Employee Health and Financial Reporting Quality

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Abstract

Extensive medical and occupational research documents the consequences of health, including the effects of health on cognition and job performance. In this study, we examine how employee health influences an important firm output - financial reporting quality. In line with medical and occupational research, we predict and find that firms with healthier employees experience greater financial reporting quality. Our results are more pronounced when financial reporting complexity is high, consistent with employee health being especially important for more cognitively intensive reporting. Our findings are robust to a battery of tests, including alternative health and reporting measures as well as tests leveraging within firm changes in employee health. Specifically, we find that a positive (negative) change in employee health is associated with an increase (decrease) in financial reporting quality. Collectively, our results underscore the importance of employee health for firms and their financial reporting outcomes.

Keywords: Health, Employee Characteristics, Financial Reporting Quality
JEL Classification: I12, M41

I. Introduction

In their review, Hanlon et al. (2022) underscore that individual-level factors – that is, the characteristics of those involved in the accounting process– explain and predict accounting phenomena beyond firm-, industry-, and market-level factors. For instance, extensive research focuses on how individuals can influence the financial reporting outcomes of firms. Many studies focus on key decision-makers in the reporting process, such as CEOs and CFOs. They find that, among other characteristics, executive education, compensation, narcissism, masculinity, overconfidence, and age influence financial reporting.[1] Other studies examine external monitors and find that various auditor, board of director, and regulator characteristics also affect reporting outcomes for firms[2] A recent stream of research focuses on the importance of firm employees, who serve as preparers and internal monitors in the financial reporting process.[3] However, the evidence on employee characteristics that influence reporting outcomes is limited to employee education and compensation. In this study, we consider a key trait of this important yet understudied player in the financial reporting process – employee health.

The link between an individual's health and job performance is well-documented in occupational research. Health is suggested to improve job performance through multiple channels, including work quality, motivation, and productivity (e.g., Ford et al. 2011). Medical research also documents the effects of health, particularly on cognitive performance. For instance, poor health

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[1] There are dozens of studies on executive characteristics that influence financial reporting, including but not limited to Armstrong et al. (2013), Bamber et al. (2010), Francoeur et al. (2023), Ham et al. (2017), He (2022), Hribar and Yang (2016), Huang et al. (2012), Jia et al. (2014), McGuire et al. (2012), and Schrand and Zechman (2012).
[2] Like with executives, there are numerous studies on external monitor characteristics that influence financial reporting, such as auditor education and compensation (Beck et al. 2018; Gul et al. 2013; Hoopes et al. 2018), audit committee diversity and expertise (Cohen et al. 2014; Felix et al. 2021), board of director gender and tenure (Srinidi et al. 2011; Huang and Hilary 2018), and SEC regulator experience (Kubic and Toynbee 2023; Kubic et al. 2024).
[3] This budding stream of research on employees studies Glassdoor ratings (Dube and Zhu 2021; Lee et al. 2021), employees' job seeking tendencies (Choi et al. 2023a,b; deHaan et al. 2023; Cao et al. 2025; Ham et al. 2024;), employees' tax planning influence (Barrios and Gallemore 2024), and firms' demand for talent (Gao et al. 2023).

can lead to brain fog, a phenomenon characterized by reduced mental acuity, cognition, concentration, and memory (Theoharides et al. 2015). Collectively, the findings of prior research suggest that health is a key determinant of job performance, especially cognitive work. Financial reporting involves considerable cognition, requiring personnel to make judgments about the likelihood of future events and the appropriateness of complex estimates. Thus, in this study, we examine whether employee health is associated with greater financial reporting quality. [4]

Our study may be of particular interest given the heightened focus on employee health in recent years.[5] Employee demand for jobs that prioritize health and wellness has increased. Consistent with the Great Resignation and "Quiet Quitting" phenomenon, 59 percent of employees reported that they have considered quitting their current positions for jobs that better support their health and well-being (Deloitte 2023). Employee turnover is costly for firms, reaching up to 200 percent of the exiting employee's salary. To attract and retain talent, firms have increased investment in their wellness programs. For instance, large firms invested an average of $11 million in well-being programs in 2022, up from $10.5 million in 2021 (Business Group on Health 2022). Further, regulators recently introduced new disclosure requirements that provide stakeholders with insights into firms' human capital (SEC 2020), in which firms are touting their support for employee health and wellness. For example, 84 firms in the S&P 100 mentioned employee health and/or wellness in their human capital disclosures in their 10-K filings for 2023. Collectively, this

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[4] We apply the World Organization of Health (WHO)'s definition of health, referring to health as "a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity."

[5] Several high-profile incidents in recent years have also brought the importance of employee health to the forefront (https://www.reuters.com/business/jpmorgan-executives-emphasize-employee-health-wellbeing-after-bofa-banker-death-2024-05-20/).

evidence underscores the increasing focus on employee health in the capital market and importance of understanding how employee health effects firm outcomes, such as financial reporting.

Employee health may affect financial reporting quality in at least two ways. First, employees can influence financial reporting through their roles as input providers. Prior research finds that health improves work quality, suggesting that healthier employees may provide higher quality inputs for financial reporting decisions. Second, employees can influence financial reporting through their monitoring roles. For instance, employees reveal more instances of fraud than both auditors and SEC regulators (Dyck et al. 2010). Given that health improves cognitive function (e.g., Pronk et al. 2004; Theoharides et al. 2015), healthy employees may be better at detecting financial reporting errors. Based on these arguments, we expect employee health to be associated with greater financial reporting quality.

To examine the reporting consequences of employee health, we collect city-level health data from the American Fitness Index (AFI). We proxy for employee health using the average health level of the workforce for the city in which the firm is headquartered.[6,7] Our main health measure is a composite score for personal health based on 19 health indicators, such as average exercise, sleep, vegetable and fruit consumption, mental health, obesity, asthma, and blood pressure in the city. The advantage of this composite health measure, relative to specific measures of factors like air quality, is that it better captures the overall health and wellness of the workforce. Our results are robust to alternative measures of health, such as average employee BMI, computed

[6] We follow the spirit of prior research. Call et al. (2017) measure employee education using the average education in the Metropolitan Statistical Area (MSA) where the firm is headquartered, and Beck et al. (2017) measure auditor education using the average education in the city where the audit office is headquartered.

[7] The accounting and finance personnel, who have the most influence over financial reporting, are likely to be located at firm headquarters. We discuss our health measure in greater detail in Section 3.2.

using accounting and finance employee LinkedIn photos and a machine learning algorithm trained to predict BMI based on headshot photos, for a subsample of firms.[8]

In our main tests, we investigate whether employee health is associated with greater financial reporting quality. Our primary measure of financial reporting quality is the Financial Statement Divergence Score (i.e., FSD-score), which is based on deviations from Benford's Law. We focus on the FSD-score because it is less dependent on firm performance, relative to other measures of financial misreporting, and captures mistakes and intentional financial reporting errors (Amiram et al. 2015). Intuitively, greater divergence from Benford's Law indicates lower financial reporting quality. Thus, we predict and find that employee health is negatively associated with the FSD-score, suggesting that employee health is associated with greater financial reporting quality.

We next corroborate our main findings. Throughout our study, we present regression results with varying fixed effect specifications to reduce concerns that improper inclusion of fixed effects may be biasing our results (Breuer and deHaan 2024; Jennings et al. 2023). Further, we examine whether our main results are robust to alternative proxies for employee health and financial reporting quality, including discretionary revenues, discretionary accruals, and restatements. We continue to find that employee health is associated with greater financial reporting quality.

We also leverage firm headquarters relocations to identify within firm changes in employee health. Firms move headquarters for a variety of reasons, including lowering corporate taxes or increasing their proximity to transport facilities (Strauss-Kahn and Vives 2009). The relocation of headquarters involves (1) the relocation of existing employees and (2) the hiring of new employees

[8] We perform several analyses to demonstrate that the effect of health on financial reporting quality is incremental to that of education. For example, we control for employee education in all our analyses. Further, we find that our results hold in subsamples of both high and low education (based on the median of our employee education measure), indicating that our results are independent of education level. Further, we present descriptive evidence that our employee health and employee education variables reflect different underlying constructs.

in the new location. In both cases, the movement of headquarters may affect average employee health. In the case of employee relocation, personal health depends in part on a city's ability to support health practices, such as sidewalks for exercise. In the case of employee hiring, new hires will likely be more (less) healthy when a firm moves to a more (less) healthy city. Based on this reasoning, we argue that the relocation of firm headquarters to a more (less) healthy city represents a positive (negative) change to employee health. As expected, we find that a positive (negative) change to employee health is associated with an increase (decrease) in financial reporting quality. This helps ease concerns that our results are driven by a correlated omitted variable.

Next, we examine the moderating role of financial reporting complexity. Prior research finds that complex financial information has higher processing costs (e.g., Blankespoor et al. 2020) and that firms invest in individuals with expertise to mitigate the adverse effects of financial reporting complexity (Chychyla et al. 2019). Collectively, prior research suggests that financial reporting complexity requires greater cognitive processing from both *preparers* and *users* of financial information. Thus, the cognitive performance of accounting personnel may be especially important when financial reporting is complex, and we predict the relation between employee health and financial reporting to be more pronounced when financial reporting is more complex.

To test this second prediction, we use three proxies to capture financial reporting complexity, including the number of accounting items (XBRL tags) in a firm's 10-K filing (Hoitash and Hoitash 2018), intangible assets (e.g., Burke et al. 2023; Chan and Liu 2023), and business segments (e.g., Miller 2010). As predicted, we find that our main results are more pronounced for firms with more accounting items in the 10-K filing, greater intangible assets, and more business segments. Taken together, these results suggest that the positive relation between employee health and financial reporting quality is moderated by complex financial reporting.

In additional analyses, we examine firms' qualitative financial reporting quality. We argue that healthier employees will produce more clear and concise reports and measure qualitative reporting using Bonsall et al. (2017)'s BOG index. As expected, we find that employee health is associated with greater qualitative financial reporting. In sensitivity tests, we apply alternative fixed effects and standard error clustering. Our main results remain unchanged.

Our study offers several contributions. First, we add to the broad literature on financial reporting quality. Many prior studies examine determinants of financial reporting quality (e.g., deHaan et al. 2013; Reid et al. 2019). These studies largely focus on management's incentives to misreport and how effective monitors can curtail management's misreporting practices. In contrast, we focus on the role of an important but understudied party, the workforce. We provide evidence that is consistent with healthy employees improving financial reporting quality for firms.

Next, we add to the research examining how individual attributes influence financial reporting outcomes. A rich stream of research finds that individual characteristics are associated with reporting outcomes. Prior studies find that executive narcissism, age, and expertise are associated with financial reporting quality (Caglio et al. 2018; Ham et al. 2017; Huang et al. 2012). We build on these studies by examining a central human characteristic: health. We find that employee health improves reporting quality, highlighting the importance of workforce health for firms.

Further, we extend the research on health and job performance by considering the broader implications of employee health. Specifically, we show that the health of a firm's workforce may influence firm outcomes. Finally, we add to the growing stream of labor research by considering an important employee characteristics – employee health. Our results are likely of interest to managers, investors, employees, and researchers, as the emphasis on employee health and wellness continues to rise.

II. Background and Hypothesis Development

2.1. Health and performance

Medical research documents the cognitive benefits of health. For instance, several studies examine brain fog, a phenomenon characterized by reduced mental acuity, cognition, concentration, and memory, and find that health is negatively associated with brain fog (Kverno 2021; Theoharides et al. 2015). Related studies focus on the link between health and memory and find that physical health is associated with reduced memory decline (Infuma and Gerstorf 2013). Physical health is also associated with lower levels of fatigue (Hulme et al. 2018; Penedo and Dahn 2005) and increased mental health (Ross and Hayes 1988; Stephens 1988). In general, many medical studies find that an individual's health affects their cognition (e.g., Knight et al. 2021; Kreitler et al. 2013), providing a basis for our study as well as many occupational studies.

Prior occupational research examines the association between health and job performance. These studies find that health, including physical health, psychological health, and behavioral health, is associated with greater work performance (see Ford et al. 2004 for a review). Health is suggested to improve job performance through multiple channels, including work quality, motivation, and productivity (e.g., Kudel et al. 2018). A growing stream of occupational research focuses on presenteeism, the loss of productivity due to employees' health. In the case of presenteeism, employees are physically present, but their performance is hindered due to health conditions, such as stress, illness, fatigue, etc. This research finds that many measures of health, such as allergies, arthritis, physical activity, and body weight, are associated with work performance (see Schultz and Edington 2007 for a review). Taken together, these occupational studies provide compelling evidence that health influences an individual's job performance.

A related stream of accounting and finance research examines the role of health and mood in the capital markets. For instance, recent research considers the career implications of CEO mental health (Cheng and Golshan 2025) and how weather influences the mood and information processing of investors (deHaan et al. 2017). Related studies focus on whether sleep and air quality influence the cognitive processing of financial market participants (Bazley et al. 2022; Dong et al. 2021; Kamstra et al. 2000; Pantzalies ans Ucar 2018). A recent study considers the constraints placed on firms when employees are absent due to illness and finds that firms shift from short-run to long-run forecasts when faced with such constraints (Chen et al. 2023). Collectively, prior studies find that *acute* health and mood changes may influence the processing of financial information in the short term. We extend this research by examining the role of employee health and wellness. Notably, in contrast to *acute changes* to well-being, employee health is ever-present and, based on prior research, is an important determinant of daily work performance.

2.2. Financial reporting quality

Extensive research examines the determinants of financial reporting quality and finds that the characteristics of those involved in the reporting process influence financial reporting outcomes. Many studies focus on the characteristics of executives, who are key decision-makers in the reporting process. Prior research finds that, among other characteristics, executive ability, narcissism, age, religiosity, and expertise, are associated with financial reporting outcomes (Caglio et al. 2018; Demerjian et al. 2013; Ham et al. 2017; Huang et al. 2012; McGuire et al. 2012). Zhang (2019) extends this stream of research by documenting that team characteristics, not just individual characteristics, influence financial reporting quality. Specifically, Zhang (2019) shows that homogeneity and shared experiences by top executives lead to better financial reporting quality.

Collectively, prior research provides compelling evidence that dozens of CEO and CFO characteristics affect financial reporting outcomes.

Related studies consider external monitors and how their characteristics influence financial reporting. For example, prior studies find that auditor education and compensation influence the financial reporting outcomes of their clients (Beck et al. 2018; Gul et al. 2013; Hoopes et al. 2018). Other studies focus on audit committees and provide evidence that committee diversity and expertise influence financial reporting outcomes (Cohen et al. 2014; Felix et al. 2021). Similarly, research suggests that the characteristics of boards of directors (e.g., Srinidi et al. 2011; Huang and Hilary 2018) and SEC regulators (Kubic and Toynbee 2023; Kubic et al. 2024) may influence the financial reporting outcomes of the firms they monitor. Taken together, these studies underscore the importance of external monitor characteristics for firms' financial reporting quality.

`A budding stream of research builds on these studies by investigating another essential party in the financial reporting process – employees. Employees serve as preparers and internal monitors of firms' financial information and, in doing so, have the potential to influence reporting outcomes. Call et al. (2017) lay the foundation for this nascent literature by documenting that employee education influences financial reporting outcomes. Using average education in the MSA of firm headquarters to proxy for employee education, they find that firms with more educated employees experience greater financial reporting quality and attribute their findings to employees' role as internal monitors. A related study finds that accounting employee compensation also improves financial reporting quality (Armgstrong et al. 2024). We add to this budding research stream by investigating what is arguably the most important human characteristic – health – and whether employee health effects firms' financial reporting quality.[9]

[9] In doing so, we answer calls by Call et al. (2017) for more research on how employee characteristics influence financial reporting outcomes.

2.3. Hypothesis 1: Employee health and financial reporting quality

Prior research documents the importance of health. For instance, medical research finds that health is associated with improved cognitive performance (e.g., Kverno 2021; Theoharides et al. 2015). In line with these findings, occupational research finds that health is associated with better job performance (e.g., Ford et al. 2011). Given the importance of health for job performance, particularly for cognitive work, we consider the effects of workforce health on firms' financial reporting quality. Financial reporting involves considerable cognition, requiring personnel to make judgments about the likelihood of future events and the appropriateness of complex estimates. Thus, we argue that employee health is associated with greater financial reporting quality.

There are several ways by which employee health may affect financial reporting quality. First, employees can influence financial reporting through their roles as input providers. Prior research finds that health is associated with better work quality, suggesting that healthier employees may provide higher quality inputs for financial reporting decisions. Second, employees can influence financial reporting through their monitoring roles. For instance, employees reveal more instances of fraud than both auditors and SEC regulators (Dyck et al. 2010). In line with Dyck et al. (2010), Call et al. (2017) find that employee education is positively associated with whistleblowing to regulators. Because health improves cognitive function (e.g., Pronk et al. 2004; Theoharides et al. 2015), healthy employees may be better at detecting financial reporting errors. Based on these arguments, we state our first hypothesis (H1) as follows:[10]

Hypothesis 1: *Employee health is associated with greater financial reporting quality.*

[10] Although we expect employee health to have a positive effect on financial reporting quality, we recognize that it could have no effect on financial reporting quality. For instance, internal controls may not allow non-executive employees enough discretion in judgments to influence financial reporting quality. Similarly, internal controls may maintain a minimum information quality for firms. However, internal controls are maintained by employees, whose health may also influence their job performance.

2.4. Hypothesis 2: The moderating role of financial reporting complexity

Prior research suggests that complex financial information has higher processing costs (e.g., Blankespoor et al. 2020). The processing costs of complex information can lead to slower price response by investors and less accurate forecasts for analysts, suggesting that both sophisticated and unsophisticated financial statement users struggle to process complex information (e.g., Francis et al. 2019; Plumlee 2003; You and Zhang 2009). Prior research finds that to mitigate these adverse effects of financial reporting complexity, firms invest in accounting expertise on their board of directors and audit committee (Chychyla et al. 2019). These findings suggest that expert monitors can improve financial reporting quality, especially when financial reporting is complex. In line with this reasoning, we argue that healthy employees may have a more pronounced on financial reporting when reporting is complex. Specifically, if more complex financial information requires more cognitive processing, and better cognitive processing contributes to higher financial reporting quality, then we expect that the effects of employee health on financial reporting quality will be more pronounced when financial information is more complex. Accordingly, we state our second hypothesis (H2) as follows:

> **Hypothesis 2:** *The association between employee health and financial reporting quality is more pronounced when financial reporting is more complex.*

III. Research Design

3.1. Sample selection

We begin our sample construction by gathering city-level health data published by the American Fitness Index (AFI). The AFI measures the overall health quality of the 100 largest cities in the US based on a variety of health behaviors, outcomes, local policies, and facilities. We discuss the AFI data in more detail in Section 3.2. We then match the city-level data to its corresponding metropolitan statistical area (MSA) and identify firms headquartered in MSAs for which we have AFI health data. This process yields our initial sample of firm-year observations. Notably, our sample begins in 2008, when the AFI first published health data, and ends just before the start of the COVID-19 pandemic in 2019.[11] We proceed to collect data for our control and outcome variables. We obtain financial statement data from COMPUSTAT, audit data from Audit Analytics, and analyst data from IBES. Our MSA data is from the University of Minnesota's Integrated Public Use Microdata Series (IPUMS-USA; Ruggles et al. 2010). IPUMS-USA provides economic microdata based on the annual US Census Bureau survey and decennial censuses. We remove foreign firms and firms in locations without matching MSA data. We then remove firms in cities without AFI coverage. Lastly, we remove firm-year observations with missing data for control variables. Our final sample consists of 18,143 firm-year observations. Table 1 describes our sample selection process.

3.2. Health measure

We measure employee health using data from the American Fitness Index (AFI). As previously mentioned, AFI is an initiative of the American College of Sports Medicine (ACSM) that measures the overall health quality of the 100 largest cities in the US. The AFI ranks the cities on a variety of health behaviors, outcomes, local policies, and facilities. The dataset covers 100 cities across 37 states. The ACSM publishes details for each city-year, and the AFI compiles data from several comprehensive sources (see Zollinger et al. 2023). For example, in their latest summary report, the AFI lists the following data providers: (1) American Community Survey – U.S. Census; (2) Behavioral Risk Factor Surveillance System, County Data – CDC; (3) Environmental Protection Agency; (4) Map the Meal Gap – Feeding America; (5) National

[11] We end our sample in 2019, just before COVID-19, which is a shock to both the economy as well as public health and renders our empirical analyses difficult to interpret.

Highway Traffic Safety Administration; (6) Smart Growth American / National Complete Streets Coalition; (7) Trust for Public Land – City Park Facts; (8) Walk Score and Bike Score; and (9) National Association of State Boards of Education. Figure 1 provides a visual representation of cities covered by the AFI, and Figure 2 presents the average rankings of the healthiest and least healthy cities over our sample period. The AFI health data is used in research across disciplines, including public health (e.g., Seo 2023) and nursing (e.g., Ralls 2014). The data is also used in many studies published in the *Translational Journal of the American College of Sports Medicine*.

We extract city-level health data from the ACSM website and use it as our measure of workforce health. The health indicators are grouped into two main categories by the AFI – personal health and community/environment health. Our main measure of employee health, *Emp_Health*, is the personal health score, which is a composite measure based on 19 weighted health indicators, including average exercise, sleep, vegetable and fruit consumption, mental health, obesity, asthma, and blood pressure in the city. The measure ranges from 0 to 100, such that a higher score indicates a healthier city and workforce.

While the AFI does not provide health data at the individual level, it captures the average health of residents in cities. Thus, we use the average health of individuals in the cities where our sample firms are headquartered to proxy for employee health.[12] In line with prior literature (e.g., Call et al. 2017; Hilary and Hui 2009), we argue that a firm's most significant employee base, especially for financial reporting roles, is maintained in the headquarters area. Thus, the AFI data is a reasonable proxy for the health of employees at our sample firms.[13]

[12] We acknowledge that certain firms might have in-house fitness facilities and that can influence the fitness of their workforce. However, the presence of these facilities is likely endogenous to the firm characteristics. We choose to rely on the AFI as a more external measure of workforce health.

[13] Further, Gu et al. (2014) investigate health by occupation. Two of the roles covered by Gu et al. (2014) relate to our study: Management/Business and Financial Operations. They find that these roles have health rates that are not statistically different from the sample mean, suggesting that the health of financial reporting personnel is not

As a rough validation test, we collect LinkedIn photos of 3,000 accounting and finance employees from 100 companies in our sample and use a machine learning algorithm to estimate their Body Mass Index (BMI). We document that companies headquartered in cities with higher Personal Health scores (*Emp_Health*) have employees with lower BMIs, suggesting that the AFI data accurately captures employee health. We also use the employee BMI measure as a proxy for health and find that our main results are robust to this alternative measure, despite limited statistical power. More information on the construction of our BMI variable is available in Appendix B.

3.3.Empirical approach

To test our first hypothesis, we employ the following OLS regression model (eq. 1):

$$FRQ_{it} = \beta_0 + \beta_1 Emp\_Health_{it} + \sum \beta_i Controls_{it} + FixedEffects + \varepsilon_{it}$$

Where *Emp_Health* is the variable of interest and is measured as the personal health score reported by the AFI for the city-year, as discussed in Section 3.2. The dependent variable (*FRQ*) reflects financial reporting quality. In our main analyses, we measure financial reporting quality using the Financial Statement Divergence Score (i.e., *FSD-score*), which is based on deviations from Benford's Law.[14,15] We measure financial reporting quality using the *FSD_score* because it is less dependent on firm performance, relative to other measures of financial misreporting, and captures mistakes and intentional financial reporting errors (Amiram et al. 2015). Intuitively, greater divergence from Benford's Law indicates lower financial reporting quality. Thus, we

different from that of personnel in other roles. This gives us comfort that the AFI health data is an appropriate proxy for employee health, including the health of employees in financial reporting roles.

[14] We thank the authors of Amiram et al. (2015) for providing their code for calculation.

[15] Benford's law suggests that if distributions are randomly selected and then samples are randomly drawn from these distributions, the leading digits of the combined mixture distribution will converge to the logarithmic or Benford distribution. Thus, Benford's Law suggests that leading digits of smaller values will appear more frequently, such that 1 will appear as the first digit 30% of the time but 9 will appear as the first digit less than 5% of the time. Benford's law also theorizes about the distribution of second digits, third digits, and so on. Methods based on the law have been used to detect errors in election and tax data. Please see Amiram et al. (2015) for more details.

predict that the coefficient on *Emp_Health* will be negative and statistically significant (B_1<0), suggesting that employee health is associated with greater financial reporting quality.

Controls is a vector of comprehensive firm- and MSA-level controls based on prior literature. We control for firm characteristics including firm size, measured as the natural logarithm of total assets (*Size*); firm performance, measured by return on average assets (*ROA*); book-to-market ratio (*BTM*); and leverage (*Lev*). We also control for external monitoring by analysts (*Follow*) and whether auditors are Big4 firms (*Big4*). Further, we control for the employee base, measured by number of employees (*Employees*) and distance to the nearest SEC office (*Distance_SEC*). We also control for the complexity of financial reporting, measured by the natural logarithm of the number of business segments (*Segments)*, intangible assets scaled by total assets, (*Intangibles*), and the natural logarithm of audit fees (*Fees*). MSA-level controls include economic factors, such as workforce size, measured as the natural logarithm of the estimated workforce size *(Population);* coincident index (*SCI*); consumer price index (*CPI*); gross domestic product (*GDP*)*;* unemployment rate (*Unemployment*); average wage of workforce (*Wages*); and average ROA of firms in the MSA (*MSA_ROA*). Additional controls for MSA-level monitoring include the number of reporters in the MSA (*Reporters*); education of employees based on the average education level in the MSA (*Education*); and religiosity, measured as the ratio of religious adherents to the total population in which a firm is headquartered (*Religion*)[16].

To test our second hypothesis, we employ the following OLS regression model (eq. 2):

$$FRQ_{it} = \beta_0 + \beta_1 Complexity_{it} + \beta_2 Emp\_Health_{it} + \beta_3 Complexity_{it} * Emp\_Health_{it} + \sum \beta_i Controls_{it} + FixedEffects + \varepsilon_{it}$$

[16] We thank the authors of Call et al. (2017) for their code for calculating MSA-level variables.

Where *Complexity* reflects financial reporting complexity and is measured based on the number of accounting items in a firm's 10-K filing (*ARC*), intangible assets intensity (*Intangibles*), or number of business segments (*Segments*). The variable of interest is that on the interaction term, *Complexity * Emp_Health*, which captures the incremental effect of employee health on financial reporting quality. We again measure financial reporting quality using the *FSD_score*. We predict that the coefficient on the interaction term, *Complexity * Emp_Health*, will be negative and statistically significant (B_3<0), suggesting that the association between employee health and financial reporting quality is more pronounced when financial reporting is complex. *Controls* are as previously described for equation 1.

For all models, standard errors are clustered by firm to account for residual dependence across time. Year fixed effects are included to control for unobservable characteristics that are the same for all firms in a given year, and industry effects are included to control for unobservable, time-invariant characteristics at the industry level (Breuer and deHaan 2023).[17] Throughout our study, we present results with varying fixed effects as well as no fixed effects to reduce concerns that improper inclusion of fixed effects may be biasing our results (e.g., Breuer and deHaan 2023; Jennings et al. 2023; Whited et al. 2022). Variables are defined in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles.

3.4. Descriptive statistics

Table 2 presents summary statistics. The sample consists of relatively large firms, which is unsurprising, as the ACSM data limits our sample to firms located in the largest US cities. The mean of the untransformed total assets (*Size*) is around \$ 467 million. Firms in our sample are generally visible, with an untransformed average (median) of 7.416 (5.000) analysts following the

[17] Our main results are robust to alternative fixed effects, such as firm, CEO or city fixed effects as well.

firm (*Follow*). These firms tend to employ auditors at Big 4 firms, as the mean on the *Big4* indicator variable is 0.667. The average education level is 7.726 (about 2 years of college), comparable to the 7.581 documented by Call et al. (2017). Further, there is notable variation in employee health (*Emp_Health*), with a mean score of 0.533 and a standard deviation of 0.152.

IV. Results

4.1. Main test: Employee health and financial reporting quality (H1)

Table 3 presents results for our first hypothesis, which predicts that employee health is associated with greater financial reporting quality. Table 3 contains four columns, each representing a different model specification with varying fixed effects to reduce concerns that our results are driven by the improper inclusion of fixed effects (Breuer and deHaan 2023; Jennings et al. 2023). In all specifications, the coefficient of interest is that of *Emp_Health*, which captures the association between employee health and firms' FSD_scores. We predict a negative coefficient on *Emp_Health*, suggesting that employee health is associated with better financial reporting.

As predicted, the coefficient on *Emp_Health* is negative and statistically significant (p<0.01) across all four specifications. Further, the coefficients on *Emp_Health* are similar across specifications, ranging from -0.002 to -0.003. In column 4, the coefficient on *Emp_Health* is -0.002, significant at the 1% level, which, in terms of economic magnitude, suggests that a one standard deviation increase in *Emp_Health* reduces *FSD_score* by -0.0003 from its (untabulated) standard deviation of 0.0114 to 0.0111, or by -2.67%. Taken together, the significantly negative coefficients on *Emp_Health* presented in Table 3 support our first hypothesis and are consistent with employee health being associated with greater financial reporting quality.[18,19,20]

4.2. Alternative employee health measure and financial reporting quality

We next consider an alternative measure of employee health - the average BMI of a firm's accounting and finance personnel. We acknowledge the limitations of BMI as a health indicator. The advantage of this measure is its focus on employees involved in a firm's financial reporting process. To construct *Emp_BMI*, we collect LinkedIn photos of 3,000 accounting and finance employees from 100 companies in our sample and use a machine learning algorithm to estimate their BMI. We then take the average of employees' BMI at the firm and use this to proxy for employee BMI in the final year of our sample. Please see Appendix B for more details. We predict a positive coefficient on *Emp_BMI*, suggesting that employee health is associated with better financial reporting

Table 4 presents the results from regressing the *FSD_score* on *Emp_BMI*. Two columns are presented, representing results with and without industry fixed effects. Similar to our main tests, the coefficient of interest is that on *Emp_BMI*, reflecting the association between employee health and financial reporting quality. As predicted, in both columns the coefficient on *Emp_BMI* is positive and statistically significant ($p<0.05 – 0.10$), despite limited statistical power. These results continue to support our first hypothesis, which predicts that employee health is associated with

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[18] In untabulated analyses, we include additional corporate governance controls such as board size, percentage of directors with financial expertise, percentage of female directors, CEO tenure, and the average tenure of board members. Our main results are qualitatively similar.

[19] One could argue that the AFI data better captures workforce health in smaller cities relative to larger, more diverse cities. Thus, in untabulated analyses, we split our sample into two subsamples based on the median city population size and rerun our main analyses. Our results continue to hold for both subsamples.

[20] In untabulated analyses, we confirm that our results hold in a subsample low-performing firms. We measure performance using ROA and rerun our analyses using firms in the bottom quartile of performance. We continue to find that employee health improves financial reporting quality for firms.

greater financial reporting quality. Notably, the results presented in Table 4 and Appendix B suggest that the AFI data provides a reasonable measure of employee health.

In untabulated analyses, we employ alternative measures of employee health. First, we consider alternative measures provided by AFI, including (1) the rank of a city's personal health score, (2) the city's overall health score, which combines the city's personal and community / environmental health scores, and (3) the rank of the city's overall health score. Next, we use data from RepRisk to construct a firm-level measure of local air pollution. Our main results are robust to these alternative measures of employee health.

4.3.Employee health and alternative measures of financial reporting quality

To triangulate our main results, we also consider alternative measures of financial reporting quality. Notably these alternative measures primarily capture intentional financial misreporting. Thus, these results better speak to employees' ability to improve financial reporting quality through their monitoring role, in line with Dyck et al. (2010) and Call et al. (2017). We begin by examining the association between employee health (*Emp_Health*) and firms' levels of discretionary revenue (*Dis_Revenue*). Stubben (2010) introduces discretionary revenue as a measure of earnings management, and many prior studies use discretionary revenues to capture financial reporting quality (e.g., Hope et al. 2013; McNicholas and Stubben 2008). We measure discretionary revenues based on Stubben (2010). Lower levels of discretionary revenues indicate better financial reporting quality. Thus, we predict a negative association between employee health (*Emp_Health*) and discretionary revenues (*Dis_Revenue*).

Table 5, Panel A presents results for tests of discretionary revenues. Four columns are presented, reflecting different model specifications with varying fixed effects. As before, the coefficient of interest is that on *Emp_Health*. As predicted, we find a negative and statistically significant ($p<0.01$) coefficient on *Emp_Health* in all four columns, indicating that healthier employees are associated with lower levels of discretionary revenues. Further, the coefficients on *Emp_Health* are similar across specifications, ranging from -0.016 to -0.022. The results in Table 5, Panel A support our prediction that employee health improves financial reporting quality.

We next consider alternative measures of financial reporting quality based on accruals, like Call et al. (2017). *Dis_Accruals_J* is based on the traditional measure of accruals presented by Jones (1991). *Dis_Accruals_K* is based on the measure of performance-matched accruals presented by Kothari et al. (2005). For each accrual measure, a lower value reflects greater financial reporting quality. Thus, we predict negative associations between employee health and accruals, consistent with employee health being associated with greater financial reporting quality.

Table 5, Panels B and C present results for regressions in which *Dis_Accruals_J* and *Dis_Accruals_K* are the dependent variables, respectively. Each panel contains four columns, representing specifications with varying fixed effects. The coefficient of interest across all panels and columns is that on *Emp_Health*. As predicted, the coefficient on *Emp_Health* is negative and statistically significant ($p<0.05$-0.10) in all four columns for Panels B and C. These results suggest that employee health is associated with improved accruals quality. [21]

Finally, we consider a more egregious form of misreporting, restatements related to fraudulent activities. This test is motivated by evidence that employees report the most instances of fraud, relative to other monitors like auditors and regulators (Dyck et al. 2010). We measure restatements due to fraud (*Restate*) following Cao et al. (2012) and predict a negative relation between employee health and restatements. Table 5, Panel D presents results for regressions in which Restate is the dependent variable. The coefficient of interest is that on Emp_Health. As predicted, the coefficient

[21] In untabulated analyses, we consider another measure of accruals quality, *Std_Residuals*, presented by Dechow and Dichev (2002). We predict and find that employee health is negatively associated with *Std_Residuals*.

on Emp_Health is negative and statistically significant (p<0.05-0.10) in all four columns, suggesting firms with healthier employees have fewer restatements due to fraud. Taken together, the evidence in Table 5 supports our main results and prediction that employee health is associated with higher quality financial reporting.

4.4. Within firm changes in employee health

Next, we leverage firm headquarters relocations to identify within firm changes in employee health. Firms move headquarters for a variety of reasons, such as taking advantage of low corporate taxes or increasing their proximity to transport facilities (Strauss-Kahn and Vives 2009). The relocation of headquarters involves (1) the relocation of existing employees to the new location and (2) the hiring of new employees in the new location. In both cases, the movement of headquarters to more (less) healthy locations may lead to an increase (decrease) in employee health and, thus, higher (lower) financial reporting quality. Regarding employee relocation, good health practices, such as going to the gym, spending time outdoors, and eating well, depend in part on the ability of one's environment to support such practices. For instance, it is difficult to exercise outdoors if one's city does not have spaces to encourage outdoor activity, such as safe parks, bike lanes, roads, and sidewalks. If an employee's new city provides more (less) support for healthy practices, the employee's health may improve (decline) following relocation. Regarding employee hiring, it seems likely that new hires will be more (less) healthy when a firm moves to a more (less) healthy city. Based on this reasoning, we argue that the relocation of headquarters to a more (less) healthy city represents a positive (negative) change in employee health and leverage this change to examine the association between employee health and financial reporting quality.

We use a difference-in-differences design to conduct our relocation analyses. We identify treatment firms as those that move to a city with a higher (lower) health score. In our first set of empirical tests, *Treat* is a categorical variable based on relocation, similar to Kreutzer and Mitze (2016).[22] *Treat* is equal to one for firms that relocate to a healthier city, negative one for firms that relocate to a less healthy city, and zero otherwise. *Post* is equal to one for the year that a firm relocated and the year that follows. We retain observations for the year preceding and following the relocation. We match control firms to treatment firms (one-to-many) based on total assets and industry. Following deHaan et al. (2013), we match firms at the start of the sample, prior to treatment. For control firms, *Post* is based on the treatment firm's relocation year. We require firms to have non-missing data in the pre-and post-relocation periods. The coefficient of interest is that on the interaction, *Treat * Post*, which reflects the effect of relocating to more (less) healthy cities on financial reporting quality. We predict a positive coefficient on the interaction term, consistent with financial reporting quality increasing (declining) after a positive (negative) change in health.

Table 6 presents the results of our tests of a within firm change in employee health via firm relocation. Four columns are presented, reflecting different model specifications with varying fixed effects. Again, the coefficient of interest is that on the interaction term, *Treat * Post*, which reflects the effect of the change in employee health on firms' financial reporting quality. As predicted, the coefficients on *Treat*Post* are negative (-0.002) and significant ($p<0.05$) across all four specifications, indicating that the positive (negative) relocation change in employee health is associated with an increase (decrease) in financial reporting quality.

Next, we consider whether the results in Table 6 are driven by relocations to more healthy or less healthy cities. We split our relocation sample into subsamples based on whether a firm experiences a positive or negative change in employee health, i.e. whether a firm moves to a more

[22] Kreutzer and Mitze (2016) employ a difference-in-difference analysis and measure treatment as a categorical variable based on firm relocation. Specifically, *Treat* is equal to zero for firms that do not relocate, one for firms that relocate only domestically, and two for firms that relocate internationally. Similarly, we measure treatment as a categorical variable in which a higher value indicates a greater degree of treatment (i.e., a healthier city).

(less) healthy city. For these analyses, *Treat* is equal to one for firms that relocate to a more (less) healthy city and zero otherwise. We predict a negative coefficient on the interaction term when firms move to a healthier city, indicating that financial reporting quality improves following a positive change in employee health. Likewise, we predict a positive coefficient on the interaction term when firms move to a less healthy city, indicating that financial reporting quality declines following a negative change in employee health.

Table 7, Panel A presents the results of our tests of a positive change in employee health. Four columns are presented, reflecting different model specifications with varying fixed effects. The coefficient of interest is that on the interaction term, *Treat * Post*, which reflects the effect of a positive change in employee health on firms' financial reporting quality. As predicted, the coefficients on *Treat*Post* are negative (-0.003) and significant ($p<0.10$) across all four specifications, indicating that the positive change in employee health is associated with an increase in financial reporting quality.

Panel B presents the results of our tests of a negative change in employee health. The coefficient of interest is that on the interaction term, *Treat * Post*, which reflects the effect of a negative change in employee health on firms' financial reporting quality. As predicted, the coefficients on *Treat * Post* are positive (0.003) and significant ($p<0.05$-0.10) in all four columns, indicating that the negative change in employee health is associated with a reduction in financial reporting quality. The results presented in Table 7 are particularly helpful in reducing identification concerns, as we find results in both directions. Collectively, the evidence in Tables 6 and 7 helps to ease concerns that our main results are driven by a correlated omitted variable.

4.5. Cross-sectional test: Financial reporting complexity (H2)

Table 8 presents the results for our second hypothesis, which examines whether the association between employee health and financial reporting quality is moderated by financial reporting complexity. Prior research suggests that financial reporting complexity requires greater processing from both *preparers* and *users* of financial information (e.g., Blankespoor et al. 2020; Chychyla et al. 2019). In line with this research, we expect the relation between employee health and financial reporting to be more pronounced when financial reporting is more complex. To test this prediction, we use three proxies of financial reporting complexity.

First, we proxy for financial reporting complexity using the Hoitash and Hoitash (2018) measure of accounting reporting complexity (*ARC*), which is based on the number of accounting items (XBRL tags) in the 10-K filing.[23] Prior research using this measure finds that accounting reporting complexity is associated with greater likelihood of misstatements, longer auditor delay, and poor performance by financial analysts (Hoitash and Hoitash 2018; Hoitash et al. 2021), consistent with the cognitive demands on financial statements users and preparers increasing with the number of accounting items in a SEC filing. As such, we expect the relation between employee health and financial reporting quality to be more pronounced for firms with more accounting items in their 10-K filings (*ARC).* Table 8, Panel A presents the results. The coefficient of interest is that on *ARC * Emp_Health.* As predicted, the coefficient on the interaction term *ARC * Emp_Health* is negative and statistically significant ($p<0.01$) in all four columns. Collectively, the results in

[23] We thank the authors for making this measure available at www.xbrlresearch.com.

Table 8, Panel A suggest that the link between employee health and financial reporting is more pronounced when financial reporting is more complex.

Second, we proxy for financial reporting complexity using intangible assets, as prior research finds that intangible assets are among the most subjective and complex estimates in the financial statements (e.g., Burke et al. 2023; Chan and Liu 2023). Given the complexity of reporting intangible assets, we expect the relation between employee health and financial reporting quality to be more pronounced for firms with greater intangible asset intensity (*Intangibles)*. Table 8, Panel B presents the results. The coefficient of interest is that on *Intangibles * Emp_Health.* As predicted, the coefficient on the interaction term *Intangibles * Emp_Health* is negative and statistically significant ($p<0.01$) in all four columns. The coefficients on the interaction terms are qualitatively similar across specifications, at values of about -0.008. Collectively, the results in Table 8, Panel B suggest that the link between employee health and financial reporting is more pronounced when financial reporting is more complex.

Finally, we follow prior research and proxy for reporting complexity using the number of business segments (e.g., Cohen and Lou 2012; Frankel et al. 2006; Miller 2010). This final measure better reflects the underlying business complexity, which may lead to more complex financial reporting. Table 8, Panel C presents the results. The coefficient of interest is that on *Segments * Emp_Health* and is predicted to be negative. As predicted, the coefficient on the interaction term *Segments* Emp_Health* is negative and statistically significant ($p<0.05$-0.10) in all four columns. The coefficients on the interaction terms are qualitatively similar across specifications, ranging from -0.001 to -0.002. The somewhat weaker evidence for cross-sectional analyses based on business segments (*Segments*) relative to the number of accounting items in the 10-K filing (*ARC*) and intangibles (*Intangibles*) is not surprising, as the number of business segments is a noisy proxy of financial reporting complexity. Nonetheless, taken together, the results in Table 8, Panels A, B, and C, support our second hypothesis, which predicts that the relation between employee health and financial reporting quality is more pronounced when financial reporting is complex.[24]

4.6. Additional analyses: Employee health and qualitative financial reporting quality

We also investigate whether employee health is associated with better qualitative financial reporting. The intuition for these analyses is similar to that in our main tests, except rather than focusing on the quality of accounting numbers presented in the financial reports, we now focus on the clarity of the written disclosure in the financial reports. To capture the qualitative financial reporting, we use the *BOG_Index* of firms' annual 10-K filings provided by Bonsall et al. (2017). The *BOG_Index* is a plain English measure of financial reporting readability. A higher *BOG_Index* reflects a less readable annual filing (i.e., lower financial reporting quality). Thus, we predict a negative relation between *Emp_Health* and *BOG_Index,* suggesting healthier employees provide more readable financial reports.

Table 9 presents the results of regressing *BOG_Index* on *Emp_Health*. There are four columns of results, each representing a different model specification with varying fixed effects. In all specifications, the coefficient of interest is that of *Emp_Health*, which captures the association between employee health and financial report readability. As predicted, the coefficient on *Emp_Health* is negative and statistically significant ($p<0.01$ – 0.10) in all specifications. Collectively, the results presented in Table 9 are consistent with employee health improving the readability of financial reports. Taken together, the results in our study suggest that employee

[24] In untabulated analyses, we proxy for complexity using the Loughran and McDonald (2023) measure of firm complexity and their measure of 10-K file size. Our results are qualitatively similar. We thank the authors for making their measures available at https://sraf.nd.edu/complexity/.

health improves both quantitative and qualitative financial reporting quality for firms, likely through employees' increased cognitive performance.

4.7.Sensitivity analyses

4.7.1. Employee health vs. employee education

We next address concerns that employee education is driving our results. First, we provide descriptive evidence that our measures of employee health and employee education capture different underlying constructs. In Panel A of Table 10, we present the Pearson correlation coefficients between employee health and several key MSA variables, including employee education.[25] The correlation between employee health (*Emp_Health*) and education (*Education*) is significant and positive at a value of about 0.552, suggesting that the two variables are correlated but still reflect different constructs.

In untabulated analyses, we compute the average employee health and average employee education for each city in our sample across our sample period (2008 to 2019). We then rank cities based on their average employee health (education) scores such that a rank of 1 reflects the best health (education). We observe significant variation in city health and education rankings. For instance, Anaheim, California is ranked 9th in health but only 56th in education, suggesting the employees in Anaheim are quite healthy but have less education, on average. In contrast, Newark, New Jersey is ranked 61st in health and 7th in education, suggesting that employees in Newark are well-educated but unhealthy. Taken together, our descriptive evidence suggests that employee health and education are different constructs and eases concerns that our results are attributable to employee education.

[25] For brevity, we only present a partial correlation matrix. In untabulated analyses, we examine a full correlation matrix. The greatest correlation for employee health is that between employee health and wages, about 0.589.

In addition, we conduct multivariate analyses based on employee education. Specifically, we split our main sample into two subsamples based on the median of our employee education measure and rerun our main analyses on the high and low education subsamples. We expect to find no difference in the association between employee health and financial reporting quality across the two samples, suggesting that our main results are not driven by education.

Table 10, Panel B presents our results. Columns 1, 3, 5, and 7 present results for the low education subsample (*Low*), and columns 2, 4, 6, and 8 present results for the high education subsample (*High*). As before, we present various fixed effect specifications. For each specification, we test the statistical difference between the coefficients on *Emp_Health* across the low and high education subsamples. Across all specifications for both subsamples, we continue to find that employee health is associated with better financial reporting quality. The coefficients on *Emp_Health* in columns 1-8 are negative and statistically significant ($p<0.05$-0.10). The coefficients are qualitatively similar, at a value of about -0.002. As expected, we find no statistical evidence that the coefficients on *Emp_Health* in the low education subsamples are different than those in the high education subsamples. Collectively, these analyses provide evidence that our main results are not driven by employee education.

4.7.2. Industry consideration

One could argue that there is variation in cultures and mindsets around health and wellness across industries, leading to variation in the relation between employee health and financial reporting quality. For instance, technology firms tend to place a greater emphasis on health relative to manufacturing firms. To address the concern that certain industries are driving our results, we include industry fixed effects in our main analyses. Our results are robust to the inclusion of industry fixed effects. To address the concern that technology firms specifically are driving our main results, we drop all technology firms and rerun our baseline regressions in additional untabulated analyses. We continue to find that workforce health is associated with greater financial reporting quality for firms in the remaining industries.

4.7.3. CEO fixed effects

To alleviate concerns that our results are driven by executive characteristics (including managerial health), rather than employee health, we repeat our main analyses with CEO fixed effects. In untabulated analyses, we rerun equation (1) using four specifications of fixed effects, including: (1) CEO fixed effects; (2) CEO and year fixed effects; (3) CEO and industry fixed effects; and (4) CEO, year, and industry fixed effects. As predicted, the coefficient on *Emp_Health* is negative and statistically significant ($p<0.05$) across all four specifications, despite a reduction in statistical power due to limited availability of CEO data. Taken together, these additional analyses suggest that our main results are driven by variation in the health of the workforce rather than executive characteristics.

4.7.4. Alternative specifications

In additional untabulated analyses, we examine the sensitivity of our main results to design choices. First, we consider alternative fixed effect specifications and find that our results are robust to the inclusion of firm and city fixed effects. Next, we nest the fixed effect units within the units by which we cluster standard errors, consistent with Breuer and deHaan (2023). We also cluster our standard errors by firm-year to mitigate bias from serial correlation and cross-sectional correlation (Gow et al. 2010). Further, to ensure that our results are not driven by the correlation of measurement error in our variable of interest (*Emp_Health*) and in one of our control variables, we repeat our main analyses, dropping one variable at a time (Jennings et al. 2023). Our results are robust across these alternative specifications.

V. Conclusion

Prior medical and occupational research find that an individual's health influences their cognitive and job performance, suggesting health may be particularly important for cognitive work (e.g., Infurna and Gerstorf 2013; Penedo and Dahn 2005; Ford et al. 2004). In this study, we examine the implications of employee health on an important firm output – financial reporting quality. Financial reporting involves considerable cognition, requiring personnel to make judgments about the likelihood of future events and the appropriateness of complex estimates. Thus, we predict that employee health is associated with greater financial reporting quality.

In our main analyses, we indeed find that employee health is associated with better financial reporting quality. Our main results are robust to several alternative measures of employee health and financial reporting quality as well as within firm changes in employee health. We next consider the moderating role of financial reporting quality. Because prior research suggests that reporting complexity demands higher processing costs for preparers and users of financial information, we expect the relation between employee health and financial reporting quality to be more pronounced when financial reporting is more complex. Using several proxies for financial reporting complexity, we find that the relation between employee health and financial reporting quality is more pronounced when reporting is complex. In additional analyses, we consider qualitative financial reporting and find that employee health is associated with more readable financial reports. Collectively, our findings underscore the importance of employee health.

The insights from this study contribute to several streams of literature. First, we add to the research on financial reporting quality by examining the influence of an important but understudied stakeholder: non-executive employees. Second, we contribute to the research on individual characteristics that influence financial reporting by documenting the effects of a vital human characteristic, personal health. We also extend the research on health and job performance by providing evidence that employee health can influence firm outcomes. Finally, we add to the growing research on employees in the financial markets. Our results may be of interest to firms, investors, and employees as the emphasis on employee health in the capital markets continues to rise, as well as regulators and academics concerned with financial reporting quality.

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Appendix A

Variable Definitions

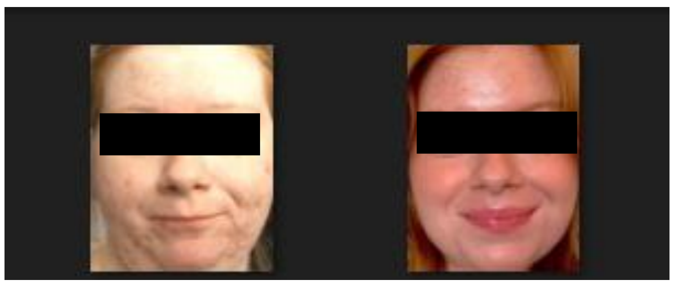
Variable	Definition	Data Source
Dependent Variables - FRQ		
FSD_Score	The MAD statistic, as calculated in Amiram et al. (2015). $\sum_{i=1}^{K} \lvert AD - ED \rvert$ where ED is the expected distribution based on Benford's law and AD is the actual distribution for the observation. We thank the authors of Amiram et al. (2015) for providing their code for calculation.	Compustat
Dis_Revenue	Discretionary revenue as calculated in Stubben (2010).	Compustat
Dis_Accruals_J	Residual from the modified Jones model, as calculated in Jones (1991).	Compustat
Dis_Accruals_K	Residual from the modified Jones (1991) model adjusted for performance as in Kothari et al. (2005).	Compustat
Restate	Equal to one if firm received a restatement related to fraud as classified by Audit Analytics, and zero otherwise.	Audit Analytics
BOG_Index	A plain English measure of financial reporting readability for a firm's annual 10-K filing. We thank the authors of Bonsall et al. (2017) for providing the data.	Brian Miller's personal website
Key Independent Variables		
Emp_Health	The personal health score as reported for the city from AFI. AFI uses 19 inputs to determine the personal health score for a community. These inputs reflect the average health of the people, such as the percent of people consuming two or more fruits per day, and the percent of people who are obese.	AFI
Emp_BMI	The average Body Mass Index (BMI) of accounting and finance employees in the most recent firm year. BMI is estimated by a trained algorithm based on employee LinkedIn headshot. Please see Appendix B for more information.	LinkedIn
Control Variables		
Size	The natural logarithm of total assets.	Compustat
Leverage	Total liabilities, scaled by total assets.	Compustat
BTM	The book to market ratio.	Compustat
ROA	Return on average assets.	Compustat

Employees	Number of employees, scaled by 100.	Compustat
Big4	Indicator variable equal to 1 if the firm is audited by a Big 4 auditor, 0 otherwise.	Audit Analytics
Follow	Number of analysts for the fiscal year obtained from the IBES summary files	IBES
Segments	Natural log of the number of business segments.	Compustat
Intangibles	Intangibles, scaled by total assets.	Compustat
ARC	The count of distinct (within each disclosure) monetary XBRL tags in the annual 10-K filing	www.xbrlresearch.com
Fees	Natural log of audit fees.	Audit Analytics
Population	Natural log of the estimated size of the workforce of the MSA as calculated in Call et al. (2017). We thank the authors of Call et al. (2017) for their code for calculating all IPUMS variables	IPUMS
SCI	Coincident index for the state where the MSA is located. SCI combines several macroeconomic factors, such as average hours worked, unemployment rate, etc.	Federal Reserve, Philadelphia
Religion	Rate of religion from the 2010 Religious Congregations and Membership Study.	ARDA
Education	Average level of education in the MSA as calculated in Call et al. (2017). We thank the authors of Call et al. (2017) for providing their code.	IPUMS
Wages	Average wages for the workforce in the MSA as calculated in Call et al. (2017). We thank the authors of Call et al. (2017) for providing their code.	IPUMS
Unemployment	MSA Unemployment rate.	BLS
GDP	Gross Domestic Product, in millions.	BLS
Distance_SEC	Distance to the nearest SEC office.	SEC.gov
Reporters	Number of reporters (Code 2810) in the MSA.	IPUMS
MSA_ROA	Average ROA for the MSA-year.	Compustat
Headquarters Relocation Variables		
Treat	In Table 6, equal to one if the firm relocates headquarters to a more healthy city, negative one if the firm relocates	AFI, Compustat

	to a less healthy city, and zero otherwise. In Table 7, equal to one if the firm relocates headquarters to a more (less) healthy city, and zero otherwise.	
Post	Equal to one for the year of the headquarters relocation and for the year that follows, and zero otherwise.	Compustat
*Treat * Post*	Interaction term reflecting the effect of relocating headquarters to a less (more) healthy city on financial reporting quality.	AFI, Compustat

Appendix B
Construction of Employee BMI Variable

As a rough validation test for our measure of employee health (*Emp_Health*), we collect LinkedIn photos of 3,000 accounting and finance employees from 100 companies in our sample and employ a machine learning algorithm to estimate their Body Mass Index (BMI). We follow the method in Kocabey et al. (2017) to write a program that can estimate BMI from facial photos. The program employs machine learning technology, and the algorithm is trained with real photos of people with known BMIs. Specifically, training data are obtained from the subreddit r/progresspics, where users post their before and after photos, usually related to weight loss or muscle gain, along with their height and weight. We can then easily calculate their BMI. Two examples are shown below (the black bars are added for privacy).



The goal is to train the model to recognize which features are important for predicting BMI. Before the images are fed into each of these models, they are first converted into numerical data (a set of 128 computer-generated measurements) and stored in a matrix. The algorithm notes certain important measurements on the face, such as the gap between eyebrows, ratio of cheek area to face area, etc. Then, these numbers are fed into the model. A random forest consists of a large number of individual decision trees that operate as an ensemble. Based on the training data, each individual tree in the random forest produces a class prediction, and the class with the most votes becomes our model's prediction. Then, we compare the prediction to the true value and evaluate their error and accuracy at different numbers of training samples (while the remaining samples are used as test samples). The accuracy rate is approximately 93% regardless of the number of observations we use as the training dataset. We then feed the photos of 3,000 employees into this program to estimate the employees' BMIs. We then compute an average BMI for each firm and regress this on their AFI measure of health for the most recent year. Results are shown below in Table A.1.

Table A.1
AFI Health Measure and BMI Measure

	Emp_BMI
Emp_Health	-0.008**
	(-2.050)
Constant	23.61***
	(118.1)
Observations	100
Adjusted R^2	0.045

The results in Table A.1 suggest that firms headquartered in cities with higher health scores have employees with lower BMIs, suggesting that our measure of employee health (*Emp_Health)* based on the AFI data captures the health of the workforce in the city

Figure 1. Geography of American fitness

Figure 1 shows the cities in the US with their corresponding AFI scores (average values across 2008-2019), with higher bars representing higher fitness level. The data is taken from the ACSM AFI website.

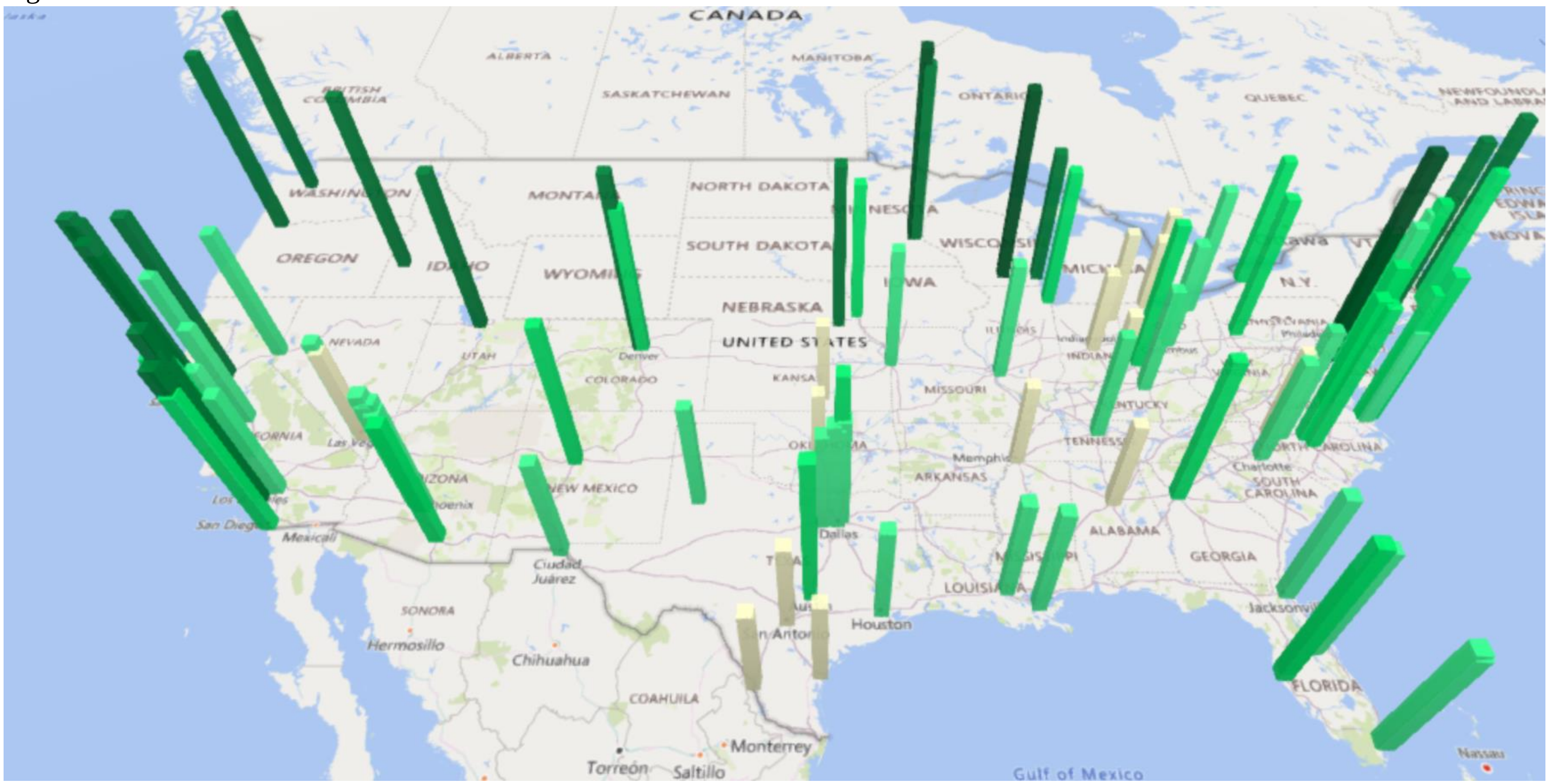


Figure 2. Top and bottom AFI scores

Figure 2 shows some cities in the US with their corresponding AFI scores (average values across 2008-2019), where we highlight the top 10 and the bottom 10 cities.

Rank	City	State	Average fitness score
Top			
1	Washington D.C.	D.C.	80.04
2	Arlington	VA	79.01
3	San Francisco	CA	77.84
4	San Jose	CA	76.52
5	Minneapolis	MN	76.51
6	Oakland	CA	75.41
7	San Diego	CA	73.24
8	Boise	ID	72.70
9	Anaheim	CA	72.44
10	Austin	TX	71.58
10	Memphis	TN	32.10
9	Indianapolis	IN	32.08
8	Detroit	MI	31.78
7	St. Louis	MO	31.15
6	Louisville	KY	27.57
5	New Orleans	LA	24.65
4	Toledo	OH	22.20
3	Birmingham	AL	21.42
2	Oklahoma City	OK	21.11
1	Corpus Christi	TX	15.50
Bottom			

Table 1

Sample Selection

	Firm-year observations
Merge of Compustat, Audit Analytics, IBES from 2008-2019	57,193
After removing foreign firms	53,926
After removing firms in locations without matching MSA data (IPUMS, SCI, CPI, GDP, Unemployment, Religion)	41,048
After removing firms in cities outside of the AFI coverage	30,197
After removing firm-years missing data for control variables	18,143
Final sample	18,143

Table 1 presents our sample selection process.

Table 2

Summary Statistics

	N	Mean	SD	25%	Median	75%
Emp_Health	18,143	0.533	0.152	0.429	0.500	0.648
Size	18,143	6.147	2.355	4.505	6.234	7.819
Leverage	18,143	0.582	0.459	0.324	0.515	0.704
BtM	18,143	0.470	0.865	0.189	0.402	0.726
ROA	18,143	-0.094	0.367	-0.100	0.023	0.071
Employees	18,143	0.099	0.251	0.002	0.013	0.067
Big4	18,143	0.667	0.471	0.000	1.000	1.000
Follow	18,143	7.416	8.726	0.000	5.000	11.000
Segments	18,143	1.386	0.791	1.099	1.099	2.197
Intangibles	18,143	0.195	0.215	0.008	0.116	0.326
Fees	18,143	13.760	1.351	12.880	13.860	14.690
Population	18,143	14.720	0.831	13.880	14.810	15.330
SCI	18,143	112.000	14.410	99.260	109.400	122.500
Religion	18,143	4.991	0.738	4.419	5.138	5.534
Education	18,143	7.726	0.348	7.432	7.769	7.967
Wages	18,143	4.770	1.089	4.000	5.000	5.000
CPI	18,143	2.050	0.465	1.465	2.210	2.409
Unemployment	18,143	6.547	2.352	4.600	6.100	8.300
GDP	18,143	1.189	0.742	0.524	1.277	1.785
Distance_SEC	18,143	1.099	1.451	0.127	0.334	2.225
Reporters	18,143	2.461	3.317	0.448	0.933	2.853
MSA_ROA	18,143	-0.081	0.070	-0.132	-0.070	-0.024

Table 2 presents descriptive statistics for our main sample. Continuous variables are winsorized at the 1st and 99th percentiles. Appendix A contains definitions for all variables.

Table 3

Employee Health and Financial Reporting Quality

		Dependent Variable:			
		FSD_Score			
	Predict	(1)	(2)	(3)	(4)
Emp_Health	(-)	-0.003***	-0.003***	-0.002***	-0.002***
		(-3.066)	(-2.970)	(-2.828)	(-2.474)
Size		-0.000***	-0.000***	-0.001***	-0.001***
		(-2.904)	(-2.834)	(-5.102)	(-5.021)
Leverage		-0.004***	-0.004***	-0.004***	-0.004***
		(-12.572)	(-12.575)	(-12.083)	(-12.077)
BtM		-0.001***	-0.001***	-0.001***	-0.001***
		(-6.993)	(-7.027)	(-5.753)	(-5.829)
ROA		-0.007***	-0.007***	-0.006***	-0.006***
		(-14.254)	(-14.245)	(-12.107)	(-12.073)
Employees		0.001***	0.001***	0.002***	0.003***
		(3.149)	(3.160)	(4.824)	(4.829)
Big4		0.002***	0.002***	0.002***	0.002***
		(6.490)	(6.485)	(6.495)	(6.512)
Follow		0.000	0.000	0.000*	0.000**
		(0.708)	(0.732)	(1.952)	(1.976)
Segments		-0.000***	-0.000***	-0.000***	-0.000***
		(-4.023)	(-3.996)	(-3.182)	(-3.175)
Intangibles		-0.006***	-0.006***	-0.005***	-0.005***
		(-13.435)	(-13.393)	(-10.479)	(-10.446)
Fees		-0.003***	-0.003***	-0.002***	-0.003***
		(-13.430)	(-13.437)	(-11.838)	(-11.917)
Population		-0.001	-0.001	0.000	-0.000
		(-1.424)	(-1.588)	(0.080)	(-0.306)
SCI		0.000***	0.000*	0.000***	0.000*
		(3.215)	(1.731)	(3.781)	(1.746)
Religion		-0.000	-0.000	-0.000	-0.000
		(-0.389)	(-0.248)	(-0.858)	(-0.612)
Education		-0.000	-0.000	0.001	0.001
		(-0.249)	(-0.075)	(0.911)	(0.952)
Wages		0.001***	0.001***	0.001***	0.001**
		(3.512)	(3.436)	(2.658)	(2.561)
CPI		0.001***	0.002***	0.000	0.001
		(2.811)	(2.956)	(0.731)	(1.055)
Unemployment		0.000	0.000*	0.000**	0.000***
		(1.515)	(1.654)	(2.369)	(2.724)
GDP		0.000	0.000	0.000	0.000

	(1.125)	(1.161)	(1.115)	(1.295)
Distance_SEC	0.000	0.000	0.000	0.000
	(1.237)	(1.376)	(1.312)	(1.577)
Reporters	0.000*	0.000*	0.000	0.000
	(1.704)	(1.786)	(0.421)	(0.598)
MSA_ROA	0.000	0.001	0.001	0.002
	(0.159)	(0.436)	(0.315)	(0.759)
Observations	18,143	18,143	18,143	18,143
Adjusted R^2	0.275	0.275	0.301	0.301
Fixed Effects	None	Year	Ind	Year, Ind

Table 3 presents the regression results from examining the association between employee health and firms' financial reporting quality. Employee health (*Emp_Health*) is measured using the average health of the workforce in a firm's headquarter city. Financial reporting quality is measured using the Financial Statement Divergence Score (*FSD-score*), which is based on deviations from Benford's Law. T-statistics are reported in paratheses. Standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (one-tailed tests for variables with predictions, otherwise two-tailed), respectively. Variables are defined in Appendix A.

Table 4
Employee BMI and Financial Reporting Quality

		Dependent Variable:	
		FSD_Score	
	Predict	(1)	(2)
Emp_BMI	(+)	0.002*	0.003**
		(1.320)	(1.744)
Observations		97	83
Adjusted R^2		0.112	0.129
Controls		Yes	Yes
Fixed Effects		None	Ind

Table 4 presents the regression results from examining the association between an alternative employee health measure, *Employee BMI*, and firms' financial reporting quality. Employee health is measured as the average BMI of accounting and finance employees at a firm (*Emp_BMI*). Please see Appendix B for more information on the construction of *Emp_BMI*. Financial reporting quality is measured using the Financial Statement Divergence Score (*FSD-score*), which is based on deviations from Benford's Law. T-statistics are reported in paratheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (one-tailed tests for variables with predictions, otherwise two-tailed), respectively. Control variables are included but not tabulated for brevity. Variables are defined in Appendix A.

Table 5

Employee Health and Alternative Financial Reporting Quality Measures

Panel A.		Dependent Variable: *Dis_Revenue*			
	Predict	(1)	(2)	(3)	(4)
Emp_Health	(-)	-0.022***	-0.017***	-0.021***	-0.016***
		(-4.756)	(-3.214)	(-4.683)	(-2.971)
Observations		18,104	18,104	18,104	18,104
Adjusted R^2		0.004	0.009	0.018	0.024

Panel B.		Dependent Variable: *Dis_Accruals_J*			
	Predict	(1)	(2)	(3)	(4)
Emp_Health	(-)	-0.094*	-0.127**	-0.094*	-0.129**
		(-1.418)	(-1.751)	(-1.397)	(-1.722)
Observations		18,143	18,143	18,143	18,143
Adjusted R^2		0.013	0.013	0.011	0.011

Panel C.		Dependent Variable: *Dis_Accruals_K*			
	Predict	(1)	(2)	(3)	(4)
Emp_Health	(-)	-0.143*	-0.183**	-0.143*	-0.180**
		(-1.423)	(-1.777)	(-1.388)	(-1.704)
Observations		18,121	18,121	18,121	18,121
Adjusted R^2		0.004	0.003	0.001	0.001

Panel D.		Dependent Variable: *Restate*			
	Predict	(1)	(2)	(3)	(4)
Emp_Health	(-)	-0.014**	-0.012*	-0.010*	-0.009*
		(-1.758)	(-1.616)	(-1.378)	(-1.346)
Observations		12,923	12,923	12,923	12,923
Adjusted R^2		0.006	0.005	0.024	0.023
For all models:					
Controls		Yes	Yes	Yes	Yes
Fixed Effects		None	Year	Ind	Year, Ind

Table 5 presents the regression results from examining the association between employee health and alternative measures of firms' financial reporting quality. Employee health (*Emp_Health*) is measured using the average health of the workforce in a firm's headquarter city. Financial reporting quality is measured based on discretionary revenue (*Dis_Revenue)* in Panel A and accruals measures (*Dis_Accruals_J*, *Dis_Accruals_K*, and *Restate* in Panels B, C, and D. T-statistics are reported in paratheses. Standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (one-tailed tests for variables with predictions, otherwise two-tailed), respectively. Control variables are included but not tabulated for brevity. Variables are defined in Appendix A.

Table 6

Shock to Employee Health and Financial Reporting Quality

		Dependent Variable:			
		FSD_Score			
	Predict	(1)	(2)	(3)	(4)
Treat		0.001	0.001	0.000	0.000
		(0.893)	(0.862)	(0.378)	(0.461)
Post		0.000	0.000	0.000	0.000
		(0.004)	(0.008)	(0.161)	(0.045)
*Treat * Post*	(-)	-0.002**	-0.002**	-0.002**	-0.002**
		(-1.909)	(-1.858)	(-1.877)	(-1.922)
Adjusted R^2		974	973	974	973
Observations		0.276	0.275	0.320	0.320
For all models:					
Controls		Yes	Yes	Yes	Yes
Fixed Effects		None	Year	Ind	Year, Ind

Table 6 presents the regression results from examining the association between a shock to employee health and firms' financial reporting quality. *Treat* is equal to one for firms that relocate to more healthy cities, negative one for firms that relocate to less healthy cities, and zero for control firms. *Post* is equal to one for year of and after the firm's relocation and zero otherwise. *Treat * Post* reflects the effect of relocating on financial reporting quality for treatment firms. Financial reporting quality is measured using the Financial Statement Divergence Score (*FSD-score*), which is based on deviations from Benford's Law. T-statistics are reported in paratheses. Standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (one-tailed tests for variables with predictions, otherwise two-tailed), respectively. Variables are defined in Appendix A.

Table 7

Shock to Employee Health and Financial Reporting Quality (subsamples)

Panel A.		*Dependent Variable:*			
		FSD_Score			
	Predict	(1)	(2)	(3)	(4)
Treat		0.001	0.001	0.001	0.001
		(0.728)	(0.601)	(0.717)	(0.675)
Post		0.001	0.001	0.001	0.001
		(1.037)	(1.003)	(1.214)	(0.989)
*Treat * Post*	(-)	-0.003*	-0.003*	-0.003*	-0.003*
		(-1.600)	(-1.373)	(-1.465)	(-1.330)
Adjusted R2		511	511	510	510
Observations		0.280	0.277	0.323	0.326
Panel B.		*Dependent Variable:*			
		FSD_Score			
	Predict	(1)	(2)	(3)	(4)
Treat		-0.001	-0.001	0.000	0.001
		(-0.455)	(-0.376)	(0.236)	(0.270)
Post		-0.000	-0.000	-0.000	0.000
		(-0.322)	(-0.166)	(-0.059)	(0.065)
*Treat * Post*	(+)	0.003**	0.003*	0.003*	0.003*
		(1.662)	(1.568)	(1.507)	(1.428)
Adjusted R2		463	462	462	461
Observations		0.288	0.287	0.317	0.318
For all models:					
Controls		Yes	Yes	Yes	Yes
Fixed Effects		None	Year	Ind	Year, Ind

Table 7 presents the regression results from examining the association between a shock to employee health and firms' financial reporting quality. In Panel A (B), we use the relocation of a firm's headquarters to a more (less) healthy city to identify a positive (negative) shock to employee health. *Treat* is equal to one for firms that relocate and zero for control firms. *Post* is equal to one for year of and after the firm's relocation and zero otherwise. *Treat * Post* reflects the effect of relocating on financial reporting quality for treatment firms. Financial reporting quality is measured using the Financial Statement Divergence Score (*FSD-score*), which is based on deviations from Benford's Law. T-statistics are reported in paratheses. Standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (one-tailed tests for variables with predictions, otherwise two-tailed), respectively. Variables are defined in Appendix A.

Table 8
Cross-Sectional Analyses Based on Financial Reporting Complexity

Panel A.		*Dependent Variable:* *FSD_Score*			
	Predict	(1)	(2)	(3)	(4)
ARC		0.000	0.000	-0.000	-0.000
		(0.636)	(0.120)	(-0.361)	(-1.082)
Emp_Health		0.004*	0.004*	0.003	0.003
		(1.914)	(1.920)	(1.448)	(1.508)
*ARC * Emp_Health*	(-)	-0.000***	-0.000***	-0.000***	-0.000***
		(-4.105)	(-4.062)	(-3.401)	(-3.326)
Observations		13,657	13,656	13,657	13,656
Adjusted R^2		0.305	0.306	0.331	0.332

Panel B.		*Dependent Variable:* *FSD_Score*			
	Predict	(1)	(2)	(3)	(4)
Intangibles		-0.002	-0.002	-0.001	-0.001
		(-1.287)	(-1.309)	(-0.700)	(-0.736)
Emp_Health		-0.001	-0.001	-0.001	-0.001
		(-0.879)	(-0.988)	(-0.711)	(-0.622)
*Intangibles * Emp_Health*	(-)	-0.008***	-0.008***	-0.008***	-0.008***
		(-2.777)	(-2.737)	(-2.815)	(-2.772)
Observations		18,143	18,143	18,143	18,143
Adjusted R^2		0.276	0.275	0.301	0.301

Panel C.		*Dependent Variable:* *FSD_Score*			
	Predict	(1)	(2)	(3)	(4)
Segments		0.000	0.000	0.000	0.000
		(0.876)	(0.862)	(0.445)	(0.439)
Emp_Health		-0.001	-0.001	-0.001	-0.001
		(-0.427)	(-0.461)	(-0.755)	(-0.617)
*Segments * Emp_Health*	(-)	-0.002**	-0.002**	-0.001*	-0.001*
		(-2.107)	(-2.086)	(-1.478)	(-1.470)
Observations		18,143	18,143	18,143	18,143
Adjusted R^2		0.275	0.275	0.301	0.301
For all models:					
Controls		Yes	Yes	Yes	Yes
Fixed Effects		None	Year	Ind	Year, Ind

Table 8 presents regression results from cross-sectional analyses based on complexity of financial reporting. Employee health (*Emp_Health*) is measured using the average health of the workforce in a firm's headquarter city. Financial reporting quality is measured using the Financial Statement Divergence Score (*FSD-score*), which is based on deviations from Benford's Law. Complexity is measured as the number of accounting items in the 10-K filing (*ARC*) in Panel A, intangible assets (*Intangibles*) in Panel B, and the number of business segments (*Segments*) in Panel C. T-statistics are reported in paratheses. Standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (one-tailed tests for variables with predictions, otherwise two-tailed), respectively. Control variables are included but not tabulated for brevity. Variables are defined in Appendix A.

Table 9

Employee Health and Qualitative Reporting Quality

		Dependent Variable: *BOG_Index*			
	Predict	(1)	(2)	(3)	(4)
Emp_Health	(-)	-3.502***	-1.335*	-3.329***	-1.177*
		(-3.726)	(-1.399)	(-3.925)	(-1.351)
Observations		17,712	17,712	17,712	17,712
Adjusted R^2		0.167	0.177	0.318	0.327
Controls		Yes	Yes	Yes	Yes
Fixed Effects		None	Year	Ind	Year, Ind

Table 9 presents the regression results from examining the association between employee health and qualitative reporting quality. Employee health (*Emp_Health*) is measured using the average health of the workforce in a firm's headquarter city. Qualitative reporting quality is measured using the *BOG Index*, which captures the plain English attributes of disclosure, provided by Bonsall et al. (2017). T-statistics are reported in paratheses. Standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (one-tailed tests for variables with predictions, otherwise two-tailed), respectively. Control variables are included but not tabulated for brevity. Variables are defined in Appendix A.

Table 10

Employee Health vs. Employee Education

Panel A.

	(1) Education	*(2) Unemployment*	*(3) Wages*	*(4) Population*	*(5) GDP*
Emp_Health	0.552***	-0.086***	0.589***	-0.058***	0.543***

Panel B.

		Dependent Variable							
		FSD_Score							
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Predict	Low	High	Low	High	Low	High	Low	High
Emp_Health	(-)	-0.002*	-0.002**	-0.002*	-0.002*	-0.002**	-0.002**	-0.002*	-0.002*
		(-1.642)	(-2.004)	(-1.538)	(-1.407)	(-1.865)	(-1.653)	(-1.631)	(-1.326)
Test Statistic		0.120		0.010		0.020		0.010	
p-value		*0.734*		*0.916*		*0.886*		*0.932*	
Observations		9,001	9,142	9,001	9,142	9,001	9,142	9,001	9,142
Adjusted R^2		0.237	0.311	0.236	0.311	0.259	0.342	0.258	0.342
Controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects		None	None	Year	Year	Ind	Ind	Year, Ind	Year, Ind

Table 10 presents results to ease concerns that employee health and employee education proxy for the same construct. Panel A presents Pearson correlations between employee health and related MSA variables. Panel B presents the regression results from examining the association between employee health and financial reporting quality for subsamples of low employee education (Low) and high employee education (High). For each fixed effect specification, we compare the coefficients on *Emp_Health* across the Low and High education subsamples. T-statistics are reported in paratheses. Standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels (one-tailed tests for variables with predictions, otherwise two-tailed), respectively. Control variables are included but not tabulated for brevity. Variables are defined in Appendix A.