# Security Code Violations, Analysts' Forecast Quality, and Corporate Culture

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**Abstract**

Using a hand-collected sample of U.S. security code violations enforced by the Financial Industry Regulatory Authority, I show that violations occurring *outside* of financial institutions' equity research divisions are positively associated with the forecast errors produced by analysts in financial institutions' equity research divisions. Further, I find that security violations are also associated with more upwardly biased forecasts following recent equity underwritings, more downwardly biased forecasts for firms that narrowly "meet or beat" consensus forecast estimates, and less informative analyst reports. The association between security code violations and forecast errors appears to be less pronounced for forecasts produced by All-Star analysts, who have higher levels of reputational capital to preserve. Overall, these findings provide evidence consistent with a common profit-oriented corporate culture influencing employee behavior across a multitude of business activities within financial institutions.

Key words: Equity Analysts, Corporate Culture, Securities Regulation, Global Settlement
JEL classification: G14, G21, G24, G28, M14.

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# I. Introduction

> It might sound surprising to a skeptical public, but culture was always a vital part of Goldman Sachs' success. It revolved around teamwork, integrity, a spirit of humility and always doing right by our clients. The culture was the secret sauce that made this place great and allowed us to earn our clients' trust for 143 years.
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> *–Greg Smith, Goldman Sachs (3/4/2012)*

Modern financial institutions are complex intermediaries that must balance the demands of a diverse set of stakeholders (e.g., shareholders, depositors, individual investors). Brokerage clients want their trades to be executed faithfully and efficiently. Research clients want accurate and objective investment advice about potential investment opportunities. Depositors want their deposits to be safe, and society wants to minimize systemic risk in the banking system. Because fulfilling these demands often comes at the expense of generating profits for their shareholders, financial institutions are subject to a host of regulations designed to protect these other stakeholders. In particular, the securities regulations enforced by the Financial Industry Regulatory Authority (FINRA) represent an important and longstanding regulatory effort to protect financial institutions' clients (i.e., individual investors) and maintain the integrity and stability of capital markets.[1]

Violations of security regulations can offer important insights to the quality of research that financial institutions generate. Significant regulatory efforts (e.g., Global Settlement, NASD 2711, NYSE 472) have been made to ensure that research divisions operate more independently, and recent studies suggest that, in general, these efforts have been successful (e.g., Barber, Lehavy, McNichols, and Trueman (2006); Ertimur, Sunder, and Sunder (2007); Chen and Chen (2009); Barniv, Hope, Myring, and Thomas (2009)). However, regulators have warned that security code violations can be indicative of more persistent and broader cultural problems within financial institutions that are difficult to address with regulation. In this study, I seek to shed light on this cultural phenomenon by examining whether and to what extent security code violations are associated with the quality of earnings forecasts generated by financial institutions' equity research departments.

Consistent with corporate culture theories (e.g., Kreps (1990); Schein (1990)), I view security code violations as an indicator for how profit-oriented the culture within the financial institution is. Corporate culture is an intangible asset designed to meet unforeseen contingencies as they arise (Kreps (1990)) and consists of the shared assumptions, values, and beliefs that inform how employees behave within a firm (Schein (1990); Guiso, Sapienza, and Zingales (2014)). Compliance with securities regulation depends heavily on the trade-offs employees make when considering the interests of the institutions' shareholders, who demand short-term profits, and the interests of individual investors, who should receive high quality investment products as financial institutions' customers. Since these trade-offs are likely to manifest themselves in the day-to-day choices that

[1] Financial institutions are also required to comply with banking regulation, in which the primary objectives are to protect creditors/depositors and prevent systemic risk (Allen and Herring (2001)). For recent studies and discussions on banking regulation and its effectiveness, see Laeven (2013); Laeven and Levine (2009); Beltratti and Stulz (2009); Ongena, Popov, and Udell (2013).

employees make, culture is an important force that can facilitate coordination when employees face choices that are difficult to regulate ex ante (O'Reilly (1989); Kreps (1990)). Moreover, contracts are likely an insufficient mechanism for enforcing appropriate behavior within the firm since the consequences of security code violations (i.e., reputational damage, litigation costs) are slow-moving and difficult to detect in advance (Williamson (1975); Hermalin (2000)) while employee tenures are typically low in the financial services industry.[2] Thus, security code violations are consistent with a profit-oriented corporate culture.

The association between financial institutions' security code violations and the quality of earnings forecasts issued by their analysts deserves better understanding because it could reveal an important and unexplored determinant of their forecast quality (i.e., firm-level culture). Corporate culture is latent and unobservable and identifying its effects empirically is challenging. Examining the association between outcomes observed *outside* of the equity research division that appear to be unrelated to equity research (e.g., unrelated security code violations in the investment banking division) and direct outcomes of the equity research division (i.e., earnings forecast quality) allows me to alleviate some of this challenge by focusing on common behaviors observed across operationally unrelated activities within the firm. This approach is similar to recent studies that have identified cultural forces as an important explanation for common behaviors observed across different business activities within a firm (e.g., Hoi, Wu, and Zhang (2013); Gao, Lisic, and Zhang (2014)).

Earnings forecasts provide a useful output for examining the effects of corporate culture since employees make similar stakeholder tradeoffs when producing earnings forecasts as they do when considering compliance decisions. Similar to complying with securities regulations, producing high quality earnings forecasts is potentially costly for financial institutions, since equity research departments are not funded directly based on the quality of their earnings forecasts. Instead, the institutional clients of the research division that ultimately fund research services, exhibit a low demand for earnings forecast accuracy and, in more severe instances, may place pressure on analysts to bias their forecasts (upwards or downwards). Thus, the emphasis that analysts place on producing high quality forecasts is a result of the trade-offs they make when considering shareholders' demands for profits and individual investors' demands for high quality earnings forecasts. Since equity research is difficult to regulate and monitor internally, the norms and values within the organization are likely to play an important role in influencing the emphasis that analysts place on producing high quality forecasts.[3] Thus, it follows that producing low quality forecasts is consistent

[2]For example, median employee tenures at JPMorgan Chase & Co and Goldman Sachs Group were approximately 2.6 years according to a recent survey (http://www.payscale.com/data-packages/employee-loyalty/full-list).

[3]In a frictionless market, analysts and financial institutions will associate by mutual choice. That is, analysts will seek jobs from financial institutions in which employees have similar values and financial institutions will try to hire analysts that have similar values. In some instances, frictions can arise that may result in analysts being temporarily employed by an institution that has inconsistent values. In such instances, the culture of the institution can influence analysts' behavior. If an analyst initially places a high emphasis on forecast quality, a shareholder-focused corporate culture can influence her to produce less accurate forecasts. Likewise, if an analyst does not initially place a high emphasis on forecast quality, a stakeholder-focused corporate culture can influence her to produce higher quality forecasts.

with a profit-oriented corporate culture. Accordingly, financial institutions' security code violations should be *positively* associated with forecast errors.

There are, however, several counteracting forces that can justify a null result. First, analysts are individual agents in the market that face strong economic incentives to produce high quality forecasts. An analyst depends heavily on being perceived credible by market participants and has strong incentives to build a reputation for providing accurate and objective forecasts (e.g., Hong, Kubik, and Solomon (2000); Mehran and Stulz (2007)). Thus, even if a financial institution fosters a profit-oriented culture, analysts may be unwilling to liquidate their personal reputational capital unless faced with a sufficiently valuable short-term payoff. Second, the profit-oriented culture suggested by security code violations may not affect equity research departments if these departments have developed distinct subcultures that contain their own set of values and norms (Hofstede (1998)). For example, the financial services industry has experienced widespread consolidation and acquisitions over the past decade and often these acquisitions have resulted in "culture clashes" between the parent firm and the new divisions.[4] It is likely that many of the norms and values that were established in the acquired divisions persist for several years after the acquisition. Third, one might take the view that financial institutions view compliance with securities regulations simply as a checklist of policies and procedures they must follow and fail to take an "enterprise-level" approach that strives to provide value for all stakeholders across all of the firms' business activities.[5] Since analysts' forecast quality is not directly regulated, security code violations should not be correlated with forecast quality if institutions fail to integrate the objectives of compliance into their overall corporate culture. Ultimately, it is an empirical question as to whether financial institutions' security code violations are associated with forecast accuracy.

I measure security code violations using a hand-collected sample of violations of all major U.S. Security Codes enforced by the Financial Industry Regulatory Authority (FINRA) and its affiliates (i.e., Nasdaq and NYSE). When financial institutions violate securities regulations, FINRA issues a fine and creates a disclosure event that is published on *BrokerCheck*, an online tool that allows investors to collect information about the financial institutions they transact with. My primary empirical measures of security code violations consist of the frequency (i.e., total number of disclosure events), severity (i.e., total dollar value of fines) and scope (i.e., number of unique security codes violated) of all annual security code violations occurring between 2005 and 2012.[6] To alleviate potential endogeneity concerns, my measures consist of only security code violations related to activities *outside* of the research department. Thus, any association between security code violations in non-research business activities and research quality can only be explained by

[4]For example, anecdotal evidence suggests significant culture clashes in the Merrill Lynch and Bank of America merger (http://online.wsj.com/news/articles/SB122662188273026611). Prior literature has also acknowledged "lack of cultural fit" as an important reason for why mergers and acquisitions fail (e.g., Weber, Shenkar, and Raveh (1996); Nahavandi and Malekzadeh (1988)).

[5]For example, see COSO Risk Management Summary. Practitioners have also discussed the importance of enterprise-level approaches in moving towards a "culture of compliance": (http://deloitte.wsj.com/cfo/2013/06/07/toward-a-culture-of-compliance-eight-initiatives-ccos-can-lead/).

[6]My main results are robust to scaling these measures by financial institution size and complexity.

common enterprise-level forces (i.e., corporate culture) in the financial institution.

I begin my analysis by testing the validity of my measures of security code violations. I first validate the link between security code violations and corporate culture. Consistent with security code violations being associated with cultural forces that are stable and slow to change, I find that security code violations are also persistent. For example, after splitting my sample into terciles based on all three proxies of security code violations, I find that 60-70% of institutions in the lowest (highest) tercile of violations remain in the lowest (highest) tercile of violations in the subsequent year. Next, I also establish the connection between security code violations and stakeholder tradeoffs, by examining its association with proxies for stakeholder protection and shareholder protection. Consistent with security code violations being associated with poor stakeholder protection, I find that security code violations are negatively associated with product quality scores from the Kinder, Lydenberg and Domini (KLD) corporate social responsibility database. To test the association between security code violations and shareholder protection, I construct proxies for shareholder protection using the level of institutional holdings, the Gompers index and the number of insiders sitting on the institution's board.[7] Consistent with security code violations being associated with more shareholder protection, I find that security code violations are positively associated with institutional holdings and negatively associated with both the Gompers index and the number of insiders sitting on the institution's board. Taken together, these results add credence to the notion that security code violations reflect a cultural force that has an impact on stakeholder tradeoffs.

My main empirical analysis examines the relationship between security code violations and the accuracy of the earnings forecasts produced by the analysts employed by these financial institutions. My results indicate statistically significant positive associations between measures of security code violations and relative forecast errors produced by financial institutions' analysts. The results also appear to be economically significant. A one-standard-deviation increase in the level of events, dollar value of fines, or number of unique security code violations an institution incurs is associated with an increase of approximately 2% to 4% in relative forecast errors. Overall, the results of this test provide evidence consistent with the notion that cultural forces affect employee behavior in operationally unrelated activities within financial institutions.

I conduct several robustness tests to strengthen my claim that the positive association between security code violations and analysts' forecast errors is indicative of broad cultural forces within financial institutions. First, I consider scenarios in which it is unlikely that brokerage or investment banking divisions of the financial institution will have any incentive to exert significant pressure on equity research divisions. The absence of such incentives increases the plausibility that business activities in the two divisions are unrelated and strengthens my claim that corporate culture drives the association. Accordingly, I find that my results continue to hold for subsamples of forecasts issued for thinly traded stocks (i.e., below the median trading volume) as well as forecasts that have no investment banking affiliation (i.e., no initial public offering or seasoned equity offering in the

[7] Prior studies have established that higher levels of institutional holdings are generally associated with stronger shareholder protection whereas lower levels on the Gompers index and fewer insiders are generally associated with stronger shareholder protection (Gompers, Ishii, and Metrick (2001); Larcker, Richardson, and Tuna (2007)).

prior twelve months). Second, I examine whether other visible channels (e.g., contracting, controls, etc.) can explain the association between violations and forecast errors. I find that the main results continue to hold after controlling for a number of other financial institution characteristics including financial constraints, internal control quality, compensation schemes, and corporate governance mechanisms. Taken together, the results from these analyses indicate that the positive association between security code violations and forecast errors is driven by indirect, enterprise-level forces that cannot be easily explained by investment banking influences and contracting or governance mechanisms.

I conduct three sets of additional analyses to provide further insight on the association between security code violations and forecast quality. My first set of additional analyses examines the extent to which security code violations are associated with more strategic forecast biases. Under certain scenarios, analysts face pressures to bias their forecasts (either upwards or downwards) and I expect a profit-oriented corporate culture to increase analysts' susceptibility to such pressures. Accordingly, I consider two scenarios in which analysts are most likely to feel such pressures. First, I examine investment banking affiliation as a setting that is likely to intensify pressures to issue *upwardly* biased forecasts. Second, I consider forecasts for firms that narrowly "meet or beat" consensus earnings forecasts as a setting in which managers are likely to pressure analysts to "lowball" forecasts and issue *downwardly* biased forecasts. Consistent with my expectations, I provide evidence that financial institutions with high levels of security code violations issue more *upwardly* biased forecasts for firms having undergone an equity offering in the prior 12 months and issue more *downwardly* biased forecasts for firms that just meet or beat the consensus earnings forecast by 1 cent than they do for the other firms they cover. I also find that pressures to bias forecasts upwards around recent equity offerings are particularly pronounced among junior analysts, corroborating recent survey evidence by Brown, Call, Clement, and Sharp (2014) that suggests that junior analysts are most susceptible to such pressures.

My second additional analysis examines the ability of analysts' personal reputation, as measured by All-Star rankings, to moderate the association between security code violations and forecast accuracy. As discussed above, the effects of corporate culture are likely to be muted if analysts have high levels of personal reputational capital to preserve. Consistent with this notion, I find that the positive association between security code violations and forecast errors is significantly less pronounced for analysts with All-Star status, suggesting that economic forces such as reputation can lessen the effects of culture on individual behavior.

My third additional analysis examines whether security code violations have consequences for the overall informativeness of analysts' reports. Analysts' reports do not necessarily bring new information to the market and often contain repackaged or retransmitted information that is not incrementally useful to individual investors (Lang and Lundholm (1996); Frankel, Kothari, and Weber (2006)). Security code violations can reduce the informativeness of analysts' reports because they are associated with a culture in which analysts choose to focus more heavily on providing soft services to their institutional clients and less on producing useful research reports for smaller clients who cannot directly benefit from soft services (i.e., individual investors). Consistent with this notion, my results indicate significantly negative associations between measures of security code violations and report informativeness.

My study contributes to the literature across several dimensions. First, I contribute to the literature examining the effects of sell-side analyst regulations and conflicts of interest. Prior studies provide evidence that Global Settlement and related regulations were generally effective in increasing the independence and objectivity of research divisions (e.g., Barber et al. (2006); Ertimur et al. (2007); Chen and Chen (2009); Barniv et al. (2009); Kadan, Madureira, Wang, and Zach (2009)). My findings suggest that, even in the presence of stricter divisional barriers within financial institutions, broad cultural forces can still compromise analysts' objectivity and lead to lower quality research.

Second, I contribute to the literature examining the effects of corporate culture. My analysis of security code violations allows me to shed important insight on how cultural forces within financial institutions can affect stakeholder tradeoffs made across a multitude of business lines and ultimately impact capital markets participants. In doing so, I contribute to a recent but growing literature examining how corporate culture can affect firm behavior and policy choices (Hoi et al. (2013); Gao et al. (2014); Popadak (2013); Guiso et al. (2014)), and demonstrate the effects of culture on the quality of security analysts' forecasts, which can have important implications for valuation.

Third, I contribute to the literature on the determinants of analysts' forecast quality. Prior studies consider financial institution characteristics such as size, business type, colleague quality and reputation to be important determinants of forecast accuracy (Clement (1999); Jacob, Lys, and Neale (1999); Cowen, Groysberg, and Healy (2006); Groysberg and Lee (2008); Fang and Yasuda (2009)). I contribute to this literature by providing indirect evidence that corporate culture is an important, unexplored financial institution-level characteristic that explains systematic differences in forecast quality across different financial institutions.

More broadly, my study has implications for regulators and practitioners, as well as academics that have begun to question the effectiveness of various compliance programs and risk management approaches (Kaplan (2011); Cassar and Gerakos (2013)). Documenting an association between unrelated business activities in financial institutions provides indirect evidence to support regulators' and practitioners' suggestions that "enterprise-level" interventions that encourage ethical behavior across all business activities (i.e., fostering a "culture of compliance") can be an effective approach to improving compliance within financial institutions.

This study proceeds as follows. Section II discusses the related literature and hypothesis development. Section III describes the sample selection and security code data. Section IV provides the baseline forecast accuracy results. Section V considers the robustness of my results to alternative explanations. Section VI examines additional analyses. Finally, Section VII concludes.

# II. Related Literature & Hypothesis Development

This section begins by summarizing the prior literature on corporate culture and discussing its effects on stakeholder tradeoffs within financial institutions. Next, I provide background on securities regulation and forecast quality and discuss the nature of stakeholder tradeoffs in these areas. Finally, I generate testable hypotheses that follow from these literature reviews.

## *A. Prior Literature on Corporate Culture*

Prior studies in economics and organizational behavior have offered several definitions for corporate culture. Within the economics literature, corporate culture is often viewed as a substitute for costly explicit communication that can help to improve coordination within the firm (Hermalin (2000)). For example, Kreps (1990) defines corporate culture as an intangible asset designed to meet unforeseen contingencies as they arise. Similarly, Crémer (1993) defines corporate culture as the unspoken code of communication among members of an organization. Within the organizational behavior literature, corporate culture is generally viewed as a form of "social control" that complements traditional control systems, such as incentives (Guiso et al. (2014)). Within this literature, corporate culture is defined as a set of assumptions, beliefs, values and norms shared by employees throughout the organization that informs which behaviors are appropriate (OReilly and Chatman (1996); Schein (1990)). One common implication offered across the various definitions of culture is that culture becomes important because employees "face choices that cannot be properly regulated ex ante" (Guiso et al. (2014)). These choices are likely to manifest themselves in day-to-day activities in which contracting is not feasible.

Identifying corporate culture empirically is challenging for at least two reasons. First, since corporate culture is latent and unobservable, it is difficult to observe in archival data. While some studies attempt to directly measure culture by developing proxies for employees' beliefs using survey instruments and employee job reviews (e.g., Guiso et al. (2014); Popadak (2013)), other studies must rely on indirectly inferring the effects of corporate culture (e.g., Fahlenbrach, Prilmeier, and Stulz (2012); Hoi et al. (2013); Gao et al. (2014)). For example, Fahlenbrach et al. (2012) observe similar stock price performance among banks across two financial crises and interpret this finding as indirect evidence of culture influencing banks' risk-taking. Similarly, Hoi et al. (2013) examine the association between irresponsible corporate social responsibility (CSR) acts and tax avoidance and attribute the association to corporate culture influencing both policies in the firm. Likewise, Gao et al. (2014) examine the relationship between CSR and insider trading and offer corporate culture as a possible explanation for the association. I adopt a similar approach to these studies by inferring the effects of corporate culture through the association between employee behaviors in operationally unrelated activities of the firm.

The second challenge to identifying corporate culture relates to its multi-dimensional nature. Prior studies have identified a number of dimensions of corporate culture including adaptability, collaboration, teamwork, customer-orientation, detail-orientation, integrity, transparency, etc.

(O'Reilly, Chatman, and Caldwell (1991)). Although it is likely that each firm has its own unique corporate culture with respect to all of these dimensions, one would not expect each of these dimensions to directly affect all policies within the firm. For example, observing employees taking coffee breaks together may be indicative of a corporate culture that fosters "teamwork," but this should not necessarily have any direct effects on how "customer-oriented" or "results-oriented" the culture is. Thus, it is critical for researchers to identify ex ante the particular dimension of corporate culture that they expect to be relevant to the outcome variables of interest.

This study focuses on one particular dimension of corporate culture (i.e., profit-oriented) and its effects on employee behavior within financial institutions. Since firms interact with a multitude of stakeholders (e.g., customers, suppliers, shareholders, etc.), profit-oriented corporate cultures are likely to have important effects for the trade-offs firms make when considering the competing demands of these stakeholders. Firms that foster profit-oriented corporate cultures which place a high emphasis on short-term profit generation are likely to take actions that are beneficial for shareholders in the short run but damaging for stakeholder value (and potentially long term shareholder value). For example, Popadak (2013) finds that corporate cultures that focus on profits and results neglect other stakeholders, ultimately leading to long-term value deterioration for shareholders. Similarly, Guiso et al. (2014) show that corporate cultures that foster integrity, or a commitment not to engage in economic calculations, have stronger future performance, but weaker shareholder governance mechanisms in place. Ultimately, how profit-oriented a firm's culture is will likely play an important role in regulating how employees deal with choices that involve competing stakeholders' interests.

### B. *Background on Securities Regulations*

Securities regulation is designed with the objective of protecting individual investors' welfare. Since individual investors' welfare is often at odds with generating short-term profits for shareholders, financial institutions have to balance the competing demands of these two stakeholders. On the one hand, complying with securities regulations is costly and pressures from shareholders can lead financial institutions to ignore regulations. For example, the SEC has warned that financial institutions' focus on short-term immediate profits often leads to compliance failures.[8] In a similar vein, academics have suggested that weaknesses in risk management and an overemphasis on shareholder value may have contributed to many of the recent scandals occurring within financial institutions (Laeven (2013); Ellul and Yerramilli (2013)). On the other hand, individual investors, who are often at an informational disadvantage with respect to the financial institutions they transact with, rely on financial institutions to exhibit a "high standard of care" and can be harmed when institutions fail to comply with securities regulations.[9] Noncompliance can exacerbate conflicts of interests

[8] https://www.sec.gov/news/speech/spch042303lar.htm

[9] More specifically, broker-dealers are subject to a suitability standard when transacting with individual investors. The SEC mandates the following: "In recommending to a customer the purchase, sale or exchange of any security, a member shall have reasonable grounds for believing that the recommendation is suitable for such customer upon the basis of the facts, if any, disclosed by such customer as to his other security holdings and as to his financial situation

and lead financial institutions to recommend unsuitable products or fail to provide their clients with objective and reliable investment advice, for example. Noncompliance also increases the risk of future litigation costs and reputational damage and can ultimately hurt long-term profitability. Thus, financial institutions must carefully consider the interests of competing stakeholders when making compliance decisions.

Corporate culture can have important effects for financial institutions' compliance because it likely affects the stakeholder trade-offs employees make in their day-to-day activities. Employees face choices relevant to compliance each day that are impossible to regulate ex ante and culture can help to communicate the norms and values that are considered acceptable within the firm. Consistent with this notion, regulators and practitioners have stressed the importance of culture in affecting subtle day-to-day compliance decisions. For example, the Basel Committee on Banking Supervision notes that compliance should be ingrained within the culture of the organization (Basel §6) and effective compliance requires institutions to place a strong emphasis on promoting standards of honesty and integrity across all of their activities (Basel §2). Further, practitioners have recommended enterprise-level approaches to compliance that treat compliance as a "cultural ethic that should function like any other business asset that reaches across an organization."[10] Moreover, the SEC has also stressed the important effects that an institution's culture can have on compliance:

> A culture of compliance [is] a culture of doing not only what is within the strict parameters of the law, but also what is right - whether or not a regulator or anyone else is looking. This culture underpins your business and the decisions and choices that you make every day, about small and not so small issues. For example, when you are confronted with decisions about how to handle a customer's complaint, how to correct a minor error in pricing or in net asset value, and how you deal with a disclosure issue - your decisions are made in the context of your firm's compliance culture. It is critical that firms establish a strong culture of compliance that guides and reinforces employees as they make decisions and choices each day. (SEC Speech, April 23, 2003)[11]

Overall, stakeholder tradeoffs are prevalent in the compliance decisions employees make within a financial institution and culture is likely to play an important role in communicating the appropriate course of action.

### *C. Background on Research Quality*

Analyst research is an important service provided by financial institutions that is also subject to significant stakeholder tradeoffs. On the one hand, analysts provide an important service to individual investors as they help to serve an informational intermediary role in capital markets and reduce information asymmetries between investors and the firms they invest in. A long literature in accounting has demonstrated the impact that analysts' forecasts can have on market prices

and needs." (http://www.sec.gov/answers/suitability.htm)

[10]http://deloitte.wsj.com/cfo/2013/06/07/toward-a-culture-of-compliance-eight-initiatives-ccos-can-lead/

[11]https://www.sec.gov/news/speech/spch042303lar.htm

and information content (e.g., Lang and Lundholm (1996); Gleason and Lee (2003); Frankel et al. (2006)). In addition, producing accurate forecasts has long-run benefits for financial institutions as it allows them to generate a reputation for credibility and generate more revenues from investment banking and brokerage businesses (Mehran and Stulz (2007); Ljungqvist, Marston, and Wilhelm (2006)). Thus, producing accurate research is beneficial to the individual investors who rely on analyst research when making investment decisions and can have long-term benefits for the financial institution.

On the other hand, analyst research is largely funded by institutional clients that exhibit a low demand for high-quality earnings forecasts. For example, Institutional Investor rankings consistently rank "earnings forecast accuracy" among the lowest items of importance for institutional clients, while softer services and skills such as "management access" and "accessibility" rank among the highest (Bradshaw (2011)).[12] Thus, shareholder pressures to maximize short-run profits may lead analysts to neglect their earnings forecasts. By neglecting their earnings forecasts, analysts are better able to focus their attention and efforts on meeting the more immediate demands of institutional clients. In practice, this might require analysts to spend a large amount of their time discussing investment strategies or performing ad hoc analyses for these clients, and less effort on producing accurate earnings estimates. In addition, a focus on short-term profits can also increase the likelihood that analysts bias their forecasts upwards or downwards, which also leads to less accurate research. For example, investment bankers might pressure analysts to issue optimistic forecasts to promote recent underwritings (Lin and McNichols (1998); Michaely and Womack (1999)). Analysts may also face pressures from firm management to bias their forecasts downwards to create easily beatable earnings targets (Ke and Yu (2006); Hilary and Hsu (2013)). Since institutional clients value access to management, these pressures are likely to be intensified within institutions that place a high emphasis on short-term profits. Overall, the importance analysts place on their earnings forecasts is likely to be a result of the trade-offs they make when considering competing stakeholders' interests.

Earnings forecasts provide a useful setting for examining the effects of corporate culture for several reasons. First, unlike other products produced by financial institutions, earnings forecasts are difficult to regulate. Although regulatory guidance urges analysts to provide "objective and reliable research," enforcing forecast quality is difficult since regulators are unable to determine the extent to which analysts neglect their forecasts, intentionally bias their forecasts to mislead investors, or are simply inaccurate due to low ability or chance.[13] Similarly, even if financial institutions wanted to set a high standard for forecast quality, it would be difficult to enforce and regulate analysts'

[12] Similarly, recent studies suggest that forecast accuracy is an insignificant determinant of analysts' compensation (Brown et al. (2014); Groysberg, Healy, and Maber (2011)). Using survey data, Brown et al. (2014) finds that equity analysts ranked forecast accuracy as the least important determinant of their compensation. Further, using proprietary data obtained from a high-status investment bank, Groysberg et al. (2011) find that while investment banking contributions are strongly correlated with compensation, there is no evidence to support accuracy influencing analysts' compensation. The director of research at one large financial institution remarked that clients "pay for the services of an analyst" and that it is not important that "they get earnings, or for that matter, stock prices, right" (Groysberg et al. (2011), p.985).

[13] http://finra.complinet.com/en/display/display_main.html?rbid=2403&element_id=7200

forecasts.[14] Thus, market forces and traditional control systems are likely to be weak deterrents in preventing analysts from acting opportunistically when generating earnings forecasts. Instead, elevating forecast quality to a level of a "value" or "norm" within the financial institution might be a more effective way of enforcing appropriate behavior. Second, prior studies examining determinants of forecast quality have noted substantial cross-sectional differences in forecast quality across different financial institutions (Clement (1999); Jacob et al. (1999); Cowen et al. (2006); Groysberg and Lee (2008)). For example, these studies have identified financial institution characteristics such as size, business type, and colleague quality to be important determinants of forecast quality. Corporate culture can be an important unexplored financial institution-level characteristic that explains systematic differences in forecast quality across different institutions. Third, Global Settlement and other significant regulatory efforts have been made in the research industry to increase analysts' objectivity. While creating divisional lines (i.e., the "Chinese Wall") between research divisions and investment banking/brokerage divisions has generally improved research quality (e.g., Ertimur et al. (2007); Chen and Chen (2009); Barniv et al. (2009); Kadan et al. (2009)), culture may be a powerful force that limits the effectiveness of these regulations.

### *D. Hypothesis Development*

Taken together, the preceding arguments imply that if a profit-oriented corporate culture affects stakeholder tradeoffs in a financial institution, security code violations are likely to be positively associated with analysts' forecast errors. As discussed above, profit-oriented corporate cultures will encourage analysts to spend less time on producing accurate earnings forecasts and potentially also allow biases to influence analysts' forecasts. Accordingly, this leads to my first hypothesis:

**Hypothesis 1:** *Financial institutions' security code violations are positively associated with absolute forecast errors.*

Hypothesis 1 does not distinguish between analysts exerting less effort on their forecasts or being more susceptible to pressures to bias their forecasts. My second set of hypotheses examines the extent to which analysts' forecasts exhibit intentional bias. As discussed earlier, analysts face pressures to bias their forecasts upward or downward from different parties, which may result in forecasts that are overall less accurate but exhibit no sign of strategic bias, on average. Thus, identifying strategic biases in their forecasts requires identifying specific settings in which these biases are more likely to appear.

To identify strategic biases in analysts' forecasts, I consider two unique settings in which analysts are likely to face pressures to bias their forecasts. The first setting relates to a scenario in which analysts are likely to face pressures to issue *upwardly* biased forecasts. Analysts generally face such pressures in the period following recent equity offerings. In this period, analysts are often expected

[14] On the other hand, regulators and firm management have had more success at regulating other components of the analyst report such as recommendations. Following Global Settlement, most financial institutions began to carefully monitor the percentage of buy/sell/hold recommendations to meet regulatory requirements (Kadan et al. (2009)).

to issue optimistic forecasts for recent investment banking clients in order to promote the firms (e.g., Lin and McNichols (1998); Michaely and Womack (1999)). Accordingly, Hypothesis 2A predicts increased levels of *upwardly* biased forecasts around equity offerings for financial institutions that have more security code violations. Specifically:

**Hypothesis 2A:** *The relation between financial institutions' security code violations and upwardly biased forecasts is more positive following recent underwriting activity.*

The second setting relates to a scenario in which analysts are likely to face pressures to issue *downwardly* biased forecasts. Analysts may face such pressures from managers of firms who are at risk of not meeting or beating earnings estimates. Managers of such firms may pressure analysts to "lowball" forecasts to increase the likelihood that they can meet the earnings threshold (e.g., Bhojraj, Hribar, Picconi, and McInnis (2009); Hilary and Hsu (2013)). Accordingly, Hypothesis 2B predicts increased levels of *downwardly* biased forecasts for firms that just meet or beat the consensus earnings forecast when those forecasts are produced by analysts at financial institutions with more security code violations. Specifically:

**Hypothesis 2B:** *The relation between financial institutions' security code violations and downwardly biased forecasts is more positive for firms that narrowly "meet or beat" consensus earnings forecasts.*

My third hypothesis examines the ability of economic forces to counteract the effects of corporate culture. The effects of corporate culture on stakeholder tradeoffs in research divisions may be lessened if analysts have strong external incentives to produce high quality forecasts. Prior studies have shown that analysts depend heavily on being perceived credible by market participants and have incentives to build a reputation for providing accurate and objective forecasts (e.g., Hong et al. (2000); Mehran and Stulz (2007)). Fang and Yasuda (2009) also show that analysts' reputational concerns are stronger than institution-level reputational concerns in disciplining analyst behavior. Thus, analysts who have developed strong reputations for producing accurate forecasts may be less likely to adhere to norms that are damaging to individual investors. Accordingly, my third hypothesis examines the ability of All-Star Analyst rankings, an important indicator of analysts' reputational capital, to moderate the association between security code violations and forecast errors.

**Hypothesis 3:** *The relation between financial institutions' security code violations and absolute forecast errors is less positive for forecasts produced by All-Star Analysts.*

My fourth and final hypothesis examines whether and to what extent security code violations have consequences for market participants, in terms of analysts' report informativeness. Analysts do not necessarily always bring new information to the market, and prior studies have demonstrated that analysts often repackage or retransmit information that is not incrementally useful to individual investors (Lang and Lundholm (1996); Frankel et al. (2006)). Further, analysts' incentives to intentionally misinform individual investors through biased forecasts also limits the ability of their reports to enhance informational efficiency. Consistent with this notion, regulators have warned that poor compliance can prevent clients from making fully-informed investment decisions.[15] Accordingly, if security code violations have negative consequences for market participants, they should be associated with less informative reports, leading to my fourth hypothesis:

**Hypothesis 4:** *Financial institutions' security code violations are negatively associated with report informativeness.*

## III. Data & Sample Selection

This section discusses the security code data used throughout the study. I begin by discussing the sample selection and the measures of security code violations. Next, I discuss key characteristics of security code violations and FINRA *BrokerCheck* disclosure events. Finally, I validate that the measures of security code violations are consistent with the claim that cultural forces affect stakeholder tradeoffs made within financial institutions.

### *A. Sample Selection*

I start my sample selection by obtaining a list of financial conglomerates with U.S. security subsidiaries from the Federal Reserve.[16] This initial sample consists of 80 security subsidiaries across 59 financial institutions. The financial institutions in this sample are among the largest and most complex financial conglomerates in the world and collectively hold the vast majority of U.S. banking assets. For each of the security subsidiaries in the initial sample, I collect SEC registration numbers from the SEC website, to ensure an accurate match to security code data.[17] Several of the institutions in the sample, such as Wells Fargo & Company, are a result of large mergers and acquisitions.[18] For these institutions, I exclude their observations prior to the merger date.

My sample is further restricted by the availability of analyst forecast data. For each of the financial institutions in the sample, I hand-collect financial institution names from I/B/E/S (using the 2007 broker translation file). To be included in the sample, I require the financial institution to employ at least one analyst covering a firm that is covered by at least one other institution in the sample. This facilitates relative comparisons of analysts' forecasts across financial institutions within my sample. Table I, Panel A presents the final sample of financial institutions, including their SEC numbers and Central Registration Depository (CRD) numbers (obtained from FINRA). The sample consists of 48 security subsidiaries across 29 financial institutions and includes 204 financial institution-years.

[15] http://www.sec.gov/News/Speech/Detail/Speech/1370539960588#.U78p_IdV8e
[16] http://www.federalreserve.gov/bankinforeg/suds.htm
[17] http://www.sec.gov/about/offices/oia/oia_regstat.htm
[18] Wells Fargo & Company merged with Wachovia Corporation near the end of 2008.

For each of the security subsidiaries in the sample, I download and collect *BrokerCheck* reports from FINRA's website using the web tool outlined in Appendix A. The *BrokerCheck* report is a tool that FINRA provides to allow investors to research the regulatory history of any financial institution or individual broker. This data also contains information regarding the types of businesses these financial institutions engage in. Table I, Panel B provides the distribution of the "Business Type" as reported by FINRA. Although my sample focuses on large financial conglomerates, there still exists some heterogeneity across the business lines in which these institutions engage in. All of the financial institutions in the sample are an underwriter or selling group participant of securities ($n$ = 29 financial institutions) and many institutions deal common products such as corporate equity securities ($n$ = 25 financial institutions). Far fewer institutions participate in more exotic businesses such as real estate syndication ($n$ = 3 financial institutions) or sales of oil and gas interests ($n = 4$ financial institutions).

The primary data for security code violations used throughout the study comes from the "Disclosure Events" section of the FINRA *BrokerCheck* reports. These events contain all relevant information related to disciplinary events, as reported by securities regulators. Table II outlines the sample selection procedure for this data. In the sample, I include all completed (i.e., not pending) disclosure events with non-missing case numbers issued between 2005 and 2012, so as to reduce the influence of Global Settlement and other related regulatory actions on my results and ensure that research divisions are operationally independent. I delete disclosure events with missing (or duplicate) case numbers, as well as disclosure events with no fines indicated in the allegations section of the report. I retain only disclosure events issued by major regulatory agencies (FINRA, NASD, and NYSE) and exclude disclosure events issued by state agencies to avoid double counting events, as many of these events are redundant. Finally, to alleviate potential endogeneity concerns, I exclude events related to research department activities. Specifically, I delete 20 observations in which the allegations mention the word "Research" or contain violations of NASD Code 1050 or NASD Code 2711, which regulate equity research. As discussed in Section II, these violations are likely rare because research quality is difficult to regulate. Nonetheless, removing these observations allows me to cleanly examine the association between employee behavior in one division of the financial institution (e.g., brokerage or investment banking divisions) and behavior in another division of the institution (i.e., research division), which I posit is driven by an overall corporate culture within the financial institution. The final sample consists of 472 disclosure events issued between 2005 and 2012.

### B. *Measures of Security Code Violations*

I create three measures of security code violations using data obtained from the "Disclosure Events" section of the *BrokerCheck* reports. The first is the number of disclosure events (*TotalEvents*) the financial institution experiences in a year. The second is the total dollar value of fines (*TotalFines*) sanctioned against the financial institution in a year. The third variable is the total number of unique security code violations (*TotalCodes*) a financial institution experiences in a year. *TotalEvents* proxies for the frequency of security code violations, while *TotalFines* better captures the severity of security code violations. *TotalCodes* captures the scope of security code violations within the financial institution, but is potentially a noisier measure as a substantial number of disclosure events fail to indicate the particular security code violated.[19] All variable definitions are also provided in Appendix B.

Figure 1 provides examples of several disclosure events. In Example 1, the financial institution was fined approximately $1,000,000 for violating short-sale regulations around five IPOs, by selling certain securities short prior to the pricing of the public offerings (to artificially depress the price) and then repurchasing them. In Example 2, the financial institution was fined $375,000 for violating NASD Rules 2110, 2210 and 3010 by selling collateralized mortgage obligation securities to unsophisticated investors.[20] Both examples are consistent with violations reflecting a profit-oriented corporate culture in which employees take actions that appear to be geared towards generating short-term profits at the expense of other stakeholders' welfare.

One potential limitation of this data is that the date of the actual violation is rarely referenced. Instead, FINRA only reports the date that the institution is sanctioned. The reports that do disclose event dates vary substantially, with some events occurring recently (e.g., prior year) and others occurring many years earlier. Thus, my financial institution-year measures of security code violations rely on the year reported within the "sanction date" and assume that compliance problems remain relatively constant between the event date and the sanction date. However, to the extent that compliance is driven by cultural forces in the firm, this assumption is consistent with prior studies that suggest that culture within firms is persistent and slow to change (e.g., Tayler and Bloomfield (2011)). I test the validity of this assumption in Section III.E.

## *C. Security Code Violation Characteristics*

As illustrated in the examples in Figure 1, disclosure events are often bundled with a number of security code violations, likely due to the fact that FINRA frequently conducts cycle audits. In order to gain a better understanding of the nature of these violations, I manually count, read and hand-collect the types of violations referred to in the "Allegations" section of all of the *BrokerCheck* reports. Across the 472 disclosure events, there are 1,108 unique security code violations.

Table III presents key characteristics of the security code violations in the sample. Panel A presents the frequency of disclosure events by the number of violations reported. The majority of the disclosure events have between 1-3 violations (12%+24%+16% = 52%). About 24% of the events do not identify a particular violation, and 7% of the events have more than 5 security code violations. These differences may be related to the level of effort that the agent reporting the violation exerts when recording the incident.[21]

[19] In subsequent analyses, I construct variables of interest based on the natural log of these three variables (i.e., *LogFines*, *LogFines*, and *LogCodes*) to reduce the influence of extreme observations on correlation and regression inferences. To ease interpretation, I refer to the raw variables when discussing the summary statistics.

[20] The allegations section of this report is truncated to preserve space.

[21] For example, the disclosure events that disclose more security code violations also appear to have more detailed

In general, FINRA regulation covers a wide array of market activities, ranging from broad rules such as FINRA 2010, which relates to poor business conduct and a general lack of "just and equitable" trading practices to more specific rules such as FINRA 3300, a rule designed to prevent money laundering. Table III, Panel B lists the top 10 most frequently occurring securities code violations that occur in the sample. Disclosure events in the sample often contain a violation of NASD 2110 (42% of events) and its successor rule, FINRA Rule 2010 (12% of events), both of which are related to violations of "Standards of Commercial Honor and Principles of Trade." Other violations are more specific. For example, 6% of events violate NASD Rule 2320 "Order Data Transmission Requirements," which requires reasonable due diligence in routing customer trades and 10% of events violate NASD Rule 6130 "Trade Report Input," which requires the institutions to submit accurate trade information. The codes I document as occurring most frequently are also consistent with the codes that FINRA warns are most frequently violated.[22]

Developing a consistent categorization of the violations is challenging since FINRA is the result of consolidation of major enforcement operations of the NASD and NYSE. Thus, the rule books have changed and evolved over time and many older rules have simply been renumbered under the new regime (e.g., NASD 2110, the former business conduct rule, appears to be equivalent to FINRA Rule 2010 now). To facilitate the analysis, I develop a framework to categorize violations by manually mapping each each of the violations in the sample to one of the major categories (i.e., 4-digit level) in the current FINRA handbook. This mapping scheme is presented in Appendix C.[23] In Table III, Panel C, I present the frequency of violations using this mapping scheme. The most frequently occurring violations are related to "Duties & Conflicts" (60% of events) and "Supervision and Responsibilities Relating to Associated Persons" (42% of events). These violations generally represent instances in which financial institutions failed to act in the best interests of their stakeholders.

### D. Disclosure Event Characteristics

Table IV displays key characteristics of the disclosure events data. Panel A presents the frequency of disclosure events by year. In general, $TotalEvents$ and $TotalCodes$ appear to be cyclical, peaking in 2007 and 2010. In 2010, the largest number of disclosure events occur ($n = 77$), perhaps indicating heightened regulatory response to the financial crisis. $TotalFines$ also appears to by cyclical, and has relative peaks in 2007 and 2011. The peak in $TotalFines$ in 2005 is attributed to a one time fine of $250 million sanctioned upon one financial institution in the sample for illegal

allegation summaries and are less likely to have spelling errors.

[22]For example, FINRA also warns that NASD Rule 2110, 3010, 6955, 6130 and 3110 are frequently violated (http://www.finra.org/Investors/ToolsCalculators/BrokerCheck/P015177).

[23]I also use this mapping scheme to create additional measures that relate to the specific security code violation related to the event. Specifically, I create indicator variables for events that contain trading rule violations that fall under the major categories outlined in Appendix C. *ClearTrade*, *DutyConflict*, *FinOps*, *InvSanct*, *Application*, *TransReport*, *SecOffer* and *Supervision* are coded 1 if the event contains at least one security code violation relating to the type, and 0 otherwise.

mutual fund activity.[24] Interestingly, the average fine per disclosure event also appears to have declined in recent years. Prior to 2008, average fines were greater than \$1 million. However, in recent years, fines are much smaller, ranging from about \$100,000 to \$700,000 each.

Table IV, Panel B presents the disclosure event frequency by anonymized financial institution. Nearly all of the institutions (25 out of 29) within the sample receive a violation during the sample period.[25] The data also suggests some important differences in the nature of the disclosure events. For example, Financial Institution 1 receives the largest number of fines over the sample period (~\$260 million), but Financial Institution 6 receives the largest number of disclosure events (62 events) and substantially less fines (~\$10 million). Thus, the disclosure events, on average, appear to be much more severe for Financial Institution 1 than for Financial Institution 6. In untabulated analyses, I find that many of the disclosure events for Financial Institution 6 are related to potentially smaller trading issues categorized in Appendix C (i.e., $ClearTrade$ or $TransReport$), while the disclosure events for Financial Institution 1 are related to supervisory failures ($Supervision$) that appear to be more serious. Interestingly, many financial institutions are sanctioned with no security code violations identified (e.g., Financial Institutions 12-14), perhaps suggesting that agents have some discretion over how they report the allegations. Overall, the trends suggest that $TotalEvents$, $TotalFines$ and $TotalCodes$ capture different dimensions of security code violations.

Table IV, Panel C presents the correlation of fines and violations within disclosure events. The correlations suggest several interesting relationships. First, the positive correlation between the natural log of total fines ($LogFines$) and the natural log of total security code violations ($LogCodes$) is 0.319, suggesting that larger fines tend to have more security code violations. Further, $LogFines$ is positively correlated with $DutyConflict$ (= 0.330) and Supervision (= 0.373), suggesting that the most heavily fined disclosure events often contain at least one violation related to a conflict of interest, breach of "duty of care," or supervisory failure. Moreover, "bundling" of security code violations also appears to be common in the sample period. For example, $LogCodes$ is highly correlated with $DutyConflict$ (= 0.784) and Supervision (= 0.593), suggesting that it is common for regulators to bundle a number of other security code violations with these particular violations. This is not surprising given that FINRA often conducts cycle examinations and files a number of complaints against a financial institution at once. In terms of the type of bundling, the positive correlation between $DutyConflict$ and $Supervision$ (= 0.457) suggests that "Duties & Conflicts" violations are often bundled with a "Supervisory" violation related to management's failure to prevent employee misconduct.

Overall, the discussions in Sections III.C and III.D provide preliminary descriptive evidence on the nature of securities regulation and common types of violations. In particular, the analyses show that while securities regulations are designed to govern a wide range of market activities, they share the common intention of protecting investor welfare. Violations of these regulations are consistent with financial institutions' failing to act in the best interest of these investors.

[24] Inferences from regressions results are also similar if I exclude this observation.

[25] My main inferences remain unchanged if I exclude the four institutions that did not receive any violations from the analysis.

*E. Measure Validity*

My hypotheses stem from the notion that security code violations are consistent with cultural forces affecting stakeholder tradeoffs that employees within financial institutions make. In this section, I attempt to validate this claim by examining the links between security code violations and culture and stakeholder/shareholder tradeoffs.

I first validate the link between security code violations and culture. Following prior studies that suggest that culture within firms is stable and slow to change (e.g., Tayler and Bloomfield (2011); Popadak (2013)), I examine the persistence of the three security code violation measures. In Table V Panel A, I examine the correlation of all three proxies for security code violations with up to three lags of each measure. The correlations range from about 50% to 75%, suggesting that violations are highly persistent. In Panel B, I construct transition matrices that measure the probability of an institution experiencing a certain level of $TotalEvents$, $TotalFines$ or $TotalCodes$ in period $t+1$, conditional on its level in period $t$. The transition matrices also suggest that these security code violations are rather persistent throughout the sample period. About 60-70% of financial institution-years that are in the lowest (highest) tercile of $TotalEvents$, $TotalFines$ or $TotalCodes$ in the current period remain in the lowest (highest) tercile in the following period. These analyses add further support to my claim that security code violations are consistent with persistent cultural forces in the firm.

I next validate the link between security code violations and stakeholder/shareholder tradeoffs. To do so, I construct proxies for stakeholder protection and shareholder protection and examine their association with all three measures of security code violations. First, I construct a proxy for stakeholder protection based on product quality ratings ($KLDProduct$) obtained from the Kinder, Lydenberg, and Domini (KLD) corporate social responsibility database. KLD evaluates firms across seven dimensions and awards firms points for their strengths, deducts points for their weaknesses, and constructs a net measure as the difference between the firm's strengths and weaknesses. Firms are awarded points for producing high quality, innovative, and socially beneficial products and points are deducted for firms that produce unsafe and poorly marketed products. If security code violations are consistent with financial institutions producing unsuitable investment products for their clients, there should be a negative association between proxies for security code violations and $KLDProduct$.

Second, following prior studies (e.g., Larcker et al. (2007)), I also consider three proxies for the quality of shareholder protection afforded by financial institutions using hand-collected data from RiskMetrics, Capital IQ and Factset. First, $InstHoldings$ is measured as the percentage of shares held by institutional investors. Second, $Gompers$ is a composite index that proxies for managerial power and is based on the last available Gompers index constructed in 2006. Third, $Insiders$ is the percentage of insiders sitting on the board. Higher levels of institutional holdings are generally associated with stronger shareholder protection whereas lower levels on the Gompers index and fewer insiders are generally associated with stronger shareholder protection. If security code violations are consistent with profit-oriented financial institutions fostering a culture that caters towards the demands of shareholders, there should be a positive association between proxies for security code violations and $InstHoldings$ and negative associations between proxies for security code violations and $Gompers$ and $Insiders$.

Table V, Panel C presents the correlation between proxies for security code violations and proxies for stakeholder/shareholder protection (bolded values are significant at the 10% level). While there are 204 financial institution-year observations in the full sample, data availability varies extensively across the four stakeholder/shareholder protection measures, potentially limiting the generalizability of these associations. Regardless, the correlations for the available data are consistent with my expectations. First, I find negative and significant correlations between my proxy for stakeholder protection ($KLDProduct$) and all three measures of security code violations. Second, I also find evidence consistent with the notion that financial institutions with high levels of security code violations have stronger shareholder protection. I find a positive association between $InstHoldings$ and all three proxies for security code violations and a negative association between both $Gompers$ and $Insiders$ and all three proxies for security code violations. Taken together, these results add support to my claim that financial institutions that violate securities regulations appear to neglect individual investors and afford better protections to their shareholders.

# IV. Forecast Sample & Regression Results

## *A. Research Design*

My main analysis examines the association between security code violations and the forecast accuracy of reports produced by financial institutions' equity research departments. To measure forecast accuracy, I construct a measure of relative forecast error ($RFError$) similar to prior studies (e.g., Clement (1999); Cowen et al. (2006)) examining relative forecast properties:

$$RFError_{i,j,t} = \frac{AFE_{i,j,t} - \overline{AFE_{j,t}}}{\overline{AFE_{j,t}}} \tag{1}$$

where $AFE_{i,j,t}$ is the absolute forecast error for analyst $i$'s forecast for firm $j$ in year $t$ and $\overline{AFE_{j,t}}$ is the mean absolute forecast error for firm $j$ in year $t$ across all analysts providing forecasts in the sample. Consistent with the prior literature, forecast errors are calculated using the last forecast issued in the first 11 months of the fiscal year. By construction, $RFError$ controls for important firm-year differences, and prior studies provide evidence that this approach is more effective than forecast level regressions that include firm and year fixed effects as separate controls (Clement (1999)).

To examine the relationship between security code violations and relative forecast errors, I employ the following regression model:

$$
\begin{aligned}
RFError_{i,j,t} = \beta_0 + \beta_1 Violations_{f,t} + \beta_2 AnalystControls_{i,j,t} \\
+ \beta_3 FIControls_{f,t} + \sum_t Year_t + \epsilon_{i,j,t}.
\end{aligned} \tag{2}
$$

where $i$ denotes analyst, $j$ denotes firm, $t$ denotes time, and $f$ denotes the financial institution (for which analyst $i$ is employed in year $t$). Proxies for *Violations* include *LogEvents*, *LogFines* and *LogCodes*. *LogEvents* is the natural log of one plus the total number of disclosure events a financial institution receives in a year, *LogFines* is the natural log of one plus the dollar value of total fines sanctioned against a financial institution in a year, and *LogCodes* is the natural log of one plus the total number of unique security code violations a financial institution receives in a year.

*AnalystControls* is a vector that includes important analyst characteristics that can potentially correlate with measures of security code violations and forecast accuracy. *RExp* is the relative forecast experience of the analyst providing the forecast (in terms of the number of years she has covered the firm). *RHorizon* is the relative forecast horizon (in terms of the number of days until the nearest earnings announcement). *RFirmsCovered* is the relative number of firms covered by the analyst. To control for important differences across firm-years, *RExp*, *RHorizon* and *RFirmsCovered* are relative to the firm-year and are constructed similarly to *RFError* (i.e., by differencing out and scaling by the the firm-year mean of each measure).

The model also includes a vector of *FIControls* that are likely to influence the quality of research products. *FIPrestige*, a proxy for reputation, is an indicator variable that takes the value of 1 if the financial institution is one of the top 10 Institutional Investor-Ranked financial institutions (as indicated on the Institutional Investor website), and 0 otherwise. *FIComplexity* is the natural log of one plus the total number of business lines in the financial institution (as observed in the FINRA *BrokerCheck* report). *FISize* is the natural log of the total number of analysts employed at the financial institution in the period. All continuous variables are winsorized at the 1st and 99th percentiles.

I also consider a modification of the baseline model that includes a set of financial institution fixed effects. As discussed earlier, security code violations are persistent and slow to change, consistent with violations representing steady cultural forces within the firm. However, it is still possible that there exist time-invariant differences in the sensitivity of financial institutions' research activities to their established corporate cultures, thus making the inclusion of financial institution fixed effects appropriate. The modified model is the same as the baseline model, except that I remove non-time-varying financial institution characteristics (i.e., *FIPrestige* and *FIComplexity*) from the model and replace these characteristics with financial institution fixed effects.

Finally, all models include year fixed effects and standard errors are clustered by financial institution and year; however, clustering by analyst instead of financial institution does not alter my main inferences. If security code violations are positively associated with absolute forecast errors, $\beta_1$ should be positive.

Table VI describes the forecast sample in more detail. Panel A provides the descriptive statistics. The first quartile, median and third quartile of $RFError$ are very similar to the reported values in Clement (1999). Not surprisingly, the financial institutions in the sample appear to be larger and more complex financial institutions. The mean forecast in the sample is issued by an analyst employed by a financial institution with nearly 100 analysts and 21 unique business lines. Moreover, the mean level of $FIPrestige$ is 0.523, suggesting that many of the forecasts appear to be issued by financial institutions that are typically regarded as prestigious and reputable by traditional rankings.

Panel B of Table VI presents the correlation among the variables of interest (bolded values indicate significance at the 1% level). Consistent with Hypothesis 1, all three measures of security code violations are positively associated with $RFError$ in the univariate correlations. The correlation between $RFError$ and *LogEvents*, *LogFines* and *LogCodes* are 0.047, 0.034, and 0.032, respectively. Interestingly, the proxies for security code violations are also negatively correlated with *RExp* and positively correlated with *RHorizon* and *RFirmsCovered*, suggesting that financial institutions with more security code violations hire less experienced analysts that cover more firms, but issue forecasts much earlier in the fiscal year.

## B. *Regression Results*

Table VII presents the regression results from estimates of Equation 2. Panel A presents the results when the security code violations proxy is *LogEvents*. Panel B presents the results when security code violations are measured as *LogFines*. Panel C presents the results when security code violations are measured as *LogCodes*. In Column 1, I first examine the association between *LogEvents* and $RFError$ without control variables. Consistent with my prediction, the coefficient on *LogEvents* is positive and significant ($p < .01$). In Column 2, I include the set of *AnalystControls* and *FIControls* as well as year fixed effects and find similar results ($p < .01$). In Column 3, I remove $FIPrestige$ and $FIComplexity$ and include a set of financial institution fixed effects and also generate similar results ($p < .01$). In addition to being statistically significant, the results also appear to be economically meaningful. A one-standard-deviation increase in *LogEvents* ($\sigma$=0.6633) is associated with a 3.5% (0.6633 $\times$ 0.0528) increase in relative forecast errors, based on the coefficient estimates in Column 2.

In Panels B and Panel C, I repeat this analysis using *LogFines* and *LogCodes* as my measures of security code violations and generate similar results. In Panel B, *LogFines* is positively and significantly correlated with $RFError$ in Column 1 ($p < .01$), and remains significant after adding a full set of controls in Column 2 ($p < .01$) and after controlling for financial institution fixed effects in Column 3 ($p < .10$). In Panel C, *LogCodes* is also positively and significantly correlated with $RFError$, as indicated in Column 1 ($p < .05$). The effect persists with the inclusion of controls in Column 2 ($p < .01$), but loses significance when I include financial institution fixed effects in Column 3. However, this measure is potentially noisy as some financial institutions receive no allegations with specified security code violations. In terms of economic significance, both *LogFines* and *LogCodes* also appear to be meaningful. A one-standard-deviation increase in *LogFines* ($\sigma$=4.4854) is associated with a 1.9% (0.0043 $\times$ 4.4854) increase in relative forecast errors, based on the coefficient estimates in Panel B, Column 2. Similarly, a one-standard-deviation increase in LogCodes ($\sigma$=1.1867) is associated with a 3.1% (0.0262 $\times$ 1.1867) increase in relative forecast errors, based on the estimates reported in Panel C, Column 2.[26]

Overall, the results in Table VII are consistent with Hypothesis 1. Financial institutions with more security code violations appear to produce relatively less accurate forecasts. Interestingly, the effects are stronger when security code violations are measured based on the number of disclosure events (i.e., *LogEvents*) and the number of unique security code violations (i.e., *LogCodes*) as opposed to the dollar value of the violations (i.e., *LogFines*), suggesting that more frequent and broad compliance problems are potentially more indicative of weaker corporate culture than are severe, but potentially more transitory violations.

## V. Robustness

In this section, I test the robustness of my main findings. I first conduct general robustness tests that include alternative scalars and measures of security code violations. Next, I conduct tests to rule out the alternative explanation that security code violations directly affect forecast accuracy. Finally, I demonstrate the persistence of my results after controlling for explanations other than corporate culture that might explain the association between security code violations and forecast accuracy.

### A. *General Robustness*

In untabulated analyses, I conduct several tests (untabulated) to test the robustness of my main results in Table VII. First, I augment the regression results to contain a set of Financial Institution $\times$ Year fixed effects and produce similar inferences. Second, I produce similar inferences when I conduct quantile regressions and reconstruct measures of security code violations based on annual terciles, quintiles, and deciles to reduce the influence of extreme observations. Third, my results remain strong when I consider composite measures of security code violations by independently ranking each of the three security code violations proxies and then averaging their ranks. Fourth, I consider different scalars, including the number of business lines (i.e., *FIComplexity*) and the number of analysts (i.e., *FISize*) and produce similar inferences. Fifth, recognizing that culture is persistent and slow to change, I also construct aggregate measures of security code violations, by summing *TotalEvents*, *TotalFines*, and *TotalCodes* over the entire sample period (and producing 29 financial institution characteristics). My inferences remain unchanged when I conduct these tests.[27] Finally, I consider the possibility that my results are driven by a subsample of financial

[26]The $R^2$ from these models are also similar to prior studies examining the effect of financial institution characteristics on forecast errors (e.g., Cowen et al. (2006)).

[27]Inferences from tests using aggregate measures should be interpreted with caution, however, as they potentially introduce a look-ahead bias and reverse causality concerns.

institutions that may be more likely to be targeted by regulators or a specific time period in which there is heightened regulatory pressure. I produce similar results among subsamples split on financial institution prestige, complexity, size and time period. Overall, the results of these analyses provide consistent evidence to support a strong positive association between measures of security code violations and the relative forecast errors produced by financial institutions' equity research departments.

### B. *Direct Effects of Security Code Violations on Forecast Accuracy*

The results in Table VII provide strong evidence of an association between security code violations and forecast accuracy. Since security code violations and forecast accuracy are outcomes of operationally unrelated activities in the financial institution, I interpret this finding as providing *indirect* evidence consistent with an overall corporate culture influencing activities across multiple areas within the institution. One alternative explanation for this finding is that security code violations *directly* affect forecast accuracy. This direct effect can occur if violations are a result of brokerage divisions or investment banking divisions directly influencing analysts' forecast quality. For example, trading commissions in the brokerage division might lead employees to pressure analysts to issue less objective forecasts (Cowen et al. (2006); Jackson (2005)). Similarly, investment banking commissions might also lead employees to pressure analysts to issue biased forecasts (Lin and McNichols (1998); Michaely and Womack (1999)).

To examine the extent to which forecast quality is directly influenced by violations in non-research divisions, I re-examine the baseline regression (i.e., Equation 2) for observations in which incentives to directly influence analysts are likely to be low. I consider two such scenarios. First, I examine forecasts issued for stocks below the median level of trading volume, since pressures are likely to be lower for thinly traded stocks that generate less brokerage commissions. Second, I examine a subsample of forecasts issued for stocks which appear to have no recent investment banking affiliation (i.e., no initial public offering or seasoned equity offering in the prior 12 months), and are thus less likely to face pressures from investment banking divisions to issue less objective forecasts.

Table VIII provides the regression results from these subsample tests. Panel A presents the subsample of forecasts issued for firms with low trading volume. Panel B presents the subsample of forecasts issued for firms with no affiliation.[28] The association between proxies for security code violations and forecast errors remains positive in all regressions and is significant in all except one test. Thus, even in scenarios where pressures for divisions to directly influence analysts' forecasts are likely to be low, there appears to be a significant association between security code violations and forecast quality, suggesting that indirect forces (i.e., corporate culture) are likely to explain this association.

[28]This subsample is relatively large since only 2,456 forecasts are "Affiliated" in the sample.

## C. Alternative Explanations

Academics and regulators have offered numerous explanations for compliance failures within financial institutions, including culture, poor internal control systems, flawed compensation schemes, poor governance, etc. (e.g., Kashyap, Rajan, and Stein (2008); Ellul and Yerramilli (2013)). Thus, it is possible that the association I document between security code violations and forecast accuracy is driven by other visible forces within the firm that may not be related to culture. In this section, I consider the ability of these alternative explanations to explain the association between security code violations and relative forecast errors.

To consider these alternative explanations, I re-examine the baseline regression (i.e., Equation 2) and include controls for other factors that may drive the association between security code violations and forecast accuracy. First, I consider general characteristics of the financial institution, including $Size$, measured as the natural log of assets, and $Profitability$, measured as net income divided by total assets. Larger and less profitable financial institutions might find it more difficult to comply with regulations if they are constrained and may also hire less experienced analysts that command lower salaries. Second, I consider internal control quality ($ICW$), an indicator variable that takes the value of 1 if the financial institution has a material weakness or significant deficiency in its internal controls, and 0 otherwise. Poor internal control systems can increase the probability that employees violate compliance protocol and may also result in analysts producing less accurate forecasts. Third, I also consider whether short-term compensation schemes within financial institutions directly motivate employees to violate regulations and neglect their forecasts. $STCompMix$ is a proxy for how short-term focused compensation contracts are within the firm and is constructed by taking the ratio of the CEO's total annual compensation divided by total calculated compensation, including stock awards and non-cash compensation. Finally, I consider corporate governance mechanisms, or specific policies and procedures within the financial institution to protect stakeholders and shareholders. My proxy for stakeholder protection is $KLDProduct$, and my proxies for shareholder protection are $InstHoldings$, $Gompers$, and $Insiders$ (as defined in Section III.E).

Table IX provides the results from regressions of forecast accuracy on security code violations including controls for alternative explanations. Data for additional financial characteristics is collected from a variety of sources including Capital IQ, Factset, AuditAnalytics, and KLD and its availability varies across the various measures. Column 1 adds controls for general financial institution characteristics. Column 2 controls for internal control quality. Column 3 controls for compensation schemes. Columns 4-8 control for various corporate governance mechanisms to protect stakeholders and shareholders. Column 9 includes all controls. For brevity, I display the results for $SecCodeRank$, a composite measure of the three proxies for security code violations, constructed by individually ranking the three security code violation measures into quintiles and then averaging their ranks. However, inferences are similar when I consider the three proxies separately. Throughout all of the models, the results provide strong evidence to suggest that the association between security code violations and forecast accuracy cannot be easily explained by the alternative explanations proposed. In each test, $SecCodeRank$ continues to load positive and significantly ($p < .01$), consistent with Hypothesis 1. These findings add additional support to the argument that corporate culture explains the association between security code violations and forecast accuracy.

## VI. Additional Analysis

In this section, I conduct three sets of additional analyses to add further insight on the association between security code violations and forecast quality. The first set of analyses examines the extent to which security code violations are associated with *upwardly* biased forecasts around recent equity offerings and *downwardly* biased forecasts for firms who narrowly "meet or beat" consensus forecasts. The second analysis examines the ability of personal reputation, as measured by All-Star rankings, to moderate the association between security code violations and forecast accuracy. The third analysis examines the market consequences of security code violations on analysts' report informativeness.

### *A. Pressures to Strategically Bias Forecasts*

The results from Table VII indicate a strong association between security code violations and forecast accuracy, which I posit is driven by an overall profit-oriented culture within the financial institution that neglects individual investors' welfare. As discussed earlier, this culture leads analysts to neglect their forecasts through either allocating their time and efforts to meet the immediate demands of institutional clients (and exerting less effort on producing accurate forecasts) or by increasing the probability that analysts will be susceptible to pressures to bias their forecasts (upwards or downwards). In this section, I examine the effects of culture on intensifying the biases that arise in analysts' forecasts.

In order to consider the effects of culture on forecast biases, I consider two unique settings in which analysts are likely to face pressures to bias their forecasts. The first setting relates to a scenario in which analysts are likely to face pressures to issue *upwardly* biased forecasts. Specifically, I examine the period following recent equity offerings as analysts are often expected to issue optimistic forecasts for recent investment banking clients in order to promote the firms (e.g., Lin and McNichols (1998); Michaely and Womack (1999)). Accordingly, Hypothesis 2A predicts that the association between security code violations and *upwardly* biased forecasts should be more positive following recent underwriting activity.

To test this hypothesis, I examine the following fully-interacted regression of upward forecast bias on security code violations interacted with analysts' investment banking affiliation:

$$
\begin{aligned}
RFBiasUp_{i,j,t} = {} & \beta_0 + \beta_1 Violations \times Affiliation_{i,j,t} + \beta_2 Violations_{f,t} \\
& + \beta_3 Affiliation_{i,j,t} + \beta_4 RFError \times Affiliation_{i,j,t} \\
& + \beta_5 AnalystControls \times Affiliation_{i,j,t} \\
& + \beta_6 FIControls \times Affiliation_{i,j,t} + \beta_7 RFError_{i,j,t} \\
& + \beta_8 AnalystControls_{i,j,t} + \beta_9 FIControls_{f,t} + \sum_t Year_t + \epsilon_{i,j,t}.
\end{aligned} \tag{3}
$$

where $i$ denotes analyst, $j$ denotes firm, $t$ denotes time, and $f$ denotes the financial institution (for which analyst $i$ is employed in year $t$). Relative upward forecast bias ($RFBiasUp$) is the difference between the last forecast issued by analyst $i$ covering firm $j$ in year $t$ less the average forecast issued by all analysts covering firm $j$ in year $t$, scaled by the standard deviation of all forecasts issued by analysts covering the firm in the period. $Affiliation$ takes the value of 1 if the analysts' employer was involved in an initial public offering or seasoned equity offering of the covered firm in the prior 12 months (as indicated by SDC), and 0 otherwise. The model specification includes all of the control variables from Equation 2 (including interacted terms), as well as forecast accuracy (i.e., $RFError$), following Cowen et al. (2006). Hypothesis 2A predicts a positive coefficient on $\beta_1$.

Table X, Panel A provides the results of this test.[29] In Columns 1 and 2, the variable of interest is $LogEvents \times Affiliation$. In Columns 3 and 4, I examine $LogFines \times Affiliation$. Columns 5 and 6 provide the results for $LogCodes \times Affiliation$. For each of the tests, I first examine univariate regressions (Columns 1, 3 and 5) followed by full regressions with all of the specified controls (Columns 2, 4 and 6).

The results provide some evidence to support Hypothesis 2A. Affiliated analysts employed by financial institutions with more security code violations issue more upwardly biased forecasts than do affiliated analysts employed by financial institutions with fewer security code violations. The coefficients on all of the measures of security code violations interacted with affiliation are positive in all models. However, after including the full set of controls, the results are only significant for $LogEvents \times Affiliation$ ($p < .1$) and $LogFines \times Affiliation$ ($p < .1$). While the coefficient on $LogCodes \times Affiliation$ is positive, it is not significant at traditional levels.

One potential explanation for somewhat weaker results in this test is that Global Settlement created stricter regulation that reduces the frequency of this form of optimistic bias. However, recent survey evidence has suggested that junior analysts still report feeling pressured to bias their forecasts upwards, even in the post Global Settlement regime (Brown et al. (2014)). For example, in a survey response to a question regarding pressures to bias forecasts upwards, one analyst noted: "I notice the younger guys get pressured a lot more. They're very much more nervous when the research director calls." Another analyst notes: "The younger analysts are also pushed around much harder by the bankers, and the more senior analysts are not." (Brown et al. (2014), p. 27) Thus, it is likely that the effects of a profit-oriented culture are more pronounced for junior analysts providing forecasts around recent equity offerings than they are for relatively senior analysts.

[29] Sample size varies slightly from the accuracy tests due to some forecasts having no dispersion.

Table X, Panel B revisits the above forecast bias analysis (Equation 3), but splits the sample based on analysts' seniority. Columns 1-3 examine the full model (with controls) for analysts with less than 2 years of general experience (i.e., *JuniorAnalysts*), while Columns 4-6 examine the results for analysts with more than 2 years of general experience (i.e., *SeniorAnalysts*). Consistent with the survey evidence, the results indicate strong support for Hypothesis 2A among the pool of junior analysts. The association between *RFBiasUp* and measures of security code violations interacted with affiliation are positive and significant for junior analysts ($p < .05$). On the other hand, there is little evidence to support Hypothesis 2A among the pool of senior analysts. Thus, it appears as if the effects of culture on optimistic forecast biases are more pronounced among junior analysts.

The second forecast bias setting I consider relates to a scenario in which analysts are likely to face pressures to issue *downwardly* biased forecasts. Specifically, I consider forecasts issued for firms that narrowly "meet or beat" the annual consensus earnings forecast. Analysts often face pressures from managers to issue *downwardly* biased forecasts (i.e., "lowball") to increase the likelihood that managers meet earnings targets (e.g., Hilary and Hsu (2013); Bhojraj et al. (2009)). Managers are most likely to pressure analysts to "lowball" forecasts when they are most at risk of not meeting the earnings target. Accordingly, Hypothesis 2B predicts that the association between security code violations and *downwardly* biased forecasts should be more positive for firms that just meet or narrowly beat the consensus earnings forecast.

To test this hypothesis, I examine the following fully-interacted regression of downward forecast bias on security code violations interacted with "LowBall" pressures:

$$\begin{aligned} RFBiasDown_{i,j,t} = {} & \beta_0 + \beta_1 Violations \times LowBall_{i,j,t} + \beta_2 Violations_{f,t} \\ & + \beta_3 LowBall_{j,t} + \beta_4 RFError \times LowBall_{i,j,t} \\ & + \beta_5 AnalystControls \times LowBall_{i,j,t} \\ & + \beta_6 FIControls \times LowBall_{i,j,t} + \beta_7 RFError_{i,j,t} \\ & + \beta_8 AnalystControls_{i,j,t} + \beta_9 FIControls_{f,t} + \sum_t Year_t + \epsilon_{i,j,t}. \end{aligned} \tag{4}$$

where $i$ denotes analyst, $j$ denotes firm, $t$ denotes time, and $f$ denotes the financial institution (for which analyst $i$ is employed in year $t$). Relative downward forecast bias (*RFBiasDown*) is equal to minus 1 times *RFBiasUp*. *LowBall* takes the value of 1 if the firm narrowly meets or beats (by 1 cent) the consensus earnings forecast based on the end of the year consensus forecast, and 0 otherwise. The model specification includes all of the control variables from Equation 3. Hypothesis 2B predicts a positive coefficient on $\beta_1$.

Table XI provides the results of this test. In Columns 1 and 2, the variable of interest is *LogEvents* $\times$ *LowBall*. In Columns 3 and 4, I examine *LogFines* $\times$ *LowBall*. Columns 5 and 6 provide the results for *LogCodes* $\times$ *LowBall*. For each of the tests, I first examine univariate regressions (Columns 1, 3 and 5) followed by full regressions with all of the specified controls (Columns 2, 4 and 6).

The results provide evidence to support Hypothesis 2B. Analysts employed by financial institutions with more security code violations issue more downwardly biased forecasts for firms when pressures to "lowball" forecasts are likely to be high than do analysts employed by financial institutions with fewer security code violations. The coefficients on all of the measures of security code violations interacted with "lowball" are positive and significant in all models at the 10% level. After including the full set of controls, the results remain significant for $LogEvents \times Lowball$ ($p < .05$) and $LogCodes \times Lowball$ ($p < .01$). While the coefficient on $LogFines \times Lowball$ is positive, it is not significant at traditional levels.

Taken together, the results from Table X and XI provide evidence to support Hypothesis 2A and 2B. The results suggest that, when pressures to bias forecasts are high, analysts employed by financial institutions with poor corporate culture are most susceptible to these pressures.

### B. *All-Star Analysts*

The evidence in Section IV is consistent with corporate culture influencing analysts' forecast quality. However, within the sell-side analyst industry, powerful external mechanisms exist that can potentially discipline analysts' behavior and counteract the effects of profit-oriented cultures. One such economic force that can reduce the effects of culture is analysts' personal reputation. Prior studies have demonstrated that analysts' personal reputation is an important determinant of their forecast quality and is even more influential than the reputation of their employer (Fang and Yasuda (2009)). Thus, analysts with high levels of reputational capital to preserve should be less willing to sacrifice investor welfare and should be more immune to the effects of corporate culture. Accordingly, Hypothesis 3 predicts that the association between security code violations and analysts' forecast errors should be less positive for analysts with All-Star status (an indicator of high reputational capital).

To test this hypothesis, I re-examine the baseline forecast accuracy model (Equation 2), but fully interact it with analysts' All-Star status:

$$\begin{aligned} RFError_{i,j,t} = \beta_0 &+ \beta_1 Violations \times AllStar_{i,j,t} + \beta_2 Violations_{f,t} \\ &+ \beta_3 AllStar_{i,j,t} + \beta_4 AnalystControls \times AllStar_{i,j,t} \\ &+ \beta_5 FIControls \times AllStar_{i,j,t} + \beta_6 AnalystControls_{i,j,t} \\ &+ \beta_7 FIControls_{f,t} + \sum_t Year_t + \epsilon_{i,j,t}. \end{aligned} \tag{5}$$

where $i$ denotes analyst, $j$ denotes firm, $t$ denotes time, and $f$ denotes the financial institution (for which analyst $i$ is employed in year $t$). *AllStar* is an indicator variables that takes the value of 1 if the analyst is ranked an All-Star analyst in the Institutional Investor rankings in the current year, and 0 otherwise. The model includes all of the control variables as in Equation 2 and is fully interacted with *AllStar* to capture any differential effects in forecast accuracy that may be related to other analyst and financial institution characteristics. Hypothesis 3 predicts a negative coefficient on $\beta_1$.

Table XII provides the result from this test.[30] In Columns 1 and 2, the variable of interest is $LogEvents \times AllStar$. In Columns 3 and 4, I examine $LogFines \times AllStar$. Columns 5 and 6 provide the results for $LogCodes \times AllStar$. For each of the tests, I first examine univariate regressions (Columns 1, 3 and 5) followed by full regressions with all of the specified controls (Columns 2, 4 and 6).

The coefficients on both $LogEvents \times AllStar$ and $LogFines \times AllStar$ are negative and significant ($p < .01$), suggesting that analysts working at financial institutions with more security code violations produce relatively more accurate forecasts when they have All-Star status. The coefficients on measures of security code violations based on the number of security code violations ($LogCodes \times AllStar$) are also negative, but not significant. In general, these results are consistent with Hypothesis 3 and demonstrate that reputation can play an important role in counteracting the negative effects of corporate culture.

### *C. Report Informativeness*

The evidence in the prior analyses suggest that corporate culture can influence analyst behavior, but do not offer any insight regarding whether this has consequences for market participants. In my final analysis, I shed light on this by examining the effects of security code violations on analysts' report informativeness. Prior studies indicate significant variation in the amount of new information that analysts bring to the market, and regulators have expressed concern that poor compliance may impede investors' abilities to make fully-informed investment decisions. Accordingly, if profit-oriented cultures have negative effects on investors' ability to make fully-informed investment decisions, one would expect security code violations to be associated with less informative reports. Accordingly, Hypothesis 4 predicts a negative association between security code violations and report informativeness.

To test this hypothesis, I examine the following regression of analyst informativeness on proxies for security code violations using an out-of-sample analysis consisting of all forecast revisions:

$$\begin{aligned} INFO_{i,j,t} = {} & \beta_0 + \beta_1 Violations_{f,t} + \beta_2 Experience_{i,t} + \beta_3 FirmsCovered_{i,t} + \beta_4 FISize_{f,t} \\ & + \beta_5 FIPrestige_f + \beta_6 FIComplexity_f + \beta_7 NumReportsAnalyst_{i,j,t} \\ & + \beta_8 NumReportsFirm_{j,t} + \beta_9 FirmRet_{j,t} + \beta_1 0 MktRet_t + \beta_1 1 SigmaRet_t \\ & + \psi TimeTrend + \epsilon_{i,j,t}. \end{aligned} \tag{6}$$

where $i$ denotes analyst, $j$ denotes firm, $t$ denotes time, and $f$ denotes the financial institution (for which analyst $i$ is employed in year $t$). $INFO$ is calculated as the absolute value of the sum of size adjusted returns around earnings forecast revision dates. I include control variables for analyst characteristics and market conditions following prior studies examining analyst informativeness (Francis, Schipper, and Vincent (2002); Kadan et al. (2009)) as well as controls for financial institu-

[30] The sample size differs from that in Table VII since I currently only have All-Star data available through 2010.

tion characteristics. *Experience* is the natural log of the number of years of experience an analyst has. *FirmsCovered* is the natural log of the number of firms covered by an analyst. *FISize* is the natural log of the number of analysts employed by the financial institution. *FIPrestige* is an indicator variable that takes the value of 1 if the financial institution is one of the top 10 II-Ranked institutions, and 0 otherwise. *FIComplexity* is natural log of the number of business lines in the financial institution. *NumReportsAnalyst* and *NumReportsFirm* control for the information environment. *NumReportsAnalyst* is the number of reports produced by the analyst for the firm in a given year. *NumReportsFirm* is the number of reports issued about a firm on the same day. *FirmRet* and *MktRet* control for momentum and are constructed as cumulative monthly returns over the 6 month period prior to the forecast revision date for the firm and market, respectively. *SigmaRet* controls for market volatility of returns over the prior 6 months. Finally, following Francis et al. (2002), I include a time trend to control for macro changes in analyst report informativeness over time. Hypothesis 4 predicts a negative coefficient on $\beta_1$.

Table XIII provides the results from this test. In Columns 1 and 2, the variable of interest is *LogEvents*. In Columns 3 and 4, I examine *LogFines*. Columns 5 and 6 provide the results for *LogCodes*. For each of the tests, I first examine univariate regressions (Columns 1, 3 and 5) followed by full regressions with all of the specified controls (Columns 2, 4 and 6). Consistent with Hypothesis 4, the coefficients on proxies for security code violations are negative and highly significant in each model ($p < .01$).[31] Further, the results also appear to be economically significant. A one-standard deviation increase in proxies for security code violations are associated with between 0.50% to 0.90% reductions in overall report informativeness.[32]

## VII. Conclusion

In this study, I examine the association between security code violations occurring *outside* of financial institutions' equity research departments and the quality of forecasts produced within these institutions' equity research departments. Using a hand-collected sample of all U.S. security code violations enforced by the Financial Industry Regulatory Authority, I document statistically significant positive associations between various proxies for security code violations and the relative forecast errors produced by financial institutions' equity research departments. I further demonstrate that these associations cannot be easily explained by other divisions directly influencing equity analysts or by traditional control or governance mechanisms. Overall, I interpret these findings as providing evidence consistent with a common profit-oriented corporate influencing stakeholder trade-offs across a multitude of business lines within financial institutions.

In additional analyses, I find that security violations are also associated with more *upwardly*

[31] Inferences remain unchanged when I exclude observations around earnings announcement dates.

[32] The untabulated standard deviations for *LogEvents*, *LogFines*, and *LogCodes* are 0.662, 4.405, and 1.178, respectively. A one-standard deviation increase in *LogEvents* is associated with 0.7% reduction in report informativeness ($\sigma$=0.662 × -0.0107). A one-standard deviation increase in *LogFines* is associated with 0.9% reduction in report informativeness ($\sigma$=4.405 × -0.0021). A one-standard deviation increase in *LogCodes* is associated with 0.5% reduction in report informativeness ($\sigma$=1.178 × -0.0046)

biased forecasts following recent equity underwritings, more *downwardly* biased forecasts for firms that narrowly "meet or beat" consensus forecast estimates, and less informative analyst reports, on average. Moreover, the association between security code violations and forecast errors appears to be less pronounced for forecasts produced by All-Star analysts, who have higher levels of reputational capital to preserve.

Overall, this study provides important implications regarding the behavior of security analysts and the role of securities regulation in the financial services industry. In particular, my findings suggest that cultural forces are an important indicator of how financial institutions make stakeholder trade-offs and can have important consequences for market participants.

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## Figure 1. Sample Disclosure Events from FINRA *BrokerCheck* Reports

This figure provides sample disclosure events obtained from the FINRA *BrokerCheck* online tool: http://www.finra.org/Investors/ToolsCalculators/BrokerCheck/. *BrokerCheck* is a free tool provided by FINRA that allows investors to search for information about financial institutions and the brokers they employ. The "Disclosure Events" portion of each report contains information about any relevant regulatory events, customer disputes or criminal matters.

**(a)** Example 1

| **Disclosure 1 of 397** | |
|---|---|
| **Reporting Source:** | Regulator |
| **Current Status:** | Final |
| **Allegations:** | WITHOUT ADMITTING OR DENYING THE FINDINGS, THE FIRM CONSENTED TO THE SANCTIONS AND TO THE ENTRY OF FINDINGS THAT ITS EQUITY PRINCIPAL STRATEGIES DESK (EPSD) SOLD CERTAIN SECURITIES SHORT DURING THE FIVE BUSINESS DAYS LEADING UP TO THE PRICING OF FIVE PUBLIC OFFERINGS, AND THEN PURCHASED SECURITIES IN THOSE OFFERINGS IN VIOLATION OF RULE 105 OF REGULATION M OF THE SECURITIES EXCHANGE ACT OF 1934 (EXCHANGE ACT). EPSD'S PROFITS AND/OR IMPROPER FINANCIAL BENEFITS FROM THESE VIOLATIVE TRANSACTIONS TOTALED APPROXIMATELY $538,626. THE FINDINGS STATED THAT FIRM'S SUPERVISORY SYSTEM DID NOT PROVIDE FOR SUPERVISION REASONABLY DESIGNED TO ACHIEVE THE FIRM'S COMPLIANCE WITH RESPECT TO THE APPLICABLE SECURITIES LAWS AND REGULATIONS CONCERNING RULE 105 OF REGULATION M OF THE EXCHANGE ACT. THE FIRM'S SUPERVISORY SYSTEM ALSO FAILED TO DESIGNATE AN APPROPRIATELY REGISTERED PRINCIPAL(S) WITH AUTHORITY TO CARRY OUT THE SUPERVISORY RESPONSIBILITIES WITH RESPECT TO THE EPSD'S COMPLIANCE WITH RULE 105 OF REGULATION M OF THE EXCHANGE ACT AND OTHER APPLICABLE SECURITIES LAWS AND REGULATIONS, AND FINRA RULES, CONCERNING ONE OF ITS PROPRIETARY ACCOUNTS. |
| **Initiated By:** | FINRA |
| **Date Initiated:** | 03/18/2014 |
| **Docket/Case Number:** | 2010022706501 |
| **Principal Product Type:** | Other |
| **Other Sanction(s)/Relief Sought:** | |
| **Resolution:** | Acceptance, Waiver & Consent(AWC) |
| **Resolution Date:** | 03/18/2014 |
| **Does the order constitute a final order based on violations of any laws or regulations that prohibit fraudulent, manipulative, or deceptive conduct?** | No |
| **Sanctions Ordered:** | Censure<br>Monetary/Fine $1,097,939.06<br>Disgorgement/Restitution |
| **Other Sanctions Ordered:** | THE FINE CONSISTS OF DISGORGEMENT OF $538,626.04 IN PROFITS AND/OR IMPROPER FINANCIAL BENEFITS FROM THE VIOLATIVE TRADING; PRE-JUDGMENT INTEREST ON THE DISGORGEMENT; UNDERTAKINGS: REVISE THE FIRM'S WRITTEN SUPERVISORY PROCEDURES |
| **Sanction Details:** | SEE ABOVE |

(b) Example 2

| Disclosure 13 of 45 | |
|---|---|
| **Reporting Source:** | Regulator |
| **Current Status:** | Final |
| **Allegations:** | NASD RULES 2110, 2210(D)(1), 2310, 3010(A) AND (B), AND INTERPRETATIVE MATERIAL-2210-8: THE FIRM OFFERED COLLATERALIZED MORTGAGE OBLIGATION SECURITIES ("CMO"), WHICH ITS REGISTERED REPRESENTATIVES SOLD TO RETAIL CUSTOMERS; AND INCLUDED AMONG THESE CMO SALES WERE THE SALES OF INVERSE FLOATING RATE CMOS ("INVERSE FLOATERS"), A RISKIER TYPE OF CMO, WHICH FINRA HAS ADVISED ARE SUITABLE ONLY FOR SOPHISTICATED INVESTORS WITH A HIGH RISK PROFILE. THE FIRM FAILED TO ESTABLISH AND MAINTAIN A SUPERVISORY SYSTEM AND WRITTEN PROCEDURES REGARDING THE SALE OF CMOS TO CUSTOMERS THAT WERE REASONABLY DESIGNED TO ACHIEVE COMPLIANCE WITH APPLICABLE SECURITIES LAWS AND REGULATIONS AND WITH FINRA RULES. THE FIRM FAILED TO ESTABLISH AND MAINTAIN A SYSTEM AND WRITTEN PROCEDURES REASONABLY DESIGNED TO SUPERVISE WHETHER THE SALES OF CMOS WERE SUITABLE FOR ITS CUSTOMERS AND THAT THE ATTENDANT RISKS OF THE PRODUCTS WERE FULLY EXPLAINED. THE FIRM DID NOT PROVIDE ITS REGISTERED REPRESENTATIVES WHO SOLD CMOS WITH SUFFICIENT TRAINING ON CMOS NOR DID IT OFFER SUFFICIENT WRITTEN GUIDANCE RELATING TO THE SALE OR SUITABILITY OF CMOS. THE FIRM'S WRITTEN SUPERVISORY PROCEDURES WARNED REPRESENTATIVES THAT CLIENTS WHO INVESTED IN MORTGAGE-BASED SECURITIES SHOULD BE ADVISED THAT THE STATED YIELD OF THE SECURITIES IS NOT GUARANTEED AND MAY NOT APPLY FOR THE ENTIRE TERM OF THE INVESTMENT, BUT IT FAILED TO PROVIDE ITS REGISTERED REPRESENTATIVES WITH THE INFORMATION THAT INVERSE FLOATERS WERE "ONLY SUITABLE ONLY FOR SOPHISTICATED INVESTORS WITH A HIGH RISK PROFILE." |
| **Initiated By:** | FINRA |
| **Date Initiated:** | 06/10/2010 |
| **Docket/Case Number:** | 2007010582702 |
| **Principal Product Type:** | Other |
| **Other Product Type(s):** | COLLATERALIZED MORTGAGE OBLIGATION SECURITIES |
| **Principal Sanction(s)/Relief Sought:** | Other |
| **Other Sanction(s)/Relief Sought:** | N/A |
| **Resolution:** | Acceptance, Waiver & Consent(AWC) |
| **Resolution Date:** | 06/10/2010 |
| **Does the order constitute a final order based on violations of any laws or regulations that prohibit fraudulent, manipulative, or deceptive conduct?** | No |
| **Sanctions Ordered:** | Censure<br>Monetary/Fine $375,000.00 |
| **Other Sanctions Ordered:** | |
| **Sanction Details:** | WITHOUT ADMITTING OR DENYING THE FINDINGS, THE FIRM CONSENTED TO THE DESCRIBED SANCTIONS AND TO THE ENTRY OF FINDINGS, THEREFORE THE FIRM IS CENSURED AND FINED $375,000. |

## Table I: Sample of Financial Institutions

This table describes the sample of Financial Institutions included in the sample. The initial sample of financial institutions and security subsidiaries is obtained from the Federal Reserve's website (http://www.federalreserve.gov/bankinforeg/suds.htm) and SEC numbers are obtained from the SEC's website (http://www.sec.gov/about/offices/oia/oia_regstat.htm). CRD Numbers are obtained from the *BrokerCheck* online tool, provided by FINRA (http://www.finra.org/Investors/ToolsCalculators/BrokerCheck/). A financial institution is included in the sample if data is available to identify the institution in the I/B/E/S database. Panel A provides the list of financial institutions and security subsidiaries included in the sample. Panel B describes the type of businesses that the institutions in the sample engage in (obtained from the *BrokerCheck* report).

*Panel A: List of Financial Institutions and their Security Subsidiaries*

| Financial Institution | Security Subsidiary | SEC Number | CRD Number |
|---|---|---|---|
| Allianz SE | Commerz Markets LLC | 8-49647 | 41957 |
| BNP Paribas | BNP Paribas Investment Services, LLC | 8-50745 | 44598 |
| BNP Paribas | BNP Paribas Securities Corp. | 8-32682 | 15794 |
| BPCE | Natixis Bleichroeder LLC | 8-719 | 1101 |
| BPCE | Natixis Securities North America, Inc. | 8-43912 | 28722 |
| Banco Santander | Santander Investment Securities, Inc. | 8-47664 | 37216 |
| Banco Santander | Santander Securities Corp. | 8-49571 | 41791 |
| Bank of Montreal | BMO Capital Markets Corp. | 8-34344 | 16686 |
| Bank of Nova Scotia | Scotia Capital (USA), Inc. | 8-3716 | 2739 |
| Canadian Imperial Bank of Commerce | CIBC World Markets Corp. | 8-18333 | 630 |
| Capital One Financial Corp. | Capital One Southcoast, Inc. | 8-50561 | 44158 |
| Cera Ancora VZW | KBC Financial Products USA, Inc. | 8-51529 | 46709 |
| Citigroup, Inc. | Citigroup Global Markets, Inc. | 8-8177 | 7059 |
| Citigroup, Inc. | Morgan Stanley Smith Barney, LLC | 8-68191 | 149777 |
| Credit Suisse Group | Credit Suisse Securities (USA), LLC | 8-422 | 816 |
| DZ Bank AG | DZ Financial Markets, LLC | 8-51687 | 47098 |
| Deutsche Bank AG | Deutsche Bank Securities, Inc. | 8-17822 | 2525 |
| DnB NOR ASA | DnB NOR Nor Markets, Inc. | 8-66024 | 127605 |
| Goldman, Sachs Group | Epoch Securities, Inc. | 8-52373 | 103899 |
| Goldman, Sachs Group | Goldman Sachs Execution & Clearing, L.P. | 8-526 | 3466 |
| Goldman, Sachs Group | Goldman Sachs JBWere Inc. | 8-26346 | 10117 |
| Goldman, Sachs Group | Goldman, Sachs and Company | 8-129 | 361 |
| HSBC Holdings PLC | Capital Financial Services, INC. | 8-25203 | 8408 |
| HSBC Holdings PLC | HSBC Securities (USA), Inc. | 8-41562 | 19585 |
| JPMorgan Chase & Co. | Chase Investment Services Corp. | 8-41840 | 25574 |
| JPMorgan Chase & Co. | J.P. Morgan Securities, Inc. | 8-35008 | 79 |
| Keycorp | KeyBanc Capital Markets | 8-30177 | 566 |
| Morgan Stanley | Morgan Stanley & Co. Incorporated | 8-15869 | 8209 |
| National Bank of Canada | National Bank of Canada Financial, Inc. | 8-39947 | 22698 |
| Rabobank Nederland | Rabo Securities USA, Inc. | 8-65525 | 122657 |
| Regions Financial Corp. | Morgan, Keegan & Company, Inc. | 8-15001 | 4161 |
| Royal Bank of Canada | RBC Capital Markets Corp. | 8-45411 | 31194 |
| Societe Generale | Newedge USA, LLC | 8-47023 | 36118 |
| Societe Generale | SG Americas Securities, LLC | 8-66125 | 128351 |
| Stifel Financial Corp. | Stifel Nicolaus & Company, Inc. | 8-1447 | 793 |
| Stifel Financial Corp. | Thomas Weisel Partners LLC | 8-51354 | 46237 |
| SunTrust Banks, Inc. | SunTrust Investment Services, Inc. | 8-35355 | 17499 |
| SunTrust Banks, Inc. | SunTrust Robinson Humphrey, Inc. | 8-17212 | 6271 |
| Toronto-Dominion Bank, The | TD Ameritrade Clearing, Inc. | 8-16335 | 5633 |
| Toronto-Dominion Bank, The | TD Ameritrade Inc. | 8-23395 | 7870 |
| Toronto-Dominion Bank, The | TD Securities (USA), LLC | 8-36747 | 18476 |
| UBS AG | UBS Financial Services, Inc. | 8-16267 | 8174 |
| UBS AG | UBS Securities, LLC | 8-22651 | 7654 |
| Wells Fargo & Company | H.D. Vest Investment Securities, Inc. | 8-29533 | 13686 |
| Wells Fargo & Company | Wells Fargo Advisors Financial Network, LLC | 8-28721 | 11025 |
| Wells Fargo & Company | Wells Fargo Advisors, LLC | 8-37180 | 19616 |
| Wells Fargo & Company | Wells Fargo Institutional Securities, LLC | 8-16600 | 5958 |
| Wells Fargo & Company | Wells Fargo Securites, LLC | 8-65876 | 126292 |

*Panel B: Types of Business Activity across Financial Institutions*

| Business Type | # of Firms | % of Firms |
|---|---|---|
| Underwriter or selling group participant (corporate securities other than mutual funds) | 29 | 100% |
| Private placements of securities | 28 | 97% |
| Broker or dealer selling corporate debt securities | 27 | 93% |
| Trading securities for own account | 26 | 90% |
| Broker or dealer retailing corporate equity securities over-the-counter | 25 | 86% |
| Other | 24 | 83% |
| Put and call broker or dealer or option writer | 23 | 79% |
| U S. government securities broker | 22 | 76% |
| Exchange member engaged in exchange commission business other than floor activities | 21 | 72% |
| U S. government securities dealer | 21 | 72% |
| Broker or dealer making inter-dealer markets in corporation securities over-the-counter | 20 | 69% |
| Broker or dealer selling interests in mortgages or other receivables | 19 | 66% |
| Investment advisory services | 19 | 66% |
| Municipal securities dealer | 18 | 62% |
| Municipal securities broker | 17 | 59% |
| Mutual fund retailer | 17 | 59% |
| Broker or dealer selling variable life insurance or annuities | 15 | 52% |
| Non-exchange member arranging for transactions in listed securities by exchange member | 13 | 45% |
| Solicitor of time deposits in a financial institution | 13 | 45% |
| Exchange member engaged in floor activities | 11 | 38% |
| Broker or dealer selling tax shelters or limited partnerships in primary distributions | 10 | 34% |
| Broker or dealer involved in a networking, kiosk or similar arrangment with a: bank, savings bank or association, or credit union | 9 | 31% |
| Broker or dealer selling tax shelters or limited partnerships in the secondary market | 9 | 31% |
| Broker or dealer selling securities of non-profit organizations (e.g., churches, hospitals) | 8 | 28% |
| Mutual fund underwriter or sponsor | 7 | 24% |
| Broker or dealer involved in a networking, kiosk or similar arrangment with a: insurance company or agency | 6 | 21% |
| Broker or dealer selling oil and gas interests | 4 | 14% |
| Real estate syndicator | 3 | 10% |
| Broker or dealer selling securities of only one issuer or associate issuers (other than mutual funds) | 2 | 7% |
| Broker or dealer | 1 | 3% |

## Table II: *BrokerCheck* Sample Selection Procedure

This table outlines the sample selection procedure. Disclosure events are obtained from the *BrokerCheck* online tool, provided by FINRA (http://www.finra.org/Investors/ToolsCalculators/BrokerCheck/). Financial institutions are matched to I/B/E/S data using the last available broker translation table.

| | |
|---|---|
| Completed Disclosure Events for Financial Institutions with available I/B/E/S Data (2005-2012) | 1,448 |
| Less: Events with missing (or duplicate) case numbers | (235) |
| Less: Events with no fines indicated | (56) |
| Less: Events issued by state agencies | (665) |
| Less: Events containing research violations | (20) |
| Final Sample | 472 |

## Table III: Security Code Violation Characteristics

This table provides descriptive statistics for security code violations identified in FINRA *BrokerCheck* reports. Panel A reports the frequency of security code violations identified across disclosure events. Panel B reports the top 10 most frequently occurring security code violations in the sample. Panel C presents the distribution of security code violations based on the framework detailed in Appendix C.

*Panel A: Frequency of Security Code Violations*

| TotalCodes | TotalEvents | %TotalEvents |
|---|---|---|
| 0 or None Identified | 115 | 24% |
| 1 | 59 | 12% |
| 2 | 113 | 24% |
| 3 | 74 | 16% |
| 4 | 54 | 11% |
| 5 | 26 | 6% |
| >5 | 31 | 7% |
| Total | 472 | 100% |

*Panel B: Top 10 Most Frequent Security Code Violations*

| Rule | Type of Violation | TotalEvents | %TotalEvents |
|---|---|---|---|
| NASD Rule 2110 | Standards of Comm. Honor and Principles of Trade | 198 | 42% |
| NASD Rule 3010 | Supervision of Employees | 147 | 31% |
| NASD Rule 6955 | Order Data Transmission Requirements | 58 | 12% |
| FINRA Rule 2010 | Standards of Comm. Honor and Principles of Trade | 55 | 12% |
| NYSE Rule 342 | Offices - Approval, Supervision and Control | 49 | 10% |
| NASD Rule 6130 | Trade Report Input | 46 | 10% |
| NASD Rule 3110 | Books and Records | 38 | 8% |
| NASD Rule 6230 | Transaction Reporting | 32 | 7% |
| NASD Rule 2320 | Best Execution and Interpositioning | 26 | 6% |
| MSRB Rule 14 | Reports of Sales or Purchases | 26 | 6% |

*Panel C: Frequency of Violations by Category*

| Violation Category | TotalEvents | %TotalEvents |
|---|---|---|
| Clearing, Transaction, and Order Data Requirements & Facility Charges | 71 | 14% |
| Duties & Conflicts | 294 | 60% |
| Financial and Operational Rules | 17 | 3% |
| Investigations & Sanctions | 6 | 1% |
| Member Application & Associated Person Registration | 24 | 5% |
| Quotation and Transaction Reporting Facilities | 89 | 18% |
| Securities Offering and Trading Standards and Practices | 43 | 9% |
| Supervision and Responsibilities Relating to Associated Persons | 206 | 42% |

## Table IV: Disclosure Event Characteristics

This table provides descriptive statistics for disclosure events identified in FINRA *BrokerCheck* reports. Panel A reports the frequency of disclosure events by year. Panel B reports the frequency of disclosure events by anonymous financial institution (in descending order of fine sanctioned). Panel C presents the correlation matrix of characteristics within disclosure events. All variables are defined in Appendix B.

*Panel A: Frequency by Year*

| Year | TotalEvents | TotalFines | TotalCodes | Avg. Fine/Event |
|---|---|---|---|---|
| 2005 | 51 | $280,589,500 | 114 | $5,501,755 |
| 2006 | 47 | $63,694,454 | 98 | $1,355,201 |
| 2007 | 69 | $71,638,250 | 154 | $1,038,236 |
| 2008 | 48 | $6,991,500 | 92 | $145,656 |
| 2009 | 56 | $10,462,000 | 147 | $186,821 |
| 2010 | 77 | $19,919,000 | 170 | $258,688 |
| 2011 | 59 | $38,365,500 | 162 | $650,263 |
| 2012 | 65 | $18,889,900 | 171 | $290,614 |
| Total | 472 | $510,550,104 | 1,108 | $1,081,674 |

*Panel B: Frequency by Financial Institution*

| Financial Institution | TotalEvents | TotalFines | TotalCodes | Avg. Fine/Event |
|---|---|---|---|---|
| Financial Institution 1 | 34 | $259,648,200 | 101 | $7,636,712 |
| Financial Institution 2 | 48 | $81,196,000 | 158 | $1,691,583 |
| Financial Institution 3 | 50 | $77,542,000 | 163 | $1,550,840 |
| Financial Institution 4 | 34 | $21,832,200 | 97 | $642,124 |
| Financial Institution 5 | 28 | $12,830,954 | 100 | $458,248 |
| Financial Institution 6 | 62 | $9,760,000 | 128 | $157,419 |
| Financial Institution 7 | 21 | $9,362,500 | 0 | $445,833 |
| Financial Institution 8 | 12 | $6,816,000 | 30 | $568,000 |
| Financial Institution 9 | 25 | $5,697,000 | 83 | $227,880 |
| Financial Institution 10 | 18 | $4,775,000 | 56 | $265,278 |
| Financial Institution 11 | 3 | $4,540,000 | 9 | $1,513,333 |
| Financial Institution 12 | 13 | $3,470,250 | 0 | $266,942 |
| Financial Institution 13 | 22 | $3,228,500 | 0 | $146,750 |
| Financial Institution 14 | 21 | $2,898,000 | 0 | $138,000 |
| Financial Institution 15 | 3 | $2,016,000 | 7 | $672,000 |
| Financial Institution 16 | 14 | $1,073,500 | 34 | $76,679 |
| Financial Institution 17 | 11 | $1,045,500 | 37 | $95,045 |
| Financial Institution 18 | 13 | $762,500 | 26 | $58,654 |
| Financial Institution 19 | 10 | $687,000 | 0 | $68,700 |
| Financial Institution 20 | 8 | $582,500 | 29 | $72,813 |
| Financial Institution 21 | 9 | $384,000 | 25 | $42,667 |
| Financial Institution 22 | 4 | $220,000 | 10 | $55,000 |
| Financial Institution 23 | 4 | $117,500 | 5 | $29,375 |
| Financial Institution 24 | 4 | $60,000 | 10 | $15,000 |
| Financial Institution 25 | 1 | $5,000 | 0 | $5,000 |
| Financial Institution 26 | 0 | $0 | 0 | NA |
| Financial Institution 27 | 0 | $0 | 0 | NA |
| Financial Institution 28 | 0 | $0 | 0 | NA |
| Financial Institution 29 | 0 | $0 | 0 | NA |
| Total | 472 | $510,550,104 | 1,108 | $1,081,674 |

*Panel C: Disclosure Event Correlation Matrix*

| *Variable* | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| LogFines | (1) | 1.000 | | | | | | | | | |
| LogCodes | (2) | 0.319 | 1.000 | | | | | | | | |
| ClearTrade | (3) | -0.094 | 0.345 | 1.000 | | | | | | | |
| DutyConflict | (4) | 0.330 | 0.784 | 0.061 | 1.000 | | | | | | |
| FinOps | (5) | -0.010 | 0.204 | 0.141 | 0.115 | 1.000 | | | | | |
| InvSanct | (6) | 0.148 | 0.140 | 0.005 | 0.094 | -0.022 | 1.000 | | | | |
| Application | (7) | 0.170 | 0.200 | -0.089 | 0.175 | -0.041 | -0.024 | 1.000 | | | |
| TransReport | (8) | -0.194 | 0.351 | 0.221 | 0.081 | 0.052 | -0.055 | -0.075 | 1.000 | | |
| SecOffer | (9) | -0.011 | 0.298 | 0.176 | 0.248 | 0.018 | -0.036 | -0.067 | 0.111 | 1.000 | |
| Supervision | (10) | 0.373 | 0.593 | 0.025 | 0.457 | 0.088 | 0.133 | -0.052 | 0.049 | 0.132 | 1.000 |

## Table V: Validity of Security Code Violations Measures

This table examines the validity of measures of security code violations. Panel A provides the correlation coefficients for each measure of security code violations with up to 3 lags of the measure. Panel B presents transition matrices for measures of security code violations, with values indicating the number (and percentage) of financial institution-year observations in each tercile of compliance violations in year $t+1$, conditional on initial tercile location in year $t$. Panel C provides correlation coefficients for measures of security code violations with proxies for stakeholder tradeoffs. Bolded values are significant at the 10% level or higher. All variables are defined in Appendix B.

*Panel A: Correlation of Security Code Violations Measures with Lags*

| | *Security Code Violation Measures=* | | | |
|---|---|---|---|---|
| | LogEvents | LogFines | LogCodes | Obs. |
| Security Code Violations (Lag 1) | 0.545 | 0.477 | 0.668 | 172 |
| Security Code Violations (Lag 2) | 0.621 | 0.553 | 0.749 | 147 |
| Security Code Violations (Lag 3) | 0.655 | 0.524 | 0.762 | 121 |

*Panel B: Transition Matrix of Security Code Violations Measures*

| | *Security Code Violation Measure=* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | *TotalEvents* | | | *TotalFines* | | | *TotalCodes* | | |
| **To/From** | Low | Medium | High | Low | Medium | High | Low | Medium | High |
| Low | 35 | 17 | 5 | 33 | 18 | 4 | 63 | 13 | 7 |
| | (61%) | (30%) | (9%) | (60%) | (33%) | (7%) | (76%) | (16%) | (8%) |
| Medium | 18 | 27 | 17 | 17 | 24 | 19 | 11 | 10 | 10 |
| | (29%) | (44%) | (27%) | (28%) | (40%) | (32%) | (36%) | (32%) | (32%) |
| High | 6 | 17 | 30 | 6 | 15 | 36 | 7 | 10 | 41 |
| | (11%) | (32%) | (57%) | (11%) | (26%) | (63%) | (12%) | (17%) | (71%) |

*Panel C: Security Code Violations & Stakeholder Tradeoffs*

| VARIABLES | LogEvents | LogFines | LogCodes | Obs. |
|---|---|---|---|---|
| *Individual Investor Protection* | | | | |
| KLDProduct | **-0.519** | **-0.441** | **-0.617** | 70 |
| *Shareholder Protection* | | | | |
| InstHoldings | 0.080 | 0.025 | 0.057 | 179 |
| Gompers | **-0.404** | **-0.396** | **-0.479** | 80 |
| Insiders | -0.080 | -0.075 | -0.080 | 179 |

## Table VI: Analyst Forecast Sample

This table provides summary statistics for the variables included in the forecast accuracy regressions. Panel A reports the sample statistics. Panel B reports the sample correlation. Bolded values indicate significance at the 1% level. All variables are defined in Appendix B.

*Panel A: Sample Statistics*

| Variable | Mean | STD | PER5 | PER25 | PER50 | PER75 | PER95 | N |
|---|---|---|---|---|---|---|---|---|
| RFError | -0.010 | 0.739 | -0.975 | -0.511 | -0.100 | 0.273 | 1.432 | 78,079 |
| TotalEvents | 3.795 | 2.789 | 0.000 | 2.000 | 3.000 | 6.000 | 9.000 | 78,079 |
| TotalFines ($Millions) | 6.744 | 32.443 | 0.000 | 0.100 | 0.588 | 1.694 | 14.933 | 78,079 |
| TotalCodes | 9.816 | 8.778 | 0.000 | 2.000 | 8.000 | 16.000 | 27.000 | 78,079 |
| RExp | -0.006 | 0.751 | -1.000 | -0.618 | -0.112 | 0.458 | 1.411 | 78,079 |
| RHorizon | -0.002 | 0.394 | -0.465 | -0.257 | -0.047 | 0.073 | 0.876 | 78,079 |
| RFirmsCovered | -0.005 | 0.407 | -0.676 | -0.259 | -0.022 | 0.227 | 0.688 | 78,079 |
| FIPrestige | 0.523 | 0.499 | 0.000 | 0.000 | 1.000 | 1.000 | 1.000 | 78,079 |
| FIComplexity | 20.823 | 4.405 | 13.000 | 20.000 | 21.000 | 24.000 | 27.000 | 78,079 |
| FISize | 99.904 | 48.091 | 22.000 | 65.000 | 111.000 | 130.000 | 182.000 | 78,079 |

*Panel B: Sample Correlation*

| *Variable* | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| RFError | (1) | 1 | | | | | | | | | |
| LogEvents | (2) | **0.047** | 1 | | | | | | | | |
| LogFines | (3) | **0.034** | **0.820** | 1 | | | | | | | |
| LogCodes | (4) | **0.032** | **0.768** | **0.657** | 1 | | | | | | |
| RExp | (5) | **-0.024** | **-0.056** | **-0.044** | **-0.031** | 1 | | | | | |
| RHorizon | (6) | **0.410** | **0.022** | **0.025** | 0.003 | **-0.025** | 1 | | | | |
| RFirmsCovered | (7) | **-0.028** | **0.052** | **0.047** | **0.061** | **0.213** | **-0.079** | 1 | | | |
| FIPrestige | (8) | 0.008 | **0.373** | **0.485** | **0.625** | **-0.013** | -0.002 | **0.015** | 1 | | |
| FIComplexity | (9) | **0.018** | **0.415** | **0.364** | **0.413** | 0.004 | 0.009 | **0.027** | **0.453** | 1 | |
| FISize | (10) | **0.026** | **0.573** | **0.565** | **0.543** | **-0.036** | **0.012** | **0.034** | **0.541** | **0.539** | 1 |

## Table VII: Regressions of Forecast Accuracy on Security Code Violations

This table provides the results of OLS regressions of relative forecast errors (i.e., *RFError*) on measures of security code violations: *LogEvents*, *LogFines*, and *LogCodes*. Panel A presents the results when the security code violations measure is *LogEvents*. Panel B presents the results when the security code violations measure is *LogFines*. Panel C presents the results when the security code violations measure is *LogCodes*. Standard errors are double clustered by financial institution and year. ***,**, and * denote 1%, 5% and 10% level of significance, respectively. All variables are defined in Appendix B.

*Panel A: Security Code Violation Proxy = LogEvents*

| VARIABLES | (1) | (2) | (3) |
|---|---|---|---|
| LogEvents | 0.0527*** | 0.0528*** | 0.0064*** |
| | (4.87) | (4.65) | (5.46) |
| RExp | | -0.0125* | -0.0082 |
| | | (-1.75) | (-1.13) |
| RHorizon | | 0.7679*** | 0.7663*** |
| | | (38.56) | (38.46) |
| RFirmsCovered | | 0.0096 | 0.0180 |
| | | (0.32) | (0.59) |
| FISize | | -0.0141 | -0.0660*** |
| | | (-0.90) | (-3.25) |
| FIPrestige | | -0.0043 | |
| | | (-0.22) | |
| FIComplexity | | 0.0015 | |
| | | (0.05) | |
| Year Fixed Effects? | No | Yes | Yes |
| FI Fixed Effects? | No | No | Yes |
| Standard Errors Clustered? | FI and Year | FI and Year | FI and Year |
| Observations | 78,079 | 78,079 | 78,079 |
| R-squared | 0.00 | 0.17 | 0.17 |

*Panel B: Security Code Violation Proxy = LogFines*

| VARIABLES | (1) | (2) | (3) |
|---|---|---|---|
| LogFines | 0.0057*** | 0.0043*** | 0.0010* |
| | (3.23) | (2.66) | (1.96) |
| RExp | | -0.0138* | -0.0082 |
| | | (-1.82) | (-1.13) |
| RHorizon | | 0.7684*** | 0.7663*** |
| | | (37.89) | (38.39) |
| RFirmsCovered | | 0.0111 | 0.0181 |
| | | (0.36) | (0.59) |
| FISize | | -0.0013 | -0.0670*** |
| | | (-0.07) | (-3.28) |
| FIPrestige | | -0.0092 | |
| | | (-0.30) | |
| FIComplexity | | 0.0168 | |
| | | (0.42) | |
| Year Fixed Effects? | No | Yes | Yes |
| FI Fixed Effects? | No | No | Yes |
| Standard Errors Clustered? | FI and Year | FI and Year | FI and Year |
| Observations | 78,079 | 78,079 | 78,079 |
| R-squared | 0.00 | 0.17 | 0.17 |

*Panel C: Security Code Violation Proxy = LogCodes*

| VARIABLES | (1) | (2) | (3) |
|---|---|---|---|
| LogCodes | 0.0199** | 0.0262*** | 0.0037 |
| | (2.07) | (2.62) | (1.18) |
| RExp | | -0.0136* | -0.0082 |
| | | (-1.79) | (-1.13) |
| RHorizon | | 0.7691*** | 0.7664*** |
| | | (38.36) | (38.42) |
| RFirmsCovered | | 0.0090 | 0.0180 |
| | | (0.29) | (0.59) |
| FISize | | -0.0018 | -0.0668*** |
| | | (-0.12) | (-3.27) |
| FIPrestige | | -0.0286 | |
| | | (-1.01) | |
| FIComplexity | | 0.0151 | |
| | | (0.35) | |
| | | | |
| Year Fixed Effects? | No | Yes | Yes |
| FI Fixed Effects? | No | No | Yes |
| Standard Errors Clustered? | FI and Year | FI and Year | FI and Year |
| Observations | 78,079 | 78,079 | 78,079 |
| R-squared | 0.00 | 0.17 | 0.17 |

## Table VIII: Do Security Code Violations Directly Affect Forecast Accuracy?

This table provides the results of OLS regressions of relative forecast errors (i.e., *RFError*) on measures of security code violations (*LogEvents*, *LogFines*, and *LogCodes*) using subsamples in which incentives to directly influence analysts are likely to be lowest. Panel A presents the results for the subset of earnings forecasts issued for thinly traded stocks (i.e., stocks below the median level of trading volume). Panel B presents the results for the subset of forecasts issued for firms with no investment banking affiliation (i.e., no initial public offering or seasoned equity offering in the prior 12 months). Standard errors are double clustered by financial institution and year. ***,**, and * denote 1%, 5% and 10% level of significance, respectively. All variables are defined in Appendix B.

*Panel A: Thinly Traded Stocks*

| VARIABLES | (1) | (2) | (3) |
|---|---|---|---|
| LogEvents | 0.0400*** | | |
| | (3.45) | | |
| LogFines | | 0.0022 | |
| | | (1.39) | |
| LogCodes | | | 0.0195** |
| | | | (2.15) |
| Controls? | Yes | Yes | Yes |
| Year Fixed Effects? | Yes | Yes | Yes |
| Standard Errors Clustered? | FI and Year | FI and Year | FI and Year |
| Observations | 39,040 | 39,040 | 39,040 |
| R-squared | 0.15 | 0.15 | 0.15 |

*Panel B: No Investment Banking Affiliation*

| VARIABLES | (1) | (2) | (3) |
|---|---|---|---|
| LogEvents | 0.0536*** | | |
| | (4.62) | | |
| LogFines | | 0.0044*** | |
| | | (2.66) | |
| LogCodes | | | 0.0268*** |
| | | | (2.68) |
| Controls? | Yes | Yes | Yes |
| Year Fixed Effects? | Yes | Yes | Yes |
| Standard Errors Clustered? | FI and Year | FI and Year | FI and Year |
| Observations | 75,623 | 75,623 | 75,623 |
| R-squared | 0.17 | 0.17 | 0.17 |

## Table IX: Alternative Explanations for the Association between Security Code Violations and Forecast Quality

This table provides the results of OLS regressions of relative forecast errors (i.e., *RFError*) on a composite measure of security code violations (*SecCodeRank*) with additional controls for alternative explanations. Column 1 includes controls for other financial institution characteristics. Column 2 includes controls for internal control quality. Column 3 includes controls for compensation. Column 4 includes controls for corporate governance policies that relate to stakeholder protection. Columns 5-8 include controls for corporate governance policies that relate to shareholder protection. Column 9 includes all controls. Standard errors are double clustered by financial institution and year. ***,**, and * denote 1%, 5% and 10% level of significance, respectively. All variables are defined in Appendix B.

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| SecCodeRank | 0.0254*** | 0.0294*** | 0.0306*** | 0.0276*** | 0.0324*** | 0.0237*** | 0.0318*** | 0.0239*** | 0.0111*** |
| | (4.13) | (4.83) | (4.04) | (5.94) | (4.78) | (7.33) | (4.78) | (7.95) | (8.19) |
| *FI Characteristics* | | | | | | | | | |
| Size | 0.0151*** | | | | | | | | 0.0806*** |
| | (3.26) | | | | | | | | (6.62) |
| Profitability | 0.5336 | | | | | | | | -1.3923 |
| | (0.58) | | | | | | | | (-0.71) |
| *Internal Control Quality* | | | | | | | | | |
| ICW | | -0.0079 | | | | | | | -0.0305 |
| | | (-0.74) | | | | | | | (-1.25) |
| *Compensation* | | | | | | | | | |
| STCompMix | | | 0.0138 | | | | | | 0.0267*** |
| | | | (0.53) | | | | | | (5.61) |
| *Stakeholder Protection* | | | | | | | | | |
| KLDProduct | | | | -0.0172** | | | | | -0.0156** |
| | | | | (-2.22) | | | | | (-2.03) |
| *Shareholder Protection* | | | | | | | | | |
| InstHoldings | | | | | 0.0000 | | | -0.0006 | 0.0026*** |
| | | | | | (0.01) | | | (-0.47) | (2.89) |
| Gompers | | | | | | -0.0048 | | -0.0058 | 0.0251*** |
| | | | | | | (-0.58) | | (-0.73) | (4.12) |
| Insiders | | | | | | | -0.0443 | -0.0311 | 0.0057 |
| | | | | | | | (-0.77) | (-0.39) | (0.03) |
| Year Fixed Effects? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Standard Errors Clustered? | FI & Year | FI & Year | FI & Year | FI & Year | FI & Year | FI & Year | FI & Year | FI & Year | FI & Year |
| Observations | 77,782 | 73,680 | 70,546 | 44,370 | 70,730 | 38,123 | 71,123 | 38,123 | 36,846 |
| R-squared | 0.17 | 0.17 | 0.17 | 0.17 | 0.17 | 0.16 | 0.17 | 0.16 | 0.16 |

## Table X: Regressions of Upwardly Biased Forecasts on Security Code Violations and Investment Banking Affiliation

This table provides the results of OLS regressions of upward forecast bias (i.e., *RFBiasUp*) on measures of security code violations (*LogEvents*, *LogFines*, and *LogCodes*) interacted with investment banking affiliation. Panel A presents the results for all analysts. Panel B presents the results for subsamples of analysts based on seniority. Columns 1-3 present the results for *Junior Analysts* (i.e., less than 2 years of experience). Columns 4-6 present the results for *Senior Analysts* (i.e., more than 2 years of experience). Standard errors are double clustered by financial institution and year. ***,**, and * denote 1%, 5% and 10% level of significance, respectively. All variables are defined in Appendix B.

*Panel A: All Analysts*

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LogEvents × Affiliation | 0.0412* | 0.0468* | | | | |
| | (1.69) | (1.88) | | | | |
| LogFines × Affiliation | | | 0.0127*** | 0.0114* | | |
| | | | (3.68) | (1.77) | | |
| LogCodes × Affiliation | | | | | 0.0134 | 0.0120 |
| | | | | | (1.54) | (0.78) |
| LogEvents | -0.0142 | -0.0182* | | | | |
| | (-1.32) | (-1.69) | | | | |
| LogFines | | | -0.0014 | -0.0025* | | |
| | | | (-1.03) | (-1.88) | | |
| LogCodes | | | | | -0.0055 | -0.0107* |
| | | | | | (-0.82) | (-1.94) |
| Affiliation | -0.0886*** | -0.0487 | -0.1984*** | -0.1307 | -0.0532*** | -0.1277 |
| | (-4.21) | (-0.19) | (-4.35) | (-0.67) | (-3.51) | (-.59) |
| Controls? | No | Yes | No | Yes | No | Yes |
| Controls×Affiliation? | No | Yes | No | Yes | No | Yes |
| Year Fixed Effects? | No | Yes | No | Yes | No | Yes |
| Standard Errors Clustered? | FI and Year | FI and Year | FI and Year | FI and Year | FI and Year | FI and Year |
| Observations | 77,415 | 77,415 | 77,415 | 77,415 | 77,415 | 77,415 |
| R-squared | 0.00 | 0.01 | 0.00 | 0.01 | 0.00 | 0.01 |

*Panel B: Subsamples based on Analyst Seniority*

| | Junior Analysts | | | Senior Analysts | | |
|---|---|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
| LogEvents × Affiliation | 0.2115** | | | 0.0055 | | |
| | (2.47) | | | (0.16) | | |
| LogFines × Affiliation | | 0.0620*** | | | 0.0018 | |
| | | (2.71) | | | (0.19) | |
| LogCodes × Affiliation | | | 0.1066** | | | -0.0169*** |
| | | | (1.99) | | | (-2.73) |
| LogEvents | -0.0235 | | | -0.0175 | | |
| | (-1.12) | | | (-1.53) | | |
| LogFines | | -0.0028* | | | -0.0024 | |
| | | (-1.72) | | | (-1.47) | |
| LogCodes | | | -0.0169** | | | -0.0096 |
| | | | (-2.00) | | | (-1.64) |
| Affiliation | 0.7742 | 0.2350 | 0.4757 | -0.3201 | -0.3183 | -0.3758** |
| | (1.16) | (0.35) | (0.80) | (-1.60) | (-1.41) | (-2.54) |
| Controls? | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls×Affiliation? | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects? | Yes | Yes | Yes | Yes | Yes | Yes |
| Standard Errors Clustered? | FI and Year | FI and Year | FI and Year | FI and Year | FI and Year | FI and Year |
| Observations | 12,340 | 12,340 | 12,340 | 65,075 | 65,075 | 65,075 |
| R-squared | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |

## Table XI: Regressions of Downwardly Biased Forecasts on Security Code Violations and "Lowball" Pressures

This table provides the results of OLS regressions of downward forecast bias (i.e., *RFBiasDown*) on measures of security code violations (*LogEvents*, *LogFines*, and *LogCodes*) interacted with "lowball" pressures. Standard errors are double clustered by financial institution and year. ***,**, and * denote 1%, 5% and 10% level of significance, respectively. All variables are defined in Appendix B.

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LogEvents × Lowball | 0.0397*** | 0.0350** | | | | |
| | (3.11) | (2.03) | | | | |
| LogFines × Lowball | | | 0.0031* | 0.0022 | | |
| | | | (1.88) | (1.43) | | |
| LogCodes × Lowball | | | | | 0.0193** | 0.0258*** |
| | | | | | (2.02) | (3.30) |
| LogEvents | 0.0076 | 0.0120 | | | | |
| | (0.78) | (0.99) | | | | |
| LogFines | | | 0.0009 | 0.0021 | | |
| | | | (0.66) | (1.40) | | |
| LogCodes | | | | | 0.0024 | 0.0062 |
| | | | | | (0.39) | (1.03) |
| Lowball | -0.0528*** | 0.0105 | -0.0360*** | -0.0497 | -0.0339*** | -0.0209 |
| | (-3.92) | (0.07) | (-3.13) | (-0.33) | (-2.75) | (-0.15) |
| Controls? | No | Yes | No | Yes | No | Yes |
| Controls × Affiliation? | No | Yes | No | Yes | No | Yes |
| Year Fixed Effects? | No | Yes | No | Yes | No | Yes |
| Standard Errors Clustered? | FI and Year | FI and Year | FI and Year | FI and Year | FI and Year | FI and Year |
| Observations | 77,415 | 77,415 | 77,415 | 77,415 | 77,415 | 77,415 |
| R-squared | 0.00 | 0.01 | 0.00 | 0.01 | 0.00 | 0.01 |

## Table XII: Regressions of Forecast Accuracy on Security Code Violations and All-Star Status

This table provides the results of OLS regressions of relative forecast errors (i.e., *RFError*) on measures of security code violations (*LogEvents*, *LogFines*, and *LogCodes*) interacted with All-Star status. Standard errors are double clustered by financial institution and year. ***,**, and * denote 1%, 5% and 10% level of significance, respectively. All variables are defined in Appendix B.

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LogEvents × AllStar | -0.0535*** | -0.0456*** | | | | |
| | (-4.29) | (-2.62) | | | | |
| LogFines × AllStar | | | -0.0128** | -0.0090*** | | |
| | | | (-2.45) | (-3.38) | | |
| LogCodes × AllStar | | | | | -0.0219 | -0.0170 |
| | | | | | (-1.38) | (-1.42) |
| LogEvents | 0.0698*** | 0.0618*** | | | | |
| | (4.73) | (4.88) | | | | |
| LogFines | | | 0.0081*** | 0.0054** | | |
| | | | (3.83) | (3.32) | | |
| LogCodes | | | | | 0.0295** | 0.0307** |
| | | | | | (2.13) | (2.59) |
| AllStar | 0.0196*** | -0.0330 | 0.1144 | -0.0114 | -0.0117 | 0.0368 |
| | (4.08) | (-0.12) | (1.51) | (-0.04) | (-0.49) | (0.12) |
| Controls? | No | Yes | No | Yes | No | Yes |
| Controls × AllStar? | No | Yes | No | Yes | No | Yes |
| Year Fixed Effects? | No | Yes | No | Yes | No | Yes |
| Standard Errors Clustered? | FI and Year | FI and Year | FI and Year | FI and Year | FI and Year | FI and Year |
| Observations | 65,428 | 65,428 | 65,428 | 65,428 | 65,428 | 65,428 |
| R-squared | 0.00 | 0.18 | 0.00 | 0.17 | 0.00 | 0.18 |

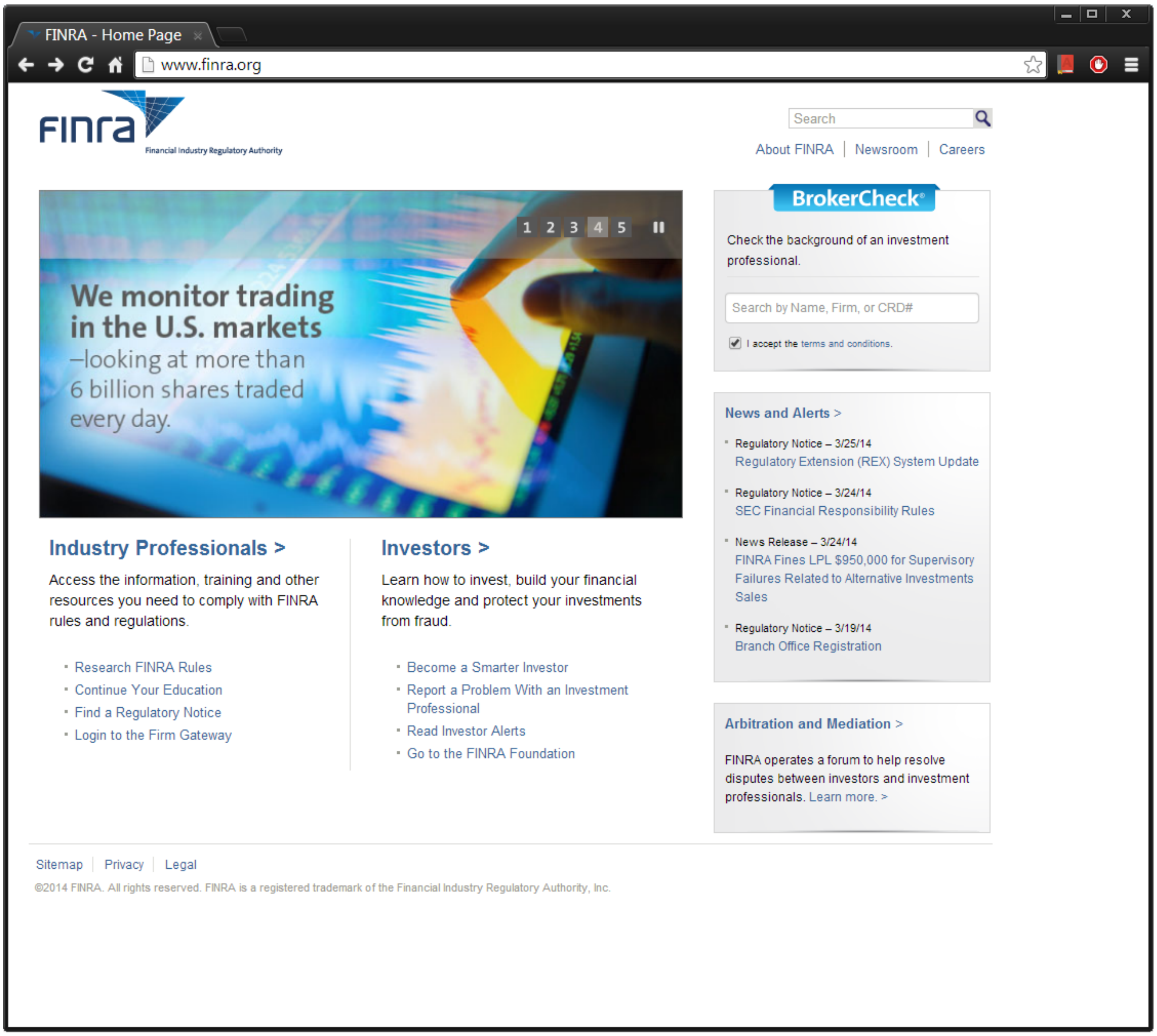
## Table XIII: Regressions of Report Informativeness on Security Code Violations

This table provides the results of OLS regressions of report informativeness (i.e., *INFO*) on measures of security code violations (*LogEvents*, *LogFines*, and *LogCodes*). Standard errors are double clustered by financial institution and year. ***,**, and * denote 1%, 5% and 10% level of significance, respectively. All variables are defined in Appendix B.

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LogEvents | -0.0198*** | -0.0107*** | | | | |
| | (-3.80) | (-4.40) | | | | |
| LogFines | | | -0.0029*** | -0.0021*** | | |
| | | | (-2.62) | (-3.01) | | |
| LogCodes | | | | | -0.0102*** | -0.0046*** |
| | | | | | (-2.61) | (-3.10) |
| Experience | | -0.0042** | | -0.0039** | | -0.0039** |
| | | (-2.37) | | (-2.35) | | (-2.25) |
| FirmsCovered | | -0.0062*** | | -0.0064*** | | -0.0064*** |
| | | (-3.08) | | (-3.27) | | (-3.20) |
| FISize | | -0.0027 | | -0.0019 | | -0.0059* |
| | | (-0.70) | | (-0.50) | | (-1.78) |
| FIPrestige | | -0.0009 | | 0.0029 | | 0.0034 |
| | | (-0.28) | | (1.30) | | (0.95) |
| FIComplexity | | 0.0092 | | 0.0070 | | 0.0068** |
| | | (1.11) | | (0.91) | | (2.34) |
| NumReportsAnalyst | | -0.0229*** | | -0.0236*** | | -0.0231*** |
| | | (-4.09) | | (-4.50) | | (-4.16) |
| NumReportsFirm | | 0.3314*** | | 0.3316*** | | 0.3316*** |
| | | (17.45) | | (17.45) | | (17.46) |
| FirmRet | | -0.0323* | | -0.0323* | | -0.0322* |
| | | (-1.69) | | (-1.69) | | (-1.68) |
| MktRet | | -0.1573*** | | -0.1552*** | | -0.1582*** |
| | | (-3.85) | | (-4.03) | | (-3.76) |
| STDRet | | 0.8750*** | | 0.8703*** | | 0.8738*** |
| | | (3.10) | | (3.07) | | (3.04) |
| TimeTrend | | -0.0025 | | -0.0027 | | -0.0024 |
| | | (-0.93) | | (-1.02) | | (-0.89) |
| Constant | 0.2000*** | 4.9668 | 0.2081*** | 5.3725 | 0.1919*** | 4.6318 |
| | (10.63) | (0.92) | (8.97) | (1.00) | (10.30) | (0.87) |
| Observations | 435,008 | 433,827 | 435,008 | 433,827 | 435,008 | 433,827 |
| R-squared | 0.00 | 0.39 | 0.00 | 0.39 | 0.00 | 0.39 |

# Appendix A. FINRA *BrokerCheck* Online Tool

This figure provides snapshots of the FINRA *BrokerCheck* online tool, available at http://www.finra.org. The *BrokerCheck* tool allows investors to collect information about the regulatory histories of the financial institutions and brokers they transact with. The first image displays the online prompt to enter institution or individual information. The second image provides a sample firm summary, which contains descriptive information as well as summary information regarding the firm's regulatory history. Data is extracted from PDF reports obtained by clicking "Get Detailed Report."



## Brokerage Firm Summary

**CITIGROUP GLOBAL MARKETS INC.**

Get Detailed Report »

CRD# 7059 SEC# 8-8177

Brokerage Firm

Investment Adviser Firm

### Disclosure Events

**This firm has disclosure events. See detailed report for more information.**

| Type | Count |
|---|---|
| Regulatory Event | 398 |
| Civil Event | 4 |
| Arbitration | 792 |

Brokerage firms are required to disclose certain criminal matters, regulatory actions, civil judicial proceedings and financial matters in which the firm or one of its control affiliates has been involved.

### Firm Profile

| Main Office Location | Mailing Address | Business Telephone Number |
|---|---|---|
| 390 - 388 GREENWICH STREET<br>NEW YORK, NY 10013-2396 | REGISTRATION DEPARTMENT<br>ONE COURT SQUARE 19TH FLOOR<br>LONG ISLAND CITY, NY 11120 | 212-816-6000 |

Regulated by the FINRA New York district office

**This firm is registered with:**

- the SEC
- 15 Self-Regulatory Organizations
- 53 U.S. states and territories:
  - Alabama
  - Alaska
  - Arizona
  - Arkansas
  - California
  - and 48 more state(s). See detailed report for more information.

**Firm Operations:**

- This firm conducts 25 types of businesses.
- This firm is affiliated with financial or investment institutions.
- This firm has referral or financial arrangements with other brokers or dealers.
- This firm is classified as a corporation.
- This firm was formed in New York on 10/15/1998.
- Its fiscal year ends in December.

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- Suitability: What Investors Need to Know
- Working With Your Investment Professional
- Avoid Common Investor Problems
- Prohibited Conduct

# Appendix B. Variable Definitions

This section provides definitions of the main variables used throughout the study (presented in order of appearance).

- **TotalEvents (LogEvents)**: Total (natural log of) number of disclosure events sanctioned against a financial institution in a year. Data obtained from FINRA *BrokerCheck* reports.
- **TotalFines (LogFines)**: Total (natural log of) dollar value of fines sanctioned against a financial institution in a year. Data obtained from FINRA *BrokerCheck* reports.
- **TotalCodes (LogCodes)**: Total (natural log of) of number of unique security code violations sanctioned against a financial institution in a year. Data obtained from FINRA *BrokerCheck* reports.
- **ClearTrade**: Indicator variable that takes the value of 1 if disclosure event contains a violation of security codes related to "Clearing, Transaction, and Order Data Requirements & Facility Charges," and 0 otherwise. Data obtained from FINRA *BrokerCheck* report. Classification of security codes provided in Appendix C.
- **DutyConflict**: Indicator variable that takes the value of 1 if disclosure event contains a violation of security codes related to "Duties and Conflicts," and 0 otherwise. Data obtained from FINRA *BrokerCheck* report. Classification of security codes provided in Appendix C.
- **FinOps**: Indicator variable that takes the value of 1 if disclosure event contains a violation of security codes related to "Financial and Operational Rules," and 0 otherwise. Data obtained from FINRA *BrokerCheck* report. Classification of security codes provided in Appendix C.
- **InvSanct**: Indicator variable that takes the value of 1 if disclosure event contains a violation of security codes related to "Investigations and Sanctions," and 0 otherwise. Data obtained from FINRA *BrokerCheck* report. Classification of security codes provided in Appendix C.
- **Application**: Indicator variable that takes the value of 1 if disclosure event contains a violation of security codes related to "Member Application & Associated Person Registration," and 0 otherwise. Data obtained from FINRA *BrokerCheck* report. Classification of security codes provided in Appendix C.
- **TransReport**: Indicator variable that takes the value of 1 if disclosure event contains a violation of security codes related to "Quotation and Transaction Reporting Facilities," and 0 otherwise. Data obtained from FINRA *BrokerCheck* report. Classification of security codes provided in Appendix C.
- **SecOffer**: Indicator variable that takes the value of 1 if disclosure event contains a violation of security codes related to "Securities Offering and Trading Standards and Practices," and 0 otherwise. Data obtained from FINRA *BrokerCheck* report. Classification of security codes provided in Appendix C.
- **Supervision**: Indicator variable that takes the value of 1 if disclosure event contains a violation of security codes related to "Supervision and Responsibilities Relating to Associated Persons," and 0 otherwise. Data obtained from FINRA *BrokerCheck* report. Classification of security codes provided in Appendix C.
- **KLDProduct**: Net product score obtained from the Kinder, Lydenberg and Domini (*KLD*) corporate social responsibility database. *KLD* awards firms points for product quality strengths (e.g., high quality, innovative, and socially beneficial products) and deducts points for product quality weaknesses (e.g., unsafe and poorly market products).
- **InstHoldings**: Percentage of shares held by Institutional Investors using data obtained from *FactSet* and *CapitalIQ*.

- **Gompers**: Composite index of managerial power. Data obtained from last available Gompers Index produced in 2006.
- **Insiders**: Percentage of board members that are insiders using data obtained from *FactSet* and *CapitalIQ*.
- **RFError**: The relative forecast error provided by analyst $i$ covering firm $j$ in year $t$. The relative forecast error is measured as analyst $i$'s last absolute forecast error for the year for firm $j$ in year $t$ less the mean absolute forecast error for firm $j$ in year $t$, scaled by the mean absolute forecast error for firm $j$ in year $t$. Forecast errors are calculated using the last forecast issued in the first 11 months of the year.
- **RExp**: The relative number of years of experience analyst $i$ covering firm $j$ in year $t$ has. Relative forecast experience is measured as the number of months analyst $i$ has covered firm $j$ as of year $t$ less the mean number of months of experience for all analysts covering firm $j$ in year $t$, scaled by the mean number of months of experience for all analysts covering firm $j$ in year $t$. Relative forecast experience is calculated using the last forecast issued in the first 11 months of the year.
- **RHorizon**: The relative number of days until the earnings announcement. Relative horizon is measured as the number of days until the earnings announcement for the last forecast issued by analyst $i$ covering firm $j$ in year $t$ less the mean number of days until the earnings announcement for all analysts covering firm $j$ in year $t$, scaled by the mean number of days until the earnings announcement for all analysts covering firm $j$ in year $t$. Relative horizon is calculated using the last forecast issued in the first 11 months of the year.
- **RFirmsCovered**: The relative number of firms covered by an analyst. Relative firm coverage is measured as the number of firms covered by analyst $i$ covering firm $j$ in year $t$ less the mean number of firms covered by all analysts covering firm $j$ in year $t$, scaled by the mean number of firms covered by all analysts covering firm $j$ in year $t$. Relative firm coverage is calculated using the last forecast issued in the first 11 months of the year.
- **FIPrestige**: An indicator variable that takes the value of 1 if the financial institution is one of the top 10 ranked Institutional Investor brokers, and 0 otherwise. Data obtained from Institutional Investor website.
- **FIComplexity**: Natural log of the total number of business lines in the financial institution (as observed in the FINRA *BrokerCheck* report).
- **FISize**: Natural log of the total number of analysts employed at the financial institution each year.
- **SecCodeRank**: Composite measure based on *LogEvents*, *LogFines* and *LogCodes*. Constructed by independently ranking observations into quintiles based on each measure and then averaging the independent ranks.
- **Size**: Natural log of total assets using data obtained from *FactSet* and *CapitalIQ*.
- **Profitability**: Net income divided by total assets using data obtained from *FactSet* and *CapitalIQ*.
- **ICW**: Indicator variable that takes the value of 1 if the financial institution has a material weakness or significant deficiency in internal controls in current year, and 0 otherwise. Internal control data is obtained from *AuditAnalytics*.
- **STCompMix**: Proxy for short-term compensation mix. Constructed by taking the ratio of CEO's total annual compensation divided by calculated compensation, including stock awards and non-cash compensation. Data obtained from *FactSet* and *CapitalIQ*.
- **RFBiasUp**: Relative upward forecast bias of forecasts provided by analyst $i$ covering firm $j$ in year $t$. Relative upward forecast bias is measured as the difference between analyst $i$'s last forecast for firm $j$ in year $t$ less the average forecast issued by all analysts covering firm $j$ in

year $t$, scaled by the standard deviation of all forecasts issued by analysts covering firm $j$ in year $t$. Relative upward forecast bias is calculated using the last forecast issued in the first 11 months of the year.

- **Affiliation**: Proxy for investment banking affiliation. Indicator variable that takes the value of 1 if the analyst's employer was involved in an initial public offering or seasoned equity offering for the covered firm in the prior 12 months (as indicated by *SDC*), and 0 otherwise.
- **RFBiasDown**: Relative downward forecast bias of forecasts provided by analyst $i$ covering firm $j$ in year $t$. Relative downward forecast bias is measured as -1 times the difference between analyst $i$'s last forecast for firm $j$ in year $t$ less the average forecast issued by all analysts covering firm $j$ in year $t$, scaled by the standard deviation of all forecasts issued by analysts covering firm $j$ in year $t$. Relative downward forecast bias is calculated using the last forecast issued in the first 11 months of the year.
- **Lowball** : An indicator variable that takes the value of 1 if actual firm earnings exceed the end of the year consensus forecast by zero or one cents, and 0 otherwise.
- **AllStar**: An indicator variable that takes the value of 1 if the analyst is ranked an "All-Star" analyst in the Institutional Investor rankings in the current year, and 0 otherwise.
- **INFO**: Absolute value of size-adjusted returns in the 3-day windows centered around a forecast revision date.
- **Experience**: Natural log of the number of years of experience an analyst has in the current year.
- **FirmsCovered**: Natural log of the number of firms covered by an analyst in the current year.
- **NumReportsAnalyst**: Number of reports produced by the analyst for a given firm in the current year.
- **NumReportsFirm**: Number of reports issued about a firm in a given day.
- **FirmRet**: Cumulative monthly firm returns over the 6 month period prior to the forecast revision date.
- **MktRet**: Cumulative monthly market returns over the 6 month period prior to the forecast revision date.
- **SigmaRet**: Standard deviation of market returns over the prior 6 months.

# Appendix C. Classification of Security Code Violations

This table presents a classificaiton scheme of all violations identified in FINRA *BrokerCheck* reports. All identified security code violations are matched to the current FINRA rulebook based on major category headings. The rulebook is available online at: http://www.finra.org/Industry/Regulation/.

| Major Category | Security Codes |
|---|---|
| Clearing, Transaction, and Order Data Requirements & Facility Charges | FINRA Codes 6130, 6230, 7230, 7330, 7410, 7440, 7450; NASD Codes 6951, 6954, 6955 |
| Duties & Conflicts | FINRA Codes 2010, 2020, 2110, 2111, 2210, 2220, 2232, 2251, 2264, 2265, 2310, 2320, 2360, 5280; MSRB Codes A-13, 2, 21, 30, 32; NASD Codes 2110, 2120, 2210, 2211, 2220, 2230, 2260, 2310, 2341, 2420, 2440, 2711, 2810, 2820, 2830, 2860; NYSE Codes 97, 104, 115, 116, 301, 304, 311, 341, 451, 460, 722, 5190, 1100, 123, 132, 134, 2010, 203, 320, 325, 342, 345, 346, 351, 401, 405, 407, 408, 409, 410, 411, 416, 421, 440, 445, 452, 472, 80, 90, 92 |
| Financial and Operational Rules | FINRA Codes 4210, 4311, 4320, 4370, 4511, 4530, 4560, 4632, 4650, 2520, 3070, 3210, 3230, 3360, 3510 |
| Investigations & Sanctions | FINRA Codes 8210, 8211, 8213; NASD Codes 8210, 8211, 8213 |
| Member Application & Associated Person Registration | FINRA 1122; NASD 1021, 1022, 1031, 1032, 1050; NYSE 10; MSRB 3 |
| Quotation and Transaction Reporting Facilities | FINRA 6182, 6279, 6380, 6440, 6622, 6624, 6633, 6634, 6730, 6740, 6760, 6830, 6955; MSRB 14; NASD 4613, 4632, 6230, 6240, 6620, 6640, 6732, 6740, 6760 |
| Securities Offering and Trading Standards and Practices | FINRA 5121, 5210, 5220, 5260, 5310, 5320, 5330; NASD 2111, 2320, 2720, 3220, 3310, 3320, 3340 |
| Supervision and Responsibilities Relating to Associated Persons | FINRA 3010, 3240, 3310; MSRB 27, 41, 8; NASD 2370, 3010, 3011, 3012, 3040, 3050, 3110, 3350, 3370; NYSE 476 |