Employee Quality and Financial Reporting Outcomes

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Abstract:

We examine the association between employee quality and financial reporting outcomes. Using the average workforce education level in MSA(s) where the firm operates as a proxy for employee quality, we find that firms with a high-quality workforce exhibit higher accruals quality, fewer internal control violations, and fewer restatements. These firms also issue superior management forecasts, in terms of frequency, timeliness, accuracy, precision, and bias. Employees located at the firm's headquarters primarily drive our findings. Our evidence suggests employee quality, particularly at a firm's headquarters, is associated with both mandatory and voluntary disclosure quality.

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"Educate and inform the whole mass of the people… They are the only sure reliance for the preservation of our liberty." - Thomas Jefferson, 1787

1. Introduction

Following a series of accounting scandals in the early 2000s (e.g., Enron and WorldCom), capital market participants questioned how auditors and regulators failed to identify the misreporting. However, in a comprehensive examination of fraud cases from 1996 to 2004, Dyck, Morse, and Zingales (2010) find that a firm's employees identify and reveal fraud more often (17 percent of the time) than both auditors (10 percent) and the corporate finance division of the Securities and Exchange Commission (SEC) (7 percent). Given that employees provide ex-post discipline of financial reporting by helping uncover fraud after it has occurred, a natural question is whether employees are able to impose ex-ante discipline on financial reporting before violations take place.

We examine whether the quality of a firm's workforce is associated with financial reporting quality. We proxy for the quality of a firm's workforce in two ways: (1) the average education level of the workforce in the Metropolitan Statistical Area (MSA) where the firm is headquartered, and (2) the average education level of the workforce across all MSAs mentioned in the firm's Form 10-K filing.[1] Using these measures, we examine two broad research questions. First, are highly educated employees associated with improved mandatory disclosure quality? Second, are highly educated employees associated with improved voluntary disclosure quality?

Prior research examines whether executive (i.e., CEO and CFO) characteristics contribute to financial reporting quality (Aier, Comprix, Gunlock, and Lee 2005; Bamber, Jiang, and Wang

[1] These proxies do not distinguish between the quality of the firm's senior executives (i.e., CEO, CFO) and the quality of its other employees. However, we note that (a) average education levels in a given MSA are more likely to capture the education level of a firm's non-executive employees, and (b) we formally control for the education level of the executives and directors named in the firm's regulatory filings. Therefore, our analyses focus on employees who are outside the C-suite, and the association between their education and financial reporting outcomes.

2010; Dyreng, Hanlon, and Maydew 2010; Ge, Matsumoto, and Zhang 2011; Demerjian, Lev, Lewis, and McVay 2013). However, the literature largely ignores whether characteristics of the firm's entire workforce are associated with financial reporting outcomes. Because a firm's financial data originate far from the C-suite, we argue that the firm's entire workforce plays an important role in shaping the quality of a firm's financial reporting. Furthermore, while lawmakers and regulators have traditionally focused on other firm monitors (i.e., investors, board of directors, the SEC, auditors, and corporate executives) to improve reporting quality, we examine whether a high-quality workforce is associated with better reporting outcomes.

High-quality employees can improve their firm's financial reporting environment in at least two ways. First, they can provide superior information as inputs to executives' reporting choices. Second, high-quality employees can identify and uncover intentional financial misreporting, perhaps even before it develops into a larger misreporting event. Our proxy for high-quality employees, the education level of the firm's workforce, is associated with both channels through which employees can improve financial reporting. First, more educated employees provide their superiors with higher-quality inputs (i.e., fewer errors), resulting in higher-quality reporting outcomes (Merchant and Rockness 1994; O'Fallon and Butterfield 2005). Second, highly educated employees are more likely to recognize when a transaction appears abnormal, elevating concerns to management before it becomes a more serious misstatement (Glaeser and Saks 2006).[2] Consistent with this point, Call, Kedia, and Rajgopal (2016) find that executives grant more stock options to rank and file employees during periods of misreporting in an effort to discourage whistleblowing, suggesting that executives engaged in misconduct believe their employees have

[2] As explained more fully in Section 3, employees need not understand generally accepted accounting principles (GAAP) to act as effective monitors over financial reporting quality. For example, an employee who recognizes when production and shipping activities are abnormal (i.e., concentrated at the end of the quarter, shipped without a purchase order) or when standard procedures are bypassed (i.e., reduction in quality-control checks, skipping planned maintenance) would be able to effectively monitor the firm's reported revenue.

the ability to uncover information that would bring financial misconduct to light.

We find significant variation in education levels throughout the United States.[3] Specifically, the highest education levels are in Boston, Silicon Valley, and several cities that are home to large public universities (e.g., Iowa City, IA, Columbia, MO, Madison, WI), suggesting that firms with operations in these areas employ more highly educated employees with greater ability to improve financial reporting quality. On the other hand, Dallas, Los Angeles, and Las Vegas are in MSAs that are among the bottom half of workforce education, suggesting that firms with operations in these areas often rely on employees with less ability to improve reporting quality.

We first examine the association between education levels and three attributes of mandatory reporting quality—the quality of the firm's accruals, the propensity of the firm to report an internal control weakness, and the likelihood the firm restates its financial statements (Dechow and Dichev 2002; Hennes, Leone, and Miller 2008; McGuire, Omer, and Sharp 2012). After controlling for several MSA-level attributes (i.e., macroeconomic indicators, microeconomic indicators, and location specific monitoring variables), we find that the average education level of a firm's workforce is positively associated with accruals quality, negatively associated with the likelihood that the firm reports an internal control weakness, and negatively associated with the likelihood that the firm restates its financial statements. These findings suggest that firms with high-quality employees exhibit superior mandatory disclosure quality.

Next, we examine whether these findings extend to the firm's voluntary reporting quality—namely, the quality of management earnings forecasts. These forecasts differ from mandatory disclosures in that they are "forward-looking" (rather than "backward-looking") and are not subject to an external audit. As a result, there is more discretion afforded to managers when making

[3] We use data from the United States Census Bureau's American Community Survey (ACS) to capture the average education level of each Metropolitan Statistical Area (MSA). See Section 4.1 and Appendix A for detailed descriptions on our data.

voluntary disclosure choices, and the impact of high-quality employees on the quality of these disclosures is unclear. Consistent with our results related to mandatory disclosures, we find that the average education level of a firm's workforce is positively associated with the frequency and horizon of management forecasts, and is negatively associated with absolute forecast errors, forecast bias, and forecast range. These findings suggest that employee quality is positively associated with voluntary disclosure quality.

In additional analyses, we find strong support for the notion that employee quality at the firm's headquarters is associated with reporting outcomes, with relatively weaker support for the role of employees at non-headquarter locations. Further, although only a very limited number of firms in our sample changed their headquarters location during our sample period, we find that changes in the education level in the headquarters location for these firms (i.e., moving from a less educated MSA to a more educated MSA) is generally positively associated with changes in both mandatory and voluntary disclosure reporting quality. We therefore conclude that our main findings are primarily driven by the quality of employees at the firm's headquarters, suggesting that aggregating and summarizing accounting data from across the firm plays a unique role in the firm's reporting outcomes. However, we note that we measure the education level of non-headquarter employees with considerable error, which may contribute to our relatively weaker results for these employees. Therefore, our findings should not be interpreted to suggest that employees at non-headquarter locations are irrelevant to financial reporting outcomes.[4]

Our study contributes to the literature on financial misreporting and corporate governance. Recent research suggests that employees play a role in monitoring the firm's financial reporting. For example, Bowen, Call, and Rajgopal (2010) find that employee whistleblowing events are

[4] We discuss the specific nature of this measurement error in more depth in Section 5.1.

associated with negative stock price reactions, future earnings restatements, subsequent lawsuits, and poor future firm performance. Similarly, Dyck et al. (2010) find that employees detect and reveal 17 percent of frauds, exceeding the rate of auditors (10 percent) and regulators (7 percent). Collectively, the findings of these studies suggest employees play an important governance role *after* fraud has been committed. We extend this research by providing evidence that employees can discipline financial reporting *before* the incidence of fraud.

We also contribute to the literature examining the effect of idiosyncratic, employee-specific attributes on financial reporting outcomes. Prior research focuses on the relation between CEO and CFO personal traits and the impact of these characteristics on their firms' policy choices. For example, CEO and CFO traits such as age, education, financial and legal expertise, and personal risk-aversion have been linked to voluntary disclosure (Bamber, Jiang, and Wang 2010), earnings quality (Demerjian et al. 2013), financial misreporting (Aier et al. 2005; Ge et al. 2011), option backdating (Dhaliwal, Erickson, and Heitzman 2009), and tax aggressiveness (Dyreng et al. 2010; Chyz 2013). We contribute to this literature as the first to establish that characteristics of employees outside the C-suite are also associated with disclosure outcomes.

Finally, our study relates to recent literature examining the effects of MSA-level attributes on reporting quality. McGuire et al. (2012) find that firms headquartered in MSAs with religiously adherent residents have fewer restatements and are less likely to be sued for accounting malfeasance. They conclude that religion acts as a substitute for other forms of monitoring. Two recent papers explore the link between education and *external* monitoring by analysts (Gunn 2013) and auditors (Beck, Francis, and Gunn 2017). We demonstrate that the education of the firm's *own employees* can serve as a form of *internal* monitoring.

2. Background and Motivation

2.1 Prior literature on education

Prior research examines whether CEO and CFO education impacts financial reporting quality. Hambrick and Mason's (1984) upper echelons theory predicts that cross-sectional differences in managers' education are likely to shape their values and cognitive biases, which in turn will affect their managerial styles. In addition, prior literature establishes that managers with an MBA develop different styles relating to conformity, conventionality, rationality, and ethics than do their counterparts without the same educational backgrounds (Chen 2004; Ghoshal 2005; Gintis and Khurana 2008). Consistent with this literature, Bamber, Jiang, and Wang (2010) find that CEOs and CFOs with an MBA issue forecasts that are more accurate, consistent with the notion that the education of senior management (i.e., CEO and CFO) is associated with reporting outcomes.

The economics literature also finds that education levels are associated with the monitoring of fraudulent behavior. Glaeser and Saks (2006) document that, from 1990 to 2002, United States federal prosecutors convicted more than 10,000 government officials of acts of corruption. They appeal to Lipset's (1960) theory that highly educated (and high-income) voters are more able and willing to monitor and take action when public employees violate the law. Consistent with this idea, they find that more educated states and, to a lesser extent, more affluent states, have lower levels of corruption.

Finally, two contemporaneous papers link the education level of capital market participants outside the firm (i.e., analysts and auditors) to improved reporting outcomes. Gunn (2013) appeals to urban economics theory and predicts that the human capital depth in a geographic area, as measured by the average education level, creates knowledge spillovers that result in positive economic outcomes (Moretti 2004; Glaeser and Gottlieb 2009). He finds that sell-side analysts located in MSAs with higher education levels issue more accurate and informative earnings forecasts than do analysts located in MSAs with lower education levels.

Beck et al. (2016) investigate a different type of capital market intermediary—the firm's auditor. They measure auditor human capital as the education level of the city in which the auditor's office is located. They find a positive association between the average education level in the MSA surrounding an auditor's local office and accrual quality of the firms they audit. Beck et al. (2016) conclude that auditors located in highly educated areas perform higher-quality audits, but acknowledge the possibility that superior reporting outcomes could also be driven by the education of the client firm's employees. They leave this issue for future research.

Three features of our study distinctly separate it from these contemporaneous papers. First, at a conceptual level, we use the education level of the community as a proxy for the quality of the employees themselves, whereas Gunn (2013) and Beck et al. (2016) argue that analysts and auditors simply benefit from living and working around educated people, regardless of their own education levels. Second, we examine education levels of the workforce in the MSA in which the *firm* is headquartered (rather than the education levels where the firm's auditor or analysts are located). Finally, we examine outcomes that are outside the scope of financial analyst reports and financial statement audits (i.e., management forecasts, internal control weaknesses, and, in supplemental analysis, whistleblowing after misreporting events), allowing our findings to speak directly to the association between firms' employees and financial reporting quality.

2.2 Prior literature on the role of a firm's workforce in financial reporting

While academic research frequently focuses on senior executives and their role in the financial reporting process (Bergstresser and Phillipon 2006; Cheng and Warfield 2005; Feng, Ge, Luo, and Shevlin 2011; Hennes et al. 2008; Bamber, Jiang, and Wang 2010), we know relatively little about the impact of the broader workforce on either voluntary or mandatory disclosure quality. Although

CFOs are ultimately responsible for the quality of the firm's financial reporting, the entire workforce not only participates in the preparation of accounting information, but also plays an indirect role in financial reporting by providing the raw internal data that form the basis for the executives' reporting choices.

Dyck et al. (2010) examine a comprehensive sample of alleged corporate fraud in large US companies and find that the firm's own employees, some of whom are not senior executives, uncover more corporate wrongdoing than do investors, regulators, auditors, or the media, suggesting that employees outside the C-suite can play an important role in bringing reporting violations to light. In describing the role of employees in monitoring firm behavior, Dyck et al. (2010) indicate that "employees clearly have the best access to information," and that "few, if any frauds can be committed without the knowledge and often the support of several employees" (page 2240). Relatedly, Call et al. (2016) find that firms grant more stock options to non-executive employees during periods of misreporting in an effort to discourage employee whistleblowing, suggesting that corporate leaders are aware that lower-level employees participate in and have the potential to monitor the firm's reporting practices.

3. Hypothesis Development

There are two ways in which a highly educated workforce can, ex ante, improve financial reporting quality. First, they can provide higher-quality information (i.e., fewer errors) as inputs to the accounting system. Specifically, highly educated employees should make fewer unintentional errors in the process of gathering and generating data that are in turn processed into financial information appearing in various financial reports (i.e., Form 10-K, Form 10-Q, Form 8-K, among others). If fewer errors are input into the accounting system, the resulting financial statements should be of higher quality.

One might question whether unintentional accounting errors offset in the aggregate. For instance, if one error has the effect of increasing earnings, another error may decrease earnings, and the *cumulative* error could be close to zero, even for firms with employees who make a large number of errors. However, in untabulated Monte Carlo and mathematical analyses, we show that the absolute cumulative error is increasing in the number of unintentional errors that are committed.[5] Thus, highly educated employees should make fewer unintentional errors, resulting in smaller absolute *cumulative* errors.[6]

Second, in addition to making fewer unintentional errors, highly educated employees are more likely to recognize when a transaction appears abnormal and possibly fraudulent, elevating that information to management before it becomes a more serious misstatement. In the context of the political process, Glaeser and Saks (2006) find that political corruption is lower when the voting population is more highly educated, as an educated voter base imposes discipline on its elected politicians. Consistent with executives believing their employees have the ability to uncover financial misconduct, Call et al. (2016) find that executives grant more stock options to lower-level employees during periods of misreporting to discourage whistleblowing.

We do not assume that a firm's workforce needs a working knowledge of generally accepted accounting principles (GAAP) to improve reporting outcomes. Employees from outside the

[5] We assume unintentional errors follow a standard normal distribution [~ IID N(0,1)]. For each simulation, we compute the cumulative error as a running sum of individual errors, starting with error 1 and continuing to error *N*. If there is only one error, the cumulative error is equal to that single error. As the number of errors grows, the cumulative error is the sum of the current error and all previous errors. In each simulation, we allow the number of errors to grow from 1 to 1,000. We then run each estimation 10,000 times. We find that the absolute value of the cumulative error across all simulations averages 14.5 and is significantly different from 0 (p-value < 0.001), suggesting that independent random errors will not offset to zero in the aggregate. We also find that, within each simulation, the absolute cumulative error is positively correlated with the number of errors, N, at 0.598, suggesting that the extent to which absolute cumulative errors offset decreases as the number of errors increases.

[6] The expected absolute cumulative error can be calculated as $\frac{\sqrt{2N\sigma^2}}{\sqrt{\pi}}$, where N is the number of errors. Therefore, under the assumption that the errors follow a standard normal distribution (i.e., $\sigma^2 = 1$), we would expect the cumulative error after the 1,000th error to be = $\sqrt{2N}$ / $\sqrt{\pi}$ = $\sqrt{2 * 1{,}000}$ / $\sqrt{\pi}$ = 25.2. Indeed, we find (untabulated) that across our 1,000 simulations, the average absolute cumulative error after the 1,000th error is 25.1.

accounting function provide information that is relevant to the ultimate reporting decision made by senior management. For example, when sales and production personnel provide better information about past and projected activity, senior management is in a better position to provide informative disclosures. Further, employees need not understand the rules surrounding revenue recognition to recognize when production and shipping activities are abnormal (i.e., concentrated at the end of the quarter, shipped without a purchase order), when standard procedures are bypassed (i.e., reduction in quality-control checks, skipping planned maintenance), or when product returns are abnormal. An employee who does not understand the nuances of GAAP but who understands when something is amiss can elevate the issue to a superior who is more likely to be financially sophisticated and have an understanding of GAAP. In fact, prior research shows that when they suspect corruption, educated individuals are more proactive than less educated individuals (Glaeser and Saks 2006). Thus, even when non-accounting employees are more educated, the firm's reporting outcomes should be superior.

We first investigate these issues in the context of mandatory reporting quality. We predict that employee education levels are associated with higher-quality accruals (i.e., the extent to which accruals map into past, present, and future cash flows (Dechow and Dichev 2002)), fewer internal control weaknesses, and fewer restatements of prior financial statements (Hennes et al. 2008; McGuire et al. 2012).

HYPOTHESIS 1A: *Employee education is positively associated with accruals quality.*

HYPOTHESIS 1B: *Employee education is negatively associated with the likelihood of internal control weaknesses.*

HYPOTHESIS 1C: *Employee education is negatively associated with the likelihood that the firm restates its financial statements.*

Unlike mandatory disclosures, voluntary management forecasts provide forward-looking information and are not subject to an external audit. Despite these differences, we predict that employee education levels are also associated with higher-quality voluntary disclosures. Research suggests that voluntary disclosure increases with the quality of managers' information (Francis, Nanda, and Olsson 2008; Ball, Jayaraman, and Shivakumar 2012; Dorantes, Li, Peters, and Richardson 2013). We argue that more educated employees provide senior executives with better information, increasing their willingness to issue voluntary disclosures. We therefore predict that highly educated employees are associated with earnings forecasts that are (1) more frequent, (2) issued earlier in the period (i.e., longer horizon), (3) more accurate (i.e., smaller absolute forecast error), and (4) more precise (i.e., smaller forecast range).[7] Further, prior research suggests greater external monitoring reduces the upward forecast bias inherent in management's estimates of future firm performance (Rogers and Stocken 2005; Ajinkya, Bhojraj, and Sengupta 2005), and we expect highly educated employees play a similar (albeit internal) monitoring role, thereby reducing any upward bias in management earnings forecasts.

HYPOTHESIS 2A: *Employee education is positively associated with the frequency and horizon of management earnings forecasts.*

HYPOTHESIS 2B: *Employee education is negatively associated with the absolute error, bias, and range of management earnings forecasts.*

4. Research Design and Empirical Results

4.1 Measuring Workforce Education and Sample Selection

The average education level of a firm's workforce is unobservable. Therefore, we rely on education data collected annually by the United States Census Bureau, as part of the much larger

[7] Management forecast errors can be driven by the noise in both forecasted earnings and the actual earnings realization. Thus, it is possible that the effect of employee education on management forecast accuracy is not incremental to its effect on actual earnings realizations (i.e., as predicted in H1 through accruals quality, internal control weaknesses, and restatements). To disentangle these effects, we (a) control for all factors that prior research suggests are related to the accuracy of both the management forecast and actual earnings, and (b) control for the specific outcomes examined in H1 (i.e., accruals quality, internal control weaknesses, and restatements). Taken together, these tests provide reasonable assurance that our results related to voluntary disclosure quality do not simply reflect the effects of employee education levels on mandatory reporting quality.

American Community Survey (ACS), to proxy for employee education levels.[8] Beginning in 2001, the ACS survey has been performed in every non-census year and involves collecting responses from a sample of the population from each MSA. While results of the ACS are available from the Census Bureau, the data require extensive manipulation before being machine-readable. Therefore, we obtain data from the University of Minnesota's Integrated Public Use Microdata Series (IPUMS–USA; Ruggles et al. 2010).[9] IPUMS–USA provides harmonized economic microdata derived from annual ACSs and decennial censuses.

IPUMS provides information about both the MSA in which the employee lives and the MSA in which the employee works. Because we are interested in the education of the workforce where firms are located, we utilize the MSA corresponding to the respondent's place of work (IPUMS data item PWMETRO). When PWMETRO is not reported, we use the respondent's home MSA (IPUMS data item METAREA) to identify the individual's location. Because information about the individual's place of work is only available from 2005 to 2011, our analysis is limited to this time period.

We compute the weighted-average education level of the MSA's workforce using the sampling weights provided in the IPUMS data (PERWT). These sampling weights indicate the estimated number of residents in an MSA with similar characteristics to the respondent. We restrict responses to records pertaining to active members of the workforce. The IPUMS education variable indicates the highest level of schooling completed by the respondent. For instance, a value of six corresponds to someone completing the 12th grade, while a value of 10 indicates four years of college. Thus, our variable of interest, *EDUC*, is the MSA-level weighted average of these responses. Appendix A provides an illustration of these calculations.

[8] A sample ACS questionnaire can be found at http://www.census.gov/acs/www/Downloads/questionnaires/2014/Quest14.pdf.
[9] https://usa.ipums.org/usa/index.shtml

Using this data, we develop two proxies for the average education level of the firm's employees. First, we use the average education level of the workforce in the MSA in which the firm is headquartered (*EDUC-HQ*). Second, we compute the average education level of all MSAs in which the firm had significant operations during the year, acknowledging that many firms have employees who work outside the firm's headquarters MSA. We capture the education level of employees at other firm locations because sales and other accounting information often originates away of headquarters. However, even if the underlying information originates elsewhere, accounting information is often aggregated and summarized by employees at firm headquarters. Therefore, we employ both proxies in our empirical tests and make no prediction about which proxy better captures the quality of the employees most closely associated with reporting outcomes.

We use Compustat to identify the headquarters address, and then obtain latitude and longitude data using Google's 'geo-coding' functionality to compute the average straight-line distance between the firm's headquarters and the center of each city named in the description of each MSA (e.g., "Dallas" and "Fort Worth" for Dallas-Fort Worth). We assign observations to the closest MSA using this average straight-line distance. The mean (median) distance between firm headquarters and the center of the nearest city named in an MSA is 7.8 (0) miles, and less than 1% of observations are more than 60 miles from the center of the closest MSA.[10] We then merge the education data based on the firm's fiscal year end.[11]

We search for locations in firms' 10-Ks using a process similar to Bernile, Kumar, and Sulaeman (2015) and Garcia and Norli (2012). Specifically, we search for city-state locations that

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[10] Our findings are not sensitive to dropping firms with headquarters more than 60 miles from the center of the closest MSA.
[11] We assume ACS data is collected throughout the year. Therefore, for firms with fiscal years prior to July 1, we use the prior year education data. For fiscal years that end after July 1, we use the current year education data.

appear in any portion (excluding the header) of a firm's 10-K filing.[12] We then validate each match using a comprehensive list of nearly 30,000 US cities, and map these city-state combinations into MSAs.[13] We find substantial variation in the number of locations identified in the 10-K. For about 20 percent of the firm-year observations in our sample, we find no mention in the 10-K of locations outside of the firm's headquarters MSA. However, for the remaining 80 percent, we identify multiple MSAs, and in these cases, we calculate the firm's employee education level as the simple average of the average education level across these MSAs (*EDUC-10K*).[14]

We obtain financial data from the CRSP-Compustat merged database. Because the ACS data is limited to the population of the United States, we delete firms headquartered outside the US. We also remove firms headquartered in Puerto Rico because local regulations likely differ when compared to firms headquartered elsewhere in the US. This process yields 34,090 firm-year observations between 2005 and early 2012. Each of our analyses begins with this population, although additional data requirements yield much smaller samples in our tests. We discuss these restrictions below.

In our analyses, we control for several MSA-level variables. Specifically, we control for the average wages in the MSA (*WAGES*), the natural log of the size of the workforce in the MSA (*LNPOP*), and the cost of living using the MSA's consumer-price index (*CPI*). We also control for the level of religious adherence (*RELIGION*), as prior research links religiosity to financial reporting (Dyreng, Mayew, and Williams 2012; McGuire et al. 2012) and the intensity of press

[12] We use a Python script to identify city-state combinations as a proper noun (or multiple proper nouns) followed by a state name or abbreviation (with or without comma separation). Bernile et al. (2015) and Garcia and Norli (2012) use a similar approach to identify unique states mentioned in the 10-K. We identify city-state combinations, rather than states, to allow for more precise mapping into MSAs. However, to validate our approach, we also searched for unique states and found that the firms in our sample mention an average of 8.2 unique states in the 10-K, compared to 8.1 unique states for Bernile et al. (2015) and 7.9 unique states for Garcia and Norli (2012).

[13] See http://opengeocode.org/download.php for the list of cities.

[14] In untabulated analysis, we also calculate a measure that weights each MSA by its number of mentions in the 10-K under the assumption that more frequently mentioned locations have a greater proportion of firm operations. Results using this alternative measure are qualitatively similar to those reported in our analyses using the simple average.

coverage (*REPORTERS*), since research identifies journalists as capable monitors (Miller 2006). Further, we control for the MSA's economic environment using unemployment (*UNEMP*), new housing starts (*HOUSESTARTS*), the state coincident index (*SCI*), a summary measure of economic condition, and average profitability and earnings volatility (*MSA_ROA* and *MSA_ROA_VOL*, respectively). We compute each of these MSA-level variables using the same two measurement bases (headquarters MSA or 10-K MSAs) described for EDUC. We expect *RELIGION* to relate positively to reporting quality based on evidence in Dyreng et al. (2012) and McGuire et al. (2012), but we make no other predictions related to these MSA variables.

We also control for several firm-level measures associated with the firm's geographic location and that may correlate with employee quality. Specifically, research suggests auditors (Choi et al. 2012), the SEC (Kedia and Rajgopal 2011), security analysts (Yu 2008), and institutional ownership (Ayers, Ramalingegowda, and Yeung 2011) are all associated with financial reporting quality. Accordingly, we control for the proximity of the firm to these monitors. Specifically, we control for the natural log of the distance between the firm's headquarters and its auditor (*AUDITORDIST*), the responsible SEC regional office (*SECDIST*), and New York City (*NYCDIST*), where more than half of all analysts are located (Gunn 2013). We expect each of these distance measures to relate negatively to financial reporting quality. We also control for local institutional ownership (*LOCMONITOR*) and analyst following (*AFOLLOW*) in all analyses.[15] We expect both of these variables to relate positively to financial reporting quality. Finally, we control for the education level of named executives and directors (*BOARDEDUC*) using degree information from BoardEx. Because of BoardEx's limited coverage, we set *BOARDEDUC* equal to zero and include an indicator variable (*MISSING_BX*) equal to one for observations without

[15] As in Ayers et al. (2011), we also control for other classifications of institutional ownership (i.e., non-local monitors, transient owners, and other owners).

BoardEx data. Appendix B provides detailed definitions of all variables.

4.2 Descriptive statistics for MSA data

Table 1 presents descriptive statistics for our MSA-level variables. In Panel A, we sort MSAs by mean education, where lower (higher) ranks correspond to a more (less) educated workforce. We report descriptive statistics for the 25 MSAs with the highest and lowest values of *EDUC*, along with any MSA that are headquarters to at least 1 percent of observations in the CRSP-Compustat universe during our sample period. A score of 7 (8) corresponds to one (two) years of college completed, and the education level corresponding to each value of *EDUC* is outlined in Appendix B. The most educated cities often correspond to “college towns” (e.g., Iowa City, Ann Arbor, Gainesville), although a few larger cities appear in this list of the 25 most educated MSAs as well (e.g., Boston, New York). The 25 MSAs with the lowest education levels represent areas typically associated with economic hardship and high poverty levels (e.g., Stockton, Modesto). Panel A also reports average *WAGES*, the average size of the workforce, and the average *CPI* for each MSA during our sample period. As expected, larger cities typically correspond to higher cost of living and wages. However, wages can also be associated with education, highlighting the importance of controlling for these potentially confounding factors.

Panel B of Table 1 reports descriptive statistics for select MSA-level variables separately for each year. Average *EDUC* exhibits a modest increase over our sample period, increasing from 7.31 in 2005 to 7.47 in 2011. For context, one scenario that could lead to this increase of 0.16 is for 16% of the workforce to complete one additional year of college. To further investigate the time-series properties of *EDUC*, Figure 1 plots *EDUC* values for the largest ten MSAs from 2005 to 2011. Consistent with Panel B of Table 1, education is increasing over time. However, there is MSA-level variation regarding the magnitude of this increase over our sample period.

In Panel C of Table 1, we sort MSAs into deciles by *EDUC*, where Decile 1 corresponds to the most educated locations. We then present the mean value of *EDUC*, along with the number and percentage of observations in our sample, within each decile. A large proportion of observations correspond to firms located in more educated cities, as approximately 60 percent of observations fall within the first three education deciles. However, nearly 17 percent of observations fall within the bottom three deciles. Panel D of Table 1 presents correlations among MSA variables. *EDUC* exhibits significant correlations with all MSA variables. Specifically, *EDUC* correlates positively with *WAGES*, *LN_POP*, *CPI*, *HOUSESTARTS*, *REPORTERS*, and *MSA_ROA_VOL*, with correlations ranging from 0.12 to 0.39. *EDUC* correlates negatively with *UNEMP*, *RELIGION*, *SCI*, and *MSA_ROA*, with correlations ranging from -0.12 to -0.21. We control for these variables in all regressions.

4.3 Research design for H1

H1A predicts that larger values of *EDUC* (*EDUC-HQ* and *EDUC-10K*) are associated with higher-quality accruals. Using a modified Dechow-Dichev measure of accruals quality (*AQ*) (Dechow and Dichev 2002; McNichols 2002), we estimate the following regression (with firm and year subscripts *i* and *t*):

$$AQ_{i,t} = \alpha_0 + \alpha_1 EDUC_{i,t} + \Sigma\beta_k MSA\ Controls + \Sigma\theta_j Other\ Controls + \Sigma\gamma_m IndustryFE + \Sigma\lambda_n YearFE + e_{i,t} \quad (1)$$

We estimate equation (1) using OLS, and assess statistical significance throughout the paper using one- (two-) sided *p*-values when predictions are (are not) made using *t*-statistics derived from robust standard errors clustered by firm. Because smaller values of *AQ* correspond to better accruals quality, we expect α_1 to be negative. *MSA Controls* refer to those variables defined in Section 4.1 (i.e., *WAGES, RELIGION, NYDIST*, etc.), and are included in all regressions.

The remaining control variables (*Other Controls*) are largely based on Francis, LaFond, Olsson, and Schipper (2004). We expect *AQ* to deteriorate (or increase in magnitude) with increases in the volatility of fundamentals (*SALEVOL* and *CFVOL*), the length of the operating cycle (*LNOPCYCLE*), the intensity of intangible assets (*INT_INT*) and the incidence of negative earnings (*NLOSSES*), because higher values of these firm characteristics make accrual estimation more difficult. Conversely, larger firms (*LNASSETS*), firms with more capital assets (*CAP_INT*), and those audited by a Big 4 auditor (*BIG4*) typically exhibit higher accruals quality. In addition to these measures, we also include firm and peer idiosyncratic shocks (*IDIOSHOCKS* and *PEERSHOCKS*) derived from returns data based on evidence in Owens, Wu, and Zimmerman (2016). We expect each of these measures to relate positively to *AQ*. We remove firms with less than $100 million in assets to avoid small denominator problems. Many variables (*CFVOL*, *SALEVOL*, *NLOSSES*) require a five-year time series to calculate. These screens result in a sample of 8,787 firm-year observations. Descriptive statistics for this sample are presented in Panel A of Table 2.[16] Appendix B presents detailed definitions of all variables.

H1B uses the effectiveness of internal controls over financial reporting (Feng, Li, and McVay 2009) to proxy for the quality of the firm's mandatory disclosures. Better internal controls decrease the likelihood that errors or irregularities go undetected. Thus, we estimate the following regression:

$$Pr(ICW_{i,t} = 1) = \Theta(\alpha_0 + \alpha_1 EDUC_{i,t} + + \Sigma\beta_k MSA\ Controls + \Sigma\theta_j Other\ Controls \\ \Sigma\gamma_m IndustryFE + \Sigma\lambda_n YearFE) \qquad (2)$$

where $\Theta(.)$ is the logistic function and $ICW_{i,t}$ is equal to one if firm *i* has an internal control weakness in year *t*, and zero otherwise.

H1B predicts that more highly educated workforces correspond to fewer internal control

[16] We winsorize all continuous, unlogged variables at the top and bottom one percent. The descriptive statistics in Panel A of Table 2 are largely consistent with those found in prior research.

weaknesses, so we expect α_1 to be negative. Again, *MSA Controls* refer to those variables defined in Section 4.1. The majority of *Other Controls* are based on Doyle, Ge, and McVay (2007), who identify determinants of internal control weaknesses. Based on their results, we control for and expect *SIZE*, *AGE*, and *INSTHOLD* (*AGGLOSS, ZSCORE, EXTSG, LNSEGS, MERGE_ACQ, LEV, RESTRUCT,* and *FOREIGN*) to relate negatively (positively) to the likelihood of an internal control weakness. We include *BIG4,* although we make no directional prediction for its coefficient. A Big 4 auditor could increase the likelihood of an internal control weakness if Big 4 auditors best ensure that the control system is designed properly. However, *BIG4* may be negatively associated with *ICW* if these audit firms avoid clients with poor internal control systems. We also include *LIT* because litigation risk may affect management's focus on internal controls. We include industry-adjusted ROA (*IA_ROA*) because employees of better performing firms have less incentive to circumvent internal controls for personal gain. Finally, we include an indicator variable equal to one for firms in the top quintile of return volatility (*HIGHVOL*) for two reasons. First, return volatility captures the firm's idiosyncratic risk, as internal control systems may be less effective in riskier firms. Second, higher return volatility potentially captures a market expectation that the firm's internal control systems, and financial reporting in general, are of poor quality (Cassell, Dreher, and Myers 2013).

Data requirements for H1B include coverage in Audit Analytics SOX – 404 Internal Controls file and the Compustat Historical Segments file. We also require CRSP Daily returns to compute *HIGHVOL*. After removing firms with insufficient data and with total assets of less than $100 million, we have a sample of 11,608 firm-year observations. Panel B of Table 2 reports descriptive statistics used to test H1B.[17] Slightly less than five percent of our sample report internal control weaknesses. This percentage is lower than the approximately 10 percent reported in prior studies (e.g., Doyle et al. 2007; Cheng, Dhaliwal, and Zhang 2013). This difference likely arises for two reasons. First, our sample excludes the early years of mandatory SOX compliance when internal control weaknesses were much more common and extends to more recent years when material weaknesses occur less frequently. Second, our sampling procedures and data requirements yield a sample of larger firms, which prior research suggests have higher-quality internal controls (Doyle et al. 2007).

H1C predicts that more educated workforces correspond to less frequent earnings restatements. To test this hypothesis, we estimate the following model:

$$Pr(RESTATE = 1) = \Theta(\alpha_0 + \alpha_1 EDUC_{i,t} + \Sigma\beta_k MSA\ Controls + \Sigma\theta_j Other\ Controls\ \Sigma\gamma_m IndustryFE + \Sigma\lambda_n YearFE) \quad (3)$$

H1C predicts a negative coefficient on *EDUC*. *MSA Controls* refer to the variables defined in Section 4.1, where we discuss our predictions. Because determinants of *ICW*, a measure of the *likelihood* of misreporting, closely align with those of *RESTATE*, a measure of the *incidence* of misreporting, we use the same set of *Other Control* variables as in our test of H1B. Further, we make the same directional predictions as in equation (2).

Because we use the same set of control variables in equation (3) as in equation (2), our sample construction consists of only minor differences between internal control data and restatement data (i.e., a slightly larger sample size of 11,696 firm-year observations compared to the 11,608 used in equation (2)). Descriptive statistics are presented in Panel B of Table 2. As shown, 12.6 percent

[17] Note that we use the same set of control variables to test H1B that tests the association between *EDUC* and the incidence of a restatement. For parsimony, we combine these samples in reporting our descriptive statistics. Because data availability in Audit Analytics' SOX 404 database varies slightly from the coverage in the Non-reliance database (which we use for restatements), the samples do not intersect perfectly, yielding a non-constant sample size for *ICW*, *RESTATE*, and control variables. Specifically, while we test the association between EDUC and internal control weaknesses (restatements) using 11,608 (11,696) firm-year observations, there are a total of 11,798 firm-year observations used in at least one of these tests.

of firm-years correspond to restatements in our sample. This percentage is consistent with the 13 percent reported in Demerjian et al. (2013) over a similar sample period. Other MSA level and firm level controls for this sample closely mirror those reported in Panel B. Panel D of Table 2 reports correlations among variables of interest. The correlation between our two *EDUC* measures, *EDUC-HQ* and *EDUC-10K*, is 0.77.

4.4 Tests of H1

In Table 3, we report estimation results for equation (1). Consistent with H1A, the coefficient on *EDUC* is significantly negative using both measures of employee education. Recall that *AQ* is measured inversely, so this coefficient implies that higher education levels are associated with higher-quality accruals (i.e., less estimation error in accruals). From an economic perspective, a one standard deviation increase in average education (0.371 reported in Panel A of Table 2) corresponds to an improvement in *AQ* of between 3.8 and 5.4 percent of the sample mean, depending whether the HQ or 10-K based measure is used.[18] Several control variables are predictably associated with *AQ*, including the distance from an SEC regional office (*SECDIST*) (Kedia and Rajgopal 2011), analyst following (*AFOLLOW*) (Yu 2008), sales and cash flow volatility (*SALEVOL*, *CFVOL*), and the existence of a Big 4 auditor (*BIG4*) (Francis, Maydew, and Sparks 1999). Consistent with Owens, Wu, and Zimmerman (2016), we also observe a significantly positive association between *IDIOSHOCKS* and *AQ*.

Table 4 presents results related to the association between workforce education and internal control weaknesses. The coefficient on both *EDUC-HQ* and *EDUC-10K* are significantly negative, suggesting that higher levels of education decrease the likelihood that the firm reports a material

[18] As reported in Table 3, the coefficient on *EDUC-HQ* (*EDUC-10K*) is -0.093 (-0.131), and the standard deviation of *EDUC* for the estimation sample is 0.371 (as reported in Panel A of Table 2). For the HQ and 10-K based measures, the product of these two values is -0.034 and -0.049, respectively, or approximately 3.8 and 5.4 percent of the *AQ* sample mean of 0.9. All marginal effects reported are computed in a similar manner.

weakness in internal controls, consistent with H1B. To assess economic significance, we estimate the marginal effect of *EDUC-HQ*, evaluated at the means of other control variables. In untabulated calculations, we find that a one standard deviation increase in *EDUC-HQ* (0.376 reported in Panel B of Table 2) is associated with a 0.8 to 1.0 percent decline in the likelihood the firm reports a material weakness, depending on the specification, or between 16 and 21 percent of the base rate of internal control weaknesses in our sample.

H1C predicts that firms with more educated employees restate prior period financial statements less frequently. Our findings reported in Table 5 are consistent with H1C, as the coefficient on both *EDUC-HQ* and *EDUC-10K* are significantly negative.[19] Further, we find that a one standard deviation increase in *EDUC-HQ* corresponds to a reduced likelihood of restatement by between 0.9 and 1.7 percent, or 7 to 14 percent of the base rate of *RESTATE*. Thus, consistent with our first set of hypotheses, highly educated (i.e., higher-quality) employees are associated with improved mandatory disclosures, as evidenced by higher-quality accruals and a lower incidence of internal control weaknesses and restatements.

4.5 Research design for H2

H2A and H2B predict that employee education levels are positively associated with various aspects of firms' management forecasting activity. To test these hypotheses, we estimate the following OLS regression models:

$$(FREQ_{i,t} \text{ or } HORIZON_{i,t}) = \alpha_0 + \alpha_1 EDUC_{i,t} + \Sigma\beta_k MSA\ Controls + \Sigma\theta_j Other\ Controls \quad \Sigma\gamma_m IndustryFE + \Sigma\lambda_n YearFE + e_{i,t} \tag{4}$$

$$(ERROR_{i,t}, BIAS_{i,t}, \text{ or } RANGE_{i,t}) = \alpha_0 + \alpha_1 EDUC_{i,t} + \Sigma\beta_k MSA\ Controls + \Sigma\theta_j Other\ Controls \quad \Sigma\gamma_m IndustryFE + \Sigma\lambda_n YearFE + e_{i,t} \tag{5}$$

[19] Several control variables reported in Table 4 (internal control weaknesses) and Table 5 (restatements) are statistically significant, including distance from New York City (*NYCDIST*), firm size (*LNMVE*), extreme sales growth (*EXTSG*), industry-adjusted ROA (*IA_ROA*), and the presence of a Big 4 auditor (*BIG4*).

H2A predicts that employee education levels (*EDUC*) are positively associated with forecast frequency (*FREQ*) and timeliness (*HORIZON*), suggesting α_1 in equation (4) will be positive. Similarly, H2B predicts that employee education levels (*EDUC*) are associated with smaller absolute forecast error (*ERROR*), less forecast bias (*BIAS*), and greater forecast precision (i.e., smaller range) (*RANGE*), suggesting α_1 in equation (5) will be negative. In an effort to be consistent with our proxies for mandatory reporting quality, each of which is measured with annual data (e.g., *AQ*, *ICW*, *RESTATE*), all guidance variables are calculated using annual forecast data. *MSA Controls* again refer to the variables described in Section 4.1.

Other Controls in equation (4) are based on prior research. For instance, prior research suggests positive associations between firm attributes such as *SIZE*, *BTM*, *BIG4*, and *LEV* and both the quantity and timeliness of management guidance (Karamanou and Vafeas 2005; Ajinkya et al. 2005; Ball et al. 2012), while firms tend to provide less extensive management guidance when they face litigation concerns (*LIT*) or losses (due to a lack of informativeness, *LOSS*) (Ajinkya et al. 2005). The association between *RETVOL* and both *FREQ* and *HORIZON* is mixed in prior literature (Baik, Farber, and Lee 2011; Ball et al. 2012). Therefore, we make no prediction for the coefficient on *RETVOL*. Prior research also suggests a negative relation between *DISPERSION* and forecasting behavior (Ajinkya et al. 2005). Waymire (1985) and Ball et al. (2012) both show that firms with more volatile earnings issue fewer forecasts, so we expect *EARNVOL* to be negatively associated with *FREQ* and *HORIZON.* Finally, research offers mixed evidence on the relation between firm risk (*BETA* and *LIT*) and forecasting behavior, so we make no predictions for the coefficients on those variables.

Other Controls in equation (5) mirror those in equation (4) with a few minor exceptions. First, we include *HORIZON* in equation (5) because research suggests longer-range forecasts exhibit greater error and bias and lower precision (Ajinkya et al. 2005). Second, we replace *ΔEARN* with *SURPRISE* to capture the news content (in absolute terms) of the forecast (Ajinkya et al. 2005).[20] Finally, we isolate the degree of analyst uncertainty immediately preceding the forecast by including *DISPERSION*, which is based on earnings estimates available in I/B/E/S immediately preceding the forecast. Note that expected coefficients are generally of the opposite sign as those predicted in equation (4) because increasing values of *ERROR*, *BIAS*, and *RANGE* correspond to *decreasing* (rather than *increasing*) disclosure quality.

Data needed to compute management guidance and analyst-related variables used in tests of H2A and H2B necessitate coverage in I/B/E/S Estimates Summary and Guidance History Detail files. We continue to eliminate observations with assets of less than $100 million to avoid small denominator problems. After performing these data screens and eliminating observations with missing values for any needed variable, we have a final sample of 5,023 firm-year observations for tests using *FREQ*.[21] *HORIZON* is defined for firms issuing forecasts, yielding a sample of 3,415 observations for that test. Measures of *BIAS* and *ERROR* are only possible for point or range forecasts, reducing the sample to 3,288 observations. Finally, we only compute *RANGE* for closed-range forecasts, eliminating another 320 observations where management issued a point estimate.[22]

Panel C of Table 2 describes the sample used for tests of H2A and H2B. The mean number of annual earnings forecasts for firms in our sample is 2.2, with 25 percent of the sample issuing four or more. Descriptive statistics for *HORIZON* suggest management issues the first annual earnings forecast between 50 and 60 days into the new fiscal year. Consistent with prior research, forecasts exhibit positive bias (mean of 0.004), and the average absolute forecast error is 1.0% of share

[20] Using *ΔEARN* when *ERROR* or *BIAS* is the dependent variable would induce a mechanical correlation because each of these variables includes current period earnings in its calculation.
[21] The biggest sources of data attrition are I/B/E/S coverage and insufficient time-series data to compute earnings volatility.
[22] Results are quantitatively and qualitatively unchanged if we set the value of *RANGE* to zero for point forecasts.

price. Finally, the range of forecasts averages about 9% of the midpoint. Panel D of Table 2 presents correlations among MSA variables and our dependent variables of interest.

4.6 Tests of H2

To test H2A, we estimate equation (4) and report the results in Table 6. The first two columns use *FREQ* as the dependent variable. The evidence suggests that employee education is positively associated with forecast frequency (*FREQ*), as the coefficient on both *EDUC-HQ* and *EDUC-10K* are significantly positive, consistent with H2A. Economically, a one standard deviation increase in *EDUC-HQ* corresponds to between 0.16 and 0.30 additional forecasts, which represents between a 7.2 and 13.5 percent increase in the number of forecasts issued for the average firm. The second and fourth columns in Table 6 replace *FREQ* with *HORIZON* as the dependent variable. This evidence also supports H2A, as the coefficient on both *EDUC-HQ* and *EDUC-10K* are significantly positive, implying that firms with a more highly educated workforce issue forecasts earlier in the period. A one standard deviation increase in *EDUC-HQ* based on the firm's HQ (10-K locations) corresponds to forecasts being issued 11 (18) days earlier, or 3.7 (5.9) percent of the sample mean.

Table 7 reports evidence regarding H2B. In Panel A we examine the association between employee education levels (*EDUC-HQ*) and *ERROR*, *BIAS*, and *RANGE*. We find that employee education is negatively associated with absolute forecast errors (*ERROR*), as the coefficient on *EDUC-HQ* is significantly negative. A one standard deviation increase in *EDUC-HQ* is associated with a 0.001 decrease in absolute forecast error, or 11 percent of the mean *ERROR* in Panel C, Table 2. We also find that *EDUC-HQ* is negatively associated with *BIAS* (i.e., the forecasts are less optimistically biased). Economically, a one standard deviation increase in *EDUC-HQ* corresponds to a reduction in *BIAS* of 0.0019, or 18.6 percent of the interquartile range of *BIAS*.[23] Finally, we also find the *EDUC-HQ* is negatively associated with *RANGE*. A one standard deviation increase in *EDUC-HQ* is associated with a decrease of 0.010, or 11.9 percent of the mean value for *RANGE* in the sample. In Panel B of Table 7 we examine these same issues using the *EDUC-10K*, and our results continue to support H2B. Economic magnitudes are also very similar to those in Panel A. Overall, our findings suggest that firms with more educated workforces not only exhibit superior mandatory disclosure quality, but also superior voluntary disclosure quality, as evidenced by better forecasting activity (*FREQ*, *HORIZON*) and higher-quality forecasts (*ERROR*, *BIAS*, *RANGE*).[24]

5. Sensitivity analyses and limitations

5.1 Does the headquarters location play a pronounced role?

We use two measures to proxy for workforce education, one based on the headquarters MSA (*EDUC-HQ*) and another using a simple average of all MSAs where a firm discloses operations (*EDUC-10K*). In this section, we assess whether the education of the workforce at the firm's headquarters (where most accounting employees likely work) plays a unique role in financial reporting quality relative to the education of the workforce at the firm's other locations.

To examine this question, we decompose *EDUC-10K* into its two components: (1) headquarters only (*EDUC-HQ*), and (2) non-headquarters (*EDUC-nonHQ*). We then regress each dependent variable on these decomposed education measures, as well as control variables (we decompose

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[23] Given *BIAS* is not strictly positive like other dependent variables, we report the marginal effect as a percentage of the interquartile range.

[24] Bamber, Hui, and Yeung (2010) find that annual earnings forecast that are rounded to the nearest nickel (e.g., $1.05) are less accurate and more optimistically biased than are non-nickel forecasts (e.g., $1.04). In untabulated tests we also find that likelihood of managers issuing rounded forecasts is decreasing in the quality of its employees, consistent with the hypothesis that employee quality is positively associated with voluntary disclosure quality.

MSA-level control variables as well). As shown in our primary analyses (i.e., Tables 3 through 7), when we include only *EDUC-HQ* in the model, we find a significant coefficient on *EDUC-HQ* in all 8 regressions ($p < 0.05$), consistent with employee quality at the headquarters being associated with financial reporting outcomes. However, when we estimate these same regressions using *EDUC-nonHQ* (e.g., the non-HQ component of *EDUC-10K*), we find a significant coefficient in the expected direction in only one out of eight regressions (*RANGE*). Furthermore, when we include both *EDUC-HQ* and *EDUC-nonHQ* in the same model, we continue to find a significant coefficient on *EDUC-HQ* in all eight regressions ($p < 0.05$), while the coefficient on *EDUC-nonHQ* is again only significant in 1 regression *(RANGE*), and the magnitude of the effect of *EDUC-HQ* is statistically greater than that of *EDUC-nonHQ* in three of the eight regressions (*AQ*, *ERROR*, and *BIAS*). Overall, these results suggest there is a unique role for the education level of employees at firm headquarters, but we highlight two important caveats. First, we cannot perfectly observe all non-headquarter locations in which a firm operates (e.g., not all firms disclose in the 10-K every location in which they operate). Second, we do not know how to weight each of these locations when measuring *EDUC-nonHQ*. Thus, our inability to find empirical evidence suggesting that employee quality at non-headquarter locations is associated with reporting outcomes does not necessarily mean that employees at these locations are irrelevant to reporting outcomes.

5.2 Changes analysis – location changes

In our primary analyses, we include several location-specific variables to control for the possibility that our findings can be explained by an omitted, location-specific variable that is correlated with both *EDUC* and reporting quality. An alternative approach to control for this possibility is to examine firms that moved their headquarters location during our sample period.

We argue that firms generally move their headquarter location for reasons unrelated to the education level of the local workforce, although we recognize that some firms make headquarter location decisions based, at least in part, on the composition of the local workforce (e.g., high tech firms in Silicon Valley).

We obtain data on headquarter location changes from Bill McDonald's website.[25] Only between 2 percent and 5 percent of sample observations (depending on the reporting outcome being examined) changed their headquarters location during our sample period. We define *ΔEDUC* as the education level at the new headquarters MSA minus the education level in the prior headquarters MSA. Thus, higher (lower) values of *ΔEDUC* indicate that the firm moved to a more (less) educated MSA. We then interact this variable with *POST*, an indicator variable equal to one for years after the move, and equal to zero for years prior to the move (we exclude the year of the move from these tests). Our design is outlined in equation (6) below:

$$DV = \alpha_0 + \alpha_1 POST + \alpha_2 \Delta EDUC + \alpha_3 POST*\Delta EDUC + \Sigma\beta_k Controls + e \qquad (6)$$

DV equals each of our eight reporting outcomes of interest (*AQ*, *ICW*, etc.). Control variables are the same as in all prior tests, and we control for changes in the MSA-based variables.

We assume that when a firm moves its headquarters, the firm employs more individuals from the new headquarters location than was true prior to the move.[26] If α_3 loads in the same direction as was originally predicted (e.g., negative for accrual quality, positive for forecast frequency), it suggests that changes in employee education levels at the firm's headquarters are associated with predictable changes in reporting outcomes in the period following the move.

We find the coefficient on this interaction loads in the predicted direction in six out of eight

[25] http://www3.nd.edu/~mcdonald/10-K_Headers/10-K_Headers.html

[26] In untabulated results, we find that firms moving headquarters experience a larger increase in employees from year *t*-1 to year *t*+1 (24 percent increase in employees) than do all other firm-year observations in our sample (13 percent, t = 4.00), consistent with the notion that these firms are likely to hire additional employees from the new headquarters location.

regressions. More importantly, despite very small sample sizes (*N* as low as 75) and resulting lack of statistical power, four of the individual results are statistically significant on their own (for H1, accrual quality (*AQ*) and restatements (*RESTATE*); for H2, management forecast error (*ERROR*), and management forecast range (*RANGE*)). In untabulated tests, we also find similar results when we examine non-headquarter employee changes (in place of headquarter changes), providing some evidence that non-HQ employees can affect reporting outcomes as well.[27]

In summary, these location change tests provide some additional evidence that changes in the average education level of a firm's employees is positively associated with changes in both external and internal reporting quality. However, we interpret these results with caution given the very small number of observations upon which these tests are based.

5.3 High-quality employees and the likelihood of whistleblowing activity

While our hypotheses predict that *EDUC* is associated with improved reporting outcomes, prior literature shows that employees can impose ex-post discipline on the firm's financial reporting (i.e., after fraudulent behavior has occurred) by blowing the whistle to external parties (Dyck et al. 2010; Bowen et al. 2010). Thus, we examine whether, conditional on a misreporting event, the education level of the firm's workforce is positively associated with the likelihood that an employee reports the violation to a regulator. We utilize the OSHA-based sample of whistleblowing violations described in Bowen et al. (2010), Wilde (2017), and Call, Martin, Sharp, and Wilde (2017). This data contains instances in which an employee whistleblower files a

[27] Specifically, we identify all firms in our sample (a) that mention a different set of locations in its 10-K relative to the locations mentioned in its prior 10-K, and (b) where the absolute change in the number of firm-wide employees exceeds 10%. We argue that these firms experienced a meaningful change in the composition and location of its non-headquarter employees from one year to the next. When we estimate a model similar to equation (6), but where $\Delta EDUC$ captures the change in non-headquarter employee quality and without the interaction terms (because firms can change locations multiple times), we find some support for H1 (fewer *ICW*, *p*-value = 0.098) and H2 (higher *FREQ*, *p*-value = 0.051; smaller *ERROR*, *p*-value = 0.006; narrower *RANGE*, *p*-value = 0.012). However, we fail to find results for *AQ*, *RESTATE*, *HORIZON*, and *BIAS*. As with our change in headquarter tests, we interpret these results with caution given the relative infrequency of large changes in the number of employees. However, this evidence provides some support for non-headquarter employees being associated with financial reporting outcomes.

complaint with OSHA for workplace discrimination for having voiced concerns about financial reporting issues.

We use Audit Analytics' Non-reliance data as our sample of misreporting firms, and set *WHISTLE* equal to one if a whistleblowing allegation occurs between the beginning of the restatement period and the date of restatement announcement, and zero otherwise.[28] We then estimate the following model:

$$Pr(WHISTLE = 1) = \Theta(\alpha_0 + \alpha_1 EDUC_{i,t} + \Sigma\beta_k MSA\ Controls + \Sigma\theta_j Other\ Controls \\ \Sigma\gamma_m IndustryFE + \Sigma\lambda_n YearFE) \quad (7)$$

Other Controls are largely derived from Bowen et al. (2010) and include measures of operating results (*SALESGROWTH, DOWNSIZE, PERFORMANCE),* opportunity and incentive for whistleblowing (*QUITAM, ICW*), size (*LNSALE)*, reputation (*REPUTATION*), age (*AGE*), investment (*RD_SALES*), and restatement severity (*DURATION*). We expect each of these measures to relate positively to *WHISTLE*.

We report these results in Table 8. We observe a significantly positive association between *EDUC-HQ* and *WHISTLE*, consistent with more highly educated employees being more likely to uncover financial impropriety. However, we fail to observe a positive and significant relation between *EDUC-10K* and *WHISTLE.* This evidence provides some support for the notion that, even after reporting violations occur, more highly educated employees, particularly those working at a firm's headquarters, provide superior disciplining of senior management.

5.4 Firm fixed effects

In our primary tests, we include a series of location-specific control variables, industry and year

[28] Because our whistleblowing data ends in March of 2010, we delete restatements announced after this date. Further, our first year of education data is 2005, so our sample is limited to restatements that started in 2006 or later and that were announced prior to March 2010. We measure *EDUC* (and other variables) as of the beginning of the restatement period, and estimate equation (3) using just one observation for each firm. If a firm has a restatement during this sample period, we retain that firm-year observation in this analysis. If a firm has multiple restatements during this period, and none correspond to a whistleblowing allegation, we retain the first restatement in our sample period.

fixed effects, and in analyses above we also examine cases where the firm changes its headquarters location. To further consider the possibility of a correlated omitted variable, we examine the sensitivity of our results to firm fixed effects. Firm fixed effects control for any time-invariant correlated omitted variable.

In untabulated results, we include firm fixed effects in all models where we have continuous dependent variables. For H1, the only continuous dependent variable is accruals quality, which exhibits minimal year-over-year variation given that it is constructed using five consecutive years of data. Perhaps unsurprisingly, the accruals quality results do not hold when controlling for firm fixed effects. However, we continue to find that education levels are associated with improved voluntary reporting outcomes when including firm fixed effects. Taken together with our primary findings and the results relating to employee location changes, these results suggest that the association between workforce education and financial reporting quality is unlikely explained by time-invariant correlated omitted variables.

5.5 Further addressing concerns about executive and board education levels

In our primary tests we control for *BOARDEDUC*, which captures the average education level of executives and directors at the firm. However, for about half our sample, this data is not available in BoardEx, and in our main tests *BOARDEDUC* is set equal to zero for these firms, weakening the power of this important control variable. In untabulated tests we re-estimate our analyses using the subset of observations with non-missing *BOARDEDUC*. We focus on results using *EDUC-HQ* due to results reported in Section 5.1 and because most executives likely work at a firm's headquarters. Despite the significant reduction in our sample size, we continue to find support for all three of our hypotheses, as *EDUC-HQ* remains positively and significantly associated with mandatory reporting quality (e.g., fewer internal control weaknesses and restatements) as well as voluntary reporting quality (e.g., management forecasts over longer horizons, with less forecast error, and lower bias). We note, however, that our results for accruals quality, forecast frequency, and forecast horizon fall below conventional significance levels (p-values between 0.15 and 0.20) when estimated over this reduced sample. Taken as a whole, these results provide reasonable assurance that our findings are not driven by the education levels of senior management or the board of directors.

5.6 Measurement error in employee education

Our proxy for workforce education might not be well suited to capture education levels of employees for certain companies that are either less reliant on the local workforce or that have a significant international presence. Specifically, large companies may not be as constrained by the education of the local workforce, and our education data, which is based on US census data, may be ill suited for firms with a large foreign presence. To empirically explore this issue, we partition the sample based on membership in the S&P 500 and test whether our findings are more pronounced among firms outside the S&P 500. We expect our proxies for education levels to be more powerful for non-S&P 500 firms, as these firms are likely more reliant on the local workforce and have fewer international employees.[29]

We present coefficient estimates for *EDUC* after partitioning our sample in Table 9. For non-S&P 500 firms, we find significant associations in the predicted directions between *EDUC-10K* and all of our financial reporting outcomes. For *EDUC-HQ*, we find significant results in the non-S&P 500 partition for all outcomes except *FREQ* and *HORIZON*. In contrast, in the S&P 500 partitions, results are generally much weaker. We interpret this evidence as consistent with the

[29] Consistent with this notion, we search each firm's 10-K and count the number of foreign countries mentioned in Exhibit 21, and find that S&P 500 firms identify approximately three times the number of foreign countries than do non-S&P 500 firms.

notion that measurement error in *EDUC* is more pronounced for large, multinational firms.[30]

6. Conclusion

We use the average education level of the firm's workforce as a proxy for the quality of its employees, and find that more highly educated employees are associated with higher-quality accruals, fewer internal control weaknesses, and fewer restatements. These findings suggest that firms that employ high-quality employees are likely to have high mandatory disclosure quality. We also find that higher education levels of the firm's workforce is associated with more frequent, more timely, more precise, more accurate, and less biased management forecasts, suggesting that high-quality employees are associated with high voluntary disclosure quality.

Future research may wish to examine whether other characteristics of employees (aside from MSA-level education) serve as a proxy for their ability to improve financial reporting outcomes. In addition, employing a high-quality workforce may be associated with other benefits for the firm, beyond the benefits we document, such as more efficient and profitable investments. Finally, if capital market participants recognize that employees provide discipline to the financial reporting process, there may be valuation implications as well.

[30] These results do not suggest that our findings reflect a "small firm effect," as our non-S&P 500 sample is comprised of firms that are larger than the typical firm in Compustat. Whether a more powerful proxy would detect an association between workforce education and reporting outcomes for large, multinational firms remains an empirical question.

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Appendix A: Illustration of Calculating an MSA's Average Education Level

The purpose of this appendix is to provide a detailed understanding of how we calculate the average education of the workforce surrounding a firm's headquarters. Figure A1 (below) presents a subset of ACS data used to illustrate calculation of MSA level variables. With the exception of the column titled "Record," which we include to illustrate the number of responses, all data comes directly from the IPUMS.

YEAR identifies the year of the ACS; SERIAL is the response identifier used to track individual ACS responses. PWMETRO identifies the MSA corresponding to the respondent's place of employment. PERNUM identifies the "person" within the household. PERWT identifies the estimated number of workforce members in the MSA with similar attributes (as estimated by the US Census Bureau). EDUC identifies the highest level of education achieved. EMPSTAT identifies employment status, and INCWAGE represents annual wages for the respondent.

For purposes of illustrating variable calculations, we restrict these responses to a single year, 2006, within a single MSA, Atlanta, GA (PWMETRO = 520). Consistent with the data used to calculate our MSA variables, we restrict responses to those corresponding to employed members of the workforce (EMPSTAT = 1).

As illustrated, the 2006 ACS included responses from 21,921 members of the Atlanta workforce. Note that the ACS is performed at the household level, so some responses include data pertaining to multiple individuals. For example, Records 21,917 and 21,918 both correspond to the same ACS response (SERIAL = 1310895). PERNUM differentiates within individual responses. *LNPOP*, our proxy for size of the workforce, is computed as the simple summation of the PERWT column. In 2006, we estimate the size of the workforce to be 2.4 million, which compares favorably with the estimated total population of 5.1 million in the same year.[31] The other two MSA variables computed from ACS data, *EDUC* and *WAGES*, represent the weighted average of individual responses. These computations are illustrated below in Figure A1.

Figure A1: Sample ACS Data

Record	YEAR	SERIAL	PWMETRO	PERNUM	PERWT	EDUC	EMPSTAT	INCWAGE
1	2006	96	520	1	93	6	1	$10,000.00
2	2006	665	520	1	62	6	1	$26,000.00
3	2006	961	520	2	157	8	1	$50,000.00
4	2006	1105	520	1	61	6	1	$10,000.00
5	2006	1234	520	2	81	10	1	$25,000.00
				…				
21,917	2006	1310895	520	1	81	10	1	$42,000.00
21,918	2006	1310895	520	2	67	10	1	$100,000.00
21,919	2006	1311417	520	2	74	6	1	$40,000.00
21,920	2006	1317531	520	1	147	6	1	$40,000.00
21,921	2006	1331857	520	2	143	6	1	$55,000.00
	Summary Statistics				2,383,152[a]	7.55[b]		$42,315.23[c]

[31] http://www.metroatlantachamber.com/docs/resources/annual-indicators-7-8-11.pdf?sfvrsn=2

Calculation Illustration:

[a] $LNPOP_{Atlanta,\ 2006} = \ln\left(\sum_{i=1}^{21,921} PERWT_i\right) = \ln(93+62+...+143) = \ln(2,383,152)$

[b] $EDUC_{Atlanta,\ 2006} = \dfrac{\sum_{i=1}^{21,921} EDUC_i \times PERWT_i}{\sum_{i=1}^{21,921} PERWT_i} = \dfrac{6\times 93+6\times 62+...+6\times 143}{93+62+...+143} = 7.55$

[c] $WAGES_{Atlanta,\ 2006} =$

$$\frac{\sum_{i=1}^{21,921} INCWAGE_i \times PERWT_i}{\sum_{i=1}^{21,921} PERWT_i} = \frac{10,000\times 93+26,000\times 62+...+55,000\times 143}{93+62+...+143} = 42,315$$

Appendix B: Variable Definitions

Education Variables

EDUC-HQ	The weighted-average education level of respondents to the American Community Survey (ACS) in the MSA where the firm is headquartered. We obtain ACS data from the Integrated Public Use Microdata Series (IPUMS), hosted by the University of Minnesota (usa.ipums.org). Education levels are coded by the IPUMS as follows: 0 – N/A or no schooling; 1 – Nursery school to grade 4; 2 – Grade 5, 6, 7, or 8; 3 – Grade 9; 4 – Grade 10; 5 – Grade 11; 6 – Grade 12; 7 – one year of college, 8 – two years of college; 9 – three years of college; 10 – 4 years of college; 11 – 5+ years of college. Note that IPUMS reports that a score of 9 was not collected for our sample period, but a small number of observations have an EDUC value of 9. Appendix A provides an illustration of this calculation.
EDUC-10K	Calculated in the same manner as EDUC-HQ, but using the average of data for the firm's headquarters MSA plus any other MSAs within 60 miles of cities listed in the firm's 10-K.

MSA Control Variables

We compute each of the following variables using two different measurement bases: (1) data corresponding to the MSA in which the firm is headquartered, and (2) the average of data for the headquarters MSA plus any other MSAs within 60 miles of cities listed in the 10-K, and in our tests we include control variables that correspond to the measurement of the EDUC variables used in the model (EDUC-HQ or EDUC-10K):

LNPOP	The natural log of the estimated size of the workforce for the MSA. Workforce population is estimated using the sample weights reported by the IPUMS in the year corresponding to fiscal year-end.
CPI	The consumer price index for the MSA. MSA-level CPI measures are obtained from the Bureau of Labor Statistics (www.bls.gov/data). For locations without MSA-level price data, we use the regionally measured CPI (i.e., Northeast, Midwest, South, and West) for "Class B/C" areas, which is defined as populations between 50 thousand and 1.5 million. CPIs are indexed using price data in 2000.
WAGES	The weighted-average wages for the employed workforce in the MSA. Wages are obtained from the ACS and are weighted by sample weights reported by the IPUMS.
RELIGION	Percentage of the population in the MSA obtained from the 2010 Religious Congregations and Membership Study, made available by the ARDA.
UNEMP	Unemployment level for firm's headquarters MSA each year. Unemployment data was obtained from the Bureau of Labor Statistics (www.bls.gov).
HOUSESTARTS	The natural log of total housing starts in the MSA. Housing starts are obtained from the United States Census Bureau (www.census.gov).
SCI	Coincident index for the state where the MSA is located. The index is a combination of nonfarm payroll employment, average hours worked in manufacturing, the unemployment rate, and wage and salary disbursements deflated by the consumer price index. See: https://www.philadelphiafed.org/research-and-data/regional-economy/indexes/coincident/.

REPORTERS	Number of employees identifying themselves as “News Analysts, Reporters, and Correspondents” (Occupation Code 2810) in the IPUMS data for the firm's headquarters MSA (or average of MSAs listed in 10-K).
MSA_ROA	Mean return on assets for firms located in the MSA.
MSA_ROA_VOL	The average earnings volatility, computed as the standard deviation of return on assets over the prior 5 years, for firms in the MSA.

Dependent Variables

AQ	Accruals quality computed using the standard deviation of residuals from years t-4 to t obtained from cross-sectional estimations of the modified Dechow-Dichev (2002) model of accruals quality. Estimations are performed on industry-year subsamples with 20 or more observations, where industry is defined using the Fama-French 48 industry classification.
ICW	An indicator variable equal to one for any period in which management reports ineffective internal controls per Audit Analytics' 'SOX 404 - Internal Controls' database.
RESTATE	An indicator variable equal to one if fiscal year t overlaps with a restated period identified in Audit Analytics' 'Non-Reliance' database. Observations corresponding to restatements arising from clerical errors are deleted.
FREQ	The number of annual earnings forecasts made during the fiscal year, according to the IBES Guidance Detail dataset.
HORIZON	The number of days between the first forecast of fiscal year t's earnings and the fiscal year-end.
ERROR	The absolute forecast error (absolute value of forecast minus actual) scaled by beginning of period price. For periods in which multiple forecasts are made, the first forecast is used. Forecast data is obtained from the IBES Management Guidance Detail File.
BIAS	The signed forecast error (forecast minus actual) scaled by beginning of period price. For periods in which multiple forecasts are made, the first forecast is used. Forecast data is obtained from the IBES Management Guidance Detail File.
RANGE	Forecast range (high estimate minus low estimate) scaled by the midpoint of the range. RANGE is only defined for range forecasts. Forecast data is obtained from the IBES Management Guidance Detail File.
WHISTLE	An indicator variable equal to one for restatement observations with corresponding whistleblowing events, as reported to the Occupational Health and Safety Administration (OSHA). WHISTLE is set to one for any whistleblowing event occurring in the period starting with the beginning of the restatement period and ending with restatement announcement. If a firm has multiple restatements during the sample period, we retain only one using the following criteria: If any restatement corresponds to a whistleblowing event, we retain that observation. Otherwise, we retain the first restatement. For the few firms with multiple whistleblowing events, we retain the first event.

Control Variables (used in all models)

AUDITORDIST	Distance between the firm's headquarters MSA and the location of the auditor office that signs the firm's 10-K filing.
SECDIST	Distance between the firm's headquarters MSA and the responsible SEC regional office (see https://www.sec.gov/contact/addresses.htm). Note that for CA firms, we used the closer of the two offices.
AFOLLOW	The average analyst following during the fiscal year obtained from IBES Summary Files.
NYCDIST	Distance from the firm's headquarters MSA (or average of MSAs listed in 10-K) and New York City (where the overwhelming majority of sell-side analysts are located, see Gunn 2013).
TRANSIENT	The percentage of a firm's institutional ownership that is classified as transient according to Brian Bushee's institutional ownership classification data, available at http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html.
LOCMONITOR	Following Ayers et al. (2012), the percentage of a firm's institutional ownership that is (1) classified as dedicated or quasi-indexer according to Brian Bushee's institutional ownership classification data, (2) ranked in the top 5 of institutional owners by ownership percentage, and located within 100 km of the firm's headquarters. We obtain investment bank locations from 13F filings.
NONLOCMONITOR	Following Ayers et al. (2012), the percentage of a firm's institutional ownership that is (1) classified as dedicated or quasi-indexer according to Brian Bushee's institutional ownership classification data, (2) ranked in the top 5 of institutional owners by ownership percentage, and located more than 100 km from the firm's headquarters. We obtain investment bank locations from 13F filings.
OTHER	Institutional ownership percentage not classified as TRANSIENT, LOCMONITOR, or NONLOCALMONITOR.
BOARDEDUC	The average education level of all executives and directors listed in BoardEx. We assign education values as follows: 0 = Less than an Associates degree; 1 = Associates degree; 2 = Bachelors degree; 3 = Masters degree; 4 = higher than Masters (e.g., JD, PhD, MD). BoardEx sometimes provides somewhat vague education levels, such as "advanced degree," which we consider to be a master's degree, or "degree," "diploma," or "graduated," which we consider to be a bachelor's degree. If the company does not appear in BoardEx, we assign a value of 0 to BOARDEDUC.
MISSING_BX	An indicator equaling 1 if the observation is missing BoardEx data.

Control Variables (used in select models)

AGE	The natural log of the number of years the firm appears in CRSP. When ICW or RESTATE (WHISTLE) is the dependent variable, AGE is measured as of the current fiscal year (beginning of the restatement period).
AGLOSS	An indicator variable equal to one for firms in which earnings (Compustat IB) in t-1 and t sum to less than 0.
BETA	Beta, obtained from firm-specific regressions of daily returns on CRSP value-weighted market return over fiscal year prior to forecast.

BIG4	An indicator variable equal to one if the firm-year audited is by a Big 4 auditor according to Compustat (data item AU).
BTM	The book value of equity (Compustat SEQ) divided by the market value of equity (Compustat PRCC_F multiplied by CSHO).
CAP_INT	The intensity of capital assets, defined as Net Property, Plant, and Equipment (Compustat PPENT) divided by total assets.
CFVOL	The volatility of operating cash flows (Compustat OANCF) from t-4 to t scaled by assets (Compustat AT).
DISPERSION	The standard deviation of analyst estimates. For OCCUR and FREQ, DISPERSION is measured as of the beginning of the fiscal year. For all other forecast variables, DISPERSION is measured using the IBES summary report dated closest to but before the management forecast date.
EARNVOL	The standard deviation of earnings (Compustat IB) scaled by assets (Compustat AT) over years t-5 to t-1.
EXTSG	An indicator variable equal to one for observations in which year-over-year industry-adjusted sales growth falls in the top quintile.
FOREIGN	An indicator variable equal to one for observations with non-zero values for Foreign Currency Translation Adjustments (Compustat FCA) in year t.
HIGHVOL	An indicator variable equal to one for firms in the highest quartile of return volatility, measured using the standard deviation of daily returns during the year.
IA_ROA	The decile ranking of industry-adjusted return on assets (Compustat IB divided by Compustat AT) in fiscal year t. Ranks are scaled such that they vary between 0 and 1.
IDIOSHOCKS	Firm-specific idiosyncratic shocks as defined in Owens et al. (2016). Specifically, IDIOSHOCKS is measured using the root-mean-squared-error from regressing monthly returns on the CRSP value-weighted index and a value-weighted 2-digit-SIC-defined industry portfolio over the 24 months concluding at the end of the current fiscal year.
INT_DUM	An indicator variable equal to one for firms with missing values for R&D (Compustat XRD) or Advertising (Compustat XAD).
INT_INT	The intensity of intangible assets, defined as R&D (Compustat XRD) plus Advertising (Compustat XAD) divided by assets. Missing values of R&D and advertising are set to 0.
LEV	Financial leverage defined as long-term debt (Compustat DLTT) plus debt due within a year (Compustat DD1) scaled by assets (Compustat AT). When ICW or RESTATE (FREQ, HORIZON, ERROR, BIAS, or RANGE) is the dependent variable, LEV is defined using data from the current (prior) fiscal year.
LIT	An indicator variable equal to one for firms in high-risk litigation industries defined as SIC codes between 2833-2836, 8731-8734, 3570-3577, 7370-7374, 3600-3674, or 5200-5961.
LNASSETS	The natural log of assets (Compustat AT) at the end of fiscal year t.

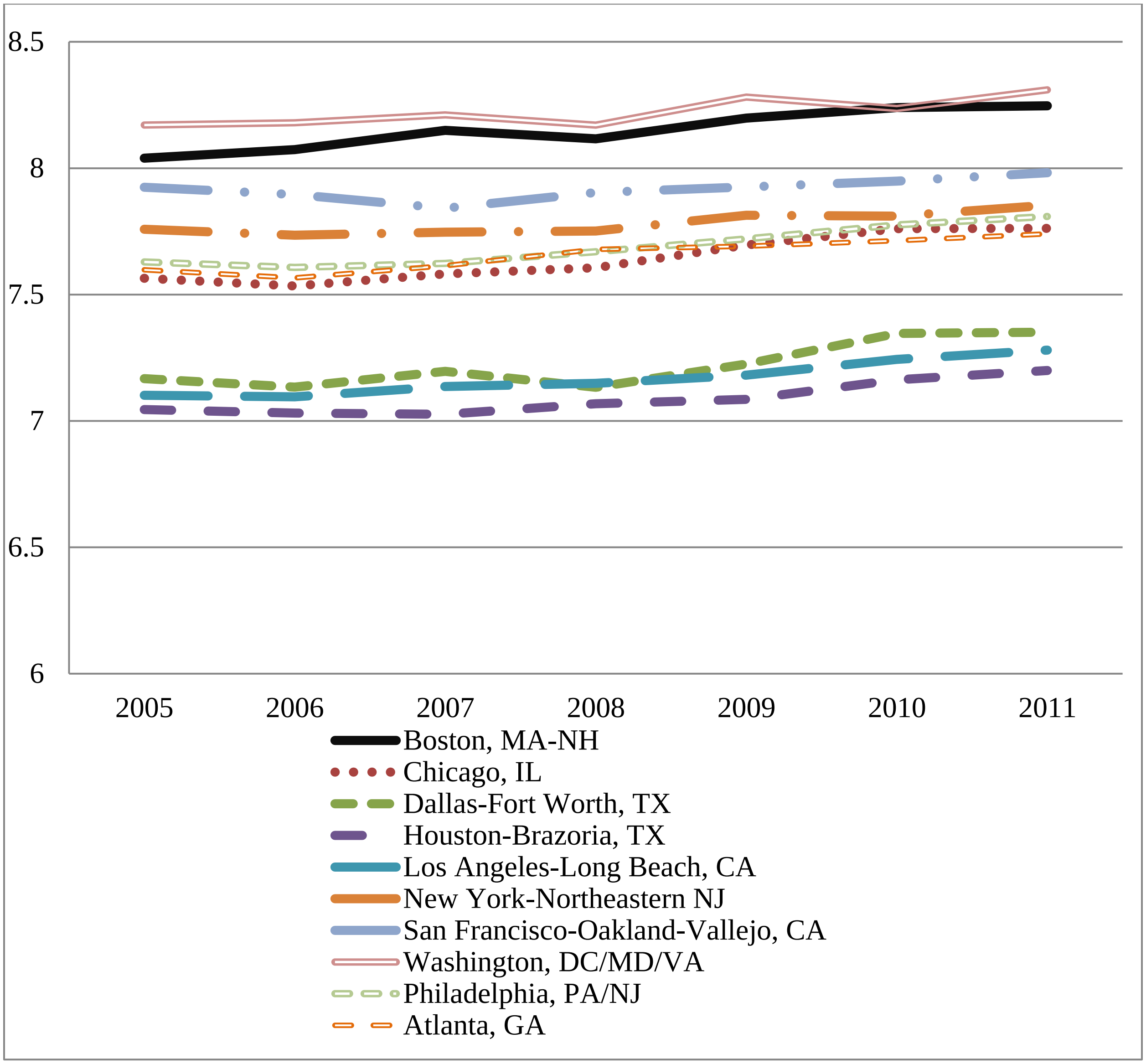
LNMVE	The natural log of the market value of equity (Compustat CSHO times PRCC_F). When ICW or RESTATE (FREQ, HORIZON, ERROR, BIAS, or RANGE) is the dependent variable, LNMVE is defined using data from the current (prior) fiscal year.
LNOPCYCLE	The natural log of the firm's operating cycle in period t, defined as 360 divided by the ratio of sales (Compustat SALE) to average accounts receivable (Compustat RECT) plus 360 divided by the ratio of Cost of Goods Sold (Compustat COGS) divided by average inventory (Compustat INVT).
LNSEG	The natural log of the sum of operating and geographic segments reported in Compustat's Historical Segments file in fiscal year t.
LOSS	An indicator variable equal to one for firms reporting negative earnings (Compustat IB) in year t.
MEANTURN	The average daily volume divided by shares outstanding over the fiscal year.
MERGE_ACQ	An indicator variable equal to one for observations with non-zero, non-missing cash flows related to acquisitons (Compustat AQP).
NLOSSES	The number of years between t-4 and t in which the firm reports negative earnings (Compustat IB).
PEERSHOCKS	The mean value of IDIOSHOCKS for year t for firms in the same 2-digit SIC code as firm i.
RESTRUCT	An indicator variable equal to one for observations in which restructuring charges (Compustat RCP) is greater than 0.
RETVOL	The standard deviation of daily returns over the fiscal year.
SALEVOL	The volatility of sales (Compustat SALE) from t-4 to t scaled by assets (Compustat AT).
SURPRISE	The absolute value of the difference between the forecast and mean analyst forecast from I/B/E/S immediately preceding the estimate.
ZSCORE	The Altman Z-score computed as the inverse cumulative density function of -4.3-4.5*ROA+5.7*Lev-0.004*Current, where ROA is Compustat IB divided by Compustat AT, Lev is Compustat LT divided by Compustat AT, and Current is Compustat ACT divided by Compustat LCT.
ΔEARN	The change in earnings (Compustat IB) from t-1 to t scaled by beginning of period assets (Compustat AT).

Whistleblowing control variables (if not defined previously)

DURATION	The number of days between the start and end of the restatement period divided by 365.
DOWNSIZE	The mean growth in employees (Compustat EMP) in the three years prior to the restatement period. For periods lacking two consecutive years of data needed to compute the change, the percentage change is set to 0.

ICW_RISK	The risk of an internal control weakness, using the model and reported coefficients from Doyle et al. (2007). Specifically, we generate fitted values from -2.182 - 0.80*SIZE - 0.136*AGE + 0.438*AGLOSS + 0.269*LNSEG + 0.311*FOREIGN + 0.227*EXTSG + 1.184*RESTRUCT. All variables are defined above and are measured in the period immediately preceding the start of the restatement period.
LNSALES	The natural log of sales (Compustat SALE) in the period immediately preceding the start of the restatement period.
LNSG	The natural log of one plus the percentage sales growth (Compustat SALE) in the period immediately preceding the restatement period.
RETURNS	The 12-month buy-and-hold stock return immediately preceding the start of the restatement period.
QUITAM	An indicator variable equal to one for observations in two-digit SIC 80 (Healthcare) or listed in the Department of Defense's "100 Companies Receiving the Largest Dollar Volume of Prime Award Contracts" in any of the three years prior to the restatement period.
RD_SALES	The ratio of R&D (Compustat XRD) to Sales (Compustat SALE) in the period immediately preceding the start of the restatement period.
REPUTATION	An indicator variable equal to one for any firms recognized in Fortune magazine's "Most Admired" or "Best Place to Work for" lists in the 5 years prior to the restatement period.

FIGURE 1: Trends in *EDUC* for 10 Largest MSAs over Time



This figure presents the trend in *EDUC* for the 10 largest MSAs from 2005 to 2011.

TABLE 1: MSA Statistics

Panel A: Descriptive Statistics for Select MSAs

MSA Description	EDUC Rank	Percent of CRSP-Compustat[a]	*EDUC*	*WAGES*	Size of Workforce	*CPI*
Iowa City, IA	1	0.03%	8.25	34,307.79	70,913.29	143.95
Washington, DC/MD/VA	2	2.73%	8.22	58,849.61	2,976,782.00	140.84
Columbia, MO	3	0.06%	8.19	34,063.06	81,844.57	143.95
Madison, WI	4	0.19%	8.19	41,268.79	281,722.80	143.95
Stamford, CT	5	2.26%	8.17	73,375.68	210,004.10	145.03
San Jose, CA	6	4.58%	8.16	64,273.12	938,541.90	140.78
Boston, MA-NH	7	4.93%	8.15	51,945.54	2,213,885.00	228.57
Ann Arbor, MI	8	0.31%	8.14	41,957.44	255,071.00	143.95
Rochester, MN	9	0.09%	8.07	47,560.97	76,169.57	143.95
Gainesville, FL	10	0.07%	8.06	35,613.85	114,436.40	140.84
Champaign-Urbana-Rantoul, IL	11	0.02%	8.04	32,794.76	96,313.86	143.95
Charlottesville, VA	12	0.10%	8.04	41,405.94	88,120.71	140.84
Portland, ME	13	0.09%	8.03	40,092.36	136,819.70	145.03
Fort Collins-Loveland, CO	14	0.06%	8.02	37,792.04	143,847.70	140.78
Trenton, NJ	15	1.15%	8.02	54,489.79	225,868.60	145.03
Raleigh-Durham, NC	16	0.57%	7.99	43,864.13	772,820.10	140.84
Seattle-Everett, WA	17	1.27%	7.97	49,525.18	1,418,476.00	233.92
Lexington-Fayette, KY	18	0.11%	7.94	38,325.38	147,376.00	140.84
Tallahassee, FL	19	0.06%	7.93	35,264.35	150,274.60	140.84
San Francisco-Oakland-Vallejo, CA	20	2.47%	7.92	52,268.93	2,404,900.00	208.10
Minneapolis-St. Paul, MN	21	2.31%	7.91	45,957.38	1,661,384.00	143.95
Bloomington-Normal, IL	22	0.07%	7.89	38,370.07	88,654.29	143.95
Albany-Schenectady-Troy, NY	23	0.19%	7.87	40,831.32	418,841.00	145.03
State College, PA	24	0.05%	7.86	32,908.63	70,127.86	145.03
New York-Northeastern NJ	25	10.30%	7.78	53,822.96	8,627,209.00	211.67
Denver-Boulder, CO	29	2.06%	7.76	43,718.77	1,271,245.00	202.10
Wilmington, DE/NJ/MD	36	1.97%	7.74	49,013.09	270,906.40	145.03
Philadelphia, PA/NJ	45	2.24%	7.69	45,807.35	2,445,447.00	220.38
Atlanta, GA	54	2.16%	7.66	43,855.38	2,375,605.00	210.37
Chicago, IL	60	6.37%	7.64	46,405.40	4,408,916.00	207.62
San Diego, CA	80	1.81%	7.55	43,505.62	1,456,278.00	230.54
Phoenix, AZ	165	1.08%	7.24	40,673.17	1,775,561.00	132.88
Dallas-Fort Worth, TX	172	3.35%	7.22	42,634.66	2,973,514.00	211.24
Los Angeles-Long Beach, CA	186	4.34%	7.17	42,776.35	6,185,291.00	220.02
Houston-Brazoria, TX	206	4.08%	7.09	43,501.37	2,579,541.00	196.10
New Bedford, MA	236	0.00%	6.91	33,201.47	70,643.00	131.12
Salem, OR	237	0.02%	6.90	31,221.22	131,958.90	140.78
Las Vegas, NV	238	0.55%	6.90	39,733.03	884,943.10	140.78
Gadsden, AL	239	0.00%	6.89	25,692.54	42,870.00	128.63
Ocala, FL	240	0.02%	6.88	30,473.61	114,343.90	140.84
Beaumont-Port Arthur-Orange,TX	241	0.01%	6.88	37,869.89	163,699.40	144.36
Lakeland-Winterhaven, FL	242	0.05%	6.87	33,079.73	217,596.70	140.84
Lancaster, PA	243	0.11%	6.86	33,659.87	240,095.00	145.03
Vineland-Milville-Bridgetown, NJ	244	0.10%	6.85	38,326.39	63,678.14	145.03
El Paso, TX	245	0.06%	6.81	28,807.94	303,409.60	140.84
Fort Smith, AR/OK	246	0.06%	6.78	30,858.35	79,789.29	140.84
Hickory-Morgantown, NC	247	0.07%	6.76	30,532.06	162,250.10	140.84
Modesto, CA	248	0.01%	6.72	34,450.39	184,624.70	143.81
Decatur, AL	249	0.02%	6.72	30,552.70	62,384.75	138.83

MSA Description	EDUC Rank	Percent of CRSP-Compustat[a]	*EDUC*	*WAGES*	Size of Workforce	*CPI*
Riverside-San Bernardino,CA	250	0.38%	6.71	34,766.95	1,491,578.00	140.78
Salinas-Sea Side-Monterey, CA	251	0.03%	6.70	34,813.15	120,877.60	140.78
Elkhart-Goshen, IN	252	0.17%	6.66	33,765.99	99,741.71	143.95
Stockton, CA	253	0.02%	6.62	34,414.50	244,691.00	138.90
Fresno, CA	254	0.09%	6.60	32,756.18	419,165.40	140.78
Houma-Thibodoux, LA	255	0.02%	6.45	36,747.92	48,852.00	140.84
Bakersfield, CA	256	0.07%	6.45	34,833.42	311,660.80	140.78
Laredo, TX	257	0.02%	6.28	25,402.30	93,251.29	140.84
Visalia-Tulare-Porterville, CA	258	0.03%	6.16	30,036.27	160,349.00	140.78
Brownsville-Harlingen-San Benito, TX	259	0.00%	6.15	25,611.81	139,303.00	151.13
McAllen-Edinburg-Pharr-Mission, TX	260	0.01%	6.12	23,453.98	243,720.30	139.97
Merced, CA	261	0.01%	6.02	29,028.91	85,121.00	134.77

[a] The percentage of firms in each MSA in the CRSP-Compustat universe is correlated with the percentage of firms in each MSA for each our samples throughout the paper at Pearson Correlations greater than 90 percent ($\rho \geq 0.90$). Thus, for brevity, we only report the percentage for the entire CRSP-Compustat universe.

Panel B: Descriptive Statistics for MSA Variables by Year

ACS Year	*EDUC*	*WAGES*	Size of Workforce	*CPI*
2005	7.31	34,241.64	410,158.00	136.05
2006	7.31	34,944.70	429,656.88	143.27
2007	7.34	36,543.42	430,614.91	148.57
2008	7.36	37,552.45	447,073.09	159.60
2009	7.42	38,045.14	435,437.28	147.82
2010	7.45	37,997.47	431,735.56	148.68
2011	7.47	38,444.71	436,804.50	159.02
Total	7.38	36,951.07	429,869.10	148.93

Panel C: CRSP/Compustat Observations by EDUC Decile

Decile	*EDUC*	*Observations*	*Percentage*	*Cumulative Percentage*
1	8.04	8,346	24.48%	24.48%
2	7.73	7,602	22.30%	46.78%
3	7.63	5,203	15.26%	62.04%
4	7.52	2,386	7.00%	69.04%
5	7.43	1,488	4.36%	73.41%
6	7.34	1,437	4.22%	77.62%
7	7.24	1,849	5.42%	83.05%
8	7.15	3,702	10.86%	93.91%
9	7.02	1,374	4.03%	97.94%
10	6.69	703	2.06%	100.00%

Panel D: Correlations among MSA-level Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) *EDUC*		0.558	0.292	0.237	0.189	-0.098	-0.140	-0.106	0.254	-0.161	0.202
(2) *WAGES*	0.386		0.578	0.400	0.393	0.053	-0.060	*-0.019*	0.200	-0.267	0.455
(3) *LNPOP*	0.136	0.085		0.210	0.723	*-0.004*	-0.079	0.110	0.271	-0.189	0.389
(4) *CPI*	0.237	0.393	0.527		-0.065	0.254	*-0.016*	-0.136	0.083	-0.111	0.219
(5) *HOUSESTARTS*	0.170	0.346	0.710	0.242		-0.309	-0.083	0.326	0.177	-0.103	0.277
(6) *UNEMP*	-0.213	*-0.013*	*-0.043*	0.070	-0.308		-0.102	-0.274	-0.084	-0.057	0.068
(7) *RELIGION*	-0.180	-0.127	0.064	-0.045	-0.112	-0.141		-0.129	-0.055	0.160	-0.060
(8) *SCI*	-0.136	*-0.024*	0.058	-0.091	0.291	-0.167	-0.149		*-0.007*	-0.082	0.130
(9) *REPORTERS*	0.118	*0.007*	*0.031*	*0.012*	*0.008*	-0.078	*0.007*	*-0.012*		-0.069	0.111
(10) *MSA_ROA*	-0.123	-0.199	-0.155	-0.128	-0.111	*-0.010*	0.141	-0.085	0.049		-0.369
(11) *MSA_ROA_VOL*	0.124	0.270	0.280	0.199	0.215	*0.024*	*-0.027*	0.165	*-0.001*	-0.412	

Panel A of Table 1 presents average MSA-level descriptive statistics over our sample period for a selection of locations where at least one firm in CRSP-Compustat database is headquartered. We rank cities by average education level and present the top 25, bottom 25, and cities with at least 1% of observations in CRSP-Compustat between 2005 and 2011. Lower (higher) *EDUC* ranks correspond to more (less) educated MSAs.

Panel B of Table 1 presents average MSA-level statistics by year.

Panel C of Table 1 presents the distribution of CRSP-Compustat observations by *EDUC* decile as well as average *EDUC* for MSAs in each decile. Lower (higher) ranks correspond to more (less) educated MSAs.

Panel D of Table 1 presents correlations between variables of interest and *EDUC*. Pearson (Spearman) correlations are reported below (above) the diagonal. Italicized correlations are insignificantly different from 0 (p>0.05).

All variables are defined in Appendix B.

Table 2: Descriptive Statistics

Panel A – Accruals Quality Sample

Variable	*N*	*Mean*	*Std. Dev*	*25%*	*50%*	*75%*
AQ (x100)	8,787	0.895	0.628	0.465	0.718	1.138
EDUC-HQ	8,787	7.581	0.371	7.280	7.605	7.813
EDUC-10K	8,787	7.518	0.279	7.323	7.500	7.691
WAGES (in 000s)	8,787	44.719	9.154	38.945	42.760	48.000
LNPOP	8,787	13.809	1.320	12.944	13.848	14.731
CPI	8,787	175.559	36.236	140.702	155.962	208.104
HOUSESTARTS	8,787	8.714	1.472	7.859	8.765	9.790
UNEMP	8,787	6.582	2.337	4.600	5.900	8.500
RELIGION	8,787	496.429	79.823	441.890	513.820	553.360
SCI	8,787	148.871	13.604	139.184	146.799	157.175
REPORTERS	8,787	0.584	0.463	0.282	0.488	0.784
MSAROA	8,787	-0.024	0.069	-0.054	-0.014	0.022
MSASDROA	8,787	0.082	0.040	0.059	0.080	0.101
NYCDIST	8,787	6.275	1.656	5.649	6.728	7.347
SECDIST	8,787	4.204	1.627	3.177	4.644	5.484
AUDITORDIST	8,787	2.250	1.916	0.029	2.413	3.364
NONLOCMONITOR	8,787	0.220	0.117	0.146	0.217	0.295
LOCMONITOR	8,787	0.015	0.039	0.000	0.000	0.000
TRANSIENT	8,787	0.137	0.098	0.062	0.124	0.195
OTHER	8,787	0.317	0.167	0.199	0.343	0.440
AFOLLOW	8,787	1.905	0.863	1.365	2.004	2.552
BOARDEDUC	8,787	1.189	1.380	0.000	0.000	2.667
MISSING_BX	8,787	0.564	0.496	0.000	1.000	1.000
SALEVOL	8,787	0.013	0.027	0.004	0.007	0.015
IDIOSHOCKS	8,787	0.022	0.015	0.013	0.019	0.028
PEERSHOCKS	8,787	0.188	0.167	0.081	0.141	0.235
CFVOL	8,787	0.046	0.042	0.022	0.035	0.056
LNOPCYCLE	8,787	4.618	0.679	4.277	4.702	5.033
LNASSETS	8,787	7.183	1.620	5.854	6.991	8.253
NUMLOSSES	8,787	1.001	1.418	0.000	0.000	2.000
CAP_INT	8,787	0.291	0.233	0.106	0.213	0.430
INT_INT	8,787	0.075	0.365	0.000	0.018	0.069
INT_DUM	8,787	0.679	0.467	0.000	1.000	1.000
BIG4	8,787	0.874	0.332	1.000	1.000	1.000

Panel B – Internal Control Weakness and Restatement Sample

Variable	*N*	Mean	Std. Dev	25%	50%	75%
ICW	11,608	0.048	0.215	0.000	0.000	0.000
RESTATE	11,696	0.126	0.332	0.000	0.000	0.000
EDUC-HQ	11,798	7.599	0.376	7.292	7.620	7.853
EDUC-10K	11,798	7.536	0.290	7.332	7.511	7.715

Variable	N	Mean	Std. Dev	25%	50%	75%
LNPOP	11,798	13.899	1.278	13.131	14.045	14.783
CPI	11,798	177.046	36.308	140.702	180.267	208.104
WAGES (in 000s)	11,798	45.330	9.236	39.272	43.482	48.759
HOUSESTARTS	11,798	8.817	1.413	8.036	8.847	9.854
UNEMP	11,798	6.590	2.351	4.600	5.900	8.600
RELIGION	11,798	495.476	80.179	441.890	511.850	553.360
SCI	11,798	148.900	13.155	139.253	146.799	157.898
REPORTERS	11,798	0.599	0.467	0.292	0.495	0.802
MSAROA	11,798	-0.027	0.069	-0.057	-0.017	0.019
MSASDROA	11,798	0.085	0.040	0.063	0.081	0.104
NYCDIST	11,798	6.314	1.638	5.628	6.771	7.395
SECDIST	11,798	4.108	1.675	3.058	4.511	5.472
AUDITORDIST	11,798	2.229	1.967	0.029	2.343	3.335
NONLOCMONITOR	11,798	0.221	0.111	0.145	0.214	0.291
LOCMONITOR	11,798	0.015	0.039	0.000	0.000	0.000
TRANSIENT	11,798	0.143	0.095	0.068	0.128	0.200
OTHER	11,798	0.298	0.154	0.174	0.315	0.416
AFOLLOW	11,798	1.861	0.847	1.344	1.946	2.485
BOARDEDUC	11,798	1.181	1.380	0.000	0.000	2.667
MISSING_BX	11,798	0.568	0.495	0.000	1.000	1.000
LNMVE	11,798	6.903	1.715	5.666	6.732	8.002
AGLOSS	11,798	0.236	0.425	0.000	0.000	0.000
ZSCORE	11,798	0.187	0.266	0.004	0.055	0.270
EXTSG	11,798	0.083	0.277	0.000	0.000	0.000
LNSEGS	11,798	1.191	0.688	0.693	1.099	1.609
MERGE_ACQ	11,798	0.160	0.366	0.000	0.000	0.000
LEV	11,798	0.204	0.197	0.011	0.174	0.318
AGE	11,798	2.744	0.866	2.215	2.768	3.390
RESTRUCT	11,798	0.333	0.471	0.000	0.000	1.000
FOREIGN	11,798	0.320	0.467	0.000	0.000	1.000
IA_ROA (unranked)	11,798	0.046	0.162	-0.013	0.035	0.099
BIG4	11,798	0.855	0.352	1.000	1.000	1.000
HIGHVOL	11,798	0.215	0.411	0.000	0.000	0.000
LIT	11,798	0.313	0.464	0.000	0.000	1.000

Panel C – Management Forecast Sample

Variable	n	Mean	Std. Dev	25%	50%	75%
FREQ	5,055	2.228	2.394	0.000	2.000	4.000
HORIZON	3,434	308.133	121.338	248.000	322.000	342.000
ERROR	3,335	0.010	0.014	0.003	0.005	0.010
BIAS	3,335	0.004	0.014	-0.002	0.003	0.008

Variable	*n*	Mean	Std. Dev	25%	50%	75%
RANGE	3,015	0.087	0.109	0.035	0.057	0.095
EDUC-HQ	5,055	7.587	0.371	7.297	7.607	7.822
EDUC-10K	5,055	7.523	0.283	7.328	7.499	7.699
LNPOP	5,055	13.841	1.295	13.011	13.903	14.724
CPI	5,055	175.098	36.235	140.372	155.962	208.104
WAGES (in 000s)	5,055	44.508	9.082	38.746	42.668	48.279
HOUSESTARTS	5,055	8.852	1.459	8.036	8.873	9.911
UNEMP	5,055	6.204	2.226	4.500	5.300	7.800
RELIGION	5,055	496.532	79.066	441.890	512.820	553.360
SCI	5,055	148.490	13.080	139.253	146.799	153.520
REPORTERS	5,055	0.619	0.479	0.294	0.509	0.881
MSAROA	5,036	-0.025	0.071	-0.054	-0.017	0.022
MSASDROA	5,030	0.081	0.041	0.054	0.081	0.100
NYCDIST	5,055	6.207	1.653	5.350	6.637	7.257
SECDIST	5,055	4.181	1.663	3.102	4.725	5.523
AUDITORDIST	5,055	2.178	1.916	0.029	2.312	3.318
NONLOCMONITOR	5,055	0.237	0.098	0.168	0.229	0.299
LOCMONITOR	5,055	0.015	0.038	0.000	0.000	0.000
TRANSIENT	5,055	0.151	0.091	0.080	0.136	0.201
OTHER	5,055	0.376	0.134	0.294	0.388	0.468
AFOLLOW	5,055	2.130	0.713	1.705	2.197	2.657
BOARDEDUC	5,055	1.318	1.392	0.000	0.000	2.750
MISSING_BX	5,055	0.517	0.500	0.000	1.000	1.000
LNMVE	5,055	7.518	1.544	6.399	7.396	8.508
BTM	5,055	0.467	0.298	0.265	0.410	0.611
LEV	5,055	0.205	0.187	0.043	0.186	0.307
RETVOL	5,055	0.020	0.010	0.014	0.019	0.025
BETA	5,055	1.136	0.465	0.799	1.079	1.414
MEANTURN	5,055	0.010	0.006	0.005	0.008	0.012
BIG4	5,055	0.910	0.287	1.000	1.000	1.000
LIT	5,055	0.321	0.467	0.000	0.000	1.000
Δ*EARN*	5,055	0.005	0.073	-0.012	0.007	0.026
LOSS	5,055	0.139	0.346	0.000	0.000	0.000
EARNVOL	5,055	0.041	0.053	0.013	0.023	0.043
DISPERSION	5,055	0.040	0.055	0.010	0.020	0.040
SURPRISE	3,335	0.003	0.006	0.001	0.001	0.004

Panel D – Correlations Among Dependent Variables of Interest and EDUC

	EDUC-HQ	*EDUC-10K*	*AQ*	*ICW*	*RESTATE*	*FREQ*	*HORIZON*	*ERROR*	*BIAS*	*RANGE*
EDUC-HQ		0.768	*-0.003*	-0.021	*-0.012*	0.042	*0.016*	-0.043	-0.040	-0.063
EDUC-10K	0.772		0.027	*-0.017*	*0.000*	*0.017*	-0.047	*-0.001*	*-0.031*	*-0.030*
AQ	*-0.012*	0.024		0.096	0.071	-0.169	-0.101	0.172	0.075	0.093
ICW	-0.019	*-0.014*	0.102		0.259	-0.073	*-0.034*	0.090	0.061	0.076
RESTATE	*-0.012*	*-0.001*	0.075	0.259		-0.053	*-0.034*	0.051	0.043	0.054
FREQ	0.029	*-0.001*	-0.139	-0.071	-0.056		0.548	0.076	0.187	*-0.018*
HORIZON	*0.008*	-0.036	-0.070	*-0.015*	*-0.020*	0.544		0.181	0.378	0.016
ERROR	-0.047	*-0.003*	0.145	0.101	*0.020*	*-0.013*	0.138		0.401	0.329
BIAS	-0.061	-0.041	0.068	0.071	*0.037*	0.084	0.265	0.341		0.002
RANGE	*-0.031*	*0.006*	0.103	0.076	*0.034*	-0.088	*-0.009*	0.382	0.118	

Table 2 presents descriptive statistics of the samples used to test our hypotheses. Variables are defined in Appendix B. Untransformed (i.e., unlogged) continuous variables are winsorized at the 1st and 99th percentiles. Panel A (Panel B, Panel C) presents samples pertaining to tests related to management's forecast activity (Internal Control Weaknesses & Restatements, Accruals Quality). For MSA control variables (e.g., *WAGES, LNPOP, CPI, HOUSESTARTS,* etc.), we report statistics for measures based on the MSA in which the firm is headquartered. Statistics for MSA control variables measured using MSAs identified in firms' 10-K filings are similar. Panel D presents correlations between variables of interest and *EDUC*. *EDUC-HQ* (*EDUC-10K*) is *EDUC* defined using the MSA in which the firm is headquartered (the average education of locations listed in the 10-K). Pearson (Spearman) correlations are reported above (below) the diagonal. Italicized correlations are insignificantly different from 0 ($p>0.05$). All variables are defined in Appendix B.

TABLE 3: Relation between Education and Accruals Quality

VARIABLES	Predicted Sign	*AQ* *EDUC-HQ* *Coef.*	*p-value*	*AQ* *EDUC-10K* *Coef.*	*p-value*
<u>*MSA-year Variables:*</u>					
EDUC	-	-0.090**	0.025	-0.125**	0.018
WAGES	?	-0.001	0.791	0.000	0.480
LNPOP	?	-0.015	0.460	0.015	0.553
CPI	?	0.000	0.862	0.000	0.498
HOUSESTARTS	?	0.037**	0.043	-0.008	0.705
UNEMP	?	-0.004	0.596	-0.008	0.372
RELIGION	-	-0.000*	0.064	-0.000	0.160
SCI	?	-0.001	0.497	0.000	0.823
REPORTERS	?	0.021	0.174	0.016	0.398
MSAROA	?	-0.227	0.202	-0.129	0.451
MSASDROA	?	-0.029	0.924	-0.020	0.949
<u>*Firm-Year Variables:*</u>					
NYCDIST	+	0.000	0.496	0.002	0.382
SECDIST	+	0.013*	0.056	0.013**	0.048
AUDITORDIST	+	-0.002	0.648	-0.004	0.790
NONLOCMONITOR	-	-0.095	0.161	-0.090	0.176
LOCMONITOR	-	0.105	0.668	-0.002	0.496
TRANSIENT	?	0.306***	0.007	0.307***	0.008
OTHER	?	-0.167**	0.020	-0.182**	0.011
AFOLLOW	-	-0.028**	0.046	-0.027*	0.056
BOARDEDUC	-	-0.018	0.298	-0.023	0.256
MISSING_BX	?	-0.013	0.887	-0.028	0.770
IDIOSHOCKS	+	1.605***	0.000	1.628***	0.000
PEERSHOCKS	+	0.885	0.150	0.725	0.197
SALEVOL	+	0.464***	0.000	0.473***	0.000
CFVOL	+	3.519***	0.000	3.501***	0.000
LNOPCYCLE	+	0.039**	0.021	0.037**	0.026
LNASSETS	-	-0.036***	0.000	-0.035***	0.000
NUMLOSSES	+	0.067***	0.000	0.066***	0.000
CAP_INT	-	-0.417***	0.000	-0.397***	0.000
INT_INT	+	-0.074	0.977	-0.073	0.976
INT_DUM	?	-0.018	0.445	-0.015	0.511
BIG4	-	-0.075**	0.021	-0.080**	0.014
Year & Industry Fixed Effects?		Yes		Yes	
n		8,787		8,787	
Adjusted R^2		0.300		0.296	

Table 3 presents estimated coefficients and associated significance levels for equation (3). All variables are defined in Appendix B. Significance levels are computed using *t*-statistics derived from robust standard errors clustered at the firm level. We report one-tailed tests when directional predictions are made and two-tailed tests otherwise. *** (**, *) denotes significance at the $p<0.01$ ($p<0.05$, $p<0.10$) level.

TABLE 4: Relation between Education and Internal Control Weaknesses

	Predicted Sign	*ICW* *EDUC-HQ*		*ICW* *EDUC-10K*	
VARIABLES		*Coef.*	*p-value*	*Coef.*	*p-value*
MSA-Year Variables					
EDUC	-	-0.818***	0.000	-1.027***	0.002
WAGES	?	0.027***	0.008	0.000**	0.040
LNPOP	?	-0.020	0.882	0.187	0.359
CPI	?	-0.000	0.897	-0.002	0.597
HOUSESTARTS	?	0.063	0.572	-0.045	0.776
UNEMP	?	-0.026	0.637	-0.089	0.197
RELIGION	-	-0.000	0.360	0.000	0.642
SCI	?	0.000	0.941	0.002	0.842
REPORTERS	?	0.237**	0.043	0.084	0.568
MSAROA	?	-1.017	0.374	-0.640	0.692
MSASDROA	?	0.985	0.587	2.458	0.333
Firm-Year Variables					
NYCDIST	+	0.108**	0.021	0.113***	0.008
SECDIST	+	-0.010	0.588	-0.004	0.536
AUDITORDIST	+	0.006	0.412	0.008	0.378
NONLOCMONITOR	-	-0.826*	0.067	-0.850*	0.059
LOCMONITOR	-	0.546	0.619	0.755	0.666
TRANSIENT	?	-0.201	0.774	-0.173	0.806
OTHER	?	0.831	0.118	0.778	0.145
AFOLLOW	?	-0.053	0.544	-0.056	0.528
BOARDEDUC	-	0.007	0.515	0.003	0.507
MISSING_BX	?	0.288	0.594	0.264	0.628
LNMVE	-	-0.403***	0.000	-0.394***	0.000
AGLOSS	+	-0.060	0.660	-0.062	0.663
ZSCORE	+	0.686***	0.003	0.657***	0.004
EXTSG	+	0.351**	0.011	0.355**	0.011
LNSEGS	+	0.159*	0.063	0.150*	0.077
MERGE_ACQ	+	0.108	0.240	0.124	0.207
LEV	+	-0.536	0.939	-0.431	0.894
AGE	-	0.062	0.796	0.071	0.828
RESTRUCT	+	0.074	0.274	0.069	0.285
FOREIGN	+	0.314***	0.006	0.281**	0.012
IA_ROA	-	-0.934***	0.000	-0.953***	0.000
BIG4	?	-0.376**	0.012	-0.384**	0.011
HIGHVOL	+	0.141	0.105	0.139	0.109
LIT	+	0.061	0.344	0.033	0.413
Industry & Year Fixed Effects?		Yes		Yes	
Observations		11,608		11,608	
Pseudo-R^2		0.147		0.147	

Table 4 presents estimated coefficients and associated significance levels for equation (4). All variables are defined in Appendix B. Significance levels are computed using *t*-statistics derived from robust standard errors clustered at the firm level. We report one-tailed tests when directional predictions are made and two-tailed tests otherwise. *** (**, *) denotes significance at the $p<0.01$ ($p<0.05$, $p<0.10$) level.

Table 5: Relation between Education and Restatements

VARIABLES	Predicted Sign	*RESTATE EDUC-HQ*		*RESTATE EDUC-10K*	
		Coef.	*p-value*	*Coef.*	*p-value*
MSA-year Variables:					
EDUC	-	-0.348**	0.040	-0.452*	0.050
WAGES	?	0.001	0.860	0.000	0.714
LNPOP	?	-0.041	0.644	-0.021	0.861
CPI	?	-0.003	0.131	-0.002	0.554
HOUSESTARTS	?	0.035	0.645	0.019	0.843
UNEMP	?	0.037	0.330	-0.012	0.793
RELIGION	-	-0.001	0.173	-0.000	0.464
SCI	?	-0.002	0.733	-0.003	0.574
REPORTERS	?	0.161**	0.022	0.144	0.108
MSAROA	?	-0.270	0.706	-0.935	0.346
MSASDROA	?	1.626	0.179	2.234	0.199
Firm-year Variables:					
NYCDIST	+	0.060*	0.051	0.080***	0.010
SECDIST	+	-0.073	0.980	-0.050	0.935
AUDITORDIST	+	-0.014	0.740	-0.001	0.519
NONLOCMONITOR	-	-0.142	0.341	-0.102	0.384
LOCMONITOR	-	2.068	0.969	1.937	0.959
TRANSIENT	?	-0.337	0.474	-0.285	0.546
OTHER	?	0.185	0.600	0.128	0.717
AFOLLOW	?	0.047	0.504	0.055	0.443
BOARDEDUC	-	0.160	0.875	0.154	0.865
MISSING_BX	?	0.483	0.216	0.476	0.225
LNMVE	-	-0.151***	0.000	-0.150***	0.000
AGLOSS	+	-0.054	0.698	-0.061	0.722
ZSCORE	+	-0.142	0.755	-0.144	0.759
EXTSG	+	0.260***	0.008	0.248**	0.011
LNSEGS	+	0.126**	0.046	0.125**	0.048
MERGE_ACQ	+	-0.048	0.694	-0.043	0.675
LEV	+	0.741***	0.003	0.767***	0.002
AGE	-	0.054	0.829	0.057	0.841
RESTRUCT	+	0.097	0.123	0.103	0.108
FOREIGN	+	0.040	0.337	0.027	0.387
IA_ROA	-	-0.539***	0.000	-0.546***	0.000
BIG4	?	0.266**	0.029	0.265**	0.029
HIGHVOL	+	0.099	0.106	0.097	0.112
LIT	+	0.085	0.225	0.071	0.267
Industry & Year Fixed Effects?		Yes		Yes	
Observations		11,696		11,696	
Pseudo-R^2		0.039		0.037	

Table 5 presents estimated coefficients and associated significance levels for equation (5). All variables are defined in Appendix B. Significance levels are computed using *t*-statistics derived from robust standard errors clustered at the firm level. We report one-tailed tests when directional predictions are made and two-tailed tests otherwise. *** (**, *) denotes significance at the $p<0.01$ ($p<0.05$, $p<0.10$) level.

TABLE 6: Relation between Workforce Education and Forecast Frequency and Horizon

		FREQ *EDUC-HQ*		*HORIZON* *EDUC-HQ*		*FREQ* *EDUC-10K*		*HORIZON* *EDUC-10K*	
VARIABLES	Predicted Sign	*Coef.*	*p-value*	*Coef.*	*p-value*	*Coef.*	*p-value*	*Coef.*	*p-value*
<u>*MSA-Year Variables*</u>									
EDUC	+	0.423**	0.021	30.625***	0.009	0.813***	0.002	49.165***	0.003
WAGES	?	-0.022***	0.004	-0.589	0.230	-0.000***	0.000	-0.002**	0.016
LNPOP	?	-0.055	0.573	-5.822	0.279	-0.015	0.909	-6.586	0.402
CPI	?	-0.004**	0.038	-0.024	0.845	-0.002	0.335	-0.061	0.699
HOUSESTARTS	?	0.109	0.235	6.736	0.213	0.041	0.723	8.270	0.242
UNEMP	?	0.023	0.569	-0.277	0.913	0.053	0.254	1.908	0.522
RELIGION	+	0.000	0.470	-0.013	0.614	0.001*	0.062	-0.019	0.638
SCI	?	-0.010**	0.025	-0.511*	0.082	-0.004	0.464	-0.139	0.653
REPORTERS	?	-0.185**	0.024	-4.096	0.403	-0.237**	0.013	-8.002	0.243
MSAROA	?	-0.110	0.901	-20.936	0.714	-0.108	0.895	-30.062	0.597
MSASDROA	?	-1.575	0.300	-34.793	0.729	-2.173	0.168	-18.239	0.845
<u>*Firm-Year Variables*</u>									
NYCDIST	-	0.002	0.517	6.949	0.999	-0.004	0.456	4.795	0.990
SECDIST	-	-0.031	0.199	-3.235	0.103	-0.004	0.452	-2.604	0.134
AUDITORDIST	-	-0.041*	0.077	0.743	0.672	-0.038*	0.082	0.421	0.607
NONLOCMONITOR	+	1.213***	0.002	12.192	0.332	1.251***	0.001	13.308	0.317
LOCMONITOR	+	1.391	0.121	47.712	0.258	1.109	0.165	46.408	0.251
TRANSIENT	?	2.640***	0.000	38.218	0.246	2.711***	0.000	40.171	0.224
OTHER	?	1.438***	0.000	66.636***	0.003	1.452***	0.000	67.360***	0.003
AFOLLOW	+	0.015	0.439	-15.320	0.984	0.030	0.385	-14.236	0.976
BOARDEDUC	+	0.176	0.115	-1.754	0.571	0.166	0.131	-2.037	0.580
MISSING_BX	+	0.309	0.450	-3.290	0.905	0.283	0.492	-5.202	0.852
LNMVE	+	0.471***	0.000	16.914***	0.000	0.470***	0.000	17.169***	0.000
BTM	+	0.294**	0.031	-8.925	0.803	0.252*	0.053	-11.166	0.858
LEV	+	0.394*	0.055	17.334	0.142	0.344*	0.080	14.082	0.188
RETVOL	?	20.911***	0.004	423.804	0.397	22.268***	0.003	346.957	0.486
BETA	?	-0.048	0.589	7.135	0.348	-0.070	0.437	6.641	0.386
MEANTURN	-	-24.970***	0.001	258.201	0.665	-25.410***	0.001	226.061	0.644
BIG4	+	0.079	0.287	-14.934	0.932	0.068	0.312	-17.230	0.958
LIT	?	-0.143	0.240	-11.542	0.134	-0.147	0.225	-12.440	0.100
ΔEARN	-	-0.547**	0.044	-26.072	0.247	-0.590**	0.030	-22.891	0.273
LOSS	-	-0.343***	0.000	16.602	0.949	-0.350***	0.000	17.790	0.961
EARNVOL	-	-2.012***	0.001	-141.146***	0.005	-1.873***	0.002	-131.403***	0.008
ADISP	-	-5.224***	0.000	-5.233	0.470	-5.269***	0.000	-8.317	0.453
Constant	?	-2.931	0.152	59.715	0.642	-7.126***	0.005	-79.416	0.598
Industry & Year Fixed Effects?		Yes		Yes		Yes		Yes	
Observations		5,023		3,415		5,023		3,415	
Adjusted R^2		0.265		0.090		0.264		0.000	

Table 6 presents estimated coefficients and associated significance levels for equation (1). All variables are defined in Appendix B. Significance levels are computed using *t*-statistics derived from robust standard errors clustered at the firm level. We report one-tailed tests when directional predictions are made and two-tailed tests otherwise. *** (**, *) denotes significance at the $p<0.01$ ($p<0.05$, $p<0.10$) level.

TABLE 7: Relation between Education and Forecast Error, Bias, and Range

Panel A: MSA-year Variables Based EDUC-HQ

		ERROR EDUC-HQ		*BIAS EDUC-HQ*		*RANGE EDUC-HQ*	
VARIABLES	Predicted Sign	*Coef.*	*p-value*	*Coef.*	*p-value*	*Coef.*	*p-value*
MSA-year Variables							
EDUC	-	-0.003**	0.012	-0.005***	0.001	-0.028**	0.014
WAGES	?	0.000	0.146	0.000**	0.045	0.001**	0.033
LNPOP	?	-0.001	0.292	-0.000	0.716	0.005	0.370
CPI	?	0.000	0.162	0.000	0.243	-0.000	0.926
HOUSESTARTS	?	0.000	0.399	0.000	0.431	-0.000	0.916
UNEMP	?	-0.000	0.940	-0.000	0.775	-0.004*	0.093
RELIGION	-	-0.000	0.329	-0.000	0.184	0.000	0.855
SCI	?	-0.000	0.257	-0.000	0.223	-0.001**	0.012
REPORTERS	?	0.001	0.125	-0.000	0.963	-0.009**	0.010
MSAROA	?	-0.005	0.375	-0.001	0.793	-0.034	0.450
MSASDROA	?	-0.006	0.549	-0.004	0.659	-0.103	0.204
Firm-year Variables							
NYCDIST	+	-0.000	0.523	0.000	0.163	0.002	0.115
SECDIST	+	-0.000	0.519	0.000	0.449	0.003*	0.074
AUDITORDIST	+	0.000	0.307	0.000*	0.083	0.003	0.120
NONLOCMONITOR	-	0.008***	0.005	-0.004*	0.091	0.008	0.566
LOCMONITOR	-	-0.012*	0.074	0.016	0.969	0.170	0.971
TRANSIENT	?	-0.006	0.177	-0.010**	0.044	-0.095**	0.035
OTHER	?	-0.004	0.194	0.003	0.393	-0.069**	0.022
AFOLLOW	-	0.000	0.553	-0.000	0.473	0.000	0.514
BOARDEDUC	-	0.000	0.675	-0.001	0.123	-0.001	0.434
MISSING_BX	-	0.001	0.560	-0.003	0.267	-0.002	0.920
LNMVE	-	-0.000	0.327	-0.001***	0.004	-0.007**	0.026
BTM	+	0.008***	0.000	0.002	0.194	0.005	0.362
LEV	+	0.008***	0.000	0.008***	0.000	0.039*	0.055
RETVOL	?	0.349***	0.000	0.075	0.347	0.833	0.141
BETA	?	-0.000	0.748	-0.000	0.708	0.011	0.114
MEANTURN	+	0.055	0.197	0.016	0.419	0.214	0.387
BIG4	-	0.002	0.943	-0.001	0.213	0.007	0.739
LIT	?	0.001	0.392	0.000	0.835	0.011	0.113
LOSS	+	0.006***	0.000	0.007***	0.000	0.063***	0.000
SURPRISE	+	0.635***	0.000	-0.407	1.000	3.692***	0.000
HORIZON	+	0.000***	0.000	0.000***	0.000	0.000**	0.022
ADISP	+	-0.012	0.919	-0.002	0.564	0.141*	0.067
EARNVOL	+	0.042***	0.000	0.015*	0.094	0.290***	0.003
Industry & Year Fixed Effects?		Yes		Yes		Yes	
Observations		3,288		3,288		2,968	
Adjusted R^2		0.337		0.149		0.251	

Panel B: MSA-year Variables Based on EDUC-10K

VARIABLES	Predicted Sign	ERROR EDUC-10K Coef.	ERROR EDUC-10K p-value	BIAS EDUC-10K Coef.	BIAS EDUC-10K p-value	RANGE EDUC-10K Coef.	RANGE EDUC-10K p-value
<u>MSA-year Variables</u>							
EDUC	-	-0.003**	0.035	-0.005***	0.006	-0.042***	0.006
WAGES	?	0.000**	0.042	0.000***	0.009	0.000**	0.018
LNPOP	?	-0.001	0.226	-0.000	0.647	0.009	0.166
CPI	?	0.000	0.198	0.000	0.209	-0.000	0.130
HOUSESTARTS	?	0.001	0.298	0.000	0.828	-0.002	0.636
UNEMP	?	0.000	0.901	-0.000	0.157	-0.004	0.183
RELIGION	-	-0.000	0.421	-0.000**	0.015	-0.000	0.376
SCI	?	-0.000	0.207	-0.000	0.486	-0.001*	0.051
REPORTERS	?	0.000	0.842	-0.000	0.549	-0.009**	0.044
MSAROA	?	-0.004	0.398	0.002	0.758	-0.020	0.659
MSASDROA	?	-0.008	0.406	-0.006	0.535	-0.085	0.287
<u>Firm-year Variables</u>							
NYCDIST	+	-0.000	0.549	0.000	0.179	0.001	0.332
SECDIST	+	-0.000	0.594	-0.000	0.769	0.002	0.136
AUDITORDIST	+	0.000	0.268	0.000	0.179	0.002	0.188
NONLOCMONITOR	-	-0.007***	0.006	-0.004*	0.092	0.002	0.515
LOCMONITOR	-	-0.013*	0.051	0.014	0.949	0.159	0.963
TRANSIENT	?	-0.006	0.175	-0.010**	0.049	-0.104**	0.021
OTHER	?	-0.004	0.186	0.003	0.382	-0.063**	0.036
AFOLLOW	-	0.000	0.550	0.000	0.537	-0.001	0.358
BOARDEDUC	-	0.000	0.685	-0.001	0.145	-0.000	0.493
MISSING_BX	?	0.002	0.533	-0.003	0.309	0.001	0.955
SIZE	-	-0.000	0.309	-0.001***	0.003	-0.006**	0.029
BTM	+	0.008***	0.000	0.002	0.174	0.004	0.383
LEV	+	0.009***	0.000	0.009***	0.000	0.043**	0.045
RETVOL	?	0.347***	0.000	0.076	0.345	0.789	0.165
BETA	?	-0.000	0.825	-0.000	0.820	0.012	0.111
MEANTURN	+	0.060	0.173	0.021	0.395	0.304	0.342
BIG4	-	0.002	0.938	-0.001	0.206	0.008	0.769
LIT	?	0.001	0.370	-0.000	0.990	0.011*	0.092
LOSS	+	0.006***	0.000	0.007***	0.000	0.063***	0.000
SURPRISE	+	0.635***	0.000	-0.406	1.000	3.757***	0.000
HORIZON	+	0.000***	0.000	0.000***	0.000	0.000**	0.014
ADISP	+	-0.012	0.920	-0.002	0.567	0.137*	0.071
EARNVOL	+	0.042***	0.000	0.014	0.111	0.287***	0.003
Industry & Year Fixed Effects?		Yes		Yes		Yes	
Observations		3,288		3,288		2,968	
Adjusted R^2		0.337		0.146		0.246	

Table 7 presents estimated coefficients and associated significance levels for equation (2). Panel A (Panel B) presents results using MSA data from the firm's headquarters (the average of MSA data from all locations in the firm's 10-K). All variables are defined in Appendix B. Significance levels are computed using *t*-statistics derived from robust standard errors clustered at the firm level. We report one-tailed tests when directional predictions are made and two-tailed tests otherwise. *** (**, *) denotes significance at the $p<0.01$ ($p<0.05$, $p<0.10$) level.

TABLE 8: Relation between Education and Whistleblowing

VARIABLES	Predicted Sign	*WHISTLE EDUC-HQ* Coef.	*WHISTLE EDUC-HQ* p-value	*WHISTLE EDUC-10K* Coef.	*WHISTLE EDUC-10K* p-value
<u>*MSA-year Variables:*</u>					
EDUC	+	1.971***	0.001	0.782	0.139
WAGES	?	-0.000***	0.004	-0.000**	0.049
LNPOP	?	0.451**	0.047	-0.225	0.502
CPI	?	0.002	0.708	0.012	0.100
HOUSESTARTS	?	0.076	0.607	0.225	0.352
UNEMP	?	-0.022	0.730	0.091	0.254
RELIGION	+	0.002	0.149	0.000	0.442
SCI	?	-0.014	0.359	-0.018	0.205
REPORTERS	?	-0.543	0.205	-0.014	0.969
MSAROA	?	-2.693	0.248	-1.067	0.604
MSASDROA	?	3.840	0.346	0.473	0.907
<u>*Firm-year Variables:*</u>					
NYCDIST	?	-0.093	0.376	-0.053	0.452
SECDIST	?	-0.151*	0.062	-0.185**	0.024
AUDITORDIST	?	-0.180***	0.003	-0.170***	0.007
NONLOCMONITOR	?	-0.314	0.770	-0.278	0.781
LOCMONITOR	?	1.438	0.555	1.210	0.619
TRANSIENT	?	1.740	0.164	1.476	0.187
OTHER	?	0.906	0.237	0.954	0.223
AFOLLOW	?	0.208	0.158	0.186	0.227
BOARDEDUC	+	0.618	0.103	0.583	0.108
MISSING_BX	?	1.280	0.342	1.299	0.319
SALESGROWTH	+	0.620	0.180	0.580	0.138
DOWNSIZE	+	-1.110	0.928	-0.850	0.894
QUITAM	+	1.309***	0.002	1.170***	0.005
LNSALES	+	0.328***	0.003	0.238**	0.023
REPUTATION	+	-0.097	0.573	-0.090	0.570
RETURNS	+	0.271	0.113	0.325**	0.046
ICW	+	-0.070	0.683	-0.112	0.792
LNAGE	+	0.003	0.494	0.010	0.478
RD_SALES	+	-2.499	0.817	-2.504	0.835
DURATION	+	0.069*	0.098	0.070*	0.093
Constant	?	-17.666***	0.003	-4.603	0.431
Year & Industry Fixed Effects?		Yes		Yes	
n		656		656	
Adjusted R^2		0.436		0.407	

Table 8 presents estimated coefficients and associated significance levels for equation (6). All variables are defined in Appendix B. Significance levels are computed using *t*-statistics derived from robust standard errors. We report one-tailed tests when directional predictions are made and two-tailed tests otherwise. *** (**, *) denotes significance at the $p<0.01$ ($p<0.05$, $p<0.10$) level.

TABLE 9: Measurement Error in Proxies for Employee Education

			EDUC-HQ				*EDUC-10K*			
			Non-S&P 500		S&P 500		Non-S&P 500		S&P 500	
Dependent Variable	*n (NonS&P / S&P)*	*Prediction*	*Coefficient*	*p-value*	*Coefficient*	*p-value*	*Coefficient*	*p-value*	*Coefficient*	*p-value*
AQ	6,922 / 1,865	-	-0.100**	0.027	-0.025	0.369	-0.116**	0.044	-0.157*	0.080
ICW	9,507 / 1,186	-	-0.778***	0.001	0.070	0.520	-1.012***	0.003	1.526	0.775
RESTATE	9,601 / 2,028	-	-0.367**	0.037	-0.026	0.486	-0.595**	0.021	0.947	0.879
FREQ	3,641 / 2,268	+	0.128	0.270	1.795***	0.002	0.541**	0.032	1.520**	0.018
HORIZON	2,268 / 1,147	+	16.913*	0.088	77.180***	0.008	28.015*	0.070	99.426***	0.003
ERROR	2,198 / 1,090	-	-0.004**	0.015	-0.001	0.292	-0.003**	0.048	-0.002*	0.079
BIAS	2,198 / 1,090	-	-0.006***	0.001	0.002	0.832	-0.007***	0.002	0.005	0.989
RANGE	2,001 / 967	-	0.002	0.832	-0.007	0.294	-0.059***	0.005	-0.006	0.360

Table 9 presents coefficient estimates and significance levels from estimating equations 1 through 5 separately for non-S&P 500 observations and S&P 500 observations. For brevity, we suppress tabulation of other coefficients. All variables are defined in Appendix B. Significance levels are computed using *t*-statistics derived from robust standard errors clustered at the firm level. *** (**, *) denotes significance at the $p<0.01$ ($p<0.05$, $p<0.10$) level (one-tailed).