Analysts' Legal Records, Opportunism, and Career Consequences

Abstract

This study empirically examines the implication of analysts' integrity on their research outputs and career success. Using analysts' off-the-job behavior, specifically their legal records, to proxy for their personal attributes of low self-control and a high disregard for ethical norms, we predict and find that analysts with legal records engage more in opportunistic behaviors, including "speaking in two tongues" and EPS forecast walk-down. Analysts with such records experience less favorable career outcomes, being less likely to be voted as star, employed by the buy side, or promoted by brokerage houses. Additional analyses demonstrate that our findings are unlikely to be attributed to analysts with legal records having low forecasting ability. In summary, our study provides large-sample empirical evidence underscoring the pivotal role of analysts' integrity as a decisive determinant of their career success.

Keywords: Analyst opportunism, career consequence, legal record, integrity
JEL Classification: G24, G41, J62

1. Introduction

The integrity of financial analysts is highlighted as one of the most important cornerstones for a well-functioning capital market.[1] Survey evidence shows that both analysts themselves and their buy-side clients consider integrity a crucial factor in determining their career success (Bradshaw, 2011; Brown et al., 2015).[2] However, empirically exploring the effect of analyst integrity is challenging, primarily because it is inherently difficult to measure. Closely related to our study, Pacelli (2019) employs a broker-level measure, specifically the number of violations observed in a brokerage house's securities activities, to capture the weak corporate culture that fails to promote ethical behavior. Distinct from Pacelli (2019), our study uses an individual analyst-level measure, specifically their off-the-job legal records, as a proxy for analysts' personal attributes of low self-control and a high disregard for social norms, and investigate its implication on analysts' opportunistic forecasting behaviors and career outcomes.

The use of one's legal record as an indication of low integrity is motivated by the criminology and psychology literature. Gottfredson and Hirschi (1990) posit that the essential element of criminality is the absence of self-control. People who lack self-control are impulsive, myopic, and tend to disregard laws or social norms. Prior studies document a positive

[1] In this study, we use "integrity" to broadly refer to the quality of having strong moral principles and adhering to them, rather than merely as a synonym for honesty.

[2] The professional bodies also emphasize ethical conduct. The Chartered Financial Analyst (CFA) Institute mandates its members, in its code of ethics and standards of professional conduct, to comprehend and comply with all applicable laws, rules, and regulations. Members are obliged to act independently and objectively to avoid any form of misrepresentation or misconduct. For more details of CFA code of ethics, please refer to: https://www.cfainstitute.org/en/ethics-standards/ethics/code-of-ethics-standards-of-conduct-guidance. In addition, *Institutional Investor*'s annual surveys suggest that investors value analysts' unbiased opinions on an industry or a firm. The *Institutional Investor*'s All-America Research Team award would quote clients' opinions on the value of each star analyst when publishing the rankings, and unbiasedness is frequently mentioned as one of the most important merits. For instance, the 1996 ranking mentioned "Peter Oakes of Merrill Lynch gets top marks for his unbiased appraisals of his stocks", and "Investors rely on Frank Governali's unbiased, non-deal-driven opinions, his wealth of contacts and his insights into trends."

correlation between agents' legal records and their on-the-job misconducts, including fraudulent financial reporting (Amir et al., 2014a; Davidson et al., 2015), opportunistic insider trading (Davidson et al., 2020), and harmful financial advice provided to investors (Law and Mills, 2019). Therefore, we argue that legal records can serve as a proxy for analysts' high propensity to violate the professional code of ethics and moral principles, i.e., a lack of integrity.

The legal records in our analyses encompass a wide range of offenses, including traffic violations (e.g., speeding, driving under the influence of alcohol (DUI)), drug-related charges, domestic violence, assault, reckless behavior, etc. We manually collect data on the population of analysts in I/B/E/S from 1994 to 2018 through SearchQuarry.com, a website that provides access to public legal records for all U.S. citizens.[3] Among the 11,298 analysts in our sample, 1,234 individuals have off-the-job legal records, representing approximately 11% of the sample. Similar to Davidson et al. (2015, 2020), most of these records are minor offenses (including misdemeanors and infractions), with only 56 analysts having felony records.

We use "off-the-job" legal records rather than "on-the-job" misconducts as the measure of analyst integrity for two reasons. First, off-the-job behavior is less likely to be affected by brokerage house characteristics, such as incentive plans and the control environment. Therefore, it provides us a clearer measure of analyst integrity. Second, most on-the-job offenses are mandated to disclose to the public through Financial Industry Regulatory Authority (FINRA), making it challenging to disentangle whether the findings are driven by the labor market's concerns regarding integrity or FINRA's disclosures per se. By contrast, the legal records used

[3] We manually search and process the legal record data by ourselves to minimize the risk of any inadvertent leakage of our research subjects' privacy. We use the legal record dataset solely for the purpose of this research and affirm that we will never disclose any personal information about the research subjects to any third party.

in our study are primarily off-the-job minor offenses that are not available in FINRA disclosure, making them a clean proxy for analyst integrity rather than a FINRA disclosure effect. We further validate the effectiveness of off-the-job legal records in capturing analyst integrity by demonstrating that analysts with legal records are 75% more likely to engage in on-the-job misconduct.

We hypothesize that analysts with legal records are more likely to engage in self-interested activities, which can be observed through their opportunistic forecasting behaviors. We examine two well-documented forms of analyst opportunism in the literature: "speaking in two tongues" and EPS forecast walk-down (e.g., Rechardson et al., 2004; Malmendier and Shanthikumar, 2014). "Speaking in two tongues" refers to the phenomenon wherein analysts issue optimistic stock recommendations to stimulate trading, while simultaneously issuing pessimistic EPS forecasts for the same firm to help managers beat the targets. EPS walk-down is the forecasting pattern wherein analysts issue optimistic EPS forecasts initially and then revise them down to below the actual EPS. By controlling for a variety of analyst incentives and year, firm, and state fixed effects, we find that analysts with legal records are more prone to engaging in these two opportunistic behaviors.

Next, we explore the implication of integrity on analyst career outcomes. Integrity may affect analysts' information gathering, analysis, and communication process (Bradshaw, 2011). Analysts' opportunistic behaviors compromise their independence and erode investors' trust in them, so in the long term, integrity should be positively related to analyst career success. However, the weak business culture in the financial sector may undermine integrity and tolerate unethical behaviors (Sapienza and Zingales, 2012; Cohn et al., 2014; Pacelli, 2019). Analysts may even gain a competitive advantage through opportunistic behaviors. Prior literature has extensively documented that analysts issue biased investment opinions to curry favor with their investment-bank business clients, cater to institutional investors for higher commission revenues, or help managers meet and beat for better access to private information (e.g., Rechardson et al., 2004; O'Brien et al.2005; Ke and Yu, 2006; Gu et al., 2013; Malmendier and Shanthikumar, 2014; Pacelli, 2019). Therefore, whether and how analyst integrity influences their career outcomes is an empirical question.

We examine four aspects of analysts' career outcomes, including analyst star status, high-status brokerage-house employment opportunities, buy-side job opportunities, and internal promotions, to comprehensively understand the effect of analysts' integrity on their career consequences. We find that analysts with legal records are 8.2% less likely to be voted as star analysts in the *Institutional Investor* (*II* afterwards) magazine's annual rakings, 1.58% less likely to be employed by high-status brokerage houses, 25% less likely to get a position in the buy side, and experience a delay of 0.267 years to get promoted from the associate to a senior position. Given that the evaluation of analysts is primarily conducted by their supervisors in brokerage houses, as well as by fund managers and buy-side analysts representing institutional investors, we interpret our findings as compelling evidence that in general, these key stakeholders value analysts' integrity and incorporate integrity into their assessment of analysts.

The findings related to analysts' career consequences are unlikely to be a mechanical outcome of background checks conducted by employers in their hiring decisions. Legal records in our sample mainly involve off-the-job minor offenses (i.e., speeding, illegal parking, and underage drinking and etc.), while employment background checks primarily focus on felonies and job-related misdemeanors.[4] We exclude analysts with felonies, and our main findings still hold.[5] Moreover, results regarding *II* All-star analyst rakings and internal promotions are unlikely to be driven by background checks, as institutional investors and research department heads rarely rely on legal records for the voting or promotion decisions.

Another concern is that legal records may capture the discrepancy in analysts' abilities, and analysts with legal records may be less capable and thus less successful. However, using forecast accuracy as a proxy for analyst ability, we find evidence contrary to this conjecture. Analysts with legal records issue more accurate EPS forecasts, and this result is robust across various measures of accuracy.[6]

A related question is why analysts with legal records have worse career outcomes despite demonstrating superior forecast accuracy. One plausible explanation is that investors value both the accuracy and credibility of analyst forecasts. While catering to managers leads to favorable access to management private information and enhances the forecast accuracy of

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[4] Fair chance laws implemented in many states regulate how employers should use criminal records in hiring decisions. If convictions turn up in a background check, employers are forbidden from using that fact alone as grounds for refusing to hire a candidate. Employers must consider the nature and gravity of the crime when denying any candidate based on their background check. For financial analysts, FINRA specifies events of disqualification related to crime, complying with Section 3(a) (39) of the Exchange Act: analysts with "certain misdemeanor and all felony criminal convictions for a period of ten years from the date of conviction" are not allowed to register in FINRA. According to FINRA Form U-4, "Certain misdemeanor" refers to a misdemeanor that involves "investments or an investment-related business or any fraud, false statements or omissions, wrongful taking of property, bribery, perjury, forgery, counterfeiting, extortion, or a conspiracy to commit any of these offenses." However, the legal records used in our sample are about off-the-job offenses.

[5] We further mitigate the concern by excluding pre-analyst-career legal records, which are relevant in background checks, and keeping legal records only after analysts start their careers. Our main results remain robust, suggesting that our findings are not a result of background checks.

[6] Our findings that analysts with legal records issue more accurate EPS forecasts seem inconsistent with the findings in Brown et al. (2010) that analysts who have disclosure issues (e.g., job-related misdemeanors, felonies, disputes with customers, regulatory punishments, etc.) on FINRA issue less accurate EPS forecasts. First, the measures used in the two studies are different, albeit closely related. FINRA only requires job-related misdemeanors and felonies to be disclosed. Instead, more than 90% of violations in our sample are off-the-job misdemeanors and infractions. Second, we have 1,237 analysts with legal records (about 11% of our sample). By contrast, Brown et al. (2010) collect disclosures for only 91 analysts. Thus, their measure may mainly reflect the extreme cases of violations or disputes. Third, their measure includes quite a few job-related cases, which are highly related to lower ability. For instance, 38% of their disclosed issues are customer complaints and bankruptcies, which could be due to either a lack of integrity, low ability, or both.

low-integrity analysts, it also diminishes investors' perception of the credibility of their forecasts. It is even possible that managers may overly guide analysts tied with them and manage reported earnings to meet their forecasts (Abarbanell and Lehavy, 2003; Gu and Xue, 2008). Although the guided or managed components would make the forecasts appear more accurate *ex post*, they may not mean better forecasts from the perspective of investors *ex ante*. To corroborate this explanation, we conduct three additional analyses. First, we explore the impact of favorable access to management on analyst forecast accuracy using the setting of Regulation FD (Reg FD hereafter). Reg FD prohibits selective disclosure of information to external parties, but prior studies indicate that private communication between management and analysts persists even post-Reg FD (e.g., Green et al., 2014; Brown et al., 2015). We find that analysts with legal records exhibit significantly higher accuracy only post Reg FD, consistent with the notion that high-integrity analysts tend to comply with this regulation more strictly while low-integrity analysts continue the private communication with managers. Second, following Gu and Xue (2008), we document that forecasts issued by analysts without legal records are more in line with investors' expectation *ex ante*, suggesting that investors tend to put more weight on forecasts issued by high-integrity analysts. Third, we examine how investors perceive the credibility of low-integrity analysts' downward forecast revisions. The market reaction to downward EPS forecast revisions by analysts with legal records is significantly lower than to those issued by analysts without such records, implying that the market recognizes low-integrity analysts' tendency to walk down forecasts and discounts its reaction accordingly.

In our main analyses, we treat all legal records equally without considering the timing of these records. Nevertheless, reverse causality is possible, wherein analysts might engage in criminal behavior due to career frustrations (such as speeding or DUI after failing to get promoted). To exclude such a possibility, we re-run the main tests using only pre-analyst-career legal records as the proxy for low integrity, and our results of opportunistic behavior and career outcomes remain consistent.

This study contributes to the literature in three folds. First, Bradshaw (2011) calls for future research to open up the "black box" of the analyst decision process and expand research scope into qualitative factors underlying the process, including analyst's integrity. A group of recent studies respond to this call (e.g., Brown et al., 2015; Bradley et al., 2017; Huang et al., 2018; Pacelli, 2019). We contribute to this literature by exploiting legal records as symptoms of low integrity and providing large-sample empirical evidence about the implications of analysts' integrity on their information outputs and career success.[7] Our research bridges the gap between practitioners' (i.e., buy-side institutions and sell-side analysts) claim and empirical evidence regarding the importance of integrity in determining analyst career success.

Second, our study complements the literature on analyst opportunism by introducing a new factor, the personal attributes of financial analysts. Our findings show that analysts' personality has important implication on the biasedness of their research outputs. The positive

[7] To the best of our awareness, two existing papers are related to sell-side analysts' integrity. Pacelli (2019) investigate the impact of brokers' corporate culture, specifically the broker-level violations observed in securities activities, on analyst outputs. Brown et al. (2010) examine the effect of NASD disclosure of analysts' background information, including their customer complaints, bankruptcies, regulatory actions, criminal records, and so on, but they concede their measure provides only "reasonable— albeit noisy—proxy for integrity and professionalism." These two studies primarily rely on on-the-job misconducts disclosed by FINRA to capture integrity, which involves several disadvantages compared to off-the-job legal records, as discussed earlier. In addition, while FINRA's background information does include certain criminal records, the frequency is low, and our coverage is relatively more comprehensive, improving the generalizability of our conclusions.

correlation between analysts' legal records and their engagement in "speaking in two tongues" and EPS forecast walk-down also confirms that these behaviors at least partially reflect analysts' opportunistic motives. In this way, we contribute to the debate on whether these biased investment opinions signify analyst strategic opportunism or genuine optimism (e.g., Bradshaw et al., 2016; Iselin et al., 2021).

Third, this paper contributes to the economic literature on the role of ethics in the labor market (e.g., Noe and Rebello, 1994; Carlin and Gervais, 2009; Algan and Cahuc, 2013; Guiso et al., 2015). Using individual-employee-level data, we demonstrate that integrity generates positive economic consequences on job performance and career outcomes, even within the financial industry, which is criticized to have weakened business culture and undermined integrity norms (Cohn et al., 2014).

The rest of the study is organized as follows. Section 2 reviews the literature and develops hypotheses. Sections 3 and 4 discuss the research design and sample, respectively. Section 5 validates legal records as a measure for integrity. Sections 6 and 7 report empirical results, and section 8 concludes.

2. Literature and hypotheses development

2.1 Legal records and analyst opportunism

Our hypothesis builds on two lines of literature. According to criminology and psychology literature, individuals with legal records lack self-control and are less likely to conform to social norms and laws (e.g., Gottfredson and Hirschi, 1990). This personal attribute often leads to engagement in various forms of "deviant behavior", driven by an inability to inhibit the urge for immediate gratification and short-term benefit (Akers, 1991; Pratt and Cullen, 2000). Prior studies find that people lack of self-control are myopic (e.g., Pedneault et al. 2017), overconfident (e.g., Garoupa, 2003; Palmer and Hollin, 2004; Walters, 2009) and more risk-taking (e.g., Grinblatt and Keloharju, 2009; Amir et al., 2014b). Accounting and finance studies document that agents with legal records are more likely to engage in fraudulent financial reporting (e.g., Davidson et al., 2015; Amir et al., 2014a), aggressive accounting policies (e.g., Amir et al., 2014a), profitable insider trading (e.g., Davidson et al., 2020), and financial advisory misconduct (e.g., Law and Mills, 2019). We conjecture that financial analysts' off-the-job legal records reflect aspects of analysts' personality that closely relate to a higher propensity for self-interested behavior and a disregard for professional codes of ethics and moral principles.

Analyst forecast biasedness reflect their self-interest. For instance, prior studies document that analysts issue biased investment opinions for favorable access to management private information or higher commission fees from their major clients, particularly large institutional investors (e.g., Ke and Yu, 2006; Gu et al., 2013; Malmendier and Shanthikumar, 2014; Pacelli, 2019), to maintain business relationships (e.g., Dechow et al., 2000; and O'Brien et al., 2005), or to seek career opportunities (Horton et al., 2017). Given these considerable benefits, we conjecture that analysts with legal records are more prone to engaging in such opportunistic forecasting behaviors while overlooking the potential loss in violating codes of ethics, such as the damage to their reputation and the erosion of trust among their clients. Additionally, the difficulty regulators face in detecting and prosecuting such subtle misconducts also heightens the incentive for analysts to engage in such opportunistic behaviors (Pacelli, 2019). In summary, we have the following hypothesis:

Hypothesis 1*: Analysts with legal records exhibit more opportunistic forecasting behaviors.*

2.2 Analysts' legal records and career success

The economic literature posits that ethics can serve as a mechanism to reduce agency costs between the principal and the agent (Noe and Rebello, 1994; Carlin and Gervais, 2009). Ethics foster trust between people and enhance cooperation among agents (Butler and Cantrell, 1984; Hosmer, 1995; Mayer et al., 1995; Algan and Cahuc, 2013). Regarding equity research, the buy side, the primary clients of sell-side research, relies on independent and unbiased opinions of the sell side to make investment decisions (Brown et al., 2010). Moreover, they are able to assess an analyst's integrity through various channels, including research reports, private phone calls, face-to-face meetings, road shows, broker-hosted conferences, etc. Analysts with legal records tend to have low self-control and have a higher propensity of ignoring the ethical code in their profession, which undermines their independence and weakens investors' trust in them. If analysts' integrity is viewed as a contributing factor to their value, the buy side will discount the credibility of these low-integrity analysts, resulting in less favorable career outcomes for them. Supervisors of analysts, including research department heads, will also regard analysts with high integrity as essential assets to their business, particularly when evaluating analysts for compensation and promotion decisions. Brown et al. (2015) conduct a direct survey on factors that determine compensation and find that over 63.99% of analysts rate professional integrity as one of the important determinants to their compensation.

However, there are reasons to doubt whether integrity is genuinely rewarded in the financial industry. The various analyst opportunistic behaviors extensively documented in academic research and widely reported by the media raise concerns about the effectiveness of the disciplinary role of analyst professional and ethical standards. In an industry where the prevailing business culture has been known to "weaken and undermine the honesty norm" (Cohn et al., 2014), analysts' integrity may not necessarily be rewarded. Analysts with low integrity may even experience more favorable career outcomes, if they can gain advantages through opportunistic activities. For instance, Hong and Kubik (2003) find promotions at investment banks depend more on optimism and analysts who issue relatively optimistic forecasts are more likely to experience favorable job separations. Pacelli (2019) documents that institutional investors pay more commission fees to brokers with weak corporate cultures that cater to their preferences. To summarize, we state our second hypothesis as follows:

Hypothesis 2: *There is no relation between analysts' legal records and career success.*

3. Regression models

3.1 Regression model to test H1

For H1, we investigate two well-documented measures of sell-side analysts' opportunistic forecasting behaviors: "speaking in two tongues" and EPS forecast walk-down (Richardson et al. 2004; Malmendier and Shanthikumar, 2014; Iselin et al., 2021). To test analyst "speaking in two tongues," we follow Malmendier and Shanthikumar (2014) and estimate the following regression model:

$$Two - tongues\ metric_{i,j,t}$$

$$= \beta_0 + \beta_1 Record_i + \sum \lambda Controls + \sum Firm + \sum State + \sum Year + \varepsilon, \quad (1)$$

where the dependent variable $Two - tongues\ metric_{i,j,t}$ is defined as the difference between an analyst i's recommendation optimism and the scaled EPS forecast optimism for a given firm *j* in year *t*. $Record_i$ represents two specific proxies for analyst integrity in the main analyses: *Legal record*, an indicator variable equal to one if an analyst has any legal record(s) and 0 otherwise, and *Legal record (minor)*, an indicator variable equal to one if an analyst has any record(s) of misdemeanors or infractions and 0 otherwise.

In equation (1), the coefficient of interest is β_1, which captures the relation between legal records and the extent of "speaking in two tongues". A positive β_1 would indicate analysts with legal records engage more in "speaking in two tongues" than analysts without such records, supporting H1. Firm fixed effects and year fixed effects are included. We also include state fixed effects to account for the variation in enforcement practices regarding legal records across various states, such as differences in the prosecution of nonviolent misdemeanors as documented by Agan et al. (2023).

To test whether analysts with legal records are more likely to engage in EPS walk-down, we estimate the following model, following Malmendier and Shanthikumar (2014):

$$\begin{aligned} Last\ Forecast\ Error_{i,j,t} \\ &= \beta_0 + \beta_1 First\ Forecast\ Error_{i,j,t} + \beta_2 Record_i \\ &+ \beta_3 First\ Forecast\ Error_{i,j,t} \times Record_{\ i} + \sum \lambda Record_i \times Controls \\ &+ \sum \gamma Controls + \sum Firm + \sum Year + \sum State + \varepsilon \qquad (2) \end{aligned}$$

$Last\ Forecast\ Error_{i,j,t}$ and $First\ Forecast\ Error_{i,j,t}$, represent the signed errors in the analyst's last annual EPS and first annual EPS forecast, respectively. Both measures are deflated by stock price at the beginning of the year. The coefficient β_3 on the interaction term $First\ Forecast\ Error_{i,j,t} \times Record_i$ captures the difference in the walk-down pattern between analysts with legal records and those without. A negative β_3 would suggest a more pronounced walk-down pattern for analysts with legal records and support H1.

Following Malmendier and Shanthikumar (2014), we include *Past star status*, *Affiliation*, *Institutional ownership*, and *Bank reputation* to control for analysts' strategic incentives or constraints on such incentives. Detailed variable definitions are provided in Appendix B. Interaction terms of $Record_i$ with control variables are included in the specifications. Firm, year, and state fixed effects are included. Heteroskedasticity-consistent standard errors are clustered by firm.

3.2 Regression model to test H2

For H2, we estimate the following regression model to examine the relation between legal records and analyst career outcomes:

$$Career_{i,t} = \beta_0 + \beta_1 Record_i + \sum \lambda Controls + \sum Industry + \sum Year + \varepsilon\,, \qquad (3)$$

where the dependent variable $Career_{i,t}$ represents measures of four aspects of analysts' career outcomes. The first measure, *All-star status*, is an indicator variable equal to 1 if an analyst is voted as a star analyst (i.e., named as *Institutional Investor*'s All-America research team) in current year, and 0 otherwise. The second measure, *Top-10*, is an indicator variable equal to 1 if an analyst is employed by one of the top-decile brokerage houses (ranked by broker size) in the year, and 0 otherwise. The third measure, *Buy-Side*, is an indicator variable set to 1 if an analyst works in a buy-side firm during the year, and 0 otherwise. The fourth measure, *Promotion Duration*, is defined as the duration in years between the commencement of an analyst's research career as an associate and the point at which she first appears in the I/B/E/S database (the time when she becomes the senior analyst and her name ranks first in the analyst report). We employ a linear probability model for the first three specifications with indicators as dependent variables and an OLS regression for the last measure.[8] The sample for testing H2 is constructed at the analyst-firm-year level.

The coefficient of interest is β_1, which captures the relation between legal records and analyst career outcomes. For the first three measures (*All-star status*, *Top-10*, and *Buy-Side*), a negative β_1 would indicate a negative relation between legal records and analyst career advancement; for the last measure (*Promotion Duration*), a positive β_1 would indicate that analysts with legal records take a longer timeframe to be promoted from an associate to a senior analyst. We follow related studies (e.g., Clement and Tse, 2005; Bradley et al. 2017) for the inclusion of control variables and fixed effects in the four specifications, respectively.[9] Detailed descriptions of the control variables used in each specification are provided in section 6 as we elaborate on the results. Appendix B presents detailed variable definitions.

4. Sample construction and descriptive statistics

4.1 Analyst legal record and other data sources

We obtain the universe of 18,809 unique financial analysts over the period 1994-2018 from the I/B/E/S recommendation file.[10] Next, we exclude 1,498 analysts that are recorded as a team or "research department" by I/B/E/S, as well as 1,067 analysts who provided fewer than five recommendations throughout the entire period. We collect analysts' personal information,

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[8] We follow the suggestion of Greene (2004), who highlights that the "incidental parameter problem" could destabilize estimates when employing binary models with high-dimensional fixed effects. Our results remain robust if we alternatively use the nonlinear logistic model.

[9] Specifically, we include *Industry* and *Year Fixed Effects* when testing *All-star status* and *Top-10*; we additionally include *First Broker Fixed Effects* and *Cohort Fixed Effects*, when examining *Buy-side*; and we additionally control for *Broker Fixed Effects* when analyzing *Promotion Duration*.

[10] We begin our analysis from 1994 due to the enhanced coverage provided by I/B/E/S from that year onward.

including their full name (first name, middle name, and surname name), age, gender, and residence from various sources including Factiva, Bloomberg, FINRA, Capital IQ, and LinkedIn.

To determine the legal records for each financial analyst, we rely on the information provided by SearchQuarry.com, a platform that synthesizes employee background information from various sources including courts, residence registration agencies, and social media. The platform claims that legal records on SearchQuarry.com are obtained from public court files in the U.S. We drop the 4,640 foreign analysts as SearchQuarry.com exclusively offers legal records for domestic offenses within the U.S. jurisdiction. We then cross-check each analyst's information, including full name, age, gender, residence, and profession, with records in SearchQuarry.com to carefully determine any legal records associated with them. We also exclude 306 analysts for whom we were unable to identify their background information using SearchQuarry.com.[11] Detailed procedures are reported in Appendix A.

Besides, we manually collect data on analysts' All-star status from *Institutional Investor* magazine. Information on analyst affiliations is obtained from Thomson One. The list of buy-side firms is sourced from Morningstar. Stock return data are obtained from CRSP, and firm fundamentals are from Compustat.

4.2 Sample and Descriptive statistics

[11] These analysts' names are exceedingly common in the US, making it challenging to pinpoint their identities based on the information available to us. These names often consist of widely-used given names and surnames, while SearchQuarry.com contains extensive criminal records associated with these names. We lack supplementary information to confirm whether these records pertain to the respective analysts or other individuals who share identical names.

Table 1 Panel A presents our sample selection process. We obtain background information and criminal records for 11,298 analysts, accounting for 60.07% of the total 18,809 analysts. This subset of identified analysts contributes to 88.01% of all 811,303 recommendations made during the sample period, mitigating concerns about sampling bias. Within this subgroup, 1,234 analysts have legal records. Table 1 Panel B presents the distribution of recommendations and EPS forecasts by year for the identified analysts in our sample and the entire dataset from the I/B/E/S U.S. file, respectively. Recommendations issued by identified analysts consistently account for 82% to 91% of the full I/B/E/S dataset across our sample period, and the pattern is similar for annual EPS forecasts.

Table 1 Panel C reports the distribution of legal records by violation types. The majority of these records, about 97.31%, are about misdemeanors and infractions, with felonies accounting for only 2.69%. The low frequency of felony records is not surprising, since U.S. firms generally conduct background checks during the hiring process and the Exchange Act clearly disqualifies analysts with felony records within the most recent 10 years. Among misdemeanors and infractions, traffic-related offenses are the most common, comprising 74.55% of all records.[12]

The sample sizes for different analyses vary due to differences in the unit of observations and data requirements for variables. Therefore, we present descriptive statistics separately for each analysis. All continuous variables are winsorized at the 1% and 99% levels to mitigate the influence of outliers.

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[12] The category "Other traffic violations" in Table 1 Panel C includes driving a car not in good condition, driving without insurance, expired license, illegal parking, and so on.

[Insert Table 1 Here]

5. Validity of legal records as a measure for integrity

To validate whether legal records can indicate analysts' low integrity and a high disregard for professional codes, we empirically examine the association between analysts' off-the-job legal records and their propensity to engage in on-the-job misconducts. Following Law and Mills (2019) and Egan et al. (2019), we use individual analysts' disciplinary disclosure events in FINRA to capture their on-the-job misconducts.[13] More specifically, the on-the-job misconducts include Customer Disputes, Employment Separation after Allegations, Civil-Final, Judgment/Lien, and Regulatory-Final.

Table 2 Panel A reports the descriptive statistics. Merging the legal records of SearchQuarry.com with BrokerCheck reports for financial advisors obtained from FINRA, we construct a sample of 4,135 analysts. Of this sample, 4% of analysts have on-the-job misconducts, and 17.2% have legal records. We follow Law and Mills (2019) and estimate the following linear probability model at individual analyst level:[14]

$$Misconduct_i = \beta_0 + \beta_1 Record_i + \beta_2\, Controls + \sum Cohort + \sum State + \sum First\ Broker + \varepsilon_i \quad (4)$$

[13] Using FINRA disclosure to identify analysts' on-the-job misconducts, Law and Mills (2019) finds that financial advisors with pre-advisor legal records do more harm to investors than those without. Egan et al. (2019) also report that approximately one-third of advisors with a history of misconducts are repeat offenders, suggesting a consistent pattern of unethical behavior. The findings of Law and Mills (2019) cannot be directly used as a validation for our measure for two main reasons. First, the populations in the two studies are distinct, with our study focusing exclusively on financial analysts, a subset of financial advisors within FINRA. Second, the nature of legal records in their study is based on self-reported data provided by brokers and advisors themselves, so this data may predominantly comprise felonies and job-related misdemeanors, potentially skewing the distribution of legal records in their dataset.

[14] Results are robust if we alternatively use the Logistic model.

Misconduct is an indicator variable equal to one when an analyst has any FINRA disclosure of on-the-job misconduct, and zero otherwise. $Record_i$ represents various forms of legal records. For control variables, we include *Years in profession*, *Tenure per firm*, and *Broker size per firm* to account for the effect of working experience, and gender (*Gender)*, MBA degree (*MBA)*, and postgraduate degree (*Postgraduate)* to control for the impact of analyst background. We also control for *Cohort Fixed Effects*, incorporating the year an analyst initially appears in I/B/E/S, to absorb any time-series variation within cohorts (i.e., trends in education or shifts in the criminal justice system), and *First Broker Fixed Effects* to absorb the impact of their first sell-side employer. *State Fixed Effects* are included to account for the variation in financial misconducts and crime rates across different geographical regions (Parsons et al., 2018; Egan et al., 2019).

Results are presented in Table 2 Panel B. In column (1), the variable of interest is whether an analyst has at least one legal record. It shows that the probability of committing on-the-job misconduct is 3% higher for analysts with legal records than those without (0.030, t =3.459). This incremental effect is economically meaningful, especially considering the 4% unconditional probability of on-the-job misconduct for the sample. We further examine whether the finding holds when we vary the type of legal records in columns (2) to (5). We find the results hold for analysts with a single criminal record (0.031, t =2.841, column (2)) and for those with multiple criminal records (0.028, t =2.336, column (2)), suggesting that single legal record should not be attributed to mere unfortunate circumstances but instead effectively captures low integrity.[15] In column (3), pre-analyst-career legal records (*Legal*

[15] In our sample, among analysts with at least one legal record, approximately 45% have multiple records.

record(pre-analyst)) exhibit a strong correlation with misconduct (0.062, t = 5.430), consistent with the criminology literature's finding that self-control is learned in early life and tends to persist. We also separately test minor offenses and felonies in column (4) and find that both categories of legal records significantly predict misconduct, suggesting that even minor offenses can reflect variations in integrity. Column (5) substantiates the validity of traffic-related records, which account for 74.55% of all offenses in our sample, and finds that traffic-related offenses can also effectively capture variations in analyst integrity (0.023, $t=2.140$).[16] Collectively, these findings provide compelling evidence for the validity of using legal records as a measure of low integrity and a disregard for laws.[17]

[Insert Table 2 here]

6. Results

6.1 Analyst integrity and forecasting opportunism

Table 3 reports the results for the relation between analysts' legal records and the opportunistic behavior of "speaking in two tongues." To conduct this analysis, we match recommendations with annual EPS forecasts made by the same analyst for the same firm on the same day, resulting in 163,057 recommendation-forecast pairs. Panel A presents the descriptive statistics for this "two tongues" sample. The positive mean (0.363) and median (0.106) of *Two-tongues metric* indicate that, on average, analysts are more optimistic in

[16] In the untabulated results, we find that analysts with a traffic-related offense record are also more likely to commit a non-traffic crime, suggesting that traffic-related offenses alone can capture analysts' low self-control. It is also consistent with the established concept of criminal versatility in criminology literature (e.g., Chapple and Hope, 2003).

[17] It might be a concern that our main findings, as subsequently reported in section 6, are driven by the subset of analysts who have both off-the-job offense records and on-the-job misconduct. To address this concern, we exclude these analysts and our findings remain robust.

recommendations than in EPS forecasts. About 13.3% of analysts have legal records, most of which are minor offenses. Panel B columns (1) and (2) report the results for two measures of analyst integrity, *Legal record* and *Legal record(minor)*, separately. Coefficients on *Legal record* and *Legal record(minor)* are both positive and significant (0.057, t=3.394, column (1); 0.064, t=3.693, column (2)), indicating that analysts with legal records (or only minor offenses) are more likely to engage in "speaking in two tongues".[18] Column (3) further include broker fixed effects to control for the broker's time-invariant influence, such as corporate culture as documented by Pacelli (2019), and the coefficient on *Legal Record* is still positive and significant (0.046, t=2.083), suggesting that individual-level analyst integrity plays a distinct role in shaping their forecasting behavior, beyond the influence of the brokerage culture.

[Insert Table 3 here]

Table 4 reports the results for analyst EPS forecast walk-down. To construct the sample, we require the analyst to issue at least two annual EPS forecasts for a specific firm during the fiscal year. This restriction arrives at 530,701 analyst-firm-year observations. Panel A presents the descriptive statistics. The mean of *First Forecast Error* (0.216) is greater than the mean of *Last Forecast Error* (-0.006), suggesting that, on average, analysts are optimistic in their first annual EPS forecasts and are slightly pessimistic in their last annual EPS forecasts. In this sample, 13.4% of analysts have legal records. Panel B columns (1) and (2) report the regression results for equation (2). Coefficients on both interaction terms, *First Forecast Error * Legal record (Legal record (minor))*, are significantly negative (-0.018, t=-3.620, column (1); -0.017;

[18] In untabulated results, we also examine the optimism in recommendations and EPS forecast separately. We find that compared to analysts without a legal record, analysts with a legal record issue more optimistic recommendations, and this pattern is not observed in EPS forecasts. These results further substantiate the conclusion on two-tongue metrics.

t=-3.205, column (2)), consistent with that analysts with legal records engage more in EPS forecast walk-down to help managers "meet or beat" the forecasts. In column (3), we include broker fixed effects to control for broker-level time-invariant effect, and results are similar.

[Insert Table 4 here]

Collectively, these results are consistent with our first hypothesis that analysts with legal records are more opportunistic in their forecasting behaviors. These findings can also be interpreted as a validation of legal records as a proxy for analysts' low integrity and high propensity to disregard ethical norms.

6.2 Analyst integrity and career outcomes

6.2.1 Analyst integrity and all-star status (employment in the high-status brokerages)

Being nominated as a star on *Institutional Investor* magazine's All-America Research Team is a significant career achievement for sell-side analysts (e.g., Bradshaw, 2011; Brown et al., 2015). In addition, high-status brokerage houses offer better compensation and are more attractive to analysts. These firms typically hire high-integrity analysts to align with their stringent compliance standards and reputation. We thus examine whether analysts with legal records are less likely to be voted as star analyst and less likely to be employed by high-status brokerage houses.

Table 5 reports the results. The sample consists of 56,607 analyst-firm-year observations over 1994–2018. Following Bradley et al. (2017), we lag all control variables by one year to mitigate the concern of reverse causality and use heteroskedasticity-consistent standard errors clustered by analyst to adjust for heteroskedasticity and within-analyst correlation.

Panel A shows that the unconditional probability of being voted as star is approximately 8.5%, and the unconditional probability of being employed by a high-status brokerage house is 50.7%. Panel B reports the regression results. After controlling for an extensive set of analyst characteristics (i.e., *Lag general experience*, *Past top10 broker*, *Lag breadth*, *Lag industries*, *Lag average PMAFE*, *Lag average firm size*, and *Past star status*), the coefficients on *Legal record* or *Legal record(minor)* are negative and significant in all columns (-0.021, *t*=-3.402, column (1); -0.007, *t*=-2.720, column (2); -0.007; *t*=-2.510, column (3)), indicating that analysts with legal records (or minor offenses) are less likely to be voted as star analysts. Relative to the unconditional mean of *All-star status*, analysts with a minor offense are about 8.2% (=0.007/0.085, in column (3)) less likely to win star status than those without. Results in Panel B provides empirical confirmation of prior survey studies' findings (e.g., Bradshaw, 2011; Brown et al., 2015) that institutional investors, who are the primary voters for *II* rankings, view integrity as a critical factor to analysts' career success. Moreover, the finding that low-integrity analysts are treated less favorably in the *II* rankings alleviates the concern about such rankings being contaminated by the sell-side's opportunistic activities.

Panel C reports the regression results of employment in high-status brokerages. Columns (1) and (2) show that the coefficients on *Legal record* and *Legal record(minor)* are both negative and significant (-0.008, *t*=-2.446, column (1); -0.008; *t*=-2.453, column (2)), indicating analysts with legal records or minor offenses are less likely to be employed by high-status brokerage houses. Relative to the unconditional probability 50.7% of *Top-10* employment, analysts with a minor offense are about 1.58% (=0.008/0.507 in column (2)) less likely to be employed by high-status brokerages than those without. These findings support the notion that prestigious brokerages care more about analysts' integrity to maintain a good reputation and ensure client satisfaction.[19]

[Insert Table 5 here]

6.2.2 Analyst integrity and job opportunity in the buy side

Both anecdotal and survey evidence implies that moving to the buy side is one of the most desired career paths for sell-side analysts.[20] Cen et al. (2017) document that sell-side analysts of superior forecasting ability are likely to be promoted to the buy side (i.e., hedge fund, private equity, and venture capital firm). We examine whether analysts with legal records experience less favorable career consequences on the buy-side job market. We construct the sample by manually gathering analysts' employment histories from LinkedIn profiles. Through this process, we successfully identified employment records for 2,939 analysts appearing in I/B/E/S between 1994 and 2018. Among those analysts, 1,082 jumped to the buy side as research analysts or fund managers after leaving a broker. We identify the buy-side institutions using the list of Morningstar mutual funds and hedge funds, and we supplement this list with large insurance companies. Using the employment-history data, we construct a sample of 53,121 analyst-employer-year observations over 1994–2018.[21] The descriptive statistics are presented

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[19] In untabulated tests, we also examine whether analysts with legal records are less likely to move from low-status to high-status brokers, following Hong and Kubik (2003). We define the dependent variable, *Move Up (Move Down)*, as a dichotomous variable equal to 1 if the analyst moves from a low-status (high-status) broker to a high-status (low-status) broker in the year. We obtain consistent findings that analysts with legal records are less likely to move from low-status to high-status brokerages.

[20] See the survey conducted by the recruitment firm Odyssey Search Partners: "Investment banks' analysts still setting sights on buy-side careers" (https://www.efinancialcareers.com/news/2016/08/why-investment-banks-retention-efforts-arent-working-despite-the-buy-sides-issues).

[21] In untabulated tests, we also investigate the relation between integrity and the buy-side job opportunity based on the subset of analysts who exit the I/B/E/S dataset. Results are similar that analysts with legal records are less likely to jump to buy-side after leaving I/B/E/S.

in Table 6 Panel A. In this sample, 11.6% of analyst-employer-year observations represent the buy-side employment.

Table 6 Panel B reports the regression results. We control for analysts' past working experience and capability (i.e., *Past top10 accuracy*, *Past top10 broker*, *Past star status*, *General experience*) and educational background (i.e., *MBA*, *Postgraduate*, *Specialty major*). *Industry Fixed Effects* are included to control for the inherent difference in entry barrier to the buy-side across industries. We also include *First Broker Fixed Effects* and *Cohort Fixed Effects*. Standard errors are clustered by employer and year to adjust for heteroskedasticity and within-employer and time-series correlation. [22] The coefficients on *Legal record* and *Legal record(minor)* are negative and significant in both columns (-0.032, *t*=-3.150, column (1); -0.029, *t*=-2.755, column (2)), suggesting that analysts with legal records (or minor offense records) are less likely to be employed by the buy side. As to the economic magnitude, analysts with legal records are about 27.6% (0.032/0.116, and 0.116 is the unconditional probability of working on the buy side in our sample) less likely to be employed by the buy side than those without. Overall, these findings on buy-side employment further reinforce our conclusion that the buy-side values sell-side analyst integrity.

[Insert Table 6 here]

6.2.3 Analyst integrity and internal promotion

We test whether analysts with legal records experience a delay in the brokerage house's internal promotion. An analyst typically starts her career as an associate (or junior analyst) and get promoted to the position of senior analyst after working for about two to three years

[22] We also cluster standard errors by analyst as in Table 5, and the results hold.

(Bradshaw et al., 2017). We treat an analyst's initial appearance in I/B/E/S as the time when she gets recognized and promoted to the role of senior analyst. Data on when an analyst starts her equity research career is manually searched through LinkedIn. We manage to collect this data for 3,181 analysts. Descriptive statistics are presented in Table 7 Panel A. On average, in our sample, it takes an analyst 3.713 years to be promoted from the role of an associate (or junior) analyst to the position of a senior analyst.

Table 7 Panel B reports the estimation results. We control for analyst characteristics when they initially appear in the I/B/E/S (i.e., *PMAFE*, *Breadth*, *Broker size*, and *Prior experience*) and educational background (i.e., *MBA*, *Postgraduate*, *Specialty major*). *PMAFE* for the year when an analyst first appears in I/B/E/S is used to proxy for her research ability. *Broker size* is included because analysts working in large brokers face greater competition and need longer time to get promoted. An analyst's prior working experience (*Prior experience*) denotes the length of working experience before she works as an associate analyst (Bradley et al., 2017). A longer prior working experience may shorten the timeframe required for promotion. We also include *Broker*, *Industry*, and *Year fixed effects* and cluster by broker to adjust for heteroskedasticity and within-broker correlation. The coefficients on *Legal record* and *Legal record(minor)* are positive and significant (0.214, t=2.145, column (1); 0.267, t=0.267, column (2)), suggesting that analysts with legal records experience a delay in the internal promotion. Regarding the economic magnitude, analysts with minor offense records take 0.267 years longer to be promoted than analysts without, which translates to 7.2% (=0.267/3.713) of the unconditional average of 3.713 years taken for promotion. Overall, these results confirm that low integrity prolongs the duration of analyst promotions.

[Insert Table 7 here]

Collectively, our findings indicate that analysts with legal records are less likely to be voted as star analysts, employed by high-status brokerage houses, or recruited by the buy side. They also experience delays in internal promotions. We interpret these results as evidence supporting that analyst integrity is valued within the investment community. The underlying rationale is that analysts' supervisors and fund managers from the buy-side engage in regular and in-depth interactions with analysts, allowing them to discern and evaluate analysts' personal attributes regarding integrity. Their assessment of analysts' integrity is not necessarily reliant on background checks. Legal records only serve as a reasonably effective proxy for integrity that enables academic researchers outside the investment community to observe the positive relation between analyst integrity and career success.

7. Supplementary analyses

7.1 The alternative explanation of analyst ability

It may be a concern that legal records merely capture analysts' inferior ability rather than low integrity. To address this concern, we examine the relation between legal records and forecast accuracy, which is widely used to measure analyst ability in the analyst literature (e.g., Hong and Kubik, 2003; Wu and Zang, 2009; Kumar, 2010).

The analysis is based on annual EPS forecasts in I/B/E/S from 1994 to 2018. Consistent with prior studies, we include forecasts issued no earlier than one year before and no later than the fiscal year end and then retain the last forecast that an analyst issues for a firm in a particular year (O'Brien, 1990; Clement and Tse, 2005). We measure analyst forecast accuracy using the *PMAFE*, along with the accuracy measures proposed by Hong and Kubik (2003) and Clement and Tse (2005) for robustness. Following prior studies (Clement and Tse, 2005; Kumar, 2010; Bradley et al. 2017), we have the following regression model of equation (5):

$$
\begin{aligned}
PMAFE_{i,j,t} = {} & \beta_0 + \beta_1 Record_{\ i} + \beta_2 Lag\ PMAFE_{i,j,t} + \beta_3 Lag\ frequency_{i,j,t} \\
& + \beta_4 Forecast\ horizon_{i,j,t} + \beta_5 Days\ elapsed_{i,j,t} + \beta_6 Past\ star\ status_{i,t} \\
& + \beta_7 Affiliation_{i,t} + \beta_8 Gender_i + \beta_9 Broker\ size_{i,t} \\
& + \beta_{10} General\ experience_{i,t} + \beta_{11} Firm\ experience_{i,j,t} + \beta_{12} Breadth_{i,t} \\
& + \beta_{13} Num\ industries_{i,t} + \beta_{14} Size_{j,t} + \beta_{15} MTB_{j,t} \\
& + \beta_{16} Past\ 12 - month\ return_{j,t} + \beta_{17} Institutional\ ownership_{j,t} \\
& + \sum Firm + \sum Year\ + \sum State\ + \varepsilon \qquad (5)
\end{aligned}
$$

Table 8 Panel B reports the regression results of equation (5). The coefficient on *Legal record* is negative and significant (-0.011, *t=-2.669* in column (1) and -0.013, *t=-3.745* in column (2)), suggesting that, on average, EPS forecasts issued by analysts with legal records are more accurate than issued by analysts without. We obtain consistent results using alternative measures of integrity (column (3)) and alternative measures of forecast accuracy (columns (4) to (7)). In untabulated tests, we also conduct the analysis on quarterly EPS forecasts and obtain similar findings. Taken altogether, analysts with legal records have better forecasting performance, alleviating the concern that legal records capture analysts' inferior forecasting ability.

A natural question arises: why do analysts with legal records have worse career outcomes despite their better forecasting performance? One plausible explanation is that their information advantage comes from opportunistic activities such as catering to managers, but such opportunistic activities erode their independence and credibility to investors in the long term.

Managers may even overly guide analysts tied with them and manage reported earnings to meet their forecasts (Abarbanell and Lehavy, 2003; Gu and Xue, 2008). Although the guided or managed components would make the forecasts appear more accurate *ex post*, they may not mean better forecasts from the perspective of investors *ex ante*. To corroborate this explanation, we conduct three additional analyses. First, following Bradley et al. (2017), we examine the impact of Reg FD on analyst accuracy to explore whether the better forecasting performance of analysts with legal records comes from their favorable access to management private information. Reg FD prohibits management from selectively disclosing private information to outsiders. However, prior studies suggest that private communication between management and analysts remains even post-Reg FD (e.g., Brown et al., 2015; Green et al., 2014). We conjecture that post-Reg FD, high-integrity analysts are more likely to comply with the requirement strictly and avoid private communication with managers; in contrast, low-integrity analysts may still seek ways to circumvent the regulation and gain advantages by catering to managers. In columns (8) and (9) of Table 8 Panel B, we find that before Reg FD, analysts with legal records do not demonstrate superior forecasting performance compared to those without (-0.001, t=-0.148, column (8)), but post Reg FD, they exhibit significantly higher forecast accuracy (-0.014, t=-3.656, column (9)). These results show that following Reg FD, analysts with high integrity are disadvantaged in obtaining information from management compared to analysts with low integrity.

[Insert Table 8 here]

Second, following Gu and Xue (2008), we examine the market's *ex-ante* perception of forecast quality between analysts with and without legal records, i.e., the extent to which the market relies on their forecasts in forming expectations. Specifically, we estimate the following equation (6):

$$EA\_CAR\ [-1,+1]_{j,t} = \beta_0 + \beta_1 Forecast\ Error_{j,t} + \sum\lambda Controls + \sum Firm + \sum Year + \varepsilon. \quad (6)$$

The dependent variable is the cumulative abnormal return (CAR) during the three-day window centered on the earnings announcement date. The coefficient β_1 is the earnings response coefficient (ERC). Forecast error is defined as the actual earnings minus the analyst forecast consensus. We apply this model separately for two sets of forecast errors, *Forecast Error_LR*, which is calculated using only forecasts issued by analysts with legal records, and *Forecast Error_NLR*, which is calculated using forecasts issued by analysts without legal records, and then we compare the two ERCs. A higher ERC means that the market puts more weight on the consensus and relies more on it to form its expectations. To facilitate comparison between the two ERCs, we use the same sample for both regressions and only firm-year observations followed by both analysts with legal records and analysts without are retained. We control for fixed fiscal year and firm effects and standard errors are clustered by firm and year.

Table 9 presents the results. The coefficients of *Forecast Error_LR* and *Forecast Error_NLR* are both positive and significant (0.336, *t*=6.054 in column (1) and 0.556, *t*=9.928 in column (2)), and more importantly, the coefficient of *Forecast Error_NLR* is significantly larger than that of *Forecast Error_LR* (Chi2(1) = 20.91), suggesting a stronger association between the cumulative abnormal return and the forecast error based on the consensus of forecasts issued by analysts without legal records. These results are consistent with the notion that, *ex ante*, investors rely more on forecasts issued by high-integrity analysts to form expectations.

[Insert Table 9 here]

Third, given that low-integrity analysts are more engaged in EPS forecast walk-down to cater to managers, we investigate whether the market recognizes this pattern and discounts the credibility of these analysts' downward forecast revisions. Specifically, we examine whether the short-window market reaction to downward EPS forecasts issued by analysts with legal records is weaker. The dependent variable is the cumulative abnormal return (CAR) during the three-day short window centered on the forecast revision date. We include the same set of control variables as in Table 8 and estimate the following equation (7):

$$FR\_CAR\ [-1,+1]_{i,j,t} = \beta_0 + \beta_1 Record_i + \beta_2 Forecast\ revision_{i,j,t} + \beta_3 Record_i * Forecast\ revision_{i,j,t} + \sum \lambda Controls + \sum Firm + \sum Year + \sum State + \varepsilon \qquad (7)$$

The variable of interest is the interaction term $Record_i * Forecast\ revision_{i,j,t}$. Column (1) of Table 10 shows that, on average, the market does not react differentially between analysts with and without legal records. We further split the sample into upward revisions and downward revisions in columns (2) and (3). The coefficient on $Record_i * Forecast\ revision_{i,j,t}$ is negative and significant (-0.080, *t*=-2.708, column (3)) for downward revisions but positive and insignificant for upward revisions (0.041, *t*=0.882, column (2)), suggesting that the market reacts less to downward EPS revisions issued by analysts with legal records than to those issued by analysts without such records. Combined with results in Table 4 that analysts with legal records are more likely to revise down their EPS forecasts, we argue that the market is aware of the pattern of EPS walk-down by low-integrity analysts and discounts the credibility of their downward EPS forecast revisions accordingly.

[Insert Table 10 here]

7.2 Pre-analyst-career legal record as a measure for low integrity

In the above tests, we ignore the timing of records and treat all records equally as the indicator of analysts' lack of self-control and low integrity. This approach is supported by criminology research showing that self-control is usually learned early in life, and once learned, is highly resistant to change (Gottfredson and Hirschi, 1990). However, reverse causality is possible; that is, analysts may be more likely to commit crime when they experience frustration and difficult times in their careers. In this section, we use pre-analyst-career legal record as a cleaner measure to mitigate the concern of reverse causality.

We repeat our main analyses on opportunism and career outcomes by splitting legal records into pre-analyst-career versus post-analyst-career legal records. Table 11 presents the regression results. Panel A and Panel B show that analysts with pre-analyst-career legal records tend to engage more in "speaking in two-tongues" and EPS walk-down, respectively. For career outcomes in Panel C, analysts with pre-analyst-career legal records are less likely to be voted as star (column 1), less likely to be employed by the buy side (column 2), and experience delays in the internal promotion (column 4). These findings alleviate the reverse-causality concern.

[Insert Table 11 here]

7.3 Legal record and risk-taking

According to the criminology literature (e.g., Gottfredson and Hirschi, 1990), individuals with low self-control are more risk-taking. Although risk-taking is not the focus of our study, we examine such behavior in this section. Prior studies document that recommendation boldness reflects analysts' inclination to stand out from the crowd and adopt aggressive styles in issuing recommendations (e.g., Jegadeesh and Kim, 2010; Jiang et al.2015). Thus, we predict a positive relation between analysts' legal records and recommendation boldness. Table 12 presents the results. In both columns, the coefficient on *Legal record* or *Legal record(minor)* is positive and significant (0.038, t=7.206, column (1); 0.040, t=7.343, column (2)), consistent with our conjecture.

[Insert Table 12 here]

8. Conclusion

In this study, we investigate whether integrity matters to the sell-side research profession. Motivated by the criminology and psychology literature, we use analysts' off-the-job behavior, specifically, legal records, to capture their low integrity. We find that analysts with legal records engage more in opportunistic behaviors such as "speaking in two tongues" and EPS forecast walk-down. We then provide robust evidence demonstrating that analysts with low integrity experience less favorable career outcomes. The negative relation between analysts' legal records and career success is neither a mechanical result of employment background checks, nor a result of disparity in analyst forecasting ability between analysts with and without legal records.

The interpretation of our results comes with an important caveat. We do not claim causality, and therefore, we do not advocate for restricting or even banning employment of analysts with such off-the-job minor offense records. Neither do we recommend that regulators should amend disclosure policies regarding the background information of financial advisors, particularly regarding these minor offenses. In this study, we use these records as a proxy for analyst integrity solely for academic research purposes. However, being a reasonable proxy in academic research does not necessarily mean that these records are sufficiently accurate for the public or investors to rely on when assessing an individual analyst's integrity. Instead, such an assessment practice may lead to substantial discrimination issues, which could outweigh any potential benefits.

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Appendix A. Identify analysts' legal records

We start by extracting the analyst's surname and the initial letter of her given name from the I/B/E/S recommendation file. Analysts recorded as teams or research departments in I/B/E/S are excluded. We then supplement the analyst's first and middle names based on data from FINRA, Capital IQ, and Factiva. Specifically, if an analyst from FINRA shares the same surname, same initial letter of the first name, and the same career path with the analyst recorded in I/B/E/S, she is considered the same analyst as in I/B/E/S. FINRA provides information for analysts active after 2008. For analysts whose information is unavailable in FINRA, we rely on Capital IQ or Factiva media reports as well as LinkedIn. This comprehensive process results in a dataset containing detailed information on an analyst's first name, initial letter of the middle name (or full middle name), last name, employment records, and addresses (if available). For a subset of analysts, we can also trace their detailed employment records (i.e., employer for each job, duration of each job, and job locations at the city or state level), age, and educational background. Foreign analysts are excluded from the analysis since their criminal records cannot be obtained from SearchQuarry.com, which only provides access to U.S. domestic criminal records.

We gather information on analyst age from multiple sources. Capital IQ, Bloomberg, and Factiva directly provide information on age for some analysts. For others, we estimate their age using LinkedIn and Capital IQ, relying on the year of their college entrance (assuming a typical college entrance age of 18). If this information is unavailable, we infer their ages based on their career records in FINRA or LinkedIn (assuming a standard career commencement age of 22). As a final step, we verify and obtain the precise age data through SearchQuarry.com.

After obtaining analysts' full name and other background information, we utilize the SearchQuarry.com to access their criminal records. An analyst is classified as clean (with no legal record) if SearchQuarry.com shows no legal record under her name. Challenges arise when SearchQuarry.com displays legal records for multiple U.S. residents sharing the same name. To avoid misclassification of an analyst's criminal status, we cross-reference residence details, including full name, age, gender, residential address, occupation, and income range to identify the specific analyst.

Appendix B: Variable definition

Variable	Definition	Data sources
Variables in Table 2		
Misconduct	Equals one for analyst who has FINRA disclosures falling into one of the following categories: Customer Disputes, Employment Separation After Allegations, Civil-Final, Judgment/Lien or Regulatory-Final, and zero otherwise.	*FINRA*
Legal record	Equals one for analysts with legal records and zero otherwise. The details on identifying legal records are described in Appendix A.	*SearchQuarry.com*
Legal record (one)	Equals one for analyst who has only one legal record and zero otherwise.	*SearchQuarry.com*
Legal record (multiple)	Equals one for analyst who has multiple legal records and zero otherwise.	*SearchQuarry.com*
Legal record (pre-analyst)	Equals one for analyst who has a legal record before appearing in I/B/E/S and zero otherwise.	*SearchQuarry.com*
Legal record (post-analyst)	Equals one for analyst who has a legal record after appearing in I/B/E/S and zero otherwise.	*SearchQuarry.com*
Legal record (minor)	Equals one for analyst who only has a record of misdemeanor or infraction, and zero otherwise.	*SearchQuarry.com*
Legal record (felony)	Equals one for analyst who has a felony record and zero otherwise.	*SearchQuarry.com*
Legal record (traffic)	Equals one for analyst who only has traffic-related legal record and zero otherwise.	*SearchQuarry.com*
Legal record (non-traffic)	Equals one for analyst who has non-traffic-related legal record and zero otherwise.	*SearchQuarry.com*
Years in profession	The logarithm of the number of years that an analyst has worked for in I/B/E/S.	*I/B/E/S-Detail history*
Tenure per firm	The logarithm of the number of years that an analyst has worked for in a broker, averaged across all brokers that have ever employed the analyst.	*I/B/E/S-Detail history*
Broker size per firm	The logarithm of the size of the broker that an analyst has worked for, averaged across all brokers that have ever employed the analyst.	*I/B/E/S-Detail history*
Gender	Indicator variable equal to one for male analyst, and zero otherwise.	*FINRA, Capital IQ & Linkedin*
MBA	Equals one if the analyst has an MBA degree, and zero otherwise.	*Capital IQ & Linkedin*
Postgraduate	Equals two if the analyst has a PhD degree, one if she has a master degree (not MBA) and zero for bachelor degree or below.	*Capital IQ & Linkedin*
New variables in Table 3		
Two-tongues metric	The difference between the analyst's recommendation optimism and forecast optimism for the firm. Recommendation optimism is the analyst' recommendation minus the consensus recommendation as of the recommendation date. Scaled forecast optimism is calculated as the EPS forecast minus consensus, normalized by share price, and multiplied by 100. The recommendation and forecast are issued by the same analyst on the same day	*I/B/E/S*

	for the same firm.	
Past star status	Equals one if an analyst was named as *Institutional Investor*'s all-star team during last year and zero otherwise.	*Institutional Investor*
Affiliation	Equals one if the brokerage house that employs the analyst was either a lead underwriter or a co-underwriter of an IPO of the covered firm in the previous five years, or of a seasoned equity offering in the past three years; zero otherwise.	*Thompson One*
Institutional ownership	Percentage of the firm's shares owned by institutional investors.	*Thomson Reuters Institutional (13f)*
Bank reputation	The underwriting market share of the analyst's bank, defined as the dollar amounts of IPOs and SEOs that the bank serves as the lead underwriter in the prior calendar year, divided by the total amount of equity raised by all issuers in that year.	*Thompson One*
New variables in Table 4		
Last Forecast Error	The signed difference between the analyst's last annual EPS forecast and the actual EPS scaled by stock price at the beginning of the calendar year.	*I/B/E/S-Detail history*
First Forecast Error	The signed difference between the analyst's first annual EPS forecast and the actual EPS scaled by stock price at the beginning of the calendar year.	*I/B/E/S-Detail history*
Time to annual EA	The number of days between forecast and EPS announcement, divided by 1000.	*I/B/E/S-Detail history*
New variables in Table 5		
All-star status	Equals one if the analyst is named as *Institutional Investor*'s All-America research team in current year, and zero otherwise.	*Institutional Investor*
Top-10	Equals one if the analyst is employed by one of the top-decile brokerage houses in terms of broker size in the current year, and zero otherwise	*I/B/E/S-Detail History*
Lag general experience	General experience in the prior year in logarithm form. General experience is the number of years of experience an analyst has worked since appearing in I/B/E/S.	*I/B/E/S-Detail History*
Past top10 broker	Equals one if the analyst worked at a top-decile brokerage house in terms of broker size in the prior year. Broker size is measured by the number of analysts employed by the broker in the year.	*I/B/E/S-Detail History*
Lag breadth	Breadth in the prior year in logarithm form. Breadth is the number of firms followed by the analyst during a year.	*I/B/E/S-Detail History*
Lag industries	Number of two-digit SICs followed by the analyst in the prior year in logarithm form.	*I/B/E/S-Detail History & Compustat*
Lag average PMAFE	Average PMAFE in the prior year. Average PMAFE is the mean of PMAFEs of all firms covered by the analyst in the year. The proportional mean absolute forecast error (PMAFE) represents the difference between the analyst's absolute forecast error (AFE) (in $) for the firm and the mean AFE of all analysts following the firm in the year, scaled by the mean AFE of all analysts following the firm in	*I/B/E/S-Detail History*

	the year.	
Lag average firm size	Average firm size in the prior year in logarithm form. Average firm size is the average size of all the firms covered by the analyst in the year.	*Compustat*
New variables in Table 6		
Buy-side	Equals one if an analyst works in a buy-side firm in the year, and zero otherwise.	*Linkedin & Morningstar*
Past top10 accuracy	Equals one if the analyst's accuracy ranked in the top decile among all analysts following the same firm before the current year, and zero otherwise.	*I/B/E/S-Detail History*
Specialty major	Equals one if the analyst specializes in major related to the industry sector she covers, including aerospace, biology, chemical, engineering, computer science, geology, media, medical, hotel or transportation.	*Linkedin*
New variables in Table 7		
Promotion Duration	The number of years between analyst becoming a research associate and first appearing in I/B/E/S.	*I/B/E/S & Linkedin*
Prior experience	The length of working experience in logarithm form before an analyst starts analyst career.	*Linkedin*
New variables in Table 8		
PMAFE	The difference between the analyst's absolute forecast error (AFE) (in \$) for the firm and the mean AFE of all analysts following the firm in the year, scaled by the mean AFE of all analysts following the firm in the year.	*I/B/E/S-Detail History*
HK Accuracy	Relative accuracy score averaged across all firms covered by the analyst during the prior year, as defined in Hong and Kubik (2003).	*I/B/E/S-Detail History*
CT Accuracy	Following Clement and Tse (2005), scaled accuracy for each analyst is defined as $CT\ Accuracy = \frac{\mathrm{AFE}_{max} - \mathrm{AFE}}{\mathrm{AFE}_{max} - \mathrm{AFE}_{min}}$, where AFE_{max} and AFE_{min} are the maximum and minimum absolute forecast errors, respectively, for analysts following a firm during a particular fiscal period.	*I/B/E/S-Detail History*
Lag frequency	The number of forecasts the analyst issues for the firm in the prior fiscal year.	*I/B/E/S-Detail History*
Forecast horizon	The number of days in logarithm form between the forecast date and fiscal period end date.	*I/B/E/S-Detail History*
Days elapsed	The number of days elapsed in logarithm form since the last forecast by any analyst following the firm in the year.	*I/B/E/S-Detail History*
Firm experience	The number of years in logarithm form the analyst has been following the firm.	*I/B/E/S-Detail history*
Size	The capitalization in logarithm form of the firm in the year.	*Compustat*
MTB	Market-to-book ratio	*Compustat*
Past 12-month return	CRSP value-weighted index-adjusted buy-and hold abnormal return (BHARs) over the twelve months prior to the announcement date of the earnings forecast.	*CRSP*
New variables in Table 9 & Table 10		
EA_CAR [-1, +1]	The cumulative abnormal return for the time window [-1, +1] surrounding the earnings announcement, calculated as	*CRSP*

	the difference between the raw return and value-weighted market return for the holding period.	
Forecast Error_LR	The difference between the actual earnings and the consensus of analysts with legal records, computed as the actual earnings minus the average forecast within the analyst group, deflated by stock price at the beginning of the year.	*I/B/E/S-Detail History*
Forecast Error_NLR	The difference between the actual earnings and the consensus of analysts without any legal record, computed as the actual earnings minus the average forecast within the analyst group, deflated by stock price at the beginning of the year.	*I/B/E/S-Detail History*
Num_analysts	The logarithmic number of analysts following the firm in the year.	*I/B/E/S-Detail History*
Forecast revision	The difference between current forecast and most recent consensus forecast, deflated by the stock price at the beginning of the year.	*I/B/E/S-Detail History*
FR_CAR [-1, +1]	The cumulative abnormal return for the time window [-1, +1] surrounding the forecast revision, calculated as the difference between the raw return and value-weighted market return for the holding period.	*CRSP*
New variables in Table 12		
Bold recommendation	Equals one if the revised rating is more than two-grade higher or lower than the prior grade and zero otherwise.	*I/B/E/S-Recommendations-Detail*
Lag frequency (reco)	The number of recommendations the analyst issues for the firm in the prior fiscal year.	*I/B/E/S-Recommendations-Detail*
Days elapsed (reco)	The number of days elapsed in logarithm form since the last recommendation by any analyst following the firm in the year.	*I/B/E/S-Recommendations-Detail*

Table 1. Sample construction

Panel A: Sample selection

	Recommendations		Analysts	
	No.	%	No.	%
Research team (department) or analyst name unknown	34,934	4.31	1,498	7.96
Analysts with less than 5 recommendations in I/B/E/S	2,023	0.25	1,067	5.67
Unidentified analysts	3,979	0.49	306	1.63
Identified as foreign analysts	56,307	6.94	4,640	24.67
Analysts without legal record	**621,899**	76.65	**10,064**	53.51
Analysts with a legal record	**92,161**	11.36	**1,234**	6.56
Total	811,303	100	18,809	100

Panel B: Recommendation and EPS distribution by year

	Recommendation			Annual EPS forecast		
Year	Sample for identified analysts	I/B/E/S sample	% of I/B/E/S sample	Sample for identified analysts	I/B/E/S sample	% of I/B/E/S sample
1994	25,232	30,750	82	78,728	94,988	83
1995	26,497	31,874	83	84,766	102,013	83
1996	26,025	30,708	85	89,968	106,161	85
1997	26,596	30,822	86	93,950	109,330	86
1998	31,089	35,726	87	102,557	117,564	87
1999	31,443	37,055	85	99,101	112,318	88
2000	28,379	32,353	88	94,830	104,612	91
2001	27,868	32,885	85	103,880	114,513	91
2002	42,970	48,903	88	99,127	112,133	88
2003	33,104	37,955	87	101,724	115,734	88
2004	30,342	34,615	88	118,238	130,761	90
2005	28,409	31,945	89	123,105	135,113	91
2006	30,325	33,751	90	127,177	139,529	91
2007	30,871	34,257	90	132,278	146,458	90
2008	33,287	36,624	91	143,419	159,735	90
2009	29,182	31,934	91	138,559	155,203	89
2010	27,454	30,247	91	144,530	161,057	90
2011	29,133	32,120	91	153,181	169,441	90
2012	26,996	29,839	90	157,101	173,163	91
2013	23,776	26,478	90	153,445	171,085	90
2014	23,444	26,139	90	155,343	182,716	85
2015	22,862	25,548	89	163,509	194,628	84
2016	42,904	47,804	90	156,160	186,439	84
2017	19,262	21,369	90	139,529	166,370	84
2018	16,610	19,602	85	152,835	184,219	83
Total	714,060	811,303	88	3,107,040	3,545,283	88

Panel C: Types of legal records

	No.	%
Felonies	73	2.69
Minor offenses (misdemeanors and infractions)		
Traffic:		
Careless driving	13	0.48
Driving when intoxicated	30	1.10
Reckless driving	24	0.88
Speeding	864	31.82
Other traffic violations	1,093	40.26
Non-traffic:		
Alcohol violation	34	1.25
Assault	5	0.18
Disorder conduct	19	0.70
Resisting officer without violence	6	0.22
Substance	67	2.47
Trespassing	6	0.22
Others and unspecified	481	17.72
Total legal records	2,715	100

This table reports the sample construction process and sample distribution. Panel A details the sample selection procedure. The sample selection starts from the analyst universe in I/B/E/S recommendation file from January 1994 to December 2018. Panel B shows the annual distribution of stock recommendations and annual EPS forecasts for analysts whose legal records can be traced. The sample period for recommendations and EPS forecasts is from January 1994 to December 2018. Panel C presents the statistics on the types of violations committed by analysts.

Table 2. Validation test

Panel A: Descriptive statistics

	N	Mean	Std. Dev.	p25	Med.	p75
Misconduct	4,135	0.040	0.196	0.000	0.000	0.000
Legal record	4,135	0.172	0.377	0.000	0.000	0.000
Legal record(one)	4,135	0.091	0.288	0.000	0.000	0.000
Legal record(multiple)	4,135	0.081	0.273	0.000	0.000	0.000
Legal record(pre-analyst)	4,135	0.087	0.282	0.000	0.000	0.000
Legal record(post-analyst)	4,135	0.085	0.279	0.000	0.000	0.000
Legal record(minor)	4,135	0.153	0.360	0.000	0.000	0.000
Legal record(felony)	4,135	0.019	0.136	0.000	0.000	0.000
Legal record(traffic)	4,135	0.097	0.296	0.000	0.000	0.000
Legal record(non-traffic)	4,135	0.075	0.263	0.000	0.000	0.000
Years in profession	4,135	2.103	0.870	1.511	2.250	2.813
Tenure per firm	4,135	1.608	0.498	1.253	1.609	1.946
Broker size per firm	4,135	3.705	0.897	3.068	3.784	4.394
Gender	4,135	0.878	0.328	1.000	1.000	1.000
MBA	4,135	0.400	0.490	0.000	0.000	1.000
Postgraduate	4,135	0.442	0.568	0.000	0.000	1.000

Panel B: Regression results

	(1)	(2)	(3)	(4)	(5)
			DV = Misconduct		
Legal record	**0.030*****				
	(3.459)				
Legal record(one)		**0.031*****			
		(2.841)			
Legal record(multiple)		**0.028****			
		(2.336)			
Legal record(pre-analyst)			**0.062*****		
			(5.430)		
Legal record(post-analyst)			**-0.003**		
			(-0.234)		
Legal record(minor)				**0.019****	
				(2.149)	
Legal record(felony)				**0.103*****	
				(4.555)	
Legal record(traffic)					**0.023****
					(2.140)
Legal record(non-traffic)					**0.037*****
					(3.065)
Years in profession	-0.004	-0.004	-0.003	-0.003	-0.003
	(-0.728)	(-0.729)	(-0.637)	(-0.726)	(-0.701)
Tenure per firm	-0.022***	-0.022***	-0.023***	-0.021***	-0.022***
	(-2.863)	(-2.861)	(-2.888)	(-2.735)	(-2.850)
Broker size per firm	-0.007*	-0.007*	-0.008*	-0.007*	-0.007*
	(-1.701)	(-1.705)	(-1.764)	(-1.672)	(-1.676)
Gender	0.013	0.013	0.013	0.013	0.013
	(1.405)	(1.404)	(1.321)	(1.378)	(1.407)
MBA	-0.014*	-0.014*	-0.014*	-0.014*	-0.014*
	(-1.882)	(-1.882)	(-1.852)	(-1.930)	(-1.895)
Postgraduate	-0.000	-0.000	-0.000	0.000	0.000
	(-0.004)	(-0.005)	(-0.053)	(0.074)	(0.011)
Constant	0.099***	0.099***	0.100***	0.097***	0.098***
	(4.985)	(4.988)	(5.041)	(4.897)	(4.939)
Observations	4,135	4,135	4,135	4,135	4,135
Adj. R-squared	0.073	0.073	0.077	0.076	0.073
Cohort FE	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES
First Broker FE	YES	YES	YES	YES	YES

This table examines the relation between legal records and on-the-job financial misconduct using a linear probability model. Panel A presents descriptive statistics and Panel B reports regression results. The dependent variable, *Misconduct*, equals to one for analysts with FINRA disclosures after the start of analyst career and zero otherwise. Observations are at analyst level. Cohort, First Broker and State fixed effects are included. See Appendix B for variables' definitions. The t statistics are reported in the parentheses. All continuous variables are winsorized at 1th and 99th percentiles. ***, **, * indicate significance at the $p < 0.01$, $p < 0.05$, and $p < 0.1$ levels, respectively.

Table 3. Analyst "speaking in two tongues"

Panel A: Descriptive statistics

	N	**Mean**	**Std. Dev.**	**p25**	**Med.**	**p75**
Two-tongues metric	163,057	0.363	2.325	-0.638	0.106	0.978
Legal record	163,057	0.133	0.340	0.000	0.000	0.000
Legal record(minor)	163,057	0.121	0.326	0.000	0.000	0.000
Past star status	163,057	0.093	0.291	0.000	0.000	0.000
Affiliation	163,057	0.035	0.183	0.000	0.000	0.000
Institutional ownership	163,057	0.666	0.252	0.516	0.715	0.865
Bank reputation	163,057	0.012	0.023	0.000	0.001	0.010

Panel B: Regression results

	(1)	(2)	(3)
		DV = Two-tongues metric	
Legal record	**0.057*** **		
	(3.394)		
Legal record(minor)		**0.064*** **	**0.046** **
		(3.693)	**(2.083)**
Past star status	-0.022	-0.022	0.057*
	(-1.067)	(-1.068)	(1.907)
Affiliation	-0.063	-0.068	0.018
	(-1.483)	(-1.570)	(0.512)
Institutional ownership	-0.166*	-0.164*	-0.170
	(-1.782)	(-1.774)	(-1.500)
Bank reputation	-0.500*	-0.521**	2.570***
	(-1.899)	(-1.964)	(5.536)
Constant	0.476***	0.475***	0.435***
	(7.630)	(7.680)	(5.787)
Observations	163,057	161,046	160,983
Adj. R-squared	0.179	0.180	0.189
Year FE	YES	YES	YES
Firm FE	YES	YES	YES
Broker FE	NO	NO	YES
State FE	YES	YES	YES

This table tests the relation between analyst legal records and "speaking in two tongues". Panel A presents the descriptive statistics and Panel B reports the regression results. The sample restricts to pairs of EPS forecast and recommendation made by the same analyst for the same firm on the same day. The dependent variable, *Two-tongues metric*, is defined following Malmendier and Shanthikumar (2014). All continuous variables are winsorized at 1 and 99 percentile levels. See Appendix B for variables' definitions. In Column (1) and (2), standard errors are clustered by firm to adjust for within-firm correlation; in Column (3), standard errors are clustered by firm and year to adjust for both within-firm and time-series correlation. The t-statistics are in parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 4. Analyst EPS forecast walk-down

Panel A: Descriptive statistics

	N	Mean	Std. Dev.	p25	Med.	p75
Last Forecast Error	530,701	-0.006	1.104	-0.206	-0.030	0.106
First Forecast Error	530,701	0.216	2.017	-0.429	-0.006	0.660
Legal record	530,701	0.134	0.340	0.000	0.000	0.000
Legal record(minor)	530,701	0.123	0.329	0.000	0.000	0.000
Time to annual EA	530,701	0.120	0.071	0.082	0.105	0.181
Past star status	530,701	0.117	0.321	0.000	0.000	0.000
Affiliation	530,701	0.041	0.199	0.000	0.000	0.000
Institutional ownership	530,701	0.675	0.248	0.529	0.724	0.871
Bank reputation	530,701	0.013	0.025	0.000	0.001	0.012

Panel B: Regression results

	(1)	(2)	(3)
VARIABLES		*DV = Last Forecast Error*	
First Forecast Error	0.275***	0.274***	0.274***
	(28.161)	(28.101)	(23.347)
Legal record	0.013***		
	(3.394)		
First Forecast Error*Legal record	**-0.018*****		
	(-3.620)		
Legal record(minor)		0.013***	0.010**
		(3.207)	(2.165)
First Forecast Error* Legal record(minor)		**-0.017*****	**-0.017*****
		(-3.205)	**(-2.995)**
Time to annual EA	0.755***	0.755***	0.756***
	(19.495)	(19.474)	(5.077)
Past star status	0.007*	0.007*	0.004
	(1.808)	(1.722)	(0.776)
Affiliation	-0.002	-0.003	-0.006
	(-0.212)	(-0.260)	(-0.539)
Institutional ownership	0.071***	0.070***	0.072**
	(2.713)	(2.688)	(2.501)
Bank reputation	0.044	0.044	0.013
	(0.840)	(0.818)	(0.123)
First Forecast Error Past star status*	-0.046***	-0.046***	-0.046***
	(-8.638)	(-8.598)	(-6.845)
*First Forecast Error*Affiliation*	0.046***	0.046***	0.046***
	(5.087)	(5.072)	(4.240)
*First Forecast Error*Institutional ownership*	-0.036**	-0.035**	-0.035*
	(-2.541)	(-2.501)	(-1.855)
*First Forecast Error*Bank reputation*	-0.054	-0.068	-0.060
	(-0.741)	(-0.925)	(-0.502)
Constant	-0.201***	-0.200***	-0.201***
	(-10.999)	(-11.002)	(-8.310)
Observations	530,701	525,142	525,086

Adj. R-squared	0.294	0.295	0.296
Year FE	YES	YES	YES
Firm FE	YES	YES	YES
Broker FE	NO	NO	YES
State FE	YES	YES	YES

This table tests the relation between legal records and EPS forecast walk-down. Panel A presents the descriptive statistics and Panel B exhibits the regression results. The dependent variable, *Last Forecast Error*, is the signed last annual EPS forecast error deflated by the stock price at the beginning of the year. All continuous variables are winsorized at their 1 and 99 percentile levels. See Appendix B for variables' definitions. In Column (1) and (2), standard errors are clustered by firm; in Column (3), standard errors are clustered by firm and year. The t-statistics are in parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 5. Legal record and analyst All-star status (employment in the high-status brokerages)

Panel A: Descriptive statistics

	N	Mean	Std. Dev.	p25	Med.	p75
All-star status	56,607	0.085	0.279	0.000	0.000	0.000
Top-10	56,607	0.507	0.500	0.000	1.000	1.000
Legal record	56,607	0.134	0.340	0.000	0.000	0.000
Legal record(minor)	56,465	0.132	0.338	0.000	0.000	0.000
Lag general experience	56,607	5.850	5.291	1.573	4.428	8.759
Past top10 broker	56,607	0.501	0.500	0.000	1.000	1.000
Lag breadth	56,607	10.889	7.491	5.000	10.000	15.000
Lag industries	56,607	2.989	2.227	1.000	2.000	4.000
Lag average PMAFE	56,607	-0.209	0.452	-0.442	-0.259	-0.060
Lag average firm size	56,607	8.308	1.545	7.274	8.383	9.429
Past star status	56,607	0.079	0.270	0.000	0.000	0.000

Panel B: Regression results

	(1)	(2)	(3)
		DV = All-star status	
Legal record	**-0.021*****	**-0.007*****	
	(-3.402)	**(-2.720)**	
Legal record(minor)			**-0.007****
			(-2.510)
Lag general experience	0.005***	0.001***	0.001***
	(9.823)	(4.759)	(4.775)
Past top10 broker	0.120***	0.047***	0.047***
	(25.661)	(23.018)	(23.010)
Lag breadth	0.004***	0.001***	0.001***
	(8.576)	(6.345)	(6.304)
Lag industries	-0.001	-0.001*	-0.001*
	(-1.069)	(-1.776)	(-1.754)
Lag average PMAFE	-0.028***	-0.014***	-0.014***
	(-11.461)	(-9.032)	(-9.048)
Lag average firm size	0.017***	0.007***	0.007***
	(12.490)	(12.119)	(12.171)
Past star status		0.644***	0.643***
		(77.147)	(77.125)
Constant	-0.188***	-0.065***	-0.066***
	(-16.924)	(-14.432)	(-14.483)
Observations	56,607	56,607	56,464
Adj. R-squared	0.120	0.459	0.459
Industry FE	YES	YES	YES
Year FE	YES	YES	YES

Panel C: Regression results

	(1)	(2)
	DV = Top-10	
Legal record	**-0.008****	
	(-2.446)	
Legal record(minor)		**-0.008****
		(-2.453)
Lag general experience	-0.002***	-0.002***
	(-6.311)	(-6.289)
Past top10 broker	0.817***	0.817***
	(251.293)	(250.760)
Lag breadth	0.001***	0.001***
	(4.267)	(4.276)
Lag industries	-0.006***	-0.006***
	(-9.716)	(-9.699)
Lag average PMAFE	-0.021***	-0.021***
	(-6.479)	(-6.476)
Lag average firm size	0.009***	0.009***
	(10.903)	(10.901)
Past star status	0.060***	0.060***
	(17.047)	(17.036)
Constant	0.030***	0.030***
	(4.277)	(4.234)
Observations	56,607	56,464
Adj. R-squared	0.705	0.706
Industry FE	YES	YES
Year FE	YES	YES

This table reports the results of testing the relation between analyst integrity and the likelihood of being voted as an II all-star analyst and employment in high-status brokerages. Panel A presents the descriptive statistics. Panel B shows the regression results for the probability of being voted as a star analyst by *Institutional Investor* magazine's annual rankings. The dependent variable, *All-star status*, equals one if the analyst is named in *Institutional Investor*'s All-America research team, and zero otherwise. Panel C reports the regression results for the probability of being employed in a top-10 brokerage house using linear probability model. The dependent variable, *Top-10*, equals to one if the analyst is employed by a top-decile brokerage house in terms of broker size, and zero otherwise. Year and Industry (2-digit SIC) fixed effects are included. See Appendix B for variables' definitions. The standard errors are clustered by analyst, following Bradley et al. (2017). The t-statistics are in parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 6. Legal record and employment in buy-side

Panel A: Descriptive statistics

	N	Mean	Std. Dev	p25	Med.	p75
Buy-side	53,121	0.116	0.321	0.000	0.000	0.000
Legal record	53,121	0.146	0.353	0.000	0.000	0.000
Legal record(minor)	53,121	0.133	0.340	0.000	0.000	0.000
Past top10 accuracy	53,121	0.254	0.435	0.000	0.000	1.000
Past top10 broker	53,121	0.497	0.500	0.000	0.000	1.000
Past star status	53,121	0.041	0.199	0.000	0.000	0.000
MBA	53,121	0.529	0.499	0.000	1.000	1.000
Postgraduate	53,121	0.479	0.605	0.000	0.000	1.000
Specialty major	53,121	0.169	0.375	0.000	0.000	0.000
General experience	53,121	2.364	0.804	1.946	2.565	2.944

Panel B: Regression results

	(1)	(2)
	DV = Buy-Side	
Legal record	**-0.032*** **	
	(-3.150)	
Legal record(minor)		**-0.029** **
		(-2.755)
Past top10 accuracy	0.002	0.002
	(0.185)	(0.206)
Past top10 broker	0.024**	0.024**
	(2.542)	(2.582)
Past star status	-0.056***	-0.057***
	(-2.860)	(-2.902)
MBA	0.012	0.012
	(1.546)	(1.558)
Postgraduate	-0.025***	-0.026***
	(-3.767)	(-3.812)
Specialty major	-0.003	-0.003
	(-0.352)	(-0.339)
General experience	0.006	0.006
	(1.297)	(1.315)
Constant	0.103***	0.102***
	(7.404)	(7.298)
Observations	53,121	52,460
Adj. R-squared	0.092	0.093
Industry FE	YES	YES
Year FE	YES	YES
First Broker FE	YES	YES
Cohort FE	YES	YES

This table examines whether analysts with legal records are more likely to work in a buy-side firm using a linear probability model. The dependent variable, *Buy-side*, equals 1 for analyst works in a buy-side firm in a given year, and 0 otherwise. Standard errors are clustered by employer and year. The t-statistics are in parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 7. Legal record and internal promotion duration

Panel A: Descriptive statistics

	N	Mean	Std. Dev.	p25	Med.	p75
Promotion Duration	3,181	3.713	2.413	2.000	3.000	5.000
Legal record	3,181	0.152	0.359	0.000	0.000	0.000
Legal record(minor)	3,181	0.139	0.346	0.000	0.000	0.000
PMAFE	3,181	-0.072	0.411	-0.295	-0.119	0.073
Breadth	3,181	1.744	0.683	1.099	1.792	2.303
Broker size	3,181	3.878	1.000	3.135	3.989	4.700
Prior experience	3,181	1.253	0.991	0.000	1.386	2.079
MBA	3,181	0.494	0.500	0.000	0.000	1.000
Postgraduate	3,181	0.477	0.602	0.000	0.000	1.000
Specialty major	3,181	0.161	0.368	0.000	0.000	0.000

Panel B: Regression results

	(1)	(2)
	DV = Promotion Duration	
Legal record	**0.214****	
	(2.145)	
Legal record(minor)		**0.267****
		(2.535)
PMAFE	-0.040	-0.039
	(-0.399)	(-0.385)
Breadth	0.154**	0.163**
	(2.409)	(2.421)
Broker size	0.307***	0.317***
	(3.896)	(4.041)
Prior experience	-0.730***	-0.737***
	(-16.011)	(-16.528)
MBA	0.037	0.064
	(0.474)	(0.826)
Postgraduate	-0.292***	-0.298***
	(-4.360)	(-4.404)
Specialty major	0.091	0.084
	(0.937)	(0.845)
Constant	3.242***	3.184***
	(9.178)	(8.886)
Observations	3,181	3,140
Adj. R-squared	0.270	0.272
Year FE	YES	YES
Broker FE	YES	YES
Industry FE	YES	YES

This table examines whether analysts with legal records take longer time to be promoted within a brokerage. The unit of observation is at analyst level. The dependent variable, *Promotion Duration*, is the number of years for an associate analyst to be promoted to a senior analyst. Year, Broker and Industry fixed effects are included. I/B/E/S. Standard errors are clustered by broker. The t-statistics are in parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 8. Analyst forecast accuracy

Panel A: Descriptive statistics

	N	Mean	Std. Dev.	p25	Med.	p75
PMAFE	483,664	-0.048	0.761	-0.578	-0.169	0.246
KH Accuracy	483,664	55.495	32.412	27.778	57.143	84.615
CT Accuracy	483,664	0.665	0.323	0.467	0.770	0.936
Legal record	483,664	0.132	0.339	0.000	0.000	0.000
Legal record(minor)	483,664	0.122	0.327	0.000	0.000	0.000
Lag frequency	483,664	4.060	2.252	2.000	4.000	5.000
Forecast horizon	483,664	4.598	0.750	4.248	4.654	5.069
Days elapsed	483,664	1.117	1.285	0.000	0.693	2.079
Past star status	483,664	0.131	0.337	0.000	0.000	0.000
Affiliation	483,664	0.038	0.190	0.000	0.000	0.000
Gender	483,664	0.896	0.306	1.000	1.000	1.000
Broker size	483,664	3.698	1.060	3.045	3.871	4.543
General experience	483,664	2.160	0.632	1.743	2.204	2.643
Firm experience	483,664	1.461	0.649	0.927	1.398	1.945
Breadth	483,664	17.260	8.728	12.000	16.000	21.000
Num industries	483,664	4.818	2.785	3.000	4.000	6.000
Size	483,664	8.065	1.711	6.840	8.001	9.253
MTB	483,664	3.590	4.573	1.558	2.466	4.143
Past 12-month return	483,664	0.022	0.401	-0.214	-0.019	0.191
Institutional ownership	483,664	0.681	0.248	0.543	0.732	0.874

Panel B: Regression results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
								Pre Reg-FD	Post Reg-FD
	DV = PMAFE			*DV = KH Accuracy*		*DV = CT Accuracy*		*DV = PMAFE*	
Legal record	**-0.011*****	**-0.013*****		**0.352****	**0.451*****	**0.003****	**0.004*****	**-0.001**	**-0.014*****
	(-2.699)	**(-3.745)**		**(2.233)**	**(3.071)**	**(2.295)**	**(3.096)**	**(-0.148)**	**(-3.656)**
Legal record(minor)			**-0.016*****						
			(-4.380)						
Controls	NO	YES	YES	NO	YES	NO	YES	YES	YES
Observations	483,664	483,664	478,779	483,664	483,664	483,664	483,664	105,581	377,663
Adj. R-squared	-0.004	0.101	0.100	0.005	0.092	0.053	0.133	0.097	0.103
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

This table tests the relation between legal records and forecast accuracy. Panel A presents the descriptive statistics and Panel B exhibits the regression results. In columns (1)-(3) and (8) to (9), the dependent variable, *PMAFE*, is the proportional mean absolute forecast error, calculated as the difference between the absolute forecast error (AFE) of the analyst for the firm and the mean absolute forecast error (MAFE) of all forecasts for the firm in the year, scaled by MAFE. In columns (4)-(5), the dependent variable, *HK Accuracy*, is the relative accuracy ranking score for analyst forecast of the firm, following Hong and Kubik (2003). In columns (6)-(7), the dependent variable, *CT Accuracy*, is another relative accuracy following Clement and Tse (2005). All continuous variables are winsorized at their 1 and 99 percentile levels. See Appendix B for variables' definitions. Standard errors are clustered by firm. The t-statistics are in parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 9. ERC analysis

	(1) *EA_CAR [-1, +1]*	(2) *EA_CAR [-1, +1]*
Forecast Error_LR	**0.336*** **	
	(6.054)	
Forecast Error_NLR		**0.556*** **
		(9.928)
Size	-0.003**	-0.003**
	(-2.347)	(-2.352)
MTB	0.000	0.000
	(0.377)	(0.416)
Past 12-month return	0.000	-0.000
	(0.027)	(-0.062)
Institutional ownership	0.009*	0.009
	(1.807)	(1.680)
Num_analysts	-0.004*	-0.004*
	(-1.842)	(-1.799)
Constant	0.035***	0.035**
	(2.818)	(2.790)
Observations	14,104	14,104
Adj. R-squared	0.045	0.051
Firm FE	YES	YES
Year FE	YES	YES
Diff. in coefficients on *Forecast Error_LR* and *Forecast Error_NLR*	Chi2(1) = 20.91	Prob > Chi2 = 0.000

This table presents regression results for the market reaction to annual EPS forecast error. The dependent variable, *EA_CAR [-1, +1]*, is the cumulative abnormal return for the time window [-1, +1] surrounding the earnings announcement date, calculated as the difference between the stock's raw return and value-weighted market return for the holding period. In column (1), *Forecast Error_LR* is the difference between actual earnings and the consensus of the forecasts issued by analysts with legal records, deflated by stock price at the beginning of the year. In column (2), *Forecast Error_NLR* is the difference between actual earnings and the consensus of the forecasts issued by analysts without legal record, deflated by stock price at the beginning of the year. See Appendix B for other variables' definitions. Firm and Year fixed effects are included. Standard errors are clustered by firm and year. The t-statistics are in parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 10. Market Reaction to EPS Forecast Revisions

VARIABLES	(1) All revisions *FR_CAR [-1, +1]*	(2) Upward revisions *FR_CAR [-1, +1]*	(3) Downward revisions *FR_CAR [-1, +1]*
Legal record	0.000	-0.000	-0.001
	(0.318)	(-0.338)	(-1.060)
Forecast revision	0.539***	0.314***	0.357***
	(22.159)	(10.372)	(16.363)
Legal record * Forecast revision	**-0.016**	**0.041**	**-0.080****
	(-0.534)	**(0.882)**	**(-2.708)**
Constant	0.023***	0.028***	0.009
	(4.444)	(5.672)	(1.669)
Controls	YES	YES	YES
Observations	483,664	238,301	243,685
Adj. R-squared	0.057	0.069	0.080
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
State FE	YES	YES	YES

This table presents the difference in market reactions to annual EPS forecast revisions. Dependent variable, *FR_CAR [-1, +1]*, is the cumulative abnormal return for the time window [-1, +1] surrounding the forecast revision, calculated as the difference between the raw return and value-weighted market return for the holding period. We include the same set of control variables as in Table 8. See Appendix B for variables' definitions. Firm, Year, and State fixed effects are included. Standard errors are clustered by firm and year. The t-statistics are in parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 11. Pre-analyst-career legal record

Panel A: Analysts' "speaking in two-tongues"

	(1) *DV = Two-tongues metric*
Legal record(pre-analyst)	**0.041****
	(2.220)
Legal record(post-analyst)	0.067*
	(1.917)
Controls	YES
Observations	162,996
Adj. R-squared	0.179
Year FE	YES
Firm FE	YES
State FE	YES

Panel B: Analyst walk-down in EPS forecast

	(1) *DV = Last Forecast Error*
First Forecast Error	0.274***
	(23.309)
Legal record(pre-analyst)	0.002
	(0.554)
First Forecast Error* Legal record(pre-analyst)	**-0.020*****
	(-2.810)
Legal record(post-analyst)	0.016**
	(2.280)
First Forecast Error Legal record(post-analyst)*	-0.017**
	(-2.612)
Controls	YES
Observations	530,643
Adj. R-squared	0.295
Year FE	YES
Firm FE	YES
Broker FE	YES
State FE	YES

Panel C: Career outcomes

	(1) *DV = All-star status*	(2) *DV = Buy-side*	(3) *DV = Top-10*	(4) *DV = Promotion Duration*
Legal record(pre-analyst)	**-0.020****	**-0.020*****	**-0.005**	**0.426*****
	(-2.719)	**(-3.933)**	**(-1.04)**	**(3.149)**
Legal record(post-analyst)	-0.032**	-0.047***	-0.022***	-0.182
	(-2.677)	(-8.582)	(-3.079)	(-1.116)
Control Variables	YES	YES	YES	YES
Observations	56,607	53,121	56,607	3,181
Adj. R-squared	0.120	0.092	0.696	0.271
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
(First) Broker FE	-	YES	-	YES
Cohort FE	-	YES	-	-

This table presents results on main analyses by splitting legal records into pre-analyst-career versus post-analyst-career legal records. Panel A presents the results on two-tongues metric, Panel B reports the estimation results on walk-down in EPS forecast, and Panel C shows the results on career outcomes. The t-statistics are in parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 12. Analyst recommendation boldness

Panel A: Descriptive statistics

	N	Mean	Std. Dev.	p25	Med.	p75
Bold recommendation	254,950	0.352	0.478	0.000	0.000	1.000
Legal record	254,950	0.128	0.334	0.000	0.000	0.000
Legal record(minor)	254,950	0.118	0.323	0.000	0.000	0.000
Lag frequency(reco)	254,950	1.346	1.041	1.000	1.000	2.000
Days elapsed(reco)	254,950	2.448	1.349	1.386	2.639	3.526
Past star status	254,950	0.119	0.324	0.000	0.000	0.000
Affiliation	254,950	0.028	0.164	0.000	0.000	0.000
Gender	254,950	0.896	0.305	1.000	1.000	1.000
Broker size	254,950	3.596	1.156	2.890	3.761	4.511
General experience	254,950	1.731	0.710	1.204	1.792	2.274
Firm experience	254,950	1.167	0.682	0.618	1.098	1.661
Breadth	254,950	12.296	8.068	7.000	11.000	15.000
Num industries	254,950	3.483	2.193	2.000	3.000	4.000
Size	254,950	7.991	1.630	6.817	7.916	9.126
MTB	254,950	3.723	4.527	1.625	2.571	4.304
Past 12-month return	254,950	0.035	0.486	-0.253	-0.028	0.217
Institutional ownership	254,950	0.654	0.257	0.504	0.702	0.855

Panel B: Regression results

	(1)	(2)
VARIABLES	*DV = Bold recommendation*	
Legal record	**0.038***** **(7.206)**	
Legal record(minor)		**0.040***** **(7.343)**
Lag frequency(reco)	0.001 (0.546)	0.001 (0.445)
Days elapsed(reco)	-0.007*** (-10.306)	-0.008*** (-10.339)
Past star status	-0.019*** (-4.299)	-0.018*** (-4.038)
Affiliation	-0.046*** (-6.227)	-0.046*** (-6.185)
Gender	0.005 (0.921)	0.003 (0.544)
Broker size	-0.042*** (-23.821)	-0.043*** (-24.096)
General experience	0.027*** (8.475)	0.026*** (8.263)
Firm experience	0.008*** (2.629)	0.008*** (2.656)
Breadth	-0.003*** (-8.085)	-0.003*** (-7.819)

Num industries	0.001	0.000
	(0.630)	(0.269)
Size	-0.001	-0.001
	(-0.216)	(-0.255)
MTB	-0.000	-0.000
	(-1.394)	(-1.390)
Past 12-month return	-0.016***	-0.015***
	(-5.383)	(-5.140)
Institutional ownership	-0.029***	-0.029***
	(-3.317)	(-3.321)
Constant	0.516***	0.522***
	(22.350)	(22.422)
Observations	254,950	252,387
Adj. R-squared	0.091	0.091
Year FE	YES	YES
Firm FE	YES	YES
State FE	YES	YES

This table presents results for the relation between analyst legal records and recommendation boldness using linear probability model. Panel A presents the descriptive statistics and Panel B reports the regression results. The dependent variable, *Bold recommendation*, equals to 1 if the revised rating is more than 2-grade higher (or lower) than the prior grade and 0 otherwise. Firm, Year, and State fixed effects are included. See Appendix B for variable definitions. Standard errors are clustered by firm. The t-statistics are in parentheses. ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.