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Integrity Culture and Analyst Forecast Accuracy

By

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Abstract:

This study examines the relationship between financial institutions' integrity culture and analysts' forecast accuracy. Integrity culture represents the extent to which norms and values within financial institutions promote high ethical standards and honesty. Using data collected from the Financial Industry Regulatory Authority (FINRA), I measure the weakness of integrity culture in financial institutions based on security code violations arising in business areas *unrelated* to equity research. I find that FINRA violations are associated with less accurate forecasts, and that these results are robust to a host of alternative explanations, including poor internal controls, weak governance, and other cultural forces. I also find that violations are associated with more strategic forecast biases and less informative earnings forecasts. These findings shed light on how cultural forces can influence the behavior of security analysts.

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I. Introduction

The issue before this Committee today is whether the global settlement will reform the culture of Wall Street, restore the integrity of stock analysts, and regenerate investor confidence.[…] I believe that the Wall Street culture must change from the top down, and I am not convinced that the global settlement has done enough to change attitudes at the top of these banks.

-Committee on Banking, Housing and Urban Affairs, United States Senate (May 7, 2003)[1]

Since the Global Settlement, the activities of sell-side equity analysts have been under heavy scrutiny by regulators and have been of increasing interest to academics. Consequently, a large literature has examined how the characteristics of the financial institutions that employ sell-side equity analysts influence the quality and objectivity of their research reports. For example, prior studies have examined a wide array of financial institution characteristics including brokerage house type (Cowen, Groysberg and Healy 2006; Groysberg, Healy, Serafeim and Shanthikumar 2013), cross-business affiliation (Chen and Martin 2011; Firth, Lin, Liu and Xuan 2013), institutional reputation (Fang and Yasuda 2009), compensation structures (Groysberg, Healy and Maber 2011; Brown, Call, Clement and Sharp 2015), availability of divisional resources (Clement 1999; Clement and Tse 2003), and diversity of colleagues (Groysberg and Lee 2008). However, one important financial institution characteristic that has long-been identified by regulators, yet remains an underexplored issue is corporate culture. This issue is particularly interesting given that regulators claim that instances of misconduct such as those that motivated the Global Settlement, are partly the results of severe cultural lapses in financial institutions.[2] While Global Settlement had obvious and immediate effects on sell-side equity analysts' recommendation behavior (e.g., Barber, Lehavy, McNichols and Trueman 2006; Barniv, Hope, Myring and Thomas 2009; Chen and Chen 2009), it is not clear whether cultural problems persisted and how they influence other less regulated dimensions of analysts' research. In this study, I seek to shed light on this issue by examining how corporate culture influences the quality of analysts' earnings forecasts.

[1] https://www.gpo.gov/fdsys/pkg/CHRG-108shrg95946/html/CHRG-108shrg95946.htm

[2] For example, please see the following speeches from former SEC director Lori Richards on this issue: https://www.sec.gov/news/speech/spch042303lar.htm; https://www.sec.gov/news/speech/2006/spch101906lar.htm; https://www.sec.gov/news/speech/2007/spch101807lar.htm.

In general, corporate culture is a multi-dimensional, intangible asset designed to meet unforeseen contingencies as they arise and consists of the shared assumptions, values and beliefs that inform how employees behave within a firm (Schein 1990; Kreps 1990). In the presence of incomplete contracts (Grossman and Hart 1986), corporate culture plays an important role in communicating the appropriate course of action and aligning employee behavior with the objectives of the firm (Guiso, Sapienza and Zingales 2014). In this study, I focus on financial institutions' integrity culture, which is one dimension of a firm's overall corporate culture that represents the extent to which norms and values within firms emphasize high ethical standards and honesty. Cultures of strong integrity constrain unethical behavior because "adherence to integrity acts as a commitment not to engage in economic calculations" that damage clients' welfare (Erhard, Jensen and Zaffron 2007; Guiso et al. 2014). This dimension of culture is especially relevant for financial institutions, and sell-side equity analysts in particular, as they serve as information intermediaries that are often faced with conflicts of interest that can lead them to sacrifice the interests of their clients.

My main prediction is that sell-side equity analysts employed by financial institutions with weak integrity culture produce earnings forecasts that are less accurate. Analysts' earnings forecasts play a critical role in the dissemination of information about firms' earnings (e.g., Gleason and Lee 2003; Clement and Tse 2003), and accurate and unbiased research is particularly useful to numerous small individual clients as they lack the sophistication to easily adjust for analysts' biases in their forecasts (e.g., Jackson 2005; Hilary and Hsu 2013). While reputational concerns can motivate financial institutions to encourage analysts to produce high quality forecasts (Cowen et al. 2006), financial institutions rarely contract on forecast accuracy in practice (Groysberg et al. 2011). Instead, analyst research is funded primarily through the revenues from investment banking and institutional brokerage business. Thus, analysts have strong incentives to cater to these affiliated firms (Brown et al. 2015). For instance, analysts may strategically withhold information from their reports or intentionally introduce biases into their forecasts, either upwards or downwards, due to the demands arising from these firms, which ultimately reduces the overall accuracy of their forecasts (Irvine, Lipson and Puckett 2007; Dugar and Nathan 1995; Ke and Yu 2006). A strong integrity culture, on the other hand, acts as a counter-balancing norm within the firm to discourage and minimize such behavior.

I measure the weakness of financial institutions' integrity culture using the number of disclosure events appearing in Financial Industry Regulatory Authority (FINRA) *BrokerCheck* reports issued between 2005 and 2012. FINRA frequently conducts cycle examinations to determine whether firms are in compliance with federal securities laws and regulations. FINRA violations provide a useful proxy for the weakness of financial institutions' integrity culture as the rules that FINRA enforces are developed to protect the clients of financial institutions and promote market integrity.[3] Moreover, regulators have suggested that violations often arise as a result of deficient corporate cultures that fail to foster ethical behavior.[4] A key feature of my empirical design is that I only measure violations arising *outside* of the research department. This design ensures that violations are not the direct result of analyst behavior and that any association between FINRA violations and analysts' forecast accuracy can only be explained by common firm-level forces (such as culture).

My main results indicate statistically significant positive associations between FINRA violations and the relative forecast errors produced by financial institutions' equity analysts. These results hold after controlling for characteristics associated with forecast accuracy, such as experience, horizon, and number of firms covered (Clement 1999) as well as financial institution characteristics including size, prestige and the variety of business activities that the financial institution engages in (Cowen et al. 2006). In additional analyses, I also demonstrate that these results are robust to different scalars (including number of analysts and number of business lines) as well as different measures of FINRA violations based on annual dollar value of fines and the unique number of security codes violated. Overall, the results of this analysis provide evidence consistent with weak integrity culture reducing the accuracy of analysts' forecasts.

I conduct several robustness analyses to strengthen my claim that the positive associations between FINRA violations and analysts' forecasts errors are consistent with integrity culture influencing analysts'

[3] https://www.finra.org/industry?f=1
[4] https://www.sec.gov/news/speech/2007/spch101807lar.htm

forecasts. Given the persistence of cultural forces, especially over the relatively short sample period after the Global Settlement, providing causal evidence through the use of exogenous variation in integrity culture is challenging.[5] Instead, I conduct analyses that eliminate alternative explanations for my findings. First, I control for other potential causes of FINRA violations. I find that the positive and significant association between FINRA violations and analysts' forecasts errors persists after controlling for an array of financial institution characteristics, including size, profitability, internal control quality, and corporate governance mechanisms. Second, I also control for other previously examined measures related to culture (e.g., Hoi, Wu and Zhang 2013; Clement, Rees and Swanson 2003). I find that my results continue to hold after controlling for employee satisfaction scores, scandals and controversies, product quality ratings, employee relations ratings, corporate social responsibility scores, and the country that the financial institution is headquartered in. Overall, the results from these additional analyses suggest that integrity culture has a distinct effect on analysts' forecast accuracy that cannot be easily explained by other characteristics of financial institutions or other cultural forces.

I conduct two additional analyses to further examine the relationship between weak integrity culture and financial analysts' forecast quality. First, I examine the association between weak integrity culture and forecast bias. I argue that one reason why analysts employed by financial institutions with weak integrity culture issue less accurate forecasts is that they are more susceptible to pressures to bias their forecasts. However, ex ante, the direction of any potential bias is not clear, as prior studies have documented instances in which analysts face pressures to issue *upwardly* biased forecasts (e.g., around recent equity offerings), as well as instances in which analysts face pressures to issue *downwardly* biased forecasts (e.g., to create an easy earnings target for managers to beat) (Dugar and Nathan 1995; Ke and Yu 2006).

Accordingly, I conduct several tests to examine how weak integrity culture relates to the biases in short-horizon forecasts (i.e., one-year ahead forecasts) and long-horizon forecasts (i.e., two-year ahead forecasts). I expect forecast horizon to be an important factor in this analysis as prior studies suggest that

[5] For example, autocorrelation coefficients on integrity culture measures range from 55%-66%.

the pressures to bias forecasts in a particular direction may vary with the horizon of the forecast (e.g., Ke and Yu 2006) and integrity culture may counter different incentives that vary with horizon. My results indicate that financial institutions with weak integrity cultures issue more downwardly biased short-horizon forecasts on average, thus creating an easier target for managers to beat. The results from these tests also indicate that analysts employed by financial institutions with weak integrity cultures issue more downwardly biased short-horizon forecasts when covered firms narrowly "meet or beat" earnings forecasts. Regarding long-horizon forecasts, I find that analysts employed by financial institutions with weak integrity culture issue more upwardly biased long-horizon forecasts for firms engaged in investment banking business with the analyst's employer.

My second additional analysis examines whether weak integrity cultures impact the informativeness of earnings forecasts, as measured as the absolute value of 3-day CARs around the earnings forecast date. Analysts' forecasts do not always bring new information to the market and may contain repackaged or biased information that is not incrementally useful to individual investors (Frankel, Kothari and Weber 2006). Weak integrity cultures can reduce the informativeness of analysts' forecasts if analysts withhold information from their public reports or introduce biases into their forecasts. Consistent with this notion, my results indicate a significantly negative association between weak integrity culture and earnings forecast informativeness. Taken together, the results of these additional analyses provide strong evidence to support the notion that weak integrity cultures reduce forecast quality.

My results contribute to the literature across several dimensions. First, I contribute to the literature examining the financial institution characteristics of analysts' reports (e.g., Clement 1999; Cowen, Groysberg and Healy 2006; Chen and Martin 2011; Groysberg, Healy and Maber 2011; Firth, Lin, Liu and Xuan 2013). My findings suggest that integrity culture is an important, unexplored financial institution-level characteristic that explains systematic differences in forecast quality across financial institutions. My findings also contribute to the literature examining the effects of sell-side analyst regulations and conflicts of interest (e.g., Barber et al. 2006; Barniv et al. 2009; Ertimur, Sunder and Sunder 2007). My results suggest that, even in the presence of stricter regulation following Global Settlement, cultural forces can still compromise analysts' objectivity in areas not directly targeted by regulation. Finally, my results contribute to an emerging literature examining corporate culture (e.g., Hoi, Wu and Zhang 2013; Gao, Lisic and Zhang 2014; Guiso et al. 2014; Liu 2015) by demonstrating how culture can influence financial analysts' forecasts.

The rest of the paper proceeds as follows. Section II discusses the related literature and develop my main hypothesis and additional testable predictions. Section III discusses the FINRA violations data. Section IV presents results examining the relationship between integrity culture and forecast accuracy. Section V presents additional analyses. Section VI concludes.

II. Related Literature & Hypothesis Development

A. Corporate Culture & Integrity

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 improve coordination within the firm (Hermalin 1999). 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 formal incentive mechanisms (Guiso et al. 2014). Within this literature, corporate culture is often viewed as a set of assumptions, beliefs, values and norms shared by employees throughout the organization that informs which behaviors are appropriate (O'Reilly 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.

This study focuses on integrity culture, which represents the extent to which norms and values within an organization emphasize high ethical standards and honesty. Formally, integrity is defined as a "state or condition of being whole, complete, and unbroken" (Erhard et al. 2009). Prior studies indicate that integrity culture is an important dimension of corporate culture as adherence to integrity within an organization serves as a commitment device for agents not to "engage in economic calculations" and is associated with positive firm outcomes, including higher productivity and profitability (Guiso et al. 2014).[6]

Integrity culture is particularly relevant for financial institutions, and specifically equity analysts, as they often face conflicts of interest that lead them to trade-off client's welfare for short-term profits.[7] While rules and regulations attempt to establish the minimum standards of conduct, many unethical activities are subtler and difficult to explicitly regulate. This concern has been highlighted by regulators who emphasize the importance of 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."[8] In this framework, a high integrity culture can act as a counter-balancing norm within the organization that discourages and minimizes unethical behavior in the presence of incomplete contracts.[9]

B. Financial Institution Characteristics Associated with Analyst Research Quality

Since the Global Settlement, there has been a growing interest in understanding how the characteristics of the financial institutions that employ sell-side equity analysts influence the quality and objectivity of their research. For example, Cowen et al. (2006) document systematic differences in forecast quality based on the type of businesses that financial institutions engage in, and find that trading incentives reduce forecast quality (as measured by optimism). Chen and Martin (2011) find that financial institutions that have banking affiliations produce more accurate forecasts, suggesting that analysts gain access to proprietary information when forming their forecasts. Firth et al. (2013) find that financial institutions' business relations with mutual funds influence analysts' recommendation optimism. More recent studies explicitly examine the relationship between financial institutions' compensation structure and analysts'

[6] Maintaining high levels of integrity capital is not without its costs. In the short run, firms may forego profits due to their efforts to not sacrifice their clients' satisfaction.
[7] See the following FINRA discussion on conflicts of interest:
https://www.finra.org/sites/default/files/Industry/p359971.pdf
[8] https://www.sec.gov/news/speech/spch042303lar.htm
[9] Several recent studies in accounting have also examined corporate culture using corporate social responsibility (CSR) measures. Hoi et al. (2013) examine the relationship between CSR and tax avoidance and find evidence consistent with corporate culture affecting tax avoidance. Gao et al. (2014) examine the association between CSR and insider trading and find that CSR-conscious firms profit less from insider trades.

report quality. For example, Groysberg et al. (2011) use proprietary data from a major financial institution and find that compensation is heavily driven by investment banking contribution and recognition (as an “All-Star” or WSJ stock picker), but is not related to forecast accuracy. Further, both Maber, Groysberg and Healy (2014) and Brown et al. (2015) find that analysts are primarily compensated based on their standing with the institutional firms they transact with as measured by broker votes. Overall, these studies suggest that the characteristics of the financial institutions that employ analysts influence their reports, and potentially compromise their objectivity.

While studies directly examining Global Settlement have found that, on average, the regulation improved the quality of analysts’ recommendation (Barber et al. 2006; Barniv et al. 2009; Chen and Chen 2009; Kadan, Madureira, Wang and Zach 2009), concerns still remain regarding the overall objectivity of analysts’ research.[10] For example, recent research suggests that many analysts still report being heavily compensated based on generating underwriting business or trading commissions and catering to institutional firms (Brown et al. 2015) and forecast accuracy remains an unimportant determinant of compensation (Groysberg et al. 2011). Recent scandals in the press suggest that analysts have taken to more subtle ways of catering to these affiliated firms. For example, Citigroup and Goldman Sachs both recently were sanctioned for selectively disclosing stock tips to affiliated firms and withholding that information from their research reports.[11]

One potential explanation for a persistent lack of objectivity in analyst research is the weakness of the integrity culture that permeates the financial institutions by which analysts are employed. Culture has long been pointed towards as a potential concern for financial institutions and analyst behavior. For example, former SEC director Lori Richards presented a series of speeches during her tenure at the SEC

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[10] While prior studies examining Global Settlement generally focus on the short-term changes in recommendation behavior of sell-side analysts, a recent study by Espahbodi, Esphabodi, and Espahbodi (2015) examines forecast accuracy. The study finds that, despite a short-run increase in forecast accuracy immediately following Global Settlement, forecast accuracy significantly declined over the long-run. The authors conclude that none of the “regulations achieved its objective (at least in the long run).”

[11] http://dealbook.nytimes.com/2014/11/24/citigroup-fined-15-million-for-failing-to-properly-supervise-analysts/?_r=0 and http://www.wsj.com/articles/SB125107135585052521

in which she encouraged financial institutions to develop cultures that "foster ethical behavior and decision-making," and instill in employees "an obligation to do what's right."[12] Moreover, the United States Senate Committee on Banking, Housing and Urban Affairs warned that despite the record monetary sanctions associated with the Global Settlement, there was still serious doubts whether the Global Settlement would reform culture on Wall Street.[13] Consistent with these concerns, a strong integrity culture can play an important role in financial institutions by reinforcing norms that discourage behavior that is damaging for financial institutions' clients. Despite its importance, integrity culture remains an unexplored dimension of financial institutions that can have potentially important implications for the quality of analyst research.

C. Hypothesis Development

My main prediction is that financial institutions with weak integrity culture produce earnings forecasts that are relatively less accurate. I focus on earnings forecasts as a setting for examining the impact of integrity culture for several reasons. First, earnings forecasts play an important role in disseminating information about earnings expectations to market participants (Gleason and Lee 2003), and consequently analysts often face pressures from managers and affiliated firms to manipulate their forecasts (e.g., Ke and Yu 2006). Second, earnings forecasts are generally not explicitly contracted on (Groysberg et al. 2011), thus providing an important role for culture. Third, regulating forecast quality explicitly and identifying misfeasance is also likely to be difficult since forecasts are a function of a multitude of unobservable attributes, including luck, skill and ability (Clement 1999). Finally, earnings forecasts have useful empirical properties as they are continuous, have a common benchmark (actual earnings) and easily facilitate relative comparisons across analysts at different financial institutions.

I posit that financial institutions with weak integrity cultures lack values and norms to discourage analysts from succumbing to pressures from institutional firms, ultimately compromising the objectivity of their earnings forecasts. These pressures may result in analysts withholding information from their

[12] https://www.sec.gov/news/speech/2006/spch101906lar.htm
[13] https://www.gpo.gov/fdsys/pkg/CHRG-108shrg95946/html/CHRG-108shrg95946.htm

forecasts, or introducing intentional biases into their forecasts (either upwards or downwards), ultimately reducing the overall accuracy of their forecasts. A strong integrity culture, on the other hand, can establish the importance of maintaining client welfare as a norm within the financial institution. When analysts consider succumbing to pressures from affiliated firms, they will consider this norm as well as the repercussions from violating this norm (e.g., ostracism from the community) (Guiso et al. 2014). Accordingly, this leads to my main hypothesis:

Main Hypothesis: *Weak financial institution integrity culture is negatively associated with analysts' forecast accuracy.*

My main hypothesis generates two additional testable predictions. The first prediction relates to the extent to which analysts introduce intentional strategic biases into their forecasts. Prior studies indicate settings in which analysts may face pressure to introduce both upwards or downward bias into their forecasts, and these pressures may vary with the horizon of the forecasts issued. For example, upward pressure can arise if analysts are expected to issue long-horizon optimistic forecasts for recent investment banking clients in order to promote the firms (e.g., Lin and McNichols 1998). Alternatively, analysts can also face downward pressures (i.e., "low-ball" pressures) from covered firms to create easily beatable forecasts (e.g., Lim 2001; Matsumoto 2002; Ge and Yu 2006). In the presence of a weak integrity culture, analysts are more likely to succumb to these pressures to introduce strategic biases into their forecasts as the institution lacks values and norms that discourage such behavior. Specifically:

Prediction 1: *Weak financial institution integrity culture is positively associated with analysts' strategic forecast biases.*

My second testable prediction examines whether and to what extent market participants value the earnings forecasts issued by analysts employed by financial institutions with weak integrity cultures. It is natural to conjecture that investors will react less to forecasts issued by analysts at weak integrity culture financial institutions if these analysts withhold information from their public reports, but provide this information privately to affiliated firms. Further, investors may even ignore forecasts issued by analysts at weak integrity financial institutions if they expect these analysts to mislead them by intentionally introducing biases into their forecasts. These predictions are consistent with prior studies that indicate that analysts' reports do not always bring new value relevant information to the market (Frankel et al. 2006). Formally, my second testable prediction is as follows:

Prediction 2: *Weak financial institution integrity culture is negatively associated with analysts' forecast informativeness.*

III. Sample Selection & Data

A. FINRA Data & Sample of Financial Institutions

I begin my sample selection by obtaining a list of financial conglomerates with U.S. security subsidiaries from the Federal Reserve.[14] 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.[15][16]

My sample is further restricted by the availability of analyst forecast data. For each of the financial institutions in the sample, I collect financial institution names from I/B/E/S. 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 1 presents the final sample of financial institutions and their associated security subsidiaries. The sample consists of 48 security subsidiaries across 29 financial institutions and includes 204 financial institution-years.

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. FINRA frequently conducts cycle

[14] http://www.federalreserve.gov/bankinforeg/suds.htm
[15] http://www.sec.gov/about/offices/oia/oia_regstat.htm
[16] Several of the institutions in the sample, such as Wells Fargo & Company, are a result of large mergers and acquisitions. For these institutions, I exclude their observations prior to the merger date since the FINRA data does not clearly distinguish between the acquirer and target prior to the merger date.

examinations to determine whether firms are in compliance with federal securities laws and regulations, and violations are published online in *BrokerCheck* reports that allow investors to observe the regulatory history of the financial institutions they conduct business with. The primary data used to measure security code violations throughout this 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.

Appendix B provides examples of several disclosure events. In the first example, 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 small clients.[17] Other common examples (unreported) indicate instances in which financial institutions recommend unsuitable investment products to their clients, mislead clients, use manipulative sales tactics and trade ahead of their clients' orders.[18] These examples suggest that the violations are indicative of weak integrity cultures that fail to protect the welfare of small clients.

Table 2 presents the sample selection procedure based on the Disclosure Events data. In the sample, I include all completed (i.e., not pending) disclosure events with non-missing case numbers issued between 2005 and 2012, due to sparse data in the early 2000s and to ensure that the violations are not directly related to Global Settlement. I delete disclosure events with 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 and its predecessors NASD and NYSE) and exclude disclosure events issued by state agencies to avoid double counting events, as many of these events are redundant. Finally, I employ an identification criteria that excludes events *directly* related to research department activities. Specifically, I delete 20 observations in which the allegations mention the word "Research'" or contain

[17] The allegations section of this report is truncated to preserve space.
[18] For a list of the commonly occurring violations, please see: http://www.finra.org/investors/top-nasd-rule-violations.

violations of NASD Code 1050 or NASD Code 2711, which regulate equity research. As discussed in Section 2, these violations are likely rare because research quality is difficult to explicitly regulate. Nonetheless, removing these observations allows me to cleanly attribute the association between activities in two *unrelated* divisions of the financial institution to a common firm-level force (such as integrity culture). The primary measure of weak integrity culture is the annual number of disclosure events and the final sample consists of 472 disclosure events issued between 2005 and 2012.[19]

B. Characteristics of FINRA Violations

Table 3 presents characteristics of financial institution violations (as measured by annual disclosure events). Panel A presents the frequency of violations by sanction year. Overall, violations appear to be cyclical, experiencing relatively high points in 2007 and 2010, with the latter perhaps related to heightened regulatory response following the financial crisis. Panel B presents the frequency of security code violations by financial institution. Nearly all of the institutions (25 out of 29) within the sample receive a violation during the sample period. However, I note that my main inferences remain unchanged if I exclude the four financial institutions that did not receive any violations from the analysis.

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 financial institution is sanctioned. The reports that do disclose event dates vary substantially, with some events occurring recently (e.g., prior year) and others occurring several years earlier. Thus, my financial institution-year measures of violations rely on the year reported within the "sanction date" and assume that integrity culture remains relatively constant between the event date and the sanction date. This assumption is consistent with the notion that corporate culture within firms can be stable over time (e.g., Heskett and Kotter 1992), especially over a relatively short smaller sample period. In Table 3, Panel C, I formally test the persistence of violations to help support the claim that they represent cultural forces. To do so, I examine the correlation of violations with up to three lags of violations. The correlations range from about 55% to 66%, confirming that violations are highly persistent.

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[19] In robustness tests, I examine alternative measures including total fines and total unique codes violated, and demonstrate that my inferences remain unchanged when using these different measures.

IV. Main Analysis

A. Research Design

My main hypothesis predicts weak integrity culture to be negatively correlated with forecast accuracy. To test this hypothesis, I examine the association between violations (i.e., my proxy for weak integrity culture) and relative forecast errors, using measures similar to prior studies (e.g., Clement 1999). Specifically, relative forecast errors is constructed as follows:

$$RFError_{ijt} = \frac{AFE_{ijt} - \overline{AFE_{Jt}}}{\overline{AFE_{Jt}}}$$

where AFE_{ijt} is the absolute forecast error for analyst *i*'s forecast for firm *j* in year *t* and $\overline{AFE_{Jt}}$ is the mean absolute forecast error for firm *j* in year *t* across all analysts providing forecasts for the firm 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 $RFError$ effectively controls for important firm-year differences within the sample (Clement 1999).

To test my main hypothesis, I employ the following regression model:

$$RFError_{ijt} = \alpha_0 + \alpha_1 Violations_{ft} + \alpha_2 AnalystControls_{ijt} + \alpha_3 FIControls_{ft} + \sum_t Year_t + \epsilon_{ijt} \quad (1)$$

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*). The proxy for weak integrity culture, *Violations,* is measured as the natural log of one plus the total number of disclosure events a financial institution receives in a year. *AnalystControls* is a vector that includes analyst characteristics that prior studies demonstrate are important determinants of forecast accuracy (Clement 1999; Jacob, Lys and Neale 1999). *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 firm-year mean of each measures).

The model also includes a vector of *FIControls* that are likely to influence the quality of analysts' forecasts. *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. *FIBusinessLines* accounts for how differences in business activities can impact analysts' forecasts (Cowen et al. 2006) as well as areas that are subject to regulation and is constructed as 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 models include year fixed effects and continuous variables are winsorized at the 1st and 99th percentiles. My main hypothesis predicts $\alpha_1 > 0$.

Table 4 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). Perhaps, not surprisingly, the financial institutions in the sample appear to be larger financial institutions with a variety of business lines. 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 4 presents the correlation among the variables of interest (bolded values indicate significance at the 1% level). Consistent with my main hypothesis, *Violations* is positively associated with *RFError* (correlation = 0.047) in the univariate test.

B. Regression Results

Table 5 presents the regression results from estimates of Equation 1. Column 1 presents the univariate regression results. Column 2 adds controls for analyst characteristics (*AnalystControls*). Column 3 adds controls for financial institution characteristics (*FIControls*) and year fixed effects. All model specifications indicate positive and significant associations between *Violations* and *RFError*, after controlling for analyst characteristics, financial institution controls and year fixed effects. In terms of economic significance, a one-standard-deviation increase in *Violations* is associated with up to a 3.5% increase in relative forecast errors (0.0528 × 0.663). Overall, the results from this analysis are consistent with my main hypothesis and provide evidence to support the notion that analysts employed by financial institutions with weak integrity cultures produce less accurate forecasts.

I next consider the robustness of the main results to alternative measures of violations. In the *BrokerCheck* reports, the inspector can set a dollar value of fines (based on her assessment of the severity and frequency of the issue) and also choose to disclose what specific aspects of the security handbook are violated. Accordingly, I construct two additional measures using this additional data from the *BrokerCheck* reports. The first measure is the natural log of the annual total dollar value of fines indicated in the disclosure events (*Fines*). The second measure is the natural log of the total unique security code rules violated each year (*Codes*).[20] I also construct a composite measure (*Composite)* based on the average quintile ranks of *Violations, Fines,* and *Codes.* Finally, I consider the robustness of my results to different scalars. Conceptually, financial institutions are more likely to violate FINRA codes when they have more activities subject to FINRA regulation, and the ideal scalar would be the number of activities subject to FINRA regulation. Since this is not easily observable, I construct proxies for the scale of financial institution operations. *Violations/FIBusinessLines* scales *Violations* by the number of unique business lines and *Violations/NumAnalysts* scales *Violations* by the number of analysts.

Table 6 provides the results for alternative measures of weak integrity culture. Column 1 presents the results using the primary measure, *Violations*. Columns 2-4 examine alternative measures based on fines, codes violated and the composite measure. Columns 5-6 consider alternative scalars for *Violations*. In all specifications, the proxies for weak integrity culture are positively and significantly associated with *RFError.* Overall, these results provide further evidence in support of my hypothesis.

C. Robustness & Alternative Explanations

[20] One limitation of these measures is that the inspector has some discretion in determining the fines and does not always disclose the specific codes violated.

I argue that the positive association between violations arising in non-research related divisions of financial institutions and forecast errors is consistent with weak integrity culture influencing analysts' behavior. A key feature of my research design is that I examine violations arising in non-research areas, thus providing a setting in which the associations I document can only be attributed to some common firm-level force, such as culture. However, there are potentially other firm-level explanations for my findings, such as a lack of corporate governance mechanisms or weakness in other dimensions of corporate culture.

Accordingly, I conduct additional robustness analyses that attempt to control for alternative explanations for my findings. My first analysis examines alternative explanations for security code violations (other than integrity culture) such as lack of sufficient resources, poor internal control systems, flawed compensation schemes, and ineffective governance (e.g., Kashyap, Rajan and Stein 2008; Ellul and Yerramilli 2013). To do so, I re-examine the baseline regression (i.e., Equation 1) and include controls for other factors that may cause financial institutions to have security code violations. 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 as smaller and less profitable financial institutions might find it more difficult to comply with regulations if they are constrained. 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 increase the likelihood of violations. Third, I also consider whether short-term compensation schemes within financial institutions directly motivate employees to violate regulations. *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 also consider explicit mechanisms in place to protect various stakeholders of the financial institution. Following prior studies (e.g., Larcker, Richardson and Tuna 2007), I construct three proxies for the quality of shareholder protection afforded by financial institutions. 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.

Table 7 provides the results from regressions of forecast accuracy on measures of security code violations after including controls for alternative explanations for security code violations. Sample sizes vary across the different models since data for additional financial institution characteristics is collected from a variety of sources including RiskMetrics, Capital IQ, Factset, and AuditAnalytics with varying data availability. Column 1 adds controls for general financial institution characteristics. Column 2 controls for internal control quality. Column 3 controls for compensation schemes. Columns 4-7 control for other stakeholders' control rights. Column 8 includes all controls. Throughout all of the models, the results provide strong evidence to suggest that the positive association between *Violations* and *RFError* cannot be easily explained by the alternative explanations proposed. In each test, *Violations* continues to load positively and significantly ($p<0.05$), consistent with my hypothesis.

My second robustness test examines alternative measures of corporate culture. Since I construct a measure of integrity culture specific to financial institutions, it is possible that my results can be explained by a broader measure of integrity culture, or even other dimensions of corporate culture. I begin by examining how cultural differences, based on country that financial institutions are headquartered in, affect forecast accuracy, as prior work by Clement et al. (2003) document that relative forecast accuracy is influenced by cross-cultural differences. Table 8, Columns 1 and 2 present the results from this analysis. In Column 1, I append country fixed effects to the main analysis, and in Column 2, I examine a sub-sample of only institutions headquartered in the United States. In both tests, the coefficient on *Violations* remains positive and significant ($p<0.01$), suggesting that the association between integrity culture and forecast accuracy is not explained by regional cultural differences.

I next examine controls using alternative measures of integrity culture, as well as other dimensions of corporate culture. I first examine a measure similar to Guiso et al. (2014). *Great Place To Work* is an employee satisfaction score based on data hand-collected from www.glassdoor.com.[21] While the measure employed by Guiso et al. (2014) broadly captures the importance of integrity capital within a firm, the measure I construct is arguably more specific to the financial services industry and the conflicts faced by equity analysts. Consistent with this notion, the results in Column 3 of Table 8 indicate that after controlling for *Great Place To Work*, the positive association between *Violations* and *RFError* persists ($p<0.01$). I also examine measures of corporate social responsibility that have been suggested to be related to corporate culture (Gao et al. 2014; Hoi et al. 2013). Specifically, I examine the amount of scandals and controversies that the financial institution has been a part of (*Controversies*), the overall quality of the financial institutions' products (*Product Quality*), the quality of employee relations (*Employee Relations*), and an overall score of the financial institutions' corporate social responsibility (*Corporate Social Responsibility Score*).[22] Columns 4-7 of Table 8 present the results after controlling for these measures. In all specifications, *Violations* continues to load positively and significantly ($p<0.01$). These findings continue to provide evidence consistent with integrity culture influencing the quality of analysts' forecasts.

While the above analyses strengthen my claim that integrity culture is an important determinant of analysts' forecasts accuracy, these findings are not without limitations. In particular, one limitation of my analysis is that I cannot provide direct causal evidence of the effects of integrity culture. As documented in Table 3, violations are highly persistent over the relatively short sample period, thus making it challenging to examine exogenous variation in integrity culture. Further, examining career movements (i.e., analyst moves) is also difficult as analysts self-select into moving and this can introduce further endogeneity concerns.[23] Empirically, movements also appear to be rare, with only 64 (36) within-sample analyst moves

[21] Guiso et al. (2014) also have proprietary survey data from firms that unfortunately is not publicly available.
[22] The data from these tests is obtained from KLD, and this significantly reduces the sample size.
[23] The implicit assumption in this study is that, in a frictionless labor market, analysts and financial institutions associate by mutual choice. That is, analysts will seek jobs from financial institutions in which potential colleagues have similar values and financial institutions will try to hire analysts with similar values as their existing employees. In some instances however, frictions can potentially arise that may result in analysts being temporarily employed by an institution in which their colleagues have inconsistent values. In such instances, the culture of the institution can influence analysts' pre-existing values. For example, an analyst that initially places a high emphasis on ethical behavior may be influenced by a poor integrity culture to produce lower quality forecasts (or vice-versa).

occurring when I require the analyst to be employed by the new employer by at least 1 (2) years after the move. Finally, natural experiments examining mergers and acquisitions of financial institutions that are plausibly exogenous to analysts (e.g., Hong and Kacperczyk 2010; Balakrishnan, Billings, Kelly and Ljungqvist 2014) are also not amenable to this setting as the majority of these mergers occurred before my sample period began, when FINRA data was more limited.[24]

Overall, the results from these analyses provide evidence consistent with my hypothesis. Analysts employed by financial institutions with weak integrity culture (as measured by violations arising in unrelated divisions in financial institutions) produces less accurate forecasts, and these effects cannot be easily explained by other financial institution characteristics.

V. Additional Analysis

A. *Strategic Forecast Bias*

The results from the prior analyses indicate a strong association between the quality of financial institutions' integrity culture and analysts' forecast accuracy. As discussed earlier in Section II, poor integrity cultures can lead analysts to withhold information from their forecasts or introduce intentional biases into their forecasts (either upwards or downwards). Accordingly, Prediction 1 predicts that the extent of strategic bias embedded in analysts' forecasts is increasing in the weakness of the integrity culture of the financial institutions that employ them. In this section, I conduct tests of Prediction 1.

I begin by constructing a relative forecast bias measures similar to the relative forecast accuracy measure I employ. Since bias is a directional measure, I modify it following prior studies (e.g., Cowen et al. 2006). Specifically:

$$RFBias_{ijt} = \frac{Forecast_{ijt} - \overline{Forecast_{Jt}}}{\sigma(Forecast_{jt})}$$

[24] For example, within my sample period, there are only three financial institutions involved in mergers in which the acquirer and target both had research divisions prior to the merger. In a concurrent study, Dimmock, Gerken and Graham (2015) examine financial advisors' propensity to commit fraud after mergers. However, their study examines a much broader sample of all financial advisors (as opposed to financial analysts), and does not require research divisions.

where $Forecast_{ijt}$ is analyst *i*'s last forecast for firm *j* in year *t*, $\overline{Forecast_{Jt}}$ is the average forecast for all analysts covering firm *j* in year *t* and $\sigma(Forecast_{jt})$ is the standard deviation of forecasts across all analysts covering firm *j* in year *t*. Higher (lower) levels of *RFBias* indicate relative upward or optimistic forecasts (downward or pessimistic forecasts). I construct this measure using two horizons. The first forecast (*Short Horizon*) uses the same forecast as used to measure *RFError* and following Clement (1999) is the last forecast issued in the first 11 months preceding the fiscal year end. The second forecast (*Long Horizon*) uses the last forecast issued in the prior fiscal year, while holding constant the fiscal year forecasted. For example, a *Short Horizon* forecast for the fiscal year ending in December 2009 may be issued in November 2009, whereas a long horizon forecast for December 2009 may be issued in December 2008. My motivation for including a longer horizon forecast in this analysis is that it may be challenging to identify upward bias in forecasts issued close to the forecast period, as analysts often face downward pressures on these forecasts to create easily beatable targets for management (Ke and Yu 2006).[25]

I examine the relationship between integrity culture and strategic forecast bias using three tests. The first test examines the main effect of *Violations* on *RFBias*. Specifically, I examine the following OLS regression:

$$RFBias_{ijt} = \beta_0 + \beta_1 Violations_{ft} + \beta_2 AnalystControls_{ijt} + \beta_3 FIControls_{ft} + \sum_t Year_t + \epsilon_{ijt} \quad (2)$$

The model is identical to Equation 1, with the exception of the dependent variable, which is now *RFBias*, instead of *RFError*. Ex ante, the predicted direction on the coefficient of interest, β_1, is not clear given that analysts face pressures to issue both upwardly and downwardly biased forecasts.

The next two tests I examine focus on particular settings in which analysts may face pressures to issue an upwardly or downwardly biased forecast. First, I examine the extent to which "low ball" pressures from managers at risk of not meeting or beating the consensus earnings forecasts interacts with weak integrity culture to influence forecast bias. To do so, I examine the following regression:

[25] I also re-examine the forecast accuracy results for longer horizons and find that my findings remain unchanged.

$$RFBias_{ijt} = \gamma_0 + \gamma_1 Violations_{ft} + \gamma_2 Violations \times LowBall_{ijt} + \gamma_3 LowBall_{ijt} + \gamma_4 AnalystControls_{ijt} + \gamma_5 FIControls_{ft} + \sum_t Year_t + \epsilon_{ijt} \quad (3)$$

where *LowBall* is an indicator variable that takes the value of one if the covered firm narrowly meets or beats (by 1 cent) the consensus end of the year forecast, and 0 otherwise. If weak integrity culture exacerbates pressures to give in to managerial pressures to issue a downwardly biased forecasts, γ_2 should be negative.

Finally, I examine the extent to which investment banking affiliation interacts with weak integrity culture to influence forecast bias. To do so, I examine the following regression:

$$RFBias_{ijt} = \delta_0 + \delta_1 Violations_{ft} + \delta_2 Violations \times Affiliation_{ijt} + \delta_3 Affiliation_{ijt} + \delta_4 AnalystControls_{ijt} + \delta_5 FIControls_{ft} + \sum_t Year_t + \epsilon_{ijt} \quad (4)$$

where *Affiliation* takes the value of one if the covered firm has recently undergone an initial public offering or seasoned equity offering with the analysts' employer in the prior 2 years, and 0 otherwise. If weak integrity culture exacerbates pressures to succumb to pressures to promote recent underwritings, δ_2 should be positive.

Table 9 presents the results from tests of strategic forecast bias (i.e., Equations 2-4). Columns 1 and 2 examine the main effect of *Violations* on *RFBias* (i.e., Equation 2). Columns 3 and 4 examine the interactive effect of *Violations X LowBall* on *RFBias* (i.e., Equation 3). Columns 5 and 6 examine the interactive effect of *Violations X Affiliation* on *RFBias* (i.e., Equation 4). For each test, I first examine *RFBias* for short-horizon forecasts (i.e., Columns 1, 3 and 5) and then examine *RFBias* for long-horizon forecasts (Columns 2, 4, and 6).

The results indicate several interesting findings. First, the main effect of *Violations* on *RFBias* is negative and significant for short-horizon forecasts ($p<0.05$), but not significant for long-horizon forecasts. This suggests that analysts at weak integrity culture financial institutions issue more downwardly biased forecasts near the fiscal year end, potentially due to managerial pressures to create beatable earnings targets.

This is also consistent with recent survey evidence suggesting that analysts are more likely to face downward pressures than upward pressures on their forecasts (Brown et al. 2015). The results in columns 3 and 4 suggest a similar message. The coefficient on *Violations X LowBall* is negative and significant for short-horizon forecasts ($p<0.05$) but not significant for long-horizon forecasts. This suggests that when "low ball" pressures are high, analysts employed at financial institutions with weak integrity culture are more likely to issue a downwardly biased forecast immediately before the fiscal year end. Finally, the results from tests of upward forecast bias in Columns 5 and 6 suggest that analysts also face upward pressures, but not in the short-horizon. The coefficient on *Violations X Affiliation* is not significant for short-horizon forecasts but is positive and significant for long-horizon forecasts ($p<0.05$). This finding suggests that for long horizon forecasts, investment banking pressures lead analysts at financial institutions with weak integrity culture to produce more upwardly biased forecasts than these pressures do at financial institutions with stronger integrity culture. Overall, the results from Table 9 provide evidence consistent with Prediction 1 and suggest that analysts employed by financial institutions with weak integrity culture issue more strategically biased forecasts.

B. Informativeness

The evidence in the prior analyses suggest that integrity culture can influence the quality of analysts' forecasts (in terms of accuracy and bias), but do not offer any insight regarding whether this has consequences for market participants. In the following analysis, I shed light issue on this by examining the effects of weak integrity culture on analysts' forecast informativeness. Prior studies indicate significant variation in the amount of new information that analysts bring to the market, with analysts sometimes repackaging or retransmitting stale, non-value relevant information (e.g., Frankel et al. 2006). If weak integrity cultures reduce the quality of earnings forecasts, they may also reduce the informativeness of the accompanying reports. Accordingly, Prediction 2 predicts a negative association between weak integrity culture and report informativeness.

To test Prediction 2, I examine the following regression of earnings forecast informativeness on security code violations:

$$INFO_{ijt} = \zeta_0 + \zeta_1 Violations_{ft} + \zeta_2 AnalystControls_{ijt} + \zeta_3 FIControls_{ft} + \zeta_4 MKTControls + \sum_t Year_t + \epsilon_{ijt} \qquad (5)$$

where *INFO* is calculated as the absolute value of the sum of size-adjusted returns for the 3-day period centered around the earnings forecast date. *Violations*, *AnalystControls* and *FIControls* are defined as in prior tests. *MKTControls* includes three market-related variables: *MktRet*, *FirmRet*, and *StdRet*. *MktRet* and *FirmRet* control for momentum and are constructed as cumulative monthly returns over the prior 6 months for the market and firm, respectively. *StdRet* controls for volatility and is measured as the standard deviation of returns over the prior 6 months. Prediction 2 predicts a negative coefficient on ζ_1.

Table 10 provides the results from estimates of Equation 5. Column 1 provides the univariate results. Column 2 provides the results after including *AnalystControls* and *FIControls*. Column 3 adds *MKTControls*. In all three specifications, *Violations* is negatively and significantly associated with earnings forecast informativeness.[26] Overall, these findings support Prediction 2 and provide evidence consistent with weak integrity culture reducing the informativeness of analysts' forecasts.

VI. Conclusion

In this study, I provide empirical evidence consistent with weak integrity cultures reducing the quality of analysts' forecasts. I measure the weakness of financial institutions' integrity culture using security code violations collected from the FINRA *BrokerCheck* service. I demonstrate that violations arising in divisions unrelated to equity research are associated with less accurate forecasts, more strategically biased forecasts, and less informative forecasts. These results are robust to a host of alternative explanations including other firm-wide forces (such as corporate governance and compensation) and other previously explored measures of corporate culture.

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

While I focus on sell-side equity analysts' forecasts, my findings are likely to have broader implications for the financial services industry, in general. In particular, recent concerns from the Federal Reserve Board and SEC have suggested that many regulatory and consumer protection problems that have arisen in recent years (e.g., LIBOR rigging, tax evasion, money laundering, etc.) are rooted in cultural problems in financial institutions.[27] My findings corroborate regulators' concerns and suggest that weak integrity cultures can limit financial institutions' roles as financial and informational intermediaries in capital markets.

While this study sheds new light on how cultural forces can impact financial analysts, it is not without its limitations. First, given the persistence of cultural forces (especially over relatively short horizons), it is an empirical challenge to generate causal evidence through the use of exogenous variation in integrity culture. I attempt to circumvent these challenges by conducting a series of tests that eliminate alternative explanations to my findings. Second, while my findings provide evidence consistent with financial institutions having a common set of values and norms placed on the importance of protecting their clients, they do not speak to how these values and norms are communicated through an organization. These values may be reflected (explicitly or implicitly) through a variety of channels within an organization including recruitment, training, promotion, performance reviews and other policies within the organization that are not easily observable. Future research can benefit from gaining a better understanding of how cultural forces permeate an organization. Such findings can better inform regulators and practitioners to solutions to improve financial institutions' integrity culture.

[27] http://www.federalreserve.gov/newsevents/speech/tarullo20141020a.htm

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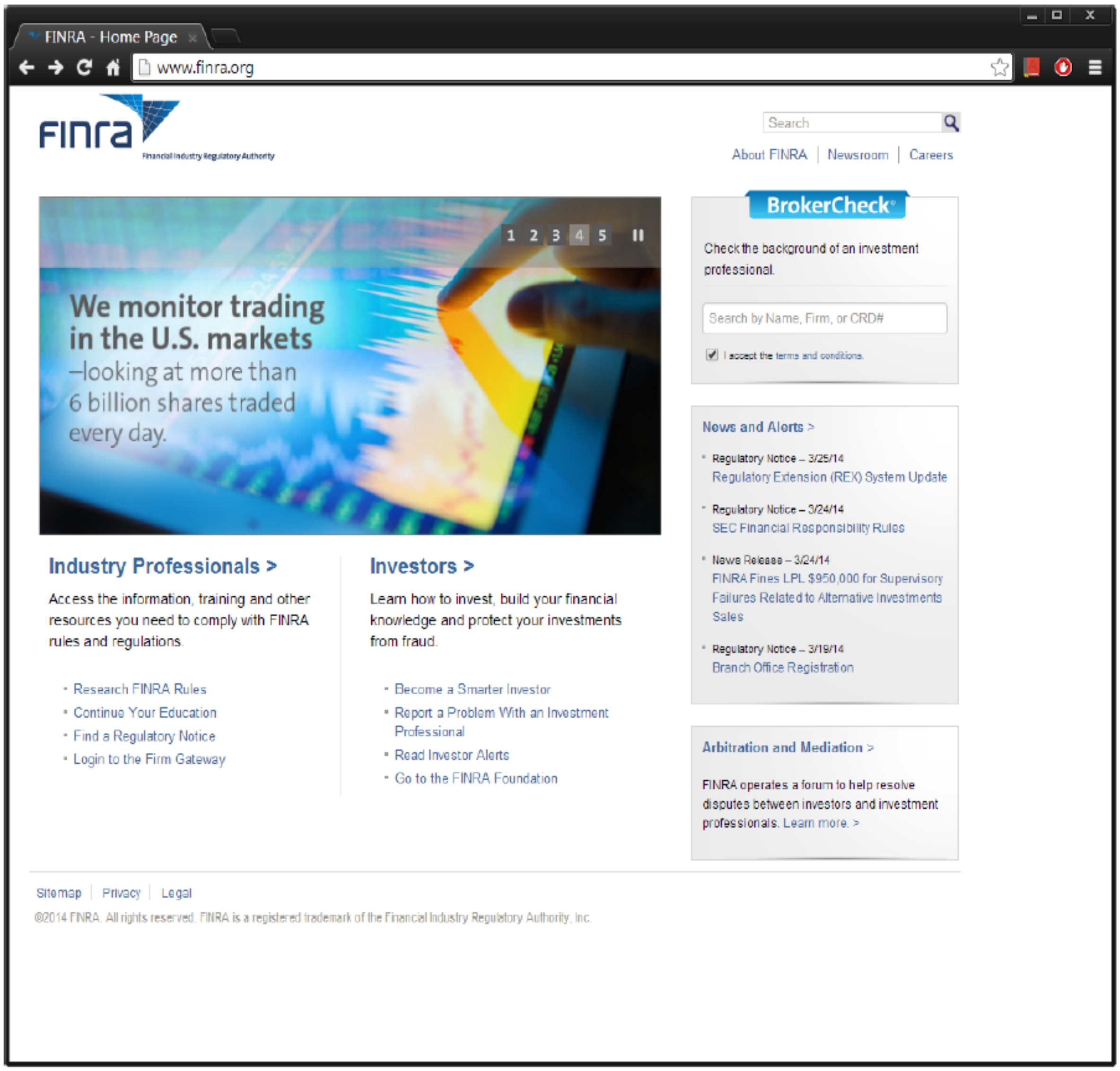
Appendix A. FINRA *BrokerCheck* Online Tool

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



FINRA BrokerCheck F ×

brokercheck.finra.org/Firm/FirmSummary.aspx?SearchGroup=Firm&FirmKey=7059&BrokerKey=-1

FINRA

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Protect Yourself | Smart Investing | Market Data

Investors > Tools & Calculators > Search > Search Results > Summary for this Firm

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 NEW YORK, NY 10013-2396	REGISTRATION DEPARTMENT ONE COURT SQUARE 19TH FLOOR 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 26 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.

BrokerCheck Links

- Search Help
- Search
- About BrokerCheck Reports
- Glossary
- FAQ
- Additional Resources
- BrokerCheck Feedback

State Regulators

More information may be available from state regulators.

Before You Invest

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

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Appendix B. Sample Disclosure Events

This figure provides sample disclosure events obtained from the FINRA *BrokerCheck* online tool: http://brokercheck.finra.org. *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.

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 Monetary/Fine $1,097,939.06 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

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 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 1 – Sample of Financial Institutions

This table lists 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). A financial institution is included in the sample if data is available to identify the institution in the I/B/E/S database.

Parent Bank	Security Subsidiary
Allianz SE	Commerz Markets LLC
BNP Paribas	BNP Paribas Investment Services, LLC
BNP Paribas	BNP Paribas Securities Corp.
BPCE	Natixis Bleichroeder LLC
BPCE	Natixis Securities North America, Inc.
Banco Santander	Santander Investment Securities, Inc.
Banco Santander	Santander Securities Corp.
Bank of Montreal	BMO Capital Markets Corp.
Bank of Nova Scotia	Scotia Capital (USA), Inc.
Canadian Imperial Bank of Commerce	CIBC World Markets Corp.
Capital One Financial Corp.	Capital One Southcoast, Inc.
Cera Ancora VZW	KBC Financial Products USA, Inc.
Citigroup, Inc.	Citigroup Global Markets, Inc.
Citigroup, Inc.	Morgan Stanley Smith Barney, LLC
Credit Suisse Group	Credit Suisse Securities (USA), LLC
DZ Bank AG	DZ Financial Markets, LLC
Deutsche Bank AG	Deutsche Bank Securities, Inc.
DnB NOR ASA	DnB NOR Nor Markets, Inc.
Goldman, Sachs Group	Epoch Securities, Inc.
Goldman, Sachs Group	Goldman Sachs Execution & Clearing, L.P.
Goldman, Sachs Group	Goldman Sachs JBWere Inc.
Goldman, Sachs Group	Goldman, Sachs and Company
HSBC Holdings PLC	Capital Financial Services, INC.
HSBC Holdings PLC	HSBC Securities (USA), Inc.
JPMorgan Chase & Co.	Chase Investment Services Corp.
JPMorgan Chase & Co.	J.P. Morgan Securities, Inc.
Keycorp	KeyBanc Capital Markets
Morgan Stanley	Morgan Stanley & Co. Incorporated
National Bank of Canada	National Bank of Canada Financial, Inc.
Rabobank Nederland	Rabo Securities USA, Inc.
Regions Financial Corp.	Morgan, Keegan & Company, Inc.
Royal Bank of Canada	RBC Capital Markets Corp.
Societe Generale	Newedge USA, LLC
Societe Generale	SG Americas Securities, LLC
Stifel Financial Corp.	Stifel Nicolaus & Company, Inc.

Stifel Financial Corp.	Thomas Weisel Partners LLC
SunTrust Banks, Inc.	SunTrust Investment Services, Inc.
SunTrust Banks, Inc.	SunTrust Robinson Humphrey, Inc.
Toronto-Dominion Bank, The	TD Ameritrade Clearing, Inc.
Toronto-Dominion Bank, The	TD Ameritrade Inc.
Toronto-Dominion Bank, The	TD Securities (USA), LLC
UBS AG	UBS Financial Services, Inc.
UBS AG	UBS Securities, LLC
Wells Fargo & Company	H.D. Vest Investment Securities, Inc.
Wells Fargo & Company	Wells Fargo Advisors Financial Network, LLC
Wells Fargo & Company	Wells Fargo Advisors, LLC
Wells Fargo & Company	Wells Fargo Institutional Securities, LLC
Wells Fargo & Company	Wells Fargo Securites, LLC

Table 2 – Sample Selection

This table outlines the sample selection procedure. Disclosure events are obtained from the *BrokerCheck* online tool, provided by FINRA. 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 violation	(20)
Final Sample	472

Table 3 – Characteristics of Security Code Violations

This table describes the security code violations. Panel A presents the frequency by Year. Panel B presents the frequency by Financial Institution. Panel C presents autocorrelation coefficients for *Violations* for up to 3 prior years.

Panel A: Frequency By Year

Year	Violations
2005	51
2006	47
2007	69
2008	48
2009	56
2010	77
2011	59
2012	65
Total	472

Panel B: Frequency By Financial Institution

Financial Institution	Violations
Allianz SE	4
BNP Paribas	11
BPCE	8
Banco Santander	3
Bank of Montreal	9
Bank of Nova Scotia	0
Canadian Imperial Bank of Commerce	14
Capital One Financial Corp.	1
Cera Ancora VZW	4
Citigroup, Inc.	48
Credit Suisse Group	21
DZ Bank AG	0
Deutsche Bank AG	28
DnB NOR ASA	0
Goldman, Sachs Group	62
HSBC Holdings PLC	21
JPMorgan Chase & Co.	34
Keycorp	13
Morgan Stanley	34
National Bank of Canada	4

Rabobank Nederland	0
Regions Financial Corp.	10
Royal Bank of Canada	25
Societe Generale	18
Stifel Financial Corp.	13
SunTrust Banks, Inc.	12
Toronto-Dominion Bank, The	22
UBS AG	50
Wells Fargo & Company	3
Total	472

Panel C: Persistence of Violations

	$Violations_t$
$Violations_{t-1}$	0.55
$Violations_{t-2}$	0.62
$Violations_{t-3}$	0.66

Table 4 – Analyst Forecasts' Sample Characteristics

This table provides summary statistics for the variables included in the forecast accuracy regressions. *RFError* is computed as AFE_{ijt} less $\overline{AFE_{jt}}$, scaled by $\overline{AFE_{jt}}$ where AFE_{ijt} the absolute forecast error for analyst *i*'s forecast for firm *j* in year *t* and $\overline{AFE_{jt}}$ is the mean absolute forecast error for firm *j* in year *t* across all analysts providing forecasts for the firm in the sample. Forecast errors are calculated using the last forecast issued in the first 11 months of the fiscal year. *Violations* is the natural log of one plus the total number of annual disclosure events, as observed in FINRA *BrokerCheck* reports. *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. *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 firm-year mean of each measures). *FIPrestige* 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. *FIBusinessLines* is constructed as 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. Panel A presents sample statistics and Panel B presents sample correlations. Bolded values indicate significance at the 1% level.

Panel A: Sample Statistics

Variable	Mean	STD	PER25	PER50	PER75
RFError	-0.010	0.739	-0.511	-0.100	0.273
Violations	1.375	0.663	1.099	1.386	1.946
RExp	-0.006	0.751	-0.618	-0.112	0.458
RHorizon	-0.002	0.394	-0.257	-0.047	0.073
RFirmsCovered	-0.005	0.407	-0.259	-0.022	0.227
FIPrestige	0.523	0.499	0.000	1.000	1.000
FIBusinessLines	20.823	4.405	20.000	21.000	24.000
FISize	99.904	48.091	65.000	111.000	130.000

Panel B: Sample Correlation

Variable		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RFError	(1)	1							
Violations	(2)	**0.047**	1						
RExp	(3)	**-0.024**	**-0.056**	1					
RHorizon	(4)	**0.410**	**0.022**	**-0.025**	1				
RFirmsCovered	(5)	**-0.028**	**0.052**	**0.213**	**-0.079**	1			
FIPrestige	(6)	0.008	**0.373**	**-0.013**	-0.002	**0.015**	1		
FIBusinessLines	(7)	**0.018**	**0.415**	0.004	0.009	**0.027**	**0.453**	1	
FISize	(8)	**0.026**	**0.573**	**-0.036**	**0.012**	**0.034**	**0.541**	**0.539**	1

Table 5 – Weak Integrity Culture & Analysts' Forecast Accuracy

This table provides the results of OLS regressions of relative forecast errors (i.e., *RFError*) on weak integrity culture, measured as *Violations*. Standard errors are clustered by financial institution. ***, **, and * denote 1%, 5% and 10% level of significance, respectively. All variables are defined in Table 4.

VARIABLES	(1) *DV = RFError*	(2) *DV = RFError*	(3) *DV = RFError*
Violations	0.0527***	0.0416***	0.0528***
	(4.72)	(4.26)	(4.71)
RExp		-0.0126**	-0.0125**
		(-2.55)	(-2.50)
RHorizon		0.7681***	0.7679***
		(48.72)	(48.50)
RFirmsCovered		0.0093	0.0096
		(0.32)	(0.33)
FISize			-0.0141
			(-0.91)
FIPrestige			-0.0043
			(-0.19)
FIBusinessLines			0.0015
			(0.04)
Year FE?	No	No	Yes
Observations	78,079	78,079	78,079
R-squared	0.22%	16.99%	17.01%

Table 6 – Alternative Measures of Weak Integrity Culture

This table provides the results of OLS regressions of relative forecast errors (i.e., *RFError*) on alternative measures of weak integrity culture. In Column 1, *Violations* is the natural log of one plus the number of disclosure events observed in annual FINRA *BrokerCheck* reports. In Column 2, *Fines* is the natural log of one plus the annual fines observed in *BrokerCheck* reports. In Column 3, *Codes* is the natural log of one plus the number of unique security codes violated, as observed in *BrokerCheck* reports. In Column 4, *Composite* is the average of the annual quintile ranks of *Violations*, *Fines* and *Codes*. In Column 5, *Violations* is scaled by the number of business lines (*Violations/FIBusinessLines*). In Column 6, *Violations* is scaled by the number of analysts *(Violations/NumAnalysts).* Standard errors are clustered by financial institution. ***, **, and * denote 1%, 5% and 10% level of significance, respectively. All other variables are defined in Table 4.

	(1)	(2)	(3)	(4)	(5)	(6)
	DV =	*DV =*	*DV =*	*DV =*	*DV =*	*DV =*
VARIABLES	*RFError*	*RFError*	*RFError*	*RFError*	*RFError*	*RFError*
Violations	0.0528***					
	(4.71)					
Fines		0.0043**				
		(2.49)				
Codes			0.0262***			
			(2.95)			
Composite				0.0322***		
				(5.17)		
Violations/FIBusinessLines					0.2395***	
					(7.03)	
Violations/NumAnalysts						0.8204***
						(4.08)
RExp	-0.0125**	-0.0138**	-0.0136**	-0.0129**	-0.0125**	-0.0129**
	(-2.50)	(-2.65)	(-2.59)	(-2.51)	(-2.48)	(-2.54)
RHorizon	0.7679***	0.7684***	0.7691***	0.7688***	0.7685***	0.7683***
	(48.50)	(48.46)	(48.19)	(48.54)	(48.36)	(48.68)
RFirmsCovered	0.0096	0.0111	0.0090	0.0099	0.0098	0.0111
	(0.33)	(0.37)	(0.30)	(0.34)	(0.33)	(0.38)
FISize	-0.0141	-0.0013	-0.0018	-0.0125	-0.0142	0.0171
	(-0.91)	(-0.06)	(-0.11)	(-0.89)	(-0.92)	(0.96)
FIPrestige	-0.0043	-0.0092	-0.0286	-0.0196	0.0084	0.0008
	(-0.19)	(-0.28)	(-0.96)	(-0.99)	(0.40)	(0.03)
FIBusinessLines	0.0015	0.0168	0.0151	0.0001	0.0300	-0.0036
	(0.04)	(0.37)	(0.31)	(0.00)	(0.72)	(-0.09)
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	78,079	78,079	78,079	78,079	78,079	78,079
R-squared	17.01%	16.91%	16.96%	17.04%	17.00%	16.99%

Table 7 – Other Explanations for Security Code Violations

This table provides the results of OLS regressions of relative forecast errors (i.e., *RFError*) on weak integrity culture, measured as *Violations*, controlling for other potential causes of security code violations. *Size* is measured as the natural log of assets. *Profitability* is measured as net income divided by total assets. *ICW* is 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. *STCompMix* is the ratio of financial institutions' CEO total annual compensation divided by total calculated compensation, including stock awards and non-cash compensation. *InstHoldings* is measured as the percentage of shares held by institutional investors. *Gompers* is a composite index that proxies for managerial power and is based on the last available Gompers index constructed in 2006. *Insiders* is the percentage of insiders sitting on the board. Standard errors are clustered by financial institution. ***, **, and * denote 1%, 5% and 10% level of significance, respectively. All other variables are defined in Table 4.

VARIABLES	(1) *DV =* *RFError*	(2) *DV =* *RFError*	(3) *DV =* *RFError*	(4) *DV =* *RFError*	(5) *DV =* *RFError*	(6) *DV =* *RFError*	(7) *DV =* *RFError*	(8) *DV =* *RFError*
Violations	0.0389***	0.0495***	0.0507***	0.0526***	0.0426***	0.0520***	0.0421**	0.0215**
	(3.70)	(4.46)	(4.37)	(4.31)	(3.17)	(3.83)	(2.85)	(2.38)
FI Characteristics								
Size	0.0159***							0.0793***
	(3.66)							(4.38)
Profitability	0.6204							-1.4320
	(0.60)							(-0.75)
Internal Control Quality								
ICW		-0.0107						-0.0360
		(-0.78)						(-1.70)
Compensation								
STCompMix			0.0189					0.0254*
			(0.93)					(1.86)
Corporate Governance								
InstHoldings				0.0003			-0.0003	0.0018
				(0.55)			(-0.35)	(1.78)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gompers					-0.0048		-0.0055	0.0134
					(-0.47)		(-0.54)	(1.16)
Inside						-0.0378	-0.0364	-0.0192
						(-0.56)	(-0.43)	(-0.16)
Baseline Controls								
RExp	-0.0119**	-0.0114**	-0.0136**	-0.0112**	-0.0113	-0.0137**	-0.0114	-0.0115
	(-2.34)	(-2.27)	(-2.64)	(-2.21)	(-1.43)	(-2.51)	(-1.43)	(-1.49)
RHorizon	0.7674***	0.7712***	0.7606***	0.7646***	0.7517***	0.7669***	0.7517***	0.7531***
	(48.55)	(46.76)	(44.67)	(43.21)	(30.68)	(43.95)	(30.82)	(30.38)
RFirmsCovered	0.0122	0.0222	0.0129	0.0089	0.0467	0.0095	0.0468	0.0455
	(0.41)	(0.72)	(0.40)	(0.27)	(0.85)	(0.29)	(0.84)	(0.81)
FISize	-0.0281*	-0.0028	-0.0127	-0.0124	0.0033	-0.0131	0.0061	-0.0388*
	(-1.75)	(-0.17)	(-0.74)	(-0.72)	(0.12)	(-0.78)	(0.24)	(-2.10)
FIPrestige	-0.0309	-0.0056	-0.0072	-0.0057	-0.0418	-0.0065	-0.0427	-0.0636**
	(-1.22)	(-0.27)	(-0.29)	(-0.28)	(-1.20)	(-0.29)	(-1.11)	(-3.13)
FIBusinessLines	0.0593	0.0160	-0.0038	-0.0080	0.0447	0.0063	0.0297	0.0722
	(1.49)	(0.42)	(-0.10)	(-0.18)	(0.45)	(0.13)	(0.30)	(0.98)
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77,782	73,680	70,546	70,730	38,123	71,123	38,123	37,699
R-squared	17.09%	17.29%	16.53%	16.82%	16.14%	17.03%	16.14%	16.27%

Table 8 – Other Dimensions of Culture

This table provides the results of OLS regressions of relative forecast errors (i.e., *RFError*) on weak integrity culture, measured as *Violations*, controlling for other cultural measures. Column 1 includes country fixed effects, and Column 2 is a subsample of US firms. *Great Place To Work* is an employee satisfaction score based on data collected from www.glassdoor.com. *Controversies* is the number of scandals and controversies that the financial institution has been a part of (based on KLD data). *Product Quality* is the overall quality of the financial institutions' products (based on KLD data). *Employee Relations* is the quality of employee relations (based on KLD data). *Corporate Social Responsibility Score* is an overall score of the financial institutions' corporate social responsibility efforts (based on KLD data). Standard errors are clustered by financial institution. ***, **, and * denote 1%, 5% and 10% level of significance, respectively. All other variables are defined in Table 4.

VARIABLES	(1) *DV = RFError*	(2) *DV = RFError*	(3) *DV = RFError*	(4) *DV = RFError*	(5) *DV = RFError*	(6) *DV = RFError*	(7) *DV = RFError*
Violations	0.0488***	0.0523***	0.0487***	0.0520***	0.0468***	0.0544***	0.0475***
	(4.48)	(4.22)	(4.94)	(4.17)	(3.88)	(4.09)	(4.91)
Corporate Culture Proxies							
Great Place To Work			0.0620				
			(1.12)				
Controversies				-0.0206			
				(-1.23)			
Product Quality					-0.0175*		
					(-2.08)		
Employee Relations						-0.0047	
						(-0.71)	
Corporate Social Responsibility Score							0.0033
							(1.13)
Baseline Controls							
RExp	-0.0102**	-0.0097	-0.0120**	-0.0099	-0.0086	-0.0095	-0.0098
	(-2.09)	(-1.52)	(-2.33)	(-1.57)	(-1.39)	(-1.56)	(-1.57)
RHorizon	0.7664***	0.7612***	0.7682***	0.7611***	0.7596***	0.7608***	0.7614***
	(47.91)	(31.31)	(47.89)	(31.19)	(31.16)	(31.00)	(31.21)

RFirmsCovered	0.0155	0.0422	0.0097	0.0430	0.0409	0.0428	0.0423
	(0.53)	(0.87)	(0.33)	(0.88)	(0.85)	(0.88)	(0.86)
FISize	-0.0037	0.0059	-0.0219	0.0050	-0.0140	0.0060	0.0078
	(-0.21)	(0.23)	(-1.32)	(0.19)	(-0.67)	(0.22)	(0.31)
FIPrestige	0.0081	-0.0061	0.0020	0.0122	-0.0147	-0.0079	-0.0101
	(0.35)	(-0.22)	(0.09)	(0.44)	(-0.61)	(-0.25)	(-0.35)
FIBusinessLines	-0.0392	-0.0090	0.0085	-0.0218	0.0426	-0.0113	-0.0056
	(-1.09)	(-0.13)	(0.24)	(-0.34)	(0.61)	(-0.16)	(-0.09)
Sample?	Full	US Only	Full	Full	Full	Full	Full
Country Fixed Effects?	Yes	No	No	No	No	No	No
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	78,079	45,149	78,066	44,370	44,370	44,370	44,370
R-squared	17.20%	16.73%	17.04%	16.91%	16.93%	16.90%	16.92%

Table 9 – Weak Integrity Culture & Analysts' Forecast Bias

This table provides the results of OLS regressions of relative forecast bias (i.e., *RFBias*) on weak integrity culture, measured as *Violations*. *RFBias* is measured as $Forecast_{ijt}$ less $\overline{Forecast_{jt}}$, scaled by $\sigma(Forecast_{jt})$ where $Forecast_{ijt}$ is analyst *i*'s last forecast for firm *j* in year *t*, $\overline{Forecast_{jt}}$ is the average forecast for all analysts covering firm *j* in year *t*, and $\sigma(Forecast_{jt})$ is the standard deviation of forecasts across all analysts covering firm *j* in year *t*. *LowBall* is an indicator variable that takes the value of 1 if the covered firm meets or beats the consensus earnings forecast by one cent, and 0 otherwise. *Affiliation* is an 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 the prior two years, and 0 otherwise. Forecasts issued in the *short* horizon sample are issued in the first 11 months of the fiscal year, following Clement (1999). Forecasts issued in the *long* horizon sample are issued in months t-24 to t-12 preceding the forecast period end. Standard errors are clustered by financial institution. ***, **, and * denote 1%, 5% and 10% level of significance, respectively. All other variables are defined in Table 4.

	Overall Effect		*LowBall Pressures*		*Investment Banking Pressures*	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*DV = RFBias*	*DV = RFBias*	*DV = RFBias*	*DV = RFBias*	*DV = RFBias*	*DV = RFBias*
Violations	-0.0242**	-0.0272	-0.0179*	-0.0216	-0.0255**	-0.0287
	(-2.51)	(-1.40)	(-1.97)	(-1.29)	(-2.70)	(-1.48)
Violations X LowBall			-0.0393**	-0.0342		
			(-2.67)	(-1.20)		
Violations X Affiliation					0.0327	0.0411**
					(1.48)	(2.46)
LowBall			0.0521***	0.0582*		
			(3.03)	(2.02)		
Affiliation					-0.0748*	-0.0952**
					(-1.98)	(-2.70)
RExp	-0.0075	0.0085	-0.0075	0.0086	-0.0075	0.0085
	(-0.85)	(0.83)	(-0.84)	(0.84)	(-0.85)	(0.83)
RHorizon	0.0833***	0.3779***	0.0833***	0.3781***	0.0836***	0.3786***
	(5.19)	(6.70)	(5.18)	(6.71)	(5.21)	(6.73)
RFirmsCovered	0.0476*	0.0202	0.0474*	0.0200	0.0479*	0.0207
	(1.80)	(0.86)	(1.79)	(0.84)	(1.81)	(0.88)
FISize	0.0045	-0.0424**	0.0043	-0.0425**	0.0059	-0.0407**
	(0.37)	(-2.68)	(0.36)	(-2.69)	(0.49)	(-2.58)

FIPrestige	0.0158	0.0305	0.0161	0.0309	0.0165	0.0315
	(0.93)	(1.26)	(0.95)	(1.27)	(0.98)	(1.30)
FIBusinessLines	-0.0049	0.0889	-0.0059	0.0879	-0.0059	0.0878
	(-0.13)	(1.36)	(-0.16)	(1.35)	(-0.16)	(1.34)
Forecast Horizon Sample?	Short	Long	Short	Long	Short	Long
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77,415	57,840	77,415	57,840	77,415	57,840
R-squared	0.19%	0.42%	0.20%	0.43%	0.20%	0.43%

Table 10 – Weak Integrity Culture & Analyst Forecast Informativeness

This table provides the results of OLS regressions of analyst forecast informativeness (i.e., *INFO*) on weak integrity culture, measured as *Violations*. *INFO* is calculated as the absolute value of the sum of size-adjusted returns around the 3-day window centered around the earnings forecast date. *MktRet* and *FirmRet* are the cumulative monthly returns over the prior 6 months for the market and firm, respectively. *StdRet* is the standard deviation of returns over the prior 6 months. Standard errors are clustered by financial institution. ***, **, and * denote 1%, 5% and 10% level of significance, respectively. All other variables are defined in Table 4.

	(1)	(2)	(3)
VARIABLES	*DV=Info*	*DV=Info*	*DV=Info*
Violations	-0.0216**	-0.0169***	-0.0170***
	(-2.55)	(-2.81)	(-2.96)
RExp		0.0063	0.0063
		(1.70)	(1.66)
RHorizon		-0.0100*	-0.0049
		(-1.95)	(-1.07)
RFirmsCovered		0.0070	0.0069
		(0.80)	(0.77)
FISize		0.0107*	0.0111*
		(1.85)	(1.92)
FIPrestige		-0.0124	-0.0126
		(-1.20)	(-1.24)
FIBusinessLines		-0.0040	-0.0043
		(-0.12)	(-0.13)
MktRet			-0.0418**
			(-2.29)
FirmRet			-0.0418***
			(-7.98)
StdRet			0.7315***
			(5.62)
Year FE?	No	Yes	Yes
Observations	68,187	68,187	68,109
R-squared	0.25%	3.36%	3.72%