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

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Abstract

We estimate Moody's preference for accurate versus biased ratings using hand-collected data on the internal labor market outcomes of its analysts. We find that accurate analysts are more likely to be promoted and less likely to depart. The opposite is true for analysts who downgrade more frequently, who assign ratings below those predicted by a ratings model, and whose downgrades are associated with large negative market reactions. Downgraded firms are also more likely to be assigned a new analyst. These patterns are consistent with Moody's balancing its desire for accuracy against its corporate clients' desire for higher ratings.

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I. Introduction

While credit ratings play an important role in bond markets and institutional investing, their objectivity has been under scrutiny for years.[1] Corporate bond ratings provide a summary assessment of a firm's credit quality that can be used by investors and regulators to assess risk. However, the structure of the industry provides the potential for conflicts of interest, not least because issuers of bonds typically pay rating agencies for the ratings on their bonds. While much research has focused on the quality of corporate and mortgage backed security ratings (e.g., Ashcraft, Goldsmith-Pinkham, and Vickery (2010); Becker and Milbourn (2011); Griffin and Tang (2012)), as yet little research has focused on the incentive structure faced by the employees generating such ratings on behalf of the credit rating agencies.[2] Our goal is to infer Moody's rating preferences from the internal labor market outcomes of its analysts. Existing theory highlights that credit rating agencies face a trade-off between preserving their reputation for accurate ratings versus catering to issuers' preferences for higher ratings (e.g., Bolton, Freixas, and Shapiro (2012); Bouvard and Levy (2013); Frenkel (2015)). Therefore, we construct analyst-level measures of ratings accuracy and bias and explore how these measures correlate with subsequent career outcomes, using hand-collected data on analyst promotions and departures between 2002 and 2011.

We choose to focus on analysts who rate corporate bonds for three reasons. First, with over $8.5 trillion in outstanding U.S. corporate debt, this market segment is important to investors and regulators.[3] Second, corporate credit ratings are a relatively stable setting in which to examine the

[1] See, for example, Cornaggia, Cornaggia, and Xia (2016) and Behr, Kisgen, and Taillard (2016).
[2] One notable exception is Fracassi, Petry and Tate (2016). In their paper, they identify credit rating analyst fixed effects and find that these effects are important determinants of bond yields and corporate policy. We focus instead on linking rating characteristics to analyst promotions and departures.
[3] At the end of 2016, SIFMA valued outstanding corporate debt at $8.5 trillion, outstanding mortgage related debt at $8.9 trillion, and outstanding treasury debt at $13.9 trillion.

incentives of analysts. Credit rating agencies have more than a century of experience rating corporate debt, providing a long history to draw from and ample time to solidify their rating practices. In contrast, the more recent introduction of structured finance products has been accompanied by multiple methodological changes and ex ante differences in the evaluation of credit risk across rating agencies (Griffin, Nickerson, and Tang (2014)), confounding the ability of researchers to identify analyst discretion. Finally, corporate bond ratings are the setting in which we might expect to find the strongest preference for accuracy from credit rating agencies, because the incentive to reward accurate ratings are arguably stronger for corporate bonds than for mortgage backed securities (Frenkel (2015)).

We collect data on Moody's analysts names and ranks from over 40,000 "announcement" and "ratings action" reports on corporate debt. Our final sample includes 177 Moody's analysts covering 1,843 firms. The lowest of the five analyst ranks is Analyst and the highest is Managing Director. We use changes in ranks to infer promotions and changes in analyst coverage to infer departures. Because we recognize that not all departures reflect forced exits, we collect data from LinkedIn on the career paths of analysts who stop authoring corporate credit reports during our sample period to distinguish unfavorable departures from external promotions.

Although theory suggests a trade-off between ratings accuracy and bias, we do not know how Moody's measures these characteristics (or, as we discuss below, whether Moody's considering characteristics beyond accuracy and bias). Therefore, to determine the role that accuracy plays in internal promotions and unfavorable departures, we consider three distinct measures of accurate ratings. Using three measures increases the likelihood of detecting any underlying preference of Moody's for accurate ratings. Our first measure of accuracy, "Stock Accurate," is based on the idea that more informative rating initiations and revisions should generate larger stock price reactions. We find that analysts whose rating initiations and revisions are associated with above-median stock price reactions in year *t-1* are significantly more likely to be promoted and significantly less likely to depart in year *t*. While this finding is consistent with Moody's valuing accuracy, we recognize that Stock Accurate may also proxy for an analyst's external reputation, which may be imperfectly correlated with their level of accuracy. Our second measure of accuracy is based on the relative tendency of S&P to adjust credit ratings towards the Moody's analyst (and vice-versa). Specifically, if S&P moves its rating towards Moody's following an initial rating disagreement in the previous year (thereby validating the earlier Moody's rating), we classify the Moody's analyst's rating as "leading." We find that an analyst with more leading ratings than the median Moody's analyst in our sample ("Rating Accurate") is significantly more likely to experience positive career outcomes at Moody's. Our third measure of accuracy focuses on changes in bond yields. We denote an analyst as "Yield Accurate" if, when the rating for firm *j* differs from S&P's rating, firm *j*'s bond yield moves in the direction implied by the Moody's rating more often than not (e.g., when the Moody's rating is more negative than S&P's rating, the yield subsequently increases). While the point estimates on Yield Accurate are economically significant, they are not statistically significant at conventional levels.[4] To increase precision and reduce measurement error, our preferred specifications combine the individual accuracy measures into an "Accuracy Index." We find that a 1-standard-deviation increase in this index increases the probability of positive career outcomes between 35% and 66%. We interpret this finding as evidence that Moody's rewards analysts who generate accurate corporate bond ratings.

Next, we examine whether promotions and departures are related to measures that might

[4] One drawback of the Yield Accurate measure is that we are only able to calculate it for 55% of our analyst-year observations. The missing observations primarily reflect missing bond yield data in TRACE. See Section V.A.

plausibly be associated with negative analyst bias (i.e., pessimism) or positive analyst bias (i.e., optimism).[5] We measure the overall pessimism or optimism of analysts in two ways, each motivated by prior empirical work. First, we evaluate the frequency that each analyst downgrades or upgrades relative to the S&P rating on a firm. Consider a firm that has a BBB rating from Moody's and an equivalent rating from S&P. We view a Moody's analyst to be more negative if the analyst downgrades the rating to BBB- but S&P does not lower its rating (defining this as a "relative downgrade"). Using S&P as a benchmark implicitly controls for changing 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 effect. We define an analyst to have a negative (positive) bias when they have more relative downgrades (upgrades) in a year than the median analyst, conditional on having at least one downgrade (upgrade). We find that analysts with negative bias in year *t-1* are approximately 30% less likely to experience positive career outcomes in year *t*. We do not find any significant effects for analysts that we classify as upgraders.

Our second approach to identifying analyst bias relies on the rating prediction model of Baghai, Servaes, and Tamayo (2014), which allows us to predict the rating for firm *j* in year *t* based on its fundamentals. We then compare each analyst's actual rating to the corresponding model predicted rating. We find that analysts classified as being "Model Predicted Pessimists," wherein more of their ratings fall below the model predicted rating than above, are approximately 35% less

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[5] When we observe that Moody's rating for firm *j* is higher than S&P's rating, the difference could reflect a strategic decision by the Moody's analyst to inflate the rating or a genuine belief that the S&P rating is too low. Because we cannot distinguish between these situations, we refer to positive bias relative to either S&P or a predictive ratings model as optimism and negative bias relative to either S&P or a predictive ratings model as pessimism. To the extent that conservative analysts prefer to issue lower ratings, pessimism is indistinguishable from conservatism.

likely to experience positive career outcomes. We also find suggestive evidence that analysts classified as “Model Predicted Optimists” are more likely to experience positive career outcomes.

When we combine the two binary measures of negative bias into a “Pessimist Index,” we find that a 1-standard-deviation increase in this index implies that more pessimistic analysts are approximately 30% less likely to experience a positive career outcome. In contrast, an “Optimist Index” based on upgrades and model predicted optimism is neither economically nor statistically significant. We conclude that analysts who exhibit a negative bias are less likely to experience positive career outcomes at Moody’s.

One plausible concern is that Moody’s only values one dimension of analyst performance (e.g., accuracy) while the empirical findings consistent with the other dimension (e.g., pessimism) are being driven by a correlation between the indices. When we include both indices in the same specification, however, we find that the point estimate from each univariate specification remains largely unchanged.[6] This finding is consistent with Moody’s valuing accuracy while also placing a discount on pessimism. The patterns are quantitatively similar and remain statistically significant when we exclude career outcomes during the financial crisis (2008 and 2009), and when we limit the sample to the three junior-most analyst ranks.[7]

To shed additional light on Moody’s preference for accuracy, we ask whether downgrades that generate large negative announcement returns are rewarded or punished by Moody’s. Downgrades with a large negative announcement return indicate that the market has received significant new information from the analyst report, either due to the information content of the report itself

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[6] When we extend the specification to include the Optimist Index, the odds ratio on this index is both economically and statistically indistinguishable from one. See Appendix Table A-3.

[7] As we highlight in Section IV, credit reports in our sample are signed by both a junior and a senior analyst. Estimating our main specification on the subsample of junior analysts minimizes concerns about the same rating appearing simultaneously in the Accuracy and Pessimist indices of two Moody’s analysts.

or the overall reputation of the analyst. In either case, these downgrades arguably help identify the most accurate analysts in our sample.[8] At the same time, because downgrades highlighting significant problems with a firm's creditworthiness are the most likely to harm relations with issuers, Moody's may choose not to reward this outcome. We find that analysts who generate in year *t-1* an abnormal equity return in the bottom quartile of the abnormal equity returns within our sample (after excluding downgrades that coincide with earnings announcements and adjusting for stock-level idiosyncratic volatility) are between 36% and 53% less likely to experience a positive career outcome in year *t*. However, we continue to find that accurate analysts (as measured by the Accuracy Index) are significantly more likely to experience positive career outcomes. Consequently, while Moody's appears to value accurate ratings, it also appears to fault analysts whose downgrades trigger a large negative equity return, essentially treating these downgrades as another form of pessimism. One interpretation is that Moody's prefers for its analysts to release bad news gradually.

In our final set of tests, we shift our focus to firm coverage decisions within Moody's. We find that firms that are downgraded by a Moody's analyst in year *t-1* are approximately 50% more likely to receive a new analyst in year *t.* This is true even when we exclude firms that require a new analyst because their former analyst departs from Moody's in year *t*. This finding complements our earlier findings that Moody's discourages pessimist ratings.[9]

Overall, our findings are consistent with Moody's valuing accuracy, but also wanting its analysts to avoid being overly pessimistic. These are precisely the patterns that we would expect

[8] Note that since the market reacts significantly to the downgrade, this does not represent a situation in which the rating was revised with a lag following the public release of bad news, which is a typical complaint against rating agencies.
[9] While we find that Moody's is more likely to reassigns pessimistic analysts, we do not find (in unreported regressions) any evidence that the new analysts assigned less pessimistic ratings the following year.

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. Our findings regarding accuracy and internal promotions also complement Kempf's (2017) finding that Moody's analysts issuing more accurate ratings on non-agency securitized finance deals are more likely to receive external promotions.

While we believe that this paper is the first to provide direct evidence that credit rating agencies reward analysts who generate accurate corporate bond ratings, there are two important caveats. First, if Moody's values analyst characteristics beyond accuracy and bias that are correlated with our measures of accuracy and bias, our point estimates may overstate or understate the precise weights that Moody's places on accuracy versus bias. Second, because we are analyzing the internal labor market at Moody's, we do not know the extent to which our findings generalize to the other two major credit rating agencies, S&P and Fitch.

The rest of our paper is organized as follows. Section II develops our main hypotheses and summarizes the existing literature. Section III highlights the three assumptions underlying our empirical strategy, including a detailed discussion of potential omitted variables bias. Section IV describes our data. Section V describes our accuracy and bias measures and then examines the correlation between these measures and career outcomes. Section VI concludes.

II. Hypothesis Development and Related Literature

We test two broad hypotheses in this paper regarding the incentive systems within rating agencies. The first hypothesis is that rating agencies internalize the preferences of institutional investors (and government agencies) for accuracy, leading them to reward analysts whose ratings are more accurate. Rating agencies are primarily information providers and rely on their reputations for providing accurate information to drive their business. This hypothesis is motivated by the theoretical work of Bouvard and Levy (2013) and Frenkel (2015), who model rating agency profits as a function of accuracy.[10] Importantly, Moody's code of conduct explicitly states, "[Moody's] will seek to provide clear, accurate, transparent, and high quality research about Rated Entities and Issuers." Moody's also regularly evaluates the accuracy of its ratings. For example, in 2015, Moody's published a report titled, "A Comprehensive History of the Performance of Moody's Corporate Ratings," examining the accuracy of its ratings over the past 100 years. If the desire for accuracy is paramount to rating agencies, they will reward analysts who provide more accurate ratings on a timely basis. Furthermore, a rating agency that places too little weight on accuracy may eventually lose its Nationally Recognized Statistical Ratings Organization (NRSRO) status, resulting in dramatically lower expected revenues. Indeed, beginning in September 2007, the Securities and Exchange Commission (SEC) began conducting annual audits of NRSROs to determine whether each NRSRO adhered to its stated rating criteria.[11]

The null hypothesis is that rating agencies do not value accuracy due to a lack of significant

[10] Bouvard and Levy (2013) argue that profitability is eventually decreasing in an agency's reputation for accuracy because perfectly accurate ratings reduce revenue 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 the preference for accuracy is stronger when a large number of issuers each solicit ratings for a small number of bonds. The main implication is that ratings for corporate bonds should be more accurate than ratings for mortgage backed securities, even within the same agency.

[11] We explore the impact of SEC audits on Moody's preferences for accuracy versus bias in Section V.E.

competition in the rating industry plus a payment model in which issuers pay for ratings. Regulations in the rating industry simultaneously increase barriers to entry and provide a guaranteed client base since many regulations for institutional bond investment depend on ratings. These regulations might lead rating agencies to place little weight on analyst accuracy in promotion and firing decisions. 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. Cornaggia and Cornaggia (2013) show that rating agencies that are paid directly by investors (rather than by issuers) provide ratings that are timelier with regard to default likelihoods.

The second hypothesis is that rating agencies internalize the preferences of issuers for optimistic ratings, leading them to reward analysts whose ratings are more optimistic and punish analysts whose ratings are more pessimistic. To attract new business (and increase agency revenues), rating agencies might forgo accuracy and offer positively biased ratings to attract clients. Bolton, Freixas, and Shapiro (2012) explicitly model this trade-off to examine the effect of increased competition among rating agencies on rating quality. In addition, institutional investors that want to engage in regulatory arbitrage will prefer optimistic ratings to accurate rating if bond yields do not fully reflect the published ratings (Opp, Opp, and Harris (2013)). Moody's code of conduct does not contain any analogous statements about prioritizing optimism or pessimism. However, Moody's Ex-Senior Vice President Harrington stated to the SEC that Moody's management and compliance officers do everything possible to make issuer clients happy—and they view analysts who do not do the same as "troublesome." Finally, we acknowledge that Moody's might have a preference for non-negative ratings that does not reflect a nefarious desire to appeal to clients. Ratings downgrades can become self-fulfilling given ratings triggers (Kisgen (2006) and

Manso (2013)). Consequently, an analyst who downgrades too frequently might generate instability in client firms that Moody's reasonably wants to avoid. Furthermore, optimism might be a character trait that is desired by Moody's for other reasons. These possibilities do not prevent us from estimating a relation between bias and career outcomes, but they do suggest that we need to be careful when it comes to interpreting these relations.

There are numerous studies related to the optimism and pessimism of credit ratings. For example, Griffin and Tang (2012) contend that optimistic ratings on mortgage backed securities contributed to the recent financial crisis. With respect to corporate bonds, Behr, Kisgen, and Taillard (2016) find that entrenchment due to ratings regulations enacted in 1975 led to ratings inflation. Becker and Milbourn (2011) document that the entry of Fitch into the market led Moody's and S&P to issue more favorable ratings. Bongaerts, Cremers, and Goetzmann (2006) find that firms shop for ratings, especially when they have split ratings from Moody's and S&P around the investment grade threshold. Kedia, Rajgopal, and Zhou (2014, 2017) present evidence that Moody's awards differentially higher ratings to firms from which it was likely to earn more revenues after it became a publicly traded firm, or that were held in the portfolios of its two largest post-IPO shareholders (Berkshire Hathaway and Davis Selected Advisors). Fracassi, Petry, and Tate (2016) examine analyst bias and show that some analysts' ratings are systematically optimistic or pessimistic. They also show that analyst-level bias affects corporate decision making, which is consistent with the evidence in Kisgen (2006). None of these studies, however, use the career outcomes of analysts to infer the preferences of credit rating agencies for accuracy, optimism, and pessimism. To the best of our knowledge, we are the first paper to do so. The most closely related paper is Kempf (2017), who finds that Moody's analysts issuing more accurate ratings for non-agency securitized finance deals are more likely to receive an external promotion.

III. Empirical Strategy

To infer Moody's preferences for accuracy and bias, we regress promotion and departure outcomes on analyst-level measures of accuracy and bias. This empirical strategy relies upon three main assumptions. The first assumption is that promotions and departures reflect, at least in part, Moody's assessment of analyst quality. 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. Cornaggia, Cornaggia, and Xia (2016) find that some analysts leave their rating agency to work for investment banks for which they previously issued a *favorable* rating. To the extent that optimistic analysts are systematically recruited away from Moody's, our specifications may underestimate any positive weight that Moody's places on optimism since some optimistic analysts will be recruited away despite Moody's having a preference for optimism (and thus work against our findings). Kempf (2017), however, finds that analysts issuing more *accurate* ratings for non-agency securitized finance deals are more likely to leave for an investment bank. To the extent that accurate analysts are systematically recruited away from Moody's, our specifications may underestimate the weight that Moody's places on accurate, since in this case accurate analysts might be recruited away despite any preference Moody's might have for accurate ratings (and thus again work against us finding any correlation between accuracy and promotions). To minimize the impact of these potential biases, we collect data on career outcomes from LinkedIn (described below), and we exclude the small number of analyst-years with an external promotion from our tests.

The second assumption is that our specification does not suffer from an omitted variables bias. We focus on accuracy and bias because, as we discuss above, these characteristics are plausibly of first-order importance to Moody's. Of course, we recognize that analysts might be also evaluated based on factors that we cannot measure, including personality, writing skills, client management skills, industry knowledge, and ability to work well in a team. As in any study trying to isolate the impact of a factor on an outcome, we assume that factors we cannot measure are uncorrelated with our measures. Fortunately, factors that fall into this category will not introduce a bias in our point estimates. Cornaggia, Cornaggia and Xia (2016) and Hong and Kubik (2003) make the same implicit assumption when evaluating labor market outcomes.

Educational pedigree is one factor that we do not measure that could be correlated with accuracy. To the extent that education affects promotions, we believe that it would affect promotions through the accuracy channel (i.e., better educated analysts are more likely to be promoted because they are more accurate). However, if educational pedigree is positively correlated with accuracy, and Moody's values both educational pedigree and accuracy (perhaps because issuers or investors overweight the value of educational pedigree), then our point estimates on measures of accuracy will overstate the actual weight that Moody's places on accuracy. Alternatively, if Moody's is willing to accept less accurate ratings from analysts that possess other valuable traits—such as persistence, charm, or the social skills that Persico, Postlewaite, and Silverman (2004) conclude are acquired by people of above-average height during high school—our point estimates on measures of accuracy will understate the actual weight that Moody's places on accuracy.

An alternative form of omitted variables bias could arise from the fact that analysts are not randomly assigned to firms. In particular, 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. We attempt to address this concern in several ways. First, three of our five main measures match Moody's analysts' ratings to S&P's ratings for the same firm (i.e., "Rating Accurate," "Yield Accurate," and "Downgrader"). 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 likely would be assigned to lower quality firms at both Moody's and S&P. Further, 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. And finally, two of our measures are based on changes in market prices (i.e., "Stock Accurate" and "Yield Accurate"). If certain analysts are assigned to low quality firms, the low quality should be reflected in market prices at the time of assignment, rather than in subsequent price changes.

The third assumption is that our proxies for accuracy and bias are positively correlated with the actual measures used by Moody's. To the extent that our proxies are uncorrelated with Moody's preferences, a violation of this assumption would manifest itself as an errors-in-variables issue, attenuating estimated coefficients and impairing our ability to reject the null hypothesis. For this reason, our preferred specifications focus on indices built from the individual proxies.

Finally, note that our analysis is intended to shed light on the preferences of Moody's, one of the three dominant credit rating agencies. Given the competition for market share between the three major credit rating agencies that is documented in the existing literature (e.g., Becker and Milbourn (2011); Griffin, Nickerson, Tang (2014)), it is plausible that S&P and Fitch have similar preferences for accuracy and bias. Analyzing the internal labor markets at S&P and Fitch, to determine whether our findings generalize to these other rating agencies, is a promising area for future research.

IV. Data

We analyze hand-collected data on Moody's analyst coverage, ratings, promotions and departures.[12] 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").[13] 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, at least five analyst reports, and where the analyst-rank spell begins in 2001 or later.[14] We further limit our sample to analyst-years with at least one firm-level credit rating. The resulting sample consists of 177 unique 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 analyst demotions (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 75 analysts whose names appear on multiple

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[12] Our decision to focus on a single credit rating agency reflects the time and effort involved in hand collecting the promotion and departure data. Even if different rating agencies place different weights on accuracy and bias, we believe that it is still informative to understand the preferences of one of the three dominant firms in the industry.

[13] 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 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.

[14] 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, which we find to be a useful predictor of both outcomes (Table 3). Our findings are qualitatively similar if we expand the sample to include analysts who were employed by Moody's in 2001, but never promoted.

corporate credit reports in year *t-1,* but on zero corporate credit reports in year *t*. We then attempt to collect data on these 75 analysts' career paths from LinkedIn.com. Of the 54 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), 24 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 45 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 the measure of departures 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 sources. We obtain Moody's credit ratings data from Moody's Default Risk Service database.[15] 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 investment-grade, whereas ratings of 10 (Ba1/BB+) and below are speculative-grade. We use daily stock return data from CRSP, and a Fama-French three factor model estimated over the prior three years of returns, to calculate three-day abnormal stock returns around the dates of ratings actions by analysts in the

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

sample. We also use the daily stock return data to measure stock-level volatility. We use RavenPack to identify the dates of corporate earnings announcements. Finally, we use the FINRA Trade Reporting and Compliance Engine (TRACE) to measure firm-level changes in bond yields between year *t-1* and year *t*. 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.

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 $161.6 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 $34.2 billion for Analysts to $386.5 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 (e.g., Jewell and Livingston (1999) and Bongaerts, Cremers, and Goetzmann (2012)).

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 seniormost rank assigned to 81.4% of firms rated A or higher, but only 55.5% of firms rated B or lower. Likewise, a Senior Vice President or higher is the juniormost rank for 27.2% of firms rated A or higher, but only 14.2% 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) and its junior analysts to cover smaller, riskier firms (e.g., junk issuers). More generally, Appendix Table A-1 reveals that the number of covered firms and level of covered assets increase with both analyst rank and years in rank, motivating us to estimate specifications that include analyst rank-by-years-in-rank fixed effects.[16]

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 *t* and there is some firm-level 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 lower rated firms. The fact that each report is signed by both a junior and a senior analyst motivates us to estimate versions of our main specifications on the subsample of junior analysts.

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

[16] We consider the possible link between accuracy, bias, and the level of covered assets in Section V.D.

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% and 6.6% of analyst-years, respectively. Of the 177 unique analysts in the sample, 45.2% receive at least one promotion and 25.4% depart from Moody's during the sample period (excluding external promotions).

The rate of both promotion and departures is highest in the two most junior positions, at 16.7% and 6.9% for an Analyst, and at 18.3% and 7.0% rate for a Senior Analyst. In addition, when we sort by the number of years in position across all levels (Panel A), we find that the likelihood of promotion is highest in the fourth and fifth years at 24.2% and 14.0% compared to 8.8% and 8.3% in the first and second years. Including analyst rank-by-years-in-rank fixed effects allows us to capture baseline differences in promotion and departure probabilities across analyst ranks and years in rank. 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 B), we also estimate specifications that include calendar year fixed effects.

V. Results

A. Measures of accuracy and bias

Our goal is to determine how ratings accuracy and bias influence the internal labor market outcomes 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 raise potential 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 three measures of Moody's analyst accuracy. The first is based on stock returns surrounding Moody's rating initiations and revisions ("Stock Accurate"), the second is based on the direction of S&P rating revisions ("Rating Accurate"), and the third is based on changes in firm-level bond yields ("Yield Accurate"). For the stock 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 (excluding any rating announcements that coincide with earnings announcements).[17] 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 the 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 analysts within the full sample.

To construct "Rating Accurate," we focus on situations in which Moody's and S&P publish different ratings for firm j in year t. In these cases, when the S&P analyst's next rating change reduces or eliminates this difference in ratings (i.e., when the S&P analyst follows the lead of the

[17] While this filter is intended to reduce the likelihood that abnormal returns are contaminated by the release of other value-relevant news, the impact of "Stock Accurate" on career outcomes is quantitatively similar to that estimated in earlier versions of the paper, which lacked this filter.

Moody's analyst), we classify the Moody's analyst's rating of firm *j* in year *t* as being "leading". We classify a Moody's analyst as "Accurate" using this measure when his percentage of "leading" ratings (as a percentage of firm assets) is greater than the median of all analysts in the sample (approximately 15% or more of the analyst's rated firm assets in year t). 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 15% (the median) of the analyst's rated firm assets. Based on this measure, 313 of the 786 analyst-year observations involve a "Rating Accurate" analyst.

Our final measure of accuracy is based on changes in firm-level bond yields. We again focus on situations where the Moody's analyst assigns a higher or lower rating to firm *j* than the S&P analyst. For each such rating, we then ask whether the firm's bond yield moves in the direction implied by the Moody's rating (e.g., the yield moves down in year *t* when the Moody's rating is lower than the S&P rating in year *t-1*). We classify an analyst as "Yield Accurate" when the number of successful predictions is larger than the number of unsuccessful predictions. We calculate this measure for every analyst-year in which we can calculate the change in bond yields for at least one covered firm. However, because we are only able to calculate changes in bond yields in TRACE for a subset of covered firms, we are only able to calculate the "Yield Accurate" dummy variable for 436 of the 786 analyst-years within our sample.[18]

To increase precision and reduce measurement error, we also combine the (binary) accuracy measures into an "Accuracy Index." The Accuracy Index used throughout much of the paper sums the "Stock Accurate" and "Rating Accurate" dummy variables. It has a mean of 0.892 and a

[18] When calculating the "Yield Accurate" measure, we restrict our sample to bonds in TRACE that are not puttable, convertible, payable-in-kind, do not have a subsidiary guarantee, and have a non-missing maturity date and a fixed coupon. Annual yield spread changes are computed from trades that fall in the December month of adjacent years.

standard deviation of 0.742. It is also highly persistent. Consider analysts for whom the Accuracy Index in year *t-1* equals zero. In year *t*, the Accuracy Index equals zero for 54.0%, one for 35.2%, and two for 10.9%. For analysts for whom the Accuracy Index in year t-1 years two, the corresponding percentages are 8.4%, 46.1%, and 45.5%. We also consider an expanded Accuracy Index that includes "Yield Accurate" (and therefore ranges between zero and three). Among the 436 analyst-years for which this index is defined, the mean is 1.686 and the standard deviation is 0.868.

To construct our first measures of negative and positive analyst bias, we consider the frequency with which each analyst downgrades or upgrades 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* the S&P 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. Moreover, the favorability of an agency's rating (relative to competitors' ratings) may help to determine its market share (e.g., Skreta and Veldkamp (2009); Becker and Milbourn (2011)).

If the analyst downgrades ratings on at least 15% 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 15% of rated firm assets in year *t* without corresponding upgrades by S&P, we set the "Upgrader" dummy variable equal to one in year *t*. (The 15% cutoff was chosen so that approximately half of analysts who downgrade at least one firm are classified as Downgraders and approximately half of analysts who upgrade at least one firm are classified as Upgraders.) Based on this approach, 316 of the 786 analyst-year observations involve Downgraders and 319 involve Upgraders. 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.

Our second measures of negative and positive analyst bias are based on the ratings prediction model of Baghai, Servaes, and Tamayo (2014), which allows us to predict the rating for firm *j* in year *t* based on its fundamentals. We then compare each analyst's actual rating to the corresponding model predicted rating. We classify an analyst as a "Model Predicted Pessimist" if more of his ratings fall below the model predicted rating than above (the control group exhibits either no bias or positive bias). This occurs in 201 (25.6%) of the 786 analyst years. Similarly, we classify an analyst as a "Model Predicted Optimist" if more of his ratings fall above the model predicted rating than below. This occurs in 272 (34.6%) of the 786 analyst years. (The remaining 313 (39.8%) observations are classified as neither model predicted pessimists or optimists.) We construct a "Pessimist Index" by summing our Downgrader and Model Predicted Pessimist dummy variables, and we construct an analogous "Optimist Index." The Pessimist Index has a mean 0.469 and a standard deviation of 0.694, while the Optimist Index has a mean of 0.474 and a standard deviation of 0.674. We find that both indices are highly persistent. For analysts with a Pessimist Index value of zero in year *t-1*, the index in year *t* equals zero for 62.0%, one for 30.7%, and two for 7.3%. For analysts with a Pessimist Index value of two in year t-1, the corresponding percentages are 14.3%, 46.7%, and 39.0%. Our evidence of persistence with respect to pessimism and optimism is consistent with Fracassi, Petry and Tate's (2016) findings of analyst fixed effects.

B. Does accuracy influence analyst career paths?

We explore the effect of analyst accuracy on promotions and departures in Figure 1 and Table 4. Figure 1 plots the fraction of analysts who are promoted or depart from Moody's in year *t* for the three different values of the Accuracy Index in year *t-1*. (We exclude the 13 departures that we classify as external promotions.) As the index increases from zero to two, the probability of promotion increases monotonically from 11.9% to 18.9% while the probability of departure decreases monotonically from 9.1% to 2.2%. These patterns suggest that Moody's rewards analysts who generate accurate corporate bond ratings.

In Table 4, we report odds ratios from ordered logit regressions that classify promotions as positive outcomes and departures as negative outcomes. The independent variables of interest are the Accuracy Index and its components, the Stock Accurate, Rating Accurate, and Yield Accurate dummy variables. Panel A focuses on the full sample of analyst-year observations, while Panel B focuses on the subsample for which we can calculate Yield Accurate. For each accuracy measure, we report both a univariate specification and a multivariate specification that includes a full set of calendar year and analyst rank-by-years-in-rank fixed effects.

Panel A reveals that the Stock Accurate and Rating Accurate dummy variables both predict positive career outcomes regardless of whether we focus on the univariate or the multivariate specification. Analysts classified as Stock Accurate are between 62% and 66% more likely to experience a positive career outcome the following year (significant at the 1-percent level), while analysts classified as Rating Accurate are between 38% and 47% more likely to do so (significant at the 10-percent level and below). The Accuracy Index, which sums the Stock Accurate and Rating Accurate dummy variables, also successfully predicts positive career outcomes within Moody's.[19]

Our findings are qualitatively similar in Panel B, where we extend the Accuracy Index to include the Yield Accurate dummy variable. The estimated odds ratios on the Stock Accurate and Rating Accurate dummy variables are slightly higher than in Panel A, and the significance levels are slightly lower. The odds ratios on Yield Accurate are economically significant, suggesting that

[19] Although we exclude external promotions from our analysis, the average level of the Accuracy Index is 1.020 for the 102 analyst-years receiving internal promotions and 1.000 for the 13 analyst-years receiving external promotions, suggesting that more accurate analysts are more likely to receive both internal and external promotions. In contemporaneous research, Kempf (2017) documents the link between accuracy and external promotions for Moody's analysts rating securitized products.

Yield Accurate analysts are between 38% and 56% more likely to experience a positive career outcome, but neither estimate is statistically significant at conventional levels. We conclude from Table 4 that Moody's internal labor market rewards analysts who issue more accurate corporate bond ratings. To the best of our knowledge, this is the first paper to find that Moody's values accurate corporate bond rating. Of course, as we discussed above, if Moody's values other (omitted) analyst characteristics that are correlated with our measures of accuracy, our point estimates may overstate or understate the precise weights that Moody's places on accuracy.

C. Does bias influence analyst career paths?

Next, we focus on analyst-level measures of negative and positive. Figures 2 and 3 present univariate patterns for the Pessimist Index and Optimist Index, respectively. Figure 2 reveals that higher levels of pessimism in year *t-1* are associated with lower probabilities of promotion and higher probabilities of departure in year *t*. Figure 3 reveals the highest probability of promotion and the lowest probability of departure when the Optimist Index equals two, but essentially no differences between these career outcomes when the index equals zero or one.

Panel A of Table 5 estimates ordered logits for the Pessimist Index and its components. Downgraders and Model Predicted Pessimists are both less likely to experience positive career outcomes in year *t* than their peers. The odds ratios on the components range between 0.620 and 0.707 (significant at the 10-percent level and below), while the odds ratios on the Pessimist Index range between 0.701 and 0.724 (significant at the 5-percent level and below). The implication is that Moody's internal labor market appears to punish analysts that downgrade relative to S&P or that issue ratings below those implied by the predicted ratings model.

Panel B estimates similar specifications for the Optimist Index and its components. The odds ratios on the Upgrader dummy variable are close to one (1.045 and 1.059) and statistically insignificant. Comparing the odds ratios in Panels A and B suggests that Moody's internal labor market punishes downgraders more than it rewards upgraders. The odds ratios on the Model Predicted Optimist dummy variable are economically larger, ranging from 1.404 in the univariate specification to 1.309 in the multivariate specification. However, we can only reject the hypothesis that the odds ratio equals one in the univariate specification, and only at the 10-percent level. Again, comparing Panels A and B, the implication appears to be that Moody's punishes model predicted pessimism more than it rewards model predicted optimism. The odds ratios on the Optimist Index vary between 1.137 and 1.182, but are statistically indistinguishable from one. We conclude from Table 5 that Moody's internal labor market punishes pessimistic analysts more than it rewards optimistic analysts.

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

We begin investigating in Table 6 whether Moody's values accuracy, the absence of pessimism, or both. Panel A reports the fraction of analyst observations that depart from Moody's in year *t* for different values of the accuracy and pessimism indices in year *t-1*. For each value of the Accuracy Index, higher values of the Pessimist Index are associated with higher departure probabilities. Similar, for each value of the Pessimist Index, lower values of the Accuracy Index are associated with higher departure probabilities. At the extremes, the probability of departure is 33.3% when the Accuracy Index equals zero and the Pessimist Index equals two, and 0.0% when the Accuracy Index equals two and the Pessimist Index equals one. Panel B, which instead reports the probability of promotion in year *t*, reinforces the possibility that Moody's internal labor market both rewards accuracy and punishes pessimism. In particular, the probability of promotion is 0.0% when the Accuracy Index equals zero and the Pessimist Index equals two, and 36.1% when the Accuracy Index equals two and the Pessimist Index equals one.

In Table 7, we estimate ordered logit regressions that include the Accuracy Index and the Pessimist Index. We also estimate logit regressions where the dependent variable equals one when the analyst is promoted in year *t* and zero otherwise (thereby treating analysts who remain at Moody's and are not promoted the same as analysts who depart from Moody's).[20] Panel A, which focuses on the full sample of analyst-year observations, contains our main findings. The probability of more favorable career outcomes increases significantly with our analyst-level Accuracy Index and decreases significantly with our analyst-level Pessimist Index. In the ordered logits, all of the odds ratios are statistically distinguishable from one at the 1-percent level. In the logits predicting promotion, the odds ratios on the Accuracy Index are closer to one. For example, in the multivariate specifications, the odds ratio falls from 1.808 to 1.502 and statistically significance falls from the 1-percent level to the 5-percent level. These differences reflect the fact that less accurate analysts are more likely to depart, highlighting the advantage of focusing on both promotions and (non-favorable) departures.

The findings in Panel A are robust to alternative samples and specifications. In Panel B, we exclude career outcomes for 2008 and 2009. Although our multivariate specifications already include calendar year fixed effects, Panel B allows for the possibility that Moody's revealed preferences for accuracy and bias were skewed during the financial crisis. The odds ratios on both indices are similar to those estimated over the full sample. In Panel C, we exclude Senior Vice Presidents and Managing Directors. There are two reasons to consider the sample of junior analysts. First, the fact that credit reports are signed by both junior and senior analysts implies that a given rating is being used to measure the accuracy and bias of two different analysts. Focusing on the sample of junior analysts greatly reduces the extent to which this is true. Second, if junior

[20] The number of analyst-year observations falls when we estimate logit regressions because we exclude Managing Directors, for whom promotions are not possible.

analysts have fewer managerial responsibilities, we might expect their promotions and departures to depend more strongly on the characteristics of their ratings. Alternatively, to increase oversight of junior analysts, Moody's might alternatively choose to hold senior analysts more accountable for the content of each credit report. The net effect is that the odds ratios and significance levels in Panel C are similar to those in Panel A.

We include two additional robustness tests in the Appendix. In Appendix Table A-3, we estimate specifications that include the Accuracy Index, Pessimist Index, and Optimist Index. While the odds ratios and significance levels on the Accuracy Index and Pessimist Index are similar to those estimated in Table 7, none of the odds ratios on the Optimist Index (which range between 0.827 and 1.033) are statistically distinguishable from one at conventional levels. If Moody's valued optimistic analysts per se, we might have expected the odds ratios on the Optimist Index to be greater than one by a statistically and economically significant margin.

Finally, in Appendix Table A-4, we replace the Optimist Index with the natural logarithm of rated assets in year *t-1*. To the extent that this variable reflects Moody's ongoing assessment on analyst ability, it is also likely to depend on the extent to which the analyst's ratings are accurate or pessimist.[21] Indeed, everything else equal, we find that analysts with more rated assets in year *t-1* are more likely to be promoted and less likely to depart in year *t*. For this reason, we prefer to exclude the measure from our main tests in Table 7. However, even controlling for the log of rated

[21] While our focus has always been on analyst promotions and departures, we explored the possibility that accurate analysts might gain covered firms and covered assets at the same time that pessimist analysts lose them. We find a positive correlation (in unreported regressions) between the Accuracy Index and the dollar value of covered assets, but it is economically modest and only statistically significant at the 10-percent level. Moreover, there is essentially no correlation between the Pessimist Index and the dollar value of covered assets, or between the levels of the accuracy and pessimist indices and changes in the number of covered firms. In other words, the impact of accuracy and bias on the level of covered assets appears to operate indirectly, through an increased probability of promotion and a decreased probability of exit, rather than as an incremental reward within rank and years in rank.

assets, we continue to find that accurate ratings are rewarded and pessimistic ratings are punished. In the ordered logit specifications, the odds ratios on the Accuracy Index and Pessimist Index are similar to those in Table 7 and Table A-3, and consistently statistically significant from one at the 1-percent level. In the logit specifications, the odds ratios on the Accuracy Index fall slightly, but remain statistically significant at the 10-percent level and below. Overall, we conclude that Moody's internal labor market punishes pessimism more than it rewards optimism.[22]

E. Time-series variation in weights on accuracy and bias?

The SEC began conducting annual audits of NRSROs in September 2007. Its stated goal was not to determine whether published ratings were accurate or biased relative to an absolute standard but rather to determine whether published ratings accurately reflected each firm's stated methodology and criteria.[23] In this section, we ask whether the weight that Moody's placed on accurate ratings was different in years with annual audits (2008-2011) than it was earlier (2002-2007). The prospect of annual audits may have prompted Moody's to increase the weight placed on accurate ratings in promotion and departure decisions. On the other hand, given the SEC's focus on internal consistency rather than absolute standards, the audits may have prompted Moody's either not to change the weight placed on accurate ratings or to decrease it. In Table 8, we report versions of our main specifications in which we interact the Accuracy Index and Pessimism Index

[22] Although investment-grade issuers have an obvious preference for remaining investment grade, we do not find that Moody's punishes analysts any more severely for downgrading firms from investment grade to speculative grade than it does for pessimism. When we include a dummy variable indicating whether analyst i downgraded one or more firms from investment grade to speculative grade in year $t-1$ to the ordered logit specifications in Table 7 Panel A, we find (in unreported regressions) that the odds ratio on this dummy variable are similar to the odds ratios on the Pessimism Index (i.e., well less than one), but not statistically distinguishable from one at conventional levels. Note, however, that because only 4.5% of analyst-years involve a downgrade from investment grade to speculative grade, we are forced to define a downgrade from investment grade to speculative grade as an unconditional reduction in Moody's rating rather than as a reduction in Moody's rating relative to S&P.

[23] We thank Abe Losice, former SEC auditor, for describing the criteria used to evaluate NRSRO ratings.

with Pre 2008 and Post 2007 dummy variables. (We also include either the Pre 2008 and Post 2007 dummy variables or the full set of calendar year fixed effects.) The odds ratio associated with the Accuracy Index falls significantly during the Post 2007 period. In the ordered logit specification with fixed effects, the odds ratio falls from 2.286 to 1.513. In the logit specification with fixed effects, it falls from 2.117 to 1.135. Both reductions are economically significant. The reduction in the odds ratios in the logit specification is also significant at the 10-percent level. In other words, we find suggestive evidence that Moody's responded to the annual SEC audits by placing *less* weight on objective measures of accuracy in its promotion decisions.

Of course, around the same time that these audits were introduced, the financial crises occurred, which put rating agencies under additional scrutiny. While this additional scrutiny might arguably have led rating agencies to place an additional emphasis on accuracy, interestingly, this is not what we find.

F. Accuracy versus extreme equity market reactions to rating decisions

To shed additional light on the extent to which 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*.[24] 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 (after scaling by firm-level volatility and excluding three day windows that include firm earnings announcements).

[24] 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.

The initial set of ordered logit and logit specifications in Table 9 replicate specifications from Table 7. The new independent variable in the remaining specifications equals one if at least one of the analyst's announcement returns in year *t-1* was in the bottom quartile of all announcement returns in our sample (-9.7% and below). We find strong evidence that low abnormal returns are associated with less favorable career outcomes, suggesting that Moody's faults those analysts whose downgrades most surprise the market. However, we also continue to find that Moody's rewards accuracy, with odds ratios that are even further above one. One interpretation of these patterns, 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.

G. 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 analyst departure, providing us with an additional way to infer the level of Moody's aversion to pessimistic ratings. We evaluate analyst reassignment at the firm-year level. Our dependent variable is a binary variable indicating whether Moody's replaces one or both of the analysts in year *t* who covered the firm in year *t-1*. To the extent that Moody's seeks to discourage pessimistic ratings, or that issuers respond to pessimistic ratings by lobbying Moody's for new analysts, we expect to observe analyst reassignment more often when Moody's rating are more pessimistic.

The independent variables in Table 10 are analogous to those used in Panel A of Table 5, except that they are defined at the firm level. "Downgrader" equals one if Moody's downgraded firm *j* in year *t-1* and S&P did not do the same, and zero otherwise. "Model Predicted Pessimist" equals one if Moody's rating for firm *j* in year *t-1* was below that predicted by the Baghai, Servaes, and Tamayo (2014) ratings model, and zero otherwise. We find that firms whose ratings were downgraded in year *t-1* are 52% more likely to receive a new analyst in year *t* (significant at the 1-percent level), but do not find any effect for model predicted pessimism.[25] When we combine the two firm-level dummy variables into a Pessimist Index, we find that the odds ratio is significantly greater than one (significant at the 1-percent level). This finding is robust to the inclusion of industry-by-calendar year fixed effects. An alternative (reverse causation) interpretation is that analysts are more likely to lower a firm's credit rating when they know that they will not be covering the firm in the future. However, our finding is also robust to the exclusion of firms covered by analysts that depart Moody's in year *t*. Overall, our findings in Table 10 complement our earlier finding that downgraders are less likely to experience positive career outcomes at Moody's.

VI. Conclusion

To shed new light on 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 multiple measures of accuracy and across multiple subsamples, and is strongest when we estimate specifications that consider the effect of accuracy on the likelihood of both positive and negative career outcomes. However, we also find that analysts who downgrade more frequently, who assign ratings below those predicted by a rat-

[25] In unreported regressions, we find that ratings are *less* likely to rebound in the year following a downgrade when a new analyst is assigned to the firm.

ings model, and whose downgrades are associated with large negative market reactions are significantly less likely to experience positive career outcomes within Moody's. Furthermore, we find that Moody's is more likely to assign new analysts to firms with pessimistic ratings from existing analysts.

If analysts are promoted for being accurate and not overly negative, one might ask why any analysts deviate from this behavior. Our preferred explanation is that accuracy is a skill that requires both talent and effort. One might ask the same question of equity analysts who are more accurate, CEOs whose companies are more profitable, hedge funds that generate greater returns, or basketball players who make more baskets. It is likely not as simple as deciding one day that you are going to be accurate. Regarding bias, our default assumption is that analysts report the rating they believe to be correct, without intentionally gaming the system. Thus, our default assumption is analyst integrity. The fact that Fracassi, Petry and Tate (2016) estimate significant fixed effects with respect to analyst optimism and pessimism adds credence of this assumption.

Because we find that Moody's rewards accurate analysts but also punishes pessimistic analysts, we conclude that Moody's internal labor market 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 may suggest that there is still room for improvement.

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Figure 1. Univariate Evidence on Influence of Accuracy on Career Outcomes

This Figure plots the fraction of analysts that are promoted by Moody's or depart from Moody's in year t, for different values of the "Accuracy Index." We exclude managing directors when calculating the fraction promoted, and we exclude 13 external promotions when calculating the fraction departing. We summarize the dummy variables underlying this index in Appendix Table A-2.

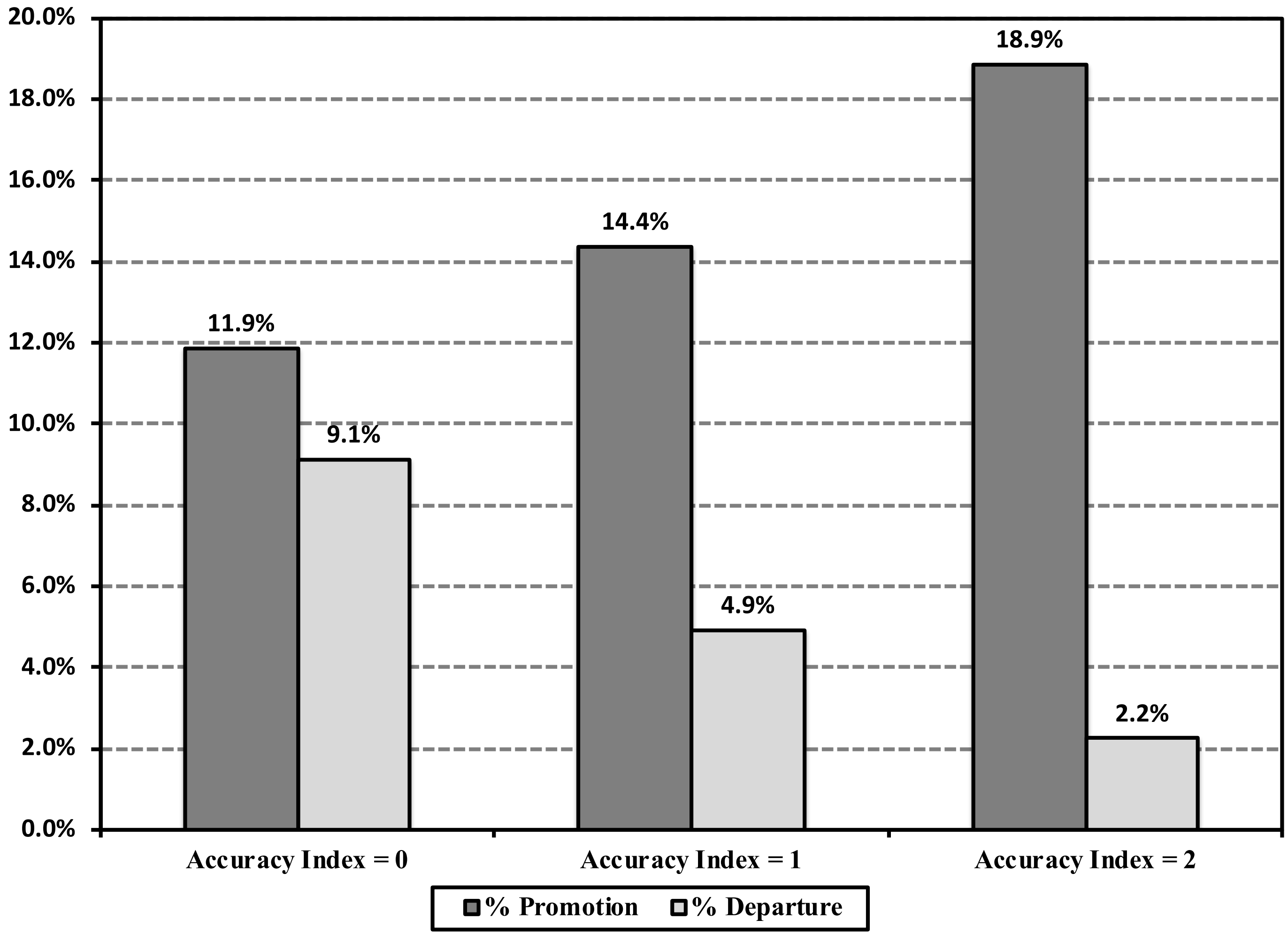

Figure 2. Univariate Evidence on Influence of Pessimism on Career Outcomes

This Figure plots the fraction of analysts that are promoted by Moody's or depart from Moody's in year t, for different values of the "Pessimist Index." We exclude managing directors when calculating the fraction promoted, and we exclude 13 external promotions when calculating the fraction departing. We summarize the dummy variables underlying this index in Appendix Table A-2.

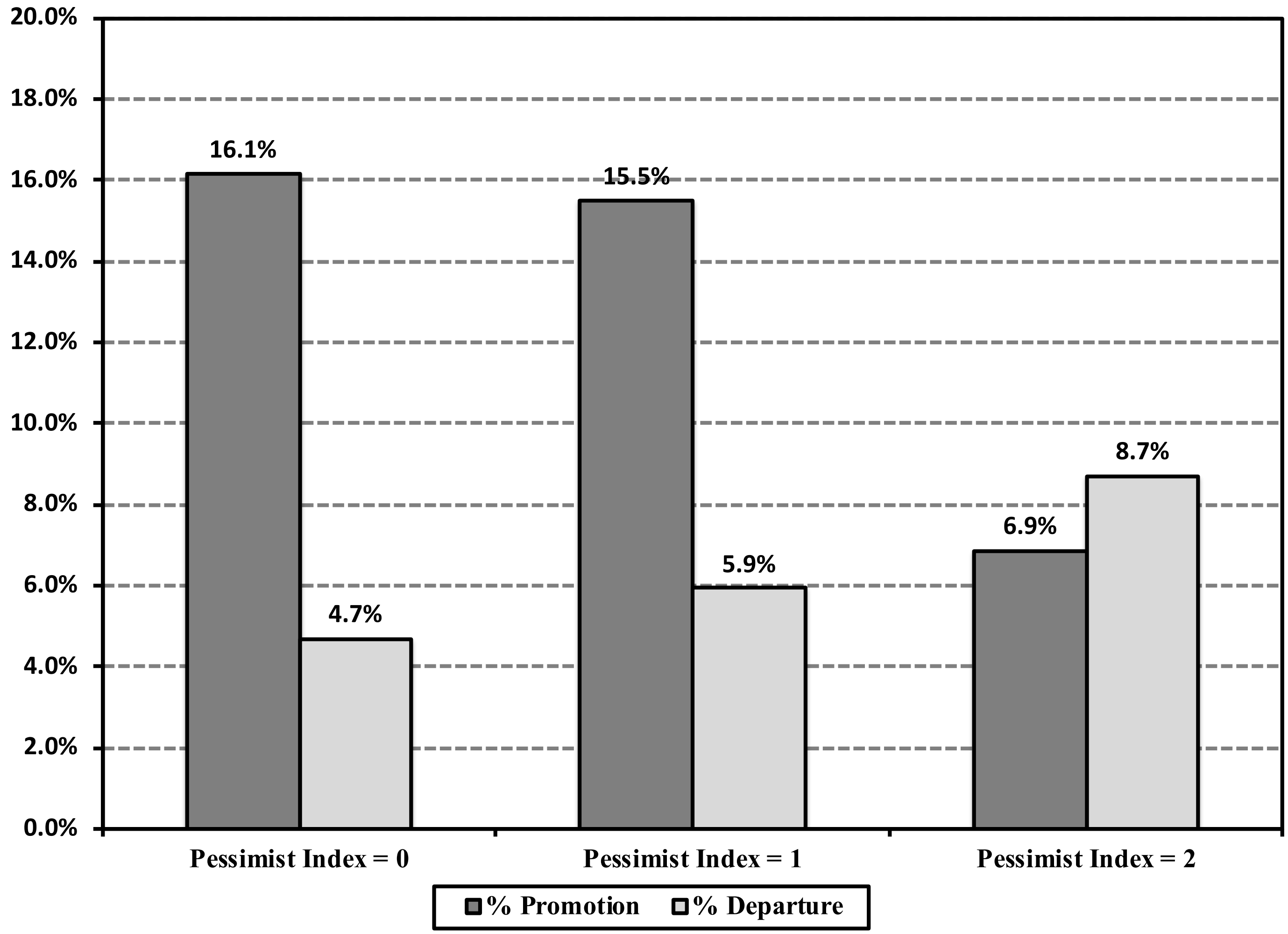

Figure 3. Univariate Evidence on Influence of Optimism on Career Outcomes

This Figure plots the fraction of analysts that are promoted by Moody's or depart from Moody's in year t, for different values of the "Optimist Index." We exclude managing directors when calculating the fraction promoted, and we exclude 13 external promotions when calculating the fraction departing. We summarize the dummy variables underlying this index in Appendix Table A-2.

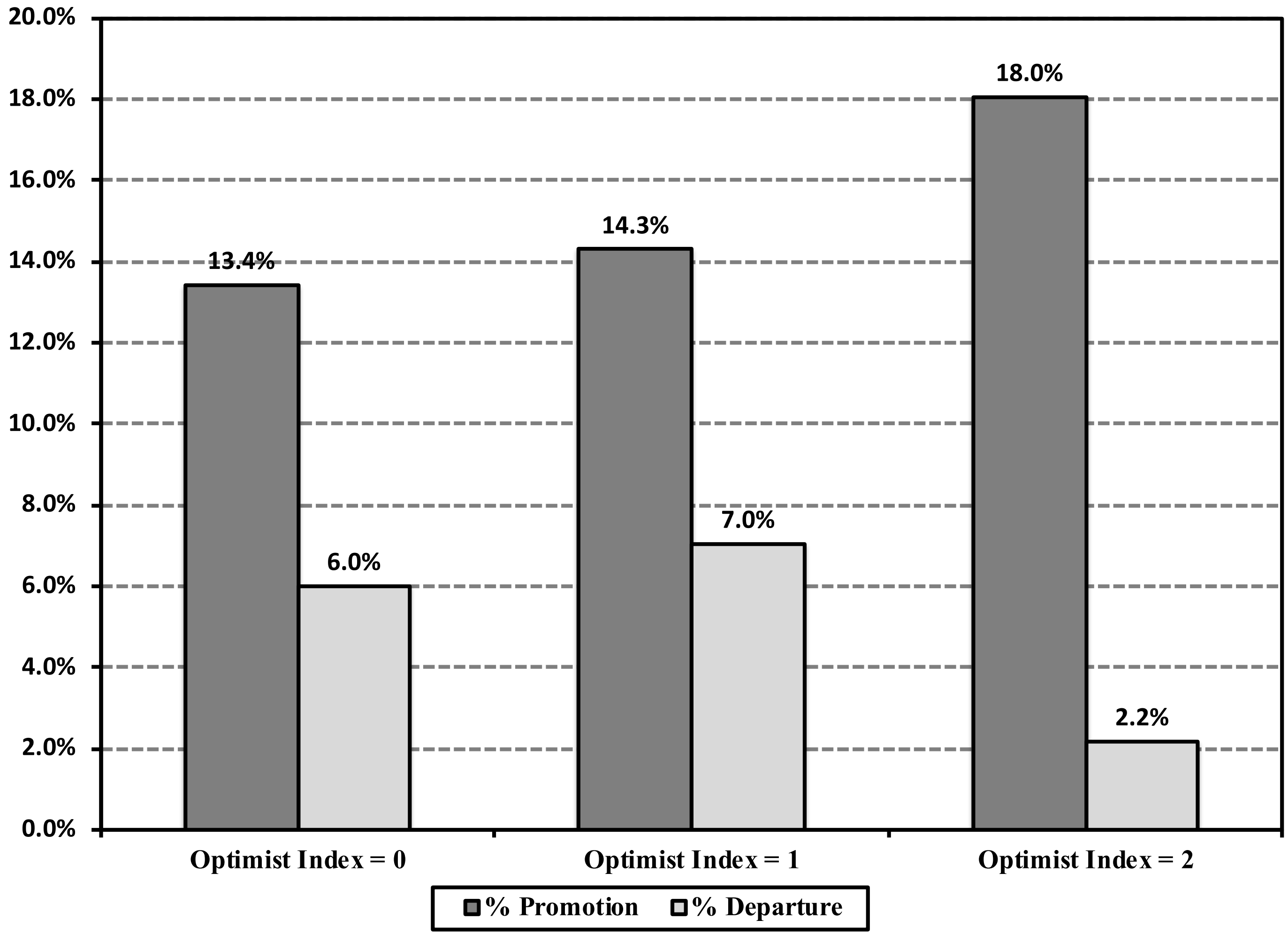

Table 1
Analyst-Level Summary Statistics

This table summarizes how the number and types of firms that analysts cover varies with analyst rank. We report statistics for all analyst-years and separately for each (beginning of year) rank within Moody's. "Analyst" is the juniormost rank and "Managing Director" is the seniormost 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					
		All Levels	**Analyst**	**Senior Analyst**	**Senior Credit Officer**	**Senior Vice President**	**Managing Director**
Variable		**N = 786**	**N = 144**	**N = 229**	**N = 158**	**N = 170**	**N = 85**
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 [$ millions]	*Mean*	$20,976	$11,591	$17,964	$30,704	$22,219	$24,710
	Median	$8,190	$3,086	$6,804	$10,232	$9,302	$13,549
Aggregate Rated Assets [$ millions]	*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 "Seniormost Analyst" is a Managing Director, Senior Vice President, or below. We also report the fraction of firm-years where the "Juniormost Analyst" is an Analyst, Senior 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 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**
Number of Analysts	2.4	2.4	2.4	2.2	2.2	2.3	2.4	2.4	2.4
Seniormost 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%
Juniormost 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 juniormost rank and "Managing Director" is the seniormost rank. Panel A reports percentages by the number of years the analyst has remained in the current rank. Panel B reports percentages by calendar year. The Total Analyst-Years row reports the average fraction of observations that are promoted or depart, either overall or within rank. The Total Analysts row reports that fraction of analysts that are promoted at least once or depart, either overall or within rank. Of the 177 unique analysts in our sample, 52 have held the rank of Analyst, 83 have held the rank of Senior Analyst, 57 have held the rank of Senior Credit Officer, 42 have held the rank of Senior Vice President, and 24 have held the rank of Managing Director.

	All Levels			Analyst		Senior Analyst		Senior Credit Officer		Senior Vice President		Managing Director
	N = 786			N = 144		N = 229		N = 158		N = 170		N = 85
	Analyst-Years	% Promoted	% Depart	% Promoted	% Depart	% Promoted	% Depart	% Promoted	% Depart	% Promoted	% Depart	% Depart
Panel A: Years in Rank												
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%	5.3%	2.2%	8.7%	10.1%	4.3%	20.5%	5.1%	3.1%	6.3%	0.0%
3 Years	156	12.8%	7.1%	8.1%	8.1%	21.8%	9.1%	16.0%	8.0%	3.8%	3.8%	0.0%
4 Years	120	24.2%	5.8%	27.6%	6.9%	43.2%	8.1%	11.1%	5.6%	13.0%	0.0%	7.7%
5+ Years	179	14.0%	6.1%	40.7%	3.7%	12.5%	6.3%	11.1%	3.7%	8.9%	5.4%	14.3%
Panel B: Calendar Year												
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%	11.1%	28.6%	14.3%	21.4%	14.3%	13.3%	20.0%	9.1%	0.0%	0.0%
2005	63	11.1%	3.2%	14.3%	14.3%	16.7%	0.0%	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%	6.9%	9.5%	0.0%	25.0%	11.1%	23.1%	0.0%	9.5%	0.0%	27.3%
2008	111	13.5%	7.2%	18.5%	7.4%	18.8%	9.4%	15.8%	5.3%	4.5%	4.5%	9.1%
2009	112	13.4%	5.4%	20.0%	8.0%	16.7%	3.3%	8.7%	4.3%	12.5%	8.3%	0.0%
2010	96	16.7%	4.2%	35.3%	0.0%	19.2%	11.5%	14.3%	4.8%	9.1%	0.0%	0.0%
2011	97	8.2%	6.2%	5.9%	17.6%	19.2%	0.0%	4.8%	4.8%	4.8%	9.5%	0.0%
Total Analyst-Years	**786**	**13.0%**	**5.7%**	**16.7%**	**6.9%**	**18.3%**	**7.0%**	**14.6%**	**5.7%**	**7.6%**	**3.5%**	**4.7%**
Total Analysts	**177**	**45.2%**	**25.4%**	**46.2%**	**19.2%**	**50.6%**	**19.3%**	**40.4%**	**15.8%**	**31.0%**	**14.3%**	**16.7%**

Table 4

Does Accuracy Influence Career Paths?

This table reports odds ratios from ordered logistic regressions of analyst-level measures of accuracy on career outcomes. 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 A focuses on the full sample of analyst-year observations. Panel B focuses on the subsample of analyst-years observations for which we can calculate the Yield Accurate dummy variable. In Panel A, the Accuracy Index is the sum of the Stock Accurate and Rating Accurate dummy variables. In Panel B, it is the sum of the Stock Accurate, Rating Accurate, and Yield Accurate dummy variables. All of the independent variables are defined in Section IV.A. The multivariate specifications include calendar year fixed effects and analyst rank-by-years-in-rank fixed effects. We report the absolute values of Z-statistics below the odds ratios. ***, **, 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. Full Sample of Analyst-Years

	Ordered Logit: *Career Path [t]*					
Explanatory Variables	[1]	[2]	[3]	[4]	[5]	[6]
Accuracy Index [t-1]	**1.474*** **			**1.464*** **		
	(3.075)			(2.785)		
Stock Accurate [t-1]		**1.621*** **			**1.662*** **	
		(2.632)			(2.655)	
Rating Accurate [t-1]			**1.465** **			**1.384* **
			(2.146)			(1.695)
Calendar Year FEs?	--	--	--	Yes	Yes	Yes
Analyst Rank * Years in Rank FEs?	--	--	--	Yes	Yes	Yes
N	786	786	786	786	786	786
Pseudo R-Squared	0.010	0.007	0.005	0.075	0.073	0.068

Panel B. Subsample of Analyst-Years with Yield Accuracy measure

	Ordered Logit: *Career Path [t]*							
Explanatory Variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Accuracy Index [t-1]	**1.667*** **				**1.762*** **			
	(3.004)				(3.284)			
Stock Accurate [t-1]		**2.137*** **				**2.263*** **		
		(2.826)				(2.880)		
Rating Accurate [t-1]			**1.573* **				**1.643* **	
			(1.828)				(1.745)	
Yield Accurate [t-1]				**1.383**				**1.568**
				(1.192)				(1.580)
Calendar Year FEs?	--	--	--	--	Yes	Yes	Yes	Yes
Analyst Rank * Years in Rank FEs?	--	--	--	--	Yes	Yes	Yes	Yes
N	436	436	436	436	436	436	436	436
Pseudo R-Squared	0.024	0.017	0.006	0.003	0.127	0.119	0.108	0.107

Table 5

Does Bias Influence Career Paths?

This table reports odds ratios from ordered logistic regressions of analyst-level measures of negative and positive bias on career outcomes. 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 A focuses on the Pessimist Index and its components, the Downgrader and Model Predicted Pessimist dummy variables. Panel B focuses on the Optimist Index and its components, the Upgrader and Model Predicted Optimist dummy variables. All of the independent variables are defined in Section IV.A. The multivariate specifications include calendar year fixed effects and analyst rank-by-years-in-rank fixed effects. We report the absolute values of Z-statistics below the odds ratios. ***, **, 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. Pessimism

	Ordered Logit: *Career Path [t]*					
Explanatory Variables	[1]	[2]	[3]	[4]	[5]	[6]
Pessimist Index [t-1]	**0.724*** **			**0.701** **		
	(2.589)			(2.488)		
Downgrader [t-1]		**0.707***			**0.678***	
		(1.857)			(1.933)	
Model Predicted Pessimist [t-1]			**0.644** **			**0.620** **
			(2.179)			(1.981)
Calendar Year FEs?	--	--	--	Yes	Yes	Yes
Analyst Rank * Years in Rank FEs?	--	--	--	Yes	Yes	Yes
N	786	786	786	786	786	786
Pseudo R-Squared	0.007	0.004	0.005	0.073	0.070	0.070

Panel B. Optimist

	Ordered Logit: *Career Path [t]*					
Explanatory Variables	[1]	[3]	[2]	[4]	[5]	[6]
Optimist Index [t-1]	**1.182**			**1.137**		
	(1.490)			(1.068)		
Upgrader [t-1]		**1.059**			**1.045**	
		(0.343)			(0.241)	
Model Predicted Optimist [t-1]			**1.404***			**1.309**
			(1.890)			(1.375)
Calendar Year FEs?	--	--	--	Yes	Yes	Yes
Analyst Rank * Years in Rank FEs?	--	--	--	Yes	Yes	Yes
N	786	786	786	786	786	786
Pseudo R-Squared	0.002	0.000	0.003	0.067	0.066	0.067

Table 6
Accuracy, Pessimism, and Career Outcomes

Panel A reports the fraction of analyst-year observations that depart from Moody's in year *t* for different values of the Accuracy Index and Pessimist Index in year *t-1* . It is based on the full sample of analyst-year observations. Panel B reports the fraction of analyst-year observations that a promoted by Moody's in year t for different values of the Accuracy Index and Pessimist Index in year t-1. It excludes Managing Directors because they are not eligible for promotion. In Panel A, more negative outcomes are shaded red. In Panel B, more positive outcomes are shaded darker blue.

Panel A. Departures

	Accuracy Index			
Pessimist Index	0	1	2	ALL
2	33.3%	8.9%	3.4%	8.7%
1	10.1%	5.8%	2.5%	5.9%
0	7.1%	3.1%	0.0%	4.7%
ALL	9.1%	4.9%	2.2%	5.7%

Panel B. Promotions

	Accuracy Index			
Pessimist Index	0	1	2	ALL
2	0.0%	5.0%	9.6%	6.9%
1	12.9%	16.0%	16.9%	15.5%
0	12.2%	15.6%	36.1%	16.1%
ALL	11.9%	14.4%	18.9%	14.6%

Table 7

Accuracy Versus Pessimism

This table reports odds ratios from ordered logistic regressions of analyst-level measures of accuracy and bias on career outcomes. 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. It also reports odds ratios from logistic regressions of accuracy and bias on internal promotions. Panel A focuses on the full sample of analyst-year observations. Panel B excludes career outcomes for 2008 and 2009. Panel C excludes Senior Vice Presidents and Managing Directors. All specifications include the Accuracy Index and the Pessimist Index, which are defined in Section IV.A. The multivariate specifications include calendar year fixed effects and analyst rank-by-years-in-rank fixed effects. We report the absolute values of Z-statistics below the odds ratios. ***, **, 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. Full Sample

	Ordered Logit: Career Path [t]		*Logit: Promoted [t]*	
Explanatory Variables	[1]	[2]	[3]	[4]
Accuracy Index [t-1]	**1.825*** **	**1.808*** **	**1.573*** **	**1.502** **
	(4.206)	(3.883)	(2.806)	(2.183)
Pessimist Index [t-1]	**0.569*** **	**0.556*** **	**0.608*** **	**0.573*** **
	(4.050)	(3.781)	(2.826)	(2.788)
Calendar Year FEs?	--	Yes	--	Yes
Analyst Rank * Years in Rank FEs?	--	Yes	--	Yes
N	786	786	701	701
Pseudo R-Squared	0.028	0.091	0.021	0.130

Panel B. Excludes career outcomes for 2008 and 2009

	Ordered Logit: Career Path [t]		*Logit: Promoted [t]*	
Explanatory Variables	[1]	[2]	[3]	[4]
Accuracy Index [t-1]	**1.980*** **	**1.919*** **	**1.666*** **	**1.567** **
	(3.913)	(3.533)	(2.701)	(2.068)
Pessimist Index [t-1]	**0.568*** **	**0.557*** **	**0.613** **	**0.568** **
	(3.336)	(3.220)	(2.436)	(2.483)
N	563	563	499	480
Pseudo R-Squared	0.032	0.090	0.024	0.122

Panel C. Excludes Senior Vice Presidents (SVP) and Managing Directors (MD)

	Ordered Logit: Career Path [t]		*Logit: Promoted [t]*	
Explanatory Variables	[1]	[2]	[3]	[4]
Accuracy Index [t-1]	**1.861*** **	**1.849*** **	**1.575*** **	**1.508** **
	(4.008)	(3.764)	(2.653)	(2.112)
Pessimist Index [t-1]	**0.578*** **	**0.544*** **	**0.671** **	**0.610** **
	(3.511)	(3.457)	(2.171)	(2.301)
N	531	531	531	531
Pseudo R-Squared	0.031	0.085	0.020	0.124

Table 8

Do Weights on Accuracy Versus Pessimism Change in Response to Annual SEC Audits?

This table extends the ordered logistic regressions and logistic regressions in Table 7 Panel A to interact the Accuracy Index and Pessimist Index with pre-2008 and post-2007 dummy variables. We include but do not report the coefficients on the Pre 2008 dummy variable in specifications [1] and [3]. It also reports p-values from hypothesis tests that the odds ratios estimated for an index in 2002-2007 are equal to the odds ratios estimated for the same index in 2008-2011. The multivariate specifications include calendar year fixed effects and analyst rank-by-years-in-rank fixed effects. We report the absolute values of Z-statistics below the odds ratios. ***, **, 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.

	Ordered Logit: Career Path [t]		*Logit: Promoted [t]*	
Explanatory Variables	[1]	[2]	[3]	[4]
Accuracy Index [t-1] * Pre 2008	**2.235***	**2.286***	**2.173***	**2.117**
	(3.840)	(3.835)	(2.998)	(2.454)
Accuracy Index [t-1] * Post 2007	**1.532**	**1.513**	**1.201**	**1.135**
	(2.443)	(2.361)	(0.936)	(0.554)
Pessimist Index [t-1] * Pre 2008	**0.536***	**0.514***	**0.546**	**0.498**
	(-3.160)	(-3.172)	(-2.413)	(-2.382)
Pessimist Index [t-1] * Post 2007	**0.575***	**0.575***	**0.633***	**0.628***
	(-2.840)	(-2.764)	(-1.810)	(-1.676)
Ho: Accuracy Pre = Accuracy Post	0.139	0.116	0.052	0.091
Ho: Pessimist Pre = Pessimist Post	0.798	0.698	0.682	0.566
Pre 2008 and Post 2007 FEs?	Yes	--	Yes	--
Calendar Year FEs?	--	Yes	--	Yes
Analyst Rank * Years in Rank FEs?	--	Yes	--	Yes
N	786	786	701	701
Pseudo R-Squared	0.030	0.035	0.027	0.135

Table 9

Career Outcomes and Extreme Announcement Returns

This table extends the ordered logistic regressions and logistic returns in Table 7 Panel A to include the Low Abnormal Return dummy variable, which is defined in Section IV.F. The multivariate specifications include calendar year fixed effects and analyst rank-by-years in rank fixed effects. We report the absolute values of Z-statistics below the odds ratios. ***, **, 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.

	Ordered Logit: *Career Path [t]*			*Logit: Promoted [t]*		
Explanatory Variables	[1]	[2]	[3]	[4]	[5]	[6]
Accuracy Index [t-1]	**1.825*** **	**1.971*** **	**1.971*** **	**1.573*** **	**1.725*** **	**1.667*** **
	(4.206)	(4.388)	(4.104)	(2.806)	(3.205)	(2.620)
Pessimist Index [t-1]	**0.569*** **	**0.585*** **	**0.572*** **	**0.608*** **	**0.636*** **	**0.601** **
	(-4.050)	(-3.835)	(-3.581)	(-2.826)	(-2.585)	(-2.547)
Low Abnormal Return [t-1]		**0.640** **	**0.619** **		**0.482** **	**0.464** **
		(-2.073)	(-1.964)		(-2.230)	(-2.160)
Calendar Year FEs?	--	--	Yes	--	--	Yes
Analyst Rank * Years in Rank FEs?	--	--	Yes	--	--	Yes
N	786	786	786	701	701	701
Pseudo R-Squared	0.028	0.031	0.095	0.021	0.030	0.137

Table 10

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 are analogous to those in Panel A of Table 5, except that they are defined at the firm level. Downgrader equals one if Moody's downgraded the firm relative to S&P in year t-1, and zero otherwise. Model Predicted Pessimist equals one if the Moody's rating is lower than that predicted by the rating prediction model of Ramin, Servaes, and Tamayo (2014). The Pessimist Index equals the sum of the Downgrader and Model Predicted Pessimist dummy variables. Columns [4] and [6] include a separate fixed effect for each of the 12 Fama-French industries each calendar year. Columns [5] and [6] exclude firms covered by analysts in year t-1 that depart Moody's in year t. We report the absolute values of Z-statistics below the odds ratios. ***, **, 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 firm.

	Logit: New Analyst [t] { New Analyst Assigned to Firm = 1, Otherwise = 0 }					
Explanatory Variables	[1]	[2]	[3]	[4]	[5]	[6]
Pessimist Index [t-1]	**1.228*** **			**1.204*** **	**1.214*** **	**1.233*** **
	(4.009)			(3.027)	(3.531)	(2.894)
Downgrader [t-1]		**1.522*** **				
		(5.302)				
Model Predicted Pessimist [t-1]			**1.041**			
			(0.616)			
Industry-by-Calendar Year FEs?	--	--	--	Yes	--	Yes
Excluding Analyst Departures	--	--	--	--	Yes	Yes
N	5,440	5,440	5,440	4,081	4,545	3,287
Pseudo R-Squared	0.002	0.004	0.000	0.002	0.002	0.003

Appendix Table A-1

Number of Rated Firms and Level of Rated Firm Assets by Analyst Rank and Years in Rank

This table reports statistics by analyst rank and years in rank. Panel A reports the average number of covered firms and the fraction of observations for which we observe an increase in the number of covered firms. Panel B reports the mean total assets of covered firms and mean change in total assets of covered firms. Panel C reports the number of analysts in each cell. The unexpectedly large number of covered firms for first-year Analysts is driven by 5 observations.

Panel A.

	Mean Number of Covered Firms					Fraction with Increase in Number of Covered Firms?				
	Years in Rank					*Years in Rank*				
Analyst Rank	1	2	3	4	5+	1	2	3	4	5+
Analyst	16.6	6.1	7.5	7.6	7.3	100.0%	65.2%	62.2%	31.0%	33.3%
Senior Analyst	8.5	9.3	10.1	10.0	7.9	50.0%	69.6%	49.1%	37.8%	27.1%
Senior Credit Officer	13.0	8.4	9.8	9.0	6.9	34.7%	33.3%	20.0%	38.9%	33.3%
Senior Vice President	24.1	25.0	29.8	29.4	23.8	69.7%	50.0%	30.8%	47.8%	26.8%
Managing Director	33.0	30.2	35.3	33.4	16.0	38.9%	55.0%	46.2%	23.1%	4.8%

Panel B.

	Mean Total Assets of Covered Firms					Mean Change in Total Assets of Covered Firms				
	Years in Rank					*Years in Rank*				
Analyst Rank	1	2	3	4	5+	1	2	3	4	5+
Analyst	21.5	27.3	39.2	37.6	37.4	10.2	19.0	6.7	6.9	-2.9
Senior Analyst	101.2	84.5	97.8	79.6	106.2	33.7	27.6	15.6	-10.1	6.3
Senior Credit Officer	136.5	136.6	112.1	77.9	98.4	50.1	8.8	15.4	6.9	14.7
Senior Vice President	182.6	232.5	294.8	383.4	357.4	53.0	70.8	37.1	45.4	34.2
Managing Director	462.3	388.8	407.0	504.4	229.9	122.7	55.4	52.5	161.7	-26.2

Panel C.

	Count					
	Years in Rank					
Analyst Rank	1	2	3	4	5+	TOTAL
Analyst	5	46	37	29	27	144
Senior Analyst	20	69	55	37	48	229
Senior Credit Officer	49	39	25	18	27	158
Senior Vice President	33	32	26	23	56	170
Managing Director	18	20	13	13	21	85
TOTAL	125	206	156	120	179	786

Appendix Table A-2
Measures of Accuracy and Bias

This table summarizes the frequency of Moody's analyst promotions and departures for our three measures of accuracy, two measures of negative bias, two measures of positive bias, and measure of low abnormal equity returns. 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 for promotion. 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. We define the low abnormal equity return dummy variable in Section IV.F and the other dummy variables in Section IV.A.

			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 = 346]*	16.8%	15.4%	22.6%	18.6%	9.4%	-
	No [N = 355]	12.4%	17.7%	14.0%	11.4%	5.4%	-
Rating Accurate [t-1]	*Yes [N = 278]*	16.5%	18.2%	21.7%	18.0%	6.2%	-
	No [N = 423]	13.2%	15.7%	15.9%	12.4%	8.6%	-
Yield Accurate [t-1]	*Yes [N = 235]*	16.6%	18.2%	21.3%	15.8%	10.4%	-
	No [N = 146]	13.0%	22.2%	17.9%	8.8%	6.5%	-
Downgrader [t-1]	*Yes [N = 275]*	13.1%	19.2%	16.1%	10.9%	6.7%	-
	No [N = 426]	15.5%	15.2%	19.9%	16.5%	8.4%	-
Model Predicted Pessimist [t-1]	*Yes [N = 181]*	9.4%	20.8%	11.9%	8.2%	2.0%	-
	No [N = 520]	16.3%	15.8%	20.6%	17.4%	9.9%	-
Upgrader [t-1]	*Yes [N = 277]*	15.2%	12.5%	20.7%	16.4%	9.5%	-
	No [N = 424]	14.2%	19.3%	16.8%	13.6%	6.3%	-
Model Predicted Optimist [t-1]	*Yes [N = 240]*	17.1%	18.0%	20.5%	16.3%	12.7%	-
	No [N = 461]	13.2%	16.0%	17.2%	13.8%	4.7%	-
Low Abnormal Return [t-1]	*Yes [N = 126]*	9.5%	13.6%	6.3%	9.1%	10.0%	-
	No [N = 575]	15.7%	17.2%	20.3%	15.4%	6.7%	-
		Panel B: Departure [N = 786]					
Stock Accurate [t-1]	*Yes [N = 388]*	3.6%	4.6%	3.5%	2.9%	3.1%	4.8%
	No [N = 398]	7.8%	8.9%	10.5%	8.0%	4.1%	4.7%
Rating Accurate [t-1]	*Yes [N = 313]*	3.5%	3.6%	6.2%	1.6%	0.0%	5.7%
	No [N = 473]	7.2%	9.0%	7.6%	8.2%	5.7%	4.0%
Yield Accurate [t-1]	*Yes [N = 266]*	3.8%	0.0%	7.9%	1.8%	1.5%	3.2%
	No [N = 170]	5.3%	11.1%	2.6%	8.8%	2.2%	4.2%
Downgrader [t-1]	*Yes [N = 316]*	7.6%	7.7%	9.7%	12.7%	2.7%	4.9%
	No [N = 470]	4.5%	6.5%	5.1%	1.9%	4.2%	4.5%
Model Predicted Pessimist [t-1]	*Yes [N = 201]*	6.5%	4.2%	10.2%	8.2%	2.0%	5.0%
	No [N = 585]	5.5%	7.5%	5.9%	4.6%	4.1%	4.6%
Upgrader [t-1]	*Yes [N = 319]*	5.3%	7.1%	6.5%	5.5%	1.4%	7.1%
	No [N = 467]	6.0%	6.8%	7.3%	5.8%	5.2%	2.3%
Model Predicted Optimist [t-1]	*Yes [N = 272]*	4.0%	8.0%	6.4%	0.0%	1.6%	3.1%
	No [N = 514]	6.6%	6.4%	7.3%	8.3%	4.7%	5.7%
Low Abnormal Return [t-1]	*Yes [N = 150]*	3.3%	0.0%	9.4%	0.0%	4.0%	0.0%
	No [N = 636]	6.3%	8.2%	6.6%	6.6%	3.3%	6.6%

Appendix Table A-3

Accuracy, Pessimism, and Optimism

This table reports ordered logit and logit specifications analogous to those estimated in Table 7, except that we now also include the Optimist Index. The absolute values of 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. Full Sample

	Ordered Logit: Career Path [t]		*Logit: Promoted [t]*	
Explanatory Variables	[1]	[2]	[3]	[4]
Accuracy Index [t-1]	**1.850*** **	**1.865*** **	**1.565*** **	**1.529** **
	(4.100)	(3.933)	(2.656)	(2.246)
Pessimist Index [t-1]	**0.565*** **	**0.549*** **	**0.610*** **	**0.569*** **
	(3.968)	(3.812)	(2.764)	(2.827)
Optimist Index [t-1]	**0.964**	**0.924**	**1.015**	**0.952**
	(0.316)	(0.631)	(0.106)	(0.320)
Calendar Year FEs?	--	Yes	--	Yes
Analyst Rank * Years in Rank FEs?	--	Yes	--	Yes
N	786	786	701	701
Pseudo R-Squared	0.028	0.095	0.030	0.137

Panel B. Excludes career outcomes for 2008 and 2009

	Ordered Logit: Career Path [t]		*Logit: Promoted [t]*	
Explanatory Variables	[1]	[2]	[3]	[4]
Accuracy Index [t-1]	**2.017*** **	**1.982*** **	**1.646** **	**1.599** **
	(3.856)	(3.571)	(2.479)	(2.056)
Pessimist Index [t-1]	**0.562*** **	**0.549*** **	**0.618** **	**0.562** **
	(3.316)	(3.278)	(2.376)	(2.532)
Optimist Index [t-1]	**0.953**	**0.918**	**1.033**	**0.949**
	(0.326)	(0.525)	(0.179)	(0.255)
N	563	563	499	480
Pseudo R-Squared	0.032	0.090	0.024	0.122

Panel C. Excludes senior vice presidents (SVP) and managing directors

	Ordered Logit: Career Path [t]		*Logit: Promoted [t]*	
Explanatory Variables	[1]	[2]	[3]	[4]
Accuracy Index [t-1]	**1.893*** **	**1.958*** **	**1.588*** **	**1.609** **
	(4.097)	(4.079)	(2.654)	(2.407)
Pessimist Index [t-1]	**0.572*** **	**0.530*** **	**0.668** **	**0.596** **
	(3.473)	(3.561)	(2.169)	(2.411)
Optimist Index [t-1]	**0.944**	**0.836**	**0.972**	**0.827**
	(0.436)	(1.224)	(0.175)	(1.033)
N	531	531	531	531
Pseudo R-Squared	0.032	0.086	0.020	0.127

Appendix Table A-4

Accuracy Versus Bias Controlling for (Log) Level of Rated Assets

This table reports ordered logit and logit specifications analogous to those estimated in Table 7, except that we now also include the natural logarithm of the level of rated assets in year t-1. The absolute values of 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. Full Sample

	Ordered Logit: Career Path [t]		*Logit: Promoted [t]*	
Explanatory Variables	[1]	[2]	[3]	[4]
Accuracy Index [t-1]	**1.784*** **	**1.721*** **	**1.518** **	**1.409* **
	(4.066)	(3.519)	(2.570)	(1.797)
Pessimist Index [t-1]	**0.552*** **	**0.522*** **	**0.590*** **	**0.546*** **
	(4.161)	(4.136)	(2.977)	(2.998)
Log Rated Assets [t-1]	**1.088**	**1.220*** **	**1.155* **	**1.351*** **
	(1.477)	(2.761)	(1.928)	(2.809)
Calendar Year FEs?	--	Yes	--	Yes
Analyst Rank * Years in Rank FEs?	--	Yes	--	Yes
N	786	786	701	701
Pseudo R-Squared	0.030	0.099	0.028	0.146

Panel B. Excludes career outcomes for 2008 and 2009

	Ordered Logit: Career Path [t]		*Logit: Promoted [t]*	
Explanatory Variables	[1]	[2]	[3]	[4]
Accuracy Index [t-1]	**1.940*** **	**1.834*** **	**1.608** **	**1.453* **
	(3.843)	(3.285)	(2.526)	(1.694)
Pessimist Index [t-1]	**0.547*** **	**0.506*** **	**0.595*** **	**0.537*** **
	(3.442)	(3.640)	(2.586)	(2.733)
Log Rated Assets [t-1]	**1.107**	**1.286*** **	**1.179* **	**1.442*** **
	(1.454)	(3.047)	(1.772)	(2.784)
N	563	563	499	480
Pseudo R-Squared	0.035	0.102	0.032	0.145

Panel C. Excludes senior vice presidents (SVP) and managing directors (MD)

	Ordered Logit: Career Path [t]		*Logit: Promoted [t]*	
Explanatory Variables	[1]	[2]	[3]	[4]
Accuracy Index [t-1]	**1.785*** **	**1.773*** **	**1.490** **	**1.416* **
	(3.721)	(3.481)	(2.291)	(1.743)
Pessimist Index [t-1]	**0.551*** **	**0.512*** **	**0.652** **	**0.581** **
	(3.756)	(3.781)	(2.329)	(2.498)
Log Rated Assets [t-1]	**1.287*** **	**1.311*** **	**1.335*** **	**1.382*** **
	(3.474)	(3.044)	(3.404)	(2.887)
N	531	531	531	531
Pseudo R-Squared	0.047	0.098	0.042	0.143