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Start-up firms and corporate culture: Evidence from advertised corporate culture

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Evidence from Advertised Corporate Culture

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Abstract

I document advertised corporate culture among start-up firms from an online job board. Two corporate-culture types emerge, one that concerns the well-being of employees (worker-centered culture) and another that emphasizes other values, such as customers, firms, and markets (firm-centered culture). The worker-centered culture attracts 20% more applications than the other culture type. Firms advertising the worker-centered culture exploit worker preference by paying 5% lower salaries than measurably similar jobs. Using a standard model of business creation, I show financially constrained start-ups are incentivized to advocate popular culture, even though doing so is not optimal without financial constraints.

Keywords: Corporate culture, Wage differentials, Entrepreneurship

JEL codes: J31, L26, M13, M14

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1 Introduction

Understanding large and persistent differences in measured productivity across firms has been a central issue in economics. Previous studies have focused on measurable firm factors such as incentive pay (e.g., Lazear (2000)), human-resource practices (e.g., Prennushi et al. (1997); Hamilton et al. (2003)), and manager/managerial practice (e.g., Bertrand and Schoar (2003); Bloom and Van Reenen (2007); Bender et al. (2018); Bandiera et al. (2020)). By contrast, the role of intangible firm characteristics is relatively less investigated despite the importance that researchers suggest it has (Syverson (2011); Crouzet et al. (2022)).

Corporate culture is often considered an important intangible asset by successful business owners and managers. Indeed, recent studies document that several measures of corporate culture are significantly associated with firm performance (e.g, Guiso et al. (2015); Graham et al. (2017); Li et al. (2019)).[1] Yet, relatively little is known about mechanisms through which corporate culture generates a real impact.

In this paper, I show that corporate culture can serve as an important nonwage component for workers in start-up firms. Using unique data from an online job board targeting high-tech start-up companies, I find popular corporate culture exists among workers, and firms advertising the popular corporate culture exploit worker preference by paying significantly lower wages. Using a simple model, I show that financially constrained start-up firms have an additional incentive to advocate popular culture, even though doing so is not optimal without financial constraints.

A unique feature of this online job board is its corporate culture section. The online job board asks each job-posting company to write about its corporate culture. The website posts each firm's reported corporate culture in a separate section below the job description so that applicants can easily view and compare them. This job-posting feature allows me to systematically analyze the corporate culture that start-up companies advocate on a large scale (about 1,350 companies). The data also contain detailed information about each job posting, the job postings to which each applicant applied, and the applicants whom each job-posting firm invites for an interview.

[1] Corporate culture in this paper refers to the notion of corporate culture *defined by a firm* in the job posting. Theoretical studies suggest various definitions of corporate culture. I discuss the relationship between the advertised corporate culture and theoretical definitions of corporate culture in section 3.3.

I first document and characterize the advertised corporate culture. Reading start-up firms' culture reveals many firms advertise their culture as something that could be attractive to young workers. For example, the most frequently used adjectives for describing a company's culture is "fun." To further characterize each firm's corporate culture, I exploit the following idea: if two firms have a similar culture, the usage of words describing their culture would be similar. To implement this idea, I conduct a cluster analysis. I find evidence of two main corporate cultures picked up via three text clusters. Two clusters describe the well-being of employees (worker-centered culture), and the remaining cluster emphasizes other values, such as customers, products, or markets (firm-centered culture).

The cluster analysis assumes corporate culture can be categorized into a set of mutually exclusive types. To check whether this particular assumption drives the result, I conduct latent Dirichlet allocation (LDA) analysis that allows the possibility that the advertised culture is a mixture of core values − groups of related words that describe coherent, underlying values or norms. With different assumptions and estimation methods from the cluster analysis, the LDA analysis generates remarkably similar results. These findings indicate the characterization of advertised corporate culture is not driven by particular assumptions or estimation methodologies of text analysis; instead, it reflects the variation in the description of posting firms' corporate culture.

With this characterization, I document new empirical findings. First, a job posted by a firm advertising a worker-centered culture attracts significantly more applications than a similar job without a worker-centered culture. For example, controlling for detailed fixed effects, a job posted by a firm advertising a worker-centered culture attracts three more applications (the average number of applications per job is 15). This finding holds with various robustness checks, suggesting some applicants prefer worker-centered culture. Second, jobs posted by firms that advertise a worker-centered culture offer significantly lower salaries than measurably similar jobs. For example, by comparing jobs for which an applicant is invited for an interview, I show the monthly salary of jobs posted by firms that advertise a worker-centered culture is about 5% less than the monthly salary of other similar job postings. This finding suggests some firms advertise a worker-centered culture to compensate for lower monetary rewards.

To understand the implication of the above empirical findings for start-up formation, I develop a simple model. The model extends Evans and Jovanovic (1989)'s model of firm creation. In their model, potential entrepreneurs with different business ideas and assets decide whether to start a business under borrowing constraints. I modify the model to incorporate start-up firms' choice of corporate culture. I focus on a particular component of corporate culture: nonwage characteristics that affect workers' preferences. To start a business, entrepreneurs need to hire a worker and invest capital. In the first period, entrepreneurs can attract workers by providing wages and corporate culture. In particular, entrepreneurs can provide two types of corporate culture: worker-centered and firm-centered culture. Depending on the type of corporate culture, a firm's productivity may change. In the second period, firms decide the amount of capital investment subject to borrowing constraints.

The model generates several implications. First, for the model to be consistent with the data, cost-saving would be an impotant motive for firms to choose a worker-centered culture. Note a firm may choose a worker-centered culture for two reasons: (1) to enhance productivity or (2) to save labor costs. Intuitively, if a majority of firms were enjoying higher productivity and a lower labor cost at the same time, we would not have observed a considerable amount of firms providing a firm-centered culture in the data (about 40% among all firms).

Second, when the wage for worker-centered culture is lower than firm-centered culture, as observed in the data, the model predicts that high-productivity or non-financially constrained firms are less likely to provide worker-centered corporate culture. To check whether this model prediction is in line with data patterns, I document who advertises the worker-centered culture. A robust finding is that firms that receive venture funding are less likely to advertise a worker-centered culture. For example, the probability that a firm advertises a worker-centered culture is about 20% lower for venture-capital-backed firms than for firms without venture funding. Given that firms receiving venture funding are more likely to be productive and less likely to be financially constrained, this empirical finding aligns with the model prediction.

Finally, financially constrained entrepreneurs can choose their corporate culture suboptimally (relative to the case without borrowing constraints) if they can save on labor costs by doing so. Therefore, a typical loan policy that helps constrained entrepreneurs relax borrowing constraints can increase efficiency not only by increasing constrained entrepreneurs' physical investment, but also by influencing their corporate culture.

This paper is related to the literature on corporate culture. Early studies theoretically characterize corporate culture and investigate a possible mechanism through which it can affect real outcomes (e.g., Kreps (1990); Crémer (1993); Hermalin (2001); Rob and Zemsky (2002); Van den Steen (2010); Kosfeld and Von Siemens (2011)).[2] Recent work proposes several ways to measure corporate culture and establish the association between measured corporate culture and firm performance (e.g., Fiordelisi and Ricci (2014); Guiso et al. (2015); Graham et al. (2017); Grennan (2019); Li et al. (2019)).[3] I contribute to this line of literature in the following ways. First, by focusing on one particular component of corporate culture, namely, a nonwage component of a job, I demonstrate that corporate culture can generate a real impact by influencing workers' application decisions. Second, most previous work focuses on already established firms and does not provide insight into how a firm's initial corporate culture is formed. The results in this paper indicate that the labor market condition (characterized by many young workers in the current market), combined with a firm's financial condition, can influence the firm's initial corporate culture.

This paper is also related to the literature on compensating wage differentials. Since the seminal work by Rosen (1974), several nonwage components of a job have been studied to understand wage differences across jobs. Those job characteristics include occupational safety (e.g., Viscusi and Aldy (2003); León and Miguel (2017); Lavetti (2018); Guardado and Ziebarth (2019)), flexible work arrangement (e.g., Bloom et al. (2015); Mas and Pallais (2017)), health benefits (e.g., Gruber (1994); Dey and Flinn (2005); Eriksson and Kristensen (2014)), and job security (e.g., Abowd and Ashenfelter (1981); Bonhomme and Jolivet (2009)).[4] Using rich information from an online job board, I show that another important nonwage aspect of a job is corporate culture. I further show some firms advocate a particular type of corporate culture to compensate for a low wage. To the best of my knowledge, this is the first paper estimating compensating wage differential for corporate culture.

More broadly, this paper contributes to the literature on entrepreneurship. Understanding the extent to which financial friction generates inefficiency in the process of firm creation

[2] Gorton and Zentefis (2019, 2020) propose a new theory of corporate culture and use it to understand racial and gender wage gaps and the boundary of the firm.

[3] For a survey of the recent development on the literature, see Gorton et al. (2022).

[4] The idea of compensating wage differentials has been applied to understand lawyers' and scientists' career choices (Weisbrod (1983); Goddeeris (1988); Stern (2004)), medical residency (Marder and Hough (1983)), and union wage premiums (Duncan and Stafford (1980); Antos (1983)).

has been a central issue in the literature (e.g, Evans and Jovanovic (1989); Hurst and Lusardi (2004); Schmalz et al. (2017)). Previous studies show financial friction can reduce firm creation and new firms' physical investment. The findings in this paper suggest financial friction can also distort an intangible aspect of a firm that might affect firm productivity. Therefore, subsidizing start-up firms can help constrained entrepreneurs increase physical investment *and* choose the "right" corporate culture.

The paper is organized as follows. Section 2 describes the data and the online job market. Section 3 characterizes the posting firms' advertised corporate culture. The main empirical findings are documented in section 4. Section 5 presents the model, and section 6 concludes.

2 Data

This paper uses data from an online job board based in Singapore. The website was established in 2016 and has been targeting tech industries in Singapore and nearby Southeast Asian countries. In this section, I overview the target market and the background of this online job board.

The recent increase in internet access among Southeast Asians has created many business opportunities for tech start-up firms in the region. Between 2015 and 2019, the aggregate sales value of the Southeast Asian tech industry has grown at a 33% annual rate, reaching the annual value of 100 billion USD in 2019. More than 3,000 tech start-ups were created between 2016 and 2019.[5]

The company that created the online job board aims to provide an online job platform for start-up firms in Southeast Asian tech industries, particularly Singapore. The service was launched in May 2016, and I use the data between May 2016 and October 2018 for this study. A unique feature of this online job board is its corporate culture section. Job-posting firms are asked to write about their corporate culture in addition to describing the job. A company's description of its culture is then posted in a separate section immediately below the job description so that applicants can easily see and compare corporate culture across

[5]The summary statistics for Southeast Asian tech industries are mainly from the report (e-Conomy SEA 2019) published by Google, Temasek, and Bain & Company.

posting firms.[6] Thanks to this unique feature, I can observe start-up firms' descriptions of their culture on a large scale. More details about the online job market are described in Appendix A.

Job postings from other countries are sometimes written in their native language, which makes consistently applying text analyses, shown below, challenging. Applicants looking for a part-time or freelance job can be substantially different from those looking for a full-time job. Therefore, I focus on firms that ever posted full-time jobs located in Singapore.

To provide a broad picture of the market, I present the summary statistics of posting firms and applicants in Appendix A.3. The market can be characterized by (1) tech start-up firms on the demand side and (2) recent college graduates on the supply side.

3 Characterizing Advertised Corporate Culture

In this section, I document and analyze the advertised corporate culture. Before conducting a formal analysis, I manually read the advertised corporate culture. Although the description of corporate culture differs across firms, many firms describe their culture as something that could be attractive to young workers. For example, one of the most frequently used adjectives for describing a company's culture is "fun," along with "passionate," "open," and "driven" (Table 1).

To further analyze the description of corporate culture by each firm, I conduct text analyses. One approach could be to impose predefined corporate culture types and map each text to one of those pre-defined corporate cultures (e.g., Fiordelisi and Ricci (2014); Li et al. (2019)). However, most previous studies on corporate culture are based on large firms. Whether the corporate culture in the current online job board, primarily based on young firms, can be characterized by the types defined from previous studies is not apparent. For this reason, rather than imposing predefined types of corporate culture, I let the data show the difference in corporate culture across firms.

[6]From a discussion with company personnel, I learned the company considers corporate culture one of the most crucial job aspects. For this reason, the company decided to devote a large space on a posting page to show each firm's corporate culture.

3.1 Cluster Analysis

I first conduct a cluster analysis. The basic idea of cluster analysis is intuitive and suitable for this analysis; if two firms have a similar culture, the usage of words describing their culture will be similar. Moreover, the procedure for cluster analysis is straightforward and transparent.

Specifically, I conduct a partition cluster analysis known as the K-means algorithm. For a predetermined number of clusters K, the algorithm randomly assigns K initial group centers among observations.[7] Each observation is assigned to the group with the closest center for a distance measure.[8] The mean of the observations assigned to each group becomes a new group center. The process is repeated until all observations remain in the same group from the previous iteration. As a result, the cluster analyses break the observations into K number of non-overlapping groups. A detailed procedure is presented in Appendix B.

No consensus exists on the optimal number of clusters. As the number of clusters increases, a goodness of fit (e.g., the within-cluster sum of squares) increases, but the readable distinction between the clusters becomes less clear. Following Bandiera et al. (2020), I find the minimum number of clusters to see a meaningful distinction between them. After experimenting with several values of K, I chose $K = 3$ as the benchmark number of clusters. When $K = 3$, a cluster distinctively different from other clusters arises (the first cluster below). The distinction between the other two clusters is not clear. This tendency holds even though I increase the number of clusters: one cluster to be distinctive and the remaining clusters similar.[9]

The most frequently observed words in each cluster are shown in Table 2. In Appendix C, I present examples of corporate cultures in each cluster. Out of 1,764 firms, 78% (1,363 firms) report their culture, whereas 22% do not. About 19% of firms are categorized into the first cluster. The most frequently used keywords within this cluster include technology, product, and market. Firms in the first cluster often emphasize the value of their market, product, or customer, but not necessarily their employees.

The second and third clusters are similar in that firms categorized into the two clusters emphasize employee-oriented values. For example, firms categorized into the second cluster

[7] I tried several (random) initial group centers. The results are similar with different initial random assignments.

[8] I use the Pearson distance measure. The definition of the measure is shown in Appendix B.

[9] As a robustness check, I generated clusters with $K = 4$ and $K = 5$ and conduct the regression analyses, which I show in section 4. The results, qualitatively and quantitatively, change only slightly.

tend to describe their culture as innovative, open, fast-paced, or energetic. Firms categorized into the third cluster describe their culture as a fun working environment with learning opportunities. Many firms claim they provide a worker-centered culture; the proportion of firms in the second and third clusters is 30% and 29%, respectively.

3.2 Latent Dirichlet Allocation (LDA) Analysis

The cluster analysis assumes corporate culture can be categorized into a set of mutually exclusive types. To check whether this particular assumption drives the result, I conduct the LDA method, an unsupervised machine-learning algorithm.[10]

The LDA assumes the advertised culture is a mixture of a K number of core values, and each word describing the culture is attributable to one of these core values. To be more specific, suppose $X = \{x_1, x_2, ..., x_W\}$ is the set of all possible words describing culture. The k^{th} core value is a probability distribution β_k over X. The corporate culture of firm i is characterized by $\{\theta^i_k\}_{k\in K}$, where θ^i_k is the share of the k^{th} core value in firm i's corporate culture. More details about the LDA analysis are explained in Appendix D. I set the number of core values to three, which is the same as the benchmark number of clusters.

Table 3 shows the estimated core values (β_k) up to the top 10 words with the highest probability. The top 10 words for the first core value are similar to the top 10 words in the first cluster. Likewise, the top 10 words for the second and third core values are similar to the top 10 words in the second and third clusters.

Figure 1 shows the estimated distribution of (θ^i_1, θ^i_3). The sum of three core values for a firm is equal to 1. Therefore, each firm is represented in the two-dimensional space of (θ^i_1, θ^i_3). A firm with $(\theta^i_1, \theta^i_3) = (1, 0)$ mostly exhibits the first core value in its description of corporate culture. Likewise, a firm with $(\theta^i_1, \theta^i_3) = (0, 0)$ and $(\theta^i_1, \theta^i_3) = (0, 1)$ mostly exhibits the second and third core values in its corporate-culture description, respectively. Relatively more mass are observed at each corner (i.e., either $(\theta^i_1, \theta^i_3) = (1, 0)$, $(\theta^i_1, \theta^i_3) = (0, 0)$, or $(\theta^i_1, \theta^i_3) = (0, 1)$). The third core value − embracing a fun working environment − seems to be the most relevant; many firms are characterized by combining the first and third values or the second and third

[10]Several recent studies use the LDA analysis to characterize CEOs' time diary (Bandiera et al. (2020)), political survey (Draca and Schwarz (2020)), or Federal Open Market Committee transcripts (Hansen et al. (2018)).

values. On the other hand, only a few firms are characterized by combining the first and second values.

3.3 Discussion

From cluster analysis, two corporate-culture types emerge: one that emphasizes employees and one that emphasizes other values such as customers, products, or markets. With different assumptions and estimation methods from the cluster analysis, the LDA analysis generates similar results. These findings indicate the characterization of advertised corporate culture in this market is not driven by particular assumptions or estimation methodologies for text analysis; instead, it reflects the variation in the description of posting firms' corporate culture.

The theoretical literature provides various definitions of the corporate culture. For example, corporate culture is defined as the firm members' stock of shared knowledge, language, and customs that reduce information-transmission costs within the organization (Crémer (1993)). Corporate culture is also defined as shared beliefs about the best technology, strategy, or course of action for a firm to adopt (Van den Steen (2010)), or the tendency of member of the firm to cooperate (Rob and Zemsky (2002); Kosfeld and Von Siemens (2011)).[11]

The advertised corporate culture that I document in sections 3.1 and 3.2 seems to reasonably reflect the definition of corporate culture proposed by Kreps (1990). Kreps (1990) defines corporate culture as principles (or norms, values) applied to adapt to unforeseen contingencies in the transaction between hierarchical superiors and hierarchical inferiors (in our case, a firm and employees). Because unforeseen contingencies arise (by definition) after a formal contract is made between a firm and employees, firms have an incentive to preserve or promote their corporate culture's reputation to attract potential employees. Corporate culture gives potential employees an idea ex ante of how the organization will react to circumstances as they arise.[12] When a firm emphasizes making the world's best product its priority, potential employees will expect action to be taken − when unforeseen circumstances arise − in a way that improves the firm's product. Likewise, when a firm emphasizes a vibrant and fun working

[11] For a survey on corporate culture in economic theory, see Hermalin (2001, 2012); Gorton et al. (2022).

[12] Kreps (1990) formalizes this idea by using a game-theoretic framework for a long-lived firm (or an entrepreneur) and short-lived employees. In his framework, corporate culture is a selection criterion by which equilibrium is selected from many.

environment that focuses on employees' well-being, potential employees will expect action to favor employees.

4 Corporate Culture and Labor Market

In this section, I document the role of advertised corporate culture in the labor market.

4.1 Summary Statistics for Job Postings

Before conducting regression analyses, I first present summary statistics for job postings.

I clean the job titles in a similar way to Marinescu and Wolthoff (2020). I first make job titles lowercase and remove company names, job location, punctuation, and any special characters. I then keep the first four words. Table 4 shows the 10 most common job titles. Given that most firms are IT-related firms, most postings are for IT technicians or marketing personnel.

Table 5 shows other characteristics of job postings. Note most applicants recently graduated from college. Because most job postings target those young applicants, the minimum requirement for previous experience is low (the median is 1).

Of 9,458 job postings, about 80% post the monthly salary range (minimum and maximum monthly salary). Because most jobs target young inexperienced workers, the average salary is not high. The mean and median are similar, suggesting the distribution is relatively symmetric. Different from a typical online job board, many postings on the website offer equity.[13] A quarter of jobs indicate the firm provides equity compensation.

Note the website provides a collection of keywords describing benefits and lets the posting firm choose keywords applicable to the firm. The selected keywords are shown in the second part of the culture section. Given that most firms do not select any keyword, I construct two dummy variables summarizing benefits: lifestyle benefits and welfare benefits. The keywords for lifestyle benefits include casual dress code, company outings, flexible working hours, free food, pet-friendly office, recreational area, and the ability to work from home. The keywords

[13] The online job board provides posting firms the option to show whether they provide equity compensation. If a posting firm clicks yes for that option, the website indicates the posted job provides equity compensation, but no further information (e.g., the amount of equity) is shown.

for welfare benefits include dental/health insurance, gym membership, employee discount, vacation time, wellness program, childcare assistance, bonuses, paid maternity/paternity leave, paid sick leave, and transportation reimbursement. The lifestyle (welfare) dummy has a value of 1 if a job posting has a keyword for lifestyle (welfare benefit) in the culture section.

Panel C of Table 5 shows the percentage of firms providing each type of benefit. Only about 10% of firms provide at least one of the benefits categorized as a lifestyle. Similarly, 10% of firms provide at least one of the benefits categorized as welfare. Among the firms using this online job board, providing welfare benefits is not common; 86% of firms do not provide any benefit. Given that most posting firms are tech-related start-ups that often lack funding, they may be less likely to commit to providing a welfare benefit.

Panel D of Table 5 shows application and acceptance information for each posting.[14] A job posting attracts, on average, 15 applicants, but the distribution is highly skewed. For example, a substantial number of postings receive zero applications. A unique feature of these data is that I can observe which applicants are invited for the first interview. Therefore, for each job-posting level (with a positive number of applications), I can define the acceptance rate, measured by the number of invited applicants divided by the total applicants. The last row of Table 5 shows the summary statistics for the acceptance rate. The average acceptance rate is 0.05, suggesting about 5% of applicants are invited for the first interview.

4.2 Does Advertised Corporate Culture Matter?

I now investigate whether different types of corporate culture attract a different number of applicants. For each job posting, I calculate the number of applicants as the independent variable and regress it on other posting characteristics, including information about corporate culture. In doing so, I compare job postings in the same year-month, with the same job title by the firms in the same industry, and with the same vacancy counts.

In the first column of Table 6, I include a dummy for a job posting to show corporate culture or not, along with other controls. First, the pecuniary components of a job are essential for attracting applicants. Providing 1,000 SGD more in maximum monthly salary attracts 0.6 more applications.[15] Providing equity attracts about five more applications. Applicants tend

[14] Throughout the paper, I call an applicant accepted if he is invited for an interview.

[15] Note that the coefficient for the salary is relatively low, given that the salary information is shown as a

to apply more to larger firms and firms with lifestyle benefits. Finally, controlling for other characteristics, a posting providing any information about the posting firm's culture attracts 2.25 more applications.

Showing corporate culture or not changes the amount of information revealed to applicants. In the second column of Table 6, I additionally control for the word count of a job posting, thereby controlling for the amount of information revealed to applicants. Even after I control for the word count, the culture dummy is significant with almost the same magnitude as in the first column of Table 6, suggesting the content of information (about corporate culture), rather than the amount of information, attracts more applications.

In the third column of Table 6, I include the 10 dummy variables for a posting to include each of the 10 most frequently used adjectives in describing corporate culture. Of the 10 adjectives, "open," "fun," and "fast-paced" attract significantly more applications than a posting without corporate-culture information. For example, a job posting by a firm describing its corporate culture with "fun" attracts about two more applications. After I control for the 10 dummy variables, the culture dummy's coefficient becomes insignificant, suggesting those firms describing their corporate culture with "open," "fun," and "fast-paced" attract significantly more applications.

In the fourth column of Table 6, I replace the 10 dummy variables for each of the 10 adjectives with the dummy variables for each of the three culture clusters. Compared with a job posting without corporate-culture information, the two clusters related to worker-centered culture attract significantly more applications. By contrast, firms that advertise firm-centered culture attract no more applications than firms that do not advertise their corporate culture.

In the last column of Table 6, I replace the dummy variables for each of the three culture clusters with the second and third core values from LDA analysis for each observation.[16] The result is consistent with the regression analysis with the cluster dummies; a corporate culture exhibiting more worker-centered core values − particularly those emphasizing a fun working environment − attracts significantly more applicants. For example, moving from the 10th to 90th percentile of the third core value (from 0 to 0.81) attracts about three more applicants.

To summarize, this section's results indicate corporate culture − in particular, a corporate

range.

[16]By construction, the sum of the three core values for a firm is equal to 1.

culture that favors employees – matters: firms advertising corporate cultures that favors employees attract significantly more applications than measurably similar job postings. Given that both the cluster and LDA analysis generate a similar characterization in section 3 and a consistent result in section 4.2, I define the "worker-centered culture" as clusters 2 and 3 and the "firm-centered culture" as cluster 1 hereafter.

4.3 Robustness Checks

The omitted-variable bias may be a concern for the results in section 4.2. I believe a unique setting in this paper alleviates this concern. As I already discussed in section A.3, most firms are categorized into relatively homogeneous high-tech industries. Moreover, I further control for detailed sub-industries when conducting regression analyses. Also, I have all the information on the online job board at the time of the application. In other words, I see what applicants saw about a job at the time of their applications. Using this information, I control for detailed firm-level characteristics (e.g., firm size, venture funding, non-monetary compensation) when I estimate the coefficients for corporate culture.

Some may be concerned that the applicant already knew more about the firm than the information posted on the job board. To address this issue, I conduct three robustness checks.

Controlling for firm ages

A subset of firms reveals their establishment year so that I can calculate the firm age at the time of job posting. Specifically, 664 out of 1,764 firms posted their establishment year in the job posting. The median and 75 percentile of firm age are 3 and 5, respectively, indicating that most firms are young.

To control for the prior information known to applicants, I include firm-age fixed effect to otherwise identical regression equations of columns (4) and (5) in Table 6. The idea is that applicants' prior information about firms can vary by firm age (applicants may have better information about older firms), and by comparing job postings by firms with the same age, we could alleviate a bias driven by different amounts of prior information.

The results are shown in Table 7. Even after controlling for the firm-age fixed effect, the results on corporate culture are robust.

Using viewing time

If the application is mainly driven by prior information, applicants may not need much time to digest the written information in the job postings. In particular, popular jobs are more likely to be known to applicants in advance and draw many applications. If the application decision is determined in advance, applicants may not need much time to read the posted information for those popular job postings.

To test this hypothesis, I exploit the "click" information for each applicant. The data provides the exact time an applicant i enters a webpage for a job posting j. I define the viewing time for a job posting j by an applicant i as

$$\text{Viewing time}_{ji} = \text{Click time}_{j,i+1} - \text{Click time}_{ji},$$

where Click time_{ji} is the time at which an applicant i enters a webpage for a job posing j and Click $\text{time}_{j,i+1}$ is the time an applicant i enters a webpage for another job posing right after visiting the job posting j.[17]

I first drop Viewing time_{ji} greater than 60 minutes because those viewing times may reflect inactive status between Click time_{ji} and Click $\text{time}_{j,i+1}$. Then, using Viewing time_{ji}, I define Viewing time for job posting j as the average viewing time for job posting j by applicants who submitted their resumes to the job posting. Out of 8,179 job postings that received at least one application, the viewing time is available for 7,726 job postings. The average and standard deviation of the viewing time for job postings are 3 and 2 minutes, respectively.

Figure 2 shows the binned scatter plot of the log viewing time for a job posting on the log application numbers for the job posting. Applicants tend to spend more time reading popular job postings. Popular jobs are more likely to be known to applicants in advance. If the application is driven by prior information, the reading time and the popularity of jobs, captured by the number of application, would not have a strong association. Contrary to this prediction, Figure 2 suggests that applicants put some effort into processing the information in the job postings, and such a tendency is higher for popular jobs.

[17] Applicant i may visit the webpage for job posting j several times. In this case, I aggregate the total viewing time by applicant i for job posting j to calculate Viewing time_{ji}.

Additional test

Oster (2019) proposes a method for calculating a consistent estimate of the bias-adjusted treatment effects. The key insight comes from Altonji et al. (2005): we may learn about the relationship between treatment (in our context, corporate culture) and unobserved variables from the relationship between treatment and observed variables. Specifically, the degree of selection on unobserved variables is assumed to be proportional to the selection on observed variables. Oster (2019) proposes estimators that converges in probability to the true treatment effect. An estimator (β^*) exhibits the following analytic solution:

$$\beta^* = \tilde{\beta} - \delta\left[\dot{\beta} - \tilde{\beta}\right]\frac{R_{max} - \tilde{R}}{\tilde{R} - \dot{R}}. \tag{1}$$

$\tilde{\beta}$ and $\dot{\beta}$ are the ordinary least squares (OLS) estimates from the benchmark regression (including all the observed variables) and the regression with the treatment as a sole control, respectively. Likewise, $\tilde{R}$ and $\dot{R}$ are the R-squared values from the benchmark regression and the regression with treatment as a sole control, respectively. δ captures the level of selection on unobserved variables relative to the selection on observed variables. A higher δ means a higher level of selection on unobserved variables. R_{max} is the R-squared from a hypothetical regression of the outcome on treatment and both observed and unobserved controls. Note $\{\tilde{\beta}, \dot{\beta}, \tilde{R}, \dot{R}\}$ can be easily calculated from the data. Therefore, one can generate a bound for β depending on the value of δ and R_{max}.

Given that the method by Oster (2019) is devised for a single treatment effect, I generate a dummy variable for worker-centered culture (clusters 2 and 3). Adding observed controls increases R-squared (from 0.004 to 0.517) and the coefficient for the worker-centered culture (from 1.96 to 2.82). Therefore, according to equation (1), the lower bound for the true estimate is the benchmark estimate.[18]

[18] Several tests proposed by Oster (2019), which depend on the values of δ and R_{max}, generate the same conclusion.

4.4 Ad hoc specification for the corporate culture

Another concern could be that this section's results may depend on an ad hoc specification for the corporate culture. I believe this concern is partially addressed by the fact that the results in section 4.2 are robust to two specifications that rely on different assumptions and estimation procedures. In this section, I also conduct a placebo test to implement the following idea. If the categorization of corporate culture does not capture the dimensions of corporate culture relevant to job applicants, the estimated effect of worker-centered corporate culture would not be different from the estimated effect of randomly selected postings with the same share of worker-centered culture. To implement this idea, I randomly select the same share of postings (61%) as the one posted by firms with a worker-centered culture (clusters 2 and 3) and create a dummy variable for them that takes a value of 1. I then compare the application behavior for this random group with the one for the worker-centered culture. If the characterization of corporate culture according to the cluster analysis is arbitrary and irrelevant to job applicants, the two results would be similar. I conduct a regression analysis identical to column (4) of Table 6, except that I replace the cluster variables with the randomly generated dummy variable. I repeat this process 1,000 times and report the distribution of the random dummy variables' estimated coefficients.

The results are presented in Figure 3. On average, the effect of the random dummy is zero, as expected. More importantly, the largest magnitude out of 1,000 simulations is 1.45, which is much lower than the actual estimate for the worker-centered culture, namely, 2.82. Moreover, none of the simulations generate as significant an estimate as the one for the employee-oriented culture ($p-$value of 1.844e-07).

To summarize, although the characterization of corporate culture by the cluster or LDA analysis inevitably contains noise, the classifications by the two text analyses seem to capture the dimensions of corporate culture relevant to job applicants.

4.5 Why Does Advertised Corporate Culture Matter?

The analysis so far shows firms that advertise their employee-oriented culture attract significantly more applicants. This finding is in sharp contrast to the findings in Guiso et al. (2015). By using the Standard and Poor's 500 (S&P 500) companies' websites, Guiso et al. (2015)

document the companies' advertised corporate culture. They find no correlation between the advertised corporate culture on a company's website and its performance, such as Tobin's q and return on sales.

The critical difference in the institutional setting may generate this difference. Large companies are more likely to advertise their corporate culture to unspecified customers who cannot verify their real culture. By contrast, start-up firms advertise their corporate culture to potential employees who, once hired, can verify the firm's claim.[19]

The finding in section 4.2 is in line with the prediction by Kreps (1990). Kreps (1990) predicts start-up owners will truthfully reveal the corporate culture to potential employees, although not doing so is beneficial in the short run. Knowing unforeseen contingencies will arise after a formal contract, potential employees would want to know principles (i.e., corporate culture) that a firm will apply to handle those contingencies. If a firm lies about those principles, not only may the current employees, who joined the firm believing the firm's advertised corporate culture, leave the firm, but also potential employees may not believe the firm's advertised principle.

4.6 Corporate Culture and Posted Wage

In this section, I show that firms that advertise the worker-centered culture pay a significantly lower salary than firms that do not.

To this end, I first regress the log value of monthly salary on job characteristics. The monthly salary is calculated by (Monthly salary min. + Monthly salary max.)/2. In particular, I include "Worker-centered culture," a dummy variable that takes a value of 1 if a firm's culture is categorized as either cluster 2 or 3. I also include dummy variables for equity provision, lifestyle, and welfare benefits (defined in section 4.1) to control for other job characteristics. Finally, I control for the job title *and* year-month fixed effect. Wages can differ across job titles (Marinescu and Wolthoff (2020)). Moreover, search friction in the online job board may affect wage variation (e.g., Hwang et al. (1998); Bonhomme and Jolivet (2009)). If two jobs with the same job title are posted in the same month, job candidates are more likely to search and

[19] After visiting many posting firms' websites, I found the advertised corporate culture in the online job board is rarely stated on their websites, suggesting firms advertise their corporate culture specifically to potential employees.

see both job postings, and the influence of search friction could be less severe among those job postings.

The estimation result is shown in the first column of Table 8. Among firms advertising the same job title posted in the same month, firms advertising a worker-centered culture pay about a 5% lower monthly salary than other firms. The wage difference associated with the worker-centered culture is in line with the idea of compensating wage differentials (Rosen (1974)): knowing some workers prefer a worker-centered culture, firms pay lower salaries when they provide a worker-centered culture.

Each job posting can target different candidates (e.g., top-tier vs. low-tier candidates), and the total compensation value (including both pecuniary and non-pecuniary values) can be different across job postings accordingly. I use the information on the application for each job posting and interview invitation (acceptance) by posting firms to control this heterogeneity.[20] The unit of observation for the regression in the second column of Table 8 is an application to each job posting.[21] Therefore, I can control for the individual fixed effect by comparing job postings to which each applicant applied. Note that I compare jobs that each candidate applied for (therefore, the jobs each candidate successfully searched). Of course, a low-tier job candidate can apply for a job targeting a high-tier job candidate. To handle this issue, I compare job postings to which a candidate applied *and* is accepted. Even with a different fixed effect, the result is consistent with the findings in the previous regressions.

Some workers are particularly popular, and every firm wants to interview them even though a firm targets a low-tier candidate. In the third column of Table 8, I exclude job applicants whose invitation number is above the top 5th percentile. The main result still holds.

4.7 Summary

So far, I have shown that firms advertising a worker-centered culture attract significantly more applications than measurably similar job postings, and those firms exploit workers' preference by offering significantly lower salaries. These empirical findings suggest one important, but

[20]Stern (2004) implements a similar approach to estimate compensating wage differentials for scientific research by scientists. By comparing multiple job offers for an individual researcher, he shows a negative relationship between wages and the permission to publish scientific research.

[21]In contrast, the unit of observations in the first regression in Table 8 is a job posting.

often overlooked, aspect of corporate culture: corporate culture can be an important nonwage job characteristic for workers in start-up firms.

5 Theoretical Framework

What is the implication of corporate culture for start-up formation when it serves as a compensating wage differential? Knowing a popular culture can attract workers with a lower wage, some start-up firms can have an incentive to provide such a culture to reduce the labor cost. In this section, I demonstrate that financially constrained start-up firms can have an additional incentive to provide a popular culture, although doing so is not optimal without financial constraints.

To this end, I develop a simple model of firm creation. The model is based on Evans and Jovanovic (1989), a seminal work on firm creation under borrowing constraints. I extend their model by allowing an entrepreneur to choose corporate culture.

5.1 Environment

Consider potential entrepreneurs who are considering starting a business. An entrepreneur i is characterized by the quality of his business idea $\theta \in \mathbb{R}_+$ and net worth $A \in \mathbb{R}_+$. Entrepreneurs have a homogeneous utility function that is linear in consumption. An entrepreneur starts a business if and only if the profit is positive.[22]

To start a business, an entrepreneur must hire a fixed number of workers, which I normalize to be one. To hire a worker, the entrepreneur can provide either one of two types of corporate culture: one that favors workers (worker-centered culture, $g = 1$) and one that does not (firm-centered culture, $g = 0$). A firm's profit (π_g) can be different depending on its corporate culture:

$$\begin{aligned}
\pi_0 &= \max_k \quad \theta k^\alpha - rk - w_0 \quad \text{if } g = 0, \\
\pi_1 &= \max_k \quad \mu\theta k^\alpha - rk - w_1 \quad \text{if } g = 1,
\end{aligned}$$

[22]In Evans and Jovanovic (1989), an agent decides whether to become an entrepreneur or a worker. Therefore, the outside option for an entrepreneur is the worker wage. To focus on an entrepreneur's choice of corporate culture, I normalized the outside option to zero.

where $\alpha \in (0, 1)$ and $\mu > 0$. k and r refer to capital investment and the risk-free gross interest rate, respectively. w_g refers to wages depending on corporate culture. By providing a worker-centered culture, the profit can change in two ways: (1) productivity can change, and (2) labor costs can change.

After deciding their corporate culture and hiring a worker, entrepreneurs choose the capital investment subject to borrowing constraints. Following the literature (e.g., Evans and Jovanovic (1989)), I assume the maximum borrowing amount depends on the entrepreneurs' net worth. Specifically, an entrepreneur can borrow up to $(\lambda - 1)A$, where $\lambda \geq 1$. As a result, the maximum amount of capital investment is $(\lambda - 1)A + A = \lambda A$.

Remarks

Before characterizing the model, I discuss some model assumptions. First, I assume homogeneous worker productivity. I make this assumption to incorporate the empirical finding that firms' preferences regarding potential employees are homogeneous (Appendix E).

Second, to capture the role of the worker-centered culture in a parsimonious way, I model it as a nonwage component that affect workers' preference and firm productivity. In particular, μ captures the productivity difference with and without a worker-centered culture. Kreps (1990) provides a micro-foundation for how μ can differ depending on the corporate culture. For example, to keep its working environment fun or favorable to employees, an entrepreneur may not be able to ask employees to work as hard as he wants them to, or he may need to favor employees when his interests and theirs are not aligned. Therefore, productivity may reduce from the firm owners' perspective. Alternatively, a culture that favors worker can encourage workers to work harder, resulting in higher productivity. Related, Lazear (1995) and Hermalin (2001) emphasize that entrepreneurs can shape or influence their firms' corporate culture. For this reason, I assume the corporate culture is a choice variable for entrepreneurs.

Finally, I assume that some entrepreneurs' investments might be constrained due to financial friction. Research shows borrowing constraints can play an important role in firm creation (e.g., Evans and Jovanovic (1989); Corradin and Popov (2015); Adelino et al. (2015); Sauer and Wilson (2016); Schmalz et al. (2017)). Building on this previous finding, I study how borrowing constraints can affect start-up firms' corporate culture.

5.2 Characterization

I first characterize entrepreneurs' decision when borrowing constraints do not exist. The optimal amount of capital investment for $g = 0$ and $g = 1$ is $\left(\frac{\alpha\theta}{r}\right)^{1/(1-\alpha)}$ and $\left(\frac{\alpha\mu\theta}{r}\right)^{1/(1-\alpha)}$, respectively. As a result, a firm's profit can be represented as

$$\begin{aligned} \pi_0 &= \Omega\theta^{1/(1-\alpha)} - w_0 \qquad \text{if } g = 0, \\ \pi_1 &= \Omega(\mu\theta)^{1/(1-\alpha)} - w_1 \quad \text{if } g = 1, \end{aligned}$$

where $\Omega = \left(\frac{\alpha}{r}\right)^{\alpha/(1-\alpha)} - r\left(\frac{\alpha}{r}\right)^{1/(1-\alpha)}$. Therefore, an entrepreneur provides a firm-centered (worker-centered) corporate culture if and only if equation (2) is positive (negative):

$$\Omega\left\{\theta^{1/(1-\alpha)} - (\mu\theta)^{1/(1-\alpha)}\right\} - (w_0 - w_1). \tag{2}$$

An immediate implication of equation (2) is that μ must be less than 1 to observe firms with $g = 0$ and a positive wage differential in equilibrium ($w_0 - w_1 > 0$). Otherwise, all firms provide a worker-centered corporate culture and we would not observe a firm with a firm-centered corporate culture.

Note $\left\{\theta^{1/(1-\alpha)} - (\mu\theta)^{1/(1-\alpha)}\right\}$ is an increasing function of θ when μ is less than 1. Therefore, if we observe both types of corporate culture in equilibrium, a threshold of θ ($\hat{\theta}$) exists so that firms with $\theta > \hat{\theta}$ provide a firm-centered culture and firms with $\theta \leq \hat{\theta}$ provide a worker-centered culture. This is because the opportunity cost of providing a worker-centered culture increases with θ, whereas the marginal benefit of providing a worker-centered culture (a reduction of wage costs) is the same regardless of θ.

To pin down the condition under which a worker-centered culture is observed in equilibrium, I define θ_0 such that $\Omega\theta_0^{1/(1-\alpha)} - w_0 = 0$. An entrepreneur with $\theta < \theta_0$ will generate a negative profit when he provides a firm-centered culture. If the entrepreneur with θ_0 generates a zero or negative profit when he provides a worker-centered culture, no firm in the economy will provide a worker-centered culture given that $\partial\left\{\theta^{1/(1-\alpha)} - (\mu\theta)^{1/(1-\alpha)}\right\}/\partial\theta > 0$. Therefore, for a worker-centered culture to be observed in equilibrium, the following condition must hold:

$$\begin{aligned} & \Omega(\mu\theta_0)^{1/(1-\alpha)} - w_1 > 0 \\ \Leftrightarrow \quad & \ln w_0 - \ln w_1 > -\frac{1}{1-\alpha}\ln\mu. \end{aligned} \tag{3}$$

Equation (3) suggests that if a reduction in productivity is too large or a reduction in the wage costs is too small, no one in the economy will choose a worker-centered corporate culture.

I now characterize an entrepreneur's decision when he is financially constrained. Specifically, I consider a case in which an entrepreneur will be financially constrained regardless of the corporate culture he chooses.[23] Given that capital investment is constrained at λA, an entrepreneur provides a firm-centered (worker-centered) corporate culture if and only if equation (4) is positive (negative):

$$(\lambda A)^{\alpha}\big\{\theta - \mu\theta\big\} - (w_0 - w_1). \tag{4}$$

Some implications are drawn from equation (4). First, unlike the case without borrowing constraints, whether to provide a worker-centered culture or not depends on an entrepreneur's net worth (A). In particular, those with a low A are more likely to provide a worker-centered culture. Second, as in the case without borrowing constraints, if μ is greater than 1, no firm chooses $g = 0$ if the wage differential $(w_0 - w_1)$ is positive in equilibrium. Third, as borrowing constraints become more severe (as λ becomes lower), more entrepreneurs provide a worker-centered culture.

To elaborate on the interaction between borrowing constraints and entrepreneurs' choice of corporate culture, I present the policy function in Figure 4. Line 1 (horizontal gray line) describes the cut-off level of θ above which entrepreneurs start a business without borrowing constraints. Entrepreneurs' net worth does not affect the decision to start a business when borrowing constraints do not exist.

Line 2 (gray dashed line) describes the threshold of θ ($\hat{\theta}$), above (below) which entrepreneurs

[23] Another possibility is that $\big(\frac{\alpha\mu\theta}{r}\big)^{1/(1-\alpha)} < \lambda A < \big(\frac{\alpha\theta}{r}\big)^{1/(1-\alpha)}$ with $\mu \in (0,1)$. In this case, an entrepreneur will not be constrained when he provides a worker-centered culture but will be constrained when he provides a firm-centered culture. Given that the main implications are similar to the case in which an entrepreneur will be financially constrained regardless of the corporate culture, I present the results based on equation (4).

provide a firm-centered (worker-centered) corporate culture without borrowing constraints. As explained earlier, low-productivity firms find it least costly to provide a worker-centered culture. Therefore, it is likely to be efficient for them to cater to workers who care more about the worker-favored corporate culture.

Line 3 (thick black line) describes the cut-off level of (θ, A), above which entrepreneurs start a business with borrowing constraints. When borrowing constraints are present, those with a low A may not be able to borrow enough to utilize their business idea, and some of them give up starting a business.

Line 4 (black dashed line) describes the cut-off level of (θ, A), above (below) which entrepreneurs provide a firm-centered (worker-centered) cororate culture with borrowing constraints. First, those with (θ, A) above line 4 do not change their decision and continue to provide a firm-centered culture even with borrowing constraints. Similarly, those with (θ, A) between lines 2 and 3 do not change their decision and continue to provide a worker-centered culture even if borrowing constraints are introduced. However, those with (θ, A) between lines 2 and 4, who previously provided a firm-centered culture without borrowing constraints, provide a worker-centered culture once borrowing constraints are imposed. When the constraint is binding, entrepreneurs cannot fully exploit their business idea, which generates an incentive for some entrepreneurs (especially entrepreneurs with a low θ or a low A) to sacrifice the output to save on labor costs.

5.3 Discussion

As already discussed, to rationalize the compensating wage differential that we see in the data, μ must be less than 1. In other words, productivity becomes lower when firms provide a worker-centered corporate culture. Intuitively, if a majority of firms were enjoying higher productivity and a lower labor cost simultaneously, we would not have observed a considerable amount of firms providing a firm-centered corporate culture in the data (about 40% among all firms).

The above implication is partly driven by the assumption that μ is homogeneous. However, a similar conclusion would hold even if we allow heterogeneous productivity effects of worker-centered culture. Namely, productivity becomes lower when firms provide a worker-centered corporate culture, at least for the firms that do not provide a worker-centered culture. Given that all firms can have apparent benefits from providing worker-centered culture (i.e., a reduction in labor costs), the only reason that can rationalize the firms not providing such a culture is the productivity loss.

The model also predicts that higher-productivity firms or financially unconstrained firms are less likely to provide a worker-centered culture if the equilibrium wage for such a culture is lower than the wage for a firm-centered culture. To check whether this model prediction is in line with data patterns, I document who advertises the worker-centered culture. The website provides some information about firm characteristics, as discussed in section A.3. To see the types of firms that advertise the worker-centered culture, I regress the worker-centered culture dummy on the minimum firm size, venture-funding dummy, and industry.

The results are presented in Table 9. First, small firms are more likely to advertise a worker-centered culture, although the relationship between the firm size and the culture type is not significant. Second, firms that receive venture funding are less likely to advertise the worker-centered culture. For example, the probability that a firm advertises a worker-centered culture is about 20% lower for venture-capital-backed firms than for firms without venture funding. The relationship between venture funding and the culture type is significant and remains the same even after controlling for the industry fixed effect.

Start-up firms backed by venture capital are less likely to be financially constrained. Also, venture capital tends to invest in high-productivity firms (e.g., Sørensen (2007); Chemmanur et al. (2011)). Therefore, the strong negative association between venture funding and the worker-centered culture suggests those firms that are less likely to be financially constrained or have higher productivity tend not to advertise the worker-centered culture, which is in line with the model prediction.

As illustrated in Figure 4, the existence of financial constraints can be an important reason for firms to choose a worker-centered culture. Therefore, the choice of the worker-centered culture can be suboptimal (compared with the case without borrowing constraints) if start-up firms are financially constrained. This finding has an important policy implication. A typical loan policy that helps constrained entrepreneurs relax borrowing constraints can increase efficiency not only by increasing the constrained entrepreneurs' physical investment, but also by influencing start-up firms' corporate culture.

6 Conclusion

I document start-up firms' corporate culture using online job-posting data. Text analyses reveal two types of corporate culture: one that emphasizes the well-being of employees (worker-centered culture) and one that emphasizes other values, such as customers, products, or markets (firm-centered culture). Worker-centered culture attracts more applicants, pays lower salaries, and is less likely to be backed by venture capital than the other culture type. These findings indicate that workers in start-up firms are mindful of the corporate culture of the firms for which they will work, and some firms exploit such a worker preference by paying lower wages. By extending a standard model of firm creation, I show that saving on labor costs is an important motive for a firm to adopt a worker-centered culture. Importantly, firms could adopt their culture suboptimally when they are financially constrained. Therefore, policies that relax start-up firms' borrowing constraints can create additional value by influencing the firms' initial corporate culture.

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Tables and Figures

Table 1: Most Frequently Used Adjectives for Describing Corporate Culture

	Proportion of firms that use each adjective
Fun	15.70
Passionate	15.58
Open	14.73
Driven	14.05
Innovative	13.88
Collaborative	11.45
Fast-paced	10.99
Energetic	7.76
Hard	7.65
Fast	6.80

NOTE: This table shows the most frequently used adjectives for describing the corporate culture and the percentage of firms that used each adjective.

Table 2: Top 10 Words for Each Cluster from Cluster Analysis

	Cluster 1	Cluster 2	Cluster 3
1	team	innov	team
2	singapor	passion	fun
3	busi	collabor	learn
4	technolog	driven	environ
5	develop	open	hard
6	industri	team	opportun
7	product	fastpac	love
8	solut	energet	join
9	startup	dai (day)	grow
10	market	progress	individu
Proportion	18.71%	30.05%	28.51%

NOTE: This table shows the most frequently observed (stemmed) word in each cluster. Note 22.73% of firms do not report their corporate culture.

Table 3: Top 10 Words for Each Core Value from the LDA Analysis

	Core value 1		Core value 2		Core value 3	
	Words	Probability	Words	Probability	Words	Probability
1	singapor	0.0239	innov	0.0768	team	0.0466
2	team	0.0233	passion	0.0760	learn	0.0196
3	busi	0.0189	collabor	0.0616	fun	0.0144
4	technolog	0.0177	driven	0.0604	hard	0.0139
5	market	0.0141	open	0.0553	opportun	0.0125
6	develop	0.0133	fastpac	0.0469	environ	0.0124
7	product	0.0133	energet	0.0385	love	0.0117
8	industri	0.131	dai (day)	0.0290	challeng	0.0116
9	asia	0.0125	progress	0.0275	grow	0.0114
10	solut	0.0122	vibrant	0.0237	build	0.0113

NOTE: The table shows the estimated core values (up to the top 10 words with the highest probability) from the LDA analysis.

Table 4: Top 10 Job Titles

	Freq.	Percent	Cum.
Software engineer	137	2.80	2.80
Full stack developer	99	2.02	4.82
Product manager	80	1.63	6.45
Business development executive	74	1.51	7.97
Data engineer	72	1.47	9.44
Business development manager	71	1.45	10.89
UI,UX designer	69	1.41	12.30
Data scientist	61	1.25	13.54
Marketing manager	61	1.25	14.79
Frontend developer	60	1.23	16.01

NOTE: This table shows the 10 most frequently posted job titles.

Table 5: Summary Statistics for Job Postings

	Obs.	Mean	Std.	10%	Median	90%
Panel A						
Minimum experience	9,458	1.27	1.73	0	1	4
Panel B						
Monetary compensation						
Salary info.	9,458	0.79	0.41	0	1	1
Monthly salary min. (SGD)	7,477	3,405	2,513	1,700	3,000	5,000
Monthly salary max. (SGD)	7,477	5,361	4,422	2,500	5,000	8,333
Equity provided	9,458	0.25	0.43	0	0	1
Panel C						
Non-monetary compensation						
Lifestyle benefit	9,458	0.10	0.30	0	0	1
Welfare benefit	9,458	0.10	0.30	0	0	1
Panel D						
Number of applicants	9,458	14.83	15.91	0	11	34
Accepted ratio	8,179	0.05	0.13	0	0	0.17

NOTE: This table shows the summary statistics for job postings. "Minimum experience" is the years of experience required by a job posting. "Salary info." refers to a dummy variable indicating whether a job posted salary information. "Equity provided" refers to a dummy variable indicating whether a job provides equity. "Lifestyle benefit" is a dummy variable for a job posting containing one of the following keywords: casual dress code, company outings, flexible working hours, free food, pet-friendly office, recreational area, and work-from-home. "Welfare benefit" is a dummy variable for a job posting containing one of the following keywords: dental/health insurance, gym membership, employee discount, vacation time, wellness program, childcare assistance, bonuses, paid maternity/paternity leave, paid sick leave, and transportation reimbursement.

Table 6: Advertised Corporate Culture and Number of Applications

VARIABLES	(1) Apply No.	(2) Apply No.	(3) Apply No.	(4) Apply No.	(5) Apply No.
Salary info	1.061	1.102	1.185	0.886	0.983
	(0.845)	(0.847)	(0.846)	(0.847)	(0.847)
Min. salary/1000	-0.201	-0.202	-0.168	-0.190	-0.155
	(0.196)	(0.196)	(0.195)	(0.196)	(0.196)
Max. salary/1000	0.600***	0.597***	0.593***	0.599***	0.580***
	(0.120)	(0.120)	(0.120)	(0.120)	(0.120)
Equity	4.569***	4.541***	4.553***	4.544***	4.311***
	(0.581)	(0.582)	(0.583)	(0.582)	(0.585)
Venture funding	1.093	1.090	0.858	0.837	0.803
	(0.973)	(0.973)	(0.980)	(0.974)	(0.970)
Min. employee/1000	1.255***	1.255***	1.383***	1.180***	1.132***
	(0.405)	(0.405)	(0.405)	(0.404)	(0.405)
Lifestyle	2.004**	2.024**	1.030	1.458	2.690**
	(1.010)	(1.010)	(1.106)	(1.030)	(1.093)
Welfare	-0.931	-0.966	-1.718	-1.602	-0.418
	(1.016)	(1.017)	(1.087)	(1.031)	(1.061)
No culture	-2.245***	-2.169***	-0.569		
	(0.740)	(0.748)	(0.796)		
Text length/1000		0.152	-0.0421	0.0995	0.0960
		(0.221)	(0.223)	(0.221)	(0.223)
Open			2.509***		
			(0.807)		
Fun			2.165***		
			(0.636)		
Fast-paced			4.967***		
			(0.929)		
Cluster 1				0.939	
				(0.864)	
Cluster 2				3.716***	
				(0.820)	
Cluster 3				3.057***	
				(0.763)	
Core value 2					-0.371
					(1.451)
Core value 3					3.599***
					(0.847)
Observations	5,333	5,333	5,333	5,333	5,333
R-squared	0.515	0.515	0.522	0.518	0.516

NOTE: This table shows the results from regression analyses for the number of applicants for a job posting (Apply No.). All regressions include the following fixed effects (FE): (1) year×month, (2) job title, (3) industry of the posting firm, (4) whether the job can be done remotely, and (5) vacancy counts for the posted job. In the third column, I control for the 10 most frequently used keywords but only present three keywords that exhibit a significant effect. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Advertised Corporate Culture and Number of Applications: Firm-Age Fixed Effects

VARIABLES	(1) Apply No.	(2) Apply No.
Salary info	-0.0916	-0.204
	(1.458)	(1.454)
Min. salary/1000	-0.313	-0.230
	(0.373)	(0.373)
Max. salary/1000	0.906***	0.865***
	(0.223)	(0.223)
Equity	6.703***	6.331***
	(1.032)	(1.037)
Venture funding	-0.00159	0.361
	(1.478)	(1.466)
Min. employee/1000	12.29***	12.31***
	(1.706)	(1.703)
Lifestyle	6.458**	6.423**
	(2.585)	(2.709)
Welfare	-0.182	0.196
	(2.344)	(2.350)
Text length/1000	-1.274***	-1.171***
	(0.415)	(0.412)
Cluster 1	1.702	
	(1.622)	
Cluster 2	6.757***	
	(1.511)	
Cluster 3	4.287***	
	(1.384)	
Core value 2		5.077
		(3.692)
Core value 3		6.051***
		(1.602)
Observations	2,450	2,450
R-squared	0.577	0.576

NOTE: The first and second regressions are identical to Columns (4) and (5) of Table 6, respectively, except that job postings that reveal firm age are used and that the firm-age fixed effect is included.

Table 8: Wage Differential for Worker-Centered Culture

VARIABLES	(1) ln(monthly salary)	(2) ln(monthly salary)	(3) ln(monthly salary)
Worker-centered culture	-0.0479**	-0.0315*	-0.0484**
	(0.0236)	(0.0176)	(0.0202)
Other job characteristics	Y	Y	Y
Job-title FE		Y	Y
Job-title×Year×Month FE	Y		
Individual FE		Y	Y
Accepted application		Y	Y
Excluding outliers			Y
Observations	2,481	3,121	2,580
R-squared	0.737	0.871	0.877

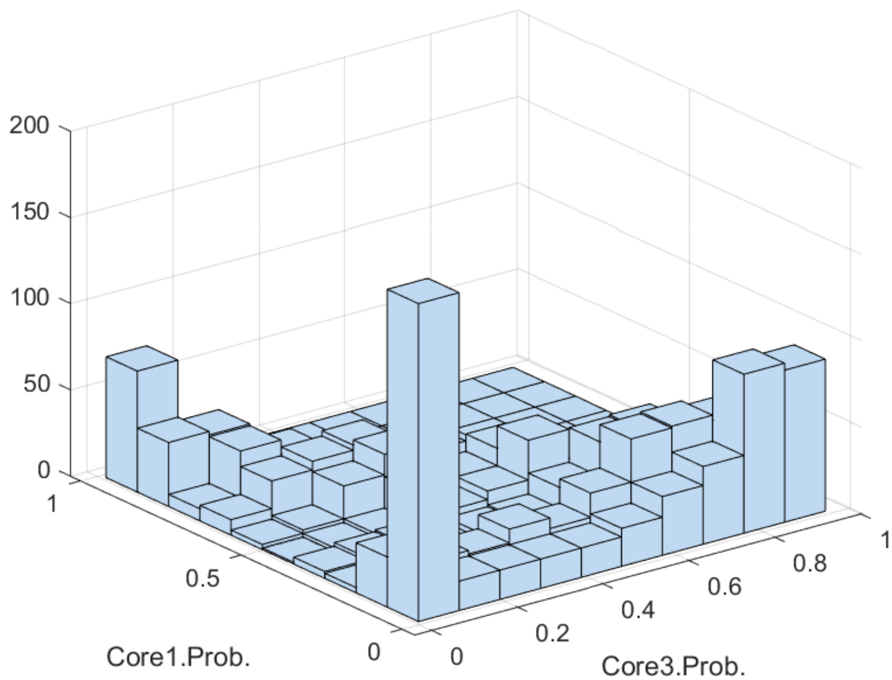
NOTE: This table shows the results from the regression of log monthly salary on worker-centered culture. The monthly salary is calculated by (Monthly salary min. + Monthly salary max.)/2. "Worker-centered culture" is a dummy variable that takes a value of 1 if the posting firm's corporate culture is categorized as either cluster 2 or 3. Other job characteristics refer to dummy variables for equity provision, lifestyle, and welfare benefits (defined in section 4.1). The unit of observation for regressions (1) is a job posting. By contrast, the unit of observation for regressions (2) and (3) is an application to each job posting. In the third column, I exclude applications by job candidates whose number of interview invitations is above the top 5th percentile. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Corporate Culture and Firm Characteristics

VARIABLES	(1) Worker-centered culture	(2) Worker-centered culture
Venture funding	-0.203***	-0.207***
	(0.0503)	(0.0522)
Min. employee/1000	-0.0175	-0.0201
	(0.0108)	(0.0153)
Industry FE		Y
Observations	1,764	1,678
R-squared	0.010	0.035

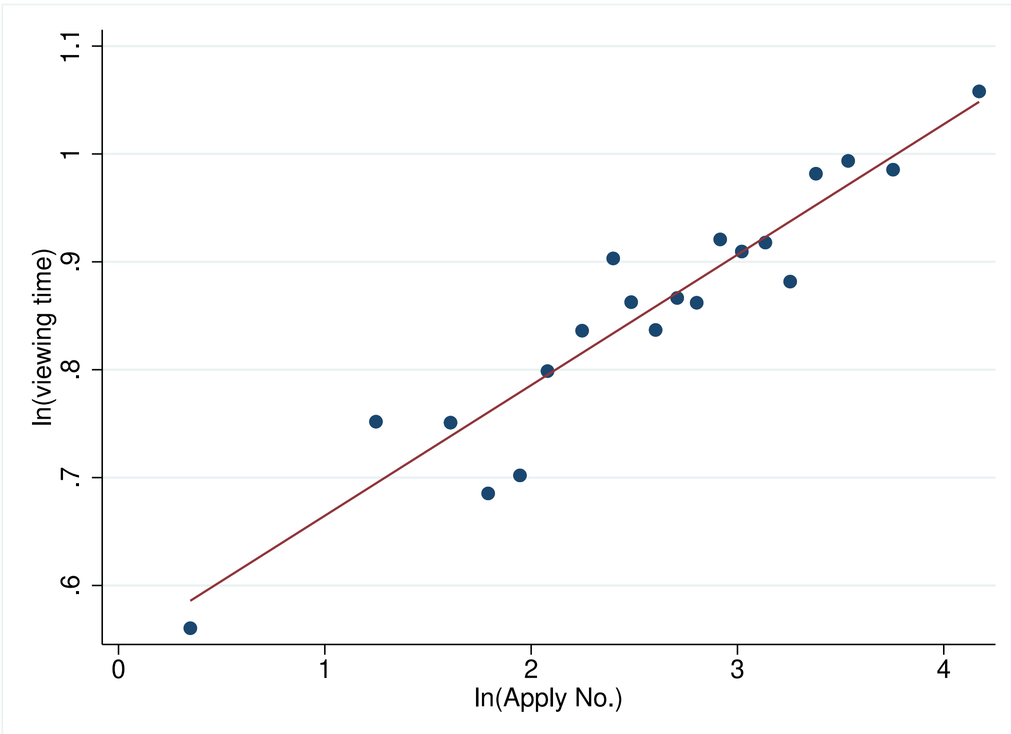
NOTE: This table shows the types of firms that advertise worker-centered culture. "Worker-centered culture" is a dummy variable that takes a value of 1 if the posting firm's corporate culture is categorized as either cluster 2 or 3. "Venture funding" is a dummy variable that takes a value of 1 if the posting firm received venture funding. *** p<0.01, ** p<0.05, * p<0.1

Figure 1: Distribution of (θ_1^i, θ_3^i)



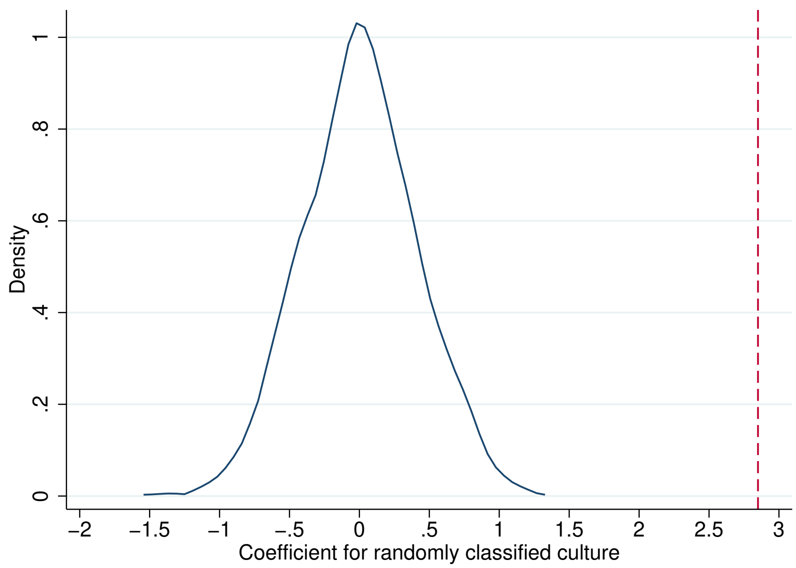
NOTE: This figure shows the estimated distribution of each firm's core values. Each firm is represented in the two-dimensional space (Core1.Prob, Core3.Prob), where Core1.Prob and Core3.Prob refer to the estimated probability of core values 1 and 3, respectively, for each firm.

Figure 2: Viewing Time and Application Number for Job Postings



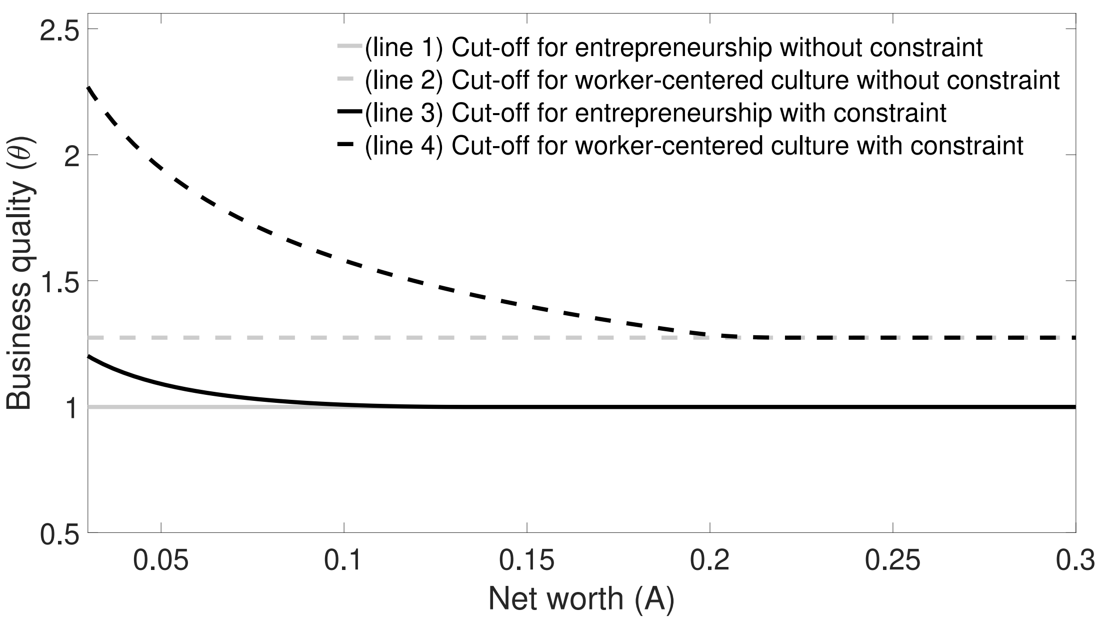
NOTE: This figure shows the binned scatter plot of the log viewing time for a job posting on the log application numbers for the job posting. The viewing time for a job posting is defined by the average viewing time spent for the job posting by the applicants.

Figure 3: Distribution of Coefficients for Randomly Classified Culture



NOTE: This figure shows the distribution of coefficients for randomly classified culture. The coefficient and the $p-$value for popular culture (cluster 1 and 2) are 2.82 (represented by the red line in the figure) and 1.844e-07, respectively

Figure 4: Policy Function



NOTE: This figure shows the policy function for potential entrepreneurs. Line 1 (horizontal gray line) describes the cut-off level of θ, above which entrepreneurs start a business without borrowing constraints. Line 2 (gray dashed line) describes the cut-off level of θ, above (below) which entrepreneurs provide a firm-centered (worker-centered) culture without borrowing constraints. Line 3 (thick black line) describes the cut-off level of (θ, A), above which entrepreneurs start a business with borrowing constraints. Line 4 (black dashed line) describes the cut-off level of (θ, A), above (below) which entrepreneurs provide a firm-centered (worker-centered) culture with borrowing constraints

Online Appendix

A The Online Job Board

A.1 Search Process

To attract enough firms and applications, the website charged no fee for either posting firms or applicants during the sample period.[24] The same front page is shown to everyone. The front page consists of job snapshots and search functions. The job snapshots show each job's summarized information, including job title, wage range, job location, occupation, industry, and job type (e.g., full vs. part time). The search function provides an option to sort posted jobs according to industry, occupation, and job location.

Once a viewer clicks a job snapshot, detailed information about the job is shown on a full page consisting of three parts. The first part is called "Job description and requirements," where the posting firm writes detailed information about the job and requirements. The second part is called "Required skill," where keywords describing the job's required skills are shown. The website provides a set of skill keywords to posting firms, and posting firms choose relevant ones, and those chosen keywords are shown in the second part.

The third part is called "Culture," which is the focus of this article. The website asks posting firms to describe their culture without any restrictions.[25] This information is shown in the first part of the culture section. The website also provides a collection of keywords describing benefits (e.g., casual dress code, flexible hours, and pet-friendly office). It lets the posting firm choose keywords applicable to the firm. The chosen keywords are shown in the second part of the culture section.

On the top right of the job-posting page is an apply button whereby applicants can apply for the job. Note that clicking the apply button is the only way to apply for a job. The website did not initially allow a link to the company's private job-posting website.[26] Therefore, given that all the clicking information is recorded, I can see the number of applicants for a job

[24] The company started to charge a fee to posting firms after the data for this article were extracted.

[25] The website also provides an option to choose keywords to describe what working at the company is like (e.g., adaptable, balanced, and collaborative).

[26] The website has allowed such a link recently after it started to charge a fee to posting firms.

posting.

A unique feature of these data is that I can observe which applicants are invited for the first interview. The website provides a platform (a web page) on which the posting firm can see the information (e.g., resumé) about all the applicants to the posting. On that web page, each applicant's information is shown according to the application time. On the right side of each applicant's information is an invitation button. When the firm clicks the invitation button, the website sends an invitation email to the applicant on behalf of the posting firm to set up the interview schedule. For each posting-applicant level, I know whether the invitation button was clicked, and therefore, who were invited for an interview.

Instead of clicking the invitation button, a posting firm may use a private phone call to invite applicants after reviewing their resumés. To check whether the private phone call is a dominant invitation mode, I test the following intuition. If the low acceptance rate is mainly due to private phone calls not being recorded, those postings whose recorded acceptance (by clicking the invitation button) is zero will not necessarily correlate with the number of applicants. I show a binned scatter plot for zero acceptance for the total number of applicants to check this intuition. The zero acceptance is a dummy variable for each job posting that has no accepted applicant. Figure 5 shows the results. Postings with zero acceptance are more likely those with a smaller number of total applicants. The probability of zero acceptance significantly decreases as the total number of applicants increases. This finding suggests the lack of adequate applicants seems to be why firms invited no applicants.

A.2 Representativeness

To gauge the job board's representativeness, I compare the number of jobs posted on the job board with job vacancies in Singapore. Given that most job-posting firms are categorized as IT-related firms, I use the quarterly vacancies within the information technology (IT) and other information services industry category. To make the number of jobs on the job board comparable, I calculate the total number of jobs posted during the corresponding month to the quarterly vacancy (March for the first quarter, June for the second quarter, September for the third quarter, and December for the fourth quarter). Figure 6 shows the results. The number of jobs posted on the online job board is comparable to about 20% of the IT-sector job vacancies in Singapore, suggesting the website covers a substantial portion of job vacancies from the IT sectors in Singapore.

A.3 Summary Statistics

This section presents the summary statistics for posting firms and applicants.

Posting Firms

Table 10 shows the size distribution of firms that ever posted a full-time job located in Singapore. Most firms have more than one employee, and most firms (77.66%) have fewer than 50 employees.

Table 11 shows the industry composition of firms that ever posted a full-time job located in Singapore. About 95% of firms (1,680 out of 1,764) report their industry.[27] Fintech firms constitute more than 10% of posting firms, followed by Professional Service and Software firms. Almost all posting firms can be categorized as tech-related firms, the online job board's intended target.

The website also shows whether the posting firm received venture funding. Of 1,764 posting firms, 5.73% ever received venture funding. Overall, a typical posting firm is a small- to a medium-sized, tech-related firm with a higher probability of receiving venture funding.

Applicants

Table 12 shows the summary statistics for applicants' characteristics. In total, 15,869 applicants ever applied to a job located in Singapore. For applicants whose educational information is available, 97% at least graduated from college. Most applicants are young; half of the applicants had graduated less than three years before applying. More than 60% of applicants resided outside of Singapore when they applied for a Singapore job.

[27]When firms register on the website, they are asked to select an industry category provided by the website.

B Note on the Cluster Analysis

Before conducting a cluster analysis, I process the text following Gentzkow et al. (2019). I format the text in lowercase and remove any punctuation or signs. I also remove from the culture section all the keywords referring to benefits.[28] I further reduce information to be analyzed as follows. I remove words that fewer than 10 firms used in their description of culture.[29] I then replace words with their roots by using the Porter stemmer (Porter (1980)). For each remaining word, I construct a dummy variable equal to 1 if a firm's culture description contains the word, and 0 otherwise. A firm's culture is thus characterized by the collection of these dummy variables for each word.[30]

For a pre-determined number of clusters K, the algorithm randomly assigns k initial group centers among observations. Each observation is assigned to the group with the closest center for a distance measure. I use the Pearson similarity measure (Pearson (1900)) for this analysis.

Note each corporate culture i is represented by the collection of dummy variables for each word ω (1 if corporate culture i uses word ω, and 0 otherwise). To define a similarity measure, consider the following matrix:

$$\begin{array}{cc|cc}
\hline
 & & \text{Firm} & i \\
 & & 1 & 0 \\
\hline
\text{Firm} & 1 & \text{a} & \text{b} \\
j & 0 & \text{c} & \text{d} \\
\hline
\end{array} \tag{5}$$

where $a = \sum_{\omega=1}^{W} \mathbb{I}_i^{\omega}\mathbb{I}_j^{\omega}$, $b = \sum_{\omega=1}^{W} \mathbb{I}_i^{\omega}(1-\mathbb{I}_j^{\omega})$, $c = \sum_{\omega=1}^{W}(1-\mathbb{I}_i^{\omega})\mathbb{I}_j^{\omega}$, and $d = \sum_{\omega=1}^{W}(1-\mathbb{I}_i^{\omega})(1-\mathbb{I}_j^{\omega})$. $\mathbb{I}_i^{\omega}$ ($\mathbb{I}_j^{\omega}$) is the dummy variable for firm i (j) using word ω. W is the total number of words from the whole sample. In other words, a refers to the number of words used by firms i and j. b refers to the number of words used by firm i but not by j. c refers to the number of words used by firm j but not by i. Finally, d refers to the number of words not used by firms i and

[28]The website provides a collection of keywords describing benefits (e.g., casual dress code, flexible hours, and pet-friendly office). It lets the posting firm choose keywords applicable to the firm. The chosen keywords are shown in the second part of the culture section.

[29]The results are similar with different thresholds (e.g., 50). I also calculated term frequency-inverse document frequency (tf–idf) and remove words with a value of tf–idf below a threshold. The results are similar as well.

[30]For the cluster analysis, I do not use the information on how many times a particular word is used in describing corporate culture. I use this information when I conduct LDA analysis.

j.

The Pearson similarity measure is defined as

$$\frac{ad - bc}{\{(a+b)(a+c)(d+b)(d+c)\}^{1/2}}. \tag{6}$$

When two firms' usage of words is identical, the measure becomes 1. When two firms' usage of words is completely different (i.e., $a = d = 0$), the measure becomes -1.[31]

The mean of the observations assigned to each group becomes a new group center. The mean of a group K is defined as $p = (p_1, p_2, ..., p_W)$, where $p_\omega = (\sum_{i=1}^{N_K} \mathbb{I}_i^\omega)/N_K$. N_K is the number of observations assigned to group K. Then, each observation is reassigned to the group with the closest (updated) center. To measure the similarity between an observation i and the K group center, the matrix (5) is updated as $a = \sum_{\omega=1}^{W} \mathbb{I}_i^\omega p_\omega$, $b = \sum_{\omega=1}^{W} \mathbb{I}_i^\omega (1 - p_\omega)$, $c = \sum_{\omega=1}^{W} (1 - \mathbb{I}_i^\omega) p_\omega$, and $d = \sum_{\omega=1}^{W} (1 - \mathbb{I}_i^\omega)(1 - p_\omega)$. The similarity between observation i and the K group center is then calculated by equation (6).

The process is repeated until all observations remain in the same group from the previous iteration. The observation is assigned to its current group for a tied distance between an observation and two or more group centers. As a result, the cluster analyses break the observations into a specific number of non-overlapping groups.

C Advertised Corporate Culture: Examples

Cluster 1

- We focus on technology innovation in its core, adopting a team strategy approach to iterate fast on any plans and ideas. Except for the company vision and mission, our employees greatest joy lies in having the ability to interface with its customers across nearly 100 countries, thus building a truly global product from day 1.

- We are a group of young, creative and talented professionals with the mission to build a world leading mobile customer engagement & loyalty technology company. We pride

[31] As a robustness check, I tried different similarity measures. The resulting clusters are similar to the ones generated by equation (6).

ourselves in our ethics, in our love for technology and in delighting our customers with an unmatched level of support, quality and integrity.

- We are a young hardworking team that wants to be a world class product development and management studio in South East Asia. We are a design driven technology company that only delivers solutions that bring value to our clients. From Design to Development to Product Management, we are all craftsmen, we are continuously honing our skills to get better at what we do, and we are always interested in providing and receiving honest feedback on how we can improve. The foundations of our team is built upon Transparency, Integrity, Quality, Grit, Creativity. We are always 100%. All in every single time. We are Absolute Collective.

Cluster 2

- We are expanding fast and seeking energetic, passionate, business development professionals. We move fast and our days are never boring. We are exposed to challenges every day and our young team is adapting to situations every day. We expect your full commitment during your time with us and in return, you can demand an extremely high learning & involvement.

- Our culture is driven by transparency, open discussion, collaboration, and direct feedback. We hate bureaucracy and slow moving decisions, and strive to create an environment where employees can speak their mind and shape the future of the company. We embrace personal development, and foster a climate where trying new things and failing without consequences is not only the norm, but expected.

- xxx is a cool, fun and young brand and it translates into our working culture. If you step into our office you can immediately feel the energy of young dreamers and blue-sky thinkers all working towards changing how people shop fashion in this part of the world. In xxx, it's the people that makes our company tick. We hire people who are smart and creative, driven by integrity and with a passion to excel. We are an open and flat organization where everyone's opinion matter. We are a mix of experts in fashion, logistics, data analytics, marketing, and design, guided by business consultants and tech geniuses. We come from all walks of life, representing the diversity of ideas that sit within the our team.

Cluster 3

- Think of a stuffy, hierarchical corporate culture where employees sit for long hours in cubicles counting down the hours doing soulless, repetitive, run-of-the-mill chores, fenced off from human warmth and personal connections. Now think of the exact opposite. That's our culture.
- We're a start-up built on the belief of personal growth & mentorship - and so is our culture. It's important that everyone is learning and we make it a point for each of us to share tidbits of knowledge from whichever area of expertise we're more inclined towards. As with most start-ups, the environment's like family. We're a small team, which makes every individual all the more valuable. Everyone pulls their weight in achieving weekly sprints (goals) then we go off and have our team event every other week.
- We are a dedicated team of industry professionals who continually push the boundaries of hospitality technology, sales and customer support. We're solving tough problems and developing elegant, beautiful software for an industry desperately in need of innovation. We know how to have fun. We love solving problems and creating ideas. We're a team of talented and diverse people from all over the world – we learn, grow and succeed this way. Our success is fuelled by a shared belief that every individual can make an impact, bringing our talents together to accomplish amazing things.

D Note on the LDA Analysis

The LDA assumes the advertised culture is a mixture of a K number of core values, and each word describing the culture is attributable to one of these core values. To be more specific, suppose $X = \{x_1, x_2, ..., x_W\}$ is the set of all possible words describing culture. The k^{th} core value is a probability distribution β_k over X. The corporate culture of firm i is characterized by $\{\theta_k^i\}_{k \in K}$, where θ_k^i is the share of the k^{th} core value in firm i's corporate culture.

Note the probability that a word in the description of firm i's corporate culture is equal to the ω^{th} word in X is $p_{i,\omega} = \sum_k \theta_k^i \beta_{k,\omega}$, where $\beta_{k,\omega}$ is the probability that a keyword x_ω is drawn from β_k. Therefore, the probability that we observe a collection of words in the description of firm i's corporate culture is $\prod_\omega (p_{i,\omega})^{\#i,\omega}$, and the overall likelihood is $\prod_i \prod_\omega (p_{i,\omega})^{\#i,\omega}$, where $\#i, \omega$ indicates how many times word x_ω is used for the description of firm i's corporate culture. The LDA algorithm finds θ_k^i and β_k for all i and k that maximize the likelihood by applying Bayesian estimation method. For a detailed procedure for estimation, see Schwarz (2018).

Before implementing the LDA algorithm, I process the text as in Appendix B. The representation is identical to the one used for the cluster analysis except that the LDA algorithm exploits the number of keywords shown in a culture's description. By contrast, the cluster analysis uses binary information for whether the keyword is ever shown in the culture description. I set the number of core values as three, which is the same as the benchmark number of clusters.

E Do Firms Search for Different Types of Applicants Depending on Their Advertised Corporate Culture?

In this section, I investigate whether firms search for different types of workers depending on their advertised corporate culture.

I observe applicants whom a posting firm invited for an interview. Therefore, for a given job posting, I can compare the characteristics of those accepted with those not accepted. I first characterize each applicant in terms of their application behavior: the average salary of jobs to which the applicant applied, the total number of applications, and the number of applications accepted by other firms. I also calculate the proportion of jobs with a worker-centered culture out of all the jobs a candidate applied for and call it the "worker-culture ratio."

Using these variables and other observable characteristics of applicants, I investigate who is more likely to be invited by firms. In particular, I test whether firms search for different types of applicants depending on their corporate culture.

I create a dummy variable for each application that takes a value of 1 if the application is accepted. I estimate a linear probability model of this dummy variable over applicants' characteristics conditional on each job posting. To see the difference between firms with different types of corporate culture, I split the sample into two: (1) applications for jobs with a worker-centered culture and (2) applications for jobs with a non-worker-centered culture.

The results are shown in the first and second columns of Table 13. Several findings emerge. First, applicants who apply less or applicants who apply for high-salary jobs are more likely to be accepted. This finding may reflect the fact that high-ability applicants tend to apply less and apply for high-salary jobs. More importantly, the estimates from the two samples are remarkably similar. Second, firms do not necessarily accept applicants who prefer their corporate culture. For example, the worker-culture ratio (the ratio of applications for jobs with a worker-centered culture relative to all the applications for a given applicant) is estimated to be insignificant for the first sample and positive for the second sample. Third, given that all the jobs are located in Singapore, firms prefer applicants who live in Singapore. Finally, firms prefer applicants who are also sought after by other firms. For example, an applicant is 0.3% more likely to be accepted by a firm if another firm accepts the applicant. Note that firms do not know whether an applicant has another offer or an interview before sending an interview invitation. Overall, firms invite highly qualified applicants living in Singapore. More importantly, the preference toward applicants is similar across the two samples.

Next, I further decompose the number of accepted applications (by other firms) into the number of applications accepted by firms advertising a worker-centered culture and by firms advertising a non-worker-centered culture. I conduct the same regression analysis in the first and second columns of Table 13, except I replace the number of accepted applications with the two decomposed variables. The results are shown in the third and fourth columns of Table 13. Firms prefer applicants accepted by other firms, independent of other firms' corporate culture; the coefficients for the two decomposed variables are similar across the two samples.

To summarize, firms search for applicants sought by other firms, regardless of their corporate culture. In other words, independent of their advertised corporate culture, firms seem to have similar preferences regarding potential employees.[32]

[32]Some theories on corporate culture (e.g., Kosfeld and Von Siemens (2011); Van den Steen (2010)) predict a positive assortative matching between firms and employees for corporate culture: firms search for employees who like their corporate culture, and vice versa. The findings in this section do not support these predictions.

Tables and Figures for Appendix

Table 10: Firm-Size Distribution of Posting Firms

No. of employees	Freq.	Percent	Cum.
1	101	6.41	5.73
$[2, 10]$	637	36.11	41.84
$[11, 50]$	632	35.83	77.66
$[51, 200]$	189	10.71	88.38
$[201, 500]$	54	3.06	91.44
$[501, 1000]$	22	1.25	92.69
$[1001, 5000]$	42	2.38	95.07
≥ 5001	87	4.93	100.00
Total	1,764	100	

NOTE: This table shows the size distribution of firms that ever posted a full-time job located in Singapore.

Table 11: Industry Composition of Posting Firms

	Freq.	Percent	Cum.
fintech	172	10.24	10.24
professional services	118	7.02	17.26
software	113	6.73	23.99
ad tech	105	6.25	30.24
ecommerce	90	5.36	35.60
general internet	88	5.24	40.83
enterprise solution	72	4.29	45.12
artificial intelligence	62	3.69	48.81
health	60	3.57	52.38
education	59	3.51	55.89
media	59	3.51	59.40
lifestyle	51	3.04	62.44
hardware	48	2.86	65.30
security	48	2.86	68.15
Logistics & Transportation	42	2.50	70.65
Other industries	493	29.35	100
Total	1,680	100	

NOTE: This table shows the industry composition of firms that ever posted a full-time job located in Singapore. Other industries include investments, food tech, market places/platforms, social networking/communications, travel, analytics, design, real estate, big data, internet infrastructure, gaming, search/discovery, developer tools, cloud computing, clean tech, recognition tech, heavy industry, music/entertainment, and the sharing economy.

Table 12: Characteristics of Applicants

	Obs.	Mean	Std.	10%	Median	90%
College	11,574	0.97	0.17	0	1	1
Year after graduation	11,574	4.12	4.68	0	3	10
Singapore resident	15,839	0.37	0.48	0	0	1

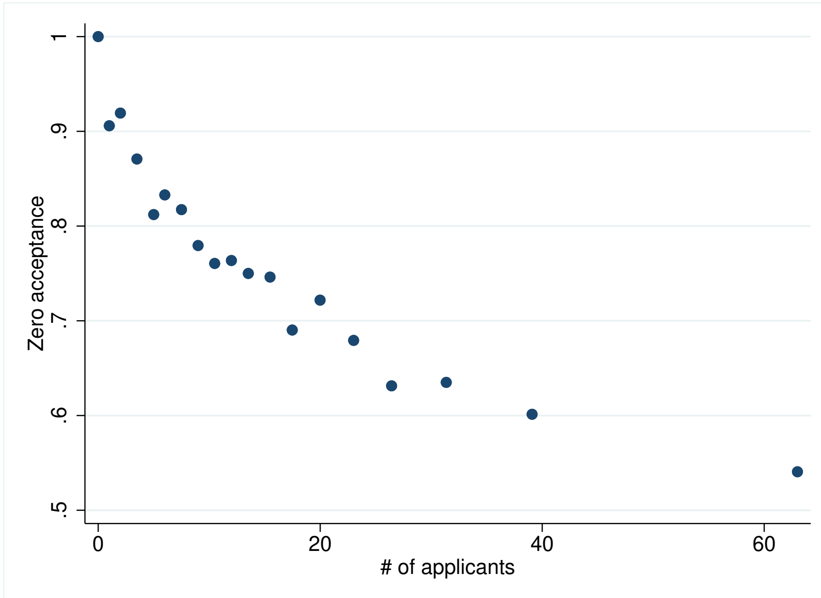
NOTE: This table shows the summary statistics for applicants' characteristics. College refers to a dummy variable indicating whether an applicant graduated from college or not.

Table 13: Applicants Whom Firms Like

VARIABLES	(1) Accepted	(2) Accepted	(3) Accepted	(4) Accepted
Total applications	-0.000156***	-0.000169***	-0.000156***	-0.000168***
	(1.38e-05)	(1.14e-05)	(1.38e-05)	(1.14e-05)
Salary ave. for applied jobs	0.00317***	0.00282***	0.00316***	0.00279***
	(0.000787)	(0.000878)	(0.000787)	(0.000879)
Employee-culture ratio	0.0146**	0.00167	0.0146**	0.00216
	(0.00602)	(0.00584)	(0.00602)	(0.00585)
College	0.000470	0.00884*	0.000464	0.00888*
	(0.00660)	(0.00508)	(0.00660)	(0.00508)
Singapore resident	0.0258***	0.0397***	0.0259***	0.0398***
	(0.00204)	(0.00161)	(0.00204)	(0.00162)
Year after graduation/10	-0.000649	0.00221	-0.000709	0.00215
	(0.00242)	(0.00198)	(0.00242)	(0.00198)
Accepted# by other firms	0.00283***	0.00351***		
	(0.000334)	(0.000272)		
Accepted# by emp. firms			0.00260***	0.00317***
			(0.000485)	(0.000394)
Accepted# by non-emp. firms			0.00341***	0.00436***
			(0.000932)	(0.000754)
Job-posting FE	Y	Y	Y	Y
Postings by non-emp. firms	Y		Y	
Postings by emp. firms		Y		Y
Observations	35,867	67,054	35,867	67,054
R-squared	0.257	0.266	0.257	0.266

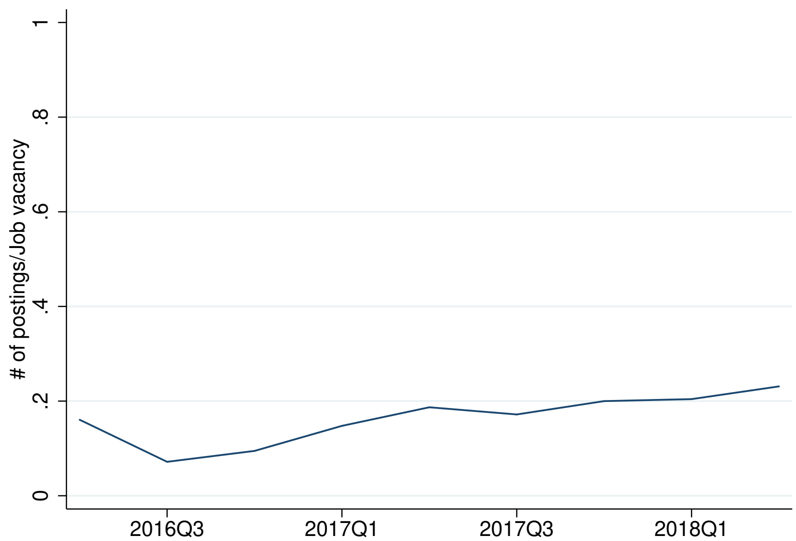
NOTE: This table shows the results from a linear probability model of being accepted over applicants' characteristics. The unit of observation is each application to a job posting. For each application to a job posting, if the application is invited for an interview, the value of "Accepted" takes a value of 1 (0 otherwise). "Salary ave. for applied jobs" refers to the average salary for jobs for which the applicant applied. "Employee-culture ratio" is the ratio of applications to jobs with an worker-centered culture relative to all the applications for a given applicant. "Accepted# by other firms" refers to the number of applications accepted by other firms. "Accepted# by emp. firms" refers to the number of applications accepted by other employee firms (firms that advertise an employee-oriented culture). "Accepted# by non-emp. firms" refers to the number of applications accepted by other non-employee firms (firms that advertise a non-employee-oriented culture). *** p<0.01, ** p<0.05, * p<0.1

Figure 5: Number of Applicants and Zero-Acceptance Probability



NOTE: This figure shows the binned scatter plot for zero acceptance regarding the number of applicants for each job posting. The zero acceptance is a dummy variable for each job posting with no accepted applicant.

Figure 6: Number of Postings-Job-Vacancy Ratio



NOTE: This figure compares the quarterly vacancies for IT and other information services in Singapore with the total number of jobs (located in Singapore) posted during the corresponding month (March, June, September, and December) to the quarterly vacancy.