Does Culture Pay? Evidence from Crowdsourced Employee Engagement Data

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For Review (Online Appendix Starts on Page 52)

Abstract

Corporate culture is increasingly important for retention and employee motivation. First, using a new survey tool with PayScale.com, I show that culture is strongly correlated with employee engagement and both firm productivity and occupational skills. Second, using plausibly exogenous variation in employees' outside options, I find that the average employee is willing to give up 1.7% of their annual earnings ($1,159/year) for a standard deviation increase in culture and that higher income employees are willing to give up even more. These results suggest that companies use culture to hire and retain talented workers.

Keywords: corporate culture, firm value, job satisfaction, turnover, compensating differentials, productivity.

JEL: L20, M51, M52, M54, M55

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1 Introduction

> There are only three measurements that tell you nearly everything you need to know about your organization's overall performance: employee engagement, customer satisfaction, and cash flow. It goes without saying that no company, small or large, can win over the long run without energized employees who believe in the mission and understand how to achieve it. – *Jack Welch, former CEO of General Electric*

While executives and organizational behavior researchers routinely emphasize culture as an integral factor behind employee engagement and retention, financial and applied economists have had less to say about how corporate culture quantitatively affects firm outcomes and the underlying practices that define culture in an organization.[1] This paper introduces a measure of corporate culture that is consistent across organizations and quantifies how companies leverage their culture to drive employee engagement and retention as an ingredient in their strategy.

According to Deloitte [2016], 78% of today's business leaders report employee engagement and retention of talent as one of their top concerns. Moreover, these concerns have been growing over time: Google Trends' index on "employee engagement" has tripled from 25 in January 2004 to 75 in November 2017. Related organizational behavior and strategy literatures have emphasized how employee engagement has been linked with a greater sense of purpose at work [Amabile and Kramer, 2012], increased creativity [Amabile et al., 2004, 2005], performance [Harter et al., 2016], and even competitive advantages in the marketplace [Chatman and Jehn, 1994, Bennett and Pierce, 2016]. Microeconomic theorists have also pointed out that managers use non-financial

[1] For example, Guiso et al. [2015] write: "With few notable exceptions, the finance literature has ignored the role corporate culture can play." Although there is some emerging literature, including Edmans [2011], Guiso et al. [2015], Graham et al. [2017a], and Graham et al. [2017b], there is generally little evidence about the quantitative significance of corporate culture. There is, however, a more developed and complementary management science literature on the causal effects of corporate social responsibility (CSR) on firm outcomes, such as innovation [Flammer and Kacperczyk, 2016] and profitability [Flammer, 2015].

instruments to form relational contracts as a mechanism for reducing principal-agent problems by promoting trust [Baker et al., 2002, Gibbons and Henderson, 2012, Blader et al., 2015].

The first part of the paper introduces a new survey instrument in partnership with PayScale, validated using the Current Population Survey (CPS) and World Management Survey from Bloom and Van Reenen [2007]. PayScale is the leading platform that individuals use to obtain information about current or prospective compensation and that firms use to benchmark their practices with over 10 million views a month. Users visit their site, fill out a salary report, and receive a predicted dollar value corresponding to the market value of their human capital based on the results of a proprietary Bayesian hierarchical learning algorithm. I define corporate culture as the sum across three indices, each on a one-to-five scale, from survey respondents about their perception of workplace practices relating to the clarity of communication, degree of recognition and appreciation, and managerial quality. Each component explains variation in employee engagement and turnover, but employee appreciation explains roughly twice the variation as the others.[2]

The second part of the paper uses this measure of corporate culture to document several descriptive statistics. For example, I show that corporate culture is higher in: (i) occupations with greater cognitive and social skill intensities, but lower in manually intensive occupations, (ii) metropolitan areas that are larger, more educated, and have lower unemployment rates, and (iii) firms that are more productive and larger (employment or assets). In fact, a 1sd rise in

[2]This approach to measuring culture complements linguistic approaches that leverage the text included in respondent ratings; see, for example, Corritore et al. [2019] for a recent introduction of a cultural cohesion measure based on Glassdoor ratings text. My measure of corporate culture is also correlated with the Great Places to Work (GPTW) survey rankings used in Edmans [2011] and but contains two substantial refinements. First, my measure of culture captures many more companies and contains a multidimensional view of culture. In contrast, the GPTW survey is limited to a subset of companies and Guiso et al. [2015], for example, are forced to define culture based on responses to two questions: "management's actions match its words" and "management is honest and ethical in its business practices". Second, my data enables me to estimate employees' willingness to pay for corporate culture using individual-level information on compensation and demographics, which is an important parameter for valuing the benefits of culture and understanding why companies invest in it.

culture is associated with a 0.59sd rise in firm revenues and a 0.71sd rise in operating income before depreciation, conditional on employment, capital, and inventory. These correlations suggest culture is linked with firm value because of its causal effect on employee engagement and retention.

The third part of the paper estimates how employees value corporate culture. Empirically recovering a marginal willingness to pay (MWTP) for corporate culture is challenging for two reasons. The first reason, which is already well-known, is that higher productivity individuals are matched into better jobs, producing upwards bias for positive job amenities [Hwang et al., 1998]. The second reason arises from the incentive effects of corporate culture on employee effort. If higher culture raises employee engagement, and the increase in effort is reflected in employee earnings, then standard least squares methods will produce even further upwards bias due to the time-varying firm-specific rent conveyed by these practices. To address these two endogeneity problems, I exploit the fact that PayScale provides users with their market valuation of their skill, which behaves as a proxy for the employee's outside option. While the details of their algorithm are proprietary, what matters is that predicted compensation represents a credible market valuation of an individual's human capital. Indeed, individuals who select into taking the survey do so precisely because they are seeking information on the market value of their human capital and competitive rates for their skill level. The combination of actual and predicted compensation allows me to control for unobserved and time-varying heterogeneity in employee heterogeneity and firm rents

My results suggest that workers are willing to pay (WTP) approximately 1.7% of their earnings for a 1sd rise in their firm's corporate culture, i.e., moving from a company in the 25th percentile, such as McDonalds or CVS, to the 75th percentile, such as Exxon Mobile or Starbucks. That amounts to $1,159 per year for the average worker in my sample. While the implied WTP may seem small relative to the 20% in Mas and Pallais [2017] for avoiding unpredictable work schedules,

it is important to keep in mind that corporate culture is a non-rival good within the firm and, therefore, is less significant for a given individual than it is for the entire firm.[3] My estimates are much closer to the willingness to pay for flexibility and security among undergraduate students estimated through a stated choice experiment by Wiswall and Zafar [forthcoming] who find that students are willing to give up 2.8-5.1% of annual earnings for a job with a percentage point lower probability of job dismissal or the option of part-time work. My paper also provides the first causal evidence that the impact of corporate culture on employee engagement is a driving factor behind the returns to intangible capital documented by Edmans [2012].

This paper contributes to several literatures. First, although there is now strong evidence that management practices [Bloom and Van Reenen, 2007, Bloom et al., 2013] and managers [Bertrand and Schoar, 2003] are important determinants of firm productivity, there is much less evidence on how managers create and sustain corporate culture and how that feeds into firm outcomes. The few recent contributions that do exist generally use the "Great Places to Work" (GPTW) list of companies. For example, using the "Great Place to Work" (GPTW) list of companies, Edmans [2011] shows that firms ranking within the top hundred have higher future abnormal stock market returns. Since integrity and trust are components of the GPTW ranking, this suggests that, while the market initially underestimates the value of these intangibles, they appreciate over time as profits begin to accrue to the firm. Similarly, Edmans [2012] shows that companies with higher

[3] Admittedly, however, Mas and Pallais [2017] point out that only a small subset of individuals have a very high valuation of work-place flexibility, in addition to the fact that several other amenities were not valued nearly as much. My results also are conceptually similar to those found by Burbano [2016] who implements a similar natural experiment varying information on the firm's degree of corporate social responsibility (CSR). While Burbano [2016] finds a large WTP of 44% lower bids after learning about employer CSR, one possibility for these differences arises from the fact that participants in her sample are bidding over gigs, rather than long-term careers where the stakes and investments are greater. In either case, these quantitative differences in estimates of WTP highlight the importance of context and motivate greater understanding into the sources of variation between natural experiments and observational studies.

job satisfaction have higher stock returns, suggesting a role for corporate social responsibility. Using the same data, Guiso et al. [2015] find that taking a company public can negatively affect "integrity capital" potentially because they are more beholden to shareholders. Grennan [2017] uses public review company review rates to examine how more stringent shareholder governance structures affect intangible (e.g., culture) versus tangible (e.g., assets) outcomes, highlighting the potential trade-off between different organizational measures of performance.

Both Graham et al. [2017a] and Graham et al. [2017b] take an alternative approach by surveying nearly 1,900 CEOs and CFOs. Survey respondents highlight the importance of culture as an ingredient in their business and factor involved in moving forward with mergers and acquisition deals. However, unlike the GPTW data, these surveys target executives—not the rank and file workers who may have vastly different views about organizational amenities. My paper differs from these prior contributions in two main ways. First, conceptually: in addition to introducing a new survey tool, my focus is on testing a specific channel that links corporate culture with firm value, specifically its impact on employee engagement. When employees enjoy working at their company more, they work longer hours and more productively. Second, empirically: my data allows me to implement a "control function approach" to recover a causal estimate of the value of corporate culture for employees. The granularity of the data also enables me to document several stylized facts that will hopefully be of interest to a broader corporate finance community.

Second, while there is now a rich microeconomic theory literature about the role of relational contracts in resolving incomplete contracts within organization [Baker et al., 2002, Gibbons and Henderson, 2012], there is little causal evidence. Closely related with Blader et al. [2015] who exploit experimental variation in the rollout of a lean management strategy to identify the effects on employee engagement, my paper provides related evidence on a broader scale about the value of

these practices among employees. In other words, by showing that corporate culture not only raises engagement by making work more enjoyable, but also is intrinsically valued among employees, my confirms the theoretical rationale developed by Halac and Prat [2016] that relational contracts can solve shirking problems arising from market incompleteness.[4] This evidence is consistent with an applied psychology literature that has documented the association between job satisfaction and performance [Ostroff, 1992, Judge et al., 2001] and perceptions of work-place conditions and firm outcomes [Harter et al., 2010]. The fact that I also show firms with greater corporate culture exhibit greater financial performance is also consistent with empirical evidence from Gartenberg et al. [2016] about the way culture helps employees feel like they are doing meaningful work.

Third, while an ongoing debate exists about the sources of wage dispersion reflecting either job amenities that are priced by the market ("compensating differentials") [Rosen, 1986] or rents that accrue to higher productivity workers [Postel-Vinay and Robin, 2002], there is little empirical evidence on their relative magnitudes. Using an identification strategy that is conceptually related to Stern [2004], my paper contributes to this literature by explicitly recovering a MWTP for corporate culture, thereby illustrating that the market values corporate culture. Other approaches, however, focus on using flows between workers and firms [Sorkin, 2018], explicit parameterizations of the sorting process [Bonhomme and Jolivet, 2009], and randomized experiments [Mas and Pallais, 2017, Burbano, 2016] to recover causal estimates. Given that machine learning algorithms are becoming more applicable in economics [Athey and Imbens, 2017, Mullainathan and Spiess, 2017], and access to administrative datasets is opening up [Card et al., 2011], implementing variants of this identification should become more viable in the years to come.

[4]These results relating corporate culture with employee engagement also build upon an older literature on organizational capital, which helps solve coordination problems in the firm [Prescott and Visscher, 1980, Andrew and Kehoe, 2005]. Dessein and Prat [2019] develop a new framework that uses organizational capital to relate different theories about the role of management practices.

2 Defining Corporate Culture and Why It Matters

There is now ample evidence that management practices affect firm productivity [Bloom and Van Reenen, 2007, Bloom et al., 2013] and corporate strategy [Bertrand and Schoar, 2003]. However, there is much less empirical evidence on the mechanisms through which they shape corporate culture and how it feeds into firm productivity. Corporate culture, broadly speaking, refers to "the values and norms widely shared and strongly held throughout the firm that help employees understand which behaviors are and are not appropriate" [O'Reilly and Chatman, 1996]. Whereas values refer to underlying principles or standards, norms refer to the basic day-to-day practices that are manifested as a function of the values. Weak culture can emerge due to a wedge between values and norms because it is the glue that holds them together.[5]

Unfortunately, measuring values and norms is empirically challenging and typically subject to the limitations of available survey data. For example, the Great Places to Work (GPTW) survey contains survey questions that ask about integrity and trust, which Guiso et al. [2015] examine before and after a company goes public. Similar approaches sometimes use rankings from available surveys. For example, Edmans [2011] and Edmans [2012] examines the stock returns of companies that are ranked within the top hundred in the GPTW survey. Other strategies involve creating and distributing surveys, such as the World Management Survey in Bloom and Van Reenen [2007] and the recent survey of corporate culture in Graham et al. [2017b]. My approach, discussed in the next section, follows most closely along these latter lines based on a crowdsourcing approach

[5]For example, Guiso et al. [2015] begin their paper by quoting a former Goldman Sachs vice president who remarked that "Culture was always a vital part of Goldman Sachs' success. It revolved around teamwork, integrity, a spirit of humility, and always doing right by our clients... I am sad to say that I look around today and find virtually no trace of the culture that made me love working for this firm for many years."

with survey questions introduced on PayScale's existing salary profile survey.

There are at least two reasons corporate culture might matter for firm outcomes and productivity. The first is through a selection channel. Firms that have a better culture make it attractive for prospective employees with similar values to self-select into their firm. For example, Southwest Airlines' mantra is exceptional customer service, meaning that employees with a taste for the value of customer service will, therefore, be more likely to self-select into the firm [Roy, 1951]. While the presence of non-wage benefits also plays a role in attracting different types of prospective employees [Liu et al., 2019], culture is another important factor.

The second is through an incentives channel. Principal-agent problems emerge since contracts are incomplete and employees are heterogeneous [Grossman and Hart, 1983]. Many tasks among employees require actions that cannot be fully contracted upon ex-ante; instead, companies create standards and processes for handling classes of tasks and events. Microeconomic models with principal-agent problems suggest that managers who develop relational contracts can help promote trust and mitigate shirking problems that may arise [Gibbons and Henderson, 2012]. For example, even if these standards and processes are effective at getting employees to make the right decisions, employee effort may still decline if employees think that management is not paying attention and recognizing their efforts [Halac and Prat, 2016], consistent with applied psychology literature linking employee job satisfaction with their perceptions about work-place practices [Ostroff, 1992, Judge et al., 2001, Riketta, 2008]. Because employee perceptions matter and influence their effort, recognizing good performance is also linked with firm performance [Harter et al., 2010].

In addition to simply helping employees feel appreciated, corporate culture can provide workers with a sense of purpose behind the work that they do, thereby feeling more motivated and raising firm performance [Harter et al., 2010, Gartenberg et al., 2016]. Firms with better corporate culture

also have higher job satisfaction, which is related with higher abnormal stock returns [Edmans, 2012]. There is also some limited experimental evidence that the introduction of lean management practices can raise employee engagement [Blader et al., 2015]. Especially in cognitive and non-routine work where the incentive to shirk might be greater since the cognitive costs of tasks is higher, employee engagement is especially important.

Appendix Section A builds a stylized theoretical model that shows that one reason companies may provide corporate culture is to raise employee engagement and, in turn, reduce the incentive to shirk. When employees face a lower disutility of labor services, they will allocate more time and/or effort towards the firm. Greater employee engagement has a number of additional benefits for firms. For example, higher job satisfaction is associated with lower turnover [Tett and Meyer, 1993, Huselid, 1995]. Employee engagement has also been linked with a greater sense of purpose at work [Amabile and Kramer, 2012], increased creativity [Amabile et al., 2004, 2005], performance [Harter et al., 2016], and even competitive advantages [Chatman and Jehn, 1994, Bennett and Pierce, 2016]. Corporate culture might be especially important in the financial services sector where the bulk of decisions are made when no one is looking [Song and Thakor, 2016].[6]

If there are a set of best practices within organizations [Baligh and Burton, 1981, 1984], why do many firms fail to adopt them? Many of these reasons overlap with the emerging literature on management and productivity (see Bloom et al. [2014] for a survey), but there is an even stronger role of organizational inertia as the source of coordination problems when it comes to employment practices. Adjustment costs may vary based not only on the external environment (e.g., regulatory), but also internal environment: the degree of flexibility in an organization's

[6]Bank culture has received significant media attention, especially after the Wells Fargo scandal in 2016 and 2017. Moreover, the federal reserve has commented on the importance of bank culture for a safe and stable banking structure (https://www.bloomberg.com/news/articles/2018-06-18/fed-s-williams-sees-rosy-economy-bank-culture-still-needs-work).

coordinating structure.[7] For rigid organizations, innovation is difficult and costly because their internal processes are not agile enough to adapt to a changing environment. External factors, like the capital intensity of production, may also affect the underlying contracting structure [Makridis and Gittleman, 2018], which in turn shapes the employment practices.

Since corporate culture is costly to implement, they may trade-off with other mechanisms firms can use to motivate employees (e.g., bonuses). The design perspective of management emphasizes that firms face different environments, which affects the returns to using different sets of practices (even if the practice itself were free). Companion work examines several channels that explain the adoption of non-wage benefits, which are conceptually similar to corporate culture [Liu et al., 2019], including: (i) the selection effects that attract and retain particular types of workers, (ii) labor market distortions (i.e., marginal income tax rates) that discourage the use of cash compensation over benefits, and (iii) the incentive effects of greater employee engagement. Another possibility, based on early theoretical work from Milgrom [1988], is that it can be optimal for management to reduce the room for discretion among employees, which may be especially likely in settings where it is more costly to observe employee quality or trustworthiness. In either case, the fact remains that certain types of work-place practices might be more advantageous in certain settings than others, explaining some of the dispersion in the data.

3 Measuring Corporate Culture and Engagement

[7] The organizational behavior literature tends to call these "vulnerability costs". Malone [1987] argued that organizations incur different costs associated with adjustment based on their coordinating structures.

3.1 Survey Tool

To measure corporate culture in the work place, I partnered with PayScale (www.payscale.com), a crowdsourcing company that uses frontier machine learning algorithms to provide better business intelligence for both companies and employees over a range of compensation issues, ranging from actual pay to human resources. PayScale's specialization is valuing human capital. PayScale has compiled over 56 million salary profiles and is rapidly transforming the landscape of compensation analysis through their combination of data analytics with market analysis. Their primary service involves offering individuals a market valuation of their human capital, which they do using a proprietary parametric Bayesian model (double-Pareto distribution).[8] Because of their large sample, together with detailed individual information on industry, occupation, experience, education, and skills, they produce detailed predicted measures of compensation.

While they have both business and consumer oriented services, its consumer oriented services provide individuals with a predicted market wage and job suggestions based on an unusually detailed set of information that individuals provide, ranging from specific skills (e.g., Matlab, Python, or search engine optimization) to metropolitan area to the university that they earned their degree from. The survey tool was recently extended in 2014 to include measurements of perceptions of work-place practices, which are listed in Table 1. Individuals respond to these survey questions on a scale of one to five.

The primary measure of corporate culture is the normalized (mean zero, standard deviation of unity) sum of the scores on communication, appreciation, and managerial relationship, which omits the contribution of scores on pay transparency and development & training opportunities; taking

[8] https://www.payscale.com/data/payscale-methodology-explained

the sum of sub-indices has precedent from prior work [Bloom and Van Reenen, 2007].[9] While each of the measures of corporate culture matters (shown in the next sub-section), Appendix Section B.1 documents, using principal-components analysis, that the first factor explains roughly 60% of the variation and the first two factors explain roughly 75% of the variation. Using a consolidated score helps reduce noise and multicollinearity, in addition to making the results more transparent. Although theory only provides some guidance on which of the indices should be used in the overall score, the main results are robust to different variations of the index. An important advantage of these measures is that they allow me to test for complementarities across different dimensions of corporate culture. Many current theories of corporate culture, for example, argue that there are trade offs in different firm values [Goffee and Jones, 1996, Groysberg et al., 2018]. However, consistent with recent evidence from Ichniowski et al. [1997] and Sull et al. [2018], I show a high correlation (i.e., complementarity) across these dimensions of corporate culture.[10]

[INSERT TABLE 1 HERE]

While these variables are "subjective" self-reported indices, it is precisely these perceptions that matter in the work-place—managers are held accountable to outcomes, which are influenced by employee perceptions even when the perceptions are "wrong". In addition, the survey tool also contains at least two advantages over standard publicly accessible labor market survey data: sample size and incentives to report truthfully.[11] First, the sample size allows PayScale to leverage the

[9] These variables are chosen because they broadly describe what many in the literature think of in terms of a "company culture" and are highly correlated with job satisfaction, as will be shown shortly. Hagerty and Land [2007] find that using equal weights over subset variables for these types of indices provides the greatest robustness and accuracy. The problem of potentially different weights also tends to be relatively innocuous of an assumption when all are highly positively correlated.

[10] These results do not rule out, however, the potential that there is simply a strong common component among them. To mitigate that concern, I regress the dimensions of culture on firm fixed effects and create leave-one-out firm averages for each firm. These resulting measures are also correlated.

[11] For example, traditional surveys, like as the Panel Study of Income Dynamics, are notorious for having large

benefits of "wisdom of the crowds", famously introduced by Surowiecki [2004], which describes how aggregating the opinions from a large number of individuals can produce more accurate forecasts than opinions from a much smaller group of experts. While this paper only uses a subset of their entire database, their "big data" approach to human resource management enables them to create reliable predictions of an individual's earnings.[12] Second, individuals reached by PayScale have an incentive to report truthfully since the quality of their predicted market wage and job suggestions is governed by the accuracy of their own situation. The "give and get" nature of the survey embeds incentives for truth-telling with recent experimental evidence validated on Glassdoor data [Chamberlain et al., 2019]. In addition to these perceptions of organizational amenities measurements, PayScale also tracks their demographic information (age, gender, experience, tenure, and race), industry and occupation classifications, metropolitan area, annual earnings ("compensation"), and bonus, commission, and profit sharing income.

What types of workers are these? Appendix Section C.1 reports some aggregate descriptive statistics separating individuals out based on whether they report a high level of an organizational state (a four or five out of the five-point scale) versus a low level (a one, two, or three out of the five-point scale). The results are documented in Table 7 in full, but, broadly speaking, they show that individuals reporting higher corporate culture have systematically higher earnings. However, they are not much more likely to be more educated, nor are they more likely to receive performance

measurement error [Bound et al., 2001, Bound and Krueger, 1991, Duncan and Fields, 1985]. Although there is the potential for measurement error arising from "cognitive dissonance"—that is, employees with low salaries might also report low culture since they might be unhappy with the firm because of low pay—these concerns are inherent in survey data. However, because of a unique feature of the PayScale data, specifically its measure of pay transparency (the degree the individual believes they are paid in a fair and transparent way), I have examined the sensitivity of the main results to the inclusion of pay transparency as an additional control; the results are invariant.

[12] PayScale's proprietary machine learning algorithms flexibly account for differences across metropolitan areas, occupations, industries, different quantities and qualities of educational attainment, job characteristics, and demographics to produce accurate predictions (after undergoing a data-cleaning process).

pay. As an additional test, I also compare the conditional correlation between standardized job satisfaction and years of employee tenure obtained from the PayScale data with the conditional correlation obtained from the National Longitudinal Survey of Youth (NLSY79). The NLSY79 is a cohort-based survey that contains roughly 6,000 individuals each year from 1979 onward. Regressing job satisfaction on years of tenure produces a coefficient of 0.0032 in the PayScale data versus a coefficient of 0.0026 in the NLSY data (significant at the 1% level), suggesting that differences in sample selection are not a major concern for external validity.

3.2 Data Validation and Firm Outcome Correlations

There are two potential concerns remain involving the representativeness of the sample. The first concern is that the sample of workers in PayScale's database is systematically different than the U.S. population, which would imply that the results are not externally valid. To address this concern, my first exercise compares the PayScale data with the Current Population Survey (CPS) between 2014 and 2016. Figure 1 plots the share of workers who are white, average age, average educational attainment, and average earnings at a two-digit occupation level between the two datasets. Although the extent of the similarity is in the eye of the beholder, PayScale does a fairly good job at matching the nationally representative data from the CPS, despite a slight oversampling of young and college-degree workers. Table 6 in Appendix Section B.2 presents more formal difference of mean comparisons by occupation with p-values. The largest differences generally exist in traditionally low skilled occupations, such as production and construction, since there are few skilled workers to begin with and PayScale is even less likely to attract them.

[INSERT FIGURE 1 HERE]

The second concern is that these indices are merely capturing noise and unobserved heterogeneity in preferences, which would invalidate them as underlying measures of corporate culture. First, Appendix Section B.2 presents correlations between PayScale's measure of culture / job satisfaction and both the Great Places to Work (GPTW) firm ranking used in Edmans [2011] and Guiso et al. [2015] and measures of life satisfaction and work-place practices from Gallup's U.S. Daily Poll used in Makridis [2019a]. Second, I now provide more formal evidence that these perceptions of corporate culture are associated with actual differences in firm outcomes (e.g., sales). Suppose firms have a Cobb-Douglas production function

$$y_{ft} = \gamma C_{ft} + \alpha^l l_{ft} + \alpha^k k_{ft} + \alpha^m m_{ft} + \epsilon_{ft} \tag{1}$$

where y denotes a measure of firm outcomes, C denotes corporate culture, l denotes logged employment, k denotes logged capital, m denotes logged materials. Firm outcomes are measured using logged revenues and operating income before depreciation on a sample of publicly traded companies contained in the PayScale data with over 10 respondents. Although there are 1,997 unique companies, only 777 have over 10 survey respondents, which is important for ensuring that the measure of culture is not simply driven by sampling variability.

These results are documented in Table 2. Starting with logged revenue as the outcome variable in columns 1-5, there is a noisy, but positive, unconditional correlation: a 1sd rise in culture is associated with a 0.092% rise in revenue. However, once subsequent controls—employment, capital, and inventories—are added, the correlation becomes more economically and statistically significant. In particular, under the preferred specification, a 1sd rise in culture is associated with a large 0.593% rise in revenues. One reason for the rise in both economic and statistical significance

arises from the correlation between sampling variability due to sample size considerations and firm characteristics—for example, logged employment explains 21% of the variation in the number of survey respondents in a firm. In this sense, these controls mitigate some of the bias that attenuates the bias in the unconditional correlation. These correlations are even larger in magnitude when the outcome variable is logged operating income before depreciation.[13]

[INSERT TABLE 2 HERE]

4 Descriptive Evidence on the Cross-section of Culture

4.1 Heterogeneity Across Firms

There is incredible variation in corporate culture across companies. After restricting the sample to companies with at least 10 respondents, Figure 2 plots the distribution of corporate culture in companies below and above the median firm size, which is proxied based on the number of respondents for a firm (median = 32). Interestingly, although the mean firm culture index is similar in larger versus small firms (10.59 versus 10.61), the distributions are very different. For example, small firms have a 44% wider dispersion in culture with a standard deviation of 0.918 versus 0.613 among their larger firm counterparts.[14] The fact that larger firms have better corporate culture is consistent with the emerging new economics of management literature that has documented a positive association between firm size and management practices [Bloom et al., 2014], which could

[13] Do these associations between firm productivity and corporate culture manifest at a more micro-level? Although data on individual productivity is not available, Table 9 in Appendix Section D shows that increases in corporate culture are robustly associated with increases in self-reported employer performance ratings and declines in both intent to leave and self-reported stress.

[14] Is this result driven by sampling variability in the selection of who participates in the survey? Even when using number of employees from Compustat as the measure of firm size, there is still less variance in self-reported corporate culture perceptions among larger (and, in general, more productive) firms.

be driven the the fact that larger companies face greater returns to promoting culture as a way of reducing shirking and attracting higher quality workers.

[INSERT FIGURE 2 HERE]

4.2 Heterogeneity Across Industries and Occupations

Figure 3 plots contours of standardized corporate culture and financial compensation by two-digit industry × occupation. Although they have a correlation of 0.78, there are some notable differences. Starting with Panel A, which plots dispersion in culture, I find that production and manufacturing workers in the agriculture, mining, manufacturing, and transportation sector report the lowest levels of culture. However, turning towards the same cells in Panel B, which plots dispersion in financial compensation, these workers actually do not have the lowest pay—service workers in legal, education, and healthcare are at the bottom. While production workers report the lowest levels of culture, service and sales/office workers tend to report fairly low levels of culture too. In contrast, business and STEM workers are near the top with managerial workers in professional services and education and healthcare reporting the highest levels.

Again, it is interesting to contrast the dispersion in culture with financial compensation in Panel B. For example, although there are some similarities, financial compensation does not start rising above the standardized value of zero until legal, education, and healthcare service workers and business and STEM workers. Compensation is highest among agriculture, mining, manufacturing, and the information, finance, insurance, and professional services sectors. These differences in pay contrast with the dispersion observed in culture where, for example, services and education and healthcare sectors among managerial workers exhibited the highest levels. These differences

highlight the potential for compensating differentials across jobs.

Appendix Section C.3 correlates culture with measures of skill intensity at the three-digit SOC level using data from the 2010 O*NET and following a similar procedure as Acemoglu and Autor [2011]. There is a remarkably strong positive gradient between corporate culture and both cognitive and social skills, reflecting the fact that these practices are concentrated in high skilled occupations—in part due to high skilled workers' demand for the and potentially due to the complementarity between work-place practices and skills. There is a negative gradient between corporate culture and manual skills, which is a predominantly low skill occupation, and a positive, but slightly noisy, positive gradient with technical skills. These differences may reflect the fact that effort is more important in higher skilled jobs, so the more important it is for companies to create cultures that make workers want to invest their time in the organization.

[INSERT FIGURE 3 HERE]

4.3 Heterogeneity Across Space and Demographics

Figure 4 plots standardized culture, job satisfaction, and compensation across different partitions of the labor market. Beginning with Panel A, there are remarkable differences in measures of culture across education brackets. For example, MBA and law graduates tend to report the highest levels of culture, together with receiving the greatest compensation, with those holding doctorates or masters degree in a close second and followed by college graduates. In contrast, those with only some college report the lowest levels of culture and some of the lowest compensation. Although the fact that their reported levels of culture and job satisfaction may appear odd in light of holding more years of schooling than, for example, those with only a high school degree or no

schooling, it is consistent with the presence of the sheepskin effect where not finishing a college degree conveys a negative signal about ability [Card and Krueger, 1992].

Turning towards Panel B, which documents dispersion across ten of the largest metropolitan areas in the sample, there are again large locational differences. For example, Pittsburgh ranks the lowest in job satisfaction, culture, and financial compensation, whereas San Francisco and San Diego rank the highest. Seattle and Washington DC also rank above average in the sample of these areas, whereas Baltimore and Chicago rank towards the bottom. If the sample were expanded towards other metropolitan areas, the scores would be slightly higher since metropolitan areas tend to attract better companies, relative to their non-metro counterparts.

[INSERT FIGURE 4 HERE]

Appendix Section C.3 correlates corporate culture with various measures of metropolitan outcomes, including logged population, the share of college (and advanced) degree workers, and the unemployment rate. There is a relatively strong inverse U-shape between corporate culture and population, but the gradient becomes strongly positive for metropolitan areas with a population over 450,000. There is also a very strong and positive gradient with educational attainment, which again reflects the fact that more skilled workers are likely to demand higher work-place practices and their tasks are likely to be more complementary to these amenities. There is a negative association with unemployment rates, which reflects the fact that more dynamic labor markets are more likely to produce and offer higher amenities.

Turning to Panels C and D in Figure 4, which plot differences across tenure and experience brackets, there is an interesting U-shape whereby those in their first year of work experience or first year on the job exhibit much greater perceived job satisfaction and corporate culture than their

counterparts who have been working for longer periods. One reason for the "honeymoon" period could arise from the change of pace, relative to their prior job, where corporate practices are new and before routines set in. However, these differences may also emerge from greater competition among companies for top talent, meaning that companies might be working especially hard to retain these new workers. Nonetheless, perceptions of corporate culture decline in both experience and tenure, whereas job satisfaction begins rising again after roughly 6-10 years of work experience or on the job. Once someone has worked for over 15 years in the job or in the labor market, their job satisfaction returns to their initial one-year level. These patterns might also reflect learning about comparative advantage and sorting across jobs.

5 Conditional Correlations of Culture and Engagement

This section explores the relative contribution of different dimensions of work-place practices towards job satisfaction and turnover. Understanding the predictive power of these dimensions, especially corporate culture, provides insight into the mechanism behind the positive association between corporate culture and firm value. If, for example, culture is a mechanism that firms introduce to raise effort and retention in the work-place, then they are able to extract more value from their employees and keep them around longer to raise productivity (e.g., since turnover is a major cost for firms [Huselid, 1995]). Although my measure of corporate culture is constructed using only three of the five—clarity of communication, appreciation, and managerial relationships—I now consider regressions of standardized job satisfaction and intent to leave (turnover) on the broader set of work-place practices detailed in Table 1 and culture.[15]

[15] In additional exercises, I also examine whether there are non-linearities by including including higher-order terms of work-place practices as controls. Interestingly, they were neither statistically or economically insignificant,

Table 3 documents the results associated with regressions of job satisfaction on work-place practices, conditional on individual covariates and year, quarter, two-digit occupation and industry fixed effects. Starting with demographic characteristics, one of the starkest observations is that males have 0.026sd lower job satisfaction after heterogeneity in work-place practices and other individual covariates are included as controls, which contrasts with the 0.07sd higher job satisfaction they exhibit in the raw data. That the magnitude of the gradient not only declines, but also flips, provides a counter-narrative to the popular press view that self-esteem and "glass ceilings" hold back female engagement at work. Age and experience enter positively, which could be consistent with workers learning about their ability and sorting into better job matches over their careers. Finally, much like gender, college attainment enters negatively despite the fact that unconditionally more educated workers have higher job satisfaction (see Figure 4).

Turning towards the gradients on different dimensions of work-place practices, Table 3 illustrates that each dimension is important—they are not simply capturing the same underlying variation, evident by the fact that they are all statistically and economically significant when included together in column 1. Recognition / appreciation is the most predictive determinant of job satisfaction—a 1sd rise in appreciation is associated with a 0.641sd rise in job satisfaction—followed by development and training opportunities and communication as close seconds. Corporate culture, which is defined as the sum of the communication, appreciation, and management indices is also a powerful predictor: a 1sd in culture is associated with a 0.71sd rise in job satisfaction, in addition to explaining 51% of the variation in job satisfaction. The fact that the gradient is higher than any of the dimensions of work-place practices on their own is consistent with empirical evidence from the personnel economics literature about the complementarity of human resource practices;

suggesting that the linear approximation here is sufficient.

"the whole is greater than the sum of its parts" [Ichniowski et al., 1997].

[INSERT TABLE 3 HERE]

To better understand how each of these corporate culture contribute to turnover, measured through an intent to leave indicator variable, I now consider logit regressions of intent to leave on each of the corporate culture, including job satisfaction.[16] Table 4 documents these results. Starting with column 1 as the baseline, males are 3.8% more likely to express an intent to leave their company, which could reflect unobserved differences in preferences about the work environment or bargaining power. Age and experience are negatively associated with intent to leave, which may reflect the accumulation of firm-specific human capital (i.e., reducing the returns to leaving since they would incur a wage reduction). Workers with a college degree also tend to exhibit roughly 0.80pp greater turnover, which could reflect their larger outside option.

Much like the earlier results from Table 3, each dimension of work-place practices is negatively associated with intent to leave. For example, improvements in perceptions of appreciation are most predictive of declines in intent to leave: a 1sd rise in perceptions of appreciation is associated with a 0.19pp decline in the probability the individual reports leaving their firm in the next six months. One difference, however, is that pay transparency is more predictive of intent to leave than it was for job satisfaction. Most importantly, however, a 1sd rise in corporate culture is associated with a 0.194pp decline in the probability of leaving, which is high when paired with the gradient associated with a comparable 1sd rise in job satisfaction, which is associated with a 0.231pp decline. While these estimates are not causal elasticities since they reflect several sources of potential endogeneity, they convey the relative predictive power that different dimensions of

[16] While intent to leave is not a perfect proxy for actual turnover, in robustness, I used the Longitudinal Employer-Household Dynamics (LEHD) data for a validation exercise. I found a correlation of 0.43 between actual turnover and my measure at a two-digit NAICS industry classification.

work-place practices have on job satisfaction and intent to leave.[17]

[INSERT TABLE 4 HERE]

6 The Strategic Value of Corporate Culture

6.1 Identification Challenges

Given that corporate culture is at least important for predicting employee engagement and turnover, I now turn towards a more causal strategy for recovering the value of culture for firms. The conventional approach in labor economics involves estimating hedonic pricing models, which relate job-specific amenities with wages where the coefficient on the job-specific amenity is interpreted as a marginal willingness to pay (MWTP) [Rosen, 1974]. These models are derived from theoretical settings where firms offer heterogeneous amenities and individuals vary in their taste for these amenities, the equilibrium matching between individuals and firms manifests in the wage.

Unfortunately, cross-sectional comparisons between wages and amenities poses at least two challenging identification problems. The first is that unobserved differences in individual productivity are correlated with variation in the provision of corporate culture across firms. Because more productive individuals are more valuable to firms, they are likely to receive job offers from companies that offer not only higher wages, but also higher amenities, thereby producing upwards bias in MWTP [Brown, 1980, Hwang et al., 1998]. The second is that reverse causality might

[17] However, to illustrate that they are not completely contaminated by either measurement error and/or time-varying sources of endogeneity, Table 8 in Appendix Section C.2 reproduces these results at the firm-level for a subset of the broader sample. Two insights emerge. The first is that changes in the demographic characteristics are not heavily correlated with the changes in job satisfaction, suggesting that the measures are not driven by composition effects. The second is that the coefficients are robust to the inclusion of firm fixed effects, which further suggests that the estimated gradients are not driven purely by selection.

imply that increases in compensate may raise employee perceptions about corporate culture.[18] Often referred to as the "halo effect", higher compensate may influence how individuals perceive behavior around them, thereby producing further upwards bias in MWTP.

6.2 Empirical Strategy

In spite of these identification issues, consider an "augmented hedonic regression":

$$\Omega_{ift} = \gamma C_{ft} + \alpha X_{ft} + \beta D_{it} + \eta_f + \lambda_t + \epsilon_{ift} \tag{2}$$

where Ω denotes logged financial compensation, X denotes firm controls, D denotes individual (demographic) controls, C denotes corporate culture, and η and λ denote firm and year fixed effects. Standard errors are clustered at the firm-level [Bertrand et al., 2004].

Identification of γ in Equation 2 requires that unobserved shocks to compensation are uncorrelated with individual perceptions of corporate culture, conditional on individual / firm covariates and firm and time fixed effects. While the inclusion of firm fixed effects is important for removing time-invariant differences across firms that might be correlated with differences across individuals, they leave open the possibility of time-varying selection in the quality of employees as a func-

[18] More generally, better paid individuals may simply perceive better corporate culture. While pay transparency is explicitly an input to the aggregate corporate culture index, and is thus part of the mechanism, there are two ways to examine this concern. First, in Appendix Section C.1, I show that the fraction of workers reporting low versus high job satisfaction is not systematically correlated with whether they receive a bonus. To the extent reverse causality is present, it would be reasonable to suspect that the provision of performance pay would be heavily associated with employee engagement; the fact that it is not is simply one placebo test. Second, in Appendix Section C.1, I also match average firm-level PayScale measures of corporate culture and show that they are positively correlated with human resource management scores from Bloom and Van Reenen [2007]. While the matched sample is very small, it still shows that companies scoring high in PayScale also tend to score high in the well-known Bloom and Van Reenen [2007] double-blind management survey. Third, the baseline estimates are also presented using a leave-one-out firm average measure, which would average out any unobserved heterogeneity that is thought to be driven by different quality of workers having different perceptions.

tion of changes in company policy. For example, if a company experiences an increase in firm value for reasons that are correlated with corporate culture (i.e., acquisition), then they may alter compensation and influence the matching process with prospective employees.

To address the potential for reverse causality, I create a leave-one-out estimate of corporate culture within each firm, which is likely to average out idiosyncratic variation in perceptions about company culture that are correlated with compensation.[19] Moreover, as a robustness exercise that also helps mitigate measurement error, I control for respondent answers to other questions that may also be subject to the halo effect, but are orthogonal to corporate culture, as in Guiso et al. [2015]. To address the potential for time-varying unobserved shocks to compensation, I exploit a unique feature of the data—PayScale's predicted market compensation for each individual—which I use to distinguish between individual human capital and labor market rents.

To implement the logic behind my estimation approach, define logged compensation as the sum of an employee's marginal product, denoted w, and their rents, denoted r:

$$\Omega_{ift} = w_{ift} + r_{ift} \tag{3}$$

Importantly, the micro-data enable me to observe not only employee compensation (Ω), but also the marketplace's valuation of the employee's skills (w), which comes from PayScale's prediction algorithm (see Appendix Section D for details and Figure 16 for a comparison of actual and predicted compensation). Predicted earnings are generated based on a hierarchical Bayesian learning algorithm that incorporates information about their occupation, industry, job title, lo-

[19] While my construction of a leave-one-out estimator might seem inconsistent with the earlier emphasis about the quality of the PayScale data, the two are separate issues. Independent of the reliability of these crowdsourced data, keeping the variation in culture at an individual-level would introduce a strong positive correlation between self-reported culture and unobserved individual heterogeneity that is correlated with wages.

cation, all full suite of demographic and education characteristics.[20] Under the assumption that predicted compensation represents an unbiased measure of the employee's marginal product, then substituting Equation 3 into Equation 2 and simplifying produces:[21]

$$w_{ift} = \gamma C_{ft} - \phi r_{it} + \alpha X_{ft} + \beta D_{it} + \eta_f + \lambda_t + \epsilon_{ift} \tag{4}$$

Crucially, γ is identified in Equation 4 from a quasi "control function approach" where variation in rents are explicitly controlled for. These rents could be due to, for example, unobserved differences across individuals (e.g., productivity) or firms (e.g., human resource management). The approach parallels, in some ways, an approach taken by Stern [2004] in using person-level variation induced by information on their outside option. The outside option focuses only on the variation that captures what the individual is giving up to work for a company that pays below the market wage for the individual's skill type. When the logged difference is negative, the fact that the individual is still working at the company reveals information about the value they place on corporate culture. To better understand the variation in the data, Table 10 in Appendix Section D documents the raw and within-firm variation in earnings and corporate culture.

Table 5 documents the results associated with both the traditional hedonic specification in Equation 2 and the augmented hedonic model in Equation 4. Starting with the standard model, there is a strong positive association between corporate culture and compensation: a 1sd rise in

[20] Information about the employer and/or information on current pay is *not* used for the prediction exercise (since doing so would defeat the purpose of predicting compensation based on employee skills and characteristics.

[21] Suppose that individual output is given by a function with decreasing returns to scale: $y = (hn)^{\alpha}$ where y denotes output, h denotes human capital, and n denotes labor supply. Since the sample is restricted to full-time workers in their prime years, let $n = 1$ such that labor supply is inelastic. Under competitive markets, then the marginal product is given by: $w = \alpha h^{\alpha-1}$. Taking logs of both sides produces: $\ln w = \ln \alpha + (\alpha - 1) \ln h$. Since the market value of the individual's skill is a proxy for their human capital, then $\ln \alpha$ gets absorbed into the constant in the subsequent regression and $(\alpha - 1)$ is simply a scaling term that can be applied to the other terms.

corporate culture is associated with a 12.5% rise in compensation (column 1). While the inclusion of individual characteristics reduces the gradient to 6.7% (column 2), the positive association is inconsistent with the presence of compensating differentials (i.e., employees are willing to pay for improvements in corporate culture). Rather, they suggest that higher quality workers attract labor market rents. However, after controlling for firm fixed effects, the gradient becomes negative, implying compensating differentials [Rosen, 1986]: individuals are willing to pay 2.4% of their annual compensation for a 1sd rise in corporate culture (column 3). The bias that arises from failing to control for time-invariant heterogeneity across firms is consistent with recent evidence that roughly 2/3 of the dispersion in wages is driven by compensating differentials [Sorkin, 2018].

While the traditional hedonic pricing model implies an estimate that is consistent with models of compensating differentials, the estimate is potentially still biased because of time-varying shocks to corporate culture. If, for example, a firm experiences an increase in revenue, then an increase in financial compensation may trade off with an increase in other job-specific amenities, thereby generating downwards bias. Turning towards the augmented hedonic pricing model, which exploits variation in PayScale's proxy for individual human capital and their labor market rents, I find lower magnitude estimates, consistent with my claim that it helps control for differences in time-varying productivity. Under the preferred specification, employee's are willing to pay 1.7% of their annual compensation for a 1sd rise in corporate culture (column 6).

[INSERT TABLE 5 HERE]

As an additional exercise for validating these results, I exploit variation in intent to leave. If these estimates reflect genuine value conveyed by corporate culture on employee productivity, then the benefits should be greatest (and valued the most) among employees who are not planning on

leaving the company in the near future. Estimating Equation 4 separately for workers who intend to leave versus those who intend to stay, I find that the effect is concentrated among those who plan on staying with only a marginally negative and statistically insignificant gradient among those who intend on leaving. In this sense, while improvements in corporate culture may reduce the probability that an individual wants to leave the organization, it is not surprising that employees do not value these improvements conditional on already wanting to leave the company.

How do these estimates compare with other amenities that have been estimated? Felfe [2012], for example, finds that mothers are willing to pay roughly 32% of their earnings to have greater flexibility over their jobs. Consistent with these results, Mas and Pallais [2017] find that the average worker is willing to pay 8% of their wage to work from home—that is, to have a flexible work schedule. Compared to their estimates, my estimate of 1.7% is reasonable because corporate culture is a broad amenity that applies equally, or at least to some extent, across a subset of workers, whereas work schedules are individual-specific. The estimate is also sensible when viewed in light of the fact that many annual raises are on the order of 2%.

Consistent with the intuition behind the stylized model, the returns to corporate culture may be higher for workers who are working longer and/or more intense hours. While the survey does not contain a reliable measure of time use, I use income as a proxy and estimate Equation 4 separately by income bracket. Figure 5 plots the estimated marginal effects separately by income bracket and finds evidence of an inverse U-shape. One reason for the much larger valuation of corporate culture among higher income earners arises from the fact that these individuals spend a lot more time at work and the complexity of their job means that improvements in the environment make work a more fruitful experience.

[INSERT FIGURE 5 HERE]

How much does a standard deviation increase in corporate culture convey in benefits to the typical publicly traded company? While the estimated gradient provides the *average* MWTP for a standard deviation rise in culture, rather than the entire MWTP function, under the assumption that preferences are homogeneous and linear with respect to culture, then the MWTP for it is constant. If all employees value an additional standard deviation in corporate culture at 1.7% of their earnings, then a firm with N employees at a W will have $0.018 \times N \times W$ in marginal benefits. Since the average firm in Compustat over these years has 134,000 employees and average income among the workers in PayScale is $68,206, then these benefits amount to $155,373,300 ($= 0.017 \times 134K \times 68,206$) for the average firm in the sample. While I do not take a stance on the costs associated with the provision of these amenities, they are likely a result of long-run investments in intangible capital [Andrew and Kehoe, 2005], which is an area for future research. Further research should focus on identifying the costs associated with different types of investments in corporate culture to help discipline calculations on the return on investment.

6.3 Addressing Potential Violations

There are at least three remaining concerns with the results thus far. First, exploiting variation in an individual's outside option might not control for variation in search frictions, which is clearly an important confounding factor in models of compensating differentials [Hwang et al., 1998, Bonhomme and Jolivet, 2009]. Appendix Section D examines the potential for bias arising from search frictions by correlating the logged difference between predicted and actual compensation with an enforceability index of non-compete agreements produced by Starr [2015]. While there is

a positive association between the two, it is statistically insignificant at the 10% level, suggesting that the margin for bias is small. One intuitive explanation comes from the complementarity between an individual's human capital and propensity for creating good matches—that is, "luck" is more likely to be attracted to skilled, hard working individuals.

Second, the potential for endogenous job mobility implies that individuals who are about to leave their job will likely get matched to a higher wage (since voluntary moves often result in wage increases), potentially producing downwards bias. To examine the potential for bias as discussed by Lavetti and Schmutte [2016], I estimate a Heckman [1979] selection model that treats $\tilde{w}$ from Equation 4 as missing if the individual reports that they are looking for another job. My orthogonality condition from the Heckman selection model is that job satisfaction affects intent to leave, but does not affect an individual's earnings after controlling for corporate culture. The intuition for the exclusion restriction comes from the fact that the primary, if not sole, purpose of these amenities is to raise employee engagement. The resulting marginal willingness to pay coefficient is -0.014, which is very close to the baseline estimates in Table 5.

Third, even though the baseline specification contains firm fixed effects, it is possible that firms vary other amenities simultaneously with corporate culture. Bias will arise if and only if these other non-wage amenities are correlated with corporate culture and variation in the market's valuation of an individual's human capital. While an example of such a violation is not clear, one scenario is a disruption in a firm's organizational structure, which leads to either an idiosyncratic or aggregate shock to the value of an individual's human capital (e.g., a new innovation that depreciates the worker's skill). While one approach would involve controlling for industry-by-year fixed effects, consistency requires assuming that the time-varying shocks enters through the broader market, rather than through the firm. To address these limitations, I implement the coefficient comparisons

test discussed by Pei et al. [2019] using the number of vacation days as a proxy for other non-wage amenities. However, including it as a control does not lead to statistically different estimates.

6.4 Why Do Some Companies Have Bad Culture?

Given these results about employee's demand for corporate culture and its effect on engagement and firm performance, why do some countries have persistently bad culture? While it is beyond the scope of this paper to provide a microeconomic theory for the decisions of some firms to optimally invest in corporate culture, I provide a brief synthesis in light of the current results.

On one hand, some work-place practices are more useful in some settings than others [Gibbons and Roberts, 2013]. For example, as discussed earlier in Appendix Section C.3, I use data from the Occupational Task Network (O*NET) database—which surveys experts across six-digit occupation classifications over an array of skill intensities, education and experience requirements, and work environment characteristics—I find that occupations with higher corporate culture also have higher concentrations of non-routine and cognitive skill intensities. That is, the returns to employee engagement might be higher in occupations that have greater demands on skill since these are the jobs requiring greater coordination and cognitive processing among employees.

On the other hand, management might be a factor of production that enables greater coordination, meaning that production is strictly increasing in managerial capabilities [Bloom et al., 2015]. For example, Bloom et al. [2015] augment a standard neoclassical model with management and show how doing so helps explain cross-country differences in productivity. In reality, both of these theories are at play: corporate culture raise employee engagement, but especially so in some settings. In this sense, one possible explanation for the wide dispersion in corporate culture is the

fact that firms are subject to different distortions (e.g., regulations), market imperfections (e.g., asymmetric information between employees and employers), or organizational inertia (e.g., see Heath and Heath [2010]). Understanding the factors that explain dispersion in corporate culture and how a given company improves its culture are fruitful areas for further work.

7 Conclusion

Companies overwhelmingly report that employee engagement and retention is one of their top strategic concerns. Thus, understanding the determinants of engagement and retention is important for financial economists to identify the causes of firm productivity. This paper introduces a new survey tool implemented between 2014 and 2016 through a partnership with PayScale (www.payscale.com), a leading data science company that values human capital, to measure corporate culture and quantify employees' valuation of it as one determinant of firm value.

After comparing the sample to the Current Population Survey and World Management Survey, I document the incidence of job satisfaction and corporate culture across a number of labor market dimensions. I find, for example, that firms with better corporate culture also earn more revenue and are larger (e.g., assets and employment) even after conditioning on firm characteristics. Metropolitan areas with higher corporate culture are more educated, have lower unemployment rates, and are larger. I also show that occupations with higher corporate culture have greater cognitive, social, and technical skill intensities.

Motivated by these empirical findings, I examine one reason culture may affect firm value: it raises labor productivity by reducing the temptation for employees to shirk. Since labor supply produces disutility, anything in the work-place that makes it more enjoyable will raise engagement

and, therefore, productivity. After showing that a naive hedonic pricing approach produces biased estimates, I exploit a unique feature of the PayScale data that allows me to control for person-specific rents in the labor market and condition on firm fixed effects. My preferred specification implies that the average worker is willing to give up 1.7% of their annual earnings for a standard deviation increase in culture, which amounts to $1,159 per year.

These results also provide many new directions for future research. First, what are the specific types of behaviors that lead to, for example, low pay transparency or appreciation? Identifying the determinants of employment practices is fundamentally linked to the emerging literature on management as a technology [Bloom et al., 2015]. Second, what role do peer effects play in the work place? Recent papers in the literature on peer effects have suggested that they play a role in increasing positive forms of social norms [Mas and Moretti, 2009], but they may also have adverse effects [Card et al., 2012]. It will be important to control for the quality of peers, e.g., through the average years of schooling among peers within a branch, and so on. Third, how do managers affect corporate culture and how long does it take? While there is a recognition that managerial heterogeneity is an important determinant of firm outcomes [Bertrand and Schoar, 2003] and their overall compensation [Graham et al., 2012], much less is known about their quantitative effects on firm culture (i.e., how leaders can affect firm outcomes [Hermalin, 1998, Komai et al., 2007]). Future work should validate these theoretical predictions by examining how specific actions undertaken by executives ultimately shape employee perceptions about firm culture. With the emergence of similar datasets, academic-industry partnerships can help accelerate our understanding of employee and firm productivity and human capital formation.

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8 Tables and Figures

Variable	Question Text
Intent to leave	In the next 6 months, I plan on actively seeking new jobs outside of my current company. (1/0 indicator)
Job satisfaction	I am extremely satisfied working for my employer.
Relative performance	I am the top performer at my company for jobs similar to mine.
Pay transparency	How pay is determined at my company is a fair and transparent process.
Employer rating	How did your employer rate you in your last review?
Communication	There is frequent, two-way communication between management and myself.
Training opportunities	My employer provides me with sufficient opportunities for learning and development.
Appreciation	I feel appreciated at work.
Future firm prospects	I am confident my employer has a bright future.
Managerial Relationship	I have a great relationship with my direct manager.

Table 1: List of PayScale Survey Measures

Notes.–Sources: PayScale, 2014-2017. The table documents the sentiment-related question text in the www.payscale.com survey tool. Each question, with the exception of intent to leave (which is a 1/0 indicator), ranges on a scale of one to five.

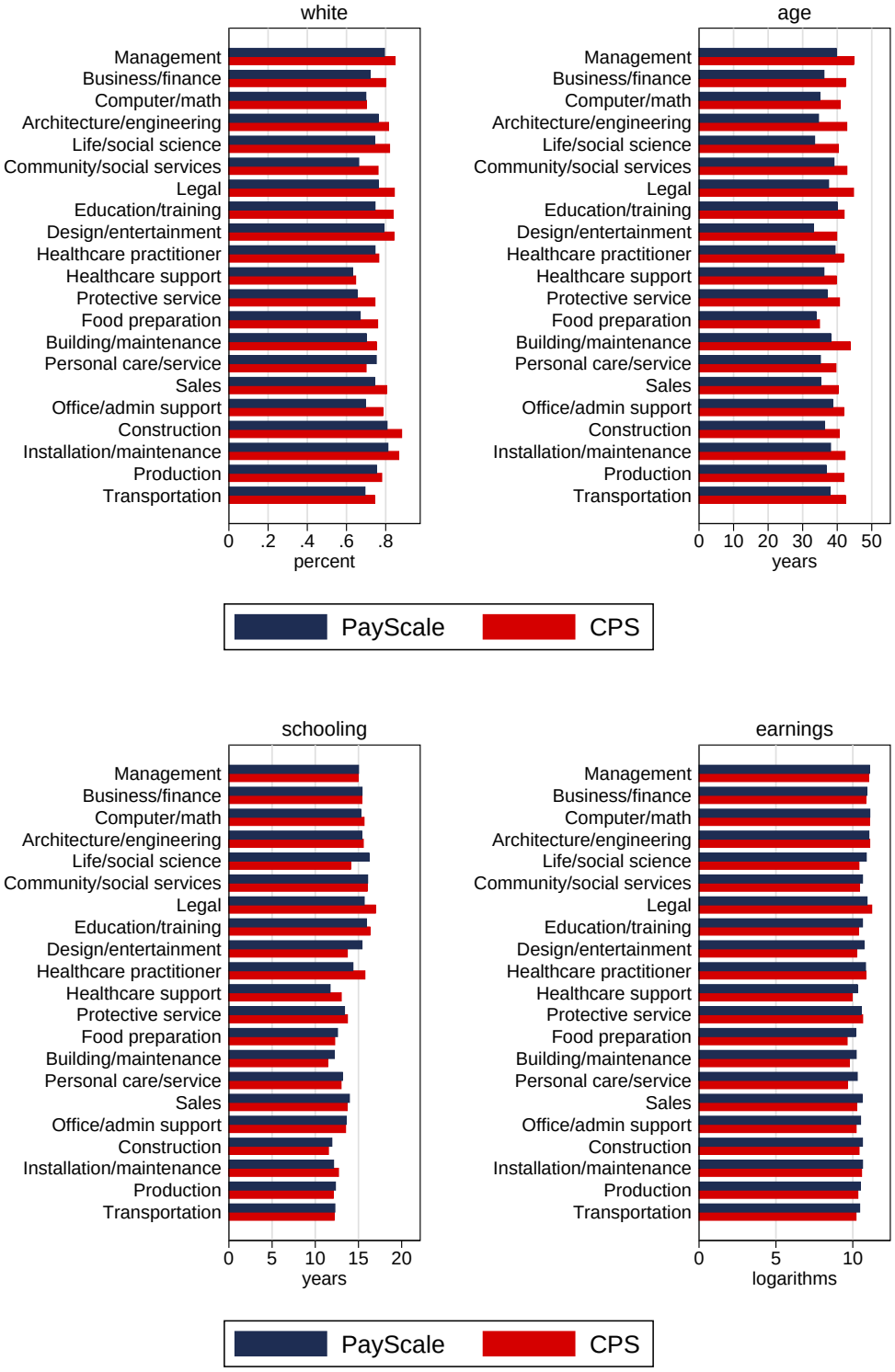

Figure 1: Comparison of Demographics between CPS and PayScale

Notes.–Sources: PayScale and Current Population Survey, 2014-2016. The figure plots the average years of schooling and logged earnings in both datasets separately for each major SOC occupation code. The CPS sample is restricted to the set of employed workers.

Table 2: Conditional Correlations between Corporate Culture and Financial Outcomes

Dep. var. =	ln(raw revenues)					ln(operating income before depreciation)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
corporate culture	.092	.677***	.259**	.514***	.593***	.464**	.942***	.542***	.834***	.707***
	[.199]	[.124]	[.118]	[.163]	[.095]	[.210]	[.164]	[.122]	[.184]	[.118]
ln(employment)		.912***			.524***		.830***			.261***
		[.037]			[.034]		[.038]			[.041]
ln(capital)			.710***		.362***			.770***		.618***
			[.028]		[.024]			[.022]		[.026]
ln(inventories)				.315***	.056***				.282***	.015
				[.020]	[.013]				[.019]	[.014]
R-squared	.00	.70	.68	.33	.81	.01	.49	.72	.28	.75
Sample Size	777	762	755	765	734	754	740	735	743	715
Sample Selection	>10	>10	>10	>10	>10	>10	>10	>10	>10	>10

Notes.–Sources: Payscale and Compustat, 2014-2016. The table reports the coefficients associated with regressions of logged firm revenues and logged operating income before depreciation on a standardized z-score of corporate culture (standardized on the sample of firms retained in the sample of public firms) and production inputs (logged employment, capital, and inventories). Standard errors are clustered at the firm-level.

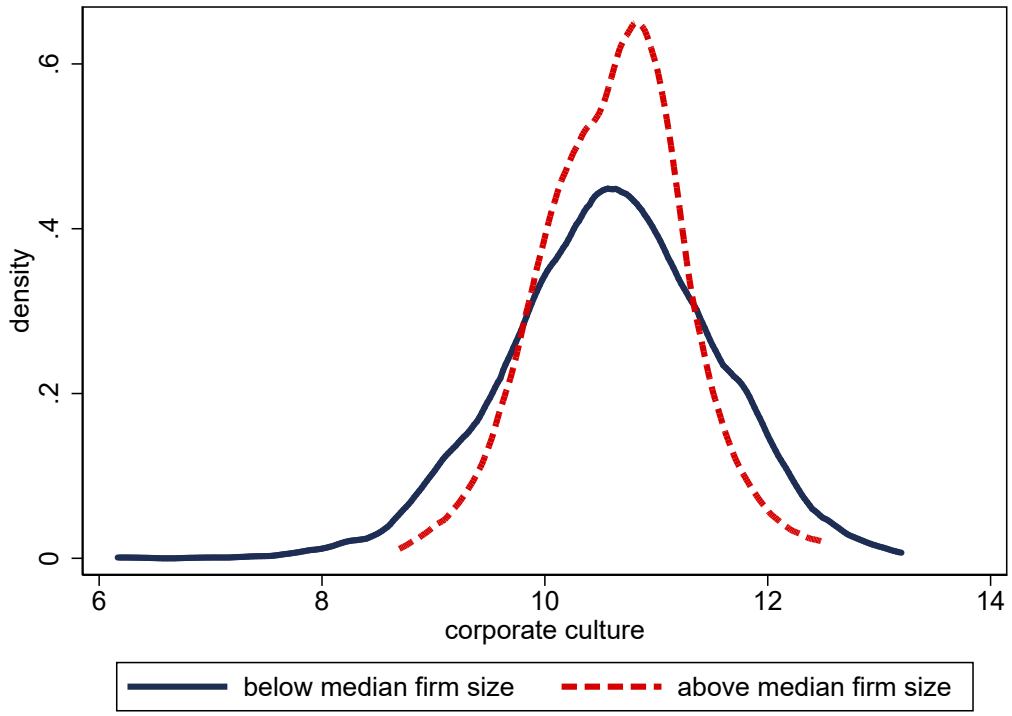

Figure 2: Distribution of Corporate Culture Across Small & Large Firms

Notes.–Sources: PayScale. The figure plots the distribution of corporate culture across small and large firms. Small firms are those with 10-32 respondents in the survey data, whereas large firms are those with over 32 respondents. 32 is chosen because it is the median number of respondents (after dropping firms with under 10 respondents to reduce the amount of noise in the sample.

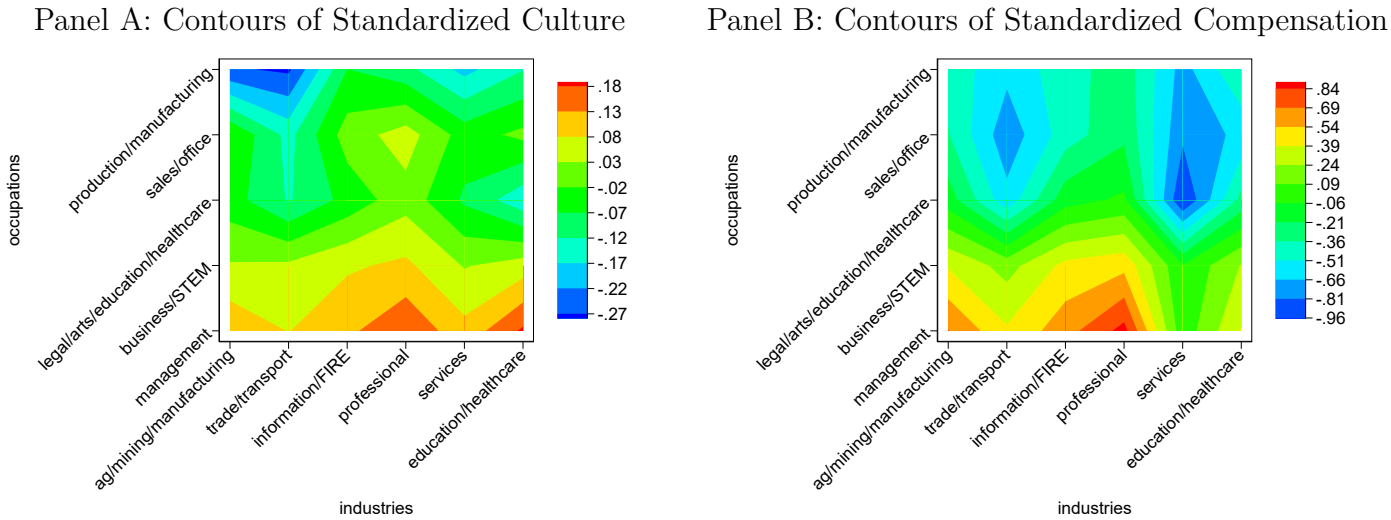

Figure 3: Corporate Culture and Compensation, by Industry and Occupation

Notes.–Sources: PayScale. Panel A plots the standardized z-score of corporate culture across industries and occupations, whereas Panel B plots the standardized logged financial compensation. Observations are unweighted in producing the industry $\times$ occupation average, so the mean in the collapsed series is not zero.

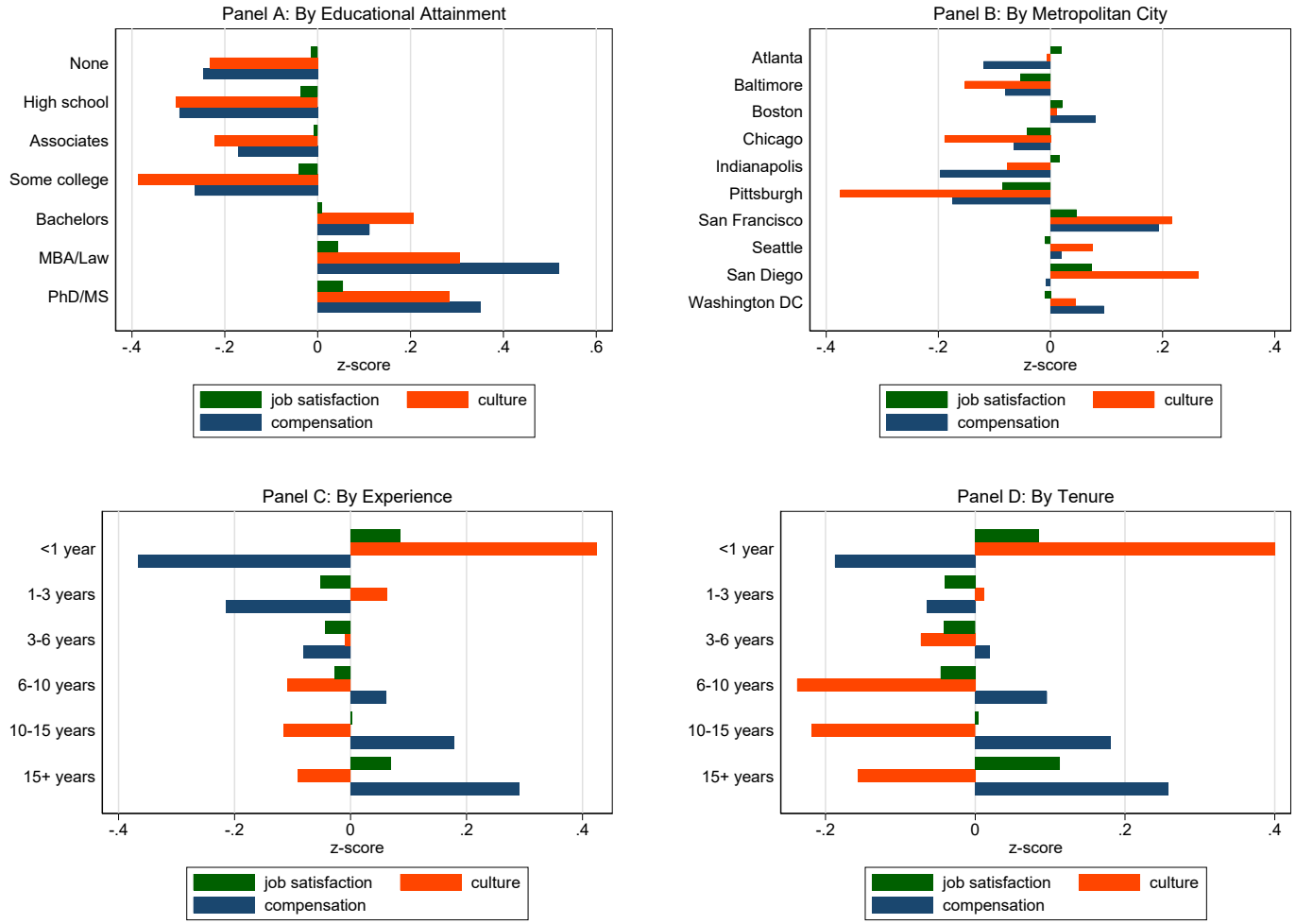

Figure 4: Measuring Standardized Corporate Culture, Job Satisfaction, and Financial Compensation, by Education, Metropolitan Area, Experience, & Tenure

Notes.–Sources: PayScale. The figure plots standardized z-scores of job satisfaction, corporate culture, and compensation across four different partitions of the labor market: education, metropolitan area, experience, and tenure. Each panel is produced by restricting the sample to the relevant observations. For example, Panel B that plots the dispersion across metropolitan areas excludes those metropolitan areas that are not in the plot when computing the z-score to make the comparison in the plot more visually accessible. The individual observations are not weighted when collapsing to each group category.

Table 3: Descriptive Correlations: Job Satisfaction and Corporate Culture

Dep. var. =	job satisfaction, z-score						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
pay transparency	.142***	.479***					
	[.002]	[.002]					
communication	.169***		.555***				
	[.002]		[.002]				
development	.180***			.562***			
	[.002]			[.002]			
appreciation	.317***				.641***		
	[.002]				[.002]		
management	.091***					.481***	
	[.002]					[.002]	
culture							.710***
							[.001]
male	-.026***	-.019***	.018***	.031***	-.017***	.024***	-.024***
	[.003]	[.004]	[.004]	[.004]	[.004]	[.004]	[.003]
age	.004***	.003***	.005***	.005***	.003***	.004***	.005***
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
experience	.001***	-.001***	-.000	.001***	.001***	.000	.001***
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
1[college]	-.051***	-.035***	-.027***	-.034***	-.059***	-.025***	-.045***
	[.003]	[.004]	[.004]	[.004]	[.004]	[.004]	[.003]
R-squared	.52	.24	.32	.33	.42	.25	.51
Sample Size	235760	235760	235760	235760	235760	235760	235760
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes.–Sources: Payscale. The table reports the coefficients associated with regressions of a standardized z-score for job satisfaction (index of one to five) on standardized measures of corporate culture, including pay transparency, communication, development/training opportunities, appreciation, and management, conditional on controls and fixed effects. All specifications include an indicator for gender, years of schooling, age, and labor market experience, as well as fixed effects on year, month, two-digit occupation, and industry. Standard errors are clustered at the firm-level.

Table 4: Descriptive Correlations: Job Turnover and Corporate Culture

Dep. var. =	intends to leave w/in 6 months							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
satisfaction	-.161***	-.231***						
	[.001]	[.001]						
pay transparency	-.029***		-.150***					
	[.001]		[.001]					
communication	.008***			-.151***				
	[.001]			[.001]				
development	-.037***				-.171***			
	[.001]				[.001]			
appreciation	-.050***					-.190***		
	[.001]					[.001]		
management	-.011***						-.142***	
	[.001]						[.001]	
culture								-.194***
								[.001]
male	.038***	.030***	.042***	.028***	.027***	.040***	.026***	.035***
	[.002]	[.002]	[.002]	[.002]	[.002]	[.002]	[.002]	[.002]
age	-.000***	.000	-.001***	-.001***	-.001***	-.001***	-.001***	-.001***
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
experience	-.001***	-.001***	-.001***	-.001***	-.002***	-.002***	-.001***	-.002***
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
1[college]	.008***	.001	.011***	.008***	.011***	.019***	.007***	.014***
	[.002]	[.002]	[.002]	[.002]	[.002]	[.002]	[.002]	[.002]
Sample Size	235761	235761	235761	235761	235761	235761	235761	235761
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes.–Sources: Payscale. The table reports the marginal effects associated with (logit) regressions of an indicator of intent to leave their job in the next six months on standardized z-scores for job satisfaction (index of one to five), pay transparency, communication, development/training opportunities, appreciation, and management, conditional on controls and two-digit industry and occupation and year / quarter fixed effects. All specifications include an indicator for gender, years of schooling, age, and labor market experience, as well as fixed effects on year, month, two-digit occupation, and industry. Standard errors are clustered at the firm-level.

Table 5: Baseline Estimates for Willingness to Pay for Corporate Culture

Dep. var. =	ln(annual compensation)			ln(marginal product of labor)		
	(1)	(2)	(3)	(4)	(5)	(6)
corporate culture	.125***	.067***	-.024***	.116***	.060***	-.017***
	[.012]	[.007]	[.004]	[.011]	[.007]	[.004]
ln(rents)				-.024*	-.147***	-.244***
				[.014]	[.011]	[.009]
R-squared	.01	.44	.62	.01	.47	.64
Sample Size	80086	69478	68842	79832	69272	68727
Controls	No	Yes	Yes	No	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes
Time FE	No	No	Yes	No	No	Yes

Notes.–Sources: Payscale and Compustat. The table reports the coefficients associated with regressions of logged predicted compensation net of actual compensation on a standardized leave-one-out average of corporate culture, conditional on controls, including: a quadratic in age, male, and indicators for seven buckets of educational attainment (high school, associates, some college, college, professional programs [MBA, health policy], and doctorate), and years of labor market experience. Predicted compensation is generated through PayScale's proprietary machine learning algorithms that use their entire salary database of 56+ million individuals in North America. Using predicted compensation as a proxy for the individual's human capital and marginal product of labor, I compute rents by taking the difference between logged financial compensation and logged predicted compensation. The sample is restricted to individuals who report their firm and firms with at least five respondents. Standard errors are clustered at the firm-level.

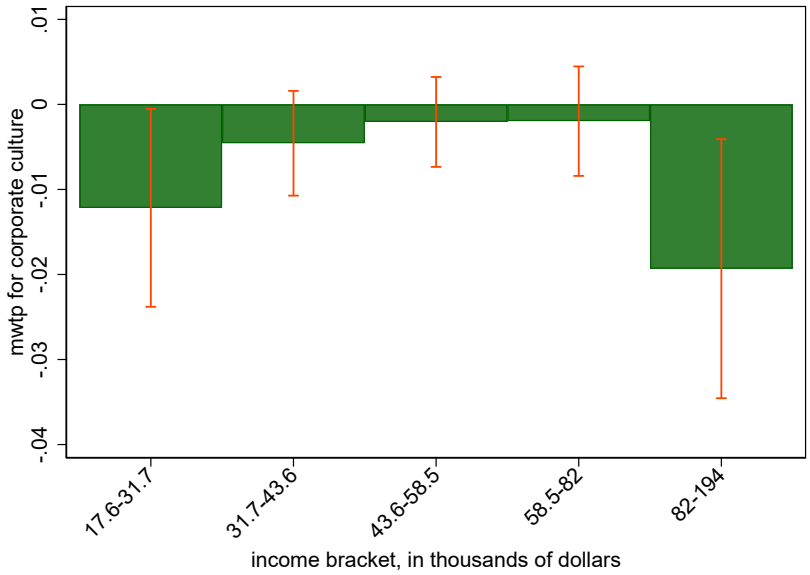

Figure 5: Heterogeneity in Marginal Willingness to Pay, by Income Bracket

Notes.–Sources: Payscale and Compustat. The table reports the coefficients associated with regressions of logged predicted compensation net of actual compensation on a standardized leave-one-out average of corporate culture separately by income bracket, conditional on controls, including: a quadratic in age, male, and indicators for seven buckets of educational attainment (high school, associates, some college, college, professional programs [MBA, health policy], and doctorate), and years of labor market experience. Predicted compensation is generated through PayScale's proprietary machine learning algorithms that use their entire salary database of 56+ million individuals in North America. Using predicted compensation as a proxy for the individual's human capital and marginal product of labor, I compute rents by taking the difference between logged financial compensation and logged predicted compensation. The sample is restricted to individuals who report their firm and firms with at least five respondents. Standard errors are clustered at the firm-level.

A Stylized Theoretical Model

Section 2 discusses the potential reasons behind the impact of corporate culture on firm outcomes. One rationale is that companies provide them to deal with a fundamental shirking problem. By raising employee engagement through the provision of these amenities, firms reduce the disutility of labor services, thereby raising the effective time employees allocate to the firm. I now outline a simple theoretical model consistent with this intuition.[22] The goal is not to produce a quantitatively realistic model, but rather create an illustrative model formalizing how companies compete on culture, in addition to standard characteristics, like pay.

Suppose employees have preferences over wage income, denoted w, corporate culture, denoted o, and effort, denoted e, with a constant absolute risk aversion (CARA) utility

$$U = -\exp\left[-\eta(w - v(e/o))\right]$$

where η denotes the intertemporal risk aversion and $v(e/o)$ characterizes the disutility of work in such a way that increases in corporate culture reduce the disutility associated with work. In this sense, although working longer hours comes at a cost, firms can make the work environment more engaging and enjoyable by raising o. Now, consider the problem of the firm. Following Holmstrom [1979], suppose that output is linear in effort and effort is unobserved

$$y = e + \varepsilon$$

[22] After producing an unpublished version of this paper, I discovered a related argument made by Ho [2013] with regards to an additional economic rent existing in the presence of moral hazard. Using the NLSY, he examines how a binary indicator over the quality of a job relating to riskiness translates into a compensating differential.

where $\varepsilon \sim \mathcal{N}(0, \sigma^2)$ denotes the noise associated with observing effort. Individuals now have a temptation to shirk since the firm cannot observe their actual effort—only an imperfect signal of it. Given that individuals have preferences over non-pecuniary job characteristics, in addition to wage income, firms now have additional options at their disposal for motivating employees. That is, firms not only have the option of designing performance pay contracts, which are assumed to contain a base (fixed) and performance (variable) component, but also of altering corporate culture. Suppose that firms can provide corporate culture at a cost ϕ such that they choose a combination of fixed pay, denoted f, variable pay, denoted b, desired effort, and corporate culture to maximize profits

$$\max E(y - w - \phi o)$$

subject to an incentive compatibility and individual rationality constraint[23]

$$e \in \arg\max_e E(-\exp\left[-\eta(w - v(e/o))\right])$$

$$E(-\exp\left[-\eta(w - v(e/o))\right]) \geq u(\overline{w})$$

where $u(\overline{w})$ denotes the reservation utility. For convenience, assume that $v(\cdot)$ is quadratic, i.e. $v(e/o) = \psi(e/o)^2$. Since preferences are CARA, then maximizing utility is equivalent to solving[24]

$$e \in \arg\max \left[f + be - \frac{1}{2}\psi(e/o)^2 - \frac{\eta}{2}b^2\sigma^2\right]$$

[23]That is, firms maximize $E(e - f - be - \phi o)$ with respect to e.
[24]See Bolton and Dewatripont [2005] for a summary.

which implies that $e = bo^2/\psi$. Not surprisingly, $\partial e/\partial o > 0$, i.e., as corporate culture improve, effort rises, capturing the hypothesis that better company-wide culture leads to greater employee engagement. Under the standard assumptions of the first-order approach, having solved for $e(b, o)$, the principal now solves

$$\max_{f,b,o} \left[\frac{bo^2}{\psi} - (f + b\frac{bo^2}{\psi}) - \phi o \right]$$

subject to the individual rationality constraint

$$f + b(\frac{bo^2}{\psi}) - \frac{1}{2}\psi(\frac{bo^2}{\psi})^2 - \frac{\eta}{2}b^2\sigma^2 = \overline{w}$$

The first-order condition on bonus compensation is given by[25]

$$b = \frac{o^2}{o^2 + \eta\sigma^2\psi} \tag{5}$$

Equation 5 produces a noteworthy predictions: $\partial b/\partial\sigma^2 < 0$, meaning that the incentive effects of bonus compensation are decreasing in the level of uncertainty—an issue examined in great detail by Prendergast [2000] and Prendergast [2002].[26] However, it is interesting to note the extent to

[25]Taking the first-order conditions on b and o produces

$$b: \quad \frac{o^2}{\psi} - \frac{2bo^2}{\psi} + \lambda(\frac{2bo^2}{\psi} - b\frac{o^2}{\psi} - \eta b\sigma^2) = 0, \quad o: \quad \frac{2bo}{\psi} - \frac{2b^2o}{\psi} - \phi + \lambda(\frac{2b^2o}{\psi} - \frac{b^2o}{\psi}) = 0$$

where $\lambda = 1$ from the FOC on f. Notice that the objective function is derived by substituting $e = bo^2/\psi$ in place of $y = e$ (plus noise) net of compensation costs and corporate culture costs. The implied solution is $o = \phi\psi/[b(2-b)]$, which means that $\partial o/\partial b > 0$ since $|b| < 1$.

[26]A second prediction, which is not explored in this paper, is that $\partial b/\partial o > 0$, meaning that firms can use corporate culture to further amplify the effectiveness of performance pay compensation (e.g., bonuses) as a means of decreasing employee's cost of effort—that is, raising employee engagement. The convexity of $v(\cdot)$ is important for this result. If the cost of effort is linear, then $b = \psi/o$ and $\partial b/\partial o$. As long as $v(\cdot)$ is not linear in e, then it appears that $\partial b/\partial o > 0$. If the cost of effort were linear, then changes in corporate culture would perfectly offset the disutility of working more, so the two would be substitutes. See Ryall and Sampson [2009] for empirical evidence behind the complementarity of formal and informal contract mechanisms.

which $\partial b/\partial \sigma^2 < 0$ varies depends on the level of corporate culture. In particular, since

$$\partial b/\partial o^2 = 1 - o^2/(o^2 + \eta\sigma^2\psi)$$

it follows that $\partial b/\partial o^2 > 0$ since $\eta\sigma^2\psi > 0$ and so $o^2/(o^2+\eta\sigma^2\psi) < 1$. That means higher levels of corporate culture weaken the impact of uncertainty on bonus compensation. The refinement to the basic trade-off between risk and uncertainty is intuitive since corporate culture reduce the incentive to shirk, which is precisely the channel through which greater uncertainty adversely affects labor supply. Even under high uncertainty associated, a good work-place environment behaves as a counteracting force that reduces the temptation to shirk.

The intuition behind the result that higher corporate culture reduce the disutility of effort can be traced to theories of relational contracts; see, for example, Baker et al. [2002]. As Gibbons and Henderson [2012] explain, and Blader et al. [2015] provide causal evidence over, relational contracts provide greater credibility behind decisions within the firm. Take, for instance, an individual's compensation. If the worker does not understand why they are paid what they are paid, even if their salary is above competitive rates, their perception will nonetheless influence their engagement, impacting productivity and retention. However, managers who are able to communicate the rationale behind an employee's pay builds an inherent relational contract, thereby overcoming typical shirking problems [Halac and Prat, 2016]. At a more general level, engaging employees over executive compensation ("say-on-pay") can promote greater transparency and satisfaction among employees, in turn raising firm performance [Cunat et al., 2015].

Appendix Section C.4 shows that individuals in performance pay jobs report higher corporate culture and job satisfaction (Figure 14), which is consistent with the theoretical prediction

of complementarity between financial incentives and organizational amenities. However, these cross-sectional differences are contaminated by the potential for non-random sorting, so they represent only conditional correlations—not causal evidence. The remainder of the paper focuses on identifying compensating differentials consistent with the prediction that firms offer organizational amenities because employees want them. If corporate culture were costly to provide, but employees did not value them, then there would be no reason to offer these amenities.[27] The model introduced here provides a theoretical foundation for understanding the presence of these compensating differentials.

B Supplemental Data Details

B.1 Constructing Aggregate corporate culture

The main text uses an aggregate index of corporate culture based on the sum of pay transparency, communication, development/communication, appreciation, and managerial relationship indices. Creating a single index helps increase variation and reduce noise, especially given the correlation across each of the indices. A principal-components analysis suggests that the first four factors explain 60%, 74%, 84%, and 92% of the variation, respectively. Figure 6 plots the eigenvalue associated with the different factors, showing that it drops below one after the first factor. That is evidence that a single index suffices in explaining the variation across these dimensions of corporate culture

[27] For example, Bergman and Jenter [2007] develop a model where firms provide non-wage characteristics (e.g., particular types of amenities or other forms of compensation) precisely because employees value them and cannot purchase them on the market.

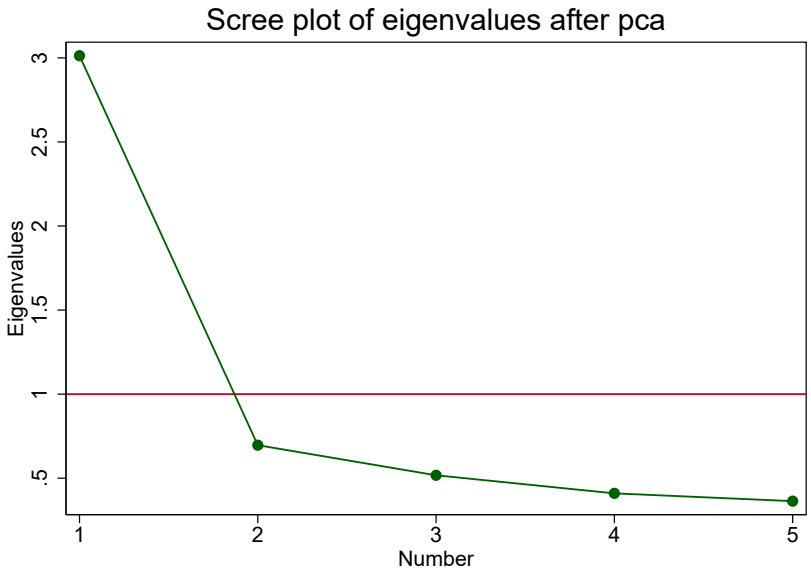

Figure 6: Evaluating the Relationship Among corporate culture Sub-Indices
Notes.–Sources: Payscale. The figure documents the scree plot of eigenvalues following a principal-components analysis on the five indices of corporate culture.

B.2 Additional Data Validation

The main text presents a comparison of means for several demographic variables between PayScale and the Current Population Survey by two-digit occupation. While there are minor differences that appear visually, I now explore them more formally by conducting a difference of means and reporting the associated p-values separately by occupation. These are documented in Table 6. Since there are 20 two-digit occupations that are displayed, I partition them into two separate panels so that they can be presented visually with ease.

Overall, there are relatively small differences in years of schooling, but there are more substantial differences in college attainment by education. For example, architecture and construction have 50% higher shares of college degree workers in PayScale, relative to the CPS. However, other differences are more minor, like business/finance and healthcare, which have 7% more and 8% less,

respectively, college degree workers. Most of the differences in college attainment are coming from traditionally lower skilled occupations that contain higher skilled workers—for example, construction jobs are primarily low skill, but there may still be some higher skilled workers in those jobs due to downskilling in the past decade [Beaudry et al., 2016].

Turning towards differences in earnings, there are some substantial differences in a few occupations, such as life / physical sciences and personal service / care, which suggest that PayScale workers have 41% and 61% higher earnings than those workers in the CPS. Several other occupations also contain large differences, but these are primarily lower skilled production and/or office related jobs. There are almost uniformly small differences in gender between the two datasets—the only occupations that truly differ are business/finance and architecture/engineering, which are already over-represented by males in the population more generally. The differences in age are also statistically significant, but relatively small—the only occupations that contain relatively large differences are again architecture/engineering and physical / social sciences. There are also relatively minor differences in race, which range only a few percentage points with the exception of physical / social sciences and community / social services.

Through a unique partnership with Gallup (discussed in companion work [Makridis, 2019a,b]), I leverage data from their U.S. Daily Poll, which surveys 1,000 people per day about subjective well-being and the perceptions about the economy. Restricting the sample to employed individuals between ages 20 and 65, I examine the correlations between their measure of life satisfaction (an index from zero to ten) and the share of individuals reporting high levels of trust in their work-place and the PayScale measures of job satisfaction and corporate culture at a state-level. Although the two survey datasets are measuring slightly different equilibrium objects, they are still somewhat comparable and, therefore, useful to test to see how well they validate one another. I focus on a

Table 6: Formal Test of Difference in Means (PayScale - CPS)

SOC code =	11	13	15	17	19	21	23	25	27	29
Panel A										
college	0.21***	0.15***	0.07***	0.11***	0.41***	0.13***	-0.06***	0.02***	0.36***	-0.08***
ln(earnings)	0.05***	0.05***	0.00	-0.08***	0.42***	0.17***	-0.34***	0.26***	0.41***	-0.03***
male	-0.08***	-0.01*	0.06***	-0.00	-0.13***	-0.04***	-0.19***	0.01*	-0.21***	-0.03***
age	-4.90***	-6.39***	-6.28***	-8.20***	-7.15***	-3.81***	-6.54***	-2.13***	-7.47***	-2.68***
white	-0.05***	-0.08***	-0.01	-0.05***	-0.08***	-0.10***	-0.07***	-0.09***	-0.05***	-0.03***
schooling	0.10***	0.05*	-0.44***	-0.18***	2.07***	0.09*	-1.40***	-0.44***	1.64***	-1.41***
SOC code =	31	33	35	37	39	41	43	47	49	51
Panel B										
college	0.21***	0.33***	0.45***	0.50***	0.40***	0.40***	0.38***	0.50***	0.39***	0.49***
ln(earnings)	0.34***	-0.12***	0.54***	0.43***	0.61***	0.33***	0.28***	0.18***	0.06***	0.16***
male	-0.02***	0.01	0.12***	0.17***	0.05***	-0.04***	-0.09***	-0.01	-0.01***	0.08***
age	-3.40***	-4.12***	-1.97***	-5.69***	-4.78***	-5.22***	-3.17***	-4.40***	-4.10***	-5.26***
white	-0.03**	-0.08***	-0.08***	-0.06**	0.04*	-0.06***	-0.09***	-0.08***	-0.04***	-0.03**
schooling	-1.32***	-0.36***	0.46***	0.88***	0.11*	0.32***	0.10***	0.30***	-0.53***	0.35***

Notes.–Sources: Payscale and Current Population Survey. The table reports the coefficients associated with differences in means between Payscale net of the CPS mean separately for each major SOC occupation code. 11 = management; 13 = business and finance; 15 = computer and math; 17 = architecture and engineering; 19 = life, physical and social science; 21 = community and social services; 23 = legal; 25 = education, training, library; 27 = arts, design, entertainment; 29 - healthcare practitioners and technical; 31 = healthcare support; 33 = protective service; 35 = food preparation and serving related; 37 = building and grounds cleaning; 39 = personal care and service; 41 = sales and related, 43 = office and administrative support; 45 = farming, fishing, forestry; 47 = construction and extraction; 49 = installation, maintenance and repair; 51 = production; 53 = transportation and material moving.

state-level average since the samples in some metropolitan areas are not sufficiently large.

Panel A in Figure 7 plots job satisfaction from PayScale and life satisfaction from Gallup, implying a correlation of 0.546. Not surprisingly, the two are not perfectly correlated because not only the samples vary in several ways, but also the measurement of life satisfaction is much broader than just feelings about a job. Panel B in Figure 7 plots corporate culture and the share of individuals reporting high levels of trust in the work-place, again displaying a strong correspondence—this time a correlation as high as 0.698. Although clearly sample differences exist, the results provide additional evidence that the PayScale survey tool is detecting meaningful heterogeneity in its sample of respondents.

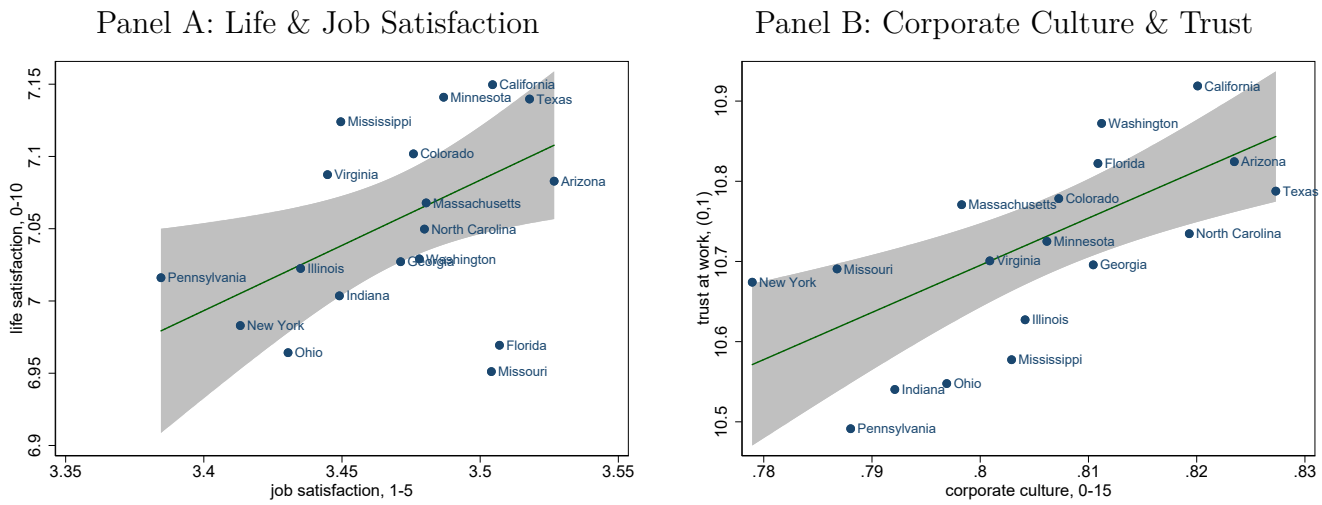

Figure 7: Comparison of Perception Indices between Gallup and PayScale

Notes.–Sources: PayScale and Gallup U.S. Daily. Panel A plots perceived life satisfaction (on a zero to ten scale) with job satisfaction (on a one to five scale) from the Gallup and PayScale data, respectively. Panel B plots corporate culture (zero to fifteen scale) with the share of individuals reporting that they perceive there is trust in their work-place. The sample is restricted to employed individuals between ages 20 and 60, as well as states with at least 5,000 individuals in the PayScale data.

The final data validation exercise introduces the Great Places to Work (GPTW) survey, which ranks companies in part based on 250 randomly selected employee survey responses on their attitudes towards management, job satisfaction, fairness, and camaraderie. The remainder of the GPTW ranking is based off of the institute's evaluation of other factors, including demographic

composition, pay and benefits, and perceived culture. Since firm must apply to be on the list and the firm must be sufficiently large, the ranking tends to capture more developed companies. These data have been widely used in recent explorations of the impact of "culture" on firm value [Edmans, 2011, 2012], although there is an ongoing debate over the features that are most relevant for predicting firm outcomes, i.e. integrity [Guiso et al., 2015].

I manually match the GPTW list with the PayScale data, displaying the correlations between the GPTW firm ranking and a firm-level average of corporate culture and job satisfaction in Figure 8. In both cases, there is a strong negative correlation between the two, suggesting that the two measures are capturing similar orderings among companies in spite of differences in the sample respondents and a relatively small sample of roughly 95 companies. Moreover, it is important to remember that the GPTW ranking is based on different criteria.

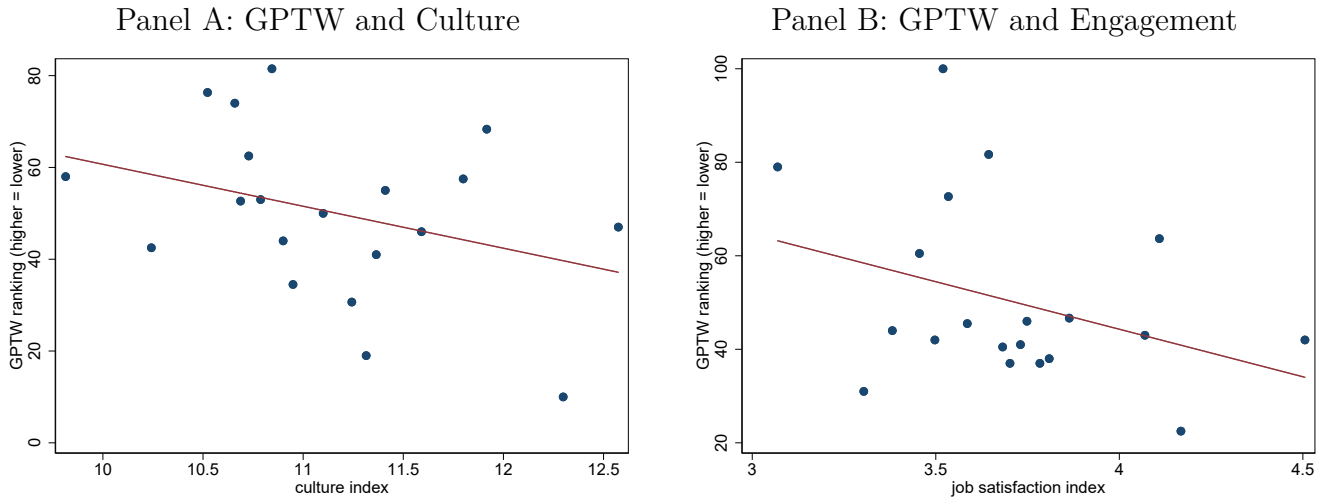

Figure 8: Comparison of Great Places to Work Ranking and Payscale

Notes.–Sources: PayScale and Great Places to Work (GPTW). The figure plots a `binscatter` plot between the GPTW firm ranking and corporate culture and job satisfaction for firms with over 10 respondents in the PayScale data. The figure shows that higher culture and engagement companies tend to have lower ranks (i.e., better places to work).

C Supplemental Descriptive Statistics

C.1 Summary Statistics

Table 7 documents a number of descriptive statistics separating out individuals based on their response to five different survey questions about their perceptions of organizational states (e.g., high job satisfaction, transparency in compensation, etc). While those reporting high levels have systematically higher earnings, and are much less likely to report that they plan to leave their company in the next six months, they are not more likely to be more educated or receive performance pay (either on the intensive or extensive margin). For example, the share of graduate-degree workers reporting high versus low job satisfaction is 71% and 70%, respectively. Looking across each of the other states—for instance, high/low levels of training/development opportunities—72% of those reporting high levels have a graduate degree versus 69% reporting low levels.

Turning towards the three measures of performance pay—bonus, commission, and profit sharing—there is no systematic difference between those reporting high/low levels. One of the endogeneity concerns is that an individual might receive a bonus and, therefore, be more willing to report higher levels of job satisfaction or organizational amenities. However, the fact that the probability of receiving performance pay is uncorrelated with levels of these amenities suggests that this form of reverse causality is not likely a first-order concern.

As an additional validation exercise and robustness exercise, I compare firm-level averages of my measures with measures of personnel and human resource management from Bloom and Van Reenen [2007] who implemented a double-blind survey methodology to measure managerial quality across firms. Unfortunately, since their sample is relatively small and only covers manufacturing firms, the match with my sample is also quite small—roughly 38 firms total, but I drop observations with less than 10 observations in the data, leading to a final sample size of 17

Table 7: Summary Statistics, Separately by High/Low Perceptions

	Job Satisfaction		Compensation		Development		Management		Firm Future	
	Bad	Good	Bad	Good	Bad	Good	Bad	Good	Bad	Good
Total earnings	54337	61014	56117	63891	54769	61149	55298	58805	55260	59320
Earnings, net of predicted	-0.06	-0.02	-0.05	0.01	-0.05	-0.02	-0.04	-0.03	-0.05	-0.03
Looking for job	0.75	0.31	0.59	0.32	0.67	0.37	0.72	0.45	0.73	0.40
College degree	0.70	0.71	0.70	0.72	0.69	0.72	0.69	0.72	0.70	0.71
Graduate degree	0.14	0.16	0.15	0.17	0.13	0.17	0.14	0.15	0.15	0.15
Age	37.1	37.8	37.4	37.5	37.9	36.9	38.0	37.2	37.4	37.5
Experience	9.4	9.8	9.5	9.9	9.9	9.3	9.9	9.5	9.6	9.6
Male	0.48	0.49	0.48	0.53	0.48	0.50	0.47	0.50	0.49	0.49
Black	0.07	0.06	0.07	0.07	0.07	0.07	0.08	0.06	0.07	0.06
White	0.74	0.75	0.75	0.72	0.74	0.74	0.73	0.75	0.73	0.75
Share receiving bonus	0.23	0.29	0.26	0.28	0.24	0.29	0.23	0.28	0.22	0.29
Share receiving sales commission	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Share receiving profit sharing	0.03	0.04	0.04	0.04	0.03	0.04	0.03	0.04	0.03	0.04
Bonus | x > 0	6567	8024	6862	9217	6620	8095	7014	7513	6920	7603
Sales commission | x > 0	14479	17383	14763	19829	15172	16750	14993	16280	15151	16389
Profit sharing | x > 0	4786	6478	5116	7792	5032	6380	5344	5923	5198	6003
Observations	160178	158512	255512	63178	174409	144281	104263	214427	130493	188197

Notes.–Sources: Payscale, 2014-2016. The table reports the averages across a set of demographic and labor market variables. Those with a graduate degree are those with a masters, PhD, MD, or law / MBA degree. The columns report different sample restrictions based on individual perceptions over the corresponding firm state. For example, "good" for job satisfaction reports the corresponding averages for individuals who report a four or five (out of a five-point scale) in response to the job satisfaction question in the survey, whereas "bad" is given by points one, two, or three (out of the five-point scale).

companies. Figure 9 shows that there is overall a high degree of correlation, especially among development and training opportunities. However, these correlations should be taken lightly since there is considerable noise since the only way to match these two datasets is to produce an average from 2006 to 2012 and match the set of these publicly traded firms.

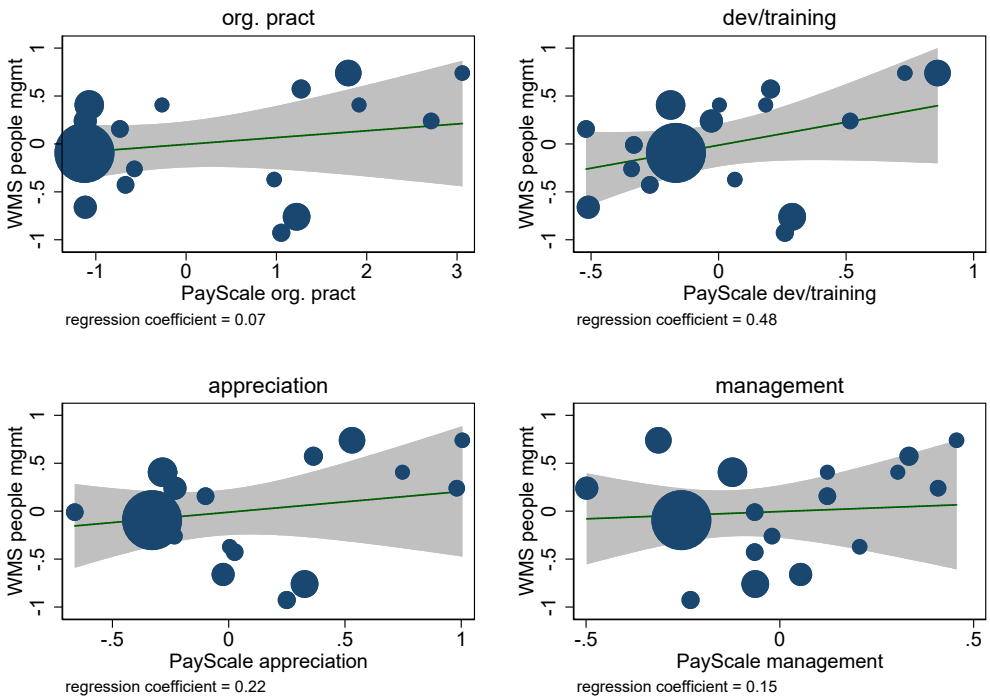

Figure 9: Comparison of PayScale and World Management Survey

Notes.–Sources: Payscale and World Management Survey. The figure reports average measures of corporate culture (including its average) with a measure of managerial ability at a firm-level, specifically human resource and people management. Firms must have at least 10 observations in the PayScale data to be present in the matched sample.

C.2 Conditional Correlations at Firm Level

The main text presents conditional correlations between job satisfaction and various inputs to corporate culture: indices of pay transparency, communication, training/development, appreciation, and management. However, one major concern is that, even though the results are merely a decomposition exercise, the estimated coefficients are based purely on measurement error and/or

compositional effects. To address this concern, Table 8 estimates the regression at the firm-level for the set of firms that have at least five respondents in the survey. If measurement error at the individual-level was driven the results in the main text, then averages at the firm-level should be much more noisy. However, this is not the case.

Column 1 presents the raw unconditional correlation without demographic controls. Column 2 weights observations by the number of people observed in each firm from the survey. The fact that the conditional correlations remain highly significant is consistent with my claim that the results are not driven by measurement error; if they were, then sampling variability would be a bigger concern, especially for larger companies. Column 3 adds compositional controls and shows that they only marginally affect the point estimates. Column 4 adds firm fixed effects. While pay transparency becomes statistically imprecise, it is still statistically greater than zero and the other coefficients remain quite significant.

Motivated by the stark differences in residualized reported corporate culture in the pooled sample and the sample of graduate degree holders in the main text, Figure 10 plots the raw distributions of corporate culture and job satisfaction across gender and age. Like before, these are obtained by restricting the sample to firms with at least 30 respondents who have and do not have a graduate degree, subsequently taking the average and pooling all responses together. Unlike Figure 2 in the main text, there is very little difference in the distributions among these different brackets, consistent with the earlier evidence that age and gender explain little in the dispersion of employee engagement and work-place amenities.

Table 8: Job Satisfaction and Corporate Culture at the Firm-level

Dep. var. =	job satisfaction, firm average z-score			
	(1)	(2)	(3)	(4)
pay transparency	.132***	.081***	.085***	.052
	[.010]	[.024]	[.025]	[.034]
communication	.187***	.216***	.229***	.244***
	[.013]	[.030]	[.030]	[.033]
development	.211***	.238***	.214***	.213***
	[.012]	[.031]	[.031]	[.037]
appreciation	.321***	.296***	.322***	.317***
	[.013]	[.032]	[.028]	[.032]
management	.047***	.065**	.058**	.065**
	[.011]	[.026]	[.027]	[.030]
male			-.045	-.053
			[.031]	[.048]
age			.004**	.003
			[.002]	[.003]
experience			.002	.002
			[.003]	[.003]
1[college]			.040	.072
			[.046]	[.061]
Sample Size	12162	12162	11865	11865
Controls	No	No	Yes	Yes
Has Weight?	No	Yes	Yes	Yes
Firm FE	No	No	No	Yes

Notes.–Sources: Payscale. The table reports the coefficients associated with regressions of a standardized z-score for job satisfaction (index of one to five) on standardized measures of corporate culture, including pay transparency, communication, development/training opportunities, appreciation, and management, conditional on controls and fixed effects. Controls include: share of males, average education, average age. These variables are all averages at a firm-level for the set of firms that have at least five respondents in the PayScale sample. Standard errors are clustered at the firm-level and observations are weighted by the number of workers observed in a firm from the sample survey.

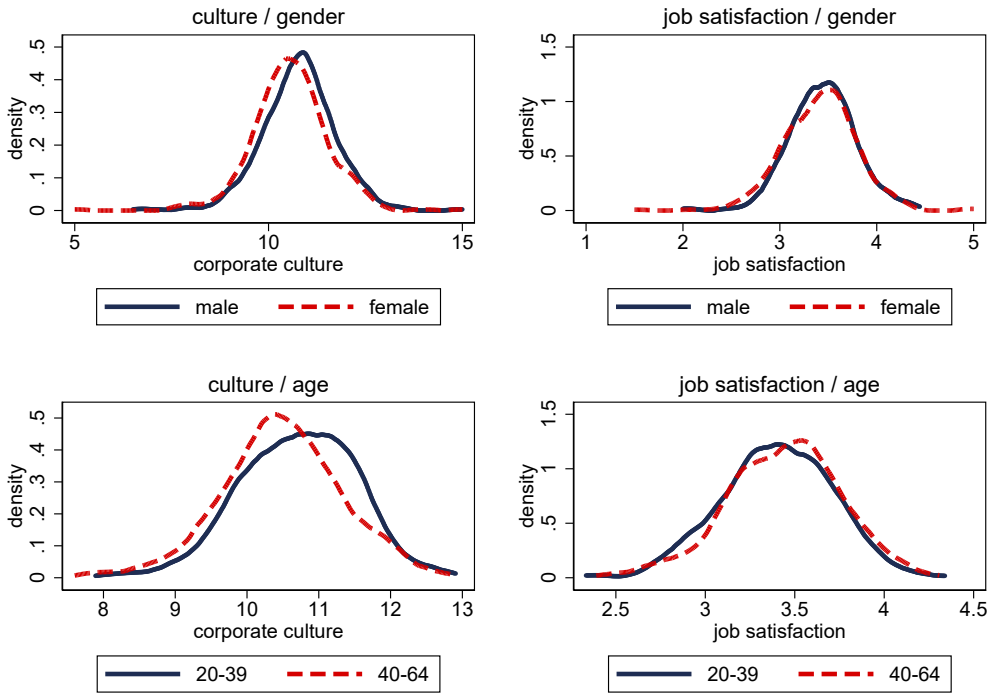

Figure 10: Distribution of Corporate Culture and Job Satisfaction Across Firms

Notes.–Sources: PayScale. The figure plots the raw value of corporate culture and job satisfaction for different partitions of the labor market. The sample is restricted to workers in firms with at least 30 graduate and non-graduate degree respondents in the data.

The main text plotted the dispersion in job satisfaction, corporate culture, and actual compensation across several sets of firms, displaying that there is a significant amount of variation. However, there is much less variation across industries. Figure 11 pools together firms with at least 30 respondents in the survey tool. Interestingly, the means and standard deviations are relatively similar with one another. The fact that these two moments are quite similar across industries suggests that there are good and bad firms in every industry—there is not, for example, evidence that certain technologies have greater or weaker returns to these practices.

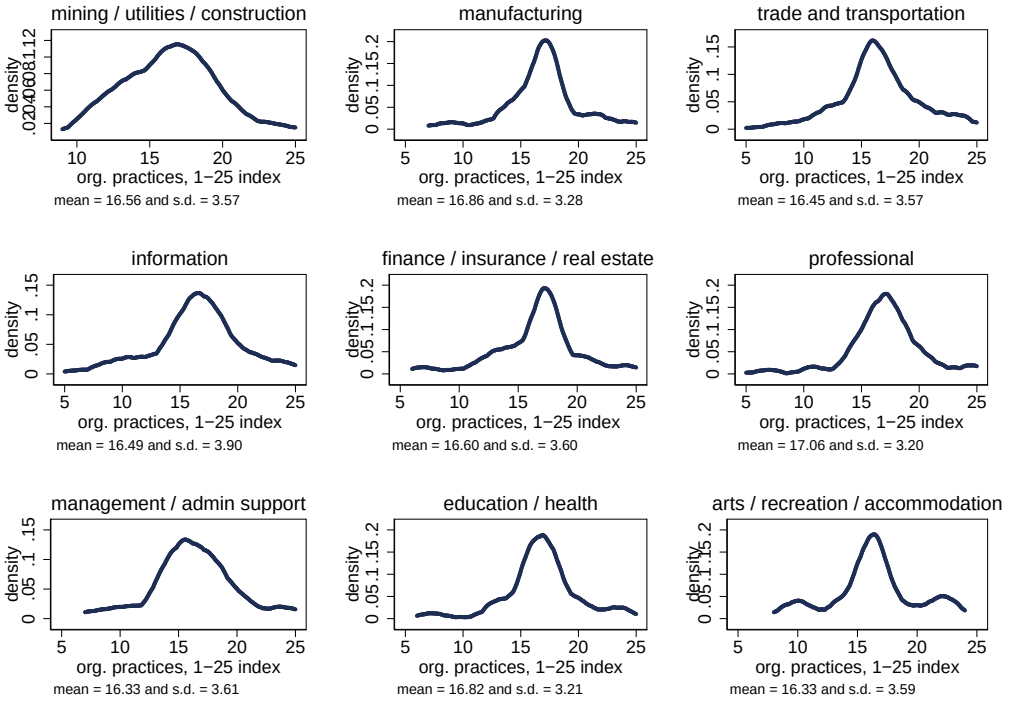

Figure 11: Corporate Culture Across Firms, by Industry

Notes.–Sources: PayScale. The figure plots the distribution of raw corporate culture separately by industry pooling across all firms in the sample with at least 30 respondents in the survey tool.

C.3 Correlations with Other Characteristics

The main text presents several descriptive statistics about the dispersion of engagement, corporate culture, and compensation. One such disaggregation is spatial—across metropolitan areas. Figure 12 shows the gradient between corporate culture and three metropolitan outcomes: logged population, college attainment (including advanced degrees), and the unemployment rate. While there is a positive gradient between population and corporate culture, it is only statistically significant for larger metropolitan areas. In fact, there is an inverse U-shape that suggests that in smaller cities, lower corporate culture might make more sense—potentially because finding and attracting talent is more costly.

Turning towards educational attainment, there is a very strong gradient between the share of college (and advanced) degree workers and corporate culture, which is consistent with the idea that better work-place practices are used to attract more skilled workers. These practices are unlikely to be purely about selection, however; they also raise labor productivity, as discussed in the main text. Finally, there is a negative relationship between the unemployment rate and corporate culture. Additional diagnostics suggest that more dynamic labor markets have better work-place cultures.

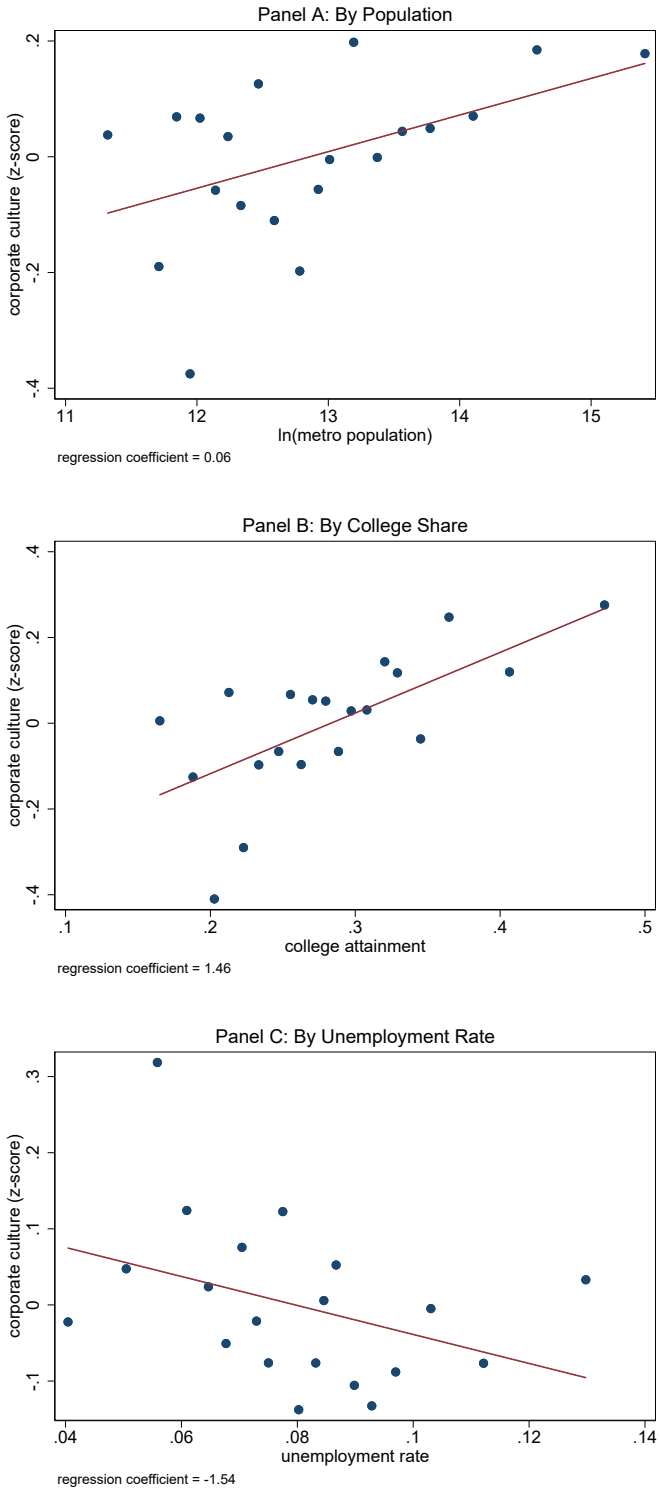

Figure 12: Metropolitan Cross-sectional Variation in corporate culture

Notes.–Sources: Payscale and Census Bureau. The figures plot the correlation between corporate culture (standardized on the set of metropolitan areas in the PayScale data with at least 100 respondents) and various metropolitan outcomes: logged population, college attainment (including advanced degrees), and the unemployment rate.

Turning towards heterogeneity across occupations, I match O*NET data on skill intensities following Acemoglu and Autor [2011] using the 2010 data. I consolidate all skills into six general categories—four of which I plot below in Figure 13, which shows the correlation with corporate culture at the three-digit level. There is a remarkably linear relationship between corporate culture and both cognitive and social skills, suggesting that these are jobs that require a high degree of skill and coordination to produce the tasks. There is a negative relationship with manual skills, which reflects the fact that lower skilled workers may also have a lower willingness to pay for work-place amenities. There is a positive, but somewhat noisy, gradient with technical skills (e.g., programming), reflecting the fact that many pure quantitative workers are not working in teams.

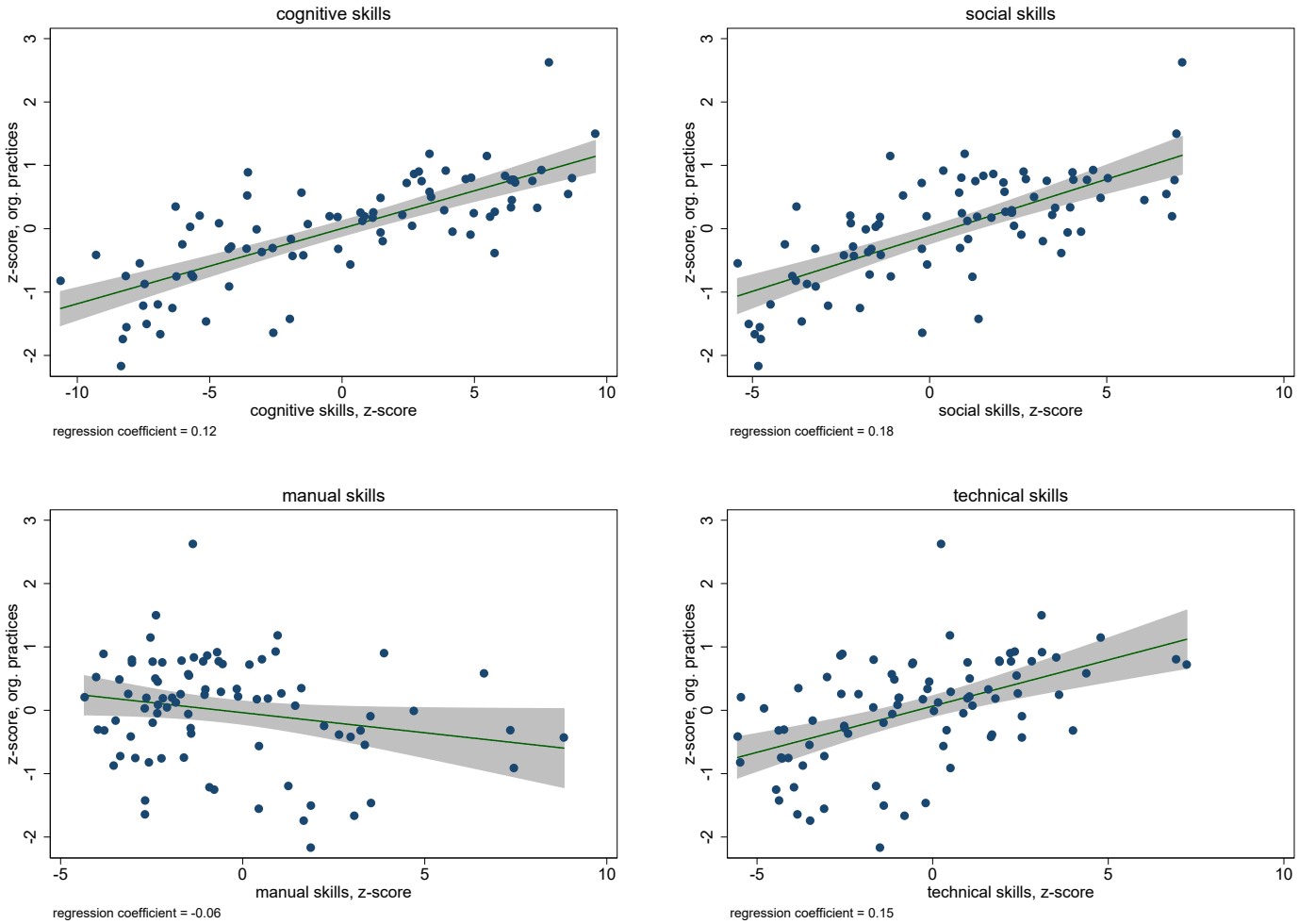

Figure 13: Occupational Cross-sectional Variation in corporate culture

Notes.–Sources: Payscale and O*NET. The figures plot the correlation between corporate culture (standardized on the set of metropolitan areas in the PayScale data with at least 100 respondents) and various measures of three-digit SOC skill intensities (cognitive, social, manual, and technical). The skill groups are as follows: (1) cognitive skills (decision making, learning strategies, listening, learning, problem solving, coordination, and critical thinking), (2) manual (repairs, equipment maintenance, equipment selection, installation, instruction), (3) technical (programming, quality control analysis, systems analysis, systems evaluation, technology design), (4) social (persuasion, social, speaking, negotiation), (5) service (management of financial resources, of material resources, of personnel resources, monitoring, service, operations control, operations monitoring, operations analysis, troubleshooting), and (5) general (math, writing, time management, reading, science). The ONET skill data is available from 2010-2014 and is made to have a mean zero and variance of 1. All occupations are harmonized to the 2010 SOC codes.

C.4 Heterogeneity in Performance Pay Jobs

Figure 14 finally examines the dispersion by major occupation (one-digit) and contract type: performance pay versus fixed wage schemes. Workers are classified as performance pay if they are in an industry and occupation that has over 50% of the labor force covered by performance pay

contracts or receives a bonus, commission, or profit sharing within that year. The former part of the definition comes from the National Compensation Survey's three-digit occupation and two-digit industry administrative records, whereas the latter comes from measurements directly reported on in the PayScale data. Performance pay workers tend to have much greater corporate culture and job satisfaction, relative to their counterparts, across the entire distribution of occupations. The only occupation that fares above average among fixed wage jobs is management, but even in management those with fixed wage contracts report about half as large magnitudes as those in performance pay jobs.

Figure 14: Job Satisfaction, corporate culture, and Pay, by Occupation and Performance Pay

Notes.–Sources: PayScale. The z-scores are created by first summing across each of the six sentiment indices (pay transparency, managerial relationship, communication, appreciation, development and training opportunities) and second standardizing across all individuals. The plot is over one-digit industry and occupation bins separated for performance pay and fixed wage industries. Performance pay workers are tagged as such if they are in a three-digit occupation and two-digit industry both with over 50% of the work force covered by performance pay contracts (obtained from the National Compensation Survey) or if they receive a bonus, commission, or profit sharing income (obtained from the PayScale data).

D Supplement to Identifying Compensating Differentials

The section began by motivating the exploration of compensating differentials by highlighting the increasing attention that company culture has received in recent years—individuals appear to be demanding better work-place amenities. There are various reasons why this might be true—non-homothetic preferences for work, for example, where incomes rise and, therefore, the demand for a better work environment rises. This paper does not take a stance on the underlying source, but rather focuses on quantifying the value of these amenities. Figure 15 plots count indices for the terms "company culture" and "employee engagement" since 2004 (the start of their trends feature). Remarkably, searches for company culture have grown by a factor of nearly three and searches for employee engagement have grown by a factor of nearly ten.

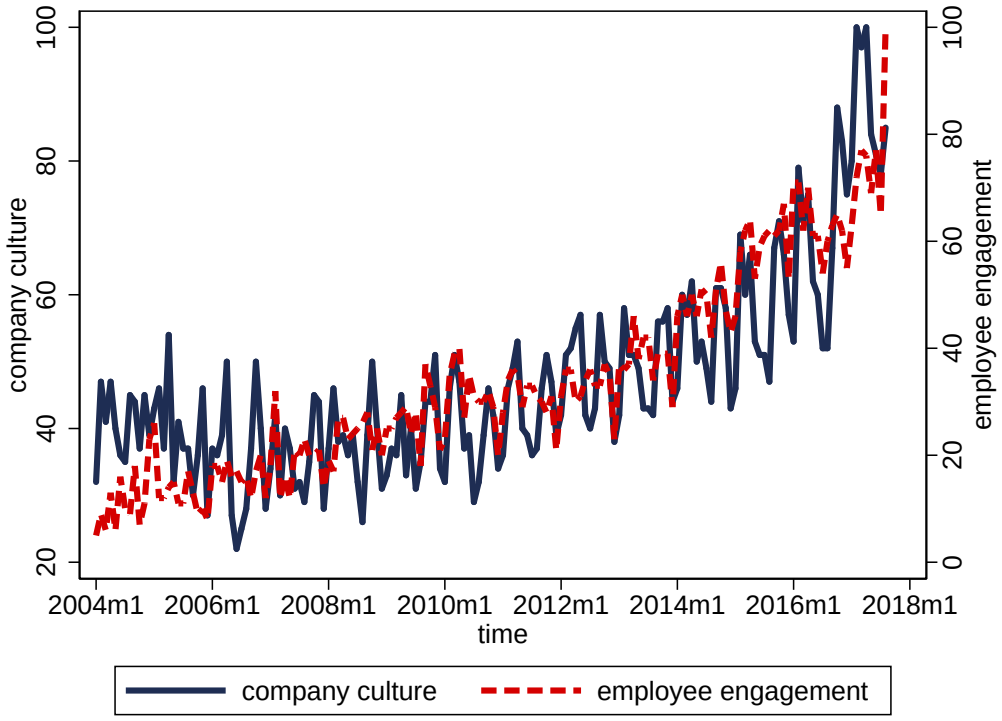

Figure 15: Google Trends Data on Engagement and Culture

Notes.–Sources: Google Trends. The figure plots the index of counts for the terms "company culture" and "employee engagement".

While the main text displays a strong association between firm revenue and corporate culture, I now examine its associations with individual proxies for productivity, such as self-reported performance ratings, intent to leave, and stress. Although these measures are far from perfect measures of productivity, they are correlated with it—that is, less productive workers would have lower performance evaluations, higher probabilities of leaving, and higher stress. Table 9 presents the results associated with regressions of these variables on self-reported corporate culture, conditional on the usual covariates and logged financial compensation in certain specifications.

Consistent with these predictions, a 1sd rise in corporate culture is associated with a 0.19sd rise in an employee's self-reported rating, which is robust to controlling for their financial compensation. Moreover, a 1sd rise in corporate culture is associated with a 0.21pp decline in the probability of looking for another job. A corresponding 1% rise in compensation, however, is only associated with a 0.05pp decline in the probability of looking for another job. Finally, a 1sd rise in culture is associated with a 0.17sd decline in self-reported stress, which again is invariant to the inclusion of compensation as an additional control. Although these results have no causal interpretation and are not genuine measures of productivity, they complement the results in the main text relating culture with firm value (e.g., revenue, operating income, etc).

Figure 16 plots actual and predicted logged total earnings. Predicted earnings is derived from PayScale's proprietary machine learning algorithms. While the specifics of the algorithm are proprietary, it is worthwhile discussing the concept behind their strategy that enables such accurate predictions. Broadly speaking, they fit pay at the job title/country level to a double-pareto log-normal distribution, with a fully Bayesian joint distribution specified through a belief network. The primary assumption (for computational tractability) is the conditional independence of certain variables. The model is fit using the expectation-maximization (EM) algorithm. Other

Table 9: Corporate Culture and Employee Outcomes: Performance, Turnover, and Stress

Dep. var. =	employee rating (z-score)		looking for a job (1/0)		stress rating (z-score)	
	(1)	(2)	(3)	(4)	(5)	(6)
corporate culture	.19***	.18***	-.21***	-.21***	-.17***	-.18***
	[.00]	[.00]	[.00]	[.00]	[.01]	[.01]
ln(compensation)		.25***	-.06***	-.06***		.28***
		[.00]	[.00]	[.00]		[.01]
R-squared	.04	.05			.04	.06
Sample Size	270885	270885	270885	270885	28511	28511
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes.–Sources: PayScale. The table reports the coefficients associated with regressions of standardized self-reported employer ratings of the employee, an indicator for intent to leave within the next six months, and standardized employee stress on logged compensation and standardized corporate culture, conditional on controls, including: a quadratic in age, male, and indicators for seven buckets of educational attainment (high school, associates, some college, college, professional programs [MBA, health policy], and doctorate), and years of labor market experience. Standard errors heteroskedasticity-robust.

variables, such as years of experience and education, are parameterized to different distributions (gamma, exponential, etc.). There is a subsequent k-nearest neighbor match among profiles that tends to pull 45 observations in the neighborhood. Each time the model is re-optimized, the distribution is also re-drawn to account for new profiles.

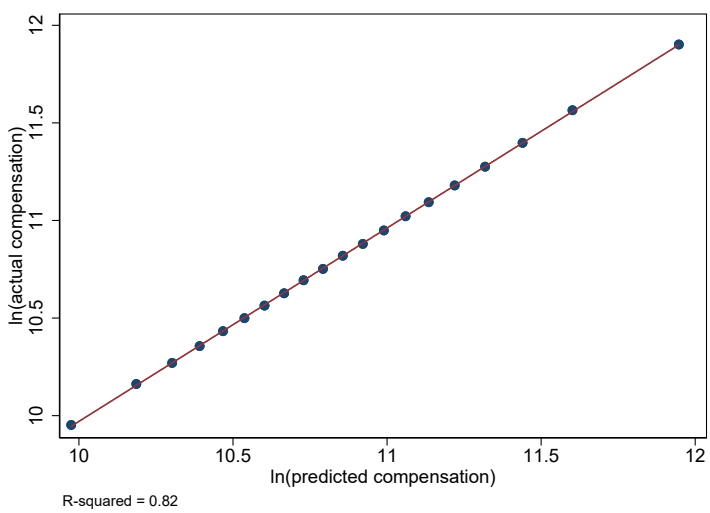

Figure 16: Comparison between Actual and Predicted Pay in PayScale

Notes.–Sources: PayScale. The figure plots a `binscatter` of actual and predicted logged compensation where predicted compensation is generated through PayScale's proprietary machine learning algorithms that uses information on the location and characteristics of individuals in their 56+ million salary database. Observations are the average at an age-bracket (young = under 45 years old), graduate education, experience bracket (13 bins), and gender level. No weights are used

Since the identifying variation is largely coming from potential job movers and/or workers

who are being promoted to another division with different corporate culture, it is important to understand the variation that exists. Figure 17 plots the distribution of earnings growth and job satisfaction using the National Longitudinal Survey of Youth 1979 cohort at a three-digit occupation level, separately for new hires and incumbents. Importantly, there are a large share of new hires who experience lower labor income than their previous job. While some of this is clearly a function of layoffs, much of it is also a function of taking an alternative job offer that pays less, but varies in other non-wage amenities—these moves reveal information about the value of different amenities. Similarly, the distribution of job satisfaction is quite disbursed with many incumbents who are not engaged in their work.

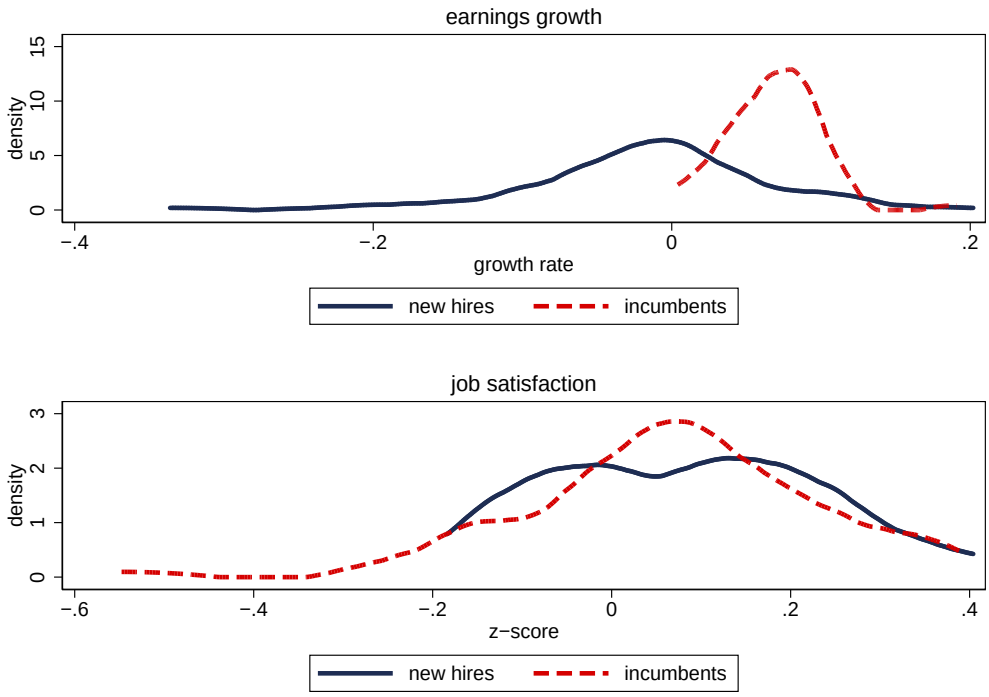

Figure 17: Distribution of Earnings Growth and Job Satisfaction, New Hires/Incumbents
Notes.–Sources: National Longitudinal Survey of Youth 1979. The figure plots the distribution of growth in earnings and job satisfaction for new hires and incumbent workers at a three-digit SOC level (to smooth out the discreteness of the job satisfaction 1-5 index). Occupations with less than 50 observations are discarded.

One potential concern with netting out predicted compensation from actual compensation is

that the wedge represents individual-specific rents, which could be correlated with search frictions. To examine the plausibility of this concern, I turn towards a measure of search frictions based on an index of non-compete enforcement produced by Starr [2015]. Figure 18 plots the two together, suggesting that, while there is a positive association, it is weak and statistically insignificant at the 10% level (p-value = 0.126).

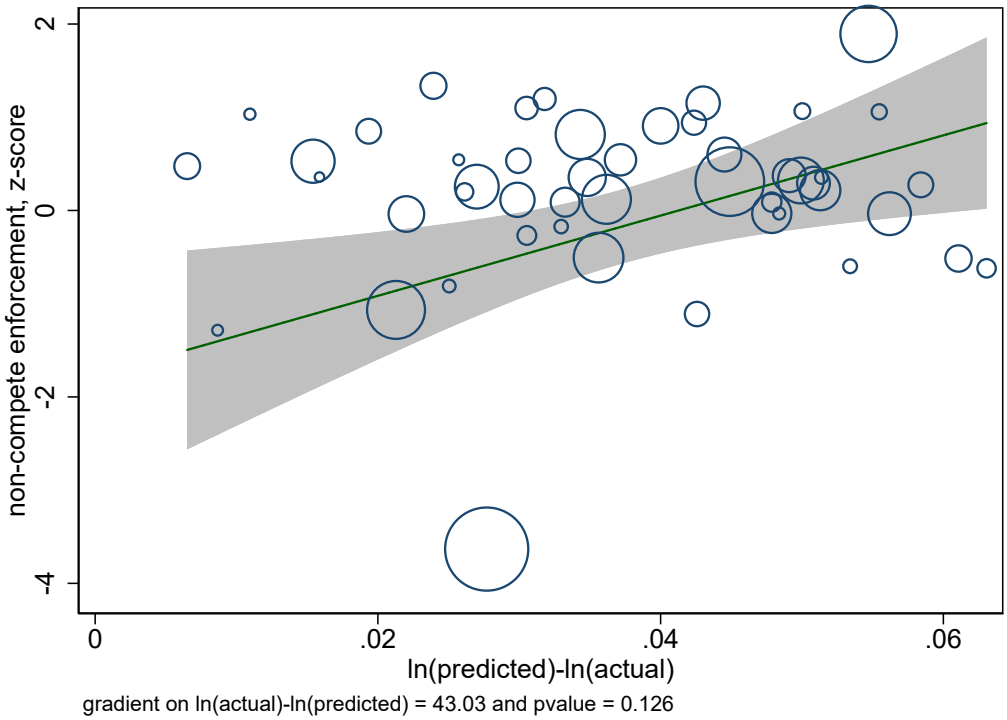

Figure 18: Deviation of Predicted from Actual Compensation with Non-compete Enforcement
Notes.–Sources: PayScale. The figure plots the logged difference between predicted and actual compensation (obtained from PayScale's prediction algorithm) with non-compete enforceability at the state-level, which is an index produced by Starr [2015]. Observations are weighted by the number of observations observed per state in the PayScale data and standard errors are clustered by state.

Three assumptions are required for consistent estimation of the hedonic price on corporate culture [Bockstael and McConnell, 2007]. First, workers must possess accurate perceptions of corporate culture in different jobs. While there is a valid concern that this does not hold given massive heterogeneity in perceptions of similar events, the validation exercises show that these practices are correlated with traditional measures of firm-productivity. Second, workers are found

in a wage-amenity equilibrium, which requires the assumption that workers are freely mobile. Despite the presence of transaction costs, within-metro labor market mobility is not an unreasonable assumption. Third, labor markets must be approximately competitive, conditional on observables. One way these imperfections are addressed is through the inclusion of location and/or firm fixed effects, which mitigates concerns about location-specific information problems.

To better understand the extent of the variation in the data, Table 10 tabulates raw and within-firm (residualized) heterogeneity in actual earnings, predicted earnings (from their prediction algorithm), and corporate culture. There is a remarkable amount of variation in the data—the standard deviation of both actual and predicted earnings is over half as much as the mean. Given the nature of the self-reported measure of corporate culture, the standard deviation is somewhat more clustered, but it is slightly over a quarter as large as its mean. Furthermore, once firm fixed effects are used to residualize these measures, considerable variation remains. Based on my diagnostics, some of this, however, is driven by changes in the composition of workers selecting into each firm to take PayScale surveys over the sample.

Observations	Mean Earnings	S.D. Earnings	Mean $\widehat{\text{Earnings}}$	S.D. $\widehat{\text{Earnings}}$	Mean OP	S.D. OP
Cross-sectional Variation from Raw Data (Baseline)						
58,689	\$64,076	\$37,970	\$64,243	\$37,768	16.54	4.76
Within-firm Variation from *Residualized* Data						
58,689	0	\$31,381	0	\$31,886	0	4.57

Table 10: Within-firm Heterogeneity in Earnings and corporate culture

Notes.–Sources: PayScale. The table restricts the sample to firms with over ten employee reports in the data, subsequently documenting the mean and standard deviation of actual earnings, predicted earnings (from their ML algorithm), and corporate culture from both the raw data and residualized data (regressing the variables on firm fixed effects and taking the residual).

The main results focuses on recovering a price on corporate culture, but the individual prices on each of the amenities (estimated separately) are relatively similar. Two separate specifications are included: (i) the baseline, and (ii) using a leave-one-out estimate of firm-level corporate culture. Table 11 documents these results. The estimates are broadly consistent with the baseline. The

highest price is on pay transparency, which produces a coefficient of 0.033-0.039. The gradients on development/training and appreciation are also fairly high, but the gradient on relationship with one's manager is relatively low and statistically insignificant when the leave-one-out estimate is used.

Table 11: Marginal Willingness to Pay for Different Amenities

Dep. var. =	ln(predicted comp.)-ln(actual comp.)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
pay transparency	-.033***	-.039***								
	[.000]	[.002]								
communication			-.008***	-.020***						
			[.000]	[.003]						
development/training					-.015***	-.030***				
					[.000]	[.002]				
appreciation							-.018***	-.026***		
							[.000]	[.002]		
management									-.005***	.002
									[.000]	[.002]
R-squared	.03	.02	.01	.01	.01	.01	.02	.01	.01	.01
Sample Size	270150	70478	270150	70478	270150	70478	270150	70478	270150	70478
Leave one out?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
hasloo	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes.–Sources: Payscale and Compustat. The table reports the coefficients associated with regressions of logged predicted compensation net of actual compensation on standardized each of the different inputs to corporate culture, conditional on controls, including: a quadratic in age, male, and indicators for seven buckets of educational attainment (high school, associates, some college, college, professional programs [MBA, health policy], and doctorate), and years of labor market experience. Predicted compensation is generated through PayScale's proprietary machine learning algorithms that use their entire salary database of 56+ million individuals in North America. Standard errors are heteroskedasticity-robust.