of Accur	rate [Yes]		60.7%	Mean of A	ccurate [Yes]		1.426
% of Accur	rate [No]		48.0%	Mean of A	ccurate [No]		-0.010
Difference	in Proportion		12.7%	Difference	e in Means		1.436
Chi-Square	ed Statistic		9.876	t-Statistic			3.700
P-Value			0.002	P-Value			0.000

Issuer-Level Summary Statistics

This table summarizes the issuers covered by the Moody's analysts in our sample between 2002 and 2011. We present statistics for the full sample of firm-year observations and separately for subsets of firms across the credit rating spectrum and firm asset size quartiles. We reports means for firm characteristics known to effect issuer ratings.

		Firm Credit Rating				Firm Asset Size Quartile				
	All Firm- Years	B or Lower	Baa	Ba	A or Higher	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile	
	N = 9,557	N = 3,081	N = 2,067	N = 716	N = 523	N = 2,365	N = 2,364	N = 2,364	N = 2,364	
Book Assets [Mill. \$]	8,891	2,393	4,931	14,390	54,514	584	1,860	4,997	30,422	
Sales [Mill. \$]	6,680	1,894	4,173	8,793	34,518	630	1,707	4,367	20,982	
Book Leverage	0.40	0.56	0.35	0.31	0.26	0.56	0.39	0.35	0.32	
Market to Book	1.49	1.35	1.46	1.35	1.85	1.54	1.45	1.50	1.51	
Operating Profitability	0.20	0.16	0.20	0.24	0.26	0.15	0.19	0.20	0.24	
Sales Growth	0.09	0.10	0.11	0.05	0.07	0.07	0.10	0.10	0.09	
CapEx to PP&E	0.20	0.21	0.22	0.15	0.17	0.22	0.20	0.20	0.18	

Do Accuracy and Extreme Announcement Returns Influence Career Paths?

This table is an alternative version of Table 6. It reports odds ratios from logistic regressions of Moody's analyst accuracy and extreme announcement returns on career outcomes. Panel A estimates an ordered logit model for promotion and departure outcomes on the full sample of analyst ranks. After dropping the 13 analyst-year observations that we classify as external promotions, we code internal promotions as 1 and all other departures from Moody's as -1. Panel B estimates a binary logit model for internal promotion for the subset of analysts below Managing Director (the senior most rank). The sample sizes are lower than in Table 6 because we limit the sample to analysts that downgraded at least one firm during year t-1. "Low Abnormal Return" is equal to one when the analyst's lowest return around a rating decision in year t-1 falls in the lowest sample quartile (a decline of 9.7 percent), and equal to zero otherwise. Abnormal returns are calculated using a Fama-French three factor model and a three day trading window around the event. "Stock Accurate" analysts in year t-1 are those analysts whose credit reports generated above-median stock price reactions in year t-1 (relative to other Moody's analysts). "Rating Accurate" analysts in year t-1 are those analysts who disagree with S&P are coded as Rating Accurate. Specifications that include analyst rank cheet offects, alendar year fixed effects, and years in rank fixed effects also control for the log of total rated firm assets in year t-1. Z-statistics are reported below the coefficients, where ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively, based on heteroskedasticity-robust standard errors that are clustered by analyst.

		Panel A: Co	areer Path			
			Ordered Logit:	Career Path [t]		
		{ Pro	omoted = 1, Resig	gned = -1 , Other	$= 0 \}$	
Explanatory Variables	[1]	[2]	[3]	[4]	[5]	[6]
Low Abnormal Return [t-1]	0.735 (-1.559)	0.723 (-1.399)	0.614** (-2.254)	0.620** (-1.978)	0.681* (-1.838)	0.667* (-1.671)
Stock Accurate [t-1]			1.958*** (2.685)	1.986*** (2.623)		
Rating Accurate [t-1]					1.503* (1.922)	1.414 (1.485)
Log of Rated Assets [t-1]		1.220** (2.104)		1.244 ** (2.271)		1.207* * (1.986)
Analyst Rank Fixed Effects	No	Yes	No	Yes	No	Yes
Year Fixed Effects [2002-2011]	No	Yes	No	Yes	No	Yes
Years in Rank Fixed Effects	No	Yes	No	Yes	No	Yes
Ν	601	601	601	601	601	601
Pseudo R-Squared	0.002	0.055	0.014	0.067	0.007	0.059

	Logit: Promoted [t] { Promoted = 1, Otherwise = 0 }											
-	[7]	[8]	[9]	[10]	[11]	[12]						
Low Abnormal Return [t-1]	0.533*** (-2.851)	0.527*** (-2.880)	0.462*** (-3.224)	0.477*** (-3.290)	0.511 *** (-3.031)	0.506*** (-3.150)						
Stock Accurate [t-1]			1.759*** (3.221)	1.746*** (2.802)								
Rating Accurate [t-1]					1.376* (1.663)	1.248 (0.900)						
Log of Rated Assets [t-1]		1.321* (1.844)		1.346* (1.954)		1.323* (1.809)						
Analyst Rank Fixed Effects	No	Yes	No	Yes	No	Yes						
Year Fixed Effects [2002-2011]	No	Yes	No	Yes	No	Yes						
Years in Rank Fixed Effects	No	Yes	No	Yes	No	Yes						
Ν	532	532	532	532	532	532						
Pseudo R-Squared	0.009	0.093	0.019	0.101	0.013	0.094						

Does Accuracy or Bias Influence the Number of Rated Firms?

This table reports odds ratios from logistic regressions of Moody's analyst accuracy and bias on a dummy variable that measures increases in the number of firms rated by analyst i between year t and year t-1. "Stock Accurate" analysts in year t-1 are those analysts whose credit reports generated above-median stock price reactions in year t-1 (relative to other Moody's analysts). "Rating Accurate" analysts in year t-1 are those analysts with more rated assets towards which S&P's ratings subsequently converge. Because it is not possible for an analyst to be Rating Accurate unless some of her ratings differ from those published by S&P, a 15 percent rated asset cutoff was chosen so that approximately half of all analysts who disagree with S&P are coded as Rating Accurate. We classify an analyst as a "Downgrader" in year t-1 if he downgraded at least 10 percent of his rated assets that year. The 10 percent cutoff was chosen so that approximately one third of analysts are classified as Downgraders. All columns include analyst rank fixed effects, calendar year fixed effects, and years in rank fixed effects. Z-statistics are reported below the coefficients, where ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively, based on heteroskedasticity-robust standard errors that are clustered by analyst.

	Logit: Number of Rated Firms Increases [t] { Increases = 1, Otherwise = 0 }							
Explanatory Variables	[1]	[2]	[3]	[4]	[5]	[6]		
Stock Accurate [t-1]	1.134 (0.536)			1.202 (0.754)		1.208 (0.789)		
Rating Accurate [t-1]		0.848 (-1.030)			0.900 (-0.646)	0.892 (-0.748)		
Downgrader [t-1]			0.752* (-1.647)	0.726* (-1.887)	0.774 (-1.465)	0.748 (-1.612)		
Upgrader [t-1]			1.004 (0.020)	0.970 (-0.143)	1.028 (0.128)	0.993 (-0.030)		
Analyst Rank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes		
Year Fixed Effects [2002-2011]	Yes	Yes	Yes	Yes	Yes	Yes		
Years in Rank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes		
Ν	786	786	786	786	786	786		
Pseudo R-Squared	0.081	0.081	0.083	0.084	0.083	0.085		

Does Accuracy Influence Career Paths?

This table is an alternative version of Table 5. The sole change is that the sample of analyst-years in both Panel A and Panel B is restricted to analysts ranked "Analyst," "Senior Analyst," or "Senior Credit Officer" in year t-1.

	I	Panel A: Care	er Path					
	Ordered Logit: Career Path [t]							
	{ Promoted = 1, Departed = -1, Otherwise = 0 }							
Explanatory Variables	[1]	[2]	[3]	[4]	[5]	[6]		
Stock Accurate [t-1]	1.703**	1.695**	1.618**					
	(2.575)	(2.502)	(2.290)					
Rating Accurate [t-1]				1.543**	1.504**	1.396		
				(2.197)	(2.002)	(1.596)		
Log of Rated Assets [t-1]			1.288***			1.287***		
			(2.818)			(2.796)		
Analyst Rank Fixed Effects	No	Yes	Yes	No	Yes	Yes		
Year Fixed Effects [2002-2011]	No	Yes	Yes	No	Yes	Yes		
Years in Rank Fixed Effects	No	Yes	Yes	No	Yes	Yes		
Ν	531	531	531	531	531	531		
Pseudo R-Squared	0.009	0.032	0.045	0.006	0.029	0.041		
		Panel B: Pro	motion					
			•	omoted [t]				
		· · · · · · · · · · · · · · · · · · ·		Otherwise = 0	,			
Explanatory Variables	[7]	[8]	[9]	[10]	[11]	[12]		
Stock Accurate [t-1]	1.442	1.360	1.294					
	(1.496)	(1.114)	(0.910)					
Rating Accurate [t-1]				1.416***	1.326**	1.231		
				(2.917)	(2.100)	(1.346)		
Log of Rated Assets [t-1]			1.390**			1.391**		
			(2.545)			(2.494)		
Analyst Rank Fixed Effects	No	Yes	Yes	No	Yes	Yes		
Year Fixed Effects [2002-2011]	No	Yes	Yes	No	Yes	Yes		
Years in Rank Fixed Effects	No	Yes	Yes	No	Yes	Yes		
N	531	531	531	531	531	531		
Pseudo R-Squared	0.005	0.050	0.071	0.005	0.050	0.070		

Do Accuracy and Extreme Announcement Returns Influence Career Paths?

This table is an alternative version of Table 6. The sole change is that the sample of analyst-years in both Panel A and Panel B is restricted to analysts ranked "Analyst," "Senior Analyst," or "Senior Credit Officer" in year t-1.

		Panel A: Co	areer Path				
			0	Career Path [t]			
- Explanatory Variables	$\{ Promoted = 1, Resigned = -1, Other = 0 \}$						
* *	[1]	[2]	[3]	[4]	[5]	[6]	
Low Abnormal Return [t-1]	0.735	0.657	0.554**	0.513**	0.671 *	0.599*	
	(-1.319)	(-1.626)	(-2.214)	(-2.340)	(-1.700)	(-1.940)	
Stock Accurate [t-1]			1.933*** (2.921)	1.838*** (2.724)			
Rating Accurate [t-1]					1.605** (2.378)	1.485 * (1.858)	
Log of Rated Assets [t-1]		1.313 *** (3.019)		1.296*** (2.884)		1.293*** (2.848)	
Analyst Rank Fixed Effects	No	Yes	No	Yes	No	Yes	
Year Fixed Effects [2002-2011]	No	Yes	No	Yes	No	Yes	
Years in Rank Fixed Effects	No	Yes	No	Yes	No	Yes	
Ν	531	531	531	531	531	531	
Pseudo R-Squared	0.002	0.040	0.014	0.051	0.009	0.044	
		Panel B: P	Promotion				
			-	omoted [t] Otherwise = 0 }			
-	[7]	[8]	[11]	[12]			
Low Abnormal Return [t-1]	0.461***	0.402***	[9] 0.370 ***	[10] 0.344***	0.424***	0.371***	
	(-3.014)	(-3.144)	(-3.251)	(-3.227)	(-3.375)	(-3.407)	
Stock Accurate [t-1]			1.705** (2.168)	1.521 (1.512)			
Rating Accurate [t-1]					1.521 *** (3.536)	1.370** (1.996)	
Log of Rated Assets [t-1]		1.397*** (2.634)		1.383** (2.570)		1.388** (2.490)	
Analyst Rank Fixed Effects	No	Yes	No	Yes	No	Yes	
Year Fixed Effects [2002-2011]	No	Yes	No	Yes	No	Yes	
Years in Rank Fixed Effects	No	Yes	No	Yes	No	Yes	
Ν	531	531	531	531	531	531	
Pseudo R-Squared	0.009	0.080	0.019	0.086	0.015	0.083	

Does Bias Influence Career Paths?

This table is an alternative version of Table 7. The sole change is that the sample of analyst-years in both Panel A and Panel B is restricted to analysts ranked "Analyst," "Senior Analyst," or "Senior Credit Officer" in year t-1.

	Pan	el A: Career	Path	Panel B: Promotion Logit: Promoted [t] { Promoted = 1, Otherwise = 0 }		
	{ Promo	Logit: <i>Caree</i> ted = 1, Resig Otherwise = 0	gned = -1 ,			
Explanatory Variables	[1]	[2]	[3]	[4]	[5]	[6]
Downgrader [t-1]	0.634* (-1.937)	0.608** (-2.010)	0.579** (-2.155)	0.724* (-1.780)	0.665* (-1.940)	0.646** (-1.997)
Upgrader [t-1]	1.057 (0.268)	1.059 (0.272)	0.984 (-0.077)	1.109 (0.541)	1.103 (0.415)	1.029 (0.110)
Log of Rated Assets [t-1]			1.320*** (3.148)			1.396*** (2.650)
Analyst Rank Fixed Effects	No	Yes	Yes	No	Yes	Yes
Year Fixed Effects [2002-2011]	No	Yes	Yes	No	Yes	Yes
Years in Rank Fixed Effects	No	Yes	Yes	No	Yes	Yes
Ν	531	531	531	531	531	531
Pseudo R-Squared	0.006	0.030	0.045	0.004	0.052	0.075

Does Accuracy or Bias Influence Career Paths?

This table is an alternative version of Table 11. The sole change is that the sample of analyst-years in both Panel A and Panel B is restricted to analysts ranked "Analyst," "Senior Analyst," or "Senior Credit Officer" in year t-1.

				i	Panel A				
Stock Accurate Downgrader		% Promoted [N=701]	% Depart [N=786]	Ordered Logit: <i>Career Path</i> [t] { Promoted = 1, Departure = -1, Otherwise = 0 }			Logit: <i>Promoted</i> [t] { Promoted = 1, Otherwise = 0 }		
[t-1] [t-1]	[[-1]	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Yes	Yes	12.5%	7.7%	0.972 (-0.097)	0.917 (-0.284)	0.861 (-0.487)	0.887 (-0.420)	0.766 (-0.766)	0.731 (-0.878)
No	Yes	15.7%	14.3%	0.774 (-0.616)	0.798 (-0.540)	0.735 (-0.719)	1.157 (0.374)	1.171 (0.404)	1.108 (0.263)
Yes	No	24.3%	2.7%	2.216*** (3.271)	2.289 *** (3.381)	2.128*** (3.114)	1.995* (1.817)	1.992* (1.714)	1.852 (1.469)
No	No	13.9%	9.6%	-	-	-	-	-	-
Control for Log of Rated Assets [t-1]? Analyst Rank, Year, and Years in Rank Fixed Effects?			No No	No Yes	Yes Yes	No No	No Yes	Yes Yes	
N Pseudo R	-Squared			786 0.015	786 0.047	786 0.054	701 0.013	701 0.075	701 0.091
		,		i	Panel B				
Stock Accurate	Downgrader	% Promoted [N=701]	% Depart [N=786]	Ordered Logit: <i>Career Path [t]</i> { Promoted = 1, Departure = -1, Otherwise = 0 }			Logit: <i>Promoted [t]</i> { Promoted = 1, Otherwise = 0 }		
[t-1] [t-1]		[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]
Yes	Yes	12.2%	8.2%	0.863 (-0.495)	0.822 (-0.647)	0.757 (-0.896)	0.825 (-0.635)	0.739 (-0.917)	0.689 (-1.090)
No	Yes	13.2%	17.1%	0.762 (-0.737)	0.725 (-0.847)	0.682 (-0.985)	1.109 (0.494)	1.009 (0.033)	0.960 (-0.153)
Yes	No	26.1%	3.5%	2.167*** (3.367)	2.125 *** (3.109)	1.923*** (2.658)	2.087*** (5.988)	1.959*** (4.308)	1.757*** (3.442)
No	No	14.1%	10.3%	-	-	-	-	-	
Control for Log of Rated Assets [t-1]? Analyst Rank, Year, and Years in Rank Fixed Effects?			No No	No Yes	Yes Yes	No No	No Yes	Yes Yes	
N Pseudo R				786 0.014	786 0.045	786 0.052	701 0.015	701 0.074	701 0.090