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Who Captures the Value from Organizational Culture? Evidence from Glassdoor Reviews and the Universe of Online Job Postings from Burning Glass Technologies

Sukti Ghoshsamaddar
INSEAD, sukti.ghosh@insead.edu

Arianna Marchetti
London Business School, amarchetti@london.edu

Victoria Sevcenko
INSEAD, victoria.sevcenko@insead.edu

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Who captures the value from cultural retention mechanisms? While firms make large investments in their corporate cultures, their effects on the labor force are yet not completely understood. We argue that strong cultures act as a retention mechanism by facilitating employees' coordination and reducing the portability of their social skills, thus capturing more value from their employees. We test these predictions on a sample of 6,208 firms based in Illinois and Michigan. We measure labor-related variables from 1,265,760 job vacancies posted by those firms, and their cultural strength from 203,093 employees' text reviews about the companies. We find that, following a regulatory shock that increases employee mobility in Illinois, strong cultures post fewer jobs and offer lower salaries than weak one, compared to Michigan.

Keywords: Organizational Culture; Collaboration; Firm-specific skills; Employee Mobility; Value Capture; Non-compete agreements (NCAs); Machine Learning (ML); Natural Language Processing (NLP)

1. INTRODUCTION

Human assets are a key source of organizational performance and sustainable competitive advantage (Coff, 1997; Lippman and Rumelt, 2003). Yet, firms must increasingly grapple with the fact that, unlike physical assets that firms own and control, employees are free to 'walk out the door each day, leaving some question about whether they will return' (Coff, 1997: 375). As a result, building and sustaining competitive advantage from human assets often requires firms to develop elaborate systems to not only attract productive employees, but also to reduce the risks of losing them to competitors.

Extant work proposes a number of financial strategies that organizations can leverage to attempt reducing their employees' mobility to competitors, as, for instance, controlling the complementary assets employees use to perform their jobs and the intellectual property their employees produce (Campbell *et al.*, 2012; Melero, Palomeras, and Wehrheim, 2020), or signing explicit and enforceable non-compete agreements with their employees that limit their future mobility to competing firms (Marx, Strumsky, and Fleming, 2009; Starr, Ganco, and Campbell, 2018). More recent literature has also started investigating the role for non-pecuniary factors in workers' job satisfaction and mobility choices, such as public awards and recognition (Kosfeld and Neckermann, 2011), employee performance visibility (Neckermann, Cueni, and Frey, 2014), meaningful work (Burbano, 2016; Sauermann and Roach, 2014; Stern, 1999; Stuart and Ding, 2006), and corporate social responsibility and engagement with the local community (Bode, Singh, and Rogan, 2015; Carnahan, Kryscynski, and Olson, 2017; Flammer and Kacperczyk, 2019).

In this paper we build on and extend these insights by considering an additional factor shaping employee retention and value capture from human capital: organizational culture, a multifaceted phenomenon studied in relative isolation from the strategic human capital literature so far. Prior research has typically focused on specific components of cultural content, i.e., "the actual substance of the culture" (Chatman and O'Reilly, 2016: 5) driving individual behaviors (Chatman *et al.*, 2014), with limited research studying its effects on employee turnover (Chatman, 1991; Sheridan, 1992). On the other hand, we focus on an alternative dimension of organizational culture: *cultural distributional properties*, or the degree of consensus among organizational members on the importance of norms, values, beliefs and cognitive structures, summarized by the extent of the organizational cultural strength, irrespective of the actual content of the culture. We inquire how the strength of an organizational culture can limit the mobility of its members and study who captures the value from cultural retention mechanisms.

We begin by recognizing that strong cultures facilitate workers' understanding of organizational norms and guiding values, create common ground, and facilitate cooperation, thus reducing the costs of, and increasing the returns to, collaboration (Kotter and Heskett, 1992; Kreps, 1996; Marchetti and Puranam, 2021; Schelling, 1978; Weber and Camerer, 2003). In turn, given the well-documented challenges intrinsic in formally enforcing collaborative actions (Gibbons and Henderson, 2012), strong cultures are expected to achieve collaboration by relying on relational contracts and informal organization (as opposed to formal contracts) to a larger extent than their weaker counterparts, thus imparting firm-specific skills and knowledge onto their employees on how to successfully work within the organization (Becker, 1964; Coff, 1997; Huckman and Pisano, 2006; Molloy and Barney, 2015). The firm-specificity of collaborating in strong cultures, we theorize, thus acts as a retention mechanism, reducing the employees' likelihood of leaving to competitors (Groysberg, 2010). We also argue that, since employees often renegotiate their salary conditions through mobility (Bidwell, 2011), strong cultures may be able to capture more value from their current employees and prospective candidates by setting lower salaries and distributing fewer benefits than comparable firms with weaker cultures.

We test our predictions on a cross-industry database of firms based in the United States in 2010-2020. We measure corporate cultural distributional properties from text reviews employees write about their organization on the job search website Glassdoor.com, applying topic modelling techniques for natural language processing (Blei et al., 2003). We measure employee turnover and compensation using data from Burning Glass Technologies, a dataset collecting job vacancies in the US. We further complement our measures of turnover with additional proxies for employee attrition from the Glassdoor database. To address the endogeneity of organizational culture and employee turnover, we exploit changes to labor market regulatory shocks in the form of supreme court decisions to increase or decrease the enforceability of employee non-compete agreements (henceforth, NCAs), thus easing turnover (Marx, Strumsky, & Fleming, 2009; Conti, 2014; Younge & Marx, 2016). We construct a series of difference-in-differences models using matched samples of firms in treated and untreated states, pre- and post-treatment.

In preliminary analyses on a sample of 6,208 firms active in Illinois (treated) and Michigan (control), we first confirm that firms in Illinois post significantly more vacancies and are significantly more likely to receive reviews from recently departed employees on Glassdoor following a reduction in NCA enforceability on June 24^{th}, 2013, in the state of Illinois, than firms in Michigan, suggesting that firms in Illinois experience more employee turnover following the shock. Second, consistent with our prediction, we find that (1) organizations with strong cultures experience a smaller increase in employee departures in Illinois relative to Michigan following the shock than organizations with weak cultures; and (2) organizations with strong cultures post vacancies with lower salaries in Illinois relative to Michigan following the shock than organizations with weak cultures.

Our paper makes three contributions to extant literature. First, while there has been limited prior research exploring the role of cultural content in determining employee mobility

(Chatman, 1991; Sheridan, 1992), we propose an alternative mechanism—namely, the distributional properties of organizational culture, irrespective of the underlying cultural content—through which organizational culture may act as a retention mechanism. Second, while both the strategic human capital (e.g., Campbell et al., 2012; Marx et al., 2009; Melero et al., 2020; Starr et al., 2018) and the organizational culture literature (e.g., Sheridan, 1992; Chatman, 1991; Srivastava et al, 2017) have generally studied the antecedents of employee turnover, in this paper we also investigate how heterogeneity in organizational cultural strength affects variation in job salaries and firms' ability to capture the value created by their employees. Third, this study is, to the best of our knowledge, the first to measure both employee turnover and organizational culture at scale by examining a large sample of firms, thus increasing the generalizability of the inferences we draw from our results on cultural strength as a retention mechanism.

2. PRIOR LITERATURE: ANTECEDENTS OF EMPLOYEE MOBILITY

A large literature in strategic human capital and labor economics explores the antecedents to employee mobility across organizations. Broadly, its conclusions can be organized along two dimensions: employee human capital and firm invectives. On the human capital side, prior work documents the role that skill transferability (namely, the ability of workers to replicate their performance across firm boundaries) plays in shaping the opportunities for employee mobility. Many of the skills that employees acquire on the job may be only partially transferable (if at all) to other organizations because such skills involve operating proprietary machinery and software, collaborating with specific colleagues who will not move with the focal employee, or engaging in a set of activities that is unique to the firm, even if each individual activity may be demanded by many other organizations (Becker 1964; Coff 1997; Lazear 2009; Molloy & Barney; Huckman & Pisano; Dess & Shaw 2001). As a result, employees who acquire experience working in an organization with unique assets and operations may struggle to generate comparable outside employment offers, and, conditional on generating such offers, may be reluctant to take them in the expectation that their post-mobility performance may decline (Groysberg, 2010).

On the incentive side, a large literature documents the role that financial incentives, promotion opportunities and non-pecuniary incentives play in reducing employee turnover. Employees are more likely to remain with an organization when their chances of internal promotion are high, when they receive competitive financial compensation such as cash compensation and stock options (Bloom and Michel, 2002; Hölmstrom, 1979; Prendergast, 1999), or when the non-pecuniary benefits offered, such as flexible work schedules, public recognition of performance and meaningful work, are unique to the firm and/or conforming with the employees' preferences and closely held values and beliefs (e.g., Anderson et al. 2013, Ashraf and Bandiera, 2014; Bareket-Bojmel, Moran and Shahar, 2016; Gubler, Larkin and Pierce, 2016; Oyer, 2008).

Organizational culture appears to be a relevant antecedent to employee mobility that has not been largely studied in previous research yet. Extant literature has established that employees culturally fitting with their organizations experience higher satisfaction than those who do not (refer to Kristof-Brown et al, 2005 for a literature review). Job satisfaction, in turn, is known to decrease employee' turnover (e.g., Holtom, Mitchell, Lee, & Eberly, 2008; Dougherty, Bluedorn, & Keon, 1985; Griffeth, Hom, & Gaertner, 2000; Joo & Park, 2010; March & Simon, 1958; Trevor, 2001).

However, with a few exceptions, research aimed at uncovering the direct link between organizational culture and employee mobility appears still limited. Studying career paths of college graduates, Sheridan (1992) finds that the specific content underlying the culture of an organization has significant effects on the rates at which new employees voluntary exited the companies. O'Reilly et al (1991) and Chatman (1991) focus on the construct of Person-

Organization Fit, and find that the degree to which an employee fits an organizational culture significantly predicts their commitment to the company and the length of their organizational membership. Finally, leveraging a corpus of 10.24 million e-mails exchanged by the employees of a high-technology firm, Srivastava et al (2017) add more nuances to the relationship between employee cultural fit and exit, finding that those workers who are rapidly enculturated at entry show lower rates of involuntary, but not voluntary, turnover, while cultural fit decreasing in time further increases voluntary departure.

Despite starting to shed some light on how organizational cultures affect employee mobility, the majority of these studies have been conducted using relatively small samples drawn from one or few organizations at bests, limiting the generalization of the findings. Further, they have been mainly focused on the role played by specific cultural content in regulating employees' behaviour. To our knowledge, systematic and large scale evidence about the relationship between organizational culture and employee mobility is still lacking, calling for further research, especially concerning the role of cultural distributional properties, irrespective of the underlying and possibly firm-specific content.

3. THEORY

3.1. Collaborating in strong cultures as a firm-specific skill and its effects on turnover

We expect organizational culture to impact employee mobility as follows: first, it enhances their ability to collaborate. Second, to the extent that a firm's culture is strong, it makes employees' collaboration patterns a firm-specific skill that may be difficult for workers to port to other organizations. The firm-specificity of collaborating in a strong culture, in turn, is expected to reduce individual turnover and thus increase the ability for value appropriation by the firm as a result.

Organizational culture is a multifaceted construct (Chatman and O'Reilly, 2016). While prior literature has focused on the organizational implications of cultural content (e.g., Chatman, 1991; O'Reilly et al., 1991; Sheridan, 1992), i.e., "the actual substance of the culture" (Chatman and O'Reilly, 2016: 5), in this paper, we propose to focus on its distributional properties to understand its effect on employees' mobility and value appropriation. The *distributional properties* of a culture summarize the extent to which its individual members are aligned around the relevant organizational cultural dimensions (Chatman *et al.*, 2014; Chatman and O'Reilly, 2016), irrespective of the specific underlying cultural content. Specifically, we focus on the degree of an organizational *cultural strength* that, we argue, may favor employee retention.

Chatman and colleagues define organizational culture as strong if its members reach consensus (i.e., agreement) on the specific cultural attributes that have the greatest intensity (i.e., are most important) to them (e.g., Chatman *et al.*, 2014; O'Reilly, 1989; O'Reilly and Chatman, 1996; Schein, 1983). Belonging to a strong culture implies that its members consider the same cultural attributes describing their organization as highly important. Following Schein (2004), such organizational attributes may be values (what is desirable), norms (what is expected and socially acceptable), beliefs (what is considered to be true), or artifacts (what are the symbols that convey values, norms, and beliefs). For a strong culture to arise, both the properties of consensus and intensity are necessary. Chatman *et al.* (2014: 788) compare and contrast a strong culture with "warring factions," characterized by high intensity, but lacking consensus by the organizational members around the cultural attributes, and "vacuous cultures," which, on the other hand, display high consensus but low intensity on the specific cultural content the organizational members deem important.

The convergence that the members of a strong culture achieve in terms of which organizational attributes are the most important to them is expected to enhance both coordination (which enables the interacting individuals to align their *actions* effectively) and cooperation (which enables the interacting individuals to align their *interests* effectively)

(Kotter and Heskett, 1992; Kreps, 1996; Marchetti and Puranam, 2021; Schelling, 1978; Weber and Camerer, 2003). Prior research shows that cultural attributes that are specific to a certain task, when shared and important among the members of a strong culture, improve the degree of coordination within the task environment (e.g., Chatman *et al.*, 2014; Sorensen, 2002; Srikanth and Puranam, 2011). The shared sense of importance the members of a strong organizational culture assign to specific cultural attributes can facilitate collaboration on a task even when the cultural attributes deemed important are *not* directly related to that specific task. Mutual awareness of the cultural markers that are important to individuals in the organization, in fact, increases in-group identification (Sherif, 1968) and homophily (Pratt and Rafaeli, 1997; Tajfel and Turner, 1979), which, in turn, makes individuals more willing to accommodate rather than exploit the other group members (Simpson, 2006).

Because of their ability to ingenerate cooperation and collaboration, strong cultures, we argue, are more likely to leverage relational contracts and informal organization to achieve collaboration among their members. Research on implicit contracting shows that attaining collaboration in organizations through formal contracting is difficult, because of the challenges firms confront in observing, measuring, and verifying collaborative actions (Gibbons and Henderson, 2012). Scholars have proposed alternative solutions to formal contracts, and culture in particular has been suggested as an alternative means to achieve the requisite levels of collaboration within organizations (Hermalin, 2013; O'Reilly and Chatman, 1996; Ouchi, 1980). The social mechanisms leading to high internal congruence over cultural attributes such as values, norms, and beliefs have the potential to achieve similar effects to formal contracts in inducing individuals to collaborate (Barnard, 1938; Dietz, Ostrom, and Stern, 2003; Ostrom, 1990; Ostrom, Gardner, and Walker, 1994; Ouchi, 1980).

Strong cultures in particular have been shown to be functionally equivalent to traditional hierarchy and formal authority (Marchetti and Puranam, 2021). Accordingly, we expect that, to achieve collaboration, they are well suited to reduce the reliance on formal contracts, and leverage the social dynamics among their members enabled by their cultural distributional properties, instead. We thus argue that organizations displaying high levels of cultural strength are less likely than their weaker counterparts to build collaboration through formal contracting, leveraging relational contracting (through which collaboration is "sustained by the shadow of the future as opposed to formal contracts enforced by courts", Gibbons and Henderson) as an alternative.

Collaborating in a strong culture can thus be seen as a skill that employees may not be able to port to competitors in case of mobility, limiting their ability to leave their employer at will. Because of the heavy reliance on the informal organization, collaborating in a strong culture requires employees to become familiar with the network of people and information, and how these can be informally leveraged to get the work done. In other words, collaborating in a strong culture results in a firm-specific skill (Groysberg, 2010). When employees consider the possibility to leave their employer, the limited portability of their firm specific skills often decreases their turnover (Becker 1964; Coff 1997; Lazear 2009; Molloy & Barney; Huckman & Pisano; Dess & Shaw 2001), as the employees would not be able to replicate their performance at the newly joined company by leveraging the previously acquired skills (Groysberg, 2010). Given the firm-specific nature of coordinating in strong cultures, we thus argue that firms exhibiting high cultural strength experience lower rates of turnover, compared to firms with weak cultures.

3.2. Cultural strength as a retention mechanism: the role of non-compete agreements

So far, we have argued that, because of their collaboration benefits, strong cultures act as a retention mechanism by increasing their reliance on informal contracts, thus imparting firm-specific skills to their members. Correspondingly, we focus on a type of formal contract aimed at reducing employee mobility: post-employment covenants not to compete (commonly referred to as non-compete agreements and henceforth, NCAs). NCAs provide an ideal empirical setting to test for our theoretical argument. They represent an explicit counterpart to implicit contracts, and are used by firms that cannot access such informal organizational aspects (namely, weak organizational cultures, in our setting) to limit the mobility of their employees (Jeffers and Lee, 2019).

We thus study the implications of organizational cultures' distributional properties on employee turnover following exogenous shocks to labor market regulations that reduce barriers to employee mobility within geographies. In particular, we focus on state-level changes in the use and enforcement of NCAs, which have been considered as a shock to the local firms' ability to leverage formal contracting tools (e.g., Jeffers and Lee, 2019), and extensively used in previous research to causally identify the antecedents of employee mobility, as well as its organizational implications (Conti, 2014; Marx *et al.*, 2009; Younge and Marx, 2016).

Appeared for the first time in fifteenth century England, NCAs have been nearly universally used to regulate employment contracts ever since (LaVan 2000, Kaplan and Stromberg 2001, Stuart and Sorenson 2003). Firms use NCAs as formal contracts to limit the mobility of their workers, in order to prevent trade secrets disclosure, ensure customer confidentiality, and limit the competitors' ability to capture value generated by the skills and knowledge of their employees (Valiulis 1985).

While the legal system regulating NCAs is quite similar in all the US states (Hyde 2003), states vary largely in the degree to which companies consider such arrangements legally binding and actively enforce them (Jeffers and Lee, 2019). As an example, while Florida enforces NCAs even for those workers that have been laid off by their employers, California notoriously does not recognize nor enforce such covenants. State-level enforceability of NCAs is determined by a combination of rulings by the Supreme Court and state laws, with state-level policy on NCAs enforcement changing over time. This is a desirable feature that makes such changes in state-level NCAs enforceability usable as exogenous shocks to the strength of formal contracting and the labor market.

Previous research has shown that, when regularly enforced, NCAs are binding (Garmaise 2009, Starr, Balasubramanian and Sakakibara 2014), and that changes to enforcement levels within states have significant effects on employees' receipt of outside employment offers (Starr, Frake & Agarwal, 2019) and employee mobility (Marx, Strumsky and Fleming 2009). Moreover, even for workers not formally bound by NCAs themselves, state-level enforcements create important negative externalities because organizations often cannot easily observe whether job candidates are bound by non-compete restrictions (Starr et al., 2019).

The use of shocks to NCAs enforcement in US states also allows us to address endogeneity issues and getting closer to a causal identification of the effects of culture as a retention mechanism. The study of the causal effects of organizational culture on employee turnover is fraught with several challenges. First, the relationship is endogenous. A firm superior ability to hire for fit with the existing employee base may in fact simultaneously favor the formation of a strong culture (e.g., Harrison and Carroll) and reduce employee turnover (Adkins and Caldwell, 2004). Further, while, as we argued, cultural strength should enhance a firm's ability to retain its employees, it may also be the case that firms that experience low levels of turnover are better able to form strong cultures, because of the ongoing socialization of long tenured employees (e.g., Van den Steen, 2010a; Carroll and Harrison, 2002).

Second, organizational cultures have been reported to be stable in time, conservative and resistant to change, likely altered only by the proactive intervention of some of its powerful members (e.g., Kilmann, Saxton, and Serpa, 1985; Meyerson and Martin, 1987; Ouchi, 1981; Pascale and Athos, 1981). As a consequence, it is hard to empirically observe relevant and significant changes in organizational cultures within a focal firm within the time windows typically available to management scholars, to understand how such changes affect the organizational ability to retain its employees.

In formulating our hypothesis about the predicted negative effect of organizational cultural strength on employee turnover, we thus follow prior research (e.g., Jeffers and Lee, 2019; Jeffers, 2019) and leverage the specific context of state-level staggered rulings on NCAs as exogenous shocks to the turnover experienced by local firms. Accordingly, we hypothesize what follows:

> ***Hypothesis 1***: *Following a reduction in mobility barriers, firms with stronger cultures will experience a* ***smaller*** *increase in employee turnover than firms with weaker cultures.*

3.3. Organizational cultural strength and value appropriation

In turn, to the extent that strong cultures allow firms to retain their employees more easily, they may also be able to appropriate a greater share of value created by such employees by setting lower salaries and offering less benefits than its competitors. Prior work documents that employees often renegotiate their salary and benefits through turnover rather than promotions within the same firm. Studying US investment banking employees, Bidwell (2011) shows that external hires are paid more than workers entering the job from inside, despite lower subsequent performance. Similarly, research on firm-specific human capital has shown that firms often display a high willingness to pay external hires for their general skills, leading to external hires earning more than internal employees (e.g., Harris and Helfat, 1997).

Thus, to the extent that strong organizational culture acts as a retention mechanism for employees and reduces overall turnover in the firm (as theorized with hypothesis 1), we also expect that organizations displaying strong cultures will offer lower salaries than otherwise comparable firms characterized by weaker cultures. We therefore formulate the following hypothesis:

> ***Hypothesis 2:*** *Following a reduction in mobility barriers, firms with stronger cultures will offer jobs with a* ***lower*** *increase in salary than firms with weaker cultures.*

4. RESEARCH DESIGN

4.1. Data and sampling strategy

4.1.1. Burning Glass Technologies data to measure employee turnover and job salaries

We obtain job vacancy listings and their characteristics from Burning Glass Technologies (henceforth, BGT), an analytics company that tracks employment data posted online. BGT collects and deduplicates the near universe of job vacancies posted online across more than 40,000 job boards and company websites in the United Stated between 2010 and 2020, inclusive. In total, at any given point, BGT tracks roughly 3.4 million unique active vacancies. For each vacancy, BGT collects the full text of the job posting, date of posting, the name of the employer seeking a candidate, details of the vacancy's location down to the level of the county and zip code, and a range of algorithmically imputed variables constructed from the text of the job posting, such as the occupation (as defined by O*NET) to which the vacancy belongs to, the skills, minimum level of education, and prior experience required, as well as estimated wages, if any, among others.

These data have recently been used by a wide range of scholars in strategy (Felten, Raj, and Seamans, 2021; Goldfarb, Taska, and Teodoridis, 2019), economics (Alekseeva, Azar, Gine, Samila, and Taska, 2021; Azar, Marinescu, Steinbaum, and Taska, 2020; Hershbein and Kahn, 2018; Sran, Vetter, and Walsh, 2020) and accounting (Gao, Merkley, Pacelli, and Schroeder, 2020), and have been compared extensively with other publicly available sources of job creation in the United States such as JOLTS and the Current Population Survey. These comparisons suggest that while job postings on BGT tend to be skewed towards more highly skilled occupations, the occupational and industry distributions remain stable over time and comparable to the aggregate trends in other sources (Hershbein & Kahn, 2016).

From BGT, we collect company names, number of vacancies each firm posted each month, the location of each vacancy, the job title for each vacancy, the full text of the vacancy listing and the estimated salary for the vacancy[1]. Given our focus on a change to NCAs enforcement in the state of Illinois occurred in 2013, we are interested in the period between 2012 and 2014 inclusive, and we thus select only those vacancy listings appearing during those dates, covering a total of 3,311,387 organizations. More details about the choice of NCAs enforcement change can be found in section 4.1.3 below.

4.1.2. Glassdoor data to measure organizational culture

To measure organizational culture at scale, we leverage text reviews employees write about their companies and post on the website Glassdoor.com. Launched in 2008, Glassdoor is a job search website with about 50 million unique monthly visitors and more than 70 million text reviews posted by employees working for about 1.3m companies covering insights about jobs and work conditions across industries and geographies[2]. The Glassdoor company reviews have been increasingly leverage by both academics and practitioners (e.g., Corritore, Goldberg, and Srivastava, 2020; Sull, Sull, and Chamberlin, 2019) to study cross-firm variations in organizational culture[3].

We restricted the Glassdoor review sample to a subset of ten industrial domains[4] where the average firm-level Glassdoor coverage (equal to the number of Glassdoor reviews available for a firm, and the number of employees) was equal to at least 25%. With this approach, which increases our confidence that the Glassdoor reviews provide a valid representation of a firm's organizational culture, we generated a subsample of 140,726 firms featured on Glassdoor, which we could match with BGT.

[1] It is important to note how BGT typically obtains salary information on vacancies. Most vacancy listings do not provide data on expected salaries directly. However, many job boards such as Glassdoor allow users to anonymously disclose the salaries they receive for a particular role in a particular firm and location. BGT obtains these user-provided data in addition to salary data listed in the job vacancies directly.

[2] Updated statistics about Glassdoor.com: https://www.glassdoor.com/about-us/ [online access: 23/05/2021]

[3] List of press releases using Glassdoor employer survey to discuss firm-level culture and employees' satisfaction: https://www.glassdoor.com/about-us/press/in-the-news/

[4] Arts, Entertainment and Recreation, Business Services, Consumer Services, Health Care, Information Technology, Insurance, Media, Real Estate, Retail, Telecommunications.

4.1.3. NCA shocks

NCAs (i.e., restrictions placed on workers that prohibit or limit their ability to join or establish competing organizations) have over the past few decades become commonplace for many workers across the United States. While comprehensive administrative data tracking the usage of NCAs in workplaces is lacking, estimates from representative workers surveys suggest that as many as 38% of all workers have signed a non-compete agreement at some point during their work experience (Starr, Prescott & Bishara, 2021). Moreover, while non-competes are more common in high-skilled work, they are also frequently used in low-skilled jobs with low remuneration (Starr et al., 2021; Garmaise, 2011). In the US, the enforceability of non-compete agreements is governed at the state level by precedent and statute and varies widely. Some states, such as California and North Dakota, do not enforce non-competes at all, while other states, such as Florida, enforce NCAs even in cases where the employer terminates the employment contract. In addition, NCAs enforceability also varies considerably within states over time through changes in precedents set by higher courts that hold lower courts accountable.

To capture these changes in our data, we follow prior literature and collect information on court rulings. There were a total of eight such rulings between 2010 and 2020, our sample period, and we focus for now specifically on one such ruling in on June 24th, 2013, in Illinois, that ruled on the case of Fifield v. Premier Dealer Services, Inc., in which an Appellate Court ruled to increase consideration requirements for the enforcement of NCAs, which the Supreme Court declined to review, creating a precedent that effectively reduced the enforceability of non-competes.

The change in Illinois is particularly valuable for our purposes due to an earlier precedent set by the Supreme court in December 2011 that effectively increased the enforceability of non-compete agreements by expanding the scope of interests that could be considered in its ruling on Reliable Fire Equipment Co. v. Arredondo. Therefore, the period of January 2012 until June 2013 constitutes our pre-shock period of relatively high enforceability of non-compete agreements, and the period from July 2013 until December 2014 our post-shock period of relatively low enforceability that at least partially reversed prior precedent.

We use as our control state the state of Michigan, the size, geographic proximity to Illinois and industry composition of which most closely mirrors that of Illinois during our observation period from January 1st 2012 until December 31st 2014.

4.1.4. Sample Construction

We begin constructing our final sample by merging the Glassdoor and BGT datasets together at the firm level. No common identifier exists across these two databases. We therefore rely on a name-matching algorithm to find eligible matches across the two datasets. Specifically, we proceed in four steps. First, we pre-clean and tokenize each firm name in the Glassdoor and BGT datasets at the n-gram level, removing common elements such as 'inc.' and 'co.', punctuation marks, and converting symbols such as '&' into words. Next, we treat each firm name as a separate document and calculate the frequency of each token in each name (document) as a fraction of the total number of tokens in each name. Third, we calculate the weights for each token using the inverse frequency of its appearance across all firm names (documents) in Glassdoor and BGT separately using the following equation:

$$\text{Inverse Document Frequency}_t = \ln\left(\#\text{ of Documents}/\#\text{ of Documents Containing Token}\right)$$

Using the inverse document frequency as a set of weights for each token, we multiply each term frequency by its inverse document frequency. Finally, we calculate the cosine similarity across the two lists of firm name vectors in the two databases and for each firm name in Glassdoor select the closest matching name in BGT, conditional on the cosine similarity being at least 0.8. To check the accuracy of this matching procedure, we manually review a random sample of matched names.

This process allows us to match 19,414 firms in Glassdoor that are also present in BGT and are based in Illinois and/or Michigan during our sample period of 2012-2014 surrounding the June 24th, 2013, Supreme Court of Illinois decision that we use as our shock. Together, these firms listed 1,265,760 vacancies over this period. We then merge these data with culture metrics at the firm level obtained from Glassdoor. This final step leaves us with 6,202 organizations that collectively posted 1,010,941 vacancies in Illinois and/or Michigan during our sample period of 2012-2014. Finally, for most of our analyses, we restrict our sample to firms that are present in both Illinois and Michigan prior to the NCA shock, which we measure by requiring that each firm posts at least one vacancy in the pre-shock period in both states. In addition, we require that the firms in our sample were founded prior to the shock date, which we calculate using firm founding dates from Glassdoor, and that they post at least one vacancy in both the pre- and post-shock period in both Illinois and Michigan separately. This leaves us with 2,130 firms that together posted 754,604 vacancies across both states during our observation period. This comprises our final sample used throughout the rest of our analyses.

However, for our analyses on vacancy salaries to test for hypothesis 2, since not all vacancies list the offered salary, we further restrict our sample to firms that have at least one vacancy with information on offered salary in both states pre- and post-shock. In addition, for salary analyses, we also require that at least 11% of firms' vacancies contain offered salary, which corresponds to dropping the bottom 10% of firms with less salary information than this threshold. Note, however, that our results are also robust to alternative cut-offs of 5%, 15% and 20% of posted salaries.

4.2. Measures

4.2.1. Dependent variables

While our ideal measure of employee turnover would capture the number of employee departures in each firm-state combination each period, obtaining such internal data across all industries present in a state is unfortunately not possible[5]. We therefore settle on the second-best approach of a combination of two alternative proxies for employee turnover: *Ln(Number of Vacancies)* and *Quit*, that we describe in turn.

Ln(Number of Vacancies). Our primary measure of employee turnover is the *Number of Vacancies* posted each month by each firm in our sample separately in each state, Illinois and Michigan. This measure is obtained directly from BGT as the count of vacancies that BGT records per firm-state-month combination. To account for the highly-skewed nature of this variable (most firms post only a few vacancies during our full three-year observation period), we take the natural logarithm of this number and add one to all values to account for firm-state-month combinations in which a firm posted zero vacancies (our qualitative results are also robust to adding values smaller than one and to taking logs without the addition of any values, thereby dropping all observations with zero posted vacancies). Note, however, that this measure suffers from one important limitation. Namely, the number of vacancies each firm posts can be driven by both: vacancies created as a result of employee departures, and vacancies created as a result of firm growth and expansion. Since we are unable to distinguish between the two drivers of vacancy creation in our data, we supplement this measure with a second operationalization of employee turnover, *Quit*, a proxy for employee departures that we calculate using data from Glassdoor.

Quit. Our second of measure employee turnover uses employee reviews from Glassdoor. Both current and former employees can post reviews for an employer online, and Glassdoor also collects information about the state in which the employee worked for a given employer. Further, in the case of former employees, Glassdoor asks reviewers to indicate the year in which they departed the firm. We use this information to calculate the number of

[5] While Census data could potentially be used for such purpose, such data are typically anonymized at the firm level, which would preclude us from matching it to firm reviews in Glassdoor.

reviews posted for each employer by employees who departed the organization in each of our observation year-state combinations. However, reviews by former employees are relatively rare and heavily skewed towards zero. For our main measure, we therefore create a dichotomous variable taking the value of one if a focal firm received at least a review by an employee who departed that firm each year, and zero otherwise. However, our results are further robust to using the natural logarithm of the total number of reviews posted by employees who departed the organization in a given state-year combination and adding an arbitrarily small value to account for zeroes. These results are available in Table A3 in the Appendix.

While the two measures, *Ln(Number of Vacancies)* and *Quit* capture somewhat different variation in employee turnover, we further confirm that the two measures are strongly and significantly positively correlated, with a correlation of 0.492 (p-value = 0.000).

Firm job vacancy salary. We obtain salary information for each job vacancy from BGT. BGT collects salary information from two sources: directly from the job vacancies when they list a salary and as estimates by current and former employees who review their roles on job boards such as Glassdoor and Ladders. As a result, while few job vacancies list their salaries directly, we can supplement many missing salaries with estimates from job boards. As BGT collects salary information from job boards periodically, these estimates are also time-stamped and vary over time even within the same role and firm. We are therefore able to observe salary changes within the same firm and role before and after the shock in NCAs. Salaries are typically listed in dollars per annum and where multiple people provide estimates for the same firm-role-location combination, they are provided as a range between a minimum and maximum total annual salary, instead of a single value. In cases where a range is observed, we calculate the median between the two extremes and use that in our final calculation. Since salaries are also highly skewed (see Figure 1), we take the natural logarithm of this variable in our regressions to allow for non-linearities and easier interpretation, arriving at our final variable, *Ln(Salary)*.

--- Insert Figure 1 here ---

4.2.2. Independent variable

Cultural strength. To measure the cultural strength of a firm, we leverage the text reviews employees post about the organization on Glassdoor. We follow Corritore *et al.* (2020) in using each employee's review as an observation about the organizational attributes that are the most important to the individuals. In this paper, we focus on the collaboration benefits of a strong culture, which require a shared structure of beliefs about the organizational attributes (irrespective of the actual content and meaning of such attributes). Accordingly, as Schein (2004) does, we intentionally adopt a broad view on what these attributes could encompass. For instance, the attributes employees discuss in their Glassdoor reviews and over which they display shared beliefs could be the importance of performance (value), the nature of teamwork (behaviour), a direct communication style (norm), or the focus on health in the work environment (artifact). In this, we follow prior studies that have considered these elements as part of organizational cultures (Balthazard, Cooke, and Potter, 2006; Chatman and O'Reilly, 2016; Cooke and Rousseau, 1988; Schein, 2004).

Given the distribution of importance over such organizational attributes (i.e., the values, norms, beliefs, or artifacts forming their corporate culture) across the members of an organization, we operationalize a strong corporate culture as one in which its members assign high *importance* to the *same* organizational attributes. Our operationalization is consistent with the definition provided by Chatman et al., (2014: 788), who define a strong culture as one characterized by "[…] both intensity around one or two key norms and broader consensus about a comprehensive set of norms." Such a definition translates into importance distributions that are highly focused on the same organizational attributes across the organizational members. It is also worth noting that, while Chatman et al., (2014) study values and norms, such definition can be extended to other theoretical constructs underlying the formation of a corporate culture.

In extracting the set of organizational attributes the organizational members deem important and discuss in their text reviews, we follow previous studies using natural language processing (e.g., Blei *et al.*, 2003; Corritore *et al.*, 2020; Hannan *et al.*, 2019; Huang *et al.*, 2018; Kaplan and Vakili, 2015), and leverage the Latent Dirichlet Allocation (henceforth, LDA) algorithm, an unsupervised machine learning algorithm for topic extraction from large corpora enough. LDA is now widely enough used in management research that we refer interested readers to other sources for a basic introduction (e.g., Hannigan *et al.*, 2019). The LDA topic model provides a suitable methodology to measure the strength of an organizational culture, since it extracts the universe of topics an organization's members discuss in their text, and summarizes how important each of the identified topics is to the individual reviewers. Critically, this approach allows us to measure the strength of an organizational culture at scale, which other traditional forms of data collection (e.g., surveys or interviews) would struggle with.

For each sampled firm, the text reviews its employees have posted on Glassdoor over time represents the corpus of text LDA operates on. We highlight three distinctive features of our empirical approach. First, to estimate the optimal number of topics to be extracted by LDA, we use the principle of "coherence" maximization: In other words, LDA is implemented on each firm-specific corpus of text reviews using the number of topics that maximizes the distance between topics (Puranam, Narayan, and Kadiyali, 2017), where a topic is a probability distributions over the corpus vocabulary. On the other hand, if we were to use an arbitrarily large (or small) number of topics under uniform prior assumptions for the Dirichlet distributions estimated in LDA, we could produce noisy and possibly biased estimates of the topical structure underlying a text corpus (Wallach, Mimno, and McCallum, 2009).

Second, since we do not assume the existence of a universal list of cultural attributes shared by all the firms in the population (known as the *etic* approach to culture (Harris, 1979)), we apply the LDA algorithm on firm-specific corpora, instead of aggregating all the Glassdoor reviews available for the sampled firms we study in a unique corpus. Our approach is consistent with an *emic* conceptualization of organizational culture (Malinowski, 1922), which allows firms to display distinctive and idiosyncratic cultural attributes, not necessarily shared with other organizations. The theoretical distinction between the emic and etic view on organizational culture has also important implications for empirically measuring the construct of cultural strength. In fact, if we were to use an etic list of organizational attributes, i.e., shared across the sampled firms, the degree of cultural strength could be underestimated if the members of an organization display homogeneous mindshare distributions only on emic that are not identified in the etic list, and overestimated if their mindshare distributions are homogenous only on those attributes that are included in the etic list, but not on the emic ones that have been excluded (Chatman *et al.*, 2014). It is worth noting that we do not have any theoretical or empirical reason to assume that the bias the etic measurement of cultural strength risks introducing would be the same (either conservative or aggressive) across all the firms in the sample, and we thus opted for an emic version of the analysis.

Finally, in measuring organizational cultural strength, we leverage the Glassdoor reviews' structure, in which users are required to separate the "pros" and "cons" about their organization, when posting the review online, to compute the metric of cultural strength on the "pros" section of the only, to account for sentiment differences across review types. We chose to compute the metric on the "pros" section of the Glassdoor reviews since individuals' overlapping mindshare over organizational attributes described with positive valence appears a more intuitive basis for collaboration than the case of negative valence (i.e., we argue that individuals are expected to find stronger homophily from shared likes than shared dislikes).

The results of the LDA analysis on the firm-level corpus of Glassdoor text reviews allow us to summarize each review as a probability distribution ϑ_r, corresponding to an empirical estimation of the distribution of importance that the employee who posted the review ascribe to organizational attributes. Such a review-level distribution ϑ_r provides an empirical estimation of the reviewers' distribution of mindshare over the attributes used to describe their organization, assuming that a) users write on Glassdoor write more about things that are more important to them, and b) topics underlying the corpus of reviews correspond to organizational attributes that employees use to describe their organizational context. These attributes, which correspond to the topics estimated by LDA, could be values, norms, beliefs, or artifacts.

Based on this analytical representation, we can summarize an organization by a matrix $A \epsilon R^{NxK}$, which comprises the ϑ_r individual mindshare distributions of the *N* organizational members over the *K* topics underlying the corpus of text and estimated by the LDA algorithm. We compute the average cross-entropy of each such firm-level matrix as $ACE = \frac{2\sum_{i=1}^{N}\sum_{j=i}^{N}\overline{CE}_{ij}, j \neq i}{N(N-1)}$. $\overline{CE}_{\vartheta_p,\vartheta_q}$ is the average cross-entropy of a pair of probability distributions ϑ_p, ϑ_q and is computed as follows: $\overline{CE}_{p,q} = \frac{[H(\vartheta_p)+D_{KL}(\vartheta_p || \vartheta_q)+[H(\vartheta_q)+D_{KL}(\vartheta_q || \vartheta_p)]}{2}$, where $H(\vartheta_p)$ is the entropy of the probability distribution ϑ_p, and $D_{KL}(\vartheta_p || \vartheta_q)$ is the Kullback-Leibler (henceforth, KL) divergence between ϑ_p and ϑ_q. Since higher ACE values correspond to a weaker culture for a sampled organization, we eased the interpretation of results by coding *Cultural strength* as negative ACE. In other words, the closer the ACE measure is to zero, the stronger the culture of the focal firm. For each firm present in Illinois or Michigan, we leveraged all the reviews posted by the employees until the date of change in NCAs enforcement to compute their degree of cultural strength.

Cross-entropy is commonly used in natural language processing application as a standard metric of distributional differences (e.g., Ghazvininejad *et al.*, 2020; Teahan and Harper, 2003). Given its formulation, it simultaneously accounts for both the shared nature (consensus across individuals) and the differential importance (intensity within individual) the employees assign to organizational attributes. Accounting for both dimensions is critical: in fact, looking at the sharedness component only would not enable to distinguish between the case that Chatman *et al*. (2014) describe as a "vacuous" culture, whose members are equally indifferent to all the topics mentioned in text reviews[6], and the case where the individual mindshare distributions are focused on the same attributes (i.e., they are from a genuinely strong culture).

Low values of ACE (coded as *Cultural strength* close to zero) correspond to the case in which the employees' mindshare distributions are focused on the same organizational attributes, therefore simultaneously capturing the two aspects of commonality and importance. On the other hand, high values of ACE (which correspond to negative and large *Cultural strength*), indicate weak cultures and could either arise from either indifference (leading to "vacuous" cultures), or conflicts (as in "warring factions", as described in Chatman et al, 2014) in what is important to the organizational members. Figure 2 summarizes graphically how different values of ACE might arise, and how these correspond to varying levels of organizational cultural strength. In the main analysis, we dichotomize the ACE metric at median values, creating a variable equal to one if a culture is strong (i.e., it displays values of ACE below the sample median) and to zero otherwise.

--- Insert Figure 2 here ---

In Appendix, we further show that our results are robust to two alternative operationalizations: one in which strong cultures are those displaying values of ACE in the bottom 20% of the sample distribution and weak cultures are those with ACE values in the top 20% of the same distribution (results reported in Table A1), and a second operationalization in which we use the continuous version of the ACE metric (reverse-coded) to proxy for cultural

[6] Other approaches are available in prior literature to compute the two dimensions of consensus and intensity in the individual distributions over organizational attributes as separate variables (e.g., Corritore *et al.*, 2020; Csaszar and Laureiro-Martínez, 2018).

strength (results reported in Table A2). We further discuss potential issues with the polarization often characterizing the data generation process of online reviews (Matakos and Tsaparas, 2016), and we show that this is unlikely at stake on Glassdoor, thus not affecting the operationalization of the *Cultural strength* variable results reported in Table A4.

5. ESTIMATION STRATEGY

As described in Section 4.1.3, our estimation strategy exploits a state-level shock to the enforceability of NCAs in Illinois, in the form of a decision on June 24th, 2013, by the Supreme Court of Illinois, not to review the decision of an Appellate Court to increase consideration requirements for the enforcement of non-compete agreements in the case of Fifield v. Premier Dealer Services, Inc. This decision created an important precedent that effectively reduced the enforceability of non-competes going forward. We use as our control state the state of Michigan. Using these two states as the treated and control states, we then collect data on firms located in *both* Illinois and Michigan before June 24th, 2013 (which we identify as all the firms posting at least one job vacancy in each state between January 1st 2012 and June 23rd, 2013, inclusive).

Our interest is in examining the effect of the shock on firm turnover and offered salaries in Illinois relative to Michigan for firms already present in both states, therefore accounting for any firm-wide changes that may have taken place in the firm during the same time period. We then use the *Strong Culture* variable to explore whether firm culture moderates the main difference-in-differences estimate of the shock. We therefore estimate the following equation:

$$\begin{aligned} Ln(Number\ of\ Vacancies)_{ijt}/Quit_{ijt}/Ln(Salary)_{ijt} \\ = \alpha + \beta Illinois_{ijt} + \gamma PostShock_{ijt} + \delta Illinois * PostShock_{ijt} + \theta Illinois * StrongCulture_{ijt} \\ + \mu PostShock * StrongCulture_{ijt} + \boldsymbol{\rho Illinois * PostShock * StrongCulture_{ijt}} + \omega_i + \tau_t + \varepsilon_{ijt} \end{aligned}$$

for firm *i* in state *j* in month or year *t*. All our estimations use OLS and include firm and time fixed effects, with errors clustered at the firm and, where appropriate, time levels, as described in the footnotes to each table. In addition, to account for the differences in salaries across different occupational groups, our estimations on salary changes also include firm-occupation fixed effects that we describe in more detail in the results section. Based on our theory, we would expect the coefficient ρ on the triple interaction between Illinois, Strong Culture and Post-Shock period dummies to be negative and significant for all three dependent variables (*Ln(Number of Vacancies)*, *Quit* and *Ln(Salary)*). This would suggest that firms with stronger cultures experience lower rates of turnover and salary increases in Illinois relative to Michigan following the NCA shock than firms with weaker cultures. In addition, we also run a series of split-sample analyses, dividing our sample into firms with strong and weak cultures, and examining the effects of the shock separately for each.

6. RESULTS

6.1. Descriptive Statistics

We begin our analyses by first plotting the relative number of vacancies posted each month by firms located in Illinois and Michigan before and after the NCA shock, together with their 95% confidence intervals, in Figure 3. As the figure shows, firms in Illinois generally post a similar number of monthly vacancies prior to the shock, with only five of the 17 pre-shock months showing a significantly different number of posted vacancies for firms in Illinois relative to Michigan. Moreover, the overall trend appears stable over time, suggesting that the two states follow a similar pattern in their vacancy postings prior to the shock. Post-shock, firms in Illinois posted *more* average monthly vacancies in eight out of the 18 post-shock months, and the average difference relative to the pre-treatment period is statistically significant at the 5% level.

--- Insert Figure 3 here ---

However, Figure 3 contains all firms, including those that also posted vacancies only in a single state throughout our observation sample, raising the question of whether firms in Illinois and Michigan are truly comparable. To address this concern, we repeat the same analyses in Figure 4 for firms present in *both* Illinois and Michigan prior to the shock, where we measure the firm geographical presence by examining whether the firm posted at least one vacancy in both states prior to the shock period. As shown in this figure, the overall pattern pre-shock remains remarkably similar to that observed in Figure 3, except now firms post a significantly different number of vacancies in Illinois relative to Michigan in only four of the 17 pre-treatment months. We therefore observe little to no significant difference in posting behavior in Illinois relative to Michigan by firms pre-shock. Post-shock, however, firms post significantly more vacancies in Illinois than Michigan in ten out of 18 months, and the average increase in posted monthly vacancies grows from less than one additional vacancy for the full sample, to nearly two additional vacancies for the sub-sample containing only firms present in both Illinois and Michigan pre-shock.

--- Insert Figure 4 here ---

Next, we examine how this shock impacts firms with stronger and weaker cultures. Table 1 contains our summary statistics for three sub-samples on which we run our analyses. The first sub-sample (reported in Panel A of Table 1) is at the firm-state-month level, where we aggregate the number of vacancies for each firm-month-state combination. We use this sub-sample to test Hypothesis 1 in Table 2. The second sub-sample (reported in Panel B of Table 1) is at the firm-state-year level, where we aggregate the number of reviews posted by former employees on Glassdoor for each firm in each of the three years during our observation period (we split the treatment year in 2013 into two equal parts) for each state separately. We use this sub-sample to test Hypothesis 1 in Table 3. Finally, the third sub-sample (reported in Panel C of Table 1) is at the vacancy level, containing all vacancies posted by firms present in both Illinois and Michigan prior to the shock and containing the offered salary for the vacancy.

--- Insert Table 1 here ---

6.2. Tests of Hypothesis 1

We start by presenting the results of our tests of Hypothesis 1, examining the impact of the NCAs shock on firm behavior in Illinois versus Michigan in Table 1. Models (1) and (2) present the direct effects of Illinois and Post-Shock on the natural logarithm of the Number of Vacancies, controlling for firm- and month-year fixed effects. As model (1) shows, on average, firms post 14.4% more vacancies in Illinois than Michigan throughout our observation period, suggesting that turnover and/or firm growth are greater in Illinois than Michigan throughout this time-period. Furthermore, the observed growth and/or turnover appear to slow down in the post-shock period relative to the pre-shock period across both states, on average. However, examining how these patterns vary between the two states, model (2) suggests that firms post significantly more vacancies (about 9.4%) in Illinois than Michigan following the shock, relative to the pre-shock period. This result suggests that employee turnover and/or firm growth likely increased in Illinois following the shock.

Models (3) and (4) further disaggregate these results by culture strength, repeating the analyses in model (2) for firms with *Weak Culture* (in the bottom 50% of firms by culture strength) and firms with *Strong Culture* (in the top 50% of firms by culture strength)[7]. As these columns show, both strong and weak culture firms post more vacancies in Illinois post-shock. However, the increase is marginally larger for weak culture firms than strong cultures firms (Chi2 = 2.44; p-value = 0.118 in a cross-model comparison of model (3) and (4) without firm fixed effects).

Finally, model (5) presents our main results. As predicted, we find that firms with stronger cultures post significantly fewer vacancies (about 3.4% less) in Illinois following the shock than firms with weaker cultures, suggesting that firms with stronger cultures may experience less turnover in Illinois following the shock compared with firms with weaker

[7] Note that the sample sizes for *Weak* and *Strong Culture* firms are not equal because firm culture is calculated and percentiles are created on the full sample of organizations, including those not present in both states prior to the shock. As *Strong* culture firms tend to be smaller than *Weak* culture firms, they are less likely to be present in both states prior to the shock, leading to a smaller number of firms with below- and above-median culture strength throughout our analyses.

cultures. However, given that the number of posted vacancies does not allow us to distinguish between vacancies posted due to increases in turnover or firm growth, we next turn to examining a direct proxy of employee turnover, employee departures.

--- Insert Table 2 here ---

Table 3 contains our results with the dependent variable *Quit*, a binary variable taking the value of one if the focal firm receives at least one employee review by a former employee who lists the focal year as their year of departure, and zero otherwise. As we only observe employee departures in Glassdoor at the year level, we aggregate our metrics to the firm-year-state level. Overall, while the patterns in Table 3 are less statistically significant, they generally support similar qualitative conclusions as in Table 2. Firms experience a higher likelihood of employee departures in Illinois relative to Michigan regardless of time period. Furthermore, while the interaction between the Illinois and Post-Shock period dummies is not statistically significant, split sample analyses in models (3) and (4) suggest different patterns for firms with weaker and stronger cultures: firms with weaker cultures appear to experience a higher rate of employee departures post-shock in Illinois than firms with weaker cultures, and while the interaction effects are not significant, the difference between the two models is significant at the 10% level (Chi2 = 2.84; p-value = 0.092 in a cross-model comparison without firm fixed effects).

Finally, our main specification in Column (5) confirms our predictions. Firms with stronger cultures appear to experience significantly fewer employee departures in Illinois post-shock than firms with stronger cultures. Together with our results on the number of posted vacancies in Table 2, these results provide support for Hypothesis 1, suggesting that stronger cultures may reduce employee mobility in the face of lower NCAs enforceability.

--- Insert Table 3 here ---

6.3. Tests of Hypothesis 2

Next, we test Hypothesis 2, in which we argue that firms with stronger cultures post vacancies with smaller increases in salary post-shock in Illinois relative to Michigan than firms with weaker cultures. Note that, to insure that we are comparing similar types of roles for which firms recruit, all models in Table 4 include firm-occupation fixed effects, where occupations are measured using 2-digit O*NET Standard Occupational Classification codes. As a result, all reported changes in salaries are within the same firm and occupation.

Table 4 report the results for hypothesis 2 testing. Model (5) confirms our hypothesis, i.e., firms with stronger cultures post vacancies with lower salaries post-shock than firms with weaker cultures. However, the preceding models (1)-(4) suggest that the drivers of our predictions may differ from those hypothesized. In particular, we theorized that both strong and weak culture firms may increase their offered salaries in response to the NCAs shock in Illinois, but weak cultures are likely to increase their salaries more than strong cultures. However, we do not find support for this prediction. Rather, we find evidence that, following the shock, firms post vacancies with lower salaries regardless of their degree of cultural strength (model 2), and this effect is driven largely by firms with stronger cultures (model 4).

This result raises important questions for future work on the role of NCAs in wage setting. Data limitations have led much of prior work to conduct analyses at the individual employee or state-industry levels, rather than the firm-level (Starr, Frake & Agarwal, 2019; Marx, Strumsky & Fleming, 2009; Marx, 2011), therefore raising the question of whether the effects on employee wages stem from changes in firm turnover or changes in the types of firms recruiting in difference NCA regimes (Starr et al., 2018).

--- Insert Table 4 here ---

7. ROBUSTNESS CHECKS AND ADDITIONAL POST-HOC ANALYSES

7.1. Robustness Tests

We perform a series of robustness tests for our tests of Hypothesis 1 available in Table A1-A3 in the Appendix. Table A1 replicates our analyses in Table 3 for firms in the top and bottom 20% of culture strength, rather than the top and bottom 50%. As the results in models (1)-(5) show, all our results in Table 3 continue to hold and the effect sizes increase considerably, with the coefficient on the triple interaction between Illinois, Post-Shock and Strong Culture almost tripling in size, to -7.2%. To address the concern that our results are driven by the culture strength cut-offs that we have chosen, e.g., 50% and 20%, Table A2 further replicates our analyses in Table 3 using a continuous metric of firm culture strength. As model (2) confirms, the coefficient on the triple interaction between Illinois, Post-Shock and Strong Culture remains negative and is only marginally statistically insignificant, with a p-value of 0.105. Together with the evidence reported in Table A1, this test suggests that our results are unlikely to be driven by our choice of the culture metric cut-off to proxy for strong cultures.

Finally, to address the concern that our measure of employee departures using Glassdoor reviews submitted by former employees is not accurately capturing the variation across firms in the number of departed employees, we replicate our analyses with the natural log of the continuous measure of the number quits, *Ln(Number of Quits)*, adding a 0.001 to all values to account for 0 quits for some firm-year observations. The results, reported in Table A3, confirm the same patterns we observe in Table 4. While the overall effect of the shock on employee turnover in Illinois relative to Michigan appears to be insignificant (model 2), once we split the sample into firms with weak and strong cultures, we observe different patterns for each. Firms with weaker cultures appear to experience higher rates of employee departures following the shock, while firms with stronger cultures appear to experience lower rates of employee departures after the shock. While the coefficients for these interactions remain statistically insignificant, their cross-model difference is significant at the 10% level (Chi2 = 2.73; p-value = 0.098 when comparing models (3) and (4)). Furthermore, as shown in model

(5), the coefficient on the triple interaction is, as predicted, negative and statistically significant, confirming our findings in Table 4.

7.2. Additional Post-Hoc Analyses

An interesting question raised by our analyses so far is whether firms in our sample are aware of the effects that the NCA shock has had on their turnover and offered salaries, and whether they attempt to react to the shock in any way by changing their approach to recruitment. While a full examination of the effects of this shock on firm adaptation is beyond the scope of this paper, we provide some initial evidence that firms may indeed be reacting to the shock by altering the way they advertise vacancies to potential job candidates.

To examine this possibility, we construct a new variable, *Discusses Culture in Vacancy Ad*. We construct this variable using the following dictionary of culture terms: 'culture, climate, atmosphere, value, norm, belief, behaviour, tips', and create a binary variable taking the value of one if the focal vacancy contains at least one such term in the job description, and zero otherwise. However, our results are also fully robust to using the total count of such terms in the job vacancy description. We then examine whether firms change their discussion of such terms in Illinois relative to Michigan post-shock, and whether these changes vary by firm culture strength.

Table 5 reports the results for this additional analysis. We find that, while the overall effect of the shock is not statistically significantly different in Illinois relative to Michigan, this masks a starkly different pattern of behavior for firms with strong and weak cultures. In particular, we find that job vacancies posted by weak culture firms rely less on culture-related terms in Illinois post-shock (model 3), while job vacancies posted by strong culture firms rely more on such terms in Illinois post-shock (model 4). Moreover, as evidenced by the triple interaction in model (5), this difference is statistically significant, with stronger culture firms being 14.1 percentage points more likely to rely on culture-related terms post-shock in Illinois than firms with weaker cultures. Note also that all our models contain firm-occupation fixed effects, where occupations are defined at the 2-digit O*NET Standard Occupational Classification code level. The reported estimates are therefore changes within the same occupation-firm combination.

--- Insert Table 5 here ---

These results provide suggestive evidence that firms may not only be experiencing the effects of the shock on turnover and salaries, but may also be actively attempting to change their approach to hiring, with firms with stronger cultures attempting to signal their cultures more in the vacancy descriptions than firms with weaker cultures. This evidence is consistent with what we theorized with Hypothesis 1: In the wake of a shock to formal employment contracts in the form of a change in the degree of NCAs enforceability, firms that can rely on informal mechanisms and relational contracts, as in the case of strong cultures, tend to do so more then before, to reduce the likelihood of their employees departing to competitors.

8. DISCUSSION AND CONCLUSIONS

The results of this study indicate that the degree of an organizational cultural strength, irrespective of its underlying content, acts as a retention mechanism for employees, thus limiting their turnover and increasing the firm ability to capture the value created by its employee base. This is because, we argue, collaborating in a strong culture is a firm-specific skill hardly portable to other organizations, thus limiting employees' ability to move to competitors.

Based on these findings, this paper contributes to the strategic human capital research investigating the antecedents of employee turnover and firms' value capture potential. While extant research has generally highlighted the role of financial incentives (e.g., Campbell et al., 2012; Melero et al., 2020; Marx et al., 2009; Starr et al., 2018), and has recently started shedding light on the effects of non-pecuniary benefits (e.g., Bode et al., 2015; Burbanom 2016;

Kosfeld and Neckermann, 2011) on employee turnover, in this paper we suggest that the distributional properties of an organizational culture, a factor often overlooked in the literature studying labor turnover, may play a crucial role in determining whether an employee stays or leaves their company.

We further extend the limited work on organizational culture and employee retention (e.g., Chatman, 1991; O'Reilly et al., 1991; Sheridan, 1992; Srivastava et al., 2017) by examining the role of the distributional properties of a culture in imparting firm-specific skills onto its employees, thus driving their turnover, irrespective of any effects of cultural content that have been studied so far (e.g., Chatman, 1991; O'Reilly et al., 1991; Sheridan, 1992). Our theory and results also offers insights to the resource-based view literature (e.g., Barney, 1986) by showcasing the role of firm culture as an isolating mechanism allowing organizations to capture value and develop competitive advantage in the labor market. Finally, our research contributes to the work on relational contracts (e.g., Gibbons and Henderson, 2012; Jeffers and Lee, 2019), showing the importance of informal organization towards collaboration in the face of changes to the scope of formal contracting.

The present study is not without limitations. First, despite our best effort in measuring employee turnover using job vacancy and quit data, we cannot observe mobility directly. However, while Census data could potentially be used for such purpose, such data are typically anonymized at the firm level, which would preclude us from matching it to firm reviews in Glassdoor to assess the degree of cultural strength of individual organizations.

Second, our sample is affected by a selection issue, in that we are only able to observe firms that post jobs online (thus featured in BGT) and for which employees post reviews on Glassdoor. This is likely to result in a higher likelihood of sampling relatively large firms, limiting the generalizability of our results to smaller organizations.

Third, we propose that cultural strength acts as a retention mechanism because collaborating within such types of organizations entails the development of firm-specific skills, which can be hardly redeployed to other companies, thus limiting the employees' ability to leave their firm at will. However, other mechanisms could be at stake in explaining why strong cultures are better able to retain their employees than their weaker counterparts. For instance, one could argue that employees working for strong cultures may enjoy the easier collaboration achieved in this type of organizations, thus displaying higher job satisfaction, which, in turn, is expected to limit their mobility (Brayfleld and Crockett, 1955; Locke, 1975; Porter and Steers, 1973; Vroom, 1964). While we uncover what we believe is an important factor explaining the retention potential of strong cultures, future research may be able to highlight additional and novel mechanisms underlying the relationship between cultural distributional properties and employee mobility.

In conclusion, despite often overlooked, organizational culture matters in forming firm-level barriers to limit employees mobility. In particular, the distributional properties of an organizational culture, by itself, may be enough to create strong ties between the firm and its workers, irrespective of its specific content. Because of their collaboration benefits, strong cultures are more likely than weak ones to leverage relational contracts and informal organization to socialize their employees, thus imparting firm-specific skills that limit their ability to move to competitors. Exploiting a change in the degree of enforceability of NCAs, which corresponds to a shock to the local firms' ability to leverage formal contracting tools to retain their employees, we observe that workers at strong cultures are less likely to leave than at weak cultures. Further, because of the retention potential of cultural strength, strong cultures are better able at capturing the value created by their employees, by setting lower wages than organizations displaying weaker cultures.

This evidence has important implications for practitioners, who may want to invest in the development of organizational cultures with certain distributional properties, to be better able to retain their employees, especially in those industries and occupations in which collaboration, and thus the reliance on relational contracts and informal organization, are particularly preeminent.

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FIGURES

Figure 1. Histogram of Observed Vacancy Salaries, in US dollars.

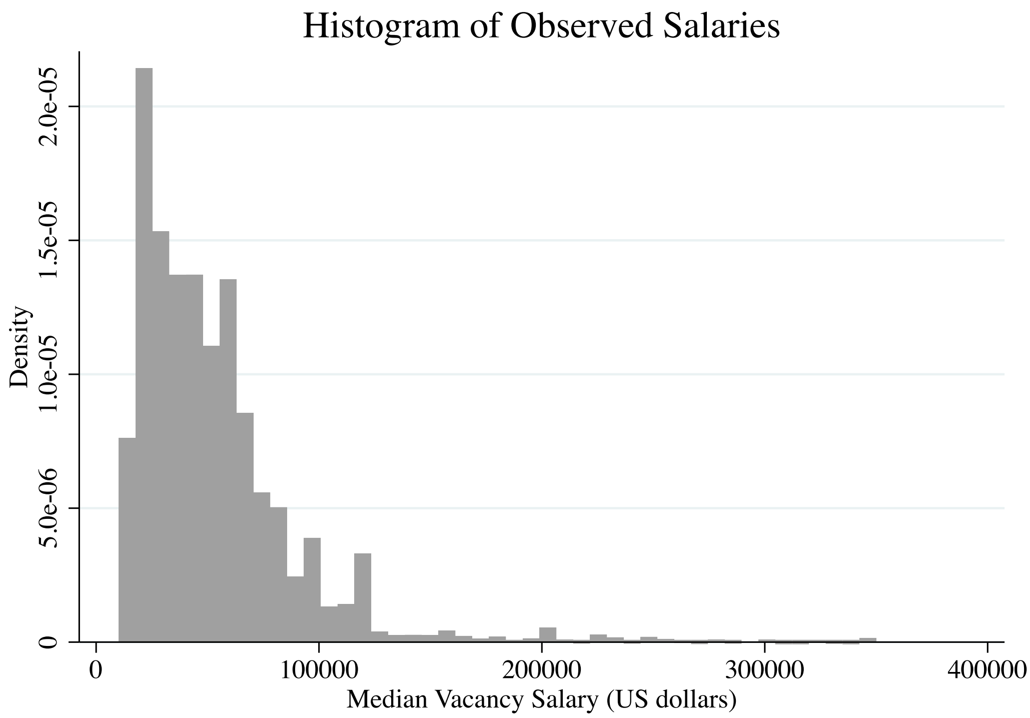
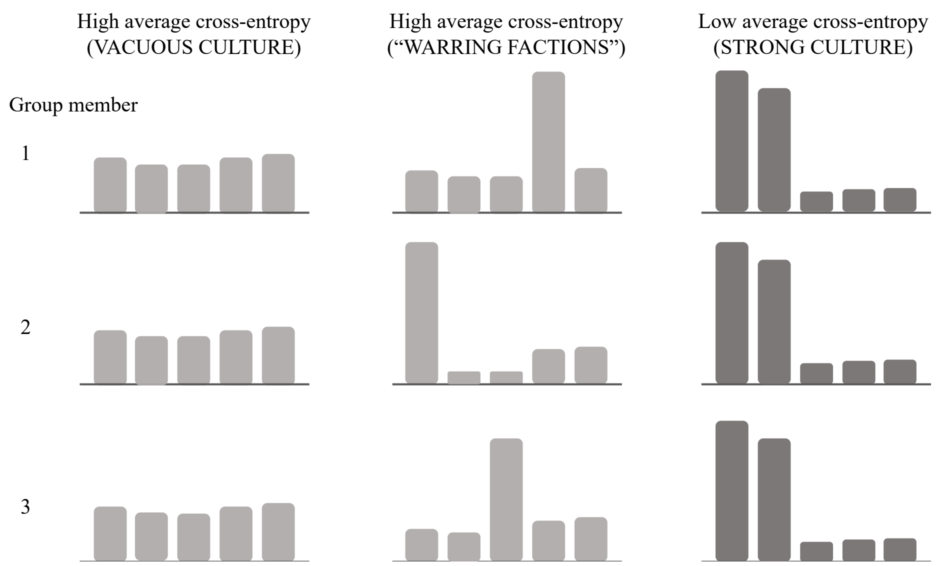


Figure 2. Examples of culture typologies based on the average cross-entropy metric.



Note. In Figure 2, an organizational culture is described based on the relative levels of average cross-entropy displayed by its members' distribution of mindshare over the characterizing cultural attributes. This allows us to identify three possible culture typologies.

Figure 3. Time-trend in the Number of Posted Vacancies Pre- and Post-Shock in Illinois Relative to Michigan.

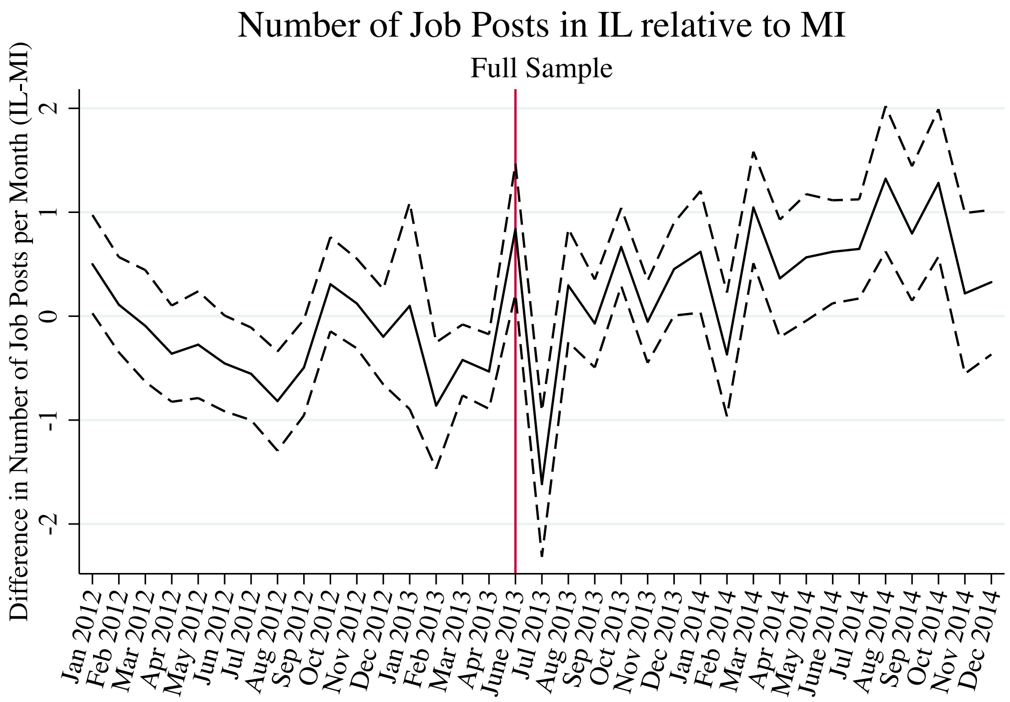
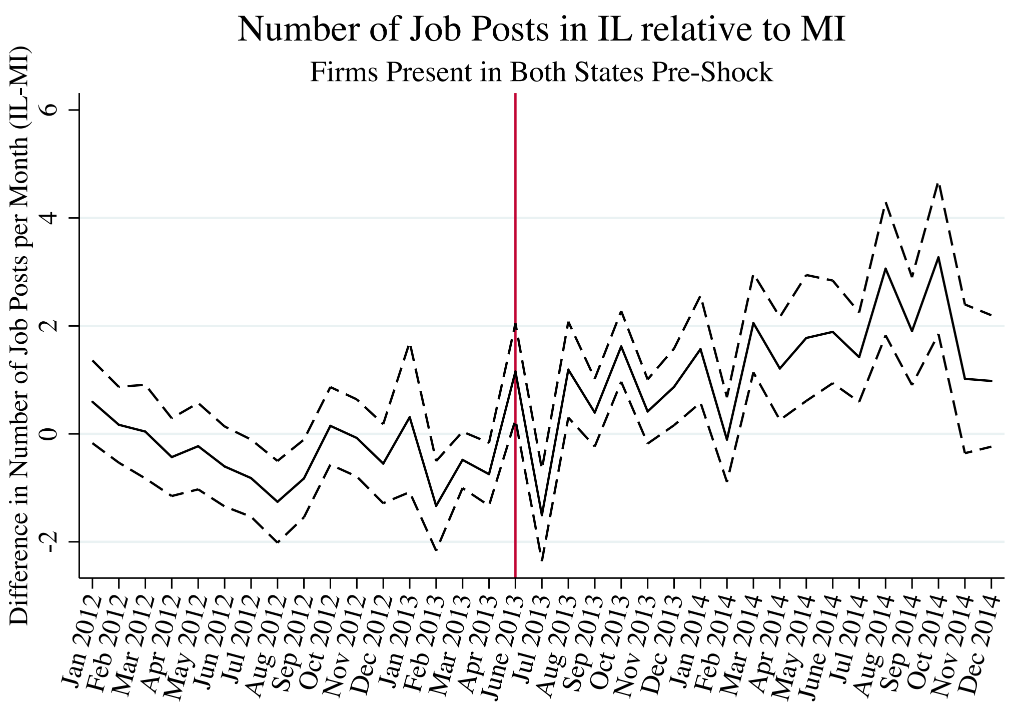


Figure 4. Time-trend in the Number of Posted Vacancies Pre- and Post-Shock in Illinois Relative to Michigan for the Subset of Firms Located in Both Illinois and Michigan Pre-Shock.



TABLES

Table 1. Summary Statistics.

Panel A Firm-Month-State Level Sample	Obs.	Mean	St. Dev.	Min	Max	1	2	3	4	5
1 Ln(Number of Vacancies)	138,114	0.63	1.09	0.00	7.40	1.00				
2 Strong Culture (50%)	138,114	0.37	0.48	0.00	1.00	-0.07	1.00			
3 Illinois	138,114	0.50	0.50	0.00	1.00	0.07	0.00	1.00		
4 Post-Shock	138,114	0.55	0.50	0.00	1.00	0.04	0.02	0.00	1.00	
5 Ln(Number of Reviews)	138,114	2.93	1.52	0.69	8.08	0.37	-0.36	0.00	-0.03	1.00

Panel B Firm-Year-State Level Sample	Obs.	Mean	St. Dev.	Min	Max	1	2	3	4	5
1 Quit	15,292	0.25	0.43	0.00	1.00	1.00				
2 Strong Culture (50%)	15,292	0.37	0.48	0.00	1.00	-0.07	1.00			
3 Illinois	15,292	0.50	0.50	0.00	1.00	0.14	0.00	1.00		
4 Post-Shock	15,292	0.53	0.50	0.00	1.00	0.01	0.02	0.00	1.00	
5 Ln(Number of Reviews)	15,292	2.94	1.52	0.69	8.08	0.36	-0.36	0.00	-0.02	1.00

Panel C Job Vacancy-Level Salary Sample	Obs.	Mean	St. Dev.	Min	Max	1	2	3	4	5
1 Ln(Salary)	35,438	10.70	0.60	9.22	12.77	1.00				
2 Strong Culture (50%)	35,438	0.23	0.42	0.00	1.00	-0.01	1.00			
3 Illinois	35,438	0.58	0.49	0.00	1.00	0.17	0.08	1.00		
4 Post-Shock	35,438	0.65	0.48	0.00	1.00	0.02	-0.20	0.02	1.00	
5 Ln(Number of Reviews)	35,438	4.14	1.60	0.69	8.08	-0.10	-0.08	-0.20	-0.02	1.00

Table 2. Test of Hypothesis 1: Number of Vacancy Postings.

VARIABLES	(1) **Ln(Number of Vacancies)** Firms in both states *All Cultures*	(2) **Ln(Number of Vacancies)** Firms in both states *All Cultures*	(3) **Ln(Number of Vacancies)** Firms in both states *Weak Culture Firms (50%)*	(4) **Ln(Number of Vacancies)** Firms in both states *Strong Culture Firms (50%)*	(5) **Ln(Number of Vacancies)** Firms in both states *All Cultures*
Illinois	0.144***	0.093***	0.087***	0.103***	0.087***
	(0.023)	(0.025)	(0.030)	(0.031)	(0.030)
Post-Shock	-0.891***	-0.941***	-0.956***	-0.933***	-0.926***
	(0.024)	(0.027)	(0.030)	(0.023)	(0.028)
Illinois * Post-Shock		0.094***	0.106***	0.073***	0.106***
		(0.022)	(0.026)	(0.021)	(0.026)
Illinois * Strong Culture (50%)					0.017
					(0.038)
Post-Shock * Strong Culture (50%)					-0.046*
					(0.025)
Illinois * Post-Shock * Strong Culture (50%)					-0.034*
					(0.019)
Constant	1.047***	1.074***	1.134***	0.983***	1.075***
	(0.021)	(0.020)	(0.024)	(0.020)	(0.020)
Observations	138,114	138,114	86,504	51,610	138,114
R-squared	0.564	0.564	0.544	0.599	0.564
Firm FE	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes

Note. Standard errors in parentheses are clustered at the firm and month-year levels. *p<0.1; **p<.05; ***p<.01

Table 3. Test of Hypothesis 1: Probability of Experiencing a Quit.

VARIABLES	(1) **Quit** Firms in both states *All Cultures*	(2) **Quit** Firms in both states *All Cultures*	(3) **Quit** Firms in both states *Weak Culture Firms (50%)*	(4) **Quit** Firms in both states *Strong Culture Firms (50%)*	(5) **Quit** Firms in both states *All Cultures*
Illinois	0.120***	0.119***	0.122***	0.115***	0.122***
	(0.009)	(0.010)	(0.014)	(0.015)	(0.014)
Post-Shock	0.001	0.000	-0.005	0.008	-0.001
	(0.001)	(0.004)	(0.005)	(0.006)	(0.006)
Illinois * Post-Shock		0.002	0.012	-0.014	0.012
		(0.008)	(0.010)	(0.012)	(0.010)
Illinois * Strong Culture (50%)					-0.007
					(0.020)
Post-Shock * Strong Culture (50%)					0.003
					(0.010)
Illinois * Post-Shock * Strong Culture (50%)					-0.026*
					(0.015)
Constant	0.192***	0.192***	0.215***	0.155***	0.192***
	(0.005)	(0.005)	(0.007)	(0.008)	(0.005)
Observations	15,292	15,292	9,584	5,708	15,292
R-squared	0.488	0.488	0.464	0.530	0.488
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Note. Standard errors in parentheses are clustered at the firm level. *p<0.1; **p<.05; ***p<.01. Difference between Columns (4) and (5) when omitting firm FEs: chi2 = 2.84; p-value = 0.092.

Table 4. Test of Hypothesis 2: Vacancy Salaries.

VARIABLES	(1) **Ln(Salary)** Firms in both states *All Cultures*	(2) **Ln(Salary)** Firms in both states *All Cultures*	(3) **Ln(Salary)** Firms in both states *Weak Culture Firms (50%)*	(4) **Ln(Salary)** Firms in both states *Strong Culture Firms (50%)*	(5) **Ln(Salary)** Firms in both states *All Cultures*
Illinois	0.037*	0.063***	0.009	0.179***	0.011
	(0.020)	(0.016)	(0.020)	(0.030)	(0.020)
Post-Shock	0.046	0.068	0.020	0.111	0.064
	(0.083)	(0.086)	(0.143)	(0.092)	(0.086)
Illinois * Post-Shock		-0.040**	-0.009	-0.101***	-0.010
		(0.020)	(0.022)	(0.033)	(0.022)
Illinois * Strong Culture (50%)					0.161***
					(0.036)
Post-Shock * Strong Culture (50%)					-0.005
					(0.029)
Illinois * Post-Shock * Strong Culture (50%)					-0.084**
					(0.039)
Observations	32,958	32,958	25,137	7,821	32,958
R-squared	0.646	0.646	0.645	0.658	0.647
Firm-Occupation FE	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes

Note. Standard errors in parentheses are clustered at the firm-occupation and month-year levels. *p<0.1; **p<.05; ***p<.01

Table 5. Post-Hoc Analyses: Discussion of Culture in Vacancy Ads.

VARIABLES	(1) **Discusses Culture in Vacancy Ad** Firms in both states *All Cultures*	(2) **Discusses Culture in Vacancy Ad** Firms in both states *All Cultures*	(3) **Discusses Culture in Vacancy Ad** Firms in both states *Weak Culture Firms (50%)*	(4) **Discusses Culture in Vacancy Ad** Firms in both states *Strong Culture Firms (50%)*	(5) **Discusses Culture in Vacancy Ad** Firms in both states *All Cultures*
Illinois	0.000	0.006	0.032***	-0.064***	0.033***
	(0.003)	(0.005)	(0.005)	(0.011)	(0.005)
Post-Shock	0.044	0.048	0.112*	-0.106*	0.067
	(0.051)	(0.051)	(0.067)	(0.064)	(0.051)
Illinois * Post-Shock		-0.008	-0.041***	0.097***	-0.042***
		(0.006)	(0.006)	(0.013)	(0.006)
Illinois * Strong Culture (50%)					-0.098***
					(0.012)
Post-Shock * Strong Culture (50%)					-0.092***
					(0.012)
Illinois * Post-Shock * Strong Culture (50%)					0.141***
					(0.014)
Observations	246,868	246,868	179,561	67,307	246,868
R-squared	0.379	0.379	0.383	0.367	0.380
Firm-Occupation FE	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes

Note. Standard errors in parentheses are clustered at the firm-occupation and year-month levels. *p<0.1; **p<.05; ***p<.01

APPENDIX

Table A1. Test of Hypothesis 1: Alternative Culture Strength Cut-off: Top and Bottom 20%.

VARIABLES	(1) **Ln(Number of Vacancies)** Firms in both states *All Cultures*	(2) **Ln(Number of Vacancies)** Firms in both states *All Cultures*	(3) **Ln(Number of Vacancies)** Firms in both states *Weak Culture Firms (20%)*	(4) **Ln(Number of Vacancies)** Firms in both states *Strong Culture Firms (20%)*	(5) **Ln(Number of Vacancies)** Firms in both states *All Cultures*
Illinois	0.155***	0.098***	0.096**	0.101**	0.096**
	(0.032)	(0.034)	(0.043)	(0.039)	(0.043)
Post-Shock	-0.918***	-0.974***	-1.012***	-0.944***	-0.970***
	(0.026)	(0.028)	(0.031)	(0.025)	(0.031)
Illinois * Post-Shock		0.104***	0.126***	0.057**	0.127***
		(0.026)	(0.032)	(0.026)	(0.032)
Illinois * Strong Culture (20%)					0.006
					(0.055)
Post-Shock * Strong Culture (20%)					-0.020
					(0.037)
Illinois * Post-Shock * Strong Culture (20%)					-0.072**
					(0.034)
Constant	1.093***	1.123***	1.213***	0.952***	1.124***
	(0.025)	(0.023)	(0.030)	(0.012)	(0.023)
Observations	61,801	61,801	42,667	19,134	61,801
R-squared	0.535	0.535	0.508	0.599	0.536
Firm FE	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes

Note. Standard errors in parentheses are clustered at the firm and month-year levels. *p<0.1; **p<.05; ***p<.01

Table A2. Test of Hypothesis 1: Continuous Culture Metric.

VARIABLES	(1) **Ln(Number of Vacancies)** Firms in both states *All Cultures*	(2) **Ln(Number of Vacancies)** Firms in both states *All Cultures*
Illinois	0.144***	0.089
	(0.023)	(0.059)
Post-Shock	-0.891***	-0.981***
	(0.024)	(0.050)
1.illinois#1.post		0.036
		(0.033)
1.illinois#c.culture_strength		-0.001
		(0.010)
1.post#c.culture_strength		-0.006
		(0.007)
1.illinois#1.post#c.culture_strength		-0.009
		(0.006)
Constant	1.047***	1.075***
	(0.021)	(0.020)
Observations	138,114	138,114
R-squared	0.564	0.564
Firm FE	Yes	Yes
Month-Year FE	Yes	Yes

Note. Standard errors in parentheses are clustered at the firm and month-year levels. *p<0.1; **p<.05; ***p<.01

Table A3. Test of Hypothesis 1: Alternative Measure of Quits, Ln(Quits).

VARIABLES	(1) **Ln(Number of Quits)** Firms in both states *All Cultures*	(2) **Ln(Number of Quits)** Firms in both states *All Cultures*	(3) **Ln(Number of Quits)** Firms in both states *Weak Culture Firms (50%)*	(4) **Ln(Number of Quits)** Firms in both states *Strong Culture Firms (50%)*	(5) **Ln(Number of Quits)** Firms in both states *All Cultures*
Illinois	0.946***	0.939***	0.944***	0.929***	0.944***
	(0.072)	(0.079)	(0.107)	(0.114)	(0.107)
Post-Shock	0.009	0.001	-0.034	0.057	-0.006
	(0.010)	(0.029)	(0.039)	(0.045)	(0.042)
Illinois * Post-Shock		0.014	0.084	-0.098	0.084
		(0.055)	(0.072)	(0.083)	(0.072)
Illinois * Strong Culture (50%)					-0.015
					(0.156)
Post-Shock * Strong Culture (50%)					0.014
					(0.074)
Post-Shock * Illinois * Strong Culture (50%)					-0.182*
					(0.110)
Constant	-5.446***	-5.442***	-5.272***	-5.726***	-5.441***
	(0.036)	(0.040)	(0.054)	(0.058)	(0.040)
Observations	15,292	15,292	9,584	5,708	15,292
R-squared	0.524	0.524	0.491	0.581	0.524
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Note. Standard errors in parentheses are clustered at the firm level. *p<0.1; **p<.05; ***p<.01

Addressing concerns about online review polarization

Online review data is often suspected of being polarized (Matakos and Tsaparas, 2016), since it is assumed that only the very satisfied or dissatisfied users are more likely to share their reviews, compared to those with average satisfaction. Given the nature of the Glassdoor reviews, this may be a concern also for the data we use to measure the distributional properties of organizational cultures. In particular, if the reviews were polarized, one may argue that the employees posting their reviews on Glassdoor are not representative of the entire organizational population, thus invalidating the cultural strength metric we derive from the data.

Relatedly, Winkler and Fuller (2019) recently expressed the concern that employers may solicit positive reviews from their employees, to artificially inflate their average ratings on the platform and being portrayed under a more positive light in the "Best Places to Work" rankings Glassdoor issue, based on employee' satisfaction metrics collected when through the employer review survey. If true, such a malpractice would increase the polarization of the Glassdoor review data.

On the one hand, it is worth noticing that, if the reviews are polarized, the issue should equally impact all the organizations in our sample. On the other hand, however, we believe that Glassdoor online reviews do not exhibit any significant polarization, for three main reasons. First, in a recent analysis Sull, Sull, and Chamberlin (2019) conducted to address Winkler and Fuller's (2019) concerns about firms soliciting positive employees' reviews, the author measured the incidence of "spike months," namely, those months in which a firm exhibits a significantly higher proportions of five-star ratings by its employees (supposedly, solicited by the employer) than surrounding months, for each company in the Glassdoor database. Sull *et al.* (2019) found that the occurrence of the spike months was limited to very few occurrences and concluded that the issue of positive polarization cannot be generalized to all the firms in the Glassdoor dataset.

Second, most Glassdoor users visit the website with the purpose of screening jobs offers. Since its launch, Glassdoor has implemented a so-called "give to get" policy, aimed at soliciting employer reviews from its users: by contributing a review about their employer, users can gain unlimited access to the Glassdoor database. Research conducted on Glassdoor data shows the efficacy of such a policy in reducing reviews' polarization (Marinescu et al., 2018).

Finally, if review polarization was a significant issue in our sample, we should observe rating data distributions characterized by fat tails. Fat tails are measured by the excess kurtosis of the rating variables, with distributions exhibiting a positive excess kurtosis classified as fat-tailed. As reported in Table A4, all the employee satisfaction variables available for the sampled organizations exhibit negative excess kurtosis. Thus, overall, we conclude that, at least in the sampled firms, the users' ratings distributions do not show signs of polarization.

Table A4. Excess kurtosis of Glassdoor employee satisfaction numerical ratings.

Satisfaction variable	Excess kurtosis
Overall rating	-1.14
Cultural fit	-1.35
Senior Management	-1.45
Career Opportunities	-1.29
Compensation and Benefits	-1.10
Work-life Balance	-1.19