

# Corporate Culture as an Implicit Contract\*

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## PRELIMINARY AND INCOMPLETE

### **Abstract**

This paper empirically studies the role of culture as an implicit contract, using connections among coworkers as a measure of employee culture. We first develop simple measures of firm internal connectivity based on LinkedIn's network data, and show these measures are strongly correlated with external ratings of employee relations and satisfaction. We then test the hypothesis that culture is a tool to form implicit contracts. Using state-level changes to employment agreements as shocks to explicit contracts, we show that these changes significantly impact employees in weakly connected firms, but the effects dissipate for strongly connected firms. Our results suggest that strong connectivity reduces the firm's dependence on explicit contracts to retain human capital.

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# 1 Introduction

Corporate culture is commonly viewed by executives as one of the most important factors that determine firm value (Graham, Harvey, Popadak and Rajgopal 2016). However, empirically, little is understood about the exact channels through which corporate culture can impact firm value. Using novel data on internal networks and employee flows, this paper provides empirical evidence that corporate culture, in the form of connectivity among coworkers, may act as an implicit contract between the firm and its employees.

Theoretical studies posit the role of corporate culture as an implicit contract (Kreps 1996). Intrafirm reputation works to create a self-enforcing implicit contract between workers and firms to facilitate optimal long-term relationships, which cannot otherwise be achieved via explicit contracts due to asymmetric information or incomplete contracts (Bull 1987), and provide a foundation for the theory of the firm (Baker, Gibbons and Murphy 2002). Whether a firm’s corporate culture aligns with values that are attractive to its employees (Meglino, Ravlin and Adkins 1989), establishes a cohesive vision (Crémer 1993), or improves coordination (Bolton, Brunnermeier and Veldkamp 2013), it can establish credible expectations between the firm and its employees that can shape the sustainability of long-term relationships and investments.

In this paper, we focus on the dimension of corporate culture that is employee engagement with the firm. We identify the strength of this dimension by quantifying coworker connectivity, using proprietary access to LinkedIn’s professional network data.<sup>1</sup> This is in line with existing studies that have argued that corporate culture impacts the structure of internal networks (Provan, Fish and Sydow 2007, Kogut 2000).

In a strongly connected workplace, interactions between employees are expected to be better defined, and information regarding corporate norms are more easily transferred to new employees. These norms help facilitate an understanding for employee-firm relationships in the form of an implicit contract between workers and firms. Ulti-

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<sup>1</sup>Access to LinkedIn’s data was granted through the LinkedIn Economic Graph Challenge.

mately, by fostering strong connections among coworkers, firms can achieve the coordination required to satisfy incentive-compatible long-term investments by both parties.

Consistent with this framework, we find that internal connectivity is strongly positively correlated with better firm-employee relationships, and with the presence of the firm on Fortune’s “100 Best Companies to Work For” lists. In order to mitigate differential connectivity between industries, we rank the connectivity of a firm within its industry and identify firms with high connectivity based on three characteristics: (1) average within-firm connections, (2) the ratio of internal to external connections, and (3) *absorption*. The first measure captures how connected coworkers are with each other; the second captures how connected coworkers are with each other, relative to their entire professional network; and the third captures how much new employees are connected with coworkers within their first year of joining. We define firms as having strong connectivity if they are above median within their industry in all three measures. Our results hold for all three measures separately, as well as the combination of measures.

This approach to quantifying intangible corporate characteristics complements existing survey-based research and case studies, by providing a “revealed preference” measure available on a large scale. It also provides some insight into the underpinnings of commonly-used employee satisfaction and well-being measures, by showing that these correlate with measures of interaction among employees.

After classifying the strength of firms’ connectivity, we test the implicit contract hypothesis by showing that shocks to the explicit contracting environment affect “weak connectivity” (WC) firms, but have a much lesser impact on “strong connectivity” (SC) firms. Specifically, we use as an experimental setting state-level changes in the enforceability of restrictive employment agreements known as a non-competes (NCs). Firms use these contract provisions to prevent employees from working in a competing activity for a period of time after they leave.<sup>2</sup> Previous work has shown that these provisions are binding for employees, causing a sharp drop-off in departures when they

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<sup>2</sup>A typical NC period is between 1 and 2 years, but can last longer.

become more enforceable, for example (Jeffers 2018). The intuition of our approach is to test whether these restrictive agreements are equally binding for SC and WC firms: if corporate culture fosters implicit contracts, SC firms should be less affected.

Our main result: we find that while changes in these restrictive agreements significantly impact WC firms, the impact dissipates almost entirely for SC firms. Specifically, departures targeted by these agreements decline by 63 basis points in WC firms, but only 3 basis points for SC firms.

This result is consistent with the view that strong corporate culture increases firms' resilience to changes in the explicit contracting environment. Under the view that firm-employee relations are defined by both explicit *and* implicit contracts, the differential impact of shocks to the explicit contracting environment highlights how strong internal networks may contribute to human capital retention through *implicit* contracts.

Our contribution is twofold. First, we propose an approach to quantitatively measuring one aspect of corporate culture using the properties and formation of internal networks. There are two advantages to this approach: (1) building quantifiable measures of firm characteristics for a broad set of firms; and (2) using data based on individually rational voluntary behavior, rather than survey responses.

Second, we complement the burgeoning literature that explores the implications of corporate culture by building a relation between the characteristics of intrafirm networks and their impact on firms' ability to retain human capital. This supports a deep theoretical literature that studies the use of implicit contracts, and complements empirical research on the link between culture and implicit or institutional structures that guide coordination (Greif 1993, Greif 1994, Sheridan 1992). Our implications on firm outcomes contribute to the ongoing debate on tradeoffs regarding the policies aimed at protecting firms' intangible capital, such as non-competes (Jeffers 2018). In addition, by highlighting a clear role through which corporate culture may directly impact firm value (Popadak 2013), we add to existing evidence that firms realize long-run benefits from cultivating strong corporate culture (Sørensen 2002, Huselid 1995,

Guiso, Sapienza and Zingales 2015b).

More broadly, this paper contributes to the literature that studies the causal impact of culture on economic growth. Corporations provide an accessible and practical setting to study and better identify the ramifications of culture (Guiso, Sapienza and Zingales 2015a). In particular, this paper provides evidence that coworker connectivity directly leads to lower dependence on explicit contracts. This builds on Bloom, Eifert, Mahajan, McKenzie and Roberts (2013), which shows that organizational structure has a significant impact on firm productivity. As human capital becomes a significant segment of firm value, we show that firm culture may play a strategic role for firms to retain key employees and make long-term investments.

The rest of the paper is as follows. Section 2 describes the data. In Section 3, we explore the relationship between connectivity and employee culture. In Section 4, we turn to the role of culture as an implicit contract. We conclude in Section 5.

## 2 Data

### 2.1 LinkedIn Network Data

In 2015, LinkedIn selected a small number of researchers to be part of the Economic Graph Challenge, an initiative to harness LinkedIn’s data to gain new economic insight.<sup>3</sup> As part of this group, we were granted access to detailed de-identified data from LinkedIn’s platform. The data contain no name information and numerical member identifiers in the data are hashed. The data include about 52 million employment histories in the US, or roughly one third of the US workforce.<sup>4</sup>

We extract employment histories from users’ profiles on LinkedIn, which includes data on employment location, work capacity, occupation, seniority, and other back-

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<sup>3</sup>LinkedIn is an online professional networking platform, which began in 2003 and has currently has over 450 million global users.

<sup>4</sup>According to the Bureau of Labor Statistics, the size of the U.S. labor force was approximately 158 million by the end of 2015.

ground information.<sup>5</sup> As users can retroactively provide past work experience, the data provide us with rich information on individual-level employment movements between firms.

Network characteristics are based on observable connections formed between members of LinkedIn. These data include the direction of connections and the time and date at which the connection was formed. Combined with employment and background information extracted from members' profiles, we are able to measure various network characteristics of firms' internal networks and their changes over time.

LinkedIn data are merged to Compustat in order to observe firm outcomes. Figure A.1 shows the coverage of LinkedIn by sector for this sample, using the number of U.S. employees observed on LinkedIn relative to the number of employees reported on Compustat. The aggregate coverage rate is 30%. Our sample also has a higher concentration of knowledge-intensive occupations. These occupations are these most likely to be affected by NCs, both directly and indirectly. We take advantage of individual-level occupation information to focus on departures most likely to be affected by NCs: the movement of individuals in knowledge-intensive occupations to positions of higher seniority than what they left (i.e., external promotions, building on the individual's prior experience). Throughout the paper, we succinctly refer to these moves as departures.

## 2.2 Employee Relations and Satisfaction

### 2.2.1 Employee Relations

We collect data on the quality of firm-employee relations from MSCI's ESG KLD STATS database (KLD). KLD is an annual data set of positive and negative environmental, social, and governance (ESG) performance indicators for publicly traded companies, and is a standard in the literature on corporate social responsibility. The data are collected by research analysts from a combination of data provided by the

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<sup>5</sup>This data is further augmented by LinkedIn through standardization, especially so that occupation type and seniority levels are more comparable. This enables us to better identify employees in knowledge-intensive occupations, for which our natural experiment is most applicable.

companies directly and independent research.

Our focus is the set of ‘employee relations’ indicators tracked by KLD. Among the positive indicators, or strengths, are traits such as employee involvement, employee relations, and human capital development. Among the negative indicators, or concerns, are traits such as negative union relations and safety concerns. Following the literature, we construct a net score of employee relations by subtracting the sum of concerns from the sum of strengths for each company year. We also provide results for strengths and concerns separately in the Appendix.

### **2.2.2 Best Companies to Work For**

To supplement the KLD data, we collect data on the presence of firms on Fortune’s “100 Best Companies to Work For” (BCW) lists. These lists, published annually by Fortune magazine, capture U.S. companies with the highest levels of employee satisfaction. Importantly, the methodology to compile these lists is completely independent from the MSCI database methodology. The lists are compiled on the basis of extensive employee surveys administered by the Great Places to Work Institute.<sup>6</sup>

## **2.3 Firm Outcomes**

Our sample consists of US firms in the merged Compustat-LinkedIn data between 2008 and 2014. We use Compustat data to measure corporate outcomes. To avoid bias from mergers or acquisitions, we exclude firm-year observations with more than 100% growth in sales or assets. We drop financial (SIC 6000-6999), utility (SIC 4900-4999), and regulated (SIC 9000-9999) industries. In addition, given that our sample overlaps with the recession, we drop firms in the construction (SIC 1500-1799) industry. Our results hold when including excluded industries. We also exclude observations with missing stock market data and missing or negative assets or sales.

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<sup>6</sup>More information is available at the site: <http://fortune.com/best-companies/>. The exact methodology changes year to year.

## 3 Connectivity and Corporate Culture

### 3.1 Measuring Coworker Connectivity

In this paper, we focus on coworker connectivity as a way of quantifying a particular dimension of corporate culture: employees' engagement with the firm. This section outlines our approach to identifying the strength of this dimension using network-based metrics.

The link between culture and intrafirm networks follows a long tradition. Whether networks serve a role as a means of efficient communication (Bolton and Dewatripont 1994), information processing (Radner 1993) or efficient distribution of work (Garicano 2000), corporate culture manifests itself in the internal structure of firms' networks by informally and/or formally dictating norms and practices within the firm.

LinkedIn's data provide a particular lens into the firm's internal network, by capturing connections initiated by individuals on a professional platform. Many factors influence the formation of connections, but two are of particular interest to us. First, connections are more likely between individuals who have interacted in some way. Therefore all else equal, we believe internal connections are likely to correlate positively with an integrated workplace. Second, employees' connection behavior on LinkedIn reflect their preferences regarding professional advancement. As a result we also believe that employees who network within the firm are likely to view their relationship with the firm as a longer term objective. Together, these two elements lead us to hypothesize that connectivity correlates with employee engagement with the firm.

Our analysis measures connectivity of firms' internal networks based on three different characteristics: (1) average connectivity, (2) internal-to-external connectivity, and (3) *absorption*.

Average connectivity is the average degree of the firm's network. Intuitively, this is the average number of within-firm connections for an employee of the firm. We compute average connectivity by summing the number of connections between employees of the same firm, and dividing by the number of employees who were in the network at



the time (i.e., who were members of LinkedIn).<sup>7</sup> Two aspects guide this decision. First, as we need to make cross-sectional comparisons between firms based on connectivity, we need to take into account the high level of heterogeneity in terms of employee size. Using raw number of connections would be biased toward firms with more employees, as the number of potential connections exponentially increases with the number of employees. Second, we need to take into account potential diseconomies of scale in network connectivity as firm size increases. For example, alternative measures, such as network density (the number of connections normalized by *potential* connections), would be heavily biased toward smaller firms, for which all employees could be connected to each other. We further address concerns about firm size when we describe results in Section 3.2, and through our second measure which accounts for size in a different way.

Internal-to-external connectivity captures the relative intensity of connections within the firm. This measure is a ratio of the number of connections between employees of the same firm, divided by the number of connections between these individuals and employees of other firms (“external” connections). This serves to capture a different dimension of connectivity from average degree. One concern with average connectivity is that some firms may have employees who are more prone to using LinkedIn, even after we condition on industry, year, and size. Taking the ratio of internal to external connections allows us to account for this firm-level heterogeneity in the intensity of LinkedIn presence. Moreover, this measure intuitively captures firm engagement as the relative importance of firm connections to outside connections for the average employee.

The third measure is what we call *absorption*. We define absorption as the intensity at which a network integrates new nodes into its network. In our setting, this is measured by observing the number of new connections formed with incoming employees in the year they join the firm, normalized by the number of new employees in that

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<sup>7</sup>Although we observe the precise time and date when connections are formed, we use end-of-year connections to construct firm-level connectivity characteristics. This is mainly due to the coarseness of employment histories, which are mostly populated at an annual frequency.

year. Absorption is aimed at capturing firms’ capacities to integrate workers into its firm. For example, firms that have more active initiatives to match new employees with existing employees and create opportunities for new employees to engage with existing employees may foster a stronger corporate identity. As opposed to the first two measures, absorption aims at capturing a dynamic property of firms’ networks. Although this measure is strongly correlated with average internal connections, it allows us to separate out those companies which may have strong internal connectivity as a legacy from a previous regime, from companies with strong internal connectivity that continues to be maintained.

From a practical standpoint, we face several challenges common to network-based analysis. First, even with normalizations, the relation between network quantities and other observable outcomes can be highly non-linear. Directly using quantities may yield results that are heavily driven by tails of the distribution, and fitting data ex-post to better understand the relation can complicate ex-ante inferences. Second, as discussed above, each measure alone may not critically distinguish strong employee engagement by itself. An additional concern specific to our approach is that participation in LinkedIn’s professional network may vary between industries due to industry-specific demand and network effects. While LinkedIn’s data has broad coverage across all industries, it has the largest concentration in technological industries.

Taking these into account, we create a final “combined connectivity” measure based on all three characteristics. For each measure, we classify firms as above or below median within their 2-digit NAICS industry code, in each year. This is similar to the approach much of the literature has taken to identify high R&D intensity, for example. We consider a firm to be strong connectivity (SC) if it is above median for all three measures. By using relative quantities, rather than absolute quantities, we avoid potential issues with non-linearities regarding network characteristics. Though remaining firms may rank high in one or two of the three factors, we refer to these firms as weak connectivity (WC) firms. As aforementioned, each measures distinct aspects of the network that may relate to strong culture. Focusing on the subset of firms that

have rank above the median for all three categories allows us to identify firms that score above median in all three statistics. Going forward, we interchangeably refer to firms that have a high rank on all three categories as highly interconnected, or SC firms. We explore alternatives to our SC definition in the Appendix.

## 3.2 Employee Relations and Satisfaction

To understand whether our connectivity measures indeed capture a dimension of corporate culture, we examine the relationship between connectivity and two different measures of employee well-being at the firm: firm-employee relationships from KLD, and employee satisfaction from the BCW lists. Table 1 provides summary statistics for these outcomes.

Table 2 reports the correlation between each of our three connectivity measures and the net quality of employee relations, as measured by KLD. All three measures are statistically significantly correlated with this measure, and this relationship remains stable when including industry by year fixed effects and size fixed effects.

In Appendix Tables A.1 and A.2, we report the break-out of the correlation with strengths and concerns. Our measures are positively correlated with strengths and negatively correlated with concerns, though the relationship is statistically stronger for strengths. This is expected, for two reasons. First, strength indicators more closely track measures related to employee relations, such as professional and human capital development, employee involvement, and employee relations. Concern indicators include union relations and safety concerns. Second, there are more indicators for strengths than concerns, which leads to greater variation in the outcome variable for Tables A.1 than Table A.2.

Table 3 reports the correlation between the SC indicator and net employee relations score from KLD. The results show that an indicator for being above median in all three metrics, relative to industry peers, is strongly statistically correlated with stronger firm-employee relationships.

As a second validation, we turn to whether connectivity relates to firms' presence

on Fortune’s Best Companies to Work For lists. These lists have been posited as a proxy for corporate culture (Edmans 2011). Importantly, the list of Best Companies to Work For are constructed entirely independently from the KLD data, as described in Section 2.2.2. Since there is a lot of persistence on the list, and the list is already small (100 companies each year), our outcome variable is an indicator for whether the company ever appears on the list of 100 Best Companies to Work For. The results in Table 4 indicate that each of our measures correlate positively with this proxy for employee satisfaction. Similarly, Table 5 shows that the combination of all three metrics, in the form of our SC indicator, correlates strongly with being a top company to work for.

Taken together, these results illustrate a systematic relationship between connectivity and corporate culture, in the form of positive employee relations and satisfaction. Interestingly, these results indicate cohesion between three very distinct sources of information on corporate culture: 1) a revealed-preference measure (connectivity); 2) a survey-based measure (BCW lists); 3) an external examiner and news-based measure (KLD indicators). In the following section, we turn our attention to what corporate culture means for the firm, in terms of governing relationships between the employees and the firm.

## **4 Corporate Culture as an Implicit Contract**

### **4.1 Background**

One of the original theoretical motivations for corporate culture is the idea that strong cultural ties can act as implicit contracts in environments with incomplete contracting (Kreps 1996). For example, Hermalin (2001) (building on Crémer (1993)) proposes that culture may act as a substitute for explicit communication, by not only creating a shared knowledge of norms but also effectively creating a common language. Similarly, Bull (1987) and Baker et al. (2002) argue that intrafirm reputation creates

self-enforcing implicit contracts between workers and firms, and these are valuable in that they facilitate long-term relationships, which cannot otherwise be achieved via explicit contracts due to asymmetric information or incomplete contracts.

In this paper, we test a particular application of this concept: we examine whether firms with strong connectivity are more resilient to shocks to employment contracts. The intuition is that, if culture serves as an implicit contract, then changes to *explicit* contracts should not matter as much for firms with strong culture. Here, the particular dimension of corporate culture we focus on is employee engagement with the firm, and therefore the explicit contracts we wish to examine are employment contracts.

While complete employment contracts are not available on a large scale, we identify a series of state-level changes to common provisions in employee contracts: non-compete agreements (NCs) (Starr, Bishara and Prescott 2016). NCs are explicit contract terms that prevent employees from moving to a competing position in another firm for a period of time (often 1-2 years) after leaving their employer. Previous work has shown that these provisions are binding (Garmaise 2009, Starr, Balasubramanian and Sakakibara 2014), and that state-level changes to the enforceability of these provisions have large effects on employee mobility (Marx, Strumsky and Fleming 2009), particularly in knowledge-intensive occupations common on LinkedIn (Jefferis 2018). We hypothesize that these explicit contract changes should primarily impact WC firms – dependent on explicit contracts – but not SC firms – where implicit contracts should mitigate the effect.

NCs are governed at the state level, which lends to heterogeneity between states. For example, while California largely does not recognize or enforce NCs, most other states enforce NCs, with some states such as Florida enforcing NCs even for workers who are laid off. Enforceability of NCs is determined at the state level by a combination of state laws and court rulings. Key dimensions of NC enforceability, as highlighted by the legal literature, include the employer’s burden of proof, the existence of a state statute, the definition of protectable interest for the employer, and whether courts are allowed to modify the contract to be suitable for enforcement (Bishara 2010).

The channel through which we expect NCs to impact mobility is through the changes in the enforceability of explicit contracting terms. This hinges on an underlying assumption that the average firm is affected by changes in its ability to use NCs as a means of preventing the loss of key human capital. But the fact that increases in enforceability can improve employee retention also reveals the incompleteness of the contracting environment. In an incomplete contracting environment, a hold-up problem may arise, which can stifle long-term investments by firms. Potential gains from long-term human capital-intensive investments may be forgone by firms that are contractually limited from retaining key workers.

As a remedy, firms may foster a corporate environment that enhances long-term incentive-compatibility for key employees. Put differently, firms may build strong corporate culture as an implicit contract to reinforce long-term firm-employee relationships, that cannot otherwise be sufficiently specified using explicit contracts. If firms with strong corporate culture have a stronger implicit contract with their workers, we expect that shocks to the explicit contracting environment should have a significantly lower impact on their employee dynamics. In our setting, we expect changes in NC enforceability to be associated with a significant difference in impact on employee mobility between SC and WC firms.

## 4.2 Empirical Methodology

Our identification strategy uses state-level staggered rulings on NCs as employed in Jeffers (2018).<sup>8</sup> Table A.3 outlines decisions used to identify changes in the enforceability of NCs, which are comprised of seven state supreme court decisions and one legislative change between 2009 and 2013.<sup>9</sup> Court decisions apply to both existing and future contracts with non competes. This provides an attractive setting to analyze whether certain firms are more or less likely to be affected by changes to the contracting

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<sup>8</sup>Several existing studies study the implications of changes in non compete enforceability. For example, see Marx et al. (2009), Garmaise (2009), and Conti (2014).

<sup>9</sup>For decisions that took place in the last quarter of a given year, the following year is assigned as the year of change.

environment.

In order to compare the response of SC and WC firms, we need to fix the indicator prior to these changes. Since all but one of the changes take effect in 2011 or later, we use the 2010 value of the indicator for the majority of the sample. The exception is Wisconsin firms, where NC enforceability changes in 2009. For these firms, we use the 2008 value of the indicator.

Table 6 provides summary statistics for both sets of firms. Examining observable firm characteristics of our sample between SC and WC firms, we see that SC firms tend to be larger than WC firms. Average departure rates are close, though SC firms appear to have higher median departure rates. Return on assets and market-to-book values are instead similar in the medians, but with much more variation in the group of WC firms. Baseline differences in levels are not a concern, as long as the differences are not trending differentially leading up to the NC enforcement changes.

Our baseline specification is a difference-in-differences regression, comparing departure rates of firms in treated and untreated states, after NC enforceability changes relative to before NC enforceability changes. For company  $i$  in industry  $j$ , state  $s$  and year  $t$ , we write the following:

$$departurerate_{ijst} = \alpha + \beta_1 \{Treated_s * Post_t\} + \gamma_i + \theta_{jt} + \kappa_{it} + \epsilon_{it} \quad (1)$$

$Treated_s * Post_t$  is 1 for an increase in enforceability, -1 for a decrease in enforceability, and 0 otherwise.

In addition, in order to compare the response of SC and WC firms, we specify a “triple difference” regression, which interacts the difference-in-differences from equation 4.2 with the ex-ante SC indicator.

$$y_{ijst} = \alpha + \beta_1 \{Treated_s * Post_t * SC_i\} + \beta_2 \{Treated_s * Post_t\} + \gamma_i + \theta_{jt} + \kappa_{it} + \epsilon_{it} \quad (2)$$

In addition to the treatment indicator, we include company fixed effects  $\gamma_i$  and

industry-year fixed effects  $\theta_{jt}$  in all regressions, with industry defined as four-digit NAICS code. Additional regressions include connectivity-year fixed effects  $\kappa_{it}$ . Errors are clustered at the state level, to reflect the level of treatment. Time-varying firm controls are excluded to avoid potentially inconsistent estimates (see Gormley and Matsa (2014)).

The coefficient estimate on  $Treated_s * Post_t * SC_i$  captures the additional change in strong connectivity firms relative to weak connectivity firms in treated states relative to untreated states, following a change in NC enforcement. The main assumption underlying this approach is that absent the NC enforcement changes, the difference in change between strong and weak connectivity firms would have been the same in both groups of states.

### 4.3 Results

Table 7 presents our main results. In Panel A, we present the estimation results for equation 4.2 in the sample of WC firms and SC firms, separately. An increase in NC enforceability leads to a decrease of 60 basis points in the targeted departure rate at WC, almost 50% relative to the average departure rate of 1.22 percentage points. In contrast, the decline in SC firms is not statistically different from zero.

This is equally true when we restrict our sample to geographically concentrated firms, for which treatment is more precise, in the following sense. In order to assign a state of location to each firm, we use the state in which most of the firm’s employees are located. However, the treatment really applies to employees located in this main state while they are working at the firm. Because we observe present-day location of employees, and we wish to include employees who move out of state, we cannot restrict our sample to main state employees directly. However, we can separate out firms that are more geographically concentrated (at least 40% of employees still in the main state), as firms that likely have a less dispersed workforce to begin with, and thus for which treatment is likely more precise.

A potential concern with Panel A is that it could be the case that we have lower



power in the SC sample, because we have fewer observations. In order to determine whether the difference in SC and WC response is statistically significant, we pool observations into the same regression and estimate equation 4.2. Panel B reports the results. Indeed, while WC firms experience declines on the order of 60 basis points in the full sample, and 70 basis points in the geographically concentrated sample, this effect dissipates almost entirely in SC firms.

These results support the hypothesis that firm-employee relationships in SC firms are less reliant on the explicit contracting setting. Even if all firms generally benefit from stronger contracting, firms that predominantly rely on explicit contracts to define firm-employee relationships directly should exhibit greater gains through explicit contractual deterrence of employee departures

One concern may be that treated firms were trending differentially from untreated firms prior to the NC enforcement changes, or that SC firms were trending differentially from WC firms. To investigate this, we break out the main effect by year relative to the timing of the change, and report the results in Table 8. Specifically, we examine the differential response in each year relative to one year prior to the change in NC enforcement. We omit  $t - 1$  rather than the first year of sample because our staggered treatment means that the first year of sample is different for each treated state. Omitting  $t - 1$  provides more consistency.

Our results show that the difference between  $t - 1$ ,  $t - 2$ , and  $t - 3+$  are not statistically different from zero – in other words, we see no differential trends. However, in the year of change as well as subsequent years, there is a statistically significant drop in the departure rate, particularly for WC firms. In Panel A, we see that there is an effect for SC firms when we restrict to the geographic concentrated sample, but the magnitude is much smaller than for WC firms. In Panel B, we confirm that this differential effect is statistically significant: the interaction of  $SC*Treatedt0$  in Column (3) is positive. Results are particularly significant in the year following the one in which the NC change takes place ( $Treatedt1$ ). Overall, our results show that while departures systematically drop in WC firms following NC enforcement changes, the drop is equally

systematically smaller in SC firms.

Taken together, these results support our main hypothesis: explicit contract changes primarily impact WC firms – dependent on explicit contracts – but not SC firms – where employee engagement creates an implicit contract that mitigates the effect. Taking a step toward understanding the implications of this pattern in terms of corporate outcomes, our final set of results consider how firms’ prospects and decisions evolve in tandem with the change in explicit contracts. As a proxy for firm prospects, we use the market-to-book ratio, which captures the value assigned to the firm by the market relative to the firm’s book value. We also consider return on assets as a measure of immediate profitability changes. Finally, in line with (Jeffers 2018), we examine the investment response.

Table 9 reports our results collapsing pre and post periods. Our estimates indicate that market-to-book is lower on average for WC firms following the enforceability changes, but this effect is reversed and in fact net positive for SC firms. This suggests that the market perceives more opportunities for SC firms in the new environment, and relatively fewer for WC firms. However, the underpinnings of this are unclear. Looking at ROA, the direction is similar, but the effect is not statistically significant. An arguments for NCs, but also for implicit contracts, is that they facilitate long-term investment. Consistent with Jeffers (2018), we find that it is the firms in which departure rate is most reduced – WC firms – that most increase investment, while investment increases less in SC firms.

To better understand the pattern of these results, we examine the time series in Table 10. The results indicate an immediate increase in MB for SC firms following the NC change. The corresponding effect in WC firms is not statistically significant year-by-year. Interestingly, when we break out coefficient estimates year-by-year, we do see a statistically significant difference in ROA. WC firms see an immediate decline in ROA. This could be driven mechanically by greater salary expenses as a result of more employees staying, which would decrease the numerator (EBITDA). In contrast, SC firms do not experience this decrease in ROA, and in fact continue to see a relatively

higher ROA in years following the NC change.

While more work remains to be done, these results suggest there may be important real implications for firms of sensitivity to explicit contract changes.

## 5 Conclusion

In this paper, we explore the role of corporate culture as an implicit contract. We first show that internal connectivity is strongly correlated with external ratings of employee relations and satisfaction. Using this network-based measure of corporate culture, we then find that firms identified as strong in this dimension of corporate culture are significantly more resilient to shocks to the explicit contracting environment. We document that while changes in enforceability to NC contracts had a substantial impact on employee mobility in WC firms, the impact is significantly weaker for SC firms.

Our paper takes an ambitious step to using network analysis to infer intangible characteristics of firms, that are recognized as making an increasingly important contribution to the growth and value of firms. In particular, we measure the connectivity of firms' internal networks in order to identify the strength of firms' culture. Our approach to analyzing network data to extract organizational properties that are difficult to observe serves as a direction for future research.

Though many studies offer a theoretical basis for the role of corporate culture in establishing strong firm-employee ties required for successful long-term investment, few studies have empirically established this function for culture. Our paper demonstrates this by showing a differential impact between firms of varying strengths of internal connectivity in a natural experiment that shocks the contracting environment.

## References

- Baker, George, Robert Gibbons, and Kevin J Murphy**, “Relational Contracts and the Theory of the Firm,” *Quarterly Journal of Economics*, 2002, pp. 39–84.
- Bishara, Norman D**, “Fifty Ways to Leave Your Employer: Relative Enforcement of Covenants not to Compete, Trends, and Implications for Employee Mobility Policy,” *U. Pa. J. Bus. L.*, 2010, *13*, 751.
- Bloom, Nicholas, Benn Eifert, Aprajit Mahajan, David McKenzie, and John Roberts**, “Does Management Matter? Evidence from India\*,” *Quarterly Journal of Economics*, 2013, *128* (1).
- Bolton, Patrick and Mathias Dewatripont**, “The firm as a communication network,” *The Quarterly Journal of Economics*, 1994, pp. 809–839.
- , **Markus K Brunnermeier, and Laura Veldkamp**, “Leadership, coordination, and corporate culture,” *The Review of Economic Studies*, 2013, *80* (2), 512–537.
- Bull, Clive**, “The existence of self-enforcing implicit contracts,” *The Quarterly Journal of Economics*, 1987, pp. 147–159.
- Conti, Raffaele**, “Do Non-Competition Agreements lead Firms to pursue Risky R&D Projects?,” *Strategic Management Journal*, 2014, *35* (8), 1230–1248.
- Crémer, Jacques**, “Corporate culture and shared knowledge,” *Industrial and corporate change*, 1993, *2* (3), 351–386.
- Edmans, Alex**, “Does the stock market fully value intangibles? Employee satisfaction and equity prices,” *Journal of Financial Economics*, 2011, *101* (3), 621–640.
- Garicano, Luis**, “Hierarchies and the Organization of Knowledge in Production,” *Journal of Political Economy*, 2000, *108* (5), 874–904.
- Garmaise, Mark J**, “Ties that Truly Bind: Noncompetition Agreements, Executive Compensation, and Firm Investment,” *Journal of Law, Economics, and Organization*, 2009.

- Gormley, Todd A and David A Matsa**, “Common errors: How to (and not to) control for unobserved heterogeneity,” *Review of Financial Studies*, 2014, 27 (2), 617–661.
- Graham, John R, Campbell R Harvey, Jillian A Popadak, and Shivaram Rajgopal**, “Corporate Culture: The Interview Evidence,” *Working paper*, 2016.
- Greif, Avner**, “Contract Enforceability and Economic Institutions in Early Trade: The Maghribi Traders’ Coalition,” *American Economic Review*, 1993, pp. 525–548.
- , “Cultural Beliefs and the Organization of Society: A Historical and Theoretical Reflection on Collectivist and Individualist Societies,” *Journal of Political Economy*, 1994, 102 (5), 912–950.
- Guiso, Luigi, Paola Sapienza, and Luigi Zingales**, “Corporate Culture, Societal Culture, and Institutions,” *American Economic Review*, 2015, 105 (5), 336–39.
- , —, and —, “The Value of Corporate Culture,” *Journal of Financial Economics*, 2015, 117 (1), 60–76.
- Hermalin, Benjamin E**, “Economics and Corporate Culture,” in “The International Handbook of Organizational Culture and Climate,” Chichester, John Wiley & Sons, 2001, chapter 10.
- Huselid, Mark A**, “The Impact of Human Resource Management Practices on Turnover, Productivity, and Corporate Financial Performance,” *Academy of Management Journal*, 1995, 38 (3), 635–672.
- Jeffers, Jessica S.**, “The Impact of Restricting Labor Mobility on Corporate Investment and Entrepreneurship,” *Working Paper*, 2018.
- Kogut, Bruce**, “The Network as Knowledge: Generative Rules and the Emergence of Structure,” *Strategic Management Journal*, 2000, pp. 405–425.
- Kreps, David M**, “Corporate culture and economic theory,” *Firms, Organizations and Contracts*, Oxford University Press, Oxford, 1996, pp. 221–275.

- Marx, Matt, Deborah Strumsky, and Lee Fleming**, “Mobility, Skills, and the Michigan Non-Compete Experiment,” *Management Science*, 2009, 55 (6), 875–889.
- Meglino, Bruce M, Elizabeth C Ravlin, and Cheryl L Adkins**, “A work values approach to corporate culture: A field test of the value congruence process and its relationship to individual outcomes,” *Journal of Applied Psychology*, 1989, 74 (3), 424.
- Popadak, Jillian A**, “A corporate culture channel: How increased shareholder governance reduces firm value,” 2013.
- Provan, Keith G, Amy Fish, and Joerg Sydow**, “Interorganizational networks at the network level: A review of the empirical literature on whole networks,” *Journal of management*, 2007, 33 (3), 479–516.
- Radner, Roy**, “The organization of decentralized information processing,” *Econometrica: Journal of the Econometric Society*, 1993, pp. 1109–1146.
- Sheridan, John E**, “Organizational Culture and Employee Retention,” *Academy of Management Journal*, 1992, 35 (5), 1036–1056.
- Sørensen, Jesper B**, “The Strength of Corporate Culture and the Reliability of Firm Performance,” *Administrative Science Quarterly*, 2002, 47 (1), 70–91.
- Starr, Evan, Natarajan Balasubramanian, and Mariko Sakakibara**, “Enforcing Covenants Not to Compete: The Life-Cycle Impact on New Firms,” in “Academy of Management Proceedings,” Vol. 2014 Academy of Management 2014, p. 13238.
- , **Norman Bishara, and James Prescott**, “Noncompetes in the US labor force,” *Working Paper*, 2016.

# Tables

Table 1: Sample Firm Characteristics

This table reports connectivity and corporate culture summary statistics for the sample from 2008 to 2014.

	N	Mean	Std Dev	Median
Average connectivity	7,907	4.93	4.85	3.68
Internal/external ratio	7,907	0.05	0.04	0.05
Absorption	7,598	3.93	3.77	3.01
SC indicator	8,122	0.30	0.46	0.00
Emp. strengths net of concerns	3,888	0.14	1.00	0.00
Emp. Relations - Number of Strengths	3,888	0.36	0.89	0.00
Emp. Relations - Number of Concerns	3,888	0.22	0.48	0.00
Presence on BCW list	12,026	0.02	0.13	0.00

Table 2: Connectivity and Net Employee Relations Score

This table reports on the relationship between the strength of employee relations and the strength of internal connections. The dependent variable is KLD's net employee relations score. In Panel A, the variable of interest is average internal connections. In Panel B, we turn to the ratio of internal to external connections. In Panel C, we consider average internal connections of new employees. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors in parentheses are clustered at the firm level. Industry is 4-digit NAICS.

Panel A: Average internal connections						
	(1)	(2)	(3)	(4)	(5)	(6)
Avg connectivity	0.0671*** (0.00772)	0.0425*** (0.00908)	0.0427*** (0.00941)	0.0461*** (0.0105)	0.0378*** (0.0103)	0.0459*** (0.0116)
Observations	3,834	3,834	3,827	3,551	3,834	3,551
R-squared	0.091	0.134	0.215	0.307	0.135	0.307
Year FE	N	Y	Y	N	Y	N
Industry FE	N	N	Y	N	N	N
Industry-Year FE	N	N	N	Y	N	Y
Network Size FE	N	N	N	N	Y	Y
Panel B: Internal/external connections						
	(1)	(2)	(3)	(4)	(5)	(6)
Internal/external ratio	0.956* (0.549)	2.778*** (0.579)	2.194*** (0.555)	2.485*** (0.652)	2.061*** (0.604)	2.245*** (0.691)
Observations	3,834	3,834	3,827	3,551	3,834	3,551
R-squared	0.002	0.122	0.205	0.297	0.125	0.298
Year FE	N	Y	Y	N	Y	N
Industry FE	N	N	Y	N	N	N
Industry-Year FE	N	N	N	Y	N	Y
Network Size FE	N	N	N	N	Y	Y
Panel C: New employee connections						
	(1)	(2)	(3)	(4)	(5)	(6)
Absorption	0.0706*** (0.0101)	0.0324*** (0.0107)	0.0251** (0.0109)	0.0290** (0.0122)	0.0228** (0.0110)	0.0236* (0.0127)
Observations	3,792	3,792	3,786	3,507	3,792	3,507
R-squared	0.055	0.117	0.202	0.295	0.123	0.296
Year FE	N	Y	Y	N	Y	N
Industry FE	N	N	Y	N	N	N
Industry-Year FE	N	N	N	Y	N	Y
Network Size FE	N	N	N	N	Y	Y



Table 3: Combined Connectivity and Net Employee Relations Score

This table reports on the relationship between the strength of employee relations and the strength of internal connections. The dependent variable is MSCI's net employee relations score. The variable of interest is an annual indicator for strong connectivity, which is 1 if the firms is above median within its 2-digit NAICS code in all of the following three categories: 1) average internal connections, 2) ratio of internal to external connections, 3) average internal connections of new employees. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors in parentheses are clustered at the firm level. Industry is 4-digit NAICS.

	(1)	(2)	(3)	(4)	(5)	(6)
Strong connectivity	0.0435*** (0.00809)	0.0446*** (0.00802)	0.0369*** (0.00746)	0.0385*** (0.00847)	0.0364*** (0.00807)	0.0348*** (0.00871)
Observations	3,792	3,792	3,786	3,507	3,792	3,507
R-squared	0.017	0.126	0.209	0.300	0.130	0.301
Year FE	N	Y	Y	N	Y	N
Industry FE	N	N	Y	N	N	N
Industry-Year FE	N	N	N	Y	N	Y
Network Size FE	N	N	N	N	Y	Y

Table 4: Connectivity and Best Companies to Work For

This table reports on the relationship between employee satisfaction and the strength of internal connections. The dependent variable is an indicator for the firm’s presence on Fortune’s “Best Places to Work For” list. In Panel A, the variable of interest is average internal connections. In Panel B, we turn to the ratio of internal to external connections. In Panel C, we consider average internal connections of new employees. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors in parentheses are clustered at the firm level. Industry is 4-digit NAICS.

Panel A: Average internal connections						
	(1)	(2)	(3)	(4)	(5)	(6)
Avg connectivity	0.00538*** (0.00115)	0.00643*** (0.00138)	0.00581*** (0.00119)	0.00614*** (0.00131)	0.00619*** (0.00157)	0.00598*** (0.00151)
Observations	11,504	11,504	11,504	11,168	11,504	11,168
R-squared	0.035	0.042	0.171	0.145	0.042	0.145
Year FE	N	Y	Y	N	Y	N
Industry FE	N	N	Y	N	N	N
Industry-Year FE	N	N	N	Y	N	Y
Network Size FE	N	N	N	N	Y	Y

  

Panel B: Internal/external connections						
	(1)	(2)	(3)	(4)	(5)	(6)
Internal/external ratio	0.540*** (0.112)	0.570*** (0.118)	0.481*** (0.0999)	0.498*** (0.107)	0.499*** (0.123)	0.446*** (0.118)
Observations	11,504	11,504	11,504	11,168	11,504	11,168
R-squared	0.028	0.030	0.164	0.137	0.031	0.137
Year FE	N	Y	Y	N	Y	N
Industry FE	N	N	Y	N	N	N
Industry-Year FE	N	N	N	Y	N	Y
Network Size FE	N	N	N	N	Y	Y

  

Panel C: New employee connections						
	(1)	(2)	(3)	(4)	(5)	(6)
Absorption	0.00382*** (0.00101)	0.00448*** (0.00119)	0.00281*** (0.000941)	0.00295*** (0.00103)	0.00310*** (0.00112)	0.00162 (0.00103)
Observations	10,903	10,903	10,902	10,574	10,903	10,574
R-squared	0.011	0.013	0.154	0.126	0.020	0.132
Year FE	N	Y	Y	N	Y	N
Industry FE	N	N	Y	N	N	N
Industry-Year FE	N	N	N	Y	N	Y
Network Size FE	N	N	N	N	Y	Y

Table 5: Combined Connectivity and Best Companies to Work For

This table reports on the relationship between the strength of employee relations and the strength of internal connections. The dependent variable is an indicator for the firm’s presence on Fortune’s “Best Places to Work For” list. The variable of interest is an annual indicator for strong connectivity, which is 1 if the firms is above median within its 2-digit NAICS code in all of the following three categories: 1) average internal connections, 2) ratio of internal to external connections, 3) average internal connections of new employees. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors in parentheses are clustered at the firm level. Industry is 4-digit NAICS.

	(1)	(2)	(3)	(4)	(5)	(6)
Strong connectivity	0.00543*** (0.00114)	0.00543*** (0.00114)	0.00451*** (0.000918)	0.00469*** (0.000990)	0.00369*** (0.00101)	0.00327*** (0.000920)
Observations	10,903	10,903	10,902	10,574	10,903	10,574
R-squared	0.015	0.015	0.159	0.132	0.020	0.134
Year FE	N	Y	Y	N	Y	N
Industry FE	N	N	Y	N	N	N
Industry-Year FE	N	N	N	Y	N	Y
Network Size FE	N	N	N	N	Y	Y

Table 6: Sample Firm Characteristics for WC and SC Firms

This table reports summary statistics for the sample from 2008 to 2014, for firms classified as WC and SC firms in 2010.

		N	Mean	Std Dev	Median
SC	Departure rate	2,466	5.36	4.00	4.39
	Upwardly mobile departure rate	2,466	1.28	1.18	1.02
	Num. employees (LinkedIn)	2,466	2,423.19	7,930.36	806
	Num. employees (Compustat)	2,330	6,225.08	13,845.85	1,898
	Num. on network	2,466	1,584.74	5,733.31	472
	ROA	2,395	0.07	0.26	0.11
	M/B	2,078	2.13	1.50	1.68
WC	Departure rate	5,533	5.47	7.23	3.70
	Upwardly mobile departure rate	5,533	1.22	2.53	0.53
	Num. employees (LinkedIn)	5,593	821.86	4,399.90	119
	Num. employees (Compustat)	5,003	3,093.29	9,372.42	497
	Num. on network	5,593	496.45	3,016.49	62
	ROA	5,306	-0.58	7.51	0.08
	M/B	4,863	6.14	53.90	1.56
Total	Departure rate	7,999	5.43	6.41	3.97
	Upwardly mobile departure rate	7,999	1.24	2.20	0.77
	Num. employees (LinkedIn)	8,059	1,311.85	5,763.50	235
	Num. employees (Compustat)	7,333	4,088.39	11,088.26	796
	Num. on network	8,059	829.46	4,076.95	132
	ROA	7,701	-0.38	6.24	0.09
	M/B	6,941	4.94	45.16	1.60

Table 7: NC Enforceability Impact in WC and SC Firms

Panel A reports results from difference in difference regressions in the WC and SC samples separately, where the dependent variable is upwardly mobile departure rate for high NC occupations. Panel B reports results from a triple difference regression with all observations pooled, controlling for firm fixed effects, and industry-year fixed effects. The dependent variable is the same. \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors in parentheses are clustered at the state level. Industry is 4-digit NAICS.

Panel A: Subsamples				
	All firms		Geographically concentrated	
	(1)	(2)	(3)	(4)
	SC	WC	SC	WC
Treated*Post	-0.0519 (0.124)	-0.595*** (0.181)	-0.141 (0.125)	-0.678** (0.261)
Observations	2,157	5,142	1,622	4,012
R-squared	0.505	0.392	0.465	0.395
Firm FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y
Panel B: Interacted				
	(1a)	(1b)	(2a)	(2b)
SC*Treated*Post	0.546*** (0.127)	0.603*** (0.138)	0.610*** (0.132)	0.669*** (0.155)
Treated*Post	-0.613*** (0.138)	-0.631*** (0.142)	-0.722*** (0.190)	-0.744*** (0.198)
Observations	7,662	7,662	5,940	5,940
R-squared	0.387	0.388	0.383	0.384
Firm FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y
Connectivity-Year FE	-	Y	-	Y

Table 8: NC Enforceability Impact in WC and SC Firms, by Year

This table breaks out the results from Table 7 by year to change. Year prior to change is our omitted category. Since NC enforceability changes occur at different points in the panel, we group together three years or more prior to change (t-3+) and three years or more after change (t3+).

Panel A: Subsamples				
	All firms		Geographically concentrated	
	(1) SC	(2) WC	(3) SC	(4) WC
Treated t-3+	-0.110 (0.115)	-0.118 (0.278)	-0.111 (0.152)	0.0131 (0.387)
Treated t-2	0.0275 (0.148)	0.111 (0.301)	0.00880 (0.207)	0.0691 (0.406)
Treated t-1	<i>omitted</i>	<i>omitted</i>	<i>omitted</i>	<i>omitted</i>
Treated t0	-0.125 (0.125)	-0.469** (0.175)	-0.283** (0.130)	-0.496** (0.209)
Treated t1	0.104 (0.116)	-0.439** (0.205)	0.00492 (0.122)	-0.511* (0.268)
Treated t2	-0.0450 (0.287)	-0.689** (0.309)	-0.238 (0.340)	-0.693* (0.378)
Treated t3+	-0.0805 (0.152)	-0.507*** (0.142)	-0.178 (0.194)	-0.564*** (0.173)
Observations	2,157	5,142	1,622	4,012
R-squared	0.506	0.392	0.466	0.395
Firm FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y

\*

Panel B: Interacted				
	All firms		Geographically concentrated	
	(1)	(2)	(3)	(4)
SC*Treated t-3+	0.269 (0.249)	0.202 (0.263)	0.171 (0.362)	0.0765 (0.387)
SC*Treated t-2	0.0960 (0.205)	0.172 (0.234)	0.135 (0.356)	0.237 (0.376)
SC*Treated t-1	<i>omitted</i>	<i>omitted</i>	<i>omitted</i>	<i>omitted</i>
SC*Treated t0	0.431*** (0.155)	0.374** (0.179)	0.365* (0.205)	0.299 (0.227)
SC*Treated t1	0.797*** (0.192)	0.853*** (0.208)	0.983*** (0.246)	1.024*** (0.281)
SC*Treated t2	0.662* (0.374)	0.773** (0.359)	0.626 (0.459)	0.752 (0.454)
SC*Treated t3+	0.359** (0.144)	0.681*** (0.190)	0.340* (0.170)	0.672*** (0.199)
Treated t-3+	-0.202 (0.262)	-0.184 (0.263)	-0.120 (0.378)	-0.0957 (0.383)
Treated t-2	0.0557 (0.252)	0.0291 (0.256)	-0.00179 (0.369)	-0.0404 (0.371)
Treated t-1	<i>omitted</i>	<i>omitted</i>	<i>omitted</i>	<i>omitted</i>
Treated t0	-0.525*** (0.142)	-0.511*** (0.150)	-0.615*** (0.174)	-0.599*** (0.185)
Treated t1	-0.551*** (0.194)	-0.567*** (0.196)	-0.658*** (0.238)	-0.676*** (0.247)
Treated t2	-0.674** (0.309)	-0.705** (0.302)	-0.715* (0.377)	-0.762** (0.370)
Treated t3+	-0.465*** (0.114)	-0.561*** (0.127)	-0.517*** (0.135)	-0.634*** (0.153)
Observations	7,662	7,662	5,940	5,940
R-squared	0.387	0.388	0.383	0.384
Firm FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y
Connectivity-Year FE	-	Y	-	Y

Table 9: NC Enforceability and WC v. SC Firm Prospects

This table reports results from a triple difference regression, where the dependent variable is natural log of market-to-book in columns (1) and (2), natural log of return on assets in columns (3) and (4), and the investment to net capital ratio in columns (5) and (6). \*\*\*, \*\*, and \* denote statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors in parentheses are clustered at the state level. Industry is 4-digit NAICS.

$$100 * \frac{Departures}{Employees}_{ijst} = \alpha + \beta\{\text{treated}_s * \text{post}_t\} + \gamma_i + \theta_{jt} + \epsilon_{it}$$

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(MB)	Ln(MB)	Ln(ROA)	Ln(ROA)	I/K	I/K
SC*Treated*Post	0.321** (0.153)	0.329** (0.160)	0.160* (0.0814)	0.0605 (0.0996)	-0.0374** (0.0183)	-0.0299 (0.0206)
Treated*Post	-0.135** (0.0654)	-0.138* (0.0687)	-0.0868 (0.0599)	-0.0543 (0.0624)	0.0704*** (0.0254)	0.0679** (0.0264)
Observations	5,826	5,826	5,000	5,000	4,129	4,129
R-squared	0.761	0.762	0.643	0.644	0.544	0.545
Firm FE	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y
Connectivity-Year FE	-	Y	-	Y	-	Y

Table 10: NC Enforceability and Firm Prospects: Time Trends

This table breaks out the results from Table 9 by year to change. Year prior to change is our omitted category. Since NC enforceability changes occur at different points in the panel, we group together three years or more prior to change (t-3+) and three years or more after change (t3+).

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(MB)	Ln(MB)	Ln(ROA)	Ln(ROA)	I/K	I/K
SC*Treated t-3+	-0.161 (0.217)	-0.231 (0.240)	0.0488 (0.137)	0.101 (0.161)	0.0488 (0.0369)	0.0438 (0.0370)
SC*Treated t-2	-0.102 (0.177)	-0.0512 (0.175)	0.118 (0.113)	0.128 (0.113)	0.00610 (0.0410)	-0.00196 (0.0465)
SC*Treated t-1	<i>omitted</i>	<i>omitted</i>	<i>omitted</i>	<i>omitted</i>	<i>omitted</i>	<i>omitted</i>
SC*Treated t0	0.294*** (0.105)	0.331*** (0.109)	0.248*** (0.0837)	0.217** (0.0999)	-0.0607* (0.0330)	-0.0564* (0.0328)
SC*Treated t1	0.126 (0.0940)	0.131 (0.123)	0.187*** (0.0636)	0.0869 (0.0832)	-0.00689 (0.0364)	0.00353 (0.0513)
SC*Treated t2	0.171 (0.179)	0.150 (0.182)	0.232*** (0.0740)	0.0993 (0.0959)	-0.0734* (0.0408)	-0.0985* (0.0522)
SC*Treated t3+	0.281* (0.139)	0.200 (0.167)	0.196** (0.0775)	0.0389 (0.112)	-0.00851 (0.0603)	-0.0481 (0.0773)
Treated t-3+	0.256 (0.171)	0.278 (0.175)	-0.000424 (0.0902)	-0.0134 (0.0923)	0.0192 (0.0336)	0.0214 (0.0303)
Treated t-2	0.114 (0.111)	0.0934 (0.115)	-0.0209 (0.0907)	-0.0229 (0.0906)	0.0456 (0.0330)	0.0487 (0.0336)
Treated t-1	<i>omitted</i>	<i>omitted</i>	<i>omitted</i>	<i>omitted</i>	<i>omitted</i>	<i>omitted</i>
Treated t0	-0.1000 (0.0821)	-0.115 (0.0870)	-0.214** (0.0823)	-0.203** (0.0841)	0.114*** (0.0262)	0.114*** (0.0273)
Treated t1	0.135 (0.0842)	0.129 (0.0939)	-0.00271 (0.0664)	0.0301 (0.0692)	0.0800*** (0.0292)	0.0771** (0.0295)
Treated t2	0.0561 (0.0741)	0.0586 (0.0784)	-0.0531 (0.0631)	-0.00868 (0.0663)	0.135*** (0.0298)	0.145*** (0.0294)
Treated t3+	-0.0806 (0.144)	-0.0588 (0.150)	-0.0434 (0.0885)	0.0151 (0.0911)	0.0553 (0.0343)	0.0704* (0.0365)
Observations	5,826	5,826	5,000	5,000	4,129	4,129
R-squared	0.762	0.762	0.644	0.645	0.545	0.546
Firm FE	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y
Connectivity-Year FE	-	Y	-	Y	-	Y



# A Appendix

Table A.1: Connectivity and Employee Relations Strengths

This table reports on the relationship between the strength of employee relations and the strength of internal connections. The dependent variable is the total sum of strengths in MSCI's employee relations data. In Panel A, the variable of interest is average internal connections. In Panel B, we turn to the ratio of internal to external connections. In Panel C, we consider average internal connections of new employees.

Panel A: Average internal connections						
	(1)	(2)	(3)	(4)	(5)	(6)
Avg internal connections	0.0454*** (0.00743)	0.0361*** (0.00920)	0.0454*** (0.00950)	0.0480*** (0.0105)	0.0289*** (0.0105)	0.0447*** (0.0117)
Observations	3,834	3,834	3,827	3,551	3,834	3,551
R-squared	0.052	0.084	0.194	0.283	0.087	0.283
Year FE	N	Y	Y	N	Y	N
Industry FE	N	N	Y	N	N	N
Industry-Year FE	N	N	N	Y	N	Y
Network Size FE	N	N	N	N	Y	Y
Panel B: Internal/external connections						
	(1)	(2)	(3)	(4)	(5)	(6)
Internal/external connections	1.631*** (0.479)	2.518*** (0.518)	2.254*** (0.479)	2.529*** (0.575)	1.655*** (0.540)	1.963*** (0.608)
Observations	3,834	3,834	3,827	3,551	3,834	3,551
R-squared	0.007	0.075	0.179	0.270	0.080	0.271
Year FE	N	Y	Y	N	Y	N
Industry FE	N	N	Y	N	N	N
Industry-Year FE	N	N	N	Y	N	Y
Network Size FE	N	N	N	N	Y	Y
Panel C: New employee connections						
	(1)	(2)	(3)	(4)	(5)	(6)
Avg int. conn. new employees	0.0432*** (0.00931)	0.0225** (0.0106)	0.0247** (0.0108)	0.0271** (0.0121)	0.0112 (0.0111)	0.0193 (0.0127)
Observations	3,792	3,792	3,786	3,507	3,792	3,507
R-squared	0.026	0.066	0.175	0.264	0.077	0.269
Year FE	N	Y	Y	N	Y	N
Industry FE	N	N	Y	N	N	N
Industry-Year FE	N	N	N	Y	N	Y
Network Size FE	N	N	N	N	Y	Y

Table A.2: Connectivity and Employee Relations Concerns

This table reports on the relationship between the strength of employee relations and the strength of internal connections. The dependent variable is the total sum of concerns in MSCI's employee relations data. In Panel A, the variable of interest is average internal connections. In Panel B, we turn to the ratio of internal to external connections. In Panel C, we consider average internal connections of new employees.

Panel A: Average internal connections						
	(1)	(2)	(3)	(4)	(5)	(6)
Avg internal connections	-0.0217*** (0.00228)	-0.00640*** (0.00215)	0.00272 (0.00229)	0.00189 (0.00239)	-0.00884*** (0.00291)	-0.00127 (0.00268)
Observations	3,834	3,834	3,827	3,551	3,834	3,551
R-squared	0.042	0.121	0.269	0.346	0.122	0.348
Year FE	N	Y	Y	N	Y	N
Industry FE	N	N	Y	N	N	N
Industry-Year FE	N	N	N	Y	N	Y
Network Size FE	N	N	N	N	Y	Y

  

Panel B: Internal/external connections						
	(1)	(2)	(3)	(4)	(5)	(6)
Internal/external connections	0.675** (0.289)	-0.260 (0.296)	0.0596 (0.288)	0.0444 (0.326)	-0.406 (0.348)	-0.282 (0.353)
Observations	3,834	3,834	3,827	3,551	3,834	3,551
R-squared	0.004	0.119	0.268	0.346	0.120	0.348
Year FE	N	Y	Y	N	Y	N
Industry FE	N	N	Y	N	N	N
Industry-Year FE	N	N	N	Y	N	Y
Network Size FE	N	N	N	N	Y	Y

  

Panel C: New employee connections						
	(1)	(2)	(3)	(4)	(5)	(6)
Avg int. conn. new employees	-0.0274*** (0.00316)	-0.00988*** (0.00262)	-0.000416 (0.00252)	-0.00190 (0.00266)	-0.0115*** (0.00312)	-0.00425 (0.00275)
Observations	3,792	3,792	3,786	3,507	3,792	3,507
R-squared	0.036	0.122	0.270	0.349	0.123	0.350
Year FE	N	Y	Y	N	Y	N
Industry FE	N	N	Y	N	N	N
Industry-Year FE	N	N	N	Y	N	Y
Network Size FE	N	N	N	N	Y	Y

Table A.3: Changes in NC Enforceability

State	Case	Enforcement Direction	Nature of Change
WI	Star Direct, Inc. v. Dal Pra. (2009)	↑	Supreme Court allows modification
SC	Invs, Inc. v. Century Builders of Piedmont, Inc. (2010)	↓	Supreme Court rejects modification
CO	Lucht's Concrete Pumping, Inc. v. Horner (2011)	↑	Supreme Court allows continued consideration
TX	Marsh v. Cook (2011)	↑	Supreme Court changes requirements on business interests
MT	Wrigg v. Junkermier (2011)	↓	Supreme Court rejects application to terminated employees
IL	Fire Equipment v. Arredondo et al (2011)	↑	Supreme Court expands scope of interests
IL	Fifield v. Premier Dealer Services (2013)	↓	Supreme Court restricts standards
VA	Assurance Data Inc. v. Malyevac (2013)	↑	Supreme Court reduces automatic dismissals
GA	2011	↑	Legislature allows modification

Figure A.1: LinkedIn Coverage by Sector

This figure presents coverage rates for firms in merged sample of LinkedIn and Compustat data. Firms are categorized by their Global Industrial Classification (GIC) sector. Worker representation for each sector is given by the total number of LinkedIn members employed in each sector in 2014 divided by the employees reported in Compustat for 2014.

