Talent in Distressed Firms: Investigating the Labor Costs of Financial Distress

Ramin P. Baghai, Rui C. Silva, Viktor Thell, and Vikrant Vig*

October 2016

*First version: April 2015. Baghai and Thell are at the Stockholm School of Economics. Silva and Vig are at the London Business School. E-mail: ramin.baghai@hhs.se; viktor.thell@phdstudent.hhs.se; rsilva@london.edu; vvig@london.edu. We thank Johan Wall at SCB for help with the data, and David Matsa, Gordon Philips, Fabiano Schivardi, Amit Seru, Henri Servaes, Elena Simintzi, Martin Strieborny, Geoffrey Tate, Luigi Zingales, and seminar and conference participants at the CSEF-EIEF-SITE conference on Labor and Finance (2015); Finance, Organizations and Markets Conference (2015); Spanish Economic Association meetings (2015); SHOF PhD conference (2015); SFS Finance Cavalcade (2016); 13th Annual Conference in Financial Economics Research, IDC, Israel (2016); EFA (2016); Banco de Mexico; Bocconi University; London Business School; Lund University School of Economics and Management; and Stockholm School of Economics (Swedish House of Finance). We are grateful for financial support from the Deloitte Institute for Innovation and Entrepreneurship at the London Business School. Thell also gratefully acknowledges financial support from the Swedish Bank Research Foundation, as well as the Jan Wallander and Tom Hedelius Foundation.
Talent in Distressed Firms: Investigating the Labor Costs of Financial Distress

ABSTRACT

The importance of skilled labor and the inalienability of human capital may expose firms to fragility stemming from possible loss of talent. Using detailed employer-employee matched data from Sweden, we document that firms lose their most skilled workers as they approach financial distress. Consequently, firms that rely more on talent operate with more conservative capital structures. In a quasi-experimental setting—employing a change in Swedish labor law that exogenously increases the mobility of workers—we find that as the risk of losing talent increases, financial leverage decreases.
I. Introduction

Ever since Modigliani and Miller’s famous irrelevance theorem, financial economists have devoted considerable efforts towards understanding the nature of the frictions that affect firms’ financial choices. While there is a clear consensus that the financial structure of a firm matters and has real effects, the various trade-offs are still under investigation. One prominent theory, the trade-off theory of capital structure, contrasts the advantages of debt, such as the interest tax shield, with the disadvantages of high leverage, such as costs of financial distress. In theory, such costs are understood to include both direct (e.g., legal fees), as well as indirect costs (e.g., loss of customers, suppliers, employees). While the notion of these costs is quite precise theoretically, empirically identifying various channels has proven to be challenging.¹

In this paper, we examine how the onset of financial distress affects firms’ ability to retain high-skilled talent in the organization. A reduced ability by financially distressed firms to retain such workers could be viewed as a cost of financial distress. We employ unique micro-level data from Sweden to shed light on this issue. Our employee-employer matched dataset contains detailed information on firm and individual worker characteristics, such as age, gender, education, measures of cognitive and non-cognitive skills, employment histories, as well as compensation. This allows us to paint an exhaustive picture of the labor force characteristics of firms approaching distress, including meaningful proxies for talent.

The notion that loss of talent could be a potential cost of financial distress is not new. The property rights view pioneered by Grossman and Hart (1986) and Hart and Moore (1990) provides a framework to analyze how inalienability of human capital affects financing capacity of firms.² A recent survey of business professionals suggests that this is not merely a theoretical possibility: “talent and skill shortages” were identified as the second most important risk facing modern organizations, only topped by the risk of “loss of customers” and ranking above other risks such as “changing legislation” (Lloyds Risk Index 2011).³

Whether talented employees are the first to desert the sinking ship is not a priori obvious. While a highly liquid market for talented workers may lead to them exiting first, it may also make them more patient, since the cost of staying with the firm is lower (e.g., lower wage discounts). To the extent that talented workers are also employed in more strategic roles, this would also accord them with some informational advantage that allows them to separate financial distress from

² Essentially, human capital introduces a contractual incompleteness that stems from the fact that, in the absence of slavery, firms do not own human capital, workers do.
³ There is anecdotal evidence such as the Saatchi and Saatchi case (e.g., Rajan and Zingales 2000) that also supports this view. When US fund managers who owned 30% of Saatchi and Saatchi vetoed the award of a generous compensation package to the firm’s chairman Maurice Saatchi, he and his brother Charles left the firm, taking with them several key senior executives and key accounts.
economic distress, which in turn would have a further bearing on the decision. Knowledge that distress is solely financial would perhaps make them more enduring. Other factors such as reputational damage (attribution of blame) may also play a role in their decision. This theoretical ambiguity that arises from the different economic forces makes for an interesting empirical investigation.

The paper is conceptually divided into two parts. In the first part, we investigate which employees present the biggest risk of abandoning firms that approach financial distress. In the second part, we analyze the consequences of this labor fragility for the ex-ante financial policy of firms. Since it is financial distress and not economic distress that matters for leverage, an effect on leverage would suggest that it is financial distress that is driving our results.

We find that when firms become financially distressed, there is a significant loss of talent, as workers with the highest skills abandon the firm. The most talented workers in the organization are 30% more likely to leave as the firm approaches distress, relative to the average worker. Further, we find that the intake of talented employees in distressed firms does not increase commensurably.

A key challenge in such an empirical analysis is separating out demand and supply side factors that lead to a change in labor composition. A move towards a labor force composition that is less reliant on talent may be the optimal behavior of a profit-maximizing firm. To separate out demand and supply side factors we focus our analysis on voluntary departures. While we do not have direct information on which departures were voluntary and which were forced (firing), we use two independent approaches to identify instances of voluntary departures. In the first approach, we examine whether the employee who left the firm was unemployed for a period of time. Our conjecture is that forced departures would, to some extent, be associated with unemployment, while voluntary departures would be less likely to result in unemployment spells.\(^4\)

Our second approach exploits an institutional feature of the labor law in Sweden. All firms that have more than 10 employees are required by law to follow a last in first out (LIFO) rule when it comes to laying off workers.\(^5\) We use this rule to identify voluntary departures. The algorithm we use can be best understood using a simple example. Suppose that a firm has 100 employees and we observe that 20 employees leave the firm. Because we know the joining date of these employees, we can determine whether these job separations adhere to the LIFO rule or not. Any deviations from this rule would provide us with a proxy for voluntary departures. We find that

\(^4\) Our results that talented employees are more likely to leave the firm early and that there is no increase in the incidence of unemployment for these workers, relative to less talented employees, provide support for this conjecture.

\(^5\) As discussed in Section III.B, both anecdotal and systematic evidence suggest that LIFO regulations de facto impact the human resources policies of firms and that there are significant costs associated with deviations from the rule.
talented employees are more likely to leave voluntarily as they “jump the queue” and leave earlier than the LIFO order would imply. Taken as a whole, our results point to talented workers voluntarily “jumping ship” in times of distress.

Another challenge is to separate financial distress from economic distress. While these two types of distress are difficult to separate empirically, it is only the cost of financial distress that matters for the ex-ante leverage choice. Thus, any effect on leverage would be indicative of financial distress. We find that the deterioration in the talent pool of the organization in times of distress has consequences for financial policies. Firms that rely more on a highly skilled and highly mobile labor force operate with a more conservative capital structure. This result is obtained not only in the cross-section, but also confirmed in a quasi-experimental setting where we analyze the impact of an exogenous change in the mobility of workers on the financial policies of talent-intensive firms.

To alleviate concerns that our results are specific to Sweden, we confirm the main implications of our findings in a different setting. Specifically, we exploit staggered changes in the enforceability of non-compete agreements across US states as a shock to the mobility of talented employees. Changes in the enforceability of these agreements were primarily due to precedent-setting court decisions and can therefore be considered exogenous and unexpected. We find that increases in labor fragility due to lower enforceability of non-compete clauses lead to a reduction in leverage.

Our paper connects several strands of literature in finance. It contributes to the literature that analyzes the capital structure of firms and its determinants (for a recent review of this literature see Graham and Leary 2011). In particular, our paper adds to the literature that documents and measures costs of financial distress (e.g., Weiss 1990, Andrade and Kaplan 1998, Maksimovic and Phillips 1998, and Hortaçsu et al. 2013) by providing evidence of the added degree of firm fragility induced by labor and by establishing labor fragility as an important determinant of capital structure.

More broadly, the paper also adds to the growing literature that studies the interactions between finance and labor. Within the labor and finance literature, our work is most closely related to research that studies the interaction between labor and capital structure (e.g., Perotti and Spier 1993; Berk, Stanton and Zechner 2010; Matsa 2010; Agrawal and Matsa 2013; Simintzi, Vig and Volpin 2014). Our work also relates to Graham, Kim, Li, and Qiu (2013), who find a significant

---

6 Several ways in which labor forces shape the financial policies of firms have been documented. For example, the internal allocation of capital in conglomerates is, to a large extent, determined by features of the internal labor market of these firms (Silva 2016). Ouimet and Zaroutski (2016) provide evidence for acquisition of labor as a motive for M&As. Tate and Yang (2015a) document that diversified firms have more active internal labor markets than focused firms and that, as a consequence, firms may diversify in order to create active internal labor markets (Tate and Yang 2015b). Other research analyzes how financial policies affect labor outcomes (e.g., Agrawal and Tambe 2016, Benmelech, Bergman and Seru 2011).
loss in the wages of workers employed by firms at the time of bankruptcy; and to Donangelo (2014), who documents an asset pricing impact of labor mobility.

Our paper adds to the recent work of Brown and Matsa (2016), who use data from an online job search portal to examine how the onset of financial distress affects a firm’s ability to hire workers. They find that not only do distressed firms receive fewer applications, but the average quality of the applicants is also lower, thus providing evidence, albeit indirect, on the labor costs of financial distress. While their findings are informative, lack of micro-level data on individuals prevents them from providing more direct evidence on talent composition around distress. For example, they do not observe the quality of the applicants, but use indirect proxies that are often generated at the zip-code level.

Our paper complements Brown and Matsa (2016) in several ways. First, we provide very direct evidence on the characteristics of workers that leave and join distressed firms. The granularity of our data allows us to measure talent very precisely. Furthermore, our data also allow us to control for other individual characteristics (such as experience, age, gender etc.) that could impact labor fragility more generally. Second, we focus on both the ability of firms to attract workers as well as the ability of firms to retain them. Failing to attract talent to the organization (as documented by Brown and Matsa 2016) would not be a severe problem if firms were not losing their most talented employees in times of distress. However, what our findings show is that firms keep attracting highly skilled workers at the same pace as less talented employees, but fail to retain their top talent. Furthermore, in contrast with Brown and Matsa (2016) who acknowledge that they “(...) must assume that the quality of the applicant pool and the quality of the person hired are affected similarly”, we focus on realized departures and hiring outcomes. This provides a holistic picture as a job posting may not capture the intensity of the search or the change in the nature of the contract that may be offered by firms in times of distress. Finally, we link firms’ ex-ante reliance on talent to financial policies and present direct evidence of the effect of labor fragility on capital structure. Overall, relative to the previous literature, we are able to paint a considerably richer picture of how labor composition changes around bankruptcy and how this relates to financial policies.

The rest of the paper is organized as follows. Section II discusses the data sources and the variable construction. In Section III we study how the composition of labor changes as firms approach distress. Section IV investigates whether firms internalize labor-induced fragility when choosing their capital structure. In addition to cross-sectional leverage regressions, we examine how an exogenous shock to labor mobility affects capital structure in talent-intensive firms. In Section V, we discuss the external validity of our findings and present evidence of the impact of labor

---

7 Our work thus also complements Hanka (1998), who documents a negative correlation between leverage and employment.
fragility on leverage in the US. In Section VI, we discuss robustness tests and additional results. Finally, Section VII concludes.

II. Data and variables

II.A Main data sources

The main dataset used in our analysis is obtained by matching longitudinal data on socio-economic outcomes for Swedish individuals during 1990-2011, the Longitudinal Database on Education, Income and Occupation (LISA) from Statistics Sweden (SCB), with data from military enlistment records, and firm-level data from the Serrano database. LISA contains detailed employee-employer matched information for the whole Swedish population. For individuals aged 16 years or older, a large set of socio-economic information, such as age, gender, employment, uncensored wages, and social security benefits are available. This dataset, thus, also allows us to track individuals over time and study their career paths.

A distinguishing strength of the Swedish data is the possibility of linking the information from LISA to measures of cognitive, non-cognitive, and leadership skills using military records. The military data cover the years 1968-2011 and are obtained from The National Archives and The National Service Administration. Between 1968 and 2009, all Swedish males aged 18 or over were required to participate in enlistment tests for one to two days. The enlistment test consisted of four parts, assessing cognitive ability, non-cognitive ability, physical ability and health status. Whether someone had to do military service was determined by their health status, and the capacity in which they served was determined by the joint outcome of all the tests. The cognitive ability test consisted of four parts: synonyms, inductions, spatial reasoning, and technical comprehension. Each part was graded on a scale from 0 to 40; the combined score from the four parts was converted to a cognitive ability score from one to nine on the Stanine scale. Non-cognitive ability was assessed through a structured interview with a psychologist, who graded test-takers on psychological abilities using the Stanine scale. In addition, leadership ability was assessed by the psychologist, for all test-takers who received an average or above average score on the cognitive ability test. Lindqvist and Vestman (2011) show that these measures relate to labor market outcomes in a meaningful way.

The Swedish firm-level data are from the Serrano database. Serrano includes financial statement data, as well as detailed information on bankruptcy filings. The data are adjusted for split financial years as well as accounting periods of different lengths and are converted to calendar year values for both stock and flow data. The data cover both privately and publicly held firms.

---

8 Since 2010, both participation in the tests and military service itself have no longer been compulsory.
9 The Stanine scale is a method of scaling test scores resulting in approximately normally distributed data with a mean of 5 and a range from 1 to 9.
II.B Sample construction

We employ three data samples in our analysis. With our first sample, we explore changes in the composition of the labor force as firms approach bankruptcy. We start with all Swedish limited liability firms and categorize them into two groups: the treatment group and the control group. Firms that constitute our treatment group are those that experience a bankruptcy event during our sample period, have non-missing accounting data and have more than five employees five years prior to bankruptcy. We also require firms to have at least one employee during each of the five years leading up to the bankruptcy event. We define a bankruptcy event as either filing for bankruptcy under the Swedish bankruptcy code or filing for reorganization under the Swedish Company Reconstruction Code; if there are multiple bankruptcy events for a single firm, we only use the first event in our analysis.\(^\text{10}\)

We then use a matching algorithm to construct our control group, which provides a counterfactual for the firms in the treatment group in the absence of bankruptcy. Five years prior to bankruptcy, each of the firms in the treatment group is matched to a firm that is similar but that does not file for bankruptcy during our sample period. Specifically, we match control firms to treatment firms using a nearest neighbor algorithm for a set of firm characteristics within strata for calendar year and 2-digit SNI industry\(^\text{11}\) (Imbens et al. 2004). We use the following firm characteristics for the matching: log of total assets, number of employees, financial leverage (total debt minus cash, divided by total assets), profitability (EBITDA divided by total assets), average worker wage (in 100 Swedish Kronor), and average talent score (non-cognitive plus cognitive score). Because our firm-level accounting data start in 1998 and our matching procedure is performed five years prior to the start of bankruptcy, our final sample includes bankruptcy events from 2003 to 2011. Table 1 compares characteristics of firms in the treatment and control groups. Unsurprisingly, treatment and control firms do not differ significantly with regard to the characteristics on which we match. The matching, however, also leads to similarity of treatment and control firms along dimensions that we can observe but on which we do not match. This suggests that the firms may not be too dissimilar with respect to characteristics that are not observable to us.\(^\text{12}\)

Figure 1 shows the distribution of corporate bankruptcies across industries for our sample. The total number of bankruptcies in our sample is 3,470; the number and frequency of bankruptcies is

---

\(^{10}\) The median number of employees in treatment firms five years prior to bankruptcy is 14.

\(^{11}\) SNI is the Swedish Standard Industrial classification, which is based on the second revision of the EU’s standard industry classification NACE.

\(^{12}\) Our findings are robust to several different ways of constructing the control group, including matching on different sets of characteristics and using firms in the treatment group that are not yet treated as control for the firms that are close to bankruptcy.
highest in the manufacturing industry, while it is lowest in the financial sector.\footnote{Note that this category excludes commercial banks, which are a separate category of limited liability companies (“Bankaktiebolag”) and for which regulations differ compared to other limited liability companies. Examples of activities pursued by the financial firms included in the sample are: financial leasing, investments, private equity, venture capital, brokerage services, and financial advisors.} Figure 2 shows the distribution of bankruptcies over time for our sample. All sample years are well represented in terms of bankruptcy events, with 2006 and 2007 being the years with the lowest numbers of bankruptcies, and 2009 and 2010 the years with the highest numbers of bankruptcies.

We match firms with their employees using the employee-employer links from LISA. For the regressions studying labor transitions into and out of financially distressed firms, the sample consists of workers employed by the firm in at least one of the five years leading up to bankruptcy. The sample spans the years 1998 to 2010 (using bankruptcies from 2003 to 2011).

For the cross-sectional leverage tests, our sample covers the years 1999-2008 and consists of all Swedish limited liability firms. Finally, the sample used in the leverage tests exploiting a 2001 labor law change is constructed as follows. As before, we focus on limited liability firms. The 2001 law change allowed firms with less than 11 employees to be exempted from LIFO (last-in-first-out) rules, so these firms constitute our treatment group. We restrict the sample to the 1999 to 2004 period, where 1999-2000 is the baseline period and 2002-2004 is the treatment period (we omit the year of the law change, 2001, from the analysis). In the analysis of leverage around the LIFO law change, we focus on firms around the 11 employee threshold, that is, firms with at least 5 employees and at most 15 employees.

II.C Variables

The two main variables we use to study employee mobility are Leave and Join. Leave is a dummy variable that takes the value of one in the year a worker leaves the firm to work for another employer, and zero otherwise. We identify “leavers” by verifying whether the main source of income comes from a different employer in the next year, indicating a change in employment. Similarly, Join is a dummy variable that takes the value of one in the year an employee joins a new firm. We identify “joiners” by verifying whether the main source of income came from a different employer in the previous year.

The variable Close to bankruptcy identifies the treatment period. Our definition of being close to bankruptcy is the time period from three to one years prior to the bankruptcy event. Figure 3 informs our choice of treatment period; the figure shows the share of workers leaving and joining firms as they approach bankruptcy. On average, the labor force appears stable until about four years prior to the onset of bankruptcy, and begins to contract thereafter. For treatment firms, Close to bankruptcy takes the value of one in the years t-3, t-2, and t-1 relative to the bankruptcy filing, and it takes a value of zero in the years t-4 and t-5. For the control firms, Close to bankruptcy is equal
to zero throughout. Our tests can thus be interpreted as difference-in-differences estimates, where we compare the probability of some workers leaving (or joining) distressed firms close to bankruptcy (t-3 to t-1) relative to “normal” times (t-5 and t-4), and relative to the control group of firms during the same time period.

Our measure of talent is based on the cognitive and non-cognitive test scores of males obtained from their military records: Talent is a dummy variable that takes the value of one if an individual has a combined score in the top five percent of the distribution of combined cognitive and non-cognitive skill scores at the firm-year level, and takes the value of zero otherwise. Approximately 0.7% of the military test-takers are volunteering females, who are excluded from regressions that employ a talent measure based on military test scores as an explanatory variable.14 Males with incomplete tests or missing test scores are also excluded. In all tests relying on military test scores, to adjust for the possibility of changes in test standards over time, we include fixed effects for the enlistment period as reported by the testing authority: 1969-1982, 1983-1997, 1998-2001, 2002-2008 and 2009-2010. For robustness, we construct three additional measures of talent based on, respectively, cognitive skills, leadership skills, and wages. We discuss these measures in Section VI and Appendix B.

$\ln(Years\ of\ education)$ is the natural logarithm of an individual’s years of schooling.15 $\ln(Wage)$ is defined as the natural logarithm of gross wage paid by the main employer.16 We define two variables measuring work experience: Experience in company is the number of years spent at the current firm, and Experience in industry is the number of years spent working in the current industry. Both variables are censored due to the start of available employment histories in 1990. Individual-level information on occupational tasks is available from 2001 onwards. This information is reported using the Swedish Standard Classification of Occupations 1996 (SSYK), which is the Swedish version of the International Standard Classification of Occupations (ISCO-88(COM)). We follow Tåg (2013) and construct a measure of hierarchy by mapping the

---

14 We do so because self-selected test takers may not be representative of the population. For example, they may be especially interested in pursuing a military career and their civilian career decisions may thus be less informative. Our results, however, remain unchanged if we include female test-takers in our sample.

15 More specifically, for each individual, Years of education is the number of scheduled schooling years required by an individual to obtain his/her highest earned degree, regardless of how many years it actually took the person to complete the degree (the latter information is unavailable): 12 years for a high school graduate, 15 years for an individual with a bachelor degree, etc.

16 In the year when an employee changes employment, the database may report more than one main source of income from more than one employer. To avoid mis-measurement of the wage variable, we take the maximum of the wage in the year the employee leaves a firm and the prior year. Similarly, when an employee joins a new firm, we use the maximum of the wage during the year an employee joins a firm and the subsequent year.
occupational codes into four different levels of hierarchy: CEOs and directors; senior staff; supervisors; and clerks and “blue-collar” workers.

We include industry \times year fixed effects in most of our specifications as a non-parametric way to control for time-varying unobservables at the industry level. Industry dummies are defined using the Swedish Standard Industrial classification (SNI). An SNI code consists of a letter and five digits. The SNI classification was changed twice during our sample period: in 2002 and 2007; we therefore map the industry codes prior to 2007 to SNI2007. We use the SNI codes to define the following industries: agriculture, manufacturing, transportation and utilities, construction and mining, finance, commerce, professional services, and other services.

In our analysis of leverage, we define Leverage as the sum of short- and long-term debt, divided by total assets. Tangibility is property, plant and equipment divided by total assets. Profitability is EBITDA divided by sales, Growth is defined as industry level sales growth over the next three years, and Firm age is the number of years since incorporation. In these firm-level regressions, our talent measure is High talent, a dummy variable that takes the value of one if the firm-year average of the combined cognitive and non-cognitive skill scores of the employees working in the firm in a given year is above the median value for all firms in the respective industry and year. In the leverage analysis we exclude financial firms and winsorize variables at the 1\textsuperscript{st} and 99\textsuperscript{th} percentiles.

We report summary statistics in Table 2. Panel A shows the variables of the sample that analyzes characteristics of workers in firms that experience a bankruptcy event during the time-period 2003-2011 (that is, the sample period is 1998-2010). Panel B shows summary statistics on worker characteristics for firms that experience a bankruptcy event during the time-period 2006-2011 (that is, the sample period is 2001-2010), for which we have occupational data for the workers during all five years leading up to bankruptcy. Both panels include workers from both treatment group and control group firms. Panel C shows summary statistics for the sample of firms used in the cross-sectional analysis of leverage. Panel D reports summary statistics for the sample of firms used in the leverage analysis around the 2001 labor law change. The samples from Panel C and D do not include worker characteristics and each observation corresponds to a firm-year. Finally, Panel E reports summary statistics for the individual characteristics of workers in the sample used to study the impact of the 2001 LIFO law change.

Figure 4 shows the talent allocation across industries in Sweden. Each panel in the figure represents a different talent measure: we use cognitive skill scores, combined cognitive and non-cognitive skill scores, leadership scores and average wages to compare the talent-intensity of different industries. The industries with the highest average scores are finance, professional services (which includes, among others, workers in IT, R&D, law, and consulting), and services (which includes workers in the education and health care sectors). Figure 5 reports the talent distribution across different levels of hierarchies. The figure shows that the two highest levels of
hierarchies tend to have more talented workers. Perhaps somewhat surprisingly, the third layer of hierarchy (“senior staff” members) tends to have more talented workers on average than the top layer (“CEOs and directors”). This is likely due to the relatively large number of small firms in the Swedish economy which tend to have flat hierarchical structures and less talented CEOs (see also Adams, Keloharju and Knupfer 2016).

III. Evolution of labor force composition around bankruptcy

III.A Composition of workers leaving distressed firms

We begin our empirical analysis by studying the evolution of the labor force composition in firms approaching bankruptcy. Specifically, we study the selection and characteristics of workers who leave and of those who join firms prior to bankruptcy events. Workers with different characteristics may have different preferences and incentives to leave (or join) firms approaching bankruptcy. Moreover, mobility of workers may be determined by the extent to which their human capital can be generally applied in the economy.

Among all workers who may be lost as firms approach bankruptcy, the loss of key talent is likely to be especially critical for the firms’ ability to create value.17 There are several reasons why the most talented workers may decide to leave the firm early, in anticipation of bankruptcy. One possibility is that these workers are better able to predict the likelihood of bankruptcy of their firm and may thus time their exit decision better. Furthermore, because more talented workers may be thought to have more influence on the performance of the firm, the cost they would face by being associated with a failed enterprise may be larger than for the average worker. On the other hand, talented workers may be better able to hedge bankruptcy risk. The availability of outside options may differ for high- and low-skilled workers. If more talented workers face a more liquid labor market, then staying in the firm longer could be less risky for them. The theoretical ambiguity that arises from the different economic forces makes it an interesting empirical question whether talented workers are indeed more likely to abandon distressed firms early. Figures 7 and 8 show graphical evidence of these effects at work. Figure 7 shows that, relative to control firms, the fraction of talented workers leaving increases as the firm approaches bankruptcy. Figure 8 further corroborates this evidence by showing that the fraction of highly talented workers who join the firms in the treatment group does not increase relative to control firms as firms approach bankruptcy, indicating an overall deterioration of the talent pool in treatment firms as they approach distress.

17 Abowd et al. (2005) find that the most skilled workers in a firm have a disproportionately positive impact on firm productivity and market value. Consistent with this notion, in Figure 6 we document an increase in the talent wage premium in Sweden over the last two decades.
We formally test whether proximity to bankruptcy is correlated with an increase in the probability that talented workers leave the firm by estimating the following specification:

\[ \text{Leave}_{it} = \alpha + \beta \cdot \text{Close to bankruptcy}_{it} + \theta \cdot (\text{Talent}_{it}) \cdot (\text{Close to bankruptcy}_{it}) + \mu \cdot \text{Talent}_{it} + X'_{it} \psi + \text{Close to bankruptcy}_{it} \cdot X'_{it} \delta + \Psi_{ft} + \epsilon_{it} \]

where \( \text{Leave} \) is a dummy variable that takes the value of one in the year the worker leaves the firm and zero otherwise, and \( \text{Close to bankruptcy} \) is a dummy variable that takes the value of one if the firm is in close proximity to bankruptcy (within three years) and zero otherwise. The coefficient \( \theta \) measures the increase in the probability of a highly talented worker leaving the firm as it approaches distress. We also include a set of individual worker characteristics that could affect the probability of leaving prior to bankruptcy events: matrix \( X \) in the regression equation above includes age, experience in the company, experience in the industry, log of years of education and log of wage. The coefficients \( \delta \) measure how being in close proximity to bankruptcy alters the selection of workers who decide to abandon the firm in these dimensions. In order to account for time-invariant differences in turnover across firms that may occur for reasons other than bankruptcy, the matrix \( \Psi \) includes firm fixed effects. \( \Psi \) also includes year-industry fixed effects that account for the evolution of the optimal composition of workers at the industry level. Our results are thus not driven by the possibility that, for example, industries where there are more bankruptcies are also those where more talented employees are leaving. Finally, we note that we cluster standard errors at the firm level.

Results are reported in Table 3. In column one, we find that being in close proximity to bankruptcy is associated with an increase in the probability of a worker leaving the firm, as the coefficient \( \beta \) is positive, and statistically and economically significant. This estimate implies that for firms in the \textit{treatment} group, the probability of workers leaving is 5.7% higher when firms are close to distress relative to normal times. In columns two and three we analyze the composition of workers who leave \textit{treatment} firms close to distress. An important pattern that emerges is the increase in the propensity of talented workers to leave as the firm approaches bankruptcy. In column two we find that male workers with high talent have a two percentage point higher probability of leaving the firm as it approaches bankruptcy than less “talented” workers. Relative to the average effect of 5.7%, this estimate implies that the most talented employees are 35% more likely to leave the firm approaching distress than the average employee.\(^{18}\) Moreover, we find that workers with more experience in the company—perhaps those that have invested more in firm-specific skills—are relatively less likely to leave as the firm approaches bankruptcy. Workers with more experience in the industry are more likely to do so.

In column 3 of Table 3 we repeat the previous analysis, but include a set of more stringent fixed effects: fixed effects for the level of hierarchy at which a worker is employed. The sample size here

\(^{18}\) Fahlenbrach, Low and Stulz (2015) find a qualitatively similar pattern for outside directors.
is reduced, as the hierarchy measure is only available from 2001 onwards (see Section II). Our results show that within a given hierarchical level, highly talented employees are significantly more likely to abandon the firm as it approaches distress. The results in column 3 alleviate concerns that what we are capturing is simply a reorganization of the activities of the firm where some hierarchical levels shrink more than others. Instead, our results imply that even after taking this potential confounding effect into account, firms that approach bankruptcy have a lower ability to retain their key talent in the organization.

III.B Voluntary vs. involuntary turnover

In periods of distress, firms facing financial constraints may have to dismiss their most talented employees, as they may also be the most expensive. Therefore, there may be the concern that what we are interpreting as workers voluntarily leaving soon-to-be bankrupt firms may instead reflect reorganization efforts initiated by the firm. We address this concern in two ways.

At the outset it should be noted that our findings cannot be driven by the desire of firms to fire their most expensive workers in times of distress, as we control for wages in our tests. We find similar results if we interact $\ln(Wage)$ with $Close\ to\ bankruptcy$ to allow firms to be especially cost-sensitive prior to bankruptcies.\(^{19}\) In other words, to be consistent with our results, if firms were choosing between two similarly paid workers to lay off, they would choose to let go of the more talented worker. Instead, the most natural explanation for our findings is that we are capturing the decision of talented workers to voluntarily leave firms.

To further distinguish between voluntary and involuntary turnover, we examine whether workers transition into unemployment after exiting the distressed firm. In the tests reported in Table 3, the variable Leave only identifies workers that leave to work for another firm; we do this to better capture voluntary turnover.\(^{20}\) To further address the concern that what we are interpreting as workers voluntarily abandoning the firm may instead reflect firms laying off their most skilled workers, we do an additional test. In columns 1 and 2 of Table 4, we repeat the analysis of Table 3, but focus on workers that leave the firm and become unemployed. Specifically, the dependent variable Unemployed takes a value of one only if a worker leaves and transitions into unemployment.\(^{21}\) We would expect that workers that become unemployed are more likely to have been laid off than those that abandon the firm and don’t experience a spell of unemployment. In column 1, we find that there is an increase in the number of workers of treated firms that transition to unemployment, relative to control firms. However, as can be seen in column 2, this

\(^{19}\) In order to save space, we do not report this additional specification. It is available upon request.

\(^{20}\) See Section II for more details on the sample construction and variable definitions. Given that some skilled workers may find alternative employment immediately after dismissal, we may still be capturing some involuntary turnover via our variable Leave.

\(^{21}\) We do not condition on the length of the unemployment spell, so a worker that is unemployed for a short period of time will still be counted as having transitioned to unemployment.
effect is not more pronounced for highly talented workers, as the coefficient on the interaction term \( \text{Close to bankruptcy} \times \text{Talent} \) is economically and statistically insignificant. This suggests that firms are not simply laying off their most talented employees when approaching distress.

Finally, our sharpest test addressing the question of whether the results in Table 3 reflect voluntary or involuntary turnover exploits a feature of the Swedish labor law that restricts firms in their ability to fire workers. When dismissing workers, firms with more than 10 employees have to follow a last-in-first-out (LIFO) rule that constrains their ability to unilaterally lay off the most skilled workers. In columns 3 and 4 of Table 4 we repeat our analysis for the subsample of firms with more than 10 employees. Because these firms are bound by LIFO rules that restrict their ability to select which workers to fire and which workers to retain, it is difficult to argue that firms simply fire the most talented workers as part of a reorganization around bankruptcy. The results are similar to those reported in Table 3. This evidence further strengthens our interpretation that the most skilled workers “jump ship”, as opposed to the view that organizations approaching bankruptcy have a reduced need for talent and as such fire highly-skilled employees.

In firms that are restricted by LIFO regulation, workers that are fired follow the inverse order in which they joined the firm. In contrast, voluntary exits may “jump the queue” and leave even if they were not in the order dictated by LIFO. We test whether talented workers are more likely to be the ones that “jump the queue” and leave “out of order”, that is, we test whether long-tenure talented employees are more likely to leave even before the firm dismisses employees with shorter tenure. Finding that talented workers are those more likely to not follow the LIFO order would be another piece of evidence pointing to these workers leaving voluntarily, instead of being fired by the firm. In columns 5 and 6 of Table 4 we construct the indicator variable \( \text{Jumped the queue} \) which takes the value of one if the worker leaves and deviates from the job separation order implied by the LIFO rule. The algorithm we use can be best understood using a simple example. Suppose that a firm has 100 employees and we observe that 20 employees leave the firm. Because we know the joining date of these employees, we can determine whether these job separations adhere to the LIFO rule or not. Any deviations from this rule would provide us with a proxy for voluntary departures. In these regressions we focus only on \( \text{treatment} \) firms—that is, firms that become bankrupt—and only retain workers in the sample that leave firms in the period \( t-3 \) to \( t-1 \) relative to bankruptcy to join other firms. We find that the most talented employees of the firm do not wait their turn to be fired. Instead they tend to leave sooner than what their tenure would predict if the firm was laying off workers according to a LIFO rule.

One worry that could arise is that LIFO is not enforced and, as such, \textit{de facto} it is not a restriction on firing. Anecdotal evidence suggests that deviating from LIFO rules is costly for firms and that
these rules affect firms’ human resources decisions. Further, we present evidence that the LIFO rule does indeed affect the firing decisions of firms. We examine a 2001 law change that exempted firms with 10 or fewer employees from LIFO rules. Until 2001, following the 1982 Employment Protection Act, all firms were required to follow a last-in-first-out (LIFO) policy if they wished to lay off workers. However, on January 1st, 2001, new legislation came into effect that relaxed this requirement for firms with less than 11 employees.

In Table 5, we test whether the relaxation of LIFO rules led to dismissals being less correlated with workers’ tenure in the company. If LIFO rules are binding, we expect that after they are relaxed firms would have greater flexibility in retaining the most recent employees and would lay off workers with longer tenure in the firm – in which case, the worker who was the last in is not necessarily the first out. We first examine this issue in a subsample of firms with 10 or fewer employees; that is, firms that become exempt from LIFO rules starting in 2001. In column one, we document that in general and consistent with LIFO rules, employees with shorter tenures are more likely to leave than workers with longer tenure. Moreover, the average firm tenure of workers who leave firms increases after 2001 for firms that become exempt from LIFO rules. We confirm this effect in column 2 when we focus on worker transitions to unemployment. These separations, where workers enter unemployment after leaving the firm, are those that are more likely to be dismissals and may thus provide a more direct test of the importance of LIFO rules. In columns 3 and 4, instead of restricting the analysis to firms with 10 employees or less, we also include firms above the threshold of 10 employees and test whether there is a differential effect between treated and control firms. Consistent with the notion that LIFO rules are a binding restriction limiting the ability of firms to select which workers to lay off, we find that after the reform, firms not bound by LIFO lay off more experienced workers relative to firms with more than 10 employees where LIFO remained in place.

Finally, if LIFO rules are limiting the choice set of firms in a meaningful way, we would expect firms to try to avoid them. In that regard, after the law change we would expect firms to keep the number of employees below the threshold of 10 employees in order to avoid triggering LIFO rules. Figure 9 provides evidence that this is indeed the case. While before 2001 there is a smooth distribution of firms around the size cutoff of 11 employees, after 2001 there is evidence of “bunching”, with the mass of firms right below the cutoff increasing and the mass of firms with 11 or more employees shrinking.

In sum, the evidence we provide in this subsection lends support to our interpretation that the effects documented in Table 3 are most consistent with high talent workers voluntarily abandoning firms that become financially distressed.

See, for example, the article “Storbolagen tappar talangerna i krisen” published by Veckans Affärer online on the 9th of October 2009 (http://www.va.se/nyheter/2009/09/10/storbolagen-tappar-talangerna-i-krisen/).
III.C Selection of workers joining distressed firms

Next, we turn to the analysis of which workers join firms approaching distress. If firms are not able to retain talent but are still able to attract it, the overall talent pool in the organization may be unaffected by the imminent threat of bankruptcy. In Table 6, we analyze the ability of firms that approach bankruptcy to attract highly talented workers, by estimating the following specification:

\[ \text{Join}_{ift} = \alpha + \beta \cdot \text{Close to bankruptcy}_{ft} + \theta \cdot (\text{Talent}_{ift}) \cdot (\text{Close to bankruptcy}_{ft}) + \mu \\cdot \text{Talent}_{ift} + X'_{ift}\gamma + \text{Close to bankruptcy}_{ft} \cdot X'_{ift}\delta + \Psi_{ft} + \epsilon_{ift} \]

This specification differs in two ways from the tests of Table 3. First, the dependent variable is an indicator that takes the value of one in the year the worker joins the firm and zero otherwise. Second, we exclude from matrix \( X \) the variable that measures experience in the firm, as by definition new joiners would have zero experience in the firm they join. We also add the variable Other municipality to test whether the firm is less likely to attract workers for whom the adjustment costs are larger; this variable is an indicator that is equal to one if a worker moves to a new municipality.

Results are reported in Table 6. The first important aspect to note in column one is that the estimate of \( \beta \) is now negative (although only marginally statistically significant), which implies that firms start having difficulties attracting employees as they approach bankruptcy. The estimate in column 1 implies that treatment firms have a 1.43% lower probability of a worker joining the firm close to bankruptcy relative to normal times. Additionally, we find that the characteristics of workers who join such firms also change. In particular, workers with more experience in the industry are more likely to join the firm. Consistent with the results in Brown and Matsa (2016) we find that firms approaching distress are less able to attract workers from distant geographic locations, for whom relocation may be too costly given the riskiness of the firm. However, regarding top talent, we find that being close to bankruptcy does not enhance the ability of firms to attract highly skilled individuals. Despite the loss of talent documented in Table 3, treatment firms are unable to replace the lost human capital by attracting highly skilled employees in sufficiently larger numbers. We find similar results when we add hierarchy fixed effects to the regression (column 3 of Table 6).

The fact that we do not find a decrease in the hiring rate of talented employees relative to less skilled workers for firms approaching distress is an additional piece of evidence against the notion that financially distressed firms choose to operate with lower levels of talent. If that were the case, firms would not only dismiss their most talented employees, they would also stop hiring talented employees. In fact, if firms were aiming to voluntarily reduce the number of talented workers they employ, the natural first step would be to stop hiring talent even before starting to lay off their most skilled workers. Instead, what we find is that firms keep hiring talented employees at the
same rate as less talented employees. Our results imply that even prior to bankruptcy, the pool of human capital available in the firm considerably deteriorates.

III.D Placebo test

Even though our treatment and control firms look very similar on observable characteristics (see Table 1), we cannot rule out the possibility that they are fundamentally different in terms of unobservables. To alleviate this concern, we conduct the following placebo test: we retain the composition of the treatment and control groups and estimate the same specifications as the ones used in Tables 3 and 6, but now conduct the analysis on the years t-8 to t-4 relative to bankruptcy. In these tests, we define the placebo treatment period to be the period t-6 to t-4 (instead of t-3 to t-1 as in our main analysis). That is, our main variable of interest Close to bankruptcy is modified and takes the value of one in years t-6, t-5 and t-4 relative to bankruptcy, and zero otherwise.

The idea underlying the test is the following. If treatment and control firms are different even in the absence of bankruptcy, we would expect to also find differences in the ability of treatment firms to attract and retain talent a number of years before bankruptcy, relative to control firms. On the other hand, if treatment and control firms are comparable absent treatment, we would expect to find no difference in the ability of treatment firms to attract and retain talent relative to the control group, when focusing on a period that is further away from bankruptcy.

In Table 7, we report the results of this placebo test. We find no evidence that, in the absence of the bankruptcy event, treatment and control firms behave differently with regard to retention (column 1) and attraction (column 2) of talent. This lends support to our identifying assumption that the control group provides a good counterfactual for the evolution of talent in treatment firms in the absence of bankruptcy.

IV. Labor fragility and capital structure

IV.A Economic versus financial distress

The analysis in the previous section provides evidence that labor may bring an added degree of fragility to the organization. As firms approach tumultuous times, key human capital leaves and, in doing so, may endanger the future of the company even further. However, the previous results may be driven by economic distress or by financial distress. The analysis so far does not distinguish between the two. If our results were solely driven by economic distress, the presence of highly mobile highly skilled workers should not affect capital structure. On the other hand, if what we are capturing is financial distress, a trade-off theory of capital structure would predict

---

23 This analysis is effectively testing the common trends assumption of our difference-in-difference test design.
that firms that face a higher ex-post risk of key employees leaving as the firm approaches distress should choose a more conservative capital structure ex-ante.\textsuperscript{24}

We test whether these forces shape financial decisions by analyzing the ex-ante capital structure choices of firms. Firms whose most talented employees are more likely to leave in times of financial distress face large (indirect) costs of financial distress and as such are expected to have lower leverage. In that sense, the employee composition of a firm and in particular a firm’s degree of reliance on highly skilled labor would be an additional factor shaping the financial policy of firms. We formally test whether talent intensity (and the associated labor fragility) at the firm level is a determinant of capital structure by estimating the following regression:

\[ \text{Leverage}_t = \alpha + \beta \cdot \text{High talent}_t + X'_t \gamma + \Psi_t + \epsilon_t \]

The matrix of controls \( X \) in these tests includes standard controls used in capital structure regressions: \( \text{Tangibility}, \text{Profitability}, \text{Ln}(\text{Assets}), \text{and Firm age} \). All regressors are lagged by one year. To capture investment opportunities, we also include the variable \( \text{Growth} \).\textsuperscript{25} Our firm-level talent measure is \( \text{High talent} \) which takes the value of one if the firm-year average of the combined cognitive and non-cognitive skill scores of the employees working in the firm in a given year is above the median value for all firms in the respective industry and year. The matrix \( \Psi \) includes year fixed effects to control for macroeconomic determinants of leverage, so our coefficients can be interpreted as cross-sectional comparisons.

Table 8 reports the results. In column 1 we regress \( \text{Leverage} \) on \( \text{High talent} \) and year fixed effects, and in column 2, we include additional controls. The results confirm the notion that the skill level of the labor force is an important determinant of leverage decisions. In both columns, leverage is negatively correlated with the average skill of the employees of the firm. If a firm is above the industry-year median of average firm talent as measured by \( \text{High talent} \), it is associated with a 0.36 percentage point decrease in leverage (column 2). Relative to the average level of leverage in the sample (21.3%), this represents a 2% decrease in leverage for the average firm.

To alleviate concerns that our results are driven by spurious correlation, we include in the estimation year fixed effects, as well as several controls for other important determinants of leverage. However, certain endogeneity concerns may remain. For example, it could be that firms with lower leverage attract more talented workers, and not that the dependence of the firm on this type of highly mobile workers is the driver of the choice of capital structure. In an effort to improve identification, we next turn to a quasi-experiment setting where we exploit exogenous

\textsuperscript{24} It should be noted that labor fragility during normal times may also have an effect on capital structure (Hart and Moore 1994). This channel is also consistent with our story.

\textsuperscript{25} Share price data are not available for a sufficient number of firms to include the asset market-to-book ratio in the regressions.
variation in the mobility of key employees and study how the financial leverage of affected firms responds.

**IV.B Impact of talent mobility on leverage: evidence from a 2001 labor law reform in Sweden**

In this section we use the implementation of a labor law reform in Sweden in 2001 as a source of exogenous variation for the mobility of talented workers, and analyze the response of Swedish firms in terms of their financial policies. As discussed in Section III.B, while prior to 2001 all firms were bound by LIFO rules, the 2001 reform exempted firms with 10 or fewer employees from this restriction. Importantly for our study, the political situation was such that until late in 2000 it was not clear whether the reform would be implemented and exactly which firms would be eligible to loosen the LIFO requirement. As such, we can think of this law change as being both exogenous and unanticipated by firms.

In our empirical analysis we exploit the timing of the law change to examine differential effects of the law on two groups—firms that have 10 or fewer employees (the “treatment” group) and firms that have more than 10 employees (the “control” group). Since we have no reason to believe that the labor market is segmented around the 10 employee threshold, both the groups will be affected by the law change. Thus, even though we refer to these groups as treatment and control groups, we acknowledge the slight abuse of terminology, but are cautious in interpreting our regression results below.

We restrict the sample to the 1999 to 2004 period. The years 1999 and 2000 are the baseline period and 2002, 2003 and 2004 are the treatment period (we exclude the year that the law was changed, 2001, from our analysis, to provide a clear before-after comparison of the effects of the law). We further restrict the sample to firms around the 10 employee threshold and focus on firms with at least 5 employees and at most 15 employees.

**Labor Mobility**

We start with the analysis of the impact of the relaxation of the LIFO rule in 2001 on the mobility of workers. Theory suggests that the relaxation of layoff restrictions would have the effect of increasing separations and increasing hires (e.g., Lazear 1990). It is natural to expect that a relaxation of layoff restrictions might lead to more layoffs. However, laxer labor regulation may also lead to an increase in the hiring rate, because the commitment associated with a new hire is lower when layoffs are less costly. In our setting, we would thus expect firms affected by the reform that experience a permanent reduction in layoff costs in 2001 to increase the rate of hiring.

---

26 See, for example, Lindbeck et al. (2006) and von Below and Thoursie (2010) for a discussion of the political economy of the law.
and firing after the implementation of the reform, relative to the control group of firms not affected by the reform.\footnote{The increase in labor mobility in treated firms could also spill over and impact the mobility of workers in control firms, which would bias our estimates towards zero.} We test this hypothesis by estimating the following OLS regression:

\[ Leave\ rate_{ft} = \beta_1 \cdot Post_t + \beta_2 \cdot Treated_f + \beta_3 \cdot Post_t \times Treated_f + X'_{ft} \gamma + \Psi_f + \epsilon_{ft} \]

where \( Leave\ rate_{ft} \) is the number of workers of firm \( f \) that leave the firm between \( t-1 \) and \( t \), divided by the total number of workers of firm \( f \) at \( t-1 \). The matrix of controls \( X \) includes lagged \( \text{Ln(Assets)} \), lagged \( \text{Tangibility} \), lagged \( \text{Profitability} \), and \( \text{Growth} \), as well as year fixed effects. The variable \( Post \) takes the value of one in the years 2002 to 2004 and zero in the years 1999 and 2000. \( Treated \) is an indicator variable that is one if the firm is at or below the 10 employee threshold in 2000, and zero if in the year 2000 the firm has more than 10 employees. Additionally, the matrix \( \Psi \) includes a set of firm fixed effects that controls for firm-level time invariant characteristics. Results are reported in Panel A of Table 9. Column 1 shows that in treated firms, more workers leave after 2001 relative to the baseline period. In column 2 we redo the analysis, but focus on highly skill-intensive firms. Specifically, we keep only firms with an average sum of cognitive and non-cognitive skill scores at or above the 50th percentile of average cognitive and non-cognitive skills in the sample used in column 1. We can see that the coefficient \( \beta_3 \) is significant and positive in both specifications; this suggests that after the law change, treated firms are more likely to have workers leaving compared to firms not affected by the law change. The magnitudes in column 2 are larger than those in column 1, which suggests that this effect may be particularly pronounced for talent-intensive firms.

Next, we analyze whether after 2001, treated firms increase the worker hiring rate. We employ the same regression specification as before when studying the effect of the law change on job separations, but use the variable \( \text{Join rate}_{ft} \) as the dependent variable. \( \text{Join rate}_{ft} \) is defined as the number of workers that join firm \( f \) between \( t-1 \) and \( t \), divided by the number of workers of firm \( f \) in \( t-1 \). Results are reported in columns 3 and 4 of Table 9. In column 3, we report the difference-in-differences coefficient \( \beta_3 \) for the full sample. In column 4 we focus on the companies above the median of average sum of cognitive and non-cognitive skills (that is, talent-intensive firms). We find that the coefficient of interest is positive in both columns, implying that treated firms hire more workers after 2001, relative to the control group. Moreover, the effect seems to be somewhat stronger for firms that rely more heavily on talent, as the coefficient \( \beta_3 \) in column 4 is larger than that in column 3. Our results are also in line with previous studies that have found qualitatively similar effects of changes in labor laws on labor mobility in Sweden (von Below and Thoursie 2010) and in the US (e.g., Autor et al. 2007).

A potential concern with the analysis in Panel A of Table 9 is that we use normalized changes as dependent variables. While economically meaningful, the use of these variables implies that one
more worker changing firm represents a larger share of workers in smaller (treated) firms than in larger (control) firms. This raises the concern that a mechanical relationship may be driving our findings in Panel A of Table 9. We therefore confirm our results on the increase in labor mobility in treated firms after 2001 by using an alternative specification: we perform our analysis in a sample where each unit of observation is an employee-count—year. That is, we aggregate workers from all firms into employee-sized bins, and run difference-in-differences regressions with this aggregated sample. These specifications, which are not subject to the above-mentioned concern and are reported in the appendix to conserve space, confirm our findings (see Table B-4 in Appendix B).

**Leverage**

Having established that the 2001 change in Swedish labor law increased mobility of talented employees, we next turn to the analysis of the impact of this law on firms' financial policies. In light of our previous results, we conjecture that an increase in the mobility of talented workers would increase the fragility of organizations. As a response to the heightened labor fragility they face, we would expect such firms to reduce their leverage after the law change. The effects would be different for our so-called “treated” and “control” groups. To test this differential response, we employ the following regression model:

\[
\text{Leverage}_{ft} = \beta_1 \cdot \text{Post}_t + \beta_2 \cdot \text{Treated}_f + \beta_3 \cdot \text{Post}_t \times \text{Treated}_f + X_{ft}'\gamma + \Psi_f + \varepsilon_{ft}
\]

As before, leverage is defined as short term plus long term debt divided by assets. We report the results of these tests in Panel B of Table 9. In column 1, we first analyze the impact of the 2001 law change on leverage in the whole sample and find a negative, albeit insignificant coefficient. Next, in column 2, we restrict the analysis to firms that rely more heavily on talent. As in Panel A, we define such firms as those at or above the median of average firm talent in the sample. We find that on average, treated firms that rely more on talent decrease leverage after 2001.

There are several channels through which the 2001 LIFO law change could impact leverage of treated firms. On the one hand, by removing the LIFO constraint, the law gave firms with less than 10 employees more operational flexibility. Such operational flexibility should potentially increase leverage (Simintzi et al. 2014). On the other hand, because this law change increased the liquidity of the labor market, post 2001, treated firms became more exposed to the risk of loss of talent. In addition, the labor law change, by relaxing firing restrictions, could have also impacted the unemployment risk for workers of treated firms. While the direction of the effect on unemployment risk is not clear,28 a potential increase in unemployment risk could lower leverage (Agarwal and Matsa 2013). In sum, the 2001 labor law change increases the labor fragility of treated firms, while the effect on unemployment risk for the workers of these firms is more ambiguous.

---

28 More labor market liquidity (conditional on being fired) may lower unemployment risk. On the other hand, a possible increase in the likelihood of getting fired could increase unemployment risk.
Because an increase in unemployment risk and an increase in labor fragility have directionally similar effects on leverage, the results in columns 1 and 2 of Panel B could be partly driven by a change in unemployment risk, instead of an increase in labor fragility.

To separate the leverage effects of the increased labor fragility from effects stemming from possible increases in unemployment risk, we analyze the evolution of leverage in control firms. These firms with more than 10 employees are always bound by LIFO rules throughout the sample period. On the one hand, workers in control firms are expected to benefit from improved outside opportunities that resulted from the LIFO law change. These firms should thus be affected by an increase in labor fragility. At the same time, control firms did not experience a change in their ability to fire workers. Thus, unchanged firing rules and better outside options through more liquid labor markets should reduce unemployment risk, since fired workers are likely to experience shorter unemployment spells. The opposing predictions coming from the two mechanisms—labor fragility and unemployment risk—allow us to test which mechanism is driving our findings. An increase in leverage would be suggestive of the unemployment insurance channel while a decrease in leverage suggests a fragility channel.

We present the results in columns 3 and 4 of Panel B of Table 9. While in column 3 we study all firms, in column 4 we focus the analysis on the firms that rely more heavily on talent. By removing the year dummies from the regression and estimating the coefficient on the variable Post, we measure the effect of the law change on control firms. A negative coefficient on Post would suggest that the negative effect on leverage stemming from the increase in labor fragility outweighs the positive effect on leverage originating from the reduction in unemployment risk. We find a negative coefficient on the variable Post, which indicates that control firms lower their leverage after the 2001 LIFO law change. The coefficient of -0.47 (column 4) implies a decrease in leverage of 4%, relative to the average in the sample of talent-intensive firms. In sum, the results reported in Panel B of Table 9 suggest that the decrease in leverage we document after the 2001 LIFO law change is unlikely to be driven by an increase in unemployment risk and more likely reflects the negative impact of labor fragility on leverage. In Section V.C, we conduct additional tests in a setting in which labor fragility increased, and where unemployment risk was unlikely to have changed. These tests corroborate the negative effect of labor fragility on leverage.

V. External validity

---

29 Indeed, an analysis of the data confirms that after 2001, the length of unemployment spells decreased.
30 As a caveat, we note that our argument relies on the ability to identify the effect of the LIFO law change on control firms, measured by the coefficient on the variable Post. To estimate that coefficient, we cannot control for changes in the overall macro environment through year fixed effects. Therefore, we cannot rule out the possibility that macro effects were driving the changes in leverage in control firms after the law change.
A concern that may arise with our analysis so far is that our results could be specific to the setting we examine: the importance of labor fragility for firms may be particularly pronounced in Sweden. For example, this could be the case because firms in Sweden are on average smaller than those in the US, or because of different institutional features of the two countries. To ensure that we are not capturing a “Sweden effect”, in this section, we extend our analysis to the United States. Our main setting employs US state-level changes in the enforceability of non-compete agreements as a quasi-experiment to study the effect of restrictions on the mobility of key employees on firms’ capital structure decisions. This setting enables us to test the following hypothesis: as the risk of loss of talented workers is reduced (because of changes in courts’ enforcement of non-compete clauses), firms respond by increasing their leverage. Such effects would be consistent with our Sweden-based evidence.

V.A Variables and data sources

Non-compete clauses (also called covenants not to compete) are contractual restrictions in employment contracts aimed at limiting an employee’s ability to work for a competing firm or start a competing business (e.g., Kaplan and Stromberg 2003; Marx, Strumsky, and Fleming 2009). The extent to which these clauses are enforceable differs across US states. The main explanatory variable in our tests is a time-varying state-level index measuring the extent to which non-compete clauses are enforced by courts in a given US state. The index (henceforth NCC index) is from Bird and Knopf (2014), who apply the same methodology to the index construction as Garmaise (2011) and extend his index from 1992 back to 1976; the index is thus available for the years 1976-2004. The NCC index is based on a series of twelve questions analyzed by Malsberger (2008) that characterize the strength of each US state’s enforcement of non-compete clauses. Higher index values imply that a state’s courts enforce more restrictive covenants not to compete. While it can theoretically range from zero to twelve, the index in practice takes values ranging from zero (e.g., California) to nine (Florida after 1996) during our sample period.

Non-compete clauses are primarily expected to matter in industries with high potential labor mobility of key employees. Therefore, following Garmaise (2011), we study how the enforceability

---

31 For example, while California invalidates most types of non-compete clauses in employment contracts, most states’ courts enforce some forms of covenants not to compete. Moreover, there are considerable differences between US states with regard to the types of clauses that are enforceable. For example, state courts differ regarding the extent to which restrictions on the dealings of former employees with former clients of the firm are permitted, the required compensation for non-compete clauses, and the geographic and temporal scope of such clauses.

32 Figure C-1 in the appendix plots the NCC index for the eight US states that changed the enforceability of non-compete clauses. For example, Florida increased the enforceability in 1990 as well as in 1996. The figure shows that there is not only considerable cross-sectional variation in index values—and thus in the extent of non-compete agreement enforceability—across states, but also meaningful time-series variation within states.
of non-compete agreements interacts with In-state competition, defined as in-state industry sales divided by total industry sales, where industry is defined at the two-digit NAICS level.\textsuperscript{33}

To examine if labor fragility explains firm leverage in the cross-section of US firms, we construct the variable Labor fragility. We first map Swedish industries into the Fama-French 12 (henceforth FF12) industry classification. To measure fragility, for each industry and year, we divide the number of Swedish workers with a combined cognitive and non-cognitive test score of at least 16 (out of possible 18) by the number of test takers.\textsuperscript{34} We then match this measure to US firms based on their FF12 industry classification. Labor fragility is available from 1990 onwards (limited by the availability of the Swedish micro-data, which starts in that year).

All our other variables are from Compustat North America. We use the following leverage measures as dependent variables: Book leverage is the sum of long-term and short-term debt divided by total assets; Market leverage is total debt divided by the sum of total debt and market equity. We employ the following control variables: \(\text{Ln(Tobin’s } Q)\) is the natural logarithm of the market-to-book ratio, computed as the ratio of (book value of assets plus market value of equity minus book value of common equity) to the book value of assets; \(\text{Ln(Assets)}\) is the natural logarithm of total assets; Profitability is EBITDA divided by sales; Tangibility is net property, plant and equipment divided by total assets; Firm age is the age of the firm in years.\textsuperscript{35}

Following convention, we exclude firms from the financial activities sector (NAICS 52 and 53), as well as utilities (NAICS 22) from the sample. We winsorize all variables (except the NCC index and Firm age) at the 99\textsuperscript{th} percentile; Profitability, In-state competition, \(\text{Ln(Tobin’s } Q)\), and \(\text{Ln(Assets)}\) are also winsorized at the first percentile (the minimum of the other explanatory variables is zero). Summary statistics on these variables are reported in Table 10.

\textbf{V.B Labor fragility and leverage in the cross-section of US firms}

We first test whether our measure of labor fragility constructed using Swedish micro-data helps to understand the cross-section of leverage decisions of US firms.\textsuperscript{36} We analyze the relationship between leverage and labor fragility in the cross-section of US firms using the following model:

\textsuperscript{33} We use historical industry information; if not available, we replace missing historical NAICS with current NAICS. We use the location of firms’ headquarters in order to assign the relevant state.
\textsuperscript{34} To reduce the effect of compositional changes in the sample, we focus on thirty-year-old individuals in each year. We find similar results with different talent-based measures (such as measures based on cognitive or non-cognitive skills only, or wage-based measures).
\textsuperscript{35} More specifically, Firm Age is the number of years the firm has been on Compustat with a non-missing stock price (prcc_f); we set age equal to missing for years prior to a firm’s first non-missing stock price.
\textsuperscript{36} Figure C-2 in the Appendix examines this relationship graphically. For the sample period 1990-2005, the figure plots the average annual book leverage of US firms by FF12 industry against the industry-level labor fragility measure and shows a linear fit. There is a robustly negative association between leverage and labor fragility at the industry level.
\[ \text{Leverage}_{ft} = \alpha + \beta \cdot \text{Labor fragility}_{ft} + X'_{ft} \gamma + \Psi_t + \epsilon_{ft} \]

where \textit{Leverage} is \textit{Book leverage} or \textit{Market leverage} in different specifications. The matrix \( X \) denotes a set of control variables (\( \text{Ln(Assets)} \), \( \text{Profitability} \), \( \text{Ln(Tobin’s Q)} \), \( \text{Tangibility} \), and \( \text{Firm age} \)) and \( \Psi_t \) denotes year fixed effects. All explanatory variables are lagged. In these regressions, we measure industry \( (i) \) at the FF12 level; as our coefficient of interest is \( \beta \), we cluster standard errors at the FF12 industry level. Our estimates, reported in Table 11, suggest an economically large and statistically significant negative relationship between labor fragility and leverage. The estimate of -0.96 in column 1 implies that an increase in fragility by one standard deviation is associated with a reduction in leverage as a fraction of the book value of assets by about 3.6 percentage points; given a sample average of book leverage of 27.9% (see Table 10), this corresponds to a reduction in leverage of about 13%.

\textbf{V.C Evidence from exogenous changes in enforcement of non-compete clauses across US states}

We hypothesize that a firm chooses a more conservative capital structure if it faces a higher risk of rival firms poaching its most talented employees, or talented employees leaving to pursue other opportunities. As we documented in the previous section with Swedish data, this risk may be particularly severe when the firm is in financial distress. Consequently, we expect that a reduction in the risk of loss of talented employees should be reflected in higher debt ratios. To identify this effect, we use plausibly exogenous variation in the enforceability of non-compete clauses in employment contracts across US states and years. The idea is that the risk of poaching and loss of talented employees can be (partly) mitigated by non-compete clauses in employment contracts, if such clauses are enforced by the applicable state’s courts. Garmaise (2011) shows that the state-level non-compete enforceability laws indeed reduce executive mobility.

Our main methodology is similar to Garmaise (2011), who argues that non-compete clauses typically have limited geographical scope and hence, that the extent to which state enforcement of non-compete clauses matters for firms depends on the competition faced within a given state. One can therefore expect the effect of the enforceability of non-compete clauses to matter primarily in cases where firms face considerable in-state competition.\footnote{The variable \textit{In-state competition} proxies for the labor mobility of key employees within the industry. To capture the notion that key workers’ mobility may transcend industry boundaries, we also employ a measure of inter-industry worker mobility based on Donangelo (2014). This measure of labor mobility captures the extent to which skills are portable across industries. Furthermore, we also examine whether changes in the enforceability of non-compete clauses matter differently in industries with different degrees of labor fragility. We discuss leverage tests with these alternative mobility measures in Appendix C.}

Because the change in enforcement of non-compete clauses is unlikely to affect the unemployment risk of workers, as there is no change in the ability of firms to lay-off workers, this test provides additional evidence
that we are capturing the effect of labor fragility on leverage as opposed to the effect of unemployment risk on leverage. In that regard, it adds to the discussion in Section IV.B.

We estimate the following firm-level regressions:

\[
\text{Leverage}_{ft} = \theta \cdot (NCC\ index_{st}) \cdot (\ln - state\ competition_{jst}) + \beta \cdot NCC\ index_{st} + \varphi \cdot \ln - state\ competition_{jst} + \Psi_f + \gamma_f + \epsilon_{ft}
\]

where the subscripts \(f, j, s,\) and \(t\) denote firm, industry, state, and year, respectively. \(\theta\) is our coefficient of interest, given by the interaction of the NCC index with In-state competition. As dependent variables, we use Book leverage and Market leverage. Matrix \(X\) includes the control variables \(\ln(\text{Assets}), \text{Profitability}, \text{Tangibility},\) and \(\ln(\text{Market-to-Book}).\) Matrix \(\Psi\) includes firm fixed effects, to control for state- and firm-level time-invariant unobserved factors; \(\Psi\) also includes year-industry fixed effects to control for time-varying industry shocks.\(^{38}\) All our explanatory variables are lagged by one year. We cluster standard errors at the state level. Our sample period is 1976-2005 (determined by the availability of the NCC index from Bird and Knopf 2014 and Garmaise 2011).

Table 12 reports the results of the leverage tests. We find that while firms in competitive industries have lower leverage (consistent with the findings in, for example, Valta 2012), tougher enforcement of non-compete clauses by state courts mitigates this effect. In terms of economic magnitudes, consider an increase in the NCC index from zero to four; this corresponds to a change from no enforceability of non-compete clauses to the median level of enforceability encountered in the sample. According to the estimates in column one, with other variables kept constant at their sample means, an increase in the NCC index from zero to four increases debt by 1.03\% of total assets; average debt in the sample is 28\% of assets, so this implies an increase in leverage of about 4\%. Column two examines the effect on market leverage. A change in the NCC index by four units increases market leverage by 1.1\%.\(^{39}\) We confirm the robustness of this result in Appendix C, where we measure the liquidity of external labor markets employing: i) the proxy for inter-

---

\(^{38}\) Due to the inclusion of firm and industry x year fixed effects we do not include Firm age in these time-series tests, as it is perfectly collinear.

\(^{39}\) Our results on leverage are consistent with recent work by Klasa, Ortiz-Molina, Serfling, and Srinivasan (2015). The authors use the staggered recognition of the Inevitable Disclosure Doctrine (IDD) by US state courts as an exogenous event that increases the protection of a firm’s trade secrets by preventing the firm’s workers who know its trade secrets from working for a rival firm. They find that after the passage of IDDs, firms located in affected states increase their leverage. The adoption by state courts of the IDD also lowers mobility of talent in the affected states; see Png and Samila (2015) for evidence of the effect of these trade secret laws on the mobility of engineers and scientists. Therefore, while their focus is on the risk of loss of intellectual property to rivals, the findings in Klasa, Ortiz-Molina, Serfling, and Srinivasan (2015) are also consistent with our hypothesis that firms that rely more on talent operate with more conservative capital structures.
industry labor mobility presented in Donangelo (2014), and ii) a measure of labor fragility constructed using Swedish micro-data.

V.D Effect of enforcement of non-compete clauses on firm value

A natural question to ask in the context of our analysis is how labor fragility affects firm value. While we cannot answer this question conclusively, we can examine whether unilaterally enhancing the contract space for firms through the possibility of restricting the mobility of key employees has a discernible effect on firm value. The effect is theoretically ambiguous. On the one hand, there may be a decrease in firm value due to a reduction in the threat of key employees leaving; a threat that keeps the moral hazard of the top management in check (see Acharya, Myers, and Rajan 2012). On the other hand, a reduction in labor fragility through increased enforceability of non-compete clauses should limit exposure of firms to inefficient talent loss in times of distress, thereby increasing firm value. We test the effect of the change in enforceability of non-compete clauses on firm value in column 1 of Table 13. The results show that in highly competitive industries, an increase in the enforceability of non-compete clauses increases firm value as measured by Tobin’s Q. In such industries, the scope for bottom-up corporate governance (Landier, Sauvagnat, Sraer and Thesmar 2013) is limited, as product market competition fulfils that role (Giroud and Mueller 2010). In that case, limiting labor mobility has a positive impact on firm value, as it reduces the scope for inefficient talent exits. On the other hand, when product market competition is weak, the possibility of talent leaving has an important governance role and reducing mobility negatively impacts firm value.

In order to further investigate whether labor fragility can act as an internal governance force in organizations, we also analyze whether the impact of restricting labor mobility on firm value depends on other corporate governance forces. In particular, we divide our sample into two groups: firms that operate in a state that adopted business combination laws ($BC=1$) and firms whose state did not adopt such legislation ($BC=0$). When external governance is relatively strong, there is likely little room for internal governance to create value, in which case exogenous reductions in labor fragility are expected to have positive valuation effects. However, when external governance is weak, the implicit (and credible) threat that key employees may abandon the firm in the event of distress may incentivize the management to keep to the straight and narrow, and, thus, exogenous reductions of labor fragility may have negative value consequences.

---

40 Despite the fact that we could not use the LIFO law change in Sweden to study this question due to the small number of publicly traded firms around the 10 employees threshold, the US setting provides us with the opportunity to extend our analysis in this direction.

41 Business combination laws are laws that limit the effectiveness of the market for corporate control as a governance mechanism by imposing obstacles to takeovers. These anti-takeover laws have been used in the past to study how governance affects managerial actions and value (e.g., Bertrand and Mullanaithan 2003, and, more recently, Gormley and Matsa 2015).
We thus expect that increases in the enforceability of non-compete clauses lead to an increase in value for firms incorporated in states without business combination laws, while it is expected to lead to a decrease in value for firms for which the anti-takeover laws are applicable.

The results are presented in columns 2 and 3 of Table 13. Column 2 shows the impact of increasing the enforceability of non-compete clauses on Tobin’s Q when business combination laws are not present. The positive coefficient implies that in this scenario, when external governance is stronger, reducing labor fragility leads to an increase in firm value. On the other hand, the estimates in column 3 show that when external governance is weak, reducing mobility and consequently reducing labor fragility may negatively impact value. In this case, the threat of losing key employees could act as an important governance mechanism that keeps the moral hazard of top management in check. Limiting the credibility of such threats could have a net negative impact on firm value.

VI. Robustness and additional discussion

In our main results we use a combination of cognitive and non-cognitive skills as our main measure of talent. Our results are robust to several different ways of measuring talent. In particular, we find very similar results when using only cognitive skills scores or only leadership scores to measure worker talent. Furthermore, even though the measures of skill based on military test scores are accurate and economically meaningful, they are only available for males. To address this limitation and to extend our analysis to include females, we also repeat our tests using a talent measure based on wages (which can be interpreted as the market price of talent). See Appendix B for a replication of our previously discussed findings with these alternative measures of talent.

In our results in Section III, we cannot distinguish whether workers leave because they anticipate bankruptcy from the possibility that the loss of talented workers is what causes the firm to go bankrupt. However, we note that both mechanisms are consistent with our interpretation that reliance on talent exposes firms to fragility and represents a labor cost of financial distress that firms take into account in capital structure decisions.

Finally, our results on leverage are consistent with two interpretations. First, consistent with a trade-off model of capital structure, the present value of labor costs of financial distress may lead

---

42 We use the state of incorporation to match the information on business combination laws to firms. As we lack information on state of incorporation for some firms, the combined number of observations in columns 2 and 3 is lower than in column 1 of Table 13.

43 This suggests that our results are not driven by equally weighting cognitive and non-cognitive skills in our measure of talent.

44 In these tests we can also include a dummy variable for gender in the matrix of individual characteristics and study whether gender affects the propensity to leave or join distressed firms.
firms to optimally demand less leverage. Second, financiers may not supply debt to firms that rely heavily on talent. In an attempt to evaluate the relative strength of the two potential channels, we use our US sample to study the effect of changes in enforceability of non-compete agreements on leverage decisions of two groups of firms: financially constrained firms and firms that are not constrained. If an adjustment in leverage is primarily observed in the group of financially unconstrained firms, then it is more plausible that the first mechanism dominates; in contrast, if one observes that leverage is mainly adjusted by financially constrained firms, this would indicate that changes in labor fragility (resulting from changes in the enforceability of non-compete agreements) primarily affect firms’ debt capacity. We use three synthetic indices that measure financial constraints (based on work by, respectively, Kaplan and Zingales 1997; Whited and Wu 2002; and Hadlock and Pierce 2010) to group firms into constrained and unconstrained sets. We discuss these results in detail in Table C-2 of Appendix C. Overall, the results show that following an increase in the enforceability of non-compete clauses, it is only financially unconstrained firms that increase leverage, while there is no change in leverage in the group of financially constrained firms. This lends support to the trade-off theory argument.

VII. Conclusion

Modern corporations rely heavily on talented employees. In the new enterprise, human capital surpasses physical capital in terms of its importance for value creation and as a source of competitive advantage (Rajan and Zingales 2000). However, the reliance on human capital and the high mobility of skilled labor also exposes firms to an added degree of fragility.

In this paper, we study labor-induced fragility in corporations by analyzing the evolution of the labor force composition as firms approach bankruptcy. We document a decrease in the ability of firms to retain talent as they approach distress. We then study how labor fragility affects financial policies. We find that the dependence of firms on highly skilled labor is associated with lower leverage in the cross-section of firms. Using a change in Swedish labor law as a source of exogenous variation for labor mobility, we find that when mobility of talented workers increases, leverage decreases. This setting confirms our cross-sectional results and allows us to interpret our findings in a causal manner. To ensure that our findings are not unique to the Swedish setting, we also employ a quasi-experiment that uses exogenous and staggered changes in the enforceability of non-compete clauses in labor contracts across US states. These state-level non-compete enforceability rules have been shown to affect key talent mobility. In this US setting, we find that as the risk of losing talented workers is reduced, firms increase their leverage.

Overall, the results in this paper suggest that firms’ reliance on human capital may involve an additional level of risk related to the possibility of loss of key talent. Although we focus on the risk that talented employees bring to the firm, there is a bright side to this fragility too. Because talented workers may threaten to leave the firm, they keep the moral hazard of the management
in check (see Acharya et al. 2012). We show that when other governance measures are not in place, talent fragility may act as a value-creating governance mechanism.\textsuperscript{45}

By establishing a link between labor-induced fragility, capital structure, and firm value, our findings highlight the importance of studying the interplay between finance and labor, a topic that remains a fruitful area for future research.

\textsuperscript{45} Similar to the incentive role of financial fragility in banks (Diamond and Rajan 2001).
References


Graham, John R., Hyungseob Kim, Si Li, and Jiaping Qiu, 2013, “Human capital loss in corporate bankruptcy”, working paper.


Lloyds Risk Index, 2011.


Silva, Rui C., 2016, “Internal labor markets, wage convergence and investment”, working paper.


Table 1: Summary statistics – comparing matched treated and control firms
This table presents the summary statistics for the characteristics of the firms in the treatment and control groups at $t-5$ relative to the start of the bankruptcy. The first three columns refer to the control group, while columns 4 to 6 refer to the treatment group. In the last column we report the p-value from the t-test of the difference between the means of the characteristics of firms in treatment and control groups. Firms in the treatment group are those that file for bankruptcy between 2003 and 2011. The variables, as well as the matching procedure used to construct the control group, are described in detail in Section II of the paper.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Control</th>
<th>Treatment</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Obs.</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>Ln(Assets)</td>
<td>3,470</td>
<td>8.5592</td>
<td>1.1508</td>
</tr>
<tr>
<td>Return on assets</td>
<td>3,470</td>
<td>0.0898</td>
<td>0.2216</td>
</tr>
<tr>
<td>Leverage</td>
<td>3,470</td>
<td>0.1000</td>
<td>0.2908</td>
</tr>
<tr>
<td>Number of employees</td>
<td>3,470</td>
<td>24.0902</td>
<td>112.9628</td>
</tr>
<tr>
<td>Avg. skill</td>
<td>3,470</td>
<td>9.7133</td>
<td>1.7842</td>
</tr>
<tr>
<td>Avg. wage</td>
<td>3,470</td>
<td>1976.2940</td>
<td>684.5137</td>
</tr>
<tr>
<td>Avg. age (not matched)</td>
<td>3,470</td>
<td>38.1062</td>
<td>6.3096</td>
</tr>
<tr>
<td>Avg. experience in company (n. m.)</td>
<td>3,470</td>
<td>5.3451</td>
<td>4.8122</td>
</tr>
<tr>
<td>Avg. experience in industry (n. m.)</td>
<td>3,470</td>
<td>7.2770</td>
<td>4.8580</td>
</tr>
<tr>
<td>Avg. years of education (n. m.)</td>
<td>3,470</td>
<td>10.9991</td>
<td>1.1893</td>
</tr>
</tbody>
</table>

Table 2: Summary statistics – Swedish setting
This table reports summary statistics for the different samples used in the paper. Panel A presents the summary statistics for individuals included in our analysis of the selection of workers who leave or join firms approaching bankruptcy in Sweden; Panel B presents summary statistics for individuals in the sub-sample used when controlling for hierarchy fixed effects. Panel C reports the summary statistics for the firms in our study of capital structure. Panel D reports the summary statistics for the characteristics of firms in the sample used to study the impact of the 2001 LIFO law change. Finally, Panel E reports summary statistics for the characteristics of workers in the sample used to study the impact of the 2001 LIFO law change. The construction of the different samples and variables are explained in Section II of the paper.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Control</th>
<th>Treatment</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
<td>Obs.</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>Leave</td>
<td>361,474</td>
<td>0.2052</td>
<td>0.4038</td>
</tr>
<tr>
<td>Join</td>
<td>361,474</td>
<td>0.2423</td>
<td>0.4285</td>
</tr>
<tr>
<td>Talent</td>
<td>361,474</td>
<td>0.1325</td>
<td>0.3390</td>
</tr>
<tr>
<td>Age</td>
<td>361,474</td>
<td>35.4999</td>
<td>10.1390</td>
</tr>
<tr>
<td>Experience in company</td>
<td>361,474</td>
<td>5.3451</td>
<td>4.8122</td>
</tr>
<tr>
<td>Experience in industry</td>
<td>361,474</td>
<td>7.2770</td>
<td>4.8580</td>
</tr>
<tr>
<td>Ln(Year of education)</td>
<td>361,474</td>
<td>2.4283</td>
<td>0.1602</td>
</tr>
<tr>
<td>Ln(Wage)</td>
<td>361,474</td>
<td>7.5454</td>
<td>0.7994</td>
</tr>
<tr>
<td>Female</td>
<td>361,474</td>
<td>0.3062</td>
<td>0.4609</td>
</tr>
</tbody>
</table>
Table 2: Summary statistics [continued]


<table>
<thead>
<tr>
<th>Variable</th>
<th>Military test takers</th>
<th>All individuals</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Obs.</td>
<td>Mean</td>
</tr>
<tr>
<td>Leave</td>
<td>228,208</td>
<td>0.1719</td>
</tr>
<tr>
<td>Join</td>
<td>228,208</td>
<td>0.1908</td>
</tr>
<tr>
<td>Talent</td>
<td>228,208</td>
<td>0.1240</td>
</tr>
<tr>
<td>Age</td>
<td>228,208</td>
<td>37.6361</td>
</tr>
<tr>
<td>Experience in company</td>
<td>228,208</td>
<td>6.1817</td>
</tr>
<tr>
<td>Experience in industry</td>
<td>228,208</td>
<td>8.5868</td>
</tr>
<tr>
<td>Ln(Years of education)</td>
<td>228,208</td>
<td>2.4370</td>
</tr>
<tr>
<td>Ln(Wage)</td>
<td>228,208</td>
<td>7.7164</td>
</tr>
<tr>
<td>Female</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel C: Firm characteristics - full sample (1999-2008)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs.</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leverage</td>
<td>230,275</td>
<td>0.2126</td>
<td>0.1992</td>
</tr>
<tr>
<td>High talent</td>
<td>230,275</td>
<td>0.4934</td>
<td>0.5000</td>
</tr>
<tr>
<td>Tangibility</td>
<td>230,275</td>
<td>0.3098</td>
<td>0.2517</td>
</tr>
<tr>
<td>Profitability</td>
<td>230,275</td>
<td>0.0723</td>
<td>0.1011</td>
</tr>
<tr>
<td>Size</td>
<td>230,275</td>
<td>9.1057</td>
<td>1.4192</td>
</tr>
<tr>
<td>Firm age</td>
<td>230,275</td>
<td>19.0752</td>
<td>15.6791</td>
</tr>
<tr>
<td>Growth</td>
<td>230,275</td>
<td>5.2846</td>
<td>4.2349</td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th>Variable</th>
<th>Full sample</th>
<th>High talent firms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Obs.</td>
<td>Mean</td>
</tr>
<tr>
<td>Leave rate</td>
<td>72,217</td>
<td>0.3770</td>
</tr>
<tr>
<td>Join rate</td>
<td>72,217</td>
<td>0.3792</td>
</tr>
<tr>
<td>Leverage</td>
<td>72,217</td>
<td>0.1510</td>
</tr>
<tr>
<td>Size</td>
<td>72,217</td>
<td>8.5179</td>
</tr>
<tr>
<td>Tangibility</td>
<td>72,217</td>
<td>0.2475</td>
</tr>
<tr>
<td>Profitability</td>
<td>72,217</td>
<td>0.0753</td>
</tr>
<tr>
<td>Growth</td>
<td>72,217</td>
<td>8.0377</td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th>Variable</th>
<th>Full sample</th>
<th>Treated firms’ workers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Obs.</td>
<td>Mean</td>
</tr>
<tr>
<td>Leave</td>
<td>2,351,000</td>
<td>0.2276</td>
</tr>
<tr>
<td>Unemployed</td>
<td>2,351,000</td>
<td>0.0743</td>
</tr>
<tr>
<td>Post</td>
<td>2,351,000</td>
<td>0.5127</td>
</tr>
<tr>
<td>Treated</td>
<td>2,351,000</td>
<td>0.5710</td>
</tr>
<tr>
<td>Age</td>
<td>2,351,000</td>
<td>36.8765</td>
</tr>
<tr>
<td>Experience in company</td>
<td>2,351,000</td>
<td>3.9712</td>
</tr>
<tr>
<td>Experience in industry</td>
<td>2,351,000</td>
<td>5.2280</td>
</tr>
<tr>
<td>Ln(Years of education)</td>
<td>2,351,000</td>
<td>2.3837</td>
</tr>
<tr>
<td>Female</td>
<td>2,351,000</td>
<td>0.3523</td>
</tr>
</tbody>
</table>
Table 3: Selection of workers that leave firms approaching distress

This table shows the composition of workers that leave firms approaching distress. We report coefficients from estimating the following OLS regression:

\[
\text{Leave}_{it} = \alpha + \beta \cdot \text{Close to bankruptcy}_{ft} + \theta \cdot \left( \text{Talent}_{it} \right) \cdot \left( \text{Close to bankruptcy}_{ft} \right) + \mu \cdot \text{Talent}_{it} + \gamma \cdot X'_{it} \\
+ \delta \cdot \text{Close to bankruptcy}_{ft} \cdot X'_{it} + \Psi_f + \varepsilon_{it}
\]

where \( \text{Leave} \) is a dummy variable that takes the value of one in the year the worker leaves the firm to work for another employer, and zero otherwise. \( \text{Close to bankruptcy} \) is a dummy variable that takes the value of one if the firm is in close proximity to bankruptcy (within three years), and zero otherwise. \( \text{Talent} \) is based on the combined cognitive and noncognitive scores. The matrix \( X \) includes \( \text{Age} \), \( \text{Experience in company} \), \( \text{Experience in industry} \), \( \ln(\text{Years of education}) \) and \( \ln(\text{Wage}) \). \( \Psi \) includes firm fixed effects and year-industry fixed effects. The regressions also include military enrollment period fixed effects. The sample used in column 1 and 2 spans the period 1998–2010. In column 3 we add hierarchy fixed effects to the specifications in column 2; due to data availability our sample period in column 3 is 2001–2010. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>\text{Close to bankruptcy}</td>
<td>0.0567***</td>
<td>0.0230</td>
<td>0.0702</td>
</tr>
<tr>
<td>\text{Close to bankruptcy} \times \text{Talent}</td>
<td>0.0201***</td>
<td>0.0177***</td>
<td></td>
</tr>
<tr>
<td>\text{Talent}</td>
<td>0.0113***</td>
<td>0.0109***</td>
<td></td>
</tr>
<tr>
<td>\text{Close to bankruptcy} \times \text{Age}</td>
<td>-0.0031***</td>
<td>-0.0027***</td>
<td></td>
</tr>
<tr>
<td>\text{Age}</td>
<td>-0.0022**</td>
<td>-0.0035***</td>
<td></td>
</tr>
<tr>
<td>\text{Close to bankruptcy} \times \text{Experience in company}</td>
<td>-0.0088***</td>
<td>-0.0066***</td>
<td></td>
</tr>
<tr>
<td>\text{Experience in company}</td>
<td>-0.0045***</td>
<td>0.0059***</td>
<td></td>
</tr>
<tr>
<td>\text{Close to bankruptcy} \times \text{Experience in industry}</td>
<td>0.0022***</td>
<td>-0.0008</td>
<td></td>
</tr>
<tr>
<td>\text{Experience in industry}</td>
<td>0.0008</td>
<td>-0.0134</td>
<td></td>
</tr>
<tr>
<td>\text{Close to bankruptcy} \times \ln(\text{Years of education})</td>
<td>-0.0011</td>
<td>0.018</td>
<td></td>
</tr>
<tr>
<td>\ln(\text{Years of education})</td>
<td>0.0388***</td>
<td>0.0475***</td>
<td></td>
</tr>
<tr>
<td>\ln(\text{Wage})</td>
<td>-0.0706***</td>
<td>-0.0440***</td>
<td></td>
</tr>
<tr>
<td>\text{Firm and (Industry \times Year) F.E.}</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>\text{Enrollment Period F.E.}</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>\text{Hierarchy F.E.}</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>361,474</td>
<td>361,474</td>
<td>228,208</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.154</td>
<td>0.176</td>
<td>0.142</td>
</tr>
</tbody>
</table>
Table 4: Selection of workers that leave firms approaching distress: voluntary vs. involuntary departures

This table shows the composition of workers that leave firms approaching distress. We report coefficients from estimating the following OLS regression:

$$Y_{it} = \alpha + \beta \cdot \text{Close to bankruptcy}_{it} + \theta \cdot (\text{Talent}_{it}) \cdot (\text{Close to bankruptcy}_{it}) + \mu \cdot \text{Talent}_{it} + \gamma \cdot X'_{it}$$

+ $\delta \cdot \text{Close to bankruptcy}_{it} \cdot X'_{it} + \Psi_{it} + \varepsilon_{it}$

In columns 1 and 2 the dependent variable is $\text{Unemployed}$, a dummy variable equal to one if a worker transitions to unemployment when leaving a firm. In columns 3 and 4 the dependent variable is $\text{Leave}$, a dummy variable equal to one in the year a worker leaves a firm to work for another employer. In columns 5 and 6 the dependent variable is $\text{Jumped the queue}$, a dummy variable equal to 1 if a worker leaves a firm and his tenure in the firm is higher than the tenure of the n:th worker ranked by tenure, where n is the number of workers leaving the firm that year. $\text{Close to bankruptcy}$ is a dummy variable that takes the value of one if the firm is in close proximity to bankruptcy (within three years), and zero otherwise. $\text{Talent}$ is based on the combined cognitive and noncognitive scores. The matrix $X$ includes $\text{Age}$, $\text{Experience in company}$, $\text{Ln(Years of education)}$, and $\text{Ln(Wage)}$. $\Psi$ includes firm fixed effects and year-industry fixed effects. The regressions also include military enrollment period fixed effects. In columns 1 to 4 the sample period spans 1998–2010. The sample underlying columns 3 to 6 only includes employees of firms with more than 10 workers. In columns 5 and 6 only workers leaving firms close to bankruptcy are included. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Close to bankruptcy</td>
<td>0.0086***</td>
<td>0.0606***</td>
<td>0.0452***</td>
<td>0.0576</td>
<td>0.0002</td>
<td>-0.0002</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.019)</td>
<td>(0.006)</td>
<td>(0.045)</td>
<td>(0.003)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Close to bankruptcy $\times$ Talent</td>
<td>-0.0169***</td>
<td>0.0151***</td>
<td>0.0212**</td>
<td>0.0195*</td>
<td>-0.0006</td>
<td>-0.0029***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.003)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.000)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Talent</td>
<td>0.0014***</td>
<td>-0.0024***</td>
<td>0.0022***</td>
<td>-0.0022***</td>
<td>-0.0006</td>
<td>-0.0029***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Close to bankruptcy $\times$ Age</td>
<td>-0.0007***</td>
<td>0.0008</td>
<td>0.0419***</td>
<td>-0.0027***</td>
<td>-0.0006</td>
<td>-0.0029***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Experience in company</td>
<td>0.0005</td>
<td>0.0049***</td>
<td>0.0419***</td>
<td>0.0027***</td>
<td>0.0277***</td>
<td>0.0654***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.007)</td>
<td>(0.005)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Close to bankruptcy $\times$ Ln(Years of education)</td>
<td>-0.0185**</td>
<td>-0.0129</td>
<td>-0.0080</td>
<td>-0.0294***</td>
<td>-0.0974***</td>
<td>0.0512***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.018)</td>
<td>(0.025)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Ln(Years of education)</td>
<td>0.9426***</td>
<td>0.0974***</td>
<td>0.0517***</td>
<td>0.0567***</td>
<td>0.0608***</td>
<td>0.0656***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Ln(Wage)</td>
<td>-0.0974***</td>
<td>-0.0974***</td>
<td>0.0512***</td>
<td>0.0512***</td>
<td>0.0512***</td>
<td>0.0512***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.010)</td>
</tr>
</tbody>
</table>

Firm, (Industry $\times$ Year) F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
Enrollment Period F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
Observations | 361,474 | 361,474 | 308,312 | 308,312 | 29,542 | 29,542 |
R-squared | 0.080 | 0.105 | 0.143 | 0.174 | 0.239 | 0.320 |
Table 5: **LIFO and tenure of departing employees**

This table analyzes the impact of the relaxation of the LIFO rule in 2001 on the tenure of workers that leave. In columns 1 and 2 we report coefficients from estimating the following OLS model:

\[ Y_{it} = \beta_1 Post_t + \beta_2 \text{Experience in company}_t + \gamma X_{it} + \Psi_f + \varepsilon_{it} \]

In columns 3 and 4 we add the variable Treated and interactions of Treated with all other variables. In columns 1 and 3, the dependent variable is Leave, a dummy variable that takes the value of one in the year the worker leaves the firm to work for another employer, and zero otherwise. In columns 2 and 4, the dependent variable is Unemployed, a dummy variable that takes the value of one in the year the worker leaves the firm and transitions to unemployment, and zero otherwise. Post is a dummy variable indicating the period after the law change. Treated is a dummy variable that takes the value of one if the firms had 10 or fewer employees in 2000 and takes the value of zero otherwise. The matrix X includes Age, Experience in company, Experience in industry, Ln(Years of education) and interactions of these variables with the variable Post. In columns 3 and 4 the matrix X also includes interactions of Treated with all other variables. \( \Psi \) includes firm fixed effects and year fixed effects. The sample period is 1999 to 2004 with the year of the law change, 2001, excluded; the sample includes firms with 5–10 workers in columns 1 and 2, and firms with 5–15 workers in columns 3 and 4. For further details on the variable construction and the sample see the data section of the paper (Section II). Robust standard errors clustered at the firm level are reported in parentheses. Statistical significance at 1%, 5% and 10% is marked with ***, ** and * respectively.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>(1) Leave</th>
<th>(2) Unemployed</th>
<th>(3) Leave</th>
<th>(4) Unemployed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Post × Experience in company</td>
<td>0.0043*** (0.000)</td>
<td>0.0056*** (0.000)</td>
<td>0.0010** (0.000)</td>
<td>0.0049*** (0.000)</td>
</tr>
<tr>
<td>Post × Treated × Experience in company</td>
<td></td>
<td></td>
<td>0.0032*** (0.001)</td>
<td>0.0007** (0.000)</td>
</tr>
<tr>
<td>Experience in company</td>
<td>-0.0145*** (0.000)</td>
<td>-0.0164*** (0.000)</td>
<td>-0.0135*** (0.000)</td>
<td>-0.0171*** (0.000)</td>
</tr>
<tr>
<td>Treated × Experience in company</td>
<td></td>
<td></td>
<td>-0.0009** (0.000)</td>
<td>0.0007** (0.000)</td>
</tr>
<tr>
<td>Post × Treated</td>
<td></td>
<td></td>
<td>-0.0315* (0.017)</td>
<td>-0.0133 (0.009)</td>
</tr>
</tbody>
</table>

| Controls | Yes | Yes | Yes | Yes |
| Firm F.E. | Yes | Yes | Yes | Yes |
| Year F.E. | Yes | Yes | Yes | Yes |
| Firms Treated & Control | 1,342,263 | 1,342,263 | 2,351,000 | 2,351,000 |
| R-squared | 0.161 | 0.100 | 0.196 | 0.121 |
Table 6: Selection of workers that join firms approaching distress

This table shows the composition of workers that join firms approaching distress. We report coefficients from estimating the following OLS regression:

\[
\text{Join}_{it} = \alpha + \beta \cdot \text{Close to bankruptcy}_{it} + \theta \cdot (\text{Talent}_{it}) \cdot \text{(Close to bankruptcy}_{it}) + \mu \cdot \text{Talent}_{it} + \gamma \cdot X'_{it} + \delta \cdot \text{Close to bankruptcy}_{it} \cdot X'_{it} + \Psi_{it} + \varepsilon_{it}.
\]

Join, the dependent variable, is a dummy variable that takes the value of one in the year the worker joins the firm, and zero otherwise. Close to bankruptcy is a dummy variable that takes the value of one if the firm is in close proximity to bankruptcy (within three years), and zero otherwise. Talent is based on the combined cognitive and noncognitive scores. The matrix X includes Age, Experience in industry, Ln(Years of education), Ln(Wage) and Other municipality (a dummy equal to one if a worker moves to a new municipality). Ψ includes firm fixed effects and year-industry fixed effects. The regressions also include military enrollment period fixed effects. The sample used in column 1 and 2 spans the period 1998–2010. In column 3 we add hierarchy fixed effects to the specifications in column 2; due to data availability our sample period in column 3 is 2001–2010. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Close to bankruptcy</td>
<td>-0.0143*</td>
<td>-0.1218***</td>
<td>-0.1503***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.042)</td>
<td>(0.049)</td>
</tr>
<tr>
<td>Close to bankruptcy × Talent</td>
<td>0.0032</td>
<td>0.0011</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.007)</td>
<td></td>
</tr>
<tr>
<td>Talent</td>
<td>-0.0063**</td>
<td>-0.0037</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
<td></td>
</tr>
<tr>
<td>Close to bankruptcy × Age</td>
<td>-0.0004</td>
<td>-0.0003</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.0010***</td>
<td>0.0015***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>Close to bankruptcy × Experience in industry</td>
<td>0.0056***</td>
<td>0.0050***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Experience in industry</td>
<td>-0.0362***</td>
<td>-0.0299***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Close to bankruptcy × Ln(Years of education)</td>
<td>0.0310</td>
<td>0.0392*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.022)</td>
<td></td>
</tr>
<tr>
<td>Ln(Years of education)</td>
<td>-0.0375***</td>
<td>-0.0039</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.010)</td>
<td></td>
</tr>
<tr>
<td>Close to bankruptcy × Other municipality</td>
<td>-0.0174**</td>
<td>-0.0066</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.012)</td>
<td></td>
</tr>
<tr>
<td>Other municipality</td>
<td>0.1088***</td>
<td>0.0836***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.007)</td>
<td></td>
</tr>
<tr>
<td>Ln(Wage)</td>
<td>-0.0580***</td>
<td>-0.0531***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.004)</td>
<td></td>
</tr>
</tbody>
</table>

Firm and (Industry × Year) F.E. | Yes | Yes | Yes |
Enrollment Period F.E. | Yes | Yes | Yes |
Hierarchy F.E. | No | No | Yes |
Observations | 361,474 | 361,474 | 228,208 |
R-squared | 0.197 | 0.278 | 0.236 |
Table 7: Placebo test

In this table, we replicate the analysis of Table 3 and Table 6 but for a placebo event period. More specifically, we keep the composition of treatment and control groups but define the sample period as $t-8$ to $t-4$ relative to bankruptcy. Further, the variable Close to bankruptcy takes a value of one in periods $t-6$ to $t-4$ (instead of $t-3$ to $t-1$ as in our main analysis) for firms that eventually go bankrupt. In column 1 of this table we present the placebo analysis of the composition of workers leaving firms in the treatment group. In column 2 we present the placebo results of the composition of workers that join treatment firms. The regressions include military enrollment period fixed effects. The sample used spans the period 1998–2007. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>(1) Leave</th>
<th>(2) Join</th>
</tr>
</thead>
<tbody>
<tr>
<td>Close to bankruptcy</td>
<td>-0.0019(0.052)</td>
<td>-0.0730(0.054)</td>
</tr>
<tr>
<td>Close to bankruptcy $\times$ Talent</td>
<td>0.0007(0.006)</td>
<td>0.0090(0.006)</td>
</tr>
<tr>
<td>Talent</td>
<td>0.0154***(0.003)</td>
<td>-0.0114***(0.003)</td>
</tr>
<tr>
<td>Close to bankruptcy $\times$ Age</td>
<td>-0.0002(0.000)</td>
<td>-0.0003(0.001)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.0021***(0.000)</td>
<td>0.0010***(0.000)</td>
</tr>
<tr>
<td>Close to bankruptcy $\times$ Experience in company</td>
<td>-0.0004(0.001)</td>
<td></td>
</tr>
<tr>
<td>Experience in company</td>
<td>-0.0093***(0.001)</td>
<td></td>
</tr>
<tr>
<td>Close to bankruptcy $\times$ Experience in industry</td>
<td>0.0009(0.001)</td>
<td>0.0053***(0.002)</td>
</tr>
<tr>
<td>Experience in industry</td>
<td>0.0013*(0.001)</td>
<td>-0.0434***(0.001)</td>
</tr>
<tr>
<td>Close to bankruptcy $\times$ Ln(Years of education)</td>
<td>0.0032(0.019)</td>
<td>0.0155(0.019)</td>
</tr>
<tr>
<td>Ln(Years of education)</td>
<td>0.0668***(0.012)</td>
<td>-0.0290*(0.014)</td>
</tr>
<tr>
<td>Close to bankruptcy $\times$ Other municipality</td>
<td>-0.0226(0.016)</td>
<td></td>
</tr>
<tr>
<td>Other municipality</td>
<td>0.1157***(0.010)</td>
<td></td>
</tr>
<tr>
<td>Ln(Wage)</td>
<td>-0.1004***(0.003)</td>
<td>-0.0400***(0.003)</td>
</tr>
</tbody>
</table>

Firm and (Industry $\times$ Year )F.E. Yes Yes
Enrollment Period F.E. Yes Yes
Observations 245,573 245,573
R-squared 0.141 0.330
Table 8: Labor fragility and leverage
This table shows the relationship between labor fragility and leverage. We report coefficients from estimating the following OLS model on the sample of Swedish firms:

\[
\text{Leverage}_{ft} = \alpha + \beta \cdot \text{High talent}_{ft} + X'_{ft}\gamma + \varepsilon_{ft}
\]

*High talent* is based on the firm-year average combined cognitive and noncognitive test scores and is equal to one if the value is above the median in the respective industry and year. All specifications include lagged *Tangibility*, lagged *Profitability*, lagged *Ln(Assets)*, lagged *Firm age* and *Growth* as controls, as well as year fixed effects (see matrix \( X \) in the equation above). The sample and variable construction is discussed in the data section of the paper (Section II). Robust standard errors clustered at the firm level are reported in parentheses. Statistical significance at 1%, 5% and 10% is marked with ***, ** and * respectively.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High talent</td>
<td>-0.0211***</td>
<td>-0.0036**</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Tangibility</td>
<td>0.3685***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td></td>
</tr>
<tr>
<td>Profitability</td>
<td>-0.1829***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td></td>
</tr>
<tr>
<td>Ln(Assets)</td>
<td>-0.0023***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Firm Age</td>
<td>-0.0005***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>Growth</td>
<td>0.0009***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>Year F.E.</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>230,275</td>
<td>230,275</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.003</td>
<td>0.193</td>
</tr>
</tbody>
</table>
Table 9: Impact of relaxation of LIFO rule on labor mobility and leverage
This table analyzes the impact of the relaxation of the LIFO rule in 2001 on the mobility of workers and financing decisions by firms. Panel A analyzes the impact on labor mobility and Panel B analyzes the impact on leverage. We report coefficients from estimating the following OLS model:

\[ Y_{ft} = \beta_1 Post_t + \beta_2 Treated_f + \beta_3 Post_t \times Treated_f + \gamma X'_{ft} + \psi_f + \varepsilon_{ft} \]

In columns 1 and 2 of Panel A, the dependent variable is Leave rate, defined as the number of workers of firm \( f \) that leave the firm between \( t-1 \) and \( t \) divided by the total number of workers of firm \( f \) at \( t-1 \). In columns 3 and 4 of Panel A, the dependent variable is Join rate, defined as the number of workers of firm \( f \) that join the firm between \( t-1 \) and \( t \), divided by the total number of workers of firm \( f \) at \( t-1 \). In Panel B, the dependent variable is Leverage. Post is a dummy variable indicating the period after the law change. Treated is a dummy variable that takes the value of one if the firms had 10 or fewer employees in 2000 and takes the value of zero otherwise. Odd-numbered columns report the results for the full sample of firms while even-numbered columns report the results for highly skill-intensive firms. We define the latter type of firms as those that are at or above the 50th percentile of the distribution of a firm-averaged talent measure (which is based on combined cognitive and non-cognitive test scores). All specifications include lagged Tangibility, lagged Profitability, lagged Ln(Assets), and Growth as controls, as well as year and firm fixed effects. The sample period is 1999 to 2004 with the year of the law change, 2001, excluded. The sample consists of firms with 5–15 workers. For further details on the variable construction and the sample see the data section of the paper (Section II). Robust standard errors clustered at the firm level are reported in parentheses. Statistical significance at 1%, 5% and 10% is marked with ***, ** and * respectively.

### Panel A: Labor mobility

<table>
<thead>
<tr>
<th>Sample</th>
<th>Leave rate</th>
<th>Join rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1) (2) (3) (4)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1) (2) (3) (4)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1) (2) (3) (4)</td>
<td></td>
</tr>
<tr>
<td>Post × Treated</td>
<td>0.0137** 0.0263*** 0.0705*** 0.0841***</td>
<td>(0.006) (0.009) (0.006) (0.009)</td>
</tr>
<tr>
<td>Ln(Assets)</td>
<td>0.0126* 0.0246** -0.0450*** -0.0346***</td>
<td>(0.007) (0.010) (0.007) (0.011)</td>
</tr>
<tr>
<td>Tangibility</td>
<td>-0.0469** -0.0649** 0.0657*** 0.0721**</td>
<td>(0.020) (0.032) (0.021) (0.033)</td>
</tr>
<tr>
<td>Profitability</td>
<td>-0.0934*** -0.0874*** 0.1118*** 0.1193***</td>
<td>(0.017) (0.024) (0.017) (0.026)</td>
</tr>
<tr>
<td>Growth</td>
<td>0.0003 0.0021 0.0013* 0.0017</td>
<td>(0.001) (0.001) (0.001) (0.001)</td>
</tr>
<tr>
<td>Firm and Year F.E.</td>
<td>Yes Yes Yes Yes</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>72,217 31,835 72,217 31,835</td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.711 0.689 0.716 0.693</td>
<td></td>
</tr>
</tbody>
</table>

### Panel B: Leverage

<table>
<thead>
<tr>
<th>Sample</th>
<th>Leverage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4)</td>
</tr>
<tr>
<td></td>
<td>(1) (2) (3) (4)</td>
</tr>
<tr>
<td></td>
<td>(1) (2) (3) (4)</td>
</tr>
<tr>
<td></td>
<td>(1) (2) (3) (4)</td>
</tr>
<tr>
<td>Post</td>
<td>-0.0094*** -0.0047*</td>
</tr>
<tr>
<td>Post × Treated</td>
<td>-0.0016 -0.0058* -0.0014 -0.0056*</td>
</tr>
<tr>
<td>Ln(Assets)</td>
<td>0.0298*** 0.0232*** 0.0273*** 0.0214***</td>
</tr>
<tr>
<td>Tangibility</td>
<td>0.2062*** 0.1870*** 0.2093*** 0.1893***</td>
</tr>
<tr>
<td>Profitability</td>
<td>-0.0951*** -0.0809*** -0.0925*** -0.0789***</td>
</tr>
<tr>
<td>Growth</td>
<td>0.0004 0.0008*** 0.0001 0.0002</td>
</tr>
<tr>
<td>Firm F.E.</td>
<td>Yes Yes Yes Yes</td>
</tr>
<tr>
<td>Year F.E.</td>
<td>Yes Yes No No</td>
</tr>
<tr>
<td>Observations</td>
<td>72,217 31,835 72,217 31,835</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.865 0.859 0.865 0.859</td>
</tr>
</tbody>
</table>

43
Table 10: Summary statistics–US setting

*Book leverage* is the sum of long-term and short-term debt divided by total assets; *Market leverage* is total debt divided by the sum of total debt and market equity. *Labor fragility* is constructed as follows: using Swedish micro-data, for each FF12 industry and year, we first divide the number of workers with a combined cognitive and non-cognitive test score of at least 16 (out of possible 18) by the number of test takers in a given industry and year; we then merge these data into the US sample using the industry assignment (FF12 codes) of US firms. *Ln*(Tobin’s Q) is the natural logarithm of the market-to-book ratio, computed as the ratio of (book value of assets plus market value of equity minus book value of common equity) to the book value of assets; *NCC index* is a time-varying state-level index that measures the extent to which non-compete clauses are enforced by courts in a given US state. *In-state competition* is in-state industry sales divided by total industry sales, where industry is defined at the two-digit NAICS level. *Ln*(Assets) is the natural logarithm of total assets; *Profitability* is EBITDA divided by sales; *Tangibility* is net property, plant and equipment divided by total assets. *Firm age* is the age of the firm in years, calculated as the number of years the firm has been on Compustat with a non-missing stock price (prcc_f); we set age equal to missing for years prior to a firm’s first non-missing stock price. *WW-index* is a financial constraints index based on Whited and Wu (2002); *KZ-index* is an index measuring financial constraints based on a regression in Kaplan and Zingales (1997) as used in Lamont, Polk, and Sa-Requejo (2001); *HP-index* is an index measuring financial constraints, based on Hadlock and Pierce (2010).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs.</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Book leverage</td>
<td>119,175</td>
<td>0.2790</td>
<td>0.3173</td>
</tr>
<tr>
<td>Market leverage</td>
<td>117,899</td>
<td>0.2647</td>
<td>0.2564</td>
</tr>
<tr>
<td>Labor fragility</td>
<td>71,765</td>
<td>0.0489</td>
<td>0.0372</td>
</tr>
<tr>
<td>Ln(Tobin’s Q)</td>
<td>127,237</td>
<td>0.4978</td>
<td>0.6783</td>
</tr>
<tr>
<td>NCC index</td>
<td>127,904</td>
<td>3.8264</td>
<td>2.1547</td>
</tr>
<tr>
<td>In-state competition</td>
<td>127,904</td>
<td>0.0546</td>
<td>0.0822</td>
</tr>
<tr>
<td>Ln(Assets)</td>
<td>127,904</td>
<td>4.2461</td>
<td>2.1981</td>
</tr>
<tr>
<td>Profitability</td>
<td>127,904</td>
<td>-0.4890</td>
<td>2.9900</td>
</tr>
<tr>
<td>Tangibility</td>
<td>127,904</td>
<td>0.2981</td>
<td>0.2265</td>
</tr>
<tr>
<td>Firm age</td>
<td>127,904</td>
<td>10.3771</td>
<td>9.4458</td>
</tr>
<tr>
<td>WW-index</td>
<td>121,866</td>
<td>-0.2056</td>
<td>0.1347</td>
</tr>
<tr>
<td>KZ-index</td>
<td>120,819</td>
<td>-5.3497</td>
<td>23.9816</td>
</tr>
<tr>
<td>HP-index</td>
<td>127,904</td>
<td>-2.6707</td>
<td>0.9844</td>
</tr>
</tbody>
</table>
Table 11: **Labor fragility and the cross-section of firm leverage in the US**

This table shows the relationship between labor fragility and firm leverage. We report coefficients from estimating the following OLS model on the sample of US firms:

\[
Y_{ft} = \theta \cdot \text{Labor fragility}_{it} + X'_{ft}\gamma + \Psi_t + \epsilon_{ft}
\]

where \(Y_{ft}\) is the dependent variable for firm \(f\) in fiscal year \(t\). We use as dependent variable *Book leverage* in column 1, and *Market leverage* in column 2. \(i\) denotes the industry, defined at the Fama-French 12 industry level, and \(s\) denotes the state. \(\Psi_t\) is a vector containing year fixed effects. \(X'_{ft}\) is a matrix containing the following control variables: \(\text{Ln(Assets)}, \text{Profitability}, \text{Tangibility}, \text{Ln(Tobin's Q)}\) and *Firm age*. We lag all explanatory variables by one year. The sample spans 1990–2005. Robust standard errors clustered at the Fama-French 12 industry level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>(1) Book leverage</th>
<th>(2) Market leverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor fragility</td>
<td>-0.9580***</td>
<td>-0.9567***</td>
</tr>
<tr>
<td></td>
<td>(0.155)</td>
<td>(0.115)</td>
</tr>
<tr>
<td>Ln(Assets)</td>
<td>-0.0185*</td>
<td>0.0022</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Profitability</td>
<td>-0.0047</td>
<td>-0.0013</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Ln(Tobin’s Q)</td>
<td>0.0552***</td>
<td>-0.1084***</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Tangibility</td>
<td>0.2910***</td>
<td>0.1876***</td>
</tr>
<tr>
<td></td>
<td>(0.068)</td>
<td>(0.051)</td>
</tr>
<tr>
<td>Firm age</td>
<td>0.0008</td>
<td>-0.0004</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Year F.E.</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>71,765</td>
<td>71,296</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.075</td>
<td>0.199</td>
</tr>
</tbody>
</table>

45
Table 12: Enforcement of non-compete agreements and leverage in the US
This table shows the relationship between labor fragility and firm leverage. We report coefficients from estimating the following OLS model on the sample of US firms:

\[ Y_{ft} = \theta \cdot (\text{NCC index}_{st}) \cdot (\text{In-state competition}_{ist}) + \beta \cdot \text{NCC index}_{st} + \psi \cdot \text{In-state competition}_{ist} + X'_{ft} \gamma + \Psi_{ft} + \varepsilon_{ft} \]

where \( Y_{ft} \) is the dependent variable for firm \( f \) in fiscal year \( t \). We use as dependent variable Book leverage in column 1, and Market leverage in column 2. \( i \) denotes the industry, defined at the two-digit NAICS level, and \( s \) denotes the state. \( \Psi_{ft} \) is a matrix containing firm fixed effects and industry \( \times \) year fixed effects. \( X'_{ft} \) is a matrix containing the following control variables: \( \text{Ln(Assets)} \), Profitability, Tangibility, and \( \text{Ln(Tobin’s Q)} \). We lag all explanatory variables by one year. The sample spans 1976–2005. Robust standard errors clustered at the state level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>(1) Book leverage</th>
<th>(2) Market leverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCC index * In-state competition</td>
<td>0.0466***</td>
<td>0.0484***</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>NCC index</td>
<td>-0.0033</td>
<td>-0.0004</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>In-state competition</td>
<td>-0.1733***</td>
<td>-0.1210**</td>
</tr>
<tr>
<td></td>
<td>(0.055)</td>
<td>(0.060)</td>
</tr>
<tr>
<td>LN(Assets)</td>
<td>-0.0130**</td>
<td>0.0279***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Profitability</td>
<td>-0.0007</td>
<td>-0.0006**</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>LN(Tobin’s Q)</td>
<td>0.0205***</td>
<td>-0.0681***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Tangibility</td>
<td>0.2381***</td>
<td>0.1899***</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.013)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm F.E.</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry ( \times ) year F.E.</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>119,175</td>
<td>117,899</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.589</td>
<td>0.679</td>
</tr>
</tbody>
</table>
Table 13: **Enforcement of non-compete agreements and firm value**

This table reports regressions that estimate the relationship between labor fragility and firm value. In column 1 we report coefficients from estimating the following OLS model on the sample of US firms:

\[
\ln(Tobin's\ Q)_{ft} = \theta \cdot (\text{NCC index}_{ist}) \cdot (\text{In-state competition}_{ist}) + \beta \cdot \text{NCC index}_{ist} + \psi \cdot \text{In-state competition}_{ist} + X'_{ft} \gamma + \Psi_{ft} + \varepsilon_{ft}
\]

In columns 2 and 3 we report coefficients from estimating the following OLS model:

\[
\ln(Tobin's\ Q)_{ft} = \theta \cdot (\text{NCC index}_{ist}) + X'_{ft} \gamma + \Psi_{ft} + \varepsilon_{ft}
\]

In both regression models, \(\ln(Tobin's\ Q)_{ft}\) is the dependent variable for firm \(f\) in fiscal year \(t\). \(i\) denotes the industry, defined at the two-digit NAICS level, and \(s\) denotes the state. \(\Psi_{ft}\) is a matrix containing firm fixed effects and industry \(\times\) year fixed effects. \(X'_{ft}\) is a matrix containing the following control variables: \(\ln(\text{Assets})\), Profitability, and Tangibility. The specification in column 1 uses the full sample, while the specification in column 2 focusses on states and years where no business combination laws have been passed. The sample underlying the regression in column 3 uses states and years where business combination laws have been passed. We lag all explanatory variables by one year. The sample spans 1976–2005. Robust standard errors clustered at the state level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>Sample:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable:</td>
<td>Full BC=0</td>
<td>BC=1</td>
<td></td>
</tr>
<tr>
<td>Ln(Tobin's Q)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCC index * In-state competition</td>
<td>0.1396***</td>
<td>(0.049)</td>
<td></td>
</tr>
<tr>
<td>In-state competition</td>
<td>-0.7035***</td>
<td>(0.170)</td>
<td></td>
</tr>
<tr>
<td>NCC index</td>
<td>-0.0208***</td>
<td>0.0125***</td>
<td>-0.0181***</td>
</tr>
<tr>
<td>Ln(Assets)</td>
<td>-0.1884***</td>
<td>-0.1967***</td>
<td>-0.2238***</td>
</tr>
<tr>
<td>Profitability</td>
<td>-0.0091***</td>
<td>-0.0092**</td>
<td>-0.0055***</td>
</tr>
<tr>
<td>Tangibility</td>
<td>-0.1254***</td>
<td>-0.1673***</td>
<td>-0.1477***</td>
</tr>
<tr>
<td>Firm F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry (\times) year F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>127,237</td>
<td>47,087</td>
<td>75,734</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.678</td>
<td>0.739</td>
<td>0.699</td>
</tr>
</tbody>
</table>
Figure 1: Corporate bankruptcies across industries
This figure shows the distribution of corporate bankruptcies across industries in our sample of Swedish limited liability firms. The total number of bankruptcies in our sample is 3,470. The sample spans the period 2003–2011.

Figure 2: Corporate bankruptcies over time
This figure shows the distribution of corporate bankruptcies over time in our sample of Swedish limited liability firms. The total number of bankruptcies in our sample is 3,470. The sample spans the period 2003–2011.
Figure 3: **Evolution of labor force in firms approaching distress**

This figure shows the share of workers leaving and joining firms as they approach bankruptcy. The timing is relative to the year the firm files for bankruptcy. The sample includes firms in the treatment group only.
Figure 4: Talent distribution across industries

This figure shows the talent allocation across industries in Sweden. Each panel represents a different talent measure: average cognitive skill scores, average leadership scores, average combined cognitive and noncognitive skill scores, and average wages. The cognitive, noncognitive and leadership skill measures are from the military enlistment records. The sample spans the period 1998–2011.
Figure 5: **Talent distribution across hierarchy levels**

This figure shows the talent allocation across levels of corporate hierarchy in Sweden. Each panel represents a different talent measure: average cognitive skill scores, average leadership scores, average combined cognitive and noncognitive skill scores, and average wages. The cognitive, noncognitive and leadership skill measures are from the military enlistment records. Levels of hierarchy are constructed using employee-level occupational codes from Statistics Sweden. The sample spans the period 2001–2011.

---

**Average cognitive test score**

- **Clerks and “Blue-collars”**
- **Supervisors**
- **Senior Staff**
- **CEOs & Directors**

**Average yearly wage (in 000’ 1998 SEK)**

- **Clerks and “Blue-collars”**
- **Supervisors**
- **Senior Staff**
- **CEOs & Directors**

**Average leadership score**

- **Clerks and “Blue-collars”**
- **Supervisors**
- **Senior Staff**
- **CEOs & Directors**

**Average combined cognitive and noncognitive test score**

- **Clerks and “Blue-collars”**
- **Supervisors**
- **Senior Staff**
- **CEOs & Directors**
Figure 6: **Talent wage premium**

The figure shows the evolution of the talent wage premium in Sweden between 1990 and 2011 for individuals that are 20 years or older. The sample includes all Swedish individuals that took military enlistment tests. The talent wage premium is obtained by estimating $w_{it} = \alpha_t T_{it} + \beta X_{it}$ using OLS. $w_{it}$ is the log of total wage; matrix $X_{it}$ includes a part-time job dummy, indicators for age interacted with year, and industry dummies. $T_{it}$ is a talent dummy interacted with year dummies. $\hat{\alpha}_t$ is the talent wage premium. Talent is defined using cognitive, noncognitive, or leadership test scores. Individuals that obtained a score of 8 or 9 (on a scale ranging from 1–9) on the respective tests are defined as talented. The talent measures are from the military enlistment records.
Figure 7: Talent leaving treatment and control firms
This figure shows the share of talented workers leaving firms in the treatment and control groups. The timing is relative to the date the firm files for bankruptcy. Each panel represents a different talent measure: cognitive skill scores, combined cognitive and noncognitive skill scores, leadership scores, and wages. The cognitive, noncognitive and leadership skills measures are obtained from the military enlistment records. The sample construction and variables definition is discussed in detail in the data section of the paper (Section II).
Figure 8: **Talent joining treatment and control firms**

This figure shows the share of talented workers joining firms in the treatment and control groups. The timing is relative to the date the firm files for bankruptcy. Each panel represents a different talent measure: cognitive skill scores, combined cognitive and noncognitive skill scores, leadership scores, and wages. The cognitive, noncognitive and leadership skills measures are obtained from the military enlistment records. The sample construction and variables definition is discussed in detail in the data section of the paper (Section II).
Figure 9: Firm size distribution before and after the change in LIFO rule
This figure shows the evolution of firm size distribution around the relaxation of the LIFO rule in 2001. The top panel shows the distribution of the number of firms in 2000 (before the law change) compared to 2004 (after the law change) by size bins from 8 to 15 employees. The bottom panel shows the evolution of the number of firms between 1998 and 2004; we separately plot the evolution of the count of firms slightly above and below the cutoff of 11 employees relevant for the law change. Firms with 9 and 10 employees are subject to the law change, and firms with 11 and 12 employees are not affected. The lines are normalized by the number of firms in 2000.
Talent in Distressed Firms: Investigating the Labor Costs of Financial Distress

Appendix

Ramin P. Baghai, Rui C. Silva, Viktor Thell, and Vikrant Vig

October 2016
Appendix A – Institutional background

A.I Bankruptcy law in Sweden

There are two main laws in Sweden that relate to corporate bankruptcy: the Swedish bankruptcy code (“Konkurslag (1987:672)”) and the Swedish Company Reconstruction Code (“Lag (1996:764) om företagsrekonstruktion”). According to Swedish bankruptcy law, insolvency occurs when a debtor permanently loses the ability to service its debt. Either the insolvent firm itself or a creditor can file for bankruptcy. If a creditor files, the filing has to be approved by court. If a firm enters bankruptcy, it is always liquidated. At the start of bankruptcy, the control rights of the firm are transferred to a trustee whose main objective is to sell the firm’s assets at the highest possible price. The trustee is bound by law to consider public interests, such as employment considerations. Employees are treated as unsecured senior claimants and are entitled to compensation for any unpaid wages from the year prior to the bankruptcy filing until one month after it. If employees are not paid in full, their wage and related claims (such as vacation pay and pension contributions) are reimbursed up to a maximum statutory amount (171,200 SEK in 2011) set by the government under the Wage Guarantee Act (“Lönegaranantläg (1992:497)

Under the Company Reconstruction Code, an administrator is appointed to oversee the reorganization and to set up a reorganization plan which must be approved by the creditors.¹ Debt write-downs are limited, and have to offer secured claimants full recovery and ensure at least 25% recovery to unsecured creditors. The envisaged duration of the reorganization procedure must not exceed one year. Since 2005, the Wage Guarantee Act has also been applicable to company reorganizations. For further details see Smith and Strömberg (2005).

A.II Employment protection legislation

The main Swedish labor law is the Employment Protection Act (“Lag (1982:80) om anställningsskydd”). According to this law, employee contracts can be terminated either collectively due to shortage of work or for individual-specific reasons. Acceptable reasons for collective redundancies include financial difficulties, strategic reorganization, or geographical relocation, but not if the employer can provide other work in the firm for affected employees. Permissible individual-specific firing reasons are, for example: disclosing sensitive information to competitors, criminal activity against the firm, assault of other workers, and disciplinary issues (e.g., skipping work, sexual harassment, bullying). The required period of notice for termination

---

¹ If the recovery for unsecured claimants is more than 50% it requires 3/5 approval, ¾ approval if recovery is more than 25% and unanimity if recovery is less than 25%. Unanimity is always required from secured claimants.
ranges from one to six months and depends on the tenure of the worker. The worker is entitled to retain pay and other benefits during the notice period; severance pay is not required by the law. The order of priority of terminations follows a “Last In, First Out” policy.

Swedish labor law leaves certain aspects of labor regulation to be decided through collective agreements between employers and unions (Rönnmar 2006). The unionization rate was 67.5% in 2011, a decline from 81.3% in 1998. Collective agreements are applicable to unionized and non-unionized workers alike, and typically differ across industries and for blue-collar and white-collar workers.

Overall, Swedish labor protection can be characterized as comparable to Continental Europe while being less stringent than Southern Europe, but more stringent than regulation in Anglo-Saxon countries. Sweden has considerably liberalized labor regulation during the last two decades (Cahuc 2010). Reforms have primarily been related to temporary forms of employment; legalization of temporary work agencies in 1993 and an introduction of fixed-term employment in 2007 are among the most noticeable changes.

Appendix B – Alternative measures of talent and additional robustness tests

B.I Alternative talent measures

In the main text, we measure talent using the sum of cognitive and non-cognitive test scores. In this appendix we show that our results are robust to different ways of measuring talent. We create three additional measures of talent based on cognitive skill scores, leadership scores, and wages.

---

2 The minimum period of notice is one month if an individual has been employed by the firm for less than two years, two months if an individual has been employed between two and four years, rising to six months for individuals who have been employed for more than ten years.

3 http://www.doingbusiness.org/data/exploreeconomies/sweden/labor-market-regulation

4 Since 2001, firms with ten or fewer employees are exempt from this rule. When a firm has more than one operational unit, the order is determined separately within each unit. If more than one unit operates in the same geographical location, a common order for the location is determined. Workers who have been laid off have rights of priority for re-employment up to nine months after their contracts are terminated. See also the discussion on the LIFO rule in Sections III and IV of the paper.


6 The 1997 reform of the Employment Regulation Act exemplifies this difference. In the reform, the order of priority of termination was changed from an age-dependent rule to one depending on tenure. The change was immediately implemented for blue-collar workers belonging to the engineering union, while it was implemented with a lag up to four years for all white-collar workers and for blue-collar workers in the construction and retail industries (Heyman and Skedinger, 2016).

7 See Figure 1 in Skedinger (2011) for a comparison of regions. In 2008 Sweden had an EPR coefficient of 2.52. The OECD average was 2.02, while the USA had 0.49, France 2.6, Germany 2.72 and the UK 1.248. Source: OECD Employment Protection Database, 2013 update. www.oecd.org/employment/protection
Talent cognitive is based on the cognitive skills of males obtained from their military records; it is a dummy variable that takes the value of one if an individual has a score in the top five percent of the distribution of cognitive skill scores at the firm-year level, and takes the value of zero otherwise. Talent leadership is defined accordingly using the scores from the leadership tests. The final measure of talent we construct is based on wages, which reflect the market price of talent. Talent wage is a dummy variable that takes the value of one if an individual’s annual real gross wage five years before the bankruptcy event is at or above the 95th percentile in the firm-year distribution of wages. This wage-based talent measure has the advantage, relative to our measures based on skills determined by the military authority, that it is available for all individuals irrespective of gender.

In Table B-1 we confirm our main findings from Table 3. We study the selection of workers that leave firms approaching distress using the three alternative measures of talent. Columns 1 to 3 include firm fixed effects and industry x year fixed effects, and columns 4 to 6 additionally include hierarchy fixed effects. The specifications that include military score-based measures also include enrollment period fixed effects to take into account the fact that tests may have changed over time. In column one we measure talent using cognitive skill scores for males and find that male workers with high cognitive skills have a 1.9 percentage point higher probability of leaving the firm as it approaches bankruptcy than less “talented” workers. Relative to the average effect of 5.7% (see column 1 in Table 3 of the main text) this estimate implies that the most talented employees are 33% more likely to leave the firm approaching distress than the average employee. In column two we replace the variable Talent cognitive with the variable Talent leadership as a measure of talent. We find that workers with more pronounced leadership skills are associated with an increase of 1.7 percentage points in the probability of abandoning the firm close to distress relative to normal times; this implies that their probability of abandoning soon-to-be bankrupt firms is 30% higher than that of the average worker. In column 3 skill is measured using Talent wage. According to this measure, key talent is 2.9 percentage points more likely to leave as the firm approaches distress. We observe that as the firm approaches distress, females are not statistically different from males in their likelihood of abandoning the firm as the coefficient on the interaction term Close to bankruptcy × Female is negative but statistically insignificant. In columns 4 to 6 we repeat the analysis including hierarchy fixed effects, and confirm the robustness of our results.

In Table B-2 we analyze the characteristics of workers joining firms approaching distress. Essentially, we repeat the analysis of Table 6, but replace the variable Talent with Talent cognitive, Talent leadership and Talent wage in different specifications. Overall we find that talented workers are not more likely to join firms close to distress, as the coefficients associated with the interaction of our talent measures and Close to bankruptcy are insignificant in all columns but one. Moreover, the coefficient on column 3, albeit positive and significant, is an order of magnitude smaller than the corresponding coefficient on the analysis of workers leaving soon-to-be distressed firms.
(contrast the coefficient of 0.0289 in Table B-1 with the coefficient 0.0093 in Table B-2). This implies that firms that are approaching distress are still experiencing a net decrease in talent, when measured with the variable Talent wage.

In Table B-3 we show that the negative relationship between firm talent and firm leverage is robust to several different ways of measuring firm talent. In particular, we replace High talent with High talent cognitive in columns one and four, High talent leadership in columns two and five, and High talent wage in columns three and six. In all columns the coefficients are negative, confirming the findings in the main text.

**B.II Robustness test: 2001 labor law change in Sweden**

In Panel A of Table 9 we study the effect of the 2001 labor law change in Sweden (which allowed firms with 10 or fewer employees—the treated firms—to be exempt from LIFO rules) on hiring and firing decisions of firms. In that analysis, we used normalized changes as dependent variables, which raised the concern that a mechanical relationship may be driving the results: one more worker changing firm represents a larger share of workers in smaller (treated) firms than in larger (control) firms. In Table B-4 we therefore aim to show that the increase in labor mobility experienced by treated firms after the law change is not a mechanical result. In this table we aggregate the number of workers by year and number of employees. For example if there are 100 firms with 9 employees, there is a total of 900 employees in the bin of firms with 9 employees. We then calculate the share of workers that leave this pool and those that join this pool, each year. We call these variables Aggregate leave rate and Aggregate join rate, respectively. The results reported in Table B-4 suggest that the 2001 LIFO law change indeed resulted in an increase in labor mobility. Because we aggregate workers at the employee-number and year level, these tests are not subject to the criticism that a mechanical relationship could be driving the results.

**Appendix C – External validity**

The tables and figures in this section of the appendix complement our discussion in Section V of the paper.

Figure C-1 shows the non-compete index (NCC index) for the eight US states that changed the enforceability of non-compete clauses. For example, Florida increased the enforceability in 1990 as well as in 1996. The figure highlights that there is considerable cross-sectional and time-series variation in index values.

Figure C-2 plots the relationship between US firm leverage and the industry-level labor fragility measure (see Section V for the variable construction). Consistent with our analysis in the paper, the figure suggests that there is a negative association between leverage and labor fragility.

In the main paper, we used the variable In-state competition as a way to proxy for the mobility of key employees within the industry. However, workers also switch jobs between different
industries. To capture the notion that worker mobility may transcend industry boundaries, we employ the proxy of worker mobility presented in Donangelo (2014), which measures the extent to which skills are portable across industries. While our main sample starts in 1976, the Donangelo (2014) labor mobility measure is available only from 1990 onwards. To have sufficient overlap in our tests, we first match the industry-level mobility measure to the firms in our sample; we then take the time-series average of the mobility measure at the state level. The resulting measure, LM, thus captures the average inter-industry mobility of workers in a given state.8

Using this measure of inter-industry mobility, we estimate the following model:

\[
\text{Leverage}_{ft} = \theta \cdot (\text{NCC index}_{st}) \cdot (\text{LM}_s) + \beta \cdot \text{NCC index}_{st} + \chi'_{ft}\gamma + \psi_{ft} + \varepsilon_{ft}
\]

The coefficient of interest is \(\theta\) and measures the degree to which labor mobility may exacerbate the impact of non-compete clauses on leverage. Table C-1, columns 1 and 2, presents the results. Consistent with Table 12, we find that restricting the mobility of workers through tougher enforcement of non-compete clauses leads to an increase in leverage for firms in states with high cross-industry labor force mobility. The coefficient in column 1 implies that the effect of non-compete enforceability on firm leverage is different in high and low labor mobility states: while the effect is negative in states with low inter-industry mobility (such as the state of Louisiana, where \(LM_s = -0.360\)), it is positive in states with higher mobility (such as the state of Massachusetts, where \(LM_s = 0.546\)).

Next, we confirm the robust nature of our findings by employing in this setting the measure of labor fragility constructed using Swedish micro-data. To this end, we re-estimate the model by replacing LM with LF. We calculate the time-series average of the labor fragility measure (the variable \(\text{Labor Fragility}\) employed in Table 11) at the state level to obtain the variable LF. The results are presented in columns 3 and 4 of Table C-1. They show that increases in the enforceability of non-compete agreements have a positive and significant effect on one of our two leverage measures in states in which labor fragility is high.

In Table C-2, we study whether the effect of the enforcement of non-compete contracts and leverage differs between financially constrained and financially unconstrained firms. We construct three measures of financial constraints: an index based on a regression in Kaplan and Zingales (1997) as used in Lamont, Polk, and Saá-Requejo (2001), the KZ-index; an index based on Whited and Wu (2002), henceforth the WW-index; and an index based on Hadlock and Pierce (2010), henceforth the HP-index. The indices are constructed as follows; unless noted otherwise, abbreviations in italics refer to Compustat data items. \(l.\) is the lag operator. The KZ-index for a given firm-year is defined as

\[
\]

---

8 We slightly abuse notation and call our variable \(LM\), which is the same variable name used in Donangelo (2014). For additional details regarding the construction of this measure please refer to that article.
index is defined as 
\[-0.091*[(ib+dp)/at] - 0.062*div + 0.021*(dltt/at) - 0.044*[\ln(at)] + 0.102*indsg - 0.035*[(\text{sale-l.sale})/l.sale]\],
where div is a dummy variable indicating years in which a firm pays cash dividends (dv), and indsg is the firm’s 3-digit NAICS industry sales growth. The HP-index is defined as 
\[-0.737*\text{size} + 0.043*\text{size}^2 - 0.040*\text{age}\],
where size is the natural log of inflation-adjusted (to 2004) book assets (at), and age is the number of years the firm has been on Compustat with a non-missing stock price (prcc.f); we set age equal to missing for years prior to a firm’s first non-missing stock price. Following Hadlock and Pierce (2010), in calculating the HP-index, size is replaced with In($4,500 million) and age with thirty-seven years if the actual values exceed these thresholds. All three financial constraints indices are winsorized at the 1\text{st} and 99\text{th} percentiles. For all three indices, higher index values denote more constrained firms. Summary statistics for the three financial constraints indices are reported in Table 10 of the paper.

We categorize a firm as constrained (unconstrained) in a given year if the relevant financial constraints index takes on a value that is higher (lower) than the sample median. Results are reported in Table C-2; Panel A shows results for firms categorized as unconstrained, while Panel B shows the sub-sample of financially constrained firms. Columns 1 and 2 use the WW-index to categorize firms, columns 3 and 4 use the KZ-index, and columns 5 and 6 employ the HP-index. Overall, the results show that following an increase in enforceability of non-compete clauses, it is primarily financially unconstrained firms that increase leverage, while effects are insignificant in the group of constrained firms.
Table B-1: Selection of workers that leave firms approaching distress

This table shows the composition of workers that leave firms approaching distress. We report coefficients from estimating the following OLS regression:

\[
\text{Leave}_{ift} = \alpha + \beta \cdot \text{Close to bankruptcy}_{ft} + \theta \cdot (\text{Talent}_{ift}) \cdot (\text{Close to bankruptcy}_{ft}) + \mu \cdot \text{Talent}_{ift} + \gamma \cdot X'_{ift} + \delta \cdot \text{Close to bankruptcy}_{ft} \cdot X'_{ift} + \Psi_{ft} + \varepsilon_{ift}
\]

\text{Leave}, the dependent variable, is a dummy variable that takes the value of one in the year the worker leaves the firm to work for another employer, and zero otherwise. \text{Close to bankruptcy} is a dummy variable that takes the value of one if the firm is in close proximity to bankruptcy (within three years), and zero otherwise. \text{Talent} is based on the cognitive score in columns 1 and 4, on leadership scores in columns 2 and 5 and on wages in columns 3 and 6. The matrix \text{X} includes \text{Age, Experience in company, Experience in industry, Ln(Years of education), Ln(Wage)} and a \text{Female} dummy. \Psi\text{ includes firm fixed effects and year-industry fixed effects. The regressions corresponding to columns 1, 2, 4 and 5 also include military enrollment period fixed effects. The sample used in columns 1 to 3 spans the period 1998–2010. In columns 4 to 6 we add hierarchy fixed effects; due to data availability our sample period in columns 4 to 6 is 2001–2010. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.}
Table B-2: Selection of workers that join firms approaching distress

This table shows the composition of workers that join firms approaching distress. We report coefficients from estimating the following OLS regression:

\[ \text{Join}_{i,t} = \alpha + \beta \cdot \text{Close to bankruptcy}_{i,t} + \theta \cdot (\text{Talent}_{i,t}) \cdot (\text{Close to bankruptcy}_{i,t}) + \mu \cdot \text{Talent}_{i,t} + \gamma \cdot \text{X}'_{i,t} + \delta \cdot \text{Close to bankruptcy}_{i,t} \cdot \text{X}'_{i,t} + \Psi_{i,t} + \varepsilon_{i,t} \]

Join, the dependent variable, is a dummy variable that takes the value of one in the year the worker joins the firm, and zero otherwise. Close to bankruptcy is a dummy variable that takes the value of one if the firm is in close proximity to bankruptcy (within three years), and zero otherwise. Talent is Talent cognitive in column 1 and 4, Talent leadership in column 2 and 5 and Talent wage in column 3 and 6. The matrix X includes Age, Experience in industry, Ln(Years of education), Ln(Wage), Female dummy and Other municipality a dummy equal to one if a worker moves to a new municipality. \( \Psi \) includes firm fixed effects and year-industry fixed effects. The regressions in columns 1, 2, 4 and 5 also include military enrollment period fixed effects. The sample used in columns 1 to 3 spans the period 1998–2010. In columns 4 to 6 of the table we add hierarchy fixed effects; due to data availability our sample period in columns 4 to 6 is 2001–2010. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>Talent measure:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable:</td>
<td>Cognitive</td>
<td>Leadership</td>
<td>Wage</td>
<td>Cognitive</td>
<td>Leadership</td>
<td>Wage</td>
</tr>
<tr>
<td>Close to bankruptcy</td>
<td>-0.1208***</td>
<td>-0.1240***</td>
<td>-0.0447***</td>
<td>-0.1503***</td>
<td>-0.1535***</td>
<td>-0.0721***</td>
</tr>
<tr>
<td>(0.043)</td>
<td>(0.042)</td>
<td>(0.021)</td>
<td>(0.050)</td>
<td>(0.049)</td>
<td>(0.029)</td>
<td></td>
</tr>
<tr>
<td>Close to bankruptcy × Talent</td>
<td>0.0047</td>
<td>-0.0006</td>
<td>0.0093***</td>
<td>0.0017</td>
<td>-0.0037</td>
<td>0.0030</td>
</tr>
<tr>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.004)</td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td>Talent</td>
<td>-0.0115***</td>
<td>-0.0077***</td>
<td>-0.0034</td>
<td>-0.0105***</td>
<td>-0.0051</td>
<td>0.0039</td>
</tr>
<tr>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td>Close to bankruptcy × Age</td>
<td>-0.0004</td>
<td>-0.0004</td>
<td>-0.0003</td>
<td>-0.0003</td>
<td>-0.0002</td>
<td>-0.0002</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.0010***</td>
<td>0.0010***</td>
<td>-0.0018***</td>
<td>0.0015***</td>
<td>0.0015***</td>
<td>-0.0004***</td>
</tr>
<tr>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>Close to bankruptcy × Experience in industry</td>
<td>0.0057***</td>
<td>0.0056***</td>
<td>0.0048***</td>
<td>0.0050***</td>
<td>0.0050***</td>
<td>0.0035***</td>
</tr>
<tr>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Experience in industry</td>
<td>-0.0362***</td>
<td>-0.0362***</td>
<td>-0.0403***</td>
<td>-0.0292***</td>
<td>-0.0292***</td>
<td>-0.0388***</td>
</tr>
<tr>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Close to bankruptcy × Ln(Years of education)</td>
<td>0.0304</td>
<td>0.0320*</td>
<td>0.0008</td>
<td>0.0391*</td>
<td>0.0405*</td>
<td>0.0122</td>
</tr>
<tr>
<td>(0.019)</td>
<td>(0.019)</td>
<td>(0.008)</td>
<td>(0.023)</td>
<td>(0.022)</td>
<td>(0.009)</td>
<td></td>
</tr>
<tr>
<td>Ln(Years of education)</td>
<td>-0.0354***</td>
<td>-0.0374***</td>
<td>-0.0795***</td>
<td>-0.0012</td>
<td>-0.0036</td>
<td>-0.0122***</td>
</tr>
<tr>
<td>(0.011)</td>
<td>(0.010)</td>
<td>(0.005)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.004)</td>
<td></td>
</tr>
<tr>
<td>Close to bankruptcy × Other municipality</td>
<td>-0.0174***</td>
<td>-0.0173**</td>
<td>-0.0143*</td>
<td>-0.0067</td>
<td>-0.0066</td>
<td>0.0028</td>
</tr>
<tr>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.008)</td>
<td>(0.012)</td>
<td>(0.012)</td>
<td>(0.008)</td>
<td></td>
</tr>
<tr>
<td>Other municipality</td>
<td>0.1089***</td>
<td>0.1088***</td>
<td>0.1518***</td>
<td>0.0837***</td>
<td>0.0836***</td>
<td>0.0918***</td>
</tr>
<tr>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td>Close to bankruptcy × Female</td>
<td>-0.0034</td>
<td>-0.0024</td>
<td>0.0017</td>
<td>0.0003</td>
<td>0.0004</td>
<td>-0.0026</td>
</tr>
<tr>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Ln(Wage)</td>
<td>-0.0582***</td>
<td>-0.0580***</td>
<td>-0.0532***</td>
<td>-0.0530***</td>
<td>-0.0530***</td>
<td>-0.0530***</td>
</tr>
<tr>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td></td>
</tr>
</tbody>
</table>

Firm and (Industry × Year) F.E. Yes Yes Yes Yes Yes Yes
Enrollment Period F.E. Yes Yes No Yes Yes No
Hierarchy F.E. No No No Yes Yes Yes
Observations 361,474 361,474 886,015 228,208 228,208 530,161
R-squared 0.278 0.278 0.290 0.236 0.236 0.233
Table B-3: Labor fragility and leverage

This table shows the relationship between labor fragility and leverage. We report coefficients from estimating the following OLS model on the sample of Swedish firms:

\[
\text{Leverage}_{ft} = \alpha + \beta \cdot \text{High talent}_{ft} + X'_{ft}\gamma + \varepsilon_{ft}
\]

*High talent* is based on the firm-year average cognitive score in columns 1 and 4, leadership score in columns 2 and 5, and wage in columns 3 and 6 and is equal to one if the value is above the median in the respective industry and year. All specifications include lagged *Tangibility*, lagged *Profitability*, lagged *Ln(Assets)*, lagged *Firm age* and *Growth* as controls, as well as year fixed effects (see matrix *X* in the equation above). The sample and variable construction is discussed in the data section of the paper (Section II). Robust standard errors clustered at the firm level are reported in parentheses. Statistical significance at 1%, 5% and 10% is marked with ***, ** and * respectively.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>High talent cognitive</td>
<td>-0.0246***</td>
<td>-0.0074***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High talent leadership</td>
<td>-0.0146***</td>
<td>-0.0024*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High talent wage</td>
<td>-0.0395***</td>
<td>-0.0202***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tangibility</td>
<td></td>
<td></td>
<td>0.3678***</td>
<td>0.3676***</td>
<td>0.3648***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td></td>
</tr>
<tr>
<td>Profitability</td>
<td></td>
<td></td>
<td>-0.1833***</td>
<td>-0.1838***</td>
<td>-0.1799***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.009)</td>
<td></td>
</tr>
<tr>
<td>Ln(Assets)</td>
<td></td>
<td></td>
<td>-0.0021***</td>
<td>-0.0032***</td>
<td>-0.0002</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Firm age</td>
<td></td>
<td></td>
<td>-0.0005***</td>
<td>-0.0005***</td>
<td>-0.0005***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>Growth</td>
<td></td>
<td></td>
<td>0.0009***</td>
<td>0.0008***</td>
<td>0.0010***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>Year F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>230,275</td>
<td>216,243</td>
<td>230,275</td>
<td>230,275</td>
<td>216,243</td>
<td>230,275</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.004</td>
<td>0.002</td>
<td>0.010</td>
<td>0.193</td>
<td>0.192</td>
<td>0.195</td>
</tr>
</tbody>
</table>
Table B-4: **Impact of LIFO relaxation rule on labor mobility—size bins**

This table analyzes the impact of the relaxation of the LIFO rule in 2001 on the mobility of workers. We report coefficients from estimating the following OLS model:

$$Y_{st} = \beta_1 Post_t + \beta_2 Treated_s + \beta_3 Post_t \times Treated_s + \Psi_s + \varepsilon_{st}$$

In column 1, the dependent variable is *Aggregate leave rate*, defined as the number of workers of firms in size bin $s$ that leave the firm between $t-1$ and $t$, divided by the total number of workers of firms in that size bin at $t-1$. In column 2, the dependent variable is *Aggregate join rate*, defined as the number of workers of firms in size bin $s$ that join the firm between $t-1$ and $t$, divided by the total number of workers of firms in that size bin at $t-1$. We create a size bin for firms with 5 employees, another one for firms with 6 employees and so on until the bin for firms with 15 employees. *Post* is a dummy variable indicating the period after the law change. *Treated* is a dummy variable that takes the value of one if the firms had 10 or fewer employees in 2000 and takes the value of zero otherwise. Both specifications include size bin fixed effects as well as year fixed effects. The sample period is 1999 to 2004 with the year of the law change, 2001, excluded. Robust standard errors clustered at the size bin level are reported in parentheses. Statistical significance at 1%, 5% and 10% is marked with ***, ** and * respectively.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variable:</strong></td>
<td>Aggregate leave rate</td>
<td>Aggregate join rate</td>
</tr>
<tr>
<td>Treated $\times$ Post</td>
<td>0.2714**</td>
<td>0.3644***</td>
</tr>
<tr>
<td></td>
<td>(0.086)</td>
<td>(0.087)</td>
</tr>
<tr>
<td>Size-Bin F.E.</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year F.E.</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>55</td>
<td>55</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.993</td>
<td>0.988</td>
</tr>
</tbody>
</table>
Table C-1: Enforcement of non-compete agreements and leverage in the US: labor mobility and labor fragility

This table shows the relationship between labor fragility and firm leverage. In columns 1 and 2 we report coefficients from estimating the following OLS model on the sample of US firms:

\[ Y_{ft} = \theta \cdot (NCC \text{ index}_{st}) \cdot (LM_{s}) + \beta \cdot NCC \text{ index}_{st} + X'_{ft}\gamma + \Psi_{ft} + \varepsilon_{ft} \]

where \( Y_{ft} \) is the dependent variable for firm \( f \) in fiscal year \( t \). We use as dependent variable Book leverage in column 1, and Market leverage in column 2. \( i \) denotes the industry, defined at the two-digit NAICS level, and \( s \) denotes the state. In columns 1 and 2, we interact the NCC index with the state-level labor mobility measure \( LM_{s} \).

In columns 3 and 4 we report coefficients from estimating the following OLS model:

\[ Y_{ft} = \theta \cdot (NCC \text{ index}_{st}) \cdot (LF_{s}) + \beta \cdot NCC \text{ index}_{st} + X'_{ft}\gamma + \Psi_{ft} + \varepsilon_{ft} \]

where \( Y_{ft} \) is the dependent variable for firm \( f \) in fiscal year \( t \). We use as dependent variable Book leverage in column 3, and Market leverage in column 4. \( i \) denotes the industry, defined at the two-digit NAICS level, and \( s \) denotes the state. In columns 3 and 4, we interact the NCC index with the state-level labor fragility measure \( LF_{s} \). In all columns \( \Psi_{ft} \) is a matrix containing firm fixed effects and industry \times\ year fixed effects. \( X'_{ft} \) is a matrix containing the following control variables: Ln(Assets), Profitability, Tangibility, and Ln(Tobin’s Q). We lag all explanatory variables by one year. The sample spans 1976–2005. Robust standard errors clustered at the state level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th></th>
<th>(1) Book Leverage</th>
<th>(2) Market Leverage</th>
<th>(3) Book Leverage</th>
<th>(4) Market Leverage</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCC Index * LM</td>
<td>0.0163***</td>
<td>0.0159***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NCC Index * LF</td>
<td></td>
<td></td>
<td>1.0946***</td>
<td>0.4082</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.380)</td>
<td>(0.422)</td>
</tr>
<tr>
<td>NCC Index</td>
<td>-0.0032*</td>
<td>-0.0000</td>
<td>-0.0453***</td>
<td>-0.0131</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.015)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Ln(Assets)</td>
<td>-0.0131**</td>
<td>0.0269***</td>
<td>-0.0130**</td>
<td>0.0270***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Profitability</td>
<td>-0.0007</td>
<td>-0.0006**</td>
<td>-0.0007</td>
<td>-0.0006**</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Ln(Tobin’s Q)</td>
<td>0.0205***</td>
<td>-0.0681***</td>
<td>0.0206***</td>
<td>-0.0681***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.003)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Tangibility</td>
<td>0.2378***</td>
<td>0.1894***</td>
<td>0.2377***</td>
<td>0.1893***</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.014)</td>
<td>(0.023)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Firm F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry * Year F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>119,177</td>
<td>117,901</td>
<td>119,177</td>
<td>117,901</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.589</td>
<td>0.679</td>
<td>0.589</td>
<td>0.679</td>
</tr>
</tbody>
</table>
Table C-2: Enforcement of non-compete agreements and leverage in the US: financial constraints

This table shows the relationship between labor fragility and firm leverage for financially constrained and unconstrained firms. We report coefficients from estimating the following OLS model on the sample of US firms:

\[ Y_{ft} = \theta \cdot (\text{NCC index}_{st}) \cdot (\text{In-state competition}_{ist}) + \beta \cdot \text{NCC index}_{st} + \psi \cdot \text{In-state competition}_{ist} + X'_{ft} \gamma + \Psi_{ft} + \varepsilon_{ft} \]

where \( Y_{ft} \), the dependent variable for firm \( f \) in fiscal year \( t \), is a measure of leverage. \( i \) denotes the industry, defined at the two-digit NAICS level, and \( s \) denotes the state. \( \Psi_{ft} \) is a matrix containing firm fixed effects and industry \( \times \) year fixed effects. \( X'_{ft} \) is a matrix containing control variables. We lag all explanatory variables by one year. In the table below Leverage controls denotes the following set of variables: \( \ln(\text{Assets}) \), Profitability, Tangibility, and \( \ln(\text{Tobin's Q}) \). Panel A reports results for firms categorized as unconstrained, while Panel B shows the sub-sample of financially constrained firms. Columns 1 and 2 use the WW-index to categorize firms, columns 3 and 4 use the KZ-index, and columns 5 and 6 employ the HP-index. The sample spans 1976–2005. Robust standard errors clustered at the state level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

### Panel A: unconstrained firms

<table>
<thead>
<tr>
<th>Financial constraints measure:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable:</td>
<td>Book Leverage</td>
<td>Market Leverage</td>
<td>Book Leverage</td>
<td>Market Leverage</td>
<td>Book Leverage</td>
<td>Market Leverage</td>
</tr>
<tr>
<td>NCC Index * In-state Competition</td>
<td>0.0570***</td>
<td>0.0844***</td>
<td>0.0660***</td>
<td>0.0607***</td>
<td>0.0681***</td>
<td>0.0874***</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.019)</td>
<td>(0.024)</td>
<td>(0.016)</td>
<td>(0.019)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>NCC Index</td>
<td>-0.0019</td>
<td>-0.0022</td>
<td>-0.0056</td>
<td>-0.0014</td>
<td>-0.0040</td>
<td>-0.0014</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>In-state Competition</td>
<td>-0.2598***</td>
<td>-0.3292***</td>
<td>-0.2902***</td>
<td>-0.2614***</td>
<td>-0.2527***</td>
<td>-0.2708***</td>
</tr>
<tr>
<td></td>
<td>(0.061)</td>
<td>(0.071)</td>
<td>(0.071)</td>
<td>(0.063)</td>
<td>(0.073)</td>
<td>(0.070)</td>
</tr>
<tr>
<td>Leverage controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Firm F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry * Year F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>56,431</td>
<td>56,431</td>
<td>53,266</td>
<td>53,266</td>
<td>60,651</td>
<td>60,651</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.720</td>
<td>0.749</td>
<td>0.790</td>
<td>0.722</td>
<td>0.671</td>
<td>0.730</td>
</tr>
</tbody>
</table>

### Panel B: constrained firms

<table>
<thead>
<tr>
<th>Financial constraints measure:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable:</td>
<td>Book Leverage</td>
<td>Market Leverage</td>
<td>Book Leverage</td>
<td>Market Leverage</td>
<td>Book Leverage</td>
<td>Market Leverage</td>
</tr>
<tr>
<td>NCC Index * In-state Competition</td>
<td>0.0390</td>
<td>0.0358</td>
<td>0.0142</td>
<td>0.0256</td>
<td>0.0412</td>
<td>0.0059</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.027)</td>
<td>(0.025)</td>
<td>(0.024)</td>
<td>(0.033)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>NCC Index</td>
<td>-0.0072</td>
<td>-0.0061</td>
<td>0.0025</td>
<td>0.0008</td>
<td>-0.0066</td>
<td>-0.0056</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.007)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.009)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>In-state Competition</td>
<td>-0.1374</td>
<td>-0.0449</td>
<td>0.0256</td>
<td>0.0437</td>
<td>-0.1130</td>
<td>0.0520</td>
</tr>
<tr>
<td></td>
<td>(0.123)</td>
<td>(0.076)</td>
<td>(0.080)</td>
<td>(0.077)</td>
<td>(0.109)</td>
<td>(0.064)</td>
</tr>
<tr>
<td>Leverage controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Firm F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry * Year F.E.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>54,471</td>
<td>54,471</td>
<td>55,751</td>
<td>55,751</td>
<td>51,974</td>
<td>51,974</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.626</td>
<td>0.699</td>
<td>0.614</td>
<td>0.695</td>
<td>0.626</td>
<td>0.700</td>
</tr>
</tbody>
</table>
Figure C-1: **Time-series variation in the non-compete enforcement index**

This figure shows the eight US states in which the enforceability of non-compete agreements changes during the sample period: Florida, Louisiana, Massachusetts, Michigan, Montana, Texas, Virginia, and Wyoming. The NCC index takes on values from zero to nine, with zero denoting that a state’s courts do not enforce non-compete agreements, and the highest score of nine indicating that a state jurisdiction enforces several types of non-compete clauses. The NCC Index data is from Bird and Knopf (2014), who extend the coding of Garmaise (2011) back to 1976.
Figure C-2: Labor fragility and firm leverage

This figure plots annual labor fragility against annual average book leverage at the Fama-French 12 (FF12) industry level. The labor fragility measure is constructed as follows: using Swedish microdata, for each FF12 industry and year, we divide the number of Swedish workers with a combined cognitive and non-cognitive test score of at least 16 (out of possible 18) by the number of test takers in a given industry and year. We then match these data to our sample of US firms. The sample period is 1990-2005.