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

RAMIN P. BAGHAI, RUI C. SILVA, VIKTOR THELL, and VIKRANT VIG

ABSTRACT

The importance of skilled labor and the inalienability of human capital expose firms to the risk of losing talent at critical times. Using Swedish microdata, we document that firms lose workers with the highest cognitive and noncognitive skills as they approach bankruptcy. In a quasi-experiment, we confirm that financial distress drives these results: following a negative export shock caused by exogenous currency movements, talent abandons the firm, but only if the exporter is highly leveraged. Consistent with talent dependence being associated with higher labor costs of financial distress, firms that rely more on talent have more conservative capital structures.

> "For embattled employees of RadioShack, Wet Seal and other companies facing bankruptcy, the time to find a new job is long before the company goes under. […] 'The best time to find a job, is when you have a job,' says

Ramin P. Baghai is with the Stockholm School of Economics. Rui C. Silva is with the Nova School of Business and Economics. Viktor Thell is with Finansinspektionen (Sweden's financial supervisory authority). Vikrant Vig is with the London Business School and the Kellogg School of Management at Northwestern University. We thank the Editor (Stefan Nagel), two anonymous referees, Ashwini Agrawal, Xavier Giroud, 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), Adam Smith Workshops (2017), UNC/Duke Corporate Finance Conference (2017), NBER Corporate Finance Summer Institute (2017), Banco de Mexico, Bocconi University, Faculdade de Economia do Porto, London Business School, Lund University School of Economics and Management, Southampton Business School, Stockholm School of Economics (Swedish House of Finance), and University of Texas at Dallas. We thank Johan Wall at Statistics Sweden for his help with the administrative data. We are grateful for financial support from the Deloitte Institute for Innovation and Entrepreneurship, the Research and Materials Development Fund at the London Business School, and the Hans Dalborg foundation. Thell gratefully acknowledges financial support from the Swedish Bank Research Foundation, as well as the Jan Wallander and Tom Hedelius Foundation. This project has also received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program (grant agreement No. 679747). We have read *The Journal of Finance* disclosure policy and have no conflicts of interest to disclose.

Correspondence: Ramin P. Baghai, Stockholm School of Economics, Department of Finance, Box 6501, SE-113 83 Stockholm, Sweden; Phone: +46 8 736 9296; e-mail: ramin.baghai@hhs.se.

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Tim Sackett, president of HRU Technical Resources, an information technology and engineering staffing firm in Lansing, Mich. 'If you aren't going to wait around, it's best to leave early. Outside companies know the best talent leaves, or gets recruited the quickest, so if you're the last one to jump ship, most people will believe you're mediocre talent.'"

"When should workers at troubled companies jump ship?" by Quentin Fottrell, MarketWatch, February 5, 2015.

EVER SINCE MODIGLIANI AND MILLER'S (1958) famous irrelevance theorem, financial economists have devoted considerable effort to understand the nature of the frictions that affect firms' financial choices. Although there is a consensus that a firm's financial structure matters and has real effects, the determinants of a firm's capital structure 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 (the costs of financial distress). In theory, the costs are understood to include both direct costs (e.g., legal and advisory fees typically incurred during bankruptcy) and indirect costs (e.g., loss of customers, suppliers, employees). However, while the notion of these costs is clear theoretically, empirically identifying various channels has proven to be difficult.

In this paper, we examine how the onset of financial distress affects firms' ability to retain highly skilled labor ("talent") in the organization. A reduced ability of financially distressed firms to retain such workers may be viewed as a cost of financial distress. This notion is not new. The property rights view pioneered by Grossman and Hart (1986) and Hart and Moore (1990) provides a framework for analyzing how the inalienability of human capital affects firms' financing capacity. Essentially, human capital introduces contractual incompleteness that stems from the fact that firms do not own human capital—workers do. A recent survey of business professionals suggests that this is not merely a theoretical possibility. Specifically, "talent and skill shortages" were identified as the second most important risk facing modern organizations, topped only by the risk of "loss of customers" and ranking above others such as "changing legislation" (Lloyds (2011)).[1]

Whether a firm's top talent is the first to desert the proverbial sinking ship is not a priori obvious. Although a liquid labor market for highly skilled workers could result in such workers exiting first, it might also make them more patient because the cost of staying with the firm may be lower (e.g., lower wage discounts and shorter unemployment spells). To the extent that high-talent workers are employed in more strategic roles, this would also give them an informational advantage that allows them to gauge the severity of the difficulties facing the firm. Other factors, such as reputational damage (e.g., attribution of

[1] Anecdotal evidence, such as the Saatchi and Saatchi case (e.g., Rajan and Zingales (2000)), also supports this view. When U.S. 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 accounts.

blame), could also affect their decision. This theoretical ambiguity that arises from various economic forces makes for an interesting empirical investigation.

Several challenges must be overcome in attempting to answer such a question. First and foremost, an in-depth analysis of the labor force in financially distressed firms requires detailed, microlevel data on individual characteristics, job nature, and reasons for departure (voluntary or involuntary), among other factors. Data of such granularity are not typically available. The empirical hurdles are further compounded by the measurement question of how to define and measure talent. Since human capital is multidimensional, this is not straightforward. Finally, one needs a suitable approach to gauge whether the distress experienced by a firm is financial or economic. This latter distinction is critical because it is the cost of financial distress that matters for financial policy.

In this paper, we employ microlevel data from Sweden to overcome these challenges. Our employee-employer matched data set contains detailed information on firm characteristics, as well as individual employee characteristics such as cognitive and noncognitive skills, age, gender, education, employment history, and compensation. These data allow us to paint a comprehensive picture of the evolution of the labor force in firms approaching financial distress.[2]

The data set also allows us to create meaningful proxies for talent. We define and measure talent as a set of cognitive and noncognitive abilities that are generally applicable across tasks and jobs. Although human capital is multifaceted, cognitive and noncognitive skills are closest to the innate concept of talent that we are attempting to capture.[3]

Prior studies show that cognitive and noncognitive skills are important determinants of education and labor market outcomes (e.g., Heckman, Stixrud, and Urzua (2006), Lindqvist and Vestman (2011)). Such skills are also closely associated with firm productivity and value creation (e.g., Abowd et al. (2005)). Employees with high cognitive and noncognitive skills may be particularly indispensable during critical times, such as financial distress, when firms face unique challenges. A firm might need to implement new and—compared to its usual modus operandi—unconventional approaches that high-talent workers may find easiest to adapt to and master. The reliance of firms on, and the risk of losing, workers with these skills, which are portable across firms and

[2] We discuss the external validity of our results in Section IV and in Section II of the Internet Appendix. The Internet Appendix is available in the online version of this article on *The Journal of Finance* website.

[3] Other forms of and proxies for human capital may also be important. However, we believe that cognitive and noncognitive skills are the most accurate proxy available to study the type of labor cost of financial distress that is of interest in this paper, which focuses on the risk of losing workers whose abilities are widely applicable and sought after in the economy. Moreover, measurement issues hinder the interpretation of proxies for other dimensions of human capital. For example, long tenure in the firm may indicate the existence of valuable firm-specific human capital. However, workers with long tenure may also be "legacy" workers who are apathetic, unmotivated, and resistant to change. Another example is education. As pointed out by Philippon and Reshef (2012), there is significant variation in human capital within similar educational groups, and the skills associated with any particular level of education may change over time.

generally valuable in the economy, can therefore expose firms to a type of "fragility" that originates in the characteristics of its workforce.

We begin by investigating whether high-talent employees are prone to leaving firms that are approaching financial distress. Our main finding is that firms that become financially distressed do indeed experience a significant loss of talent. Workers with the highest cognitive and noncognitive skills are 65% more likely to abandon the firm as it approaches distress, relative to the average worker. Further, we find that the intake of talent in distressed firms does not increase commensurably. Given the importance of talent for firm productivity and value, the fact that high-talent workers abandon firms that are approaching bankruptcy can be seen as a labor cost of financial distress.

In our study, it is critical to separate demand- and supply-side factors that lead to a change in the labor composition of distressed firms. For instance, a lower reliance on talent may be the optimal strategy of a profit-maximizing firm that is experiencing financial distress. Information on which departures are voluntary and which are forced (i.e., firing) is rarely coded in any data set. Although we do not have access to such information, we use two approaches to identify voluntary departures. Under the first approach, we examine whether an employee who leaves a firm is subsequently unemployed. Our conjecture is that forced departures would tend to be associated with unemployment, while voluntary departures would be less likely to result in unemployment. We find no evidence of firms firing high-talent workers at an increased rate during financial distress.

Our second strategy exploits a unique institutional feature of labor laws in Sweden to separate voluntary from involuntary turnover. Firms with 11 or more employees are required by law to follow a last-in-first-out (LIFO) rule when laying workers off.[4] Because we know employees' joining date, we can determine whether job separations follow the LIFO rule. Deviations from this rule provide us a proxy for voluntary departures. We find that high-talent employees are more likely to leave voluntarily—in effect, "jumping the queue" and leaving earlier than their LIFO order should dictate. Taken together, our results point to firms' top talent voluntarily "abandoning the sinking ship" in times of financial distress.

After establishing that we are indeed documenting voluntary rather than involuntary departures by highly skilled employees, we conduct a test aimed at empirically separating financial distress from economic distress. That is, we address the question: Does top talent leave because the firm ceases to be economically viable or because the firm is financially distressed? To answer this question, we consider a sample of Swedish firms exporting to different countries. The idea underlying the test is that a large, exogenous decrease in the value of exports due to unfavorable exchange rate movements is likely to be detrimental to all exporting firms, but the likelihood of financial distress will increase more for highly levered exporters. This allows us to

[4] Sections I.B and III.C of the Internet Appendix discuss the Swedish LIFO regulations and their impact on firms' human resources policies in more detail.

distinguish between financial and economic distress. To implement the test, we follow Caggese, Cunat, and Metzger (2019) and determine an exporter's exposure to a set of currencies based on the exporting firm's trade partners at the start of the sample period. We then define a shock as a large depreciation of the trading partners' currencies relative to the domestic currency (Swedish Krona).[5]

We first document that the likelihood of a firm going bankrupt in the years immediately following an unfavorable exchange rate shock significantly increases, but only if the firm is highly leveraged ex ante. After confirming that the setting is indeed helpful in disentangling the effects of financial and economic distress, we study the impact of this shock on the likelihood of talent leaving. We find that following a large negative export shock, top talent in highly leveraged firms (compared to such talent in low-leverage firms experiencing the shock) are significantly more likely to leave. This constitutes compelling evidence that our main results are indeed driven by financial distress. In addition, by observing the shock that led to the financial distress, this test helps rule out the concern that labor market forces (such as key employees leaving the firm) drive the bankruptcy filing in the first place.

Finally, we provide some evidence supporting the view that the risk of losing employee talent may affect firm leverage ex ante, a prediction consistent with the trade-off theory of capital structure. The risk of losing talent could affect firms with a high average level of talent, but it might also pose a threat to firms whose talent is concentrated in a small group of employees. The reason is that firms in which the entire workforce has a high level of talent may be better able to survive the departure of key employees than a firm in which talent is concentrated and hence such departures would severely deplete the overall talent pool. We find that the dependence of firms on a highly skilled and highly mobile labor force is associated with lower leverage in the cross-section of Swedish firms. We show that it is not only the average talent level in the organization that matters—the degree to which cognitive and noncognitive skills are concentrated in a few key individuals within the firm is also negatively associated with financial leverage. This suggests that a firm's dependence on a small number of high-talent individuals constitutes a source of fragility. Taken as a whole, the results support the view that employees with the highest talent are more likely to desert a firm that is in financial distress, thereby providing evidence of an indirect cost of financial distress associated with the loss of talent.

Our paper connects several strands of literature in finance. First, our paper contributes to a growing literature that studies the interactions between finance and labor.[6] Within that literature, our work is most closely related to research that studies the interaction between labor and capital structure (see

[5] One major difference between our setting and that of Caggese, Cunat, and Metzger (2019) is that we focus on voluntary, rather than involuntary, turnover.

[6] Prior research documents several ways in which labor factors shape firms' corporate and, more specifically, financial policies. For example, Silva (2021) studies the role of internal labor markets as a determinant of internal allocation of capital in conglomerates. Tate and Yang (2015a)

Matsa (2018) for a recent review of this literature). Specifically, our work adds to Graham et al. (2016), who find a significant loss in the wages of workers employed by firms at the time of bankruptcy, and Caggese, Cunat, and Metzger (2019), who argue that financial constraints distort firms' firing decisions.

Our paper also complements recent work by 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 applicants is also lower, thus providing evidence on the labor costs of financial distress. We build on this key insight in several ways. First, we explicitly document the characteristics of workers who leave and join financially distressed firms. The granularity of our data allows us to measure talent, our main characteristic of interest, very precisely. Because we can also measure other individual traits (job tenure, age, gender, etc.), we can provide ancillary evidence on the characteristics of employees who leave and join financially distressed firms.[7] Second, we focus on the ability of firms to both attract and retain workers. Failing to attract talent to the organization (as documented by Brown and Matsa (2016)) would not be a significant problem if firms were not losing high-talent employees in times of financial distress. However, we find that firms fail to retain their top talent. Furthermore, by focusing on realized departures, hiring outcomes, and leverage decisions, we are able to paint a comprehensive picture of how labor composition changes around bankruptcy and how this relates to financial policies.

Finally, our paper contributes to the literature on firms' capital structures and their determinants (for a recent review of this literature, see Graham and Leary (2011)). Specifically, we add to the literature that documents and measures the costs of financial distress (e.g., Weiss (1990), Andrade and Kaplan (1998), Maksimovic and Phillips (1998), Hortaçsu et al. (2013)). We provide evidence that a firm's reliance on talent can make it fragile, especially when that talent is embodied by a small elite within the firm, and we propose such fragility as a potential determinant of capital structure.

I. Data and Variables

A. Main Data Sources

The main data set used in our analysis is obtained by matching longitudinal data on socioeconomic outcomes for Swedish individuals from 1990 to 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 (1998 to 2011). LISA contains detailed employee-employer matched information for the entire Swedish population

document that diversified firms have more active internal labor markets than focused firms; Tate and Yang (2015b) show that firms may diversify to create active internal labor markets.

[7] Because of data limitations, Brown and Matsa (2016) use indirect proxies for applicant quality (often at the ZIP code level).

aged 16 years or older. A large set of socioeconomic variables, such as age, gender, employment, uncensored wages, and social security benefits, are available. Thus, this data set allows us to track individuals over time and examine their career paths.

A distinguishing strength of the Swedish data is the possibility of linking the information from LISA to measures of cognitive and noncognitive skills using military records. The military data cover the period 1968 to 2011 and are obtained from the *National Archives* ("Riksarkivet") and the *Swedish Defence Recruitment Agency* ("Rekryteringsmyndigheten").[8] Between 1968 and 2009, all Swedish males aged 18 or over were required to participate in enlistment tests for one to two days.[9] The enlistment tests consisted of four parts, assessing cognitive ability, noncognitive ability, physical ability, and health status. Whether someone had to perform military service was determined by their health status, while the capacity in which they served was determined by the joint outcome of all of the tests. The cognitive ability test comprised four parts: synonyms, inductions, spatial reasoning, and technical comprehension; the combined score from the four parts was converted to a cognitive ability score from one to nine on the Stanine scale.[10] Noncognitive ability was assessed through a structured interview with a psychologist, who graded test-takers on psychological abilities (the score was also mapped onto the Stanine scale). Individuals who have the following character traits obtain high noncognitive test scores: willingness to assume responsibility, independence, outgoing character, persistence, emotional stability, initiative, and ability to work in groups (for further details, see Lindqvist and Vestman (2011)). In addition, the psychologist assessed leadership ability in all test-takers who received at least an average score on the cognitive ability test. Lindqvist and Vestman (2011) and Adams, Keloharju, and Knüpfer (2018) show that these measures relate to labor market outcomes in a meaningful way.

The Swedish firm-level data come 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 differing lengths, and they cover both privately and publicly held firms. Finally, we obtain data on Swedish firms' exporting activity (by country of destination and product) from Statistics Sweden; these data are available for the period 2000 to 2011.

[8] Since February 2021, the Swedish Defence Recruitment Agency has been known as the Swedish Defence Conscription and Assessment Agency ("Plikt- och prövningsverket").

[9] Since 2010, both military service and participation in the tests are no longer compulsory.

[10] The Stanine scale is a method of scaling test scores resulting in approximately normally distributed data with a mean of five and a range from one to nine.

B. Sample Construction

B.1. Main Sample

We employ several 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 first group, which we call the *bankruptcy* group, contains firms that experience a bankruptcy during our sample period, have nonmissing accounting data, and have at least five military test-takers five years prior to bankruptcy.[11] We also require firms to have at least one military test-taker during each of the five years preceding the bankruptcy event.[12] 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 (see Section I.A of the Internet Appendix for a detailed discussion of the Swedish bankruptcy law).

We next use a matching algorithm to construct a second group of firms, the *nonbankruptcy* group, which serves as a counterfactual for the firms approaching bankruptcy in the absence of such financial distress. Five years prior to bankruptcy, each of the firms in the *bankruptcy* group is matched to a firm that is observationally similar to but does not file for bankruptcy during our sample period. Specifically, we match *nonbankruptcy* firms to *bankruptcy* firms using a nearest-neighbor algorithm for a set of firm characteristics within calendar year and industry (Imbens et al. (2004)).[13] We use the following firm characteristics for the matching: *Ln(Assets)*, the natural logarithm of total assets; *Leverage*, total debt divided by total assets; *Profitability*, EBITDA divided by total assets; number of employees; average worker wage; and *Average skills*, the firm-year average of all workers' (additively combined) noncognitive and cognitive skill scores. Because the 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.

The average firm in the Swedish economy is small. In our sample, the average number of employees five years prior to bankruptcy is 33, and the

[11] Table IA.XXIV in the Internet Appendix shows the distribution of test-takers by firm in Sweden during our sample period (also encompassing firms that are not included in our main bankruptcy sample).

[12] One caveat is that our methodology could lead to selection bias, as we condition on survival in the period of $t-5$ to $t-1$ relative to the bankruptcy. Because we impose the same restriction on the group of *nonbankruptcy* firms that we match with, this methodology is unlikely to affect the interpretation of our tests.

[13] We define the following industries using SNI codes (the Swedish Standard Industrial classification): agriculture, manufacturing, transportation and utilities, construction and mining, commerce, professional services, other services, and finance. In the Internet Appendix, we present results using a narrower industry definition for the matching (Tables IA.XII and IA.XIII in the Internet Appendix). While matching at a finer industry level allows for greater comparability between *bankruptcy* and *nonbankruptcy* firms in terms of industrial classification, it leads to worse matching on other observable dimensions. Given this trade-off, we report the results using this alternative matching strategy in the Internet Appendix.

median is 18.[14] Panel A of Table I> compares characteristics of *bankruptcy* and *nonbankruptcy* firms in the matching year (t – 5). Unsurprisingly, *bankruptcy* and *nonbankruptcy* firms do not differ significantly along the characteristics on which we match. However, the matching also leads to similarities between *bankruptcy* and *nonbankruptcy* firms along dimensions that we observe but on which we do not match, such as workers' average number of years of education, the number of workers who took military enlistment tests, the average combined cognitive and noncognitive skills of the top 5% of workers, and export volume.[15]

Panel B of Table I shows the distribution of corporate bankruptcies across industries in our sample. The total number of bankruptcies is 2,448; the number and frequency of bankruptcies is highest in the manufacturing industry, while it is lowest in the agriculture and financial sectors.[16] Panel C of Table I shows the distribution of bankruptcies over time in 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 2003 and 2009 the years with the highest numbers.

We match firms with their employees using the employee-employer links from LISA. For regressions studying labor transitions into and out of financially distressed firms, the sample consists of male workers with military test scores that are employed by the firm in at least one of the five years preceding bankruptcy. Workers are only part of the sample in the years they are employed by firms in the *bankruptcy* and *nonbankruptcy* groups. The sample spans the years 1998 to 2010 (using bankruptcies from 2003 to 2011).[17]

B.2. Sample Used in the Analysis of Exporting Firms

Our second sample consists of exporting, nonfinancial limited liability firms. For the years 2000 to 2011, we have information on export revenue broken down by year and destination currency. We focus on exporting firms (firms with nonzero exports) with nonmissing information on assets, at least five employees, and at least five consecutive years of data. Firms enter this exporter sample the first year in which they have at least five military test-takers among their staff. Moreover, we exclude the first two observations of each firm from

[14] In Section III of the Internet Appendix, we show that our results are robust to imposing larger firm size cutoffs (we report results for firms with a minimum size of 10 to 50 employees) for the regression sample (see Table IA.XI in the Internet Appendix).

[15] Our findings are robust to alternative ways of constructing the *nonbankruptcy* group, including matching on different sets of characteristics. We discuss a few of these alternative specifications in Section IV.

[16] The "finance" category excludes commercial banks, which are a separate category of limited liability companies ("Bankaktiebolag") and for which regulations differ. Thus, banks are not contained in our sample. 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.

[17] *Serrano* data start in 1998. We require two years of consecutive data to determine whether a worker leaves a firm (see Section I.C), and hence the sample ends in 2010.

Table I

Summary Statistics: Matched Sample of Bankruptcy and Nonbankruptcy Firms

Panel A of this table presents summary statistics for characteristics of the firms in the *bankruptcy* and *nonbankruptcy* groups in year $t-5$ relative to the start of the bankruptcy. The abbreviation "n.m." (short for "not matched") added to a variable name indicates that a given variable has not been used in the matching procedure. The last column reports the p-value of the t-test of the difference between the mean characteristics of firms in the two groups. Firms in the *bankruptcy* group are those that file for bankruptcy between 2003 and 2011. The variables, as well as the matching procedure used to construct the *nonbankruptcy* group, are described in Section I. Panel B reports the distribution of bankruptcies across industries in our matched sample. Panel C tabulates the number of bankruptcies in our matched sample across years.

Panel A: Characteristics of Bankruptcy and Nonbankruptcy Firms

	Nonbankruptcy			Bankruptcy			Difference
	Observations (1)	Mean (2)	*SD* (3)	Observations (4)	Mean (5)	*SD* (6)	t-Test (p-Value) (7)
Ln(Assets)	2,448	8.761	1.158	2,448	8.723	1.195	0.255
Profitability	2,448	0.093	0.157	2,448	0.088	0.165	0.254
Leverage	2,448	0.200	0.208	2,448	0.206	0.207	0.308
Number of employees	2,448	30.354	132.791	2,448	33.195	137.369	0.462
Tangibility (n. m.)	2,448	0.273	0.243	2,448	0.243	0.230	0.000
Firm age (n. m.)	2,448	17.621	14.764	2,448	14.491	13.249	0.000
Average skills	2,448	9.701	1.449	2,448	9.686	1.483	0.715
Average wage	2,448	1,980.533	688.059	2,448	1,976.742	710.715	0.850
Average age (n. m.)	2,448	36.932	5.961	2,448	36.542	6.026	0.023
Short tenure share (n. m.)	2,448	0.443	0.279	2,448	0.525	0.295	0.000
Average experience in industry (n. m.)	2,448	6.817	2.544	2,448	6.274	2.571	0.000
Average education years (n. m.)	2,448	11.000	1.104	2,448	11.029	1.054	0.344
Talent concentration (n. m.)	2,448	0.070	0.009	2,448	0.071	0.009	0.023
Number of test-takers (n. m.)	2,448	13.741	57.659	2,448	15.392	67.507	0.358
Avg. skills in top 5% (n. m.)	2,448	13.479	1.919	2,448	13.548	1.890	0.206
Ln(Exports) (n. m.)	1,775	3.035	5.782	1,775	3.330	6.005	0.137

(*Continued*)

Table I—*Continued*

Panel B: Corporate Bankruptcies across Industries

Industry	Number of Bankruptcies (1)	Percentage (2)
Agriculture	22	0.9
Commerce	412	16.8
Construction and mining	450	18.4
Finance	159	6.5
Manufacturing	587	24.0
Professional services	357	14.6
Other services	224	9.2
Transportation and utilities	237	9.7
Total	2,448	100

Panel C: Corporate Bankruptcies over Time

Year	Number of bankruptcies (1)	Percentage (2)
2003	360	14.7
2004	313	12.8
2005	241	9.8
2006	183	7.5
2007	175	7.2
2008	226	9.2
2009	393	16.1
2010	314	12.8
2011	243	9.9
Total	2,448	100

the final regression sample. The reason is that in our regression models, we want to hold fixed a firm's leverage and export exposure using information preceding the regression estimation ("pretreatment"). We therefore construct these variables using the first two years of data for each firm and then discard these two observations from the regression sample (which therefore starts in 2002).

B.3. Sample Used in the Cross-Sectional Leverage Analysis

Finally, the third sample, which we employ in the cross-sectional leverage tests, consists of nonfinancial limited liability firms. We focus on observations with nonmissing information on assets, at least five employees, and at least five consecutive years of data. Furthermore, a firm is only included in the sample starting in the first year in which it has at least five military test-takers among its staff. Because we employ lagged variables in the regressions, the sample covers the years 1999 to 2011.

C. Variables

In this subsection, we discuss the variables employed in our analyses. Detailed variable definitions are reported in Table A.I.

C.1. Main Variables

The two main variables that we use to study employee mobility are *Leave* and *Join*. The first, *Leave*, is a dummy variable that takes the value of 1 in the year a worker leaves the employer, and 0 otherwise. A worker's "employer" in a given calendar year is the firm that provides an individual with the most labor income in that year. To better capture voluntary turnover, the variable is 0 when a worker leaves an employer but collects unemployment benefits (even if only temporarily). The second main variable, *Join*, is a dummy variable that takes the value of 1 in the year an employee joins a new firm. We identify "joiners" by verifying whether the main source of labor income changed vis-à-vis the previous year.[18]

The (time-invariant) dummy variable *Bankrupt* takes the value of 1 for firms that at some point during our sample period file for bankruptcy. The variable *Close* identifies the period of interest, from three years to one year prior to the

[18] One limitation of the annual frequency of the data is that the timing of job switches may sometimes be imprecisely measured. For example, suppose that an employee switches employer and has the same wages at both jobs. In LISA, the end of December is the cutoff date for considering annual income and for recording the employer that provided the largest source of income during the preceding 12 months. Because "leavers" are defined as having a different largest source of income in the next year, an employee who switches in July of year t will be classified as departing in year t, while an employee who switches in June of year t, will be classified as departing in year $t-1$. The same applies to the variable *Join*. The fact that this data limitation applies equally to *bankruptcy* firms and *nonbankruptcy* firms should mitigate concerns that it is driving our results.

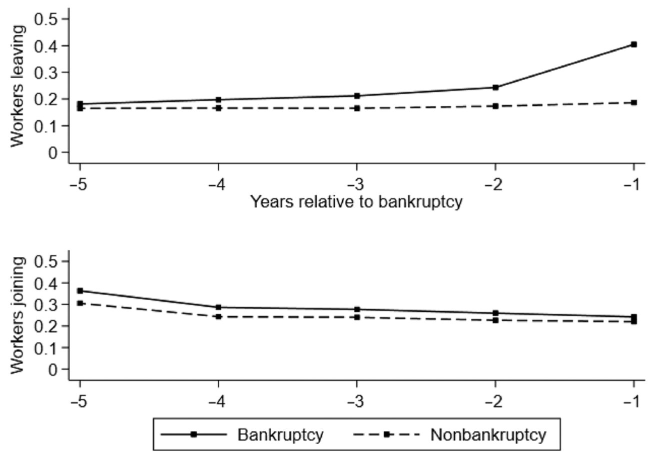

Figure 1. Evolution of labor force in firms approaching bankruptcy. This figure shows the average share of workers leaving and joining *bankruptcy* and *nonbankruptcy* firms in a given year. The timing is relative to the year a firm files for bankruptcy (*t*0) and to the matching year (*t* – 5). The sample construction is discussed in detail in Section I.

bankruptcy event. Figure 1, which shows the share of workers leaving and joining firms as they approach bankruptcy, suggests that our choice is meaningful. On average, the labor force appears stable until about four years prior to the onset of bankruptcy and then begins to contract. For *bankruptcy* firms, *Close* takes the value of 1 in years $t - 3$, $t - 2$, and $t - 1$ relative to the bankruptcy filing and a value of 0 in years $t - 4$ and $t - 5$. It also takes the value of 1 for *nonbankruptcy* firms in years $t - 3$ to $t - 1$ relative to the matching date (which occurs at $t - 5$); in other instances, *Close* takes the value of 0. Our tests can thus be interpreted as difference-in-differences estimates, where we compare the probability of 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 matched *nonbankruptcy* firms.

Our measure of talent is based on the sum of the cognitive and noncognitive test scores of males obtained from their military records. Cognitive skills refer to an individual's ability to perform various mental activities closely associated with learning and problem solving. Noncognitive skills refer to personality, social, and emotional traits, such as empathy, sociability, conscientiousness, and perseverance. We define *Top talent* as a dummy variable that takes the value of 1 if an individual has a combined cognitive and noncognitive test score in the top 5% of the distribution at the firm-year level, and 0 otherwise.[19] We thus define talent with reference to the distribution of skills within the firm. We do so because average skill levels vary across firms and industries (see Table II, Panel A, for a summary of how cognitive and noncognitive

[19] The firm-year distribution of test scores is based on all workers who received their main labor income from the firm during that year.

Table II

Skill Distribution across Industries and Levels of Corporate Hierarchies

We report averages of the sum of cognitive and noncognitive skill scores (from military enlistment records) across industries (Panel A) and across levels of the corporate hierarchy (Panel B). Hierarchy levels are constructed following Tåg (2013) using employee-level occupational codes from Statistics Sweden. The underlying sample of employers consists of Swedish limited liability firms, with nonmissing information on assets, at least five employees, at least five consecutive years of data, and at least five military test-takers in the first year they enter this sample. The sample spans the period 1998 to 2011 in Panel A and 2001 to 2011 in Panel B.

Panel A: Skill Distribution across Industries

Industry	Mean (1)	*SD* (2)
Agriculture	10.112	2.982
Commerce	10.272	2.832
Construction and mining	9.627	2.645
Finance	10.124	3.002
Manufacturing	9.930	2.984
Professional services	11.152	2.981
Other services	10.723	2.963
Transportation and utilities	9.714	2.892

Panel B: Skill Distribution across Levels of Hierarchy

Hierarchy level	Mean (1)	*SD* (2)
Clerks and “blue-collar” workers	9.183	2.739
Supervisors	11.719	2.544
Senior staff	12.088	2.547
CEOs and directors	11.714	2.719

skill scores vary across industries), and we are interested in understanding whether within each organization, high-talent workers comprise those most likely to “jump ship” as the firm becomes financially distressed.[20] In cases in which the top 5^{th} percentile cannot be unambiguously determined (because a firm has fewer than 20 workers who took the military tests or because the top scores are shared by more than 5% of the workers), *Top talent* takes the value of 1 for all workers who share the top score.[21] In all tests relying on military

[20] If, instead, we defined talent in an “economy-wide” way based on absolute scores, some firms would comprise an exclusively low-talent or high-talent workforce. We discuss robustness tests related to the definition of talent in Section IV.

[21] Approximately 0.7% of the military test-takers are volunteering females, who are excluded from the regressions that employ *Top talent* as an explanatory variable. Males with incomplete tests or missing test scores are also excluded. We exclude female test-takers because self-selected test-takers could be especially interested in pursuing a military career and thus their civilian career decisions might be less informative. However, our results remain unchanged if we include female test-takers in our sample.

test scores, to adjust for the possibility of changes in test standards over time, we include fixed effects for the enrollment period as reported by the testing authority: 1969 to 1982, 1983 to 1997, 1998 to 2001, 2002 to 2008, and 2009 to 2010. For robustness, we construct additional measures of talent based on (respectively) cognitive skills, noncognitive skills, leadership skills, and wages (the latter proxy is available for both men and women). We discuss these alternative proxies in Section IV.

Panel A of Table II shows the distribution of skills across industries in Sweden. Specifically, it shows industry averages of the sum of workers' cognitive and noncognitive skill scores. The industries for which these skills are highest are professional services (which includes, among others, workers in IT, R&D, law, and consulting) and other services (which includes workers in education and health care). Panel B of Table II reports the skill distribution across different hierarchy levels. The table shows that higher hierarchy levels tend to have more highly skilled workers. Perhaps somewhat surprisingly, the third hierarchy level ("senior staff" members) tends to have marginally more highly skilled workers on average than the top level ("CEOs and directors"). This is due to the relatively large number of small firms in the Swedish economy that tend to have flat hierarchical structures and less skilled CEOs, as measured by cognitive and noncognitive skill scores (see also Adams, Keloharju, and Knüpfer (2018)).[22]

Ln(Years of education) is the natural logarithm of an individual's years of schooling.[23] *Ln(Wage)* is the natural logarithm of gross wage, paid by the main employer (i.e., the employer that provided the largest source of income during the year). We define two variables measuring work experience: *Short tenure* is a dummy variable that takes the value of 1 if the number of years worked at the current firm is fewer than the sample median,[24] and *Experience in industry* is the number of years worked in the current industry. Both variables are censored due to the start of available employment histories in 1990. *Other municipality* is an indicator that is equal to 1 if a worker moves to a new municipality (that is, changes place of residence to a different municipality, whether or not he or she changes employment).

Individual-level information on occupational tasks is available from 2001 onward. 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). We follow Tåg (2013) and

[22] In Figures IA.5 and IA.6 in the Internet Appendix, we report the distribution of skills across (respectively) industries and hierarchy levels and employ various alternative skill proxies based on cognitive test scores, noncognitive test scores, leadership scores, and wages.

[23] More specifically, for each individual, we consider 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's degree, and so on.

[24] The median worker tenure—determined using both female and male workers—in the firms used for studying labor force turnover during periods of financial distress (Tables IV to VII) is three years.

construct a measure of hierarchy by mapping occupational codes into four different hierarchy levels: CEOs and directors, senior staff, supervisors, and clerks and "blue-collar" workers.

Finally, in our worker-level analysis, we also employ two alternative dependent variables in certain specifications. First, *Unemployed* is an indicator variable that takes the value of 1 if a worker leaves a firm and transitions into unemployment. A transition into unemployment is recorded if a worker receives any unemployment insurance payments in the year of the separation or the next.[25] Second, *Jumped the queue* is a dummy variable that takes the value of 1 in a given year if (i) a worker is no longer with the same employer in the following year, and (ii) this separation event deviates from the order mandated by the LIFO rule, which is based on the tenure of workers at the firm in that year. The variable is set to 0 if (i) the worker is no longer at the same employer in the following year but the separation is consistent with the LIFO rule, or (ii) the worker collects unemployment insurance benefits in the year of the separation or the next. This variable is only defined for workers who leave a bankrupt firm in years $t-3$ to $t-1$ relative to the bankruptcy filing year.

In Panel A of Table III, we report summary statistics for the variables used in the analysis of characteristics of workers who leave and join firms that experience a bankruptcy event during the period 2003 to 2011 (the underlying sample period is 1998 to 2010). The sample and summary statistics cover workers from firms in both the *bankruptcy* and *nonbankruptcy* groups.[26]

C.2. Variables Used in the Analysis of Exporting Firms

In Section II.E, we exploit movements in exchange rates as a source of exogenous variation for financial distress. We first construct a vector of a firm *f*'s exposure to different currencies, *Export exposure*$_f$. To ensure that a currency shock is exogenous to the firm's and workers' actions, we calculate the export exposure using information from the first two years that the firm is in the sample, but we subsequently exclude these two ("pretreatment") years from the

[25] One potential caveat in defining unemployment status using information from unemployment insurance payments is that if unemployment insurance take-up is low, we may falsely categorize workers as not having experienced an unemployment period even when they did. While this may be problematic in some countries (for example, Anderson and Meyer (1997) report that unemployment insurance take-up is below 50% in the United States), it is unlikely to bias our results in the Swedish setting. In Sweden, voluntary contributions to top-up governmental unemployment insurance are made by more than 85% of workers (Kolsrud et al. (2018)). Such contributions would not make financial sense if unemployment insurance take-up were low. Nevertheless, we cannot fully rule out the concern that unemployment insurance take-up may be lower for workers with high talent. We refer the reader to Kolsrud et al. (2018) and Landais et al. (2018) for a more complete analysis of unemployment insurance in Sweden.

[26] Table IA.XIV in Section III of the Internet Appendix reports summary statistics for the subsample for which we have occupational data (SSYK codes) for workers during all five years preceding bankruptcy. Specifically, the sample reported in Table IA.XIV in the Internet Appendix is used for regressions in which we control for hierarchy fixed effects (specifications (5) and (6) in Tables IV and VI) and covers the period 2001 to 2010.

Table III

Summary Statistics: Regression Samples

This table reports summary statistics for the different regression samples. Panel A presents the summary statistics for individuals included in the analysis of the selection of workers who leave or join firms approaching bankruptcy (Tables IV to VII). Panel B reports summary statistics for the characteristics of firms in the sample of exporting firms (Table VIII). Panel C reports summary statistics for the characteristics of workers in the sample of exporting firms (Tables IX and X). Finally, Panel D reports the summary statistics for the firms in our cross-sectional study of capital structure (Table XI). For details, see Section I.

Panel A: Worker Characteristics: Baseline Sample (1998 to 2010)

	Observations (1)	Mean (2)	*SD* (3)
Leave	349,009	0.188	0.391
Join	349,009	0.244	0.430
Top talent	349,009	0.108	0.310
Close	349,009	0.592	0.491
Bankrupt	349,009	0.518	0.500
Age	349,009	35.237	10.100
Short tenure	349,009	0.373	0.483
Experience in industry	349,009	7.826	5.206
Ln(Years of education)	349,009	2.428	0.158
Ln(Wage)$_{t-1}$	349,009	7.105	1.805
Other municipality	349,009	0.064	0.244
Unemployed	349,009	0.078	0.268
Jumped the queue	33,487	0.279	0.449

Panel B: Firm Characteristics: Export Sample (2002 to 2011)

	Observations (1)	Mean (2)	*SD* (3)
Bankrupt in <3 years	64,390	0.014	0.116
High leverage	64,390	0.504	0.500
Exchange rate shock	64,390	0.061	0.239
Tangibility	64,379	0.191	0.190
Profitability	64,379	0.115	0.145
Ln(Assets)	64,379	10.682	1.450

Panel C: Worker Characteristics: Export Sample (2002 to 2010)

	Observations (1)	Mean (2)	*SD* (3)
Leave	4,094,587	0.129	0.335
High leverage	4,094,587	0.292	0.455
Exchange rate shock	4,094,587	0.057	0.232
Top talent	4,094,587	0.061	0.239
Age	4,094,587	37.807	10.168
Short tenure	4,094,587	0.449	0.497
Experience in industry	4,094,587	9.815	5.721
Ln(Years of education)	4,094,587	2.475	0.174
Ln(Wage)$_{t-1}$	4,094,587	7.607	1.448

(*Continued*)

Table III—*Continued*

Panel D: Firm Characteristics: Cross-sectional Leverage Sample (1999 to 2011)			
	Observations (1)	Mean (2)	*SD* (3)
Leverage	408,329	0.133	0.186
Talent concentration	408,329	0.069	0.009
Average skills	408,329	10.043	1.607
Average experience in industry	408,329	8.042	2.971
Short tenure share	408,329	0.491	0.266
Tangibility	408,329	0.234	0.238
Profitability	408,329	0.131	0.160
Ln(Assets)	408,329	9.357	1.482
Firm age	408,329	20.901	17.052
Constrained	226,288	0.485	0.500

regression sample.[27] Specifically, for each firm and for the first two years that a firm is in the sample, we first calculate a firm's exports in EUR, USD, GBP, NOK, and DKK (expressed in SEK) divided by the firm's total sales (in SEK) in that year; we then take the average of the year one and year two shares for each firm.[28] A firm f's *Export exposure*$_f$ then corresponds to the vector:

$$Export\ exposure_f = \left(\frac{Exports\ in\ EUR}{Total\ Sales} \ldots \frac{Exports\ in\ DKK}{Total\ Sales} \right).$$

Next, we construct an annual exchange rate movement index by calculating the scalar product between the *Export exposure* vector and a vector of relative exchange rate changes between the current and previous year for the five currencies considered (the exchange rates in the currency vector are quoted as SEK per foreign currency). Finally, our main variable of interest is the *Exchange rate shock* dummy variable, which takes the value of 1 when a firm suffers a negative shock to the value of its exports, that is, when the firm (given its export exposure) experiences negative exchange rate movements. Specifically, the dummy takes the value of 1 when (i) the annual exchange rate movement index (the scalar product between the *Export exposure* vector and the currency vector) is negative, indicating an appreciation of the Swedish Krona vis-à-vis the exporter's relevant trading partner currencies, and (ii) the exchange rate

[27] For a new firm, the first year may not be representative of its steady-state export intensity, and thus, we also consider the second year.

[28] Exports denominated in these five currencies account for more than two-thirds of total Swedish exports during our sample period. We focus on these top five export currencies to simplify the analysis. The distribution of exports during our sample period is as follows: 38% of exports (by value) are to Eurozone countries, 9% to Norway, 9% to the United States, 8% to the United Kingdom, and 6% to Denmark. Other countries comprise 30% of exports; the biggest three are China (2.5%), Poland (2%), and Russia (1.5%).

movement index is in the bottom 5% of the distribution of the index across all years of the sample.[29]

To differentiate between high-leverage and low-leverage firms, we construct the (time-invariant) dummy variable *High leverage*. As in the case of export shares, we average the first two observations of *Leverage* for each firm in the sample; *High leverage* takes the value of 1 if a firm's average leverage ratio is above the sample median. We note that both *Export exposure* and *High leverage* are defined using historical information (relative to the information used in the regressions) and hence are less subject (albeit not immune) to endogeneity concerns, such as firms adjusting leverage or the choice of their trade partners as a consequence of a negative currency shock. Finally, the variable *Bankrupt in <3 years* takes the value of 1 if a given firm files for bankruptcy in the current year, next year, or year thereafter, and 0 otherwise.

Panels B and C of Table III report summary statistics for the variables used in the tests studying the effects of exchange rate shocks on exporting firms. Panel B reports statistics for the firm-level sample, while Panel C shows summary statistics for the employee-employer matched sample.

C.3. Variables Used in the Cross-Sectional Leverage Analysis

We define *Leverage* as the sum of short- and long-term bank debt (plus corporate bonds, if any) divided by total assets, *Tangibility* as property, plant, and equipment divided by total assets, *Ln(Assets)* as the natural logarithm of total assets, and *Profitability* as EBITDA divided by total assets. These four measures are winsorized at the 1^{st} and 99^{th} percentiles. We next define *Short tenure share* and *Average experience in industry* as, respectively, the mean of *Short tenure* and mean *Experience in industry* at the firm-year level, while *Firm age* is the number of years since incorporation. We also examine differences in leverage between financially constrained and unconstrained firms. The typical financial constraint measures considered in the empirical corporate finance literature are constructed using U.S. data and cannot be directly applied in a Swedish setting. However, we conceptually follow Hadlock and Pierce (2010) to group firms into constrained and unconstrained sets.[30] The variable *Constrained* is a dummy variable that takes the value of 1 for firms that are "small and young" and 0 for firms that are "large and old." Specifically, we sort observations into two quantiles of firm age and two quantiles of assets (deflated to 1998 SEK). We then classify a firm as financially constrained in a given year (that is, *Constrained* takes the value of 1) if both its age and assets are less than or equal to the sample median, and as unconstrained if both its age and assets are above the sample median.

In these firm-level regressions, we employ two measures of firm talent: *Average skills*, the mean of the combined cognitive and noncognitive skill scores

[29] Our results are robust to considering the bottom 10% of firms as "shocked" (see Table IA.XXIII in the Internet Appendix).

[30] Hadlock and Pierce (2010, p. 1912) "recommend that researchers rely solely on firm size and age, two relatively exogenous firm characteristics, to identify constrained firms."

of the employees working in a firm in a given year, and *Talent concentration*, the fraction of the total combined cognitive and noncognitive skills at a firm in a given year that are held by the top 5% of workers within that firm-year.[31] The latter measure, which is the firm-level analog of the dummy variable *Top talent* in our worker mobility analysis, captures the firm's dependence on the human capital of its most skilled employees.

Panel D of Table III reports summary statistics for the sample of firms used in the cross-sectional analysis of leverage. Each observation corresponds to a firm-year.

II. Evolution of Labor Force Composition around Bankruptcy

A. *Characteristics of Workers Leaving Financially Distressed Firms*

We begin by studying the evolution of the labor force composition in firms approaching bankruptcy. Specifically, we examine the selection and characteristics of workers who leave and of those who join firms prior to bankruptcy. Workers with different characteristics may have different preferences and incentives to leave (or join) firms approaching bankruptcy. Moreover, the 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 desert a firm as it becomes financially distressed, the loss of key talent (defined using innate cognitive and noncognitive abilities that are generally applicable in different tasks and jobs) is likely to be especially critical for the firm's ability to survive and create value.[32] Consistent with this notion, we observe a positive and increasing talent wage premium in Sweden (Figure 2). This increase is particularly pronounced at the top of the talent distribution: workers above the 95$^{\text{th}}$ percentile of the distribution of cognitive and noncognitive skills in the economy experienced considerably larger growth in their wage premium than those above the median.

There are several reasons why high-talent workers may decide to leave a firm early, in anticipation of bankruptcy. One possibility is that these workers are better able to predict the likelihood of their firm's bankruptcy and thus time their exit decision better. Furthermore, because such workers are likely to have more influence on firm performance, the cost they may face in being associated with a failed enterprise could be larger than for the average worker. However, high-talent workers may be better able to hedge bankruptcy risk.

[31] Specifically, this variable is defined as follows. For each firm and year, we rank workers based on their combined cognitive and noncognitive ability scores to identify the workers in the top 5$^{\text{th}}$ percentile ("top 5% workers"; see the procedure described for the variable *Top talent*). We then sum the cognitive and noncognitive ability scores for the top 5% workers and divide this number by the total sum of the cognitive and noncognitive ability scores of all workers in the firm-year. This ratio is then adjusted by the factor (0.05/share of workers in the top 5% of the talent distribution), which ensures that this variable does not mechanically capture a firm size effect. The resulting number is the variable *Talent concentration*.

[32] Abowd et al. (2005) find that the most skilled workers in a firm have a disproportionately positive impact on the firm's productivity and market value.

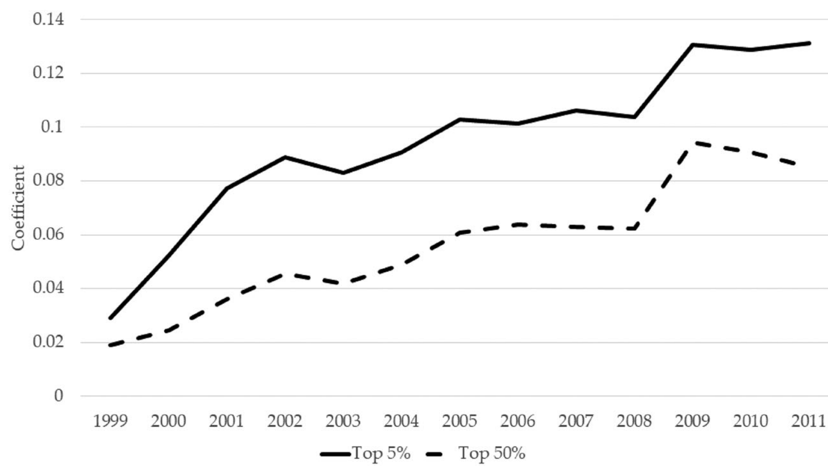

Figure 2. Evolution of the talent wage premium, 1998 to 2011. The figure shows the evolution of the talent wage premium in Sweden between 1998 and 2011. The sample is constructed as follows. The underlying sample consists of workers in Swedish limited liability firms; we focus on firms with nonmissing information on assets, at least five employees, at least five military test-takers in the first year that the firm enters the sample, and at least five consecutive years of data. Furthermore, we consider all individuals who took military enlistment tests. We estimate the regression model $Ln(Wage)_{i,t} = \alpha_t\, T_{i,t} + X'\beta$. *Ln(Wage)* is the natural logarithm of the labor income obtained by an individual from the main employer in a given year. The matrix X includes the following fixed effects: worker age × year, industry, years of education, and *Talent (economy-wide)*, where *Talent (economy-wide)* is a dummy variable that takes the value of 1 if a given worker is in the top 5% (alternatively, top 50%) of the skill distribution in the economy in a given year, and skill is measured using the combined cognitive and noncognitive military test scores. T is *Talent (economy-wide)* interacted with year dummies. The coefficients α_t, plotted in the figure below, denote the talent wage premium in a given year relative to that in 1998.

The availability of outside options may also differ for workers with higher or lower skills. If high-talent workers face a more liquid labor market, staying in the firm longer could be less risky for them.[33] The theoretical ambiguity that arises from the different economic forces makes the question of whether high-talent workers are indeed more likely to abandon distressed firms early an interesting one.

Figures 1 and 3 examine these effects graphically. Figure 1 shows that, relative to *nonbankruptcy* firms, the fraction of workers leaving increases as a firm approaches bankruptcy. In contrast, the fraction of workers joining the firm evolves similarly for firms in the *bankruptcy* and *nonbankruptcy* groups. Figure 3 shows the share of high-talent workers (as a fraction of total male workers with cognitive and noncognitive skill scores employed in the firm-year) leaving and joining firms. The pattern documented in Figure 3 indicates

[33] Consistent with this argument, in Table IA.XXI in Section III.C of the Internet Appendix, we show that high-talent workers, controlling for various other observable characteristics, are less likely to become unemployed and have shorter unemployment spells, conditional on being unemployed.

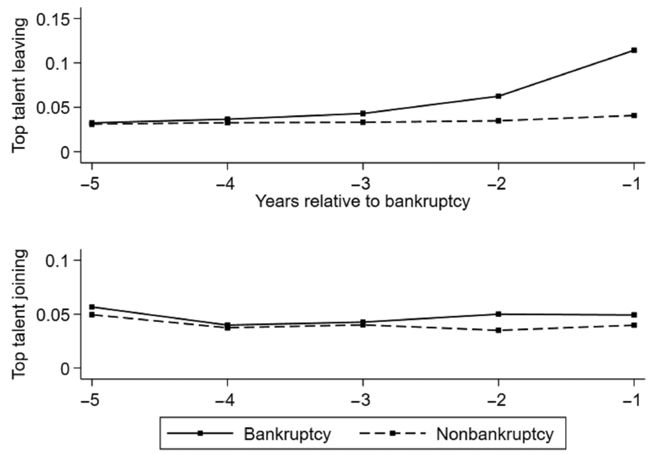

Figure 3. Talent leaving and joining bankruptcy and nonbankruptcy firms. This figure shows the share of top talent (as a fraction of male workers with information on cognitive and noncognitive scores employed in the firm in a given year) leaving and joining *bankruptcy* and *nonbankruptcy* firms. *Top talent* workers are those who lie in the top 5% of the distribution of the sum of cognitive and noncognitive skill scores within the firm in a given year. The timing is relative to the year a firm files for bankruptcy ($t0$) and to the matching year ($t - 5$). Sample construction and variable definitions are discussed in detail in Section I.

an overall deterioration of the talent pool in *bankruptcy* firms over time. High-talent workers are significantly more likely to leave a firm as it approaches bankruptcy, while there is no evidence of an increase in the fraction of talent joining soon-to-be bankrupt firms.

We formally test whether proximity to bankruptcy is correlated with an increase in the probability that top talent workers leave the firm by estimating a linear probability model. We compare the probability that a worker at the top of the within-firm talent distribution abandons the firm as it approaches distress, relative to high-talent workers in *nonbankruptcy* firms. The regression specification that we estimate also includes a set of individual worker characteristics that could affect the probability of leaving prior to bankruptcy events. In particular, we control for worker age, tenure in the firm, experience in the industry, years of education, and wages (lagged by one year). Moreover, we estimate the extent to which workers who depart close to bankruptcy differ from those who leave at other times. To account for time-invariant differences in turnover across firms that may occur for reasons other than bankruptcy, the regressions also include firm fixed effects. Industry-year fixed effects account for the evolution of the optimal composition of workers at the industry level. Thus, our results are not driven by the possibility that, for example, industries with more bankruptcies are also those from which more talented employees are leaving. Finally, we cluster standard errors at the firm level.

Results are reported in Table IV. In column (1), we find that being in close proximity to bankruptcy is associated with a statistically and economically

Table IV

Selection of Workers Who Leave Firms Approaching Bankruptcy

This table reports coefficients of OLS regression models examining the composition of workers who leave firms approaching bankruptcy. *Leave*, the dependent variable, is a dummy variable that takes the value of 1 in the year the worker leaves the firm, and 0 otherwise. *Bankrupt* takes the value of 1 for workers employed by a firm that goes bankrupt at some point during the sample period. *Close* takes the value of 1 in years $t-3$, $t-2$, and $t-1$ relative to the bankruptcy event ($t0$) and the matching year ($t-5$). *Top talent* is a dummy variable taking the value of 1 for the top 5% of talent (measured using combined cognitive and noncognitive skill test scores) within a firm. The sample in specifications (1) to (4) spans the period 1998 to 2010, while it covers the years 2001 to 2010 in specifications (5) and (6) due to (hierarchy) data availability. Robust standard errors, clustered at the firm level, are reported in parentheses below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Leave					
	(1)	(2)	(3)	(4)	(5)	(6)
Close × Bankrupt	0.067***	0.062***	0.051		0.053	
	(0.007)	(0.007)	(0.070)		(0.087)	
Top talent × Close × Bankrupt		0.042***	0.041***	0.020**	0.040***	0.037***
		(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
Top talent		0.041***	0.041***	0.043***	0.033***	0.033***
		(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Top talent × Close		–0.029***	–0.027***	–0.016***	–0.024***	–0.024***
		(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Top talent × Bankrupt		–0.017**	–0.016**	–0.005	–0.020**	–0.018**
		(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Ln(Wage)_{t-1}			–0.024***	–0.024***	–0.015***	–0.015***
			(0.001)	(0.001)	(0.003)	(0.003)
Ln(Wage)_{t-1} × Close			–0.004*	–0.005***	–0.004*	–0.004*
			(0.002)	(0.002)	(0.002)	(0.002)
Ln(Wage)_{t-1} × Bankrupt			0.003*	0.003	0.002	0.002
			(0.002)	(0.002)	(0.003)	(0.003)
Ln(Wage)_{t-1} × Close × Bankrupt			0.003	0.003	0.008**	0.007**
			(0.003)	(0.003)	(0.003)	(0.003)
Age			–0.005***	–0.005***	–0.003***	–0.003***
			(0.000)	(0.000)	(0.000)	(0.000)
Age × Close			0.000	0.000	–0.000	–0.000
			(0.000)	(0.000)	(0.000)	(0.000)
Age × Bankrupt			–0.001**	–0.001*	–0.000	–0.000
			(0.000)	(0.000)	(0.000)	(0.000)
Age × Close × Bankrupt			–0.000	–0.000	–0.000	–0.000
			(0.000)	(0.000)	(0.000)	(0.000)

(Continued)

Table IV—*Continued*

	Leave					
	(1)	(2)	(3)	(4)	(5)	(6)
Short tenure			0.019***	0.021***	0.032***	0.032***
			(0.006)	(0.005)	(0.007)	(0.007)
Short tenure × Close			–0.004	0.001	–0.020**	–0.020**
			(0.008)	(0.006)	(0.009)	(0.008)
Short tenure × Bankrupt			–0.006	0.006	–0.023**	–0.023**
			(0.008)	(0.007)	(0.011)	(0.011)
Short tenure × Close × Bankrupt			0.002	–0.013	0.016	0.016
			(0.010)	(0.009)	(0.013)	(0.013)
Experience in industry			–0.003***	–0.003***	–0.002***	–0.002***
			(0.001)	(0.000)	(0.001)	(0.001)
Experience in industry × Close			0.001	0.001*	–0.000	–0.000
			(0.001)	(0.001)	(0.001)	(0.001)
Experience in industry × Bankrupt			0.003***	0.001**	0.001	0.001*
			(0.001)	(0.001)	(0.001)	(0.001)
Experience in industry × Close × Bankrupt			–0.001	0.000	0.000	0.000
			(0.001)	(0.001)	(0.001)	(0.001)
Ln(Years of education)			0.008	0.005	0.046**	0.043**
			(0.019)	(0.020)	(0.018)	(0.018)
Ln(Years of education) × Close			–0.018	–0.007	–0.012	–0.006
			(0.013)	(0.013)	(0.016)	(0.016)
Ln(Years of education) × Bankrupt			–0.004	–0.014	0.020	0.025
			(0.027)	(0.027)	(0.027)	(0.024)
Ln(Years of education) × Close × Bankrupt			–0.003	0.003	–0.025	–0.034
			(0.027)	(0.022)	(0.031)	(0.027)
Firm F.E.	Yes	Yes	Yes		Yes	Yes
Industry × year F.E.	Yes	Yes	Yes		Yes	Yes
Firm × year F.E.				Yes		
Hierarchy F.E.					Yes	
Close × Bankrupt × hierarchy F.E.						Yes
Close × enrollment period F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	349,009	349,009	349,009	348,569	271,490	271,490
Adjusted R^2	0.121	0.121	0.141	0.209	0.119	0.119

significant increase in the probability of a worker leaving the firm. The estimate implies that for firms in the *bankruptcy* group, the probability of workers leaving is 6.7 percentage points higher when firms are close to distress than in normal times. In columns (2) and (3), we analyze the composition of workers who leave *bankruptcy* firms close to distress. An important pattern that emerges is an increase in the propensity of top talent to leave as a firm approaches bankruptcy. In column (2), we show that workers with high talent have a 4.2 percentage point higher probability of leaving the firm as it approaches bankruptcy than less skilled workers. Relative to the average effect of 6.7%, this estimate suggests that top talent is roughly 65% more likely to leave a firm approaching distress than the average employee. The specification reported in column (3) is augmented with a wide range of worker characteristics and their interactions with *Close* and *Bankrupt*.

In columns (4) to (6), we test additional specifications of the regression model to ensure the robustness of our findings. In column (4), we add firm-year fixed effects to our regression; our results remain qualitatively similar. In column (5), we repeat the previous analysis but include a set of fixed effects for the hierarchy level at which a worker is employed. In column (6), we include the interaction between *Close*, *Bankrupt*, and hierarchy fixed effects. The sample size is reduced in the latter two specifications, as the hierarchy measure is only available from 2001 onward (see Section I). The results show that within any given hierarchical level, high-talent employees are significantly more likely to abandon the firm as it approaches distress. The results in columns (5) and (6) alleviate concerns that what we are capturing is simply a reorganization of the firm through which some hierarchical levels shrink more than others. Instead, our results suggest that even after taking this potential confounding effect into account, firms approaching bankruptcy have less ability to retain their key talent.

B. Voluntary versus Involuntary Turnover

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

At the outset, it should be noted that our findings reported in Table IV are unlikely to be driven by firms firing their most expensive workers in times of distress because we control for wages in our tests. We also interact *Ln(Wage)* with *Close* $\times$ *Bankrupt* to allow for the possibility that firms may be particularly cost-sensitive prior to bankruptcy. 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 skilled worker. Instead, the most natural explanation for our findings is that we are capturing the decision of high-talent workers to leave firms voluntarily. Second, in the tests reported above, the variable *Leave* excludes transitions to unemployment, to capture voluntary turnover as accurately as possible.

To further distinguish between voluntary and involuntary turnover, we examine which workers transition into unemployment after exiting the distressed firm. The logic here is that workers who become unemployed are more likely to have been laid off than those who abandon the firm and do not experience a period of unemployment. Specifically, in columns (1) and (2) of Table V, we repeat the analysis from Table IV but use a new dependent variable: *Unemployed*, which takes a value of 1 only if a worker leaves and transitions into unemployment. In column (1), we show that workers from *bankruptcy* firms are more likely to transition to unemployment compared to workers from *non-bankruptcy* firms. However, as shown in column (2), this effect is not more pronounced for high-talent workers, as the coefficient on the interaction term *Close* × *Bankrupt* × *Top talent* is economically and statistically insignificant.[34] This suggests that firms are not simply laying off their most skilled employees when approaching bankruptcy. One caveat with this analysis is that laid-off workers with high ability may be more likely to find other employment before collecting unemployment insurance benefits than low-ability workers (Table IA.XXI in the Internet Appendix provides some evidence that high-talent workers face a more liquid labor market than other workers). Next, we conduct two tests that exploit specific firing restrictions of the Swedish labor law to provide additional evidence that our main results are primarily a manifestation of voluntary departures.

When dismissing workers, firms with 11 or more employees must follow a LIFO rule that constrains their ability to lay off workers arbitrarily.[35] In columns (3) and (4) of Table V, we repeat our analysis for the subsample of firms that are bound by LIFO rules (firms with 11+ workers). Because these firms are limited in their ability to select which workers to fire and which to retain, it is difficult to argue that they simply fire the most skilled workers as part of a reorganization around bankruptcy. The results are similar to those reported in Table IV. This evidence further strengthens our interpretation that the most skilled workers "jump ship," in contrast to the view that organizations approaching bankruptcy have reduced need for talent and, as such, fire highly skilled employees.

In firms that are restricted by LIFO regulation, workers who are fired follow the inverse order in which they join the firm. In contrast, voluntary exits may "jump the queue" by leaving regardless of their LIFO order. Because we know the years that workers join any given firm, we can test whether high-talent workers are more likely to be the ones who "jump the queue." Finding that high-talent workers are less likely to follow their LIFO order would be another piece of evidence consistent with these workers leaving voluntarily, instead of

[34] Consistent with Caggese, Cunat, and Metzger (2019), who investigate financially constrained firms, we find that workers with short tenure in the bankrupt firm are more likely to be fired, using transitions to unemployment as a proxy for firings.

[35] See Section I.B of the Internet Appendix for a general discussion of the labor laws in Sweden and of LIFO rules in particular.

Table V

Selection of Workers Who Leave Firms Approaching Bankruptcy: Voluntary versus Involuntary Departures

This table reports coefficients of OLS regression models examining the composition of workers who leave firms approaching bankruptcy. In columns (1) and (2), the dependent variable is *Unemployed*, a dummy variable equal to 1 if a worker transitions to unemployment when leaving a firm. In columns (3) and (4), the dependent variable is *Leave*, a dummy variable equal to 1 in the year a worker leaves a firm. In columns (5) and (6), the dependent variable is *Jumped the queue*, a dummy variable equal to 1 if a worker leaves a firm and his tenure in the firm is longer than the tenure of the n^{th} worker ranked by tenure, where n is the number of workers leaving the firm that year. The sample underlying columns (3) to (6) only includes employees of firms with 11 or more workers. In columns (5) and (6), only workers leaving firms during $t-3$ to $t-1$ relative to the bankruptcy are included. The sample period is 1998 to 2010. Robust standard errors, clustered at the firm level, are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Unemployed		Leave		Jumped the queue	
	(1)	(2)	(3)	(4)	(5)	(6)
Close × Bankrupt	0.030***	0.031	0.062***	0.030		
	(0.003)	(0.031)	(0.008)	(0.073)		
Top talent × Close × Bankrupt		0.002		0.038***		
		(0.006)		(0.009)		
Top talent × Close		0.007**		–0.025***		
		(0.004)		(0.006)		
Top talent × Bankrupt		–0.004		–0.018**		
		(0.004)		(0.008)		
Top talent		–0.027***		0.048***	0.031***	0.032***
		(0.003)		(0.005)	(0.008)	(0.008)
Ln(Wage)$_{t\text{-}1}$		–0.005***		–0.024***		0.031***
		(0.001)		(0.002)		(0.002)
Age		0.001***		–0.005***		–0.003***
		(0.000)		(0.000)		(0.000)
Experience in industry		–0.004***		–0.003***		0.027***
		(0.000)		(0.001)		(0.001)
Ln(Years of education)		0.047***		0.017		0.005
		(0.009)		(0.019)		(0.018)
Short tenure		0.057***		0.019***		
		(0.004)		(0.007)		

(*Continued*)

Table V—*Continued*

	Unemployed		Leave		Jumped the Queue	
	(1)	(2)	(3)	(4)	(5)	(6)
$Ln(Wage)_{t-1}$ × Close		0.004***		–0.004*		
		(0.001)		(0.002)		
$Ln(Wage)_{t-1}$ × Bankrupt		0.001		0.003*		
		(0.001)		(0.002)		
$Ln(Wage)_{t-1}$ × Close × Bankrupt		0.004**		0.003		
		(0.002)		(0.003)		
Age × Close		–0.000		0.000		
		(0.000)		(0.000)		
Age × Bankrupt		0.000		–0.001**		
		(0.000)		(0.000)		
Age × Close × Bankrupt		0.000		–0.000		
		(0.000)		(0.000)		
Short tenure × Close		–0.004		–0.004		
		(0.004)		(0.008)		
Short tenure × Bankrupt		0.002		–0.006		
		(0.005)		(0.009)		
Short tenure × Close × Bankrupt		0.013**		0.002		
		(0.006)		(0.011)		
Experience in industry × Close		–0.000		0.001		
		(0.000)		(0.001)		
Experience in industry × Bankrupt		–0.001**		0.003***		
		(0.001)		(0.001)		
Experience in industry × Close × Bankrupt		0.000		–0.001		
		(0.001)		(0.001)		
Ln(Years of education) × Close		–0.013		–0.027*		
		(0.009)		(0.014)		
Ln(Years of education) × Bankrupt		0.001		–0.011		
		(0.013)		(0.028)		
Ln(Years of education) × Close × Bankrupt		–0.017		0.006		
		(0.013)		(0.028)		
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry × year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Close × enrollment period F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	349,009	349,009	321,069	321,069	33,487	33,487
Adjusted R^2	0.066	0.084	0.124	0.144	0.173	0.252

being fired by the firm. In the specifications reported in columns (5) and (6) of Table V, we employ the dependent variable *Jumped the queue*. This indicator variable takes the value of 1 if the worker leaves and, in doing so, deviates from the job separation order dictated by the LIFO rule.[36]

The algorithm we use can be best understood with a simple example. Suppose that a firm has 100 employees, and we observe 20 employees leave the firm. Because we know when these employees joined, 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 on *bankruptcy* firms, that is, firms that become bankrupt, and we retain in the sample only those workers who leave firms in years $t-3$ to $t-1$ relative to bankruptcy. We find that the most skilled employees of the firm do not wait their turn to be fired. Instead, they tend to leave earlier than what their tenure would predict if the firm were laying off workers according to a LIFO rule.

One potential concern is that LIFO is not enforced and, as a result, is not a de facto firing restriction. However, von Below and Thoursie (2010) provide evidence to the contrary: they find that both hiring and separation probabilities significantly increased for small firms after the LIFO restriction was relaxed in 2001 for such firms. We provide similar evidence in Section III of the Internet Appendix. Specifically, we report tests that show that the LIFO rule does indeed affect the firing decisions of firms (see Table IA.XXII and Figure IA.1 in the Internet Appendix).

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

C. Selection of Workers Joining Distressed Firms

Next, we analyze which workers join firms approaching bankruptcy and the ability of financially distressed firms to attract talent. If firms cannot retain high-talent workers but can still attract them, the overall talent pool in the organization might be unaffected by the imminent threat of bankruptcy.

The specifications that we use here differ from the tests on employee departures reported in Table IV in three ways. First, the dependent variable, *Join*, is an indicator that takes the value of 1 in the year the worker joins the firm, and 0 otherwise. Second, we exclude from the list of control variables *Short tenure* as, by definition, new joiners would not have experience in the firm they join. Third, we add the variable *Other municipality* to certain specifications to test whether the firm is less likely to attract workers for whom the adjustment costs are larger.

[36] Note that we do not include the variable *Short tenure* in these regressions because the dependent variable (*Jumped the queue*) is a function of worker tenure.

Results are reported in Table VI. We first note that the estimate of *Close* × *Bankruptcy* in column (1) is negative, which implies that firms attract fewer employees as they approach bankruptcy. According to column (1), *bankruptcy* firms have a 0.8 percentage point lower fraction of new employees in the three years preceding bankruptcy relative to normal times (this coefficient is not statistically significantly different from zero). Importantly, in regressions reported in columns (2) and (3), we find that being close to bankruptcy does not enhance the ability of firms to attract highly skilled individuals in an economically or statistically significant way. Despite the loss of talent documented in Table IV, *bankruptcy* firms are unable to replace the human capital lost by attracting highly skilled employees in sufficiently larger numbers. We also find that the characteristics of workers who join financially distressed firms differ from the types of employees joining firms at other times. According to column (3) of Table VI, workers commanding higher wages and those coming from other municipalities are less likely to join the firm, although these effects are not precisely estimated.

Columns (4) to (6) of Table VI report additional specifications. In particular, we find similar results when estimating a regression with firm-year fixed effects (column (4)), a specification with hierarchy fixed effects (column (5)), and a regression that includes interactions of hierarchy fixed effects with *Close* × *Bankrupt* (column (6)).

The fact that we do not find a decrease in the hiring rate of high-talent employees relative to less skilled workers in firms approaching bankruptcy suggests that financially distressed firms do not *choose* to operate with lower levels of talent. If that were the case, firms would not only dismiss their most skilled employees, but would also likely stop hiring high-talent employees. In fact, if firms were aiming to voluntarily reduce the number of high-talent workers they employ, the natural first step would be to stop hiring talent even before beginning to lay off their most skilled workers. However, Brown and Matsa (2016) show that financially distressed firms continue posting job vacancies. In addition, we find that firms keep hiring high-talent employees at the same rate as less-skilled employees. In sum, our results suggest that even prior to bankruptcy, the pool of human capital available in the firm may deteriorate considerably.

D. Placebo Test

Even though our *bankruptcy* and *nonbankruptcy* firms appear similar in terms of observable characteristics (see Table I), 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 *bankruptcy* and *nonbankruptcy* groups and estimate the same specifications as reported in columns (1) to (3) of Tables IV and VI but now define the placebo "treatment" period as $t-6$ to $t-4$ (instead of $t-3$ to

Table VI

Selection of Workers Who Join Firms Approaching Bankruptcy

This table reports coefficients of OLS regression models examining the composition of workers who join firms approaching bankruptcy. *Join*, the dependent variable, is a dummy variable that takes the value of 1 in the year the worker joins the firm, and 0 otherwise. The sample in specifications (1) to (4) spans the period 1998 to 2010, while it covers the years 2001 to 2010 in specifications (5) and (6) due to (hierarchy) data availability. Robust standard errors clustered at the firm level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Join					
	(1)	(2)	(3)	(4)	(5)	(6)
Close × Bankrupt	–0.008	–0.008	–0.081		–0.158**	
	(0.009)	(0.009)	(0.058)		(0.072)	
Top talent × Close × Bankrupt		0.000	–0.006	–0.001	–0.001	–0.001
		(0.010)	(0.009)	(0.008)	(0.012)	(0.011)
Top talent		–0.002	–0.009*	0.001	–0.000	0.001
		(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
Top talent × Close		0.007	0.011*	0.003	0.002	0.000
		(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
Top talent × Bankrupt		–0.004	0.001	0.001	–0.004	–0.003
		(0.009)	(0.008)	(0.007)	(0.010)	(0.009)
Ln(Wage)_{t-1}			–0.100***	–0.099***	–0.110***	–0.110***
			(0.002)	(0.002)	(0.002)	(0.002)
Ln(Wage)_{t-1} × Close			–0.006***	–0.006***	–0.006**	–0.006**
			(0.002)	(0.002)	(0.002)	(0.003)
Ln(Wage)_{t-1} × Bankrupt			0.006**	0.006**	0.007**	0.007**
			(0.003)	(0.003)	(0.003)	(0.003)
Ln(Wage)_{t-1} × Close × Bankrupt			–0.002	–0.001	–0.001	–0.002
			(0.003)	(0.003)	(0.004)	(0.004)
Age			0.003***	0.003***	0.001***	0.002***
			(0.001)	(0.000)	(0.000)	(0.000)
Age × Close			–0.001**	–0.001	0.000	–0.000
			(0.000)	(0.000)	(0.001)	(0.001)
Age × Bankrupt			–0.001	–0.001	–0.001	–0.000
			(0.001)	(0.001)	(0.001)	(0.001)

(Continued)

Table VI—*Continued*

	Join					
	(1)	(2)	(3)	(4)	(5)	(6)
Age × Close × Bankrupt			0.001	0.001	0.001	0.000
			(0.001)	(0.000)	(0.001)	(0.001)
Experience in industry			–0.026***	–0.024***	–0.021***	–0.021***
			(0.001)	(0.001)	(0.001)	(0.001)
Experience in industry × Close			0.008***	0.005***	0.004***	0.004***
			(0.001)	(0.001)	(0.001)	(0.001)
Experience in industry × Bankrupt			–0.000	0.000	–0.001	–0.001
			(0.002)	(0.002)	(0.002)	(0.002)
Experience in industry × Close × Bankrupt			0.000	–0.001	0.002	0.002
			(0.002)	(0.002)	(0.002)	(0.002)
Ln(Years of education)			0.058***	0.053***	0.019	0.027**
			(0.012)	(0.010)	(0.014)	(0.013)
Ln(Years of education) × Close			0.002	0.004	0.009	–0.001
			(0.015)	(0.013)	(0.017)	(0.016)
Ln(Years of education) × Bankrupt			–0.010	–0.002	–0.018	–0.009
			(0.017)	(0.016)	(0.021)	(0.021)
Ln(Years of education) × Close × Bankrupt			0.028	0.009	0.048*	0.031
			(0.023)	(0.019)	(0.026)	(0.027)
Other municipality			0.053***	0.052***	0.050***	0.050***
			(0.008)	(0.008)	(0.011)	(0.011)
Other municipality × Close			0.007	0.009	0.013	0.013
			(0.010)	(0.010)	(0.012)	(0.012)
Other municipality × Bankrupt			–0.002	–0.004	0.002	0.003
			(0.011)	(0.011)	(0.015)	(0.015)
Other municipality × Close × Bankrupt			–0.015	–0.015	–0.023	–0.024
			(0.013)	(0.013)	(0.017)	(0.017)
Firm F.E.	Yes	Yes	Yes		Yes	Yes
Industry × year F.E.	Yes	Yes	Yes		Yes	Yes
Firm × year F.E.				Yes		
Hierarchy F.E.					Yes	
Close × Bankrupt × hierarchy F.E.						Yes
Close × enrollment period F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	349,009	349,009	349,009	348,569	271,490	271,490
Adjusted R^2	0.162	0.162	0.361	0.404	0.299	0.299

$t-1$, as in our main analysis).[37] That is, our new variable of interest, *Placebo close*, takes the value of 1 in years $t-6$, $t-5$, and $t-4$ relative to bankruptcy, and 0 otherwise. The sample period is $t-8$ to $t-4$ relative to bankruptcy (which occurs at $t0$); this period is also well-defined for *nonbankruptcy* firms due to the matching of both groups of firms at $t-5$ relative to the bankruptcy event.

The idea underlying the test is as follows: if *bankruptcy* and *nonbankruptcy* firms are different even in the absence of bankruptcy, we would expect to also find differences in the ability of *bankruptcy* and *nonbankruptcy* firms to attract and retain talent several years before bankruptcy. In contrast, if *bankruptcy* and *nonbankruptcy* firms are comparable absent bankruptcy, we would expect to find no difference in the ability of *bankruptcy* firms to attract and retain talent relative to the *nonbankruptcy* group when focusing on a period further away from bankruptcy.

Table VII reports results of this placebo test. Note that while we retain all of the variables in our regressions, we only report the coefficients associated with the interactions between *Placebo close* × *Bankruptcy* and the individual worker characteristics, to simplify the reading of the table (coefficients on the noninteracted worker characteristics are comparable to those reported in Tables IV and VI). We find that the coefficients on the interactions of the placebo treatment dummy *Placebo close* × *Bankruptcy* and the different worker characteristics are economically small and statistically insignificant. The only exception is with respect to employee age, where the triple interaction *Placebo close* × *Bankruptcy* × *Age* is statistically significant at the 5% level in column (5) and at the 10% level in column (6). Importantly, we find no evidence that in years more distant from the bankruptcy event, *bankruptcy* and *nonbankruptcy* firms behave differently with regard to retention (columns (1) to (3)) or attraction (columns (4) to (6)) of talent. This lends support to our identifying assumption that the *nonbankruptcy* group provides a good counterfactual for the evolution of talent in *bankruptcy* firms in the absence of bankruptcy. Of course, this test does not rule out differences in unobservables, which are inherently untestable.

E. Financial versus Economic Distress: Evidence from Exogenous Currency Shocks in Exporting Firms

Our evidence thus far suggests that firms that become bankrupt (compared to a matched sample of firms that do not) lose talent. To ensure that our results are not driven by economic distress, we examine a quasi-experimental setting that focuses on a sample of exporting firms with (ex ante) different capital structures. The setting is conceptually similar to that in Caggese, Cunat, and Metzger (2019). The idea underlying the test is that a large, exogenous decrease in the value of exports due to changes in exchange rates is likely

[37] This analysis effectively tests the parallel trends assumption of our difference-in-differences test design.

Table VII

Placebo Test

In this table, we repeat the analyses of Tables IV and VI but for a "placebo" event period: we keep the composition of *bankruptcy* and *nonbankruptcy* groups but define the sample period as $t-8$ to $t-4$ relative to bankruptcy. The variable *Placebo close* takes a value of 1 in the years $t-6$ to $t-4$ relative to the bankruptcy event ($t0$) and the matching year ($t-5$). Columns (1) to (3) report the placebo analysis for "leavers" while columns (4) to (6) report the placebo results for "joiners." In all specifications, we include but do not report the constituent interaction terms between *Placebo close*, *Bankrupt*, and *Top talent*. We also include the following variables in the regressions in columns (2) and (3) (including all the interactions with *Placebo close* and *Bankrupt*) but do not report coefficients, for the sake of brevity: *Age*, *Short tenure*, *Experience in industry*, *Ln(Years of education)*, and lagged *Ln(Wage)*. In columns (5) and (6), we also include the following variables (including all the interactions with *Placebo close* and *Bankrupt*), but do not report coefficients: *Age*, *Other municipality*, *Experience in industry*, *Ln(Years of education)*, and lagged *Ln(Wage)*. The sample period is 1998 to 2007. Robust standard errors, clustered at the firm level, are reported in parentheses. ** and * denote significance at the 5% and 10% levels, respectively.

	Leave			Join		
	(1)	(2)	(3)	(4)	(5)	(6)
Top talent × Placebo close × Bankrupt	0.004	0.003	0.013	–0.018	–0.008	–0.009
	(0.010)	(0.010)	(0.010)	(0.012)	(0.010)	(0.009)
$\text{Ln(Wage)}_{t\text{-}1}$ × Placebo close × Bankrupt		0.000	0.001		0.003	0.002
		(0.003)	(0.003)		(0.004)	(0.004)
Age × Placebo close × Bankrupt		–0.001	–0.001		–0.002**	–0.002*
		(0.000)	(0.000)		(0.001)	(0.001)
Experience in industry × Placebo close × Bankrupt		0.001	0.001		0.003	0.002
		(0.001)	(0.001)		(0.003)	(0.003)
Ln(Years of education) × Placebo close × Bankrupt		0.029	0.015		–0.038	–0.012
		(0.021)	(0.023)		(0.034)	(0.021)
Short tenure × Placebo close × Bankrupt		0.000	–0.001			
		(0.008)	(0.010)			
Other municipality × Placebo close × Bankrupt					–0.004	–0.008
					(0.020)	(0.019)
Firm F.E.	Yes	Yes		Yes	Yes	
Industry × year F.E.	Yes	Yes		Yes	Yes	
Placebo close × enrollment period F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm × year F.E.			Yes			Yes
Observations	283,333	283,333	283,063	283,333	283,333	283,063
Adjusted R^2	0.103	0.126	0.142	0.197	0.386	0.447

Table VIII

Export Shock and Financial Distress

This table reports coefficients from OLS regressions examining the relationship between leverage, exchange rate shocks, and bankruptcy. *Bankrupt in <3 years* is a dummy variable that takes the value of 1 if the firm files for bankruptcy in the current year, next year, or year thereafter, and 0 otherwise. *High leverage* is a dummy variable that takes the value of 1 if the firm's average leverage in the first two years in the sample is above the sample median (the first two sample years of each firm are excluded from the regression analysis). *Exchange rate shock* is a dummy variable that takes the value of 1 in the year the firm is subject to an unfavorable exchange rate shock, and 0 otherwise. The control variables *Tangibility*, *Profitability*, and *Ln(Assets)* are lagged by one year. Sample and variable construction are discussed in Section I. Robust standard errors, clustered at the firm level, are reported in parentheses below the coefficients. *** and ** denote significance at the 1% and 5% levels, respectively.

	Bankrupt in <3 years	
	(1)	(2)
High leverage × Exchange rate shock	0.007**	0.007**
	(0.003)	(0.003)
Exchange rate shock	–0.002	–0.002
	(0.002)	(0.002)
Tangibility		–0.003
		(0.008)
Profitability		–0.037***
		(0.006)
Ln(Assets)		–0.008***
		(0.002)
Firm F.E.	Yes	Yes
Industry × year F.E.	Yes	Yes
Observations	64,390	64,379
Adjusted R^2	0.547	0.548

to be detrimental to all affected firms, but it will increase the likelihood of financial distress more for highly levered exporters, allowing us to distinguish between financial and economic distress. The richness of our data allows us to construct *firm-level* exposures to different currencies, as we observe the value of exports by country of destination for each firm. We can therefore exploit, for identification purposes, the fact that a depreciation of the dollar, for example, would negatively impact the demand of firms that export to the United States while not directly affecting firms that only export to Norway.

First, as a validation of our identification strategy, we estimate the impact of an exchange rate shock on the probability of filing for bankruptcy. Because different firms export to different markets, the exogenous variation that we exploit varies both over time and across firms, even within the same industry. This allows us to control for firm and industry-year fixed effects, as well as for a set of time-varying firm controls.

We present the results of this test in Table VIII. We find that exporting firms with high leverage (but not those with low leverage) are significantly more likely to file for bankruptcy in the years following an unfavorable exchange rate shock. Specifically, in column (1), we show that an exchange rate shock is associated with a 0.7 percentage point increase in the probability that a highly levered firm will file for bankruptcy in the year of the shock or the subsequent two years. Relative to the unconditional mean of the variable *Bankrupt in* <3 *years* of 0.014 (see Table III), this constitutes an increase of 50% in the likelihood of going bankrupt. In column (2), we include a set of firm controls and find a quantitatively similar result. The results reported in Table VIII help us distinguish economic from financial distress: they show that a negative exchange rate shock, while plausibly harmful to the bottom line of all affected exporters, leads to financial distress only in firms that were highly leveraged ex ante.

After confirming that the setting is helpful in disentangling the effects of financial and economic distress, we study the impact of this shock on the likelihood of high-talent workers leaving. In these worker-level tests, the dependent variable is *Leave*, which, as before, takes the value of 1 in the year that a worker leaves the firm, and 0 otherwise. The coefficient of interest in these tests is the interaction between *High leverage*, *Exchange rate shock*, and *Top talent* (defined as in our previous tests). Since we are interested in estimating the increase in the likelihood of a high-talent worker leaving relative to that of other workers in the firm, these regressions include firm-year fixed effects that account for any time-varying firm-level unobservable. We report results in Table IX. In column (1), we find that the probability of a high-talent worker leaving a firm following an unfavorable exchange rate shock increases in the case of highly levered firms, as the interaction of *Exchange rate shock*, *High leverage*, and *Top talent* is positive and statistically significant. Relative to the average effect of being a *Top talent* worker on the probability of leaving a firm in a non-shock year (0.036), a high-talent worker is about 39% more likely to leave a highly leveraged exporter following a negative exchange rate shock. In column (2), we add hierarchy fixed effects to the specification of column (1) and observe similar results.

One potential concern with the tests that exploit exchange rate movements in different currencies in addition to differences in ex ante capital structures is that firms with different levels of leverage and different export activity may differ along other dimensions. In Table A.II, we report separate summary statistics for firms in the export sample with high (above-median) and low leverage (Panel A), firms with high (above-median) and low export volume (Panel B), and export-intensive firms (those with above-median exports) with high and low leverage (Panel C). Unsurprisingly, and consistent with large literatures in corporate finance and international trade, we observe that capital structure and export activity are not randomly assigned: there are statistically significant differences—although most of them are economically small—between high- and low-leverage firms and between firms that export more and those that export less. Economically, the most significant differences are in terms of average numbers of employees. Low-leverage firms have more than twice the number of employees as high-leverage firms (Panels A and C of Table A.II), and high-export firms have almost twice the number of employees as low-export firms (Panel B of Table A.II). However, despite these differences in

Table IX

Financial Distress and Labor Mobility

This table reports coefficients from OLS regression models examining the composition of workers leaving firms following an unfavorable exchange rate shock. *Leave*, the dependent variable, is a dummy variable that takes the value of 1 in the year the worker leaves the firm, and 0 otherwise. *High leverage* is a dummy variable that takes the value of 1 if the firm's average leverage in the first two years in the sample is above the sample median (the first two sample years of each firm are excluded from the regression analysis). *Exchange rate shock* is a dummy variable that takes the value of 1 in the year the firm is subject to an unfavorable exchange rate shock, and 0 otherwise. In specifications (3) and (4), F1*(Exchange rate shock)* is the one-year lead term of the variable *Exchange rate shock*. Sample and variable construction are discussed in Section I. Robust standard errors, clustered at the firm level, are reported in parentheses below coefficients. *** and ** denote significance at the 1% and 5% levels, respectively.

	Leave			
	(1)	(2)	(3)	(4)
Top talent × Exchange rate shock × High leverage	0.014**	0.013**	0.015**	0.014**
	(0.006)	(0.006)	(0.007)	(0.006)
Top talent × Exchange rate shock	0.000	–0.003	0.001	–0.002
	(0.004)	(0.003)	(0.004)	(0.004)
Top talent × High leverage	–0.000	–0.001	–0.000	–0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Top talent	0.036***	0.029***	0.036***	0.029***
	(0.001)	(0.001)	(0.001)	(0.001)
Top talent × F1(Exchange rate shock) × High leverage			–0.003	–0.000
			(0.007)	(0.007)
Top talent × F1(Exchange rate shock)			–0.001	–0.003
			(0.003)	(0.003)
Firm × year F.E.	Yes	Yes	Yes	Yes
Enrollment period F.E.	Yes	Yes	Yes	Yes
Hierarchy F.E.		Yes		Yes
Observations	4,094,587	3,872,270	4,094,587	3,872,270
Adjusted R^2	0.205	0.211	0.205	0.211

the size of the labor force, there are economically small differences in terms of the composition of the labor force among these groups of firms.

The inclusion of firm-year fixed effects in our regression specifications (reported in Table IX) allows us to control for any time-varying unobservable factor that homogeneously affects all workers in any given firm and thus alleviates concerns that our results are driven by such firm-level omitted variables. However, if there are firm characteristics that differentially affect high-talent workers, our estimates may be biased. Given the exogenous nature of the exchange rate shock we employ, our analysis would recover the causal effect of financial distress on talent retention if worker turnover (as captured by the variable *Leave*) evolved similarly for shocked and nonshocked firms in the absence of the shock.

Although it is not easy to envisage the kind of economic mechanism that would give rise to the empirical patterns we document, we test whether firms not *yet* affected by the shock experience any premature response, which would raise concerns about the nature of the shock or the differences between firms that are experiencing a shock and those that are not. Specifically, in columns (3) and (4) of Table IX we test whether, prior to the exchange rate shock, firms that will be affected by an exchange rate shock in the following year experience more talent departures than firms that do not experience an exchange rate shock. For this purpose, we use the variable *F*1*(Exchange rate shock)*, the one-year lead term of the variable *Exchange rate shock*. We find that in the absence of the shock, these two groups of firms do not behave differently. Although we cannot completely rule out the possibility that unobservable differences across firms may differentially affect high-talent workers, the evidence suggests that differences in unobservables are unlikely to be driving the results. Therefore, with all necessary caveats, we conclude that talent departures are likely driven by financial, rather than economic, distress.

In Table X, we report coefficients from additional specifications in which we control for worker characteristics and include interactions between *Exchange rate shock*, *High leverage*, and, respectively, the variables *Age*, *Short tenure*, *Experience in industry*, *Ln(Years of education*), and lagged *Ln(Wage)*. These specifications confirm our previous evidence: when highly levered exporting firms suffer a currency shock, their most skilled workers are more likely to subsequently abandon the firm. In contrast, the estimates on the interactions between *High leverage*, *Exchange rate shock*, and the remaining worker-level characteristics yield economically small and (for the most part) statistically insignificant coefficients.

In this quasi-experimental setting, the effects we document did not originate from the labor market: we can trace the origin of the employment effects back to exogenous exchange rate movements. This reduces concerns of reverse causality in our main tests (Tables IV to VI), namely, that firms go bankrupt *because* high-talent workers leave. Furthermore, this analysis increases our confidence that the results discussed in subsections A to C of Section II are driven by financial, rather than economic, distress. Finally, this "shock-based" research design also addresses concerns that unobserved differences between *bankruptcy* and *nonbankruptcy* firms may be driving our findings.

Table X

Financial Distress and Labor Mobility: Additional Specifications

This table reports coefficients from OLS regression models examining the composition of workers leaving firms following an unfavorable exchange rate shock. *Leave*, the dependent variable, is a dummy variable that takes the value of 1 in the year the worker leaves the firm, and 0 otherwise. *High leverage* is a dummy variable that takes the value of 1 if the firm's average leverage in the first two years in the sample is above the sample median (the first two sample years of each firm are excluded from the regression analysis). *Exchange rate shock* is a dummy variable that takes the value of 1 in the year the firm is subject to an unfavorable exchange rate shock, and 0 otherwise. We also include the following control variables (coefficients are not reported for the sake of brevity): *Age*, *Short tenure*, *Experience in industry*, *Ln(Years of education)*, and lagged *Ln(Wage)*. In addition, specifications (3) and (4) contain triple-interactions between *Exchange rate shock, High leverage*, and each of the control variables (lower order interactions are included in the regression but not reported for the sake of brevity). Sample and variable construction are discussed in Section I. Robust standard errors, clustered at the firm level, are reported in parentheses below the regression coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Leave			
	(1)	(2)	(3)	(4)
Top talent × Exchange rate shock × High leverage	0.014**	0.015***	0.014**	0.014**
	(0.006)	(0.006)	(0.006)	(0.006)
Top talent × Exchange rate shock	–0.002	–0.006*	–0.006*	–0.006*
	(0.003)	(0.003)	(0.003)	(0.003)
Top talent × High leverage	0.000	–0.000	–0.000	–0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Top talent	0.032***	0.022***	0.032***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)
Age × Exchange rate shock × High leverage			–0.001*	–0.000
			(0.000)	(0.000)
Short tenure × Exchange rate shock × High leverage			–0.014	–0.018
			(0.015)	(0.015)
Experience in industry × Exchange rate shock × High leverage			–0.001**	–0.001*
			(0.001)	(0.001)
Ln(Years of education) × Exchange rate shock × High leverage			0.008	0.013
			(0.014)	(0.012)
Ln(Wage)$_{t-1}$ × Exchange rate shock × High leverage			–0.004	–0.006*
			(0.003)	(0.003)
Firm × year F.E.	Yes	Yes	Yes	Yes
Enrolment period F.E.	Yes	Yes	Yes	Yes
Hierarchy F.E.		Yes		Yes
Observations	4,094,587	3,872,270	4,094,587	3,872,270
Adjusted R^2	0.229	0.221	0.229	0.221

III. Talent and Capital Structure

The analysis in the previous section provides evidence that as firms approach financial distress, talent leaves. This may endanger the future of the company even further. Labor may thus bring an added degree of fragility to the organization, especially in cases in which most of the firm's human capital is concentrated in these key employees. In this section, we investigate whether the risk of talent loss may help explain firms' leverage choices.[38]

We test whether the extent to which a firm relies on talent shapes its financial decisions by analyzing the capital structure choices of firms in the cross-section. Firms whose most skilled employees are more likely to leave in times of financial distress face large (indirect) bankruptcy costs and thus are expected to have lower leverage. In that sense, the employee composition of a firm, and in particular a firm's reliance on its highly skilled labor, would be an additional factor shaping firms' financial policy. We formally test whether the average level of talent and its concentration within the firm correlate with capital structure by estimating the regression:

$$\begin{aligned} Leverage_{ft} &= \alpha + \beta_1 \cdot Average\,talent_{ft-1} + \beta_2 \cdot Talent\,concentration_{ft-1} \\ &\quad + X'_{ft-1}\gamma + \Psi_{ft} + \varepsilon_{ft}. \end{aligned}$$

The matrix X includes standard controls used in capital structure regressions: *Tangibility*, *Profitability*, *Ln(Assets)*, and *Firm age*. Our firm-level talent measures are *Average skills*, the average of the combined cognitive and noncognitive skill scores of the employees working in a firm in a given year, and *Talent concentration*, the share of the firm's total endowment of cognitive and noncognitive skills that is held by the workers in the top 5% of the talent distribution within the firm. The matrix Ψ includes year fixed effects or, in some specifications, industry-year fixed effects to control for macroeconomic determinants of leverage. Thus, the coefficients in these regressions can be interpreted as cross-sectional comparisons.

Table XI, Panel A, reports the results. In column (1), we regress *Leverage* on our firm talent measures and year fixed effects, while in column (2) we include additional controls. The results confirm that the average level of talent in a firm's labor force is an important determinant of capital structure decisions. In both columns, leverage is negatively correlated with the *Average skills* of a firm. A one-standard-deviation increase in a firm's *Average skills* is associated with a 1.1 percentage point lower leverage ratio (column (2)). Relative to the average level of leverage in the sample (13.3%), this is 8.5% lower leverage than in the average firm. For comparison, a one-standard-deviation increase in *Tangibility, Profitability, Ln(Assets)*, and *Firm age* is associated with 9.6, −2.5, −0.4, and −0.9 percentage point changes, respectively, in leverage. The estimate associated with *Average skills* is thus larger than the effect of a one-

[38] The risk of talent loss during "normal times" may also affect capital structure (Hart and Moore (1994)). This channel is consistent with our hypothesis.

Table XI

Talent Intensity and Leverage in the Cross-Section of Firms

This table reports coefficients from regression models examining the relationship between the talent-intensity of firms and financial leverage. Panel A considers all firms, while Panel B focuses on the role of financial constraints. *Average skills* is the average of the combined cognitive and noncognitive skill scores of the employees working in a given firm-year. *Talent concentration* is the fraction of a given firm's total combined skill scores that is accounted for by workers who are at or above the 95^{th} percentile of the combined skill distribution in the firm-year. In Panel B, *Constrained* is a dummy variable that takes the value of 1 for firms that are "small and young," and 0 for firms that are "large and old." All explanatory variables in the regressions are lagged by one year. The sample in Panel B only includes firms that have below-median age and assets (i.e., constrained firms) and those that have above-median age and assets. For details, see Section I. Robust standard errors, clustered at the firm level, are reported in parentheses below the coefficients. Statistical significance at 1% and 5% is market with *** and **, respectively.

Panel A: Cross-Sectional Leverage Regressions

	Leverage				
	(1)	(2)	(3)	(4)	(5)
Talent concentration	–0.680***	–0.457***	–0.276***	–0.460***	–0.347***
	(0.082)	(0.070)	(0.070)	(0.071)	(0.070)
Average skills	–0.022***	–0.007***	–0.003***	–0.007***	–0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average experience in industry				0.000	0.000
				(0.000)	(0.000)
Short tenure share				0.003	0.023***
				(0.002)	(0.002)
Tangibility		0.402***	0.411***	0.402***	0.411***
		(0.003)	(0.004)	(0.003)	(0.004)
Profitability		–0.157***	–0.156***	–0.157***	–0.155***
		(0.003)	(0.003)	(0.003)	(0.003)
Ln(Assets)		–0.003***	–0.006***	–0.003***	–0.006***
		(0.001)	(0.001)	(0.001)	(0.001)
Firm age		–0.000***	–0.001***	–0.000***	–0.001***
		(0.000)	(0.000)	(0.000)	(0.000)
Year F.E.	Yes	Yes		Yes	
Industry × year F.E.			Yes		Yes
Observations	408,329	408,329	407,923	408,329	407,923
Adjusted R^2	0.034	0.282	0.299	0.282	0.300

(*Continued*)

Table XI—*Continued*

Panel B: Cross-Sectional Leverage Regressions, the Role of Financial Constraints

	Leverage				
	(1)	(2)	(3)	(4)	(5)
Talent concentration × Constrained	0.959***	0.491***	0.425**	0.490***	0.397**
	(0.212)	(0.184)	(0.183)	(0.184)	(0.183)
Talent concentration	–1.618***	–0.940***	–0.727***	–0.938***	–0.773***
	(0.171)	(0.155)	(0.155)	(0.156)	(0.155)
Average skills × Constrained	0.014***	0.000	–0.001	0.000	–0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Average skills	–0.030***	–0.007***	–0.003***	–0.007***	–0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constrained	–0.215***	–0.055***	–0.027	–0.055***	–0.028
	(0.023)	(0.020)	(0.020)	(0.020)	(0.020)
Average experience in industry				0.000	0.000
				(0.000)	(0.000)
Short tenure share				0.002	0.022***
				(0.003)	(0.003)
Tangibility		0.390***	0.402***	0.390***	0.402***
		(0.004)	(0.005)	(0.004)	(0.005)
Profitability		–0.170***	–0.169***	–0.170***	–0.170***
		(0.004)	(0.004)	(0.004)	(0.004)
Ln(Assets)		–0.005***	–0.007***	–0.005***	–0.007***
		(0.001)	(0.001)	(0.001)	(0.001)
Firm age		–0.001***	–0.001***	–0.001***	–0.001***
		(0.000)	(0.000)	(0.000)	(0.000)
Year F.E.	Yes	Yes		Yes	
Industry × year F.E.			Yes		Yes
Observations	226,288	226,288	226,108	226,288	226,108
Adjusted R^2	0.033	0.270	0.285	0.270	0.286

standard-deviation change in firm size and firm age and somewhat smaller than the effect of a one-standard-deviation change in profitability.

In addition, we find that talent concentration at the top of the organization is also negatively correlated with leverage. A one-standard-deviation increase in *Talent concentration* is associated with a 0.4 percentage point decrease in leverage (column (2)). Relative to the sample mean of 13.3%, this corresponds to a 3% lower leverage ratio. The magnitude of this effect is economically similar to that of a one-standard-deviation increase in *Ln(Assets)*. While Mueller, Ouimet, and Simintzi (2017) highlight the benefits associated with the existence of within-firm inequality, our results underscore the risks that may be associated with firms' dependence on a few (highly mobile) individuals. To the best of our knowledge, our paper is the first to document that the degree of concentration of human capital within the firm may have implications for financial policy.

In column (3), we add industry-year fixed effects to the specification to identify cross-sectional differences in leverage within firms in the same industry and year. In columns (4) and (5), we add two additional measures of worker human capital to the specification: *Short tenure share* and *Average experience in industry*. These variables serve as proxies for the endowment of the firm's labor force with firm- and industry-specific human capital. The coefficient on *Short tenure share* is positive and significant in column (5). This could be because workers are unwilling to invest in firm-specific human capital for risky firms. Alternatively, it could suggest that firms with long-tenured workers (who may not be easily fired) have high operating leverage, which decreases their debt capacity (along the lines of Simintzi, Vig, and Volpin (2015)). The coefficient associated with *Average experience in industry* is economically small and statistically insignificant in both columns. The coefficients associated with *Average skills* and *Talent concentration* remain statistically and economically significant in these specifications.

The results reported in Panel A are consistent with two interpretations. First, according to a trade-off model of capital structure, the increased present value of the labor costs of financial distress due to increased talent departures at the onset of bankruptcy could lead firms to optimally use less leverage ex ante. Second, financiers may not supply debt to firms that rely heavily on talent. Both channels are in line with our hypothesis that a firm's reliance on talent introduces a degree of fragility that affects the firm's observed equilibrium capital structure. In a first attempt to evaluate the relative strength of the two potential channels, in Panel B of Table XI, we examine the correlation between talent intensity and financial leverage among two groups of firms: financially constrained firms and firms that are not constrained.[39] If the correlation between our talent measures and leverage is more negative in the

[39] The number of observations in the regressions reported in Panel B is smaller than in the full sample in Panel A. The reason is that in Panel B, we focus on firms that are either constrained (below-median age and assets) or unconstrained (above-median age and assets), eschewing observations for firms that cannot be unambiguously categorized into one of these groups. See Section I for a detailed definition of the variable *Constrained*.

group of financially unconstrained firms, it is plausible that the first mechanism (firms use less leverage if the risk of talent loss increases) dominates. In contrast, if one observes that the correlation between a firm's reliance on talent and leverage is more negative among financially constrained firms, this would lend more support to the debt capacity channel. In the specifications reported in Panel B, we interact *Constrained* with the two talent measures. Overall, we find support for the trade-off theory channel: the negative correlation between our talent measures and leverage is quantitatively larger in the group of financially unconstrained firms.

To alleviate concerns that our results are driven by spurious correlation, we include in the tests reported in Table XI year fixed effects and industry-year fixed effects, as well as several controls for other important determinants of leverage. We also present a variety of alternative specifications of these tests using different talent measures, additional controls, and variations of the regression sample (see Section III of the Internet Appendix). Notwithstanding, given the nature of these cross-sectional correlations, endogeneity concerns remain. For example, firms with lower leverage could attract workers who have higher talent instead of the firm's dependence on talent driving the choice of capital structure.

IV. Robustness and Additional Discussion

In our tests, we use the sum of cognitive and noncognitive skill scores to construct measures of talent. Our results are robust to several alternative ways of measuring talent, particularly more narrow measures reflecting cognitive skills only, noncognitive skills only, or leadership ability. Furthermore, even though the measures of skill based on military test scores are accurate and economically meaningful (as documented in, e.g., Lindqvist and Vestman (2011)), they are only available for males. To extend our analysis to include females, we repeat our tests using a talent measure based on wages (which proxies for the market price of talent). We report a replication of our previously discussed findings on labor turnover and leverage based on these alternative measures of talent in Tables IA.VII, IA.VIII, and IA.XVI of the Internet Appendix.

When studying the evolution of the labor force composition, we defined high-talent employees as those whose combined cognitive and noncognitive skill scores belong to the top 5% of the distribution within the firm. In Table IA.IX of the Internet Appendix, we use 25% and 50% as the cutoff for the within-firm talent definition and continue to find that the most skilled employees are more likely to leave the firm as it approaches bankruptcy. The fact that the point estimates decrease as we make the talent definition more encompassing suggests that the probability that a worker "jumps ship" increases monotonically with cognitive and noncognitive skills. Although workers in the top 5% of the distribution of skills are about 65% more likely to leave firms approaching distress than their less-skilled colleagues, the magnitude is 42% for workers with above-median cognitive and noncognitive skills. In Table IA.X of the Internet Appendix, we define high-talent workers as those at the top of the skill distribution in the industry, or with reference to the economy-wide distribution of cognitive and noncognitive skill scores.

In Section III of the Internet Appendix, we also present robustness tests studying the workforce composition in financially distressed firms in which we focus on firms of different minimum size, as measured by the number of employees (Table IA.XI). We also report tests that employ alternative matching procedures to construct the *nonbankruptcy* group of firms (Tables IA.XII and IA.XIII). Overall, we find qualitatively and quantitatively similar results as in Tables IV and VI.

As our results are based on firms and workers in Sweden, external validity may be a concern. For example, Sweden's strong social safety nets, LIFO protections, and specific bankruptcy regulations could limit the applicability of our results to other settings. Strictly speaking, a study is only valid with respect to the setting it is analyzing. Just as the findings of a study in the United States (with its relatively weak social safety nets) might not be applicable elsewhere, the findings of our study could be limited to Europe (or Sweden, more specifically). However, we do not believe that this is the case. Like many other countries, Sweden is a market economy with a strong entrepreneurial culture.

Nevertheless, we try to address this concern not only qualitatively, but also by conducting an additional analysis using data from a different setting. In Section II of the Internet Appendix, we conduct a series of tests on the relationship between leverage and proxies for the mobility of highly skilled workers in the United States. In these tests, we exploit staggered changes in the enforceability of noncompete clauses in labor contracts across U.S. states as a natural experiment. We find that as the risk of talent loss is reduced due to increased enforceability of noncompete agreements by state courts, firms increase their financial leverage (see Klasa et al. (2018) for additional analysis of labor mobility and leverage). As in the Swedish setting, we find that these results are driven by financially unconstrained firms. This result is conceptually consistent with our more granular evidence based on Swedish data and suggests that our findings are not specific to the Swedish setting.

V. Conclusion

Modern corporations rely heavily on talent. In the new enterprise, human capital surpasses physical capital in its importance for value creation and as a source of competitive advantage (Rajan and Zingales (2000), Abowd et al. (2005)). However, the reliance on human capital and the high mobility of skilled labor—stemming from ample outside options in the labor market—also expose firms to an added degree of fragility. In critical times, talent may leave the firm and seek employment elsewhere. This loss of talent in times of financial distress constitutes an additional source of risk that unlevered firms do not have to bear. Hence, firms that rely to a larger extent on talent face higher costs of financial distress and may therefore choose to operate with lower leverage.

In this paper, we analyze 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 financial distress. To ensure that our findings are indeed driven by financial distress, we study a quasi-experiment that employs exogenous currency shocks in a sample of export-intensive firms with different capital structures. We find that following a large negative export shock, high-talent workers become more prone to leaving the firm, but only if the exporter experiencing the negative shock is highly leveraged. We interpret this as further evidence that our results are driven by financial and not economic distress.

We next study how this risk of losing highly skilled employees affects ex ante financial policies. To capture the subtle effects of talent on leverage, we study two dimensions of talent at the firm level: average skill and talent concentration. Our evidence suggests that both dimensions are relevant: both the average skill level in the organization and the degree to which skills are concentrated in a few key individuals within the firm are negatively associated with financial leverage.

Overall, the results presented in this paper suggest that the reliance on talent may introduce an additional level of risk for leveraged firms due to the possibility of losing key employees during times of financial distress.

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Appendix

Table A.I
Variable Definitions

This table contains detailed definitions of the variables used in this study, listed in alphabetical order. We use the following data sources. *LISA* refers to the "Longitudinell integrationsdatabas för sjukförsäkrings- och arbetsmarknadsstudier" database from Statistics Sweden, which combines various types of register-based data (i.e., data contained in records kept by government agencies). *Serrano* refers to the "Serrano Database," which is a commercial database by PAR/Bisnode, covering the financial statements of Swedish firms. *Military test database* refers to enlistment test scores from the National Archives (Riksarkivet) and the Swedish Defence Recruitment Agency (Rekryteringsmyndigheten).

Variable	Definition
Age	Current year minus birth year. Data from LISA.
Average age	Average, by firm and year, of the variable *Age*.
Average education years	Average, by firm and year, of the years of schooling of all employees. Because the actual years of schooling are not reported, we use 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: 12 years for a high school graduate, 15 years for an individual with a bachelor's degree, and so on. Data from LISA.

(*Continued*)

Table A.I—*Continued*

Variable	Definition
Average experience in industry	Average, by firm and year, of the variable *Experience in industry*.
Average skills	The average of the combined cognitive and noncognitive ability scores of the employees working in a firm-year. Both the cognitive ability score and the noncognitive ability score range from one to nine on the Stanine scale and are obtained from the Military test database.
Average skills in top 5%	The average of the combined cognitive and noncognitive ability scores of the top 5% employees working in a firm-year, that is, those employees for whom the variable *Top talent* takes the value of 1. Both the cognitive ability score and the noncognitive ability score range from one to nine on the Stanine scale and are obtained from the Military test database.
Average wage	Average, by firm and year, of the gross yearly wage in 100 SEK paid by the firm to its workers. Because it may reflect only part of the year, we replace the wage in year t with the $t-1$ wage for employees who leave in year t (if the wage in year t is below that in year $t-1$) or with the $t+1$ wage for employees who join in year t (if the wage in year t is below that in year $t+1$). Data from LISA.
Bankrupt	Indicator variable that takes the value of 1 for firms that at some point during the sample period file for bankruptcy or reorganization. Information on the corporate bankruptcy filing year comes from *Serrano*.
Bankrupt in <3 years	Indicator variable that takes the value of 1 if a given firm in year t goes bankrupt in year t, $t+1$, or $t+2$, and 0 otherwise. Bankruptcy information comes from *Serrano*.
Close	Indicator variable that takes the value of 1 for *bankruptcy* firms during years $t-3$ to $t-1$ relative to the year of the bankruptcy filing (which is at $t0$); it also takes the value of 1 for *nonbankruptcy* firms in the years $t-3$ to $t-1$ relative to the matching year (which is $t-5$). In other instances, the variable *Close* takes the value of 0. Information on the corporate bankruptcy filing date comes from *Serrano*.
Constrained	Indicator variable that takes the value of 1 if the firm is financially constrained. Observations are sorted into two quantiles of firm age and two quantiles of total assets (deflated to 1998 SEK). A firm is defined as financially constrained in a given year (that is, *Constrained* takes the value of 1) if both its age and assets are less than or equal to the sample median, while it is unconstrained if both its age and assets are above the sample median. Data from *Serrano*.

(*Continued*)

Table A.I—*Continued*

Variable	Definition
Exchange rate shock	Indicator variable that takes the value of 1 when a firm suffers a negative shock to the value of its exports, that is, when the firm (given its export exposure) experiences negative exchange rate movements. First, we define a vector of the exposure of a firm to different currencies, *Export exposure*, for each firm *f* (the export exposure is fixed for each firm; it is calculated as the average of the first two years that a firm is in the sample). The elements of this vector contain the firm's exports denominated in EUR, USD, GBP, NOK, and DKK divided by the firm's sales (all in Swedish Krona) in the respective year: $Export\ exposure_f = \left(\frac{Exports\ in\ EUR}{Total\ sales} \ \ldots \ \frac{Exports\ in\ DKK}{Total\ sales}\right)$. Next, we construct an annual exchange rate movement index by calculating the scalar product between the *Export exposure* vector for each firm and a vector of relative exchange rate changes between the current and previous years for the five currencies considered (the exchange rate in the currency vector is quoted as SEK per foreign currency). Finally, the dummy variable *Exchange rate shock* takes the value of 1 when (i) the annual exchange rate movement index is negative, indicating an appreciation of the Swedish Krona vis-à-vis the exporter's relevant trading partner currencies, and (ii) the index is in the bottom 5% over the full sample period. Firm-level export data are from Statistics Sweden, sales are from *Serrano*, and exchange rate data are from the Riksbank.
Experience in industry	This variable captures the total number of years (starting in 1990 at the earliest) that an employee has worked in the current industry. To define the main industry of the employer, we proceed as follows. The industries are defined using SNI codes (the Swedish Standard Industrial classification). There have been four different classification standards for SNI: 1969, 1992, 2002, and 2007, which *Serrano* (which covers the period 1998 to 2011) combines into one SNI variable. Using this SNI variable, we define the following "coarse" industry categories: agriculture, manufacturing, transportation and utilities, construction and mining, commerce, professional services, other services, and finance. For the years 1990 to 1997 (no *Serrano* coverage), we proceed as follows. If a firm is in *Serrano* during the period 1998 to 2011, we use the coarse industry category of that firm from the 1998 to 2011 period. If a firm is not in *Serrano* between 1998 and 2011, we first obtain the SNI code from LISA and assign to it the most common coarse industry of the firms that are in *Serrano* between 1998 and 2011 and have the corresponding SNI code. For example, suppose that firm A is not in *Serrano*. In 1996, it has an SNI92 code of 36110, according to LISA. For SNI92 36110 in 1996, we consider the coarse industry of firms that are in Serrano between 1998 and 2011. Most of the firms with SNI92 36110 in 1996 that are later also in Serrano have "manufacturing" as their coarse industry, so we assign manufacturing as the coarse industry for firm A in 1996.
Firm age	The number of years since incorporation of the firm. Incorporation date from *Serrano*.
High leverage	Indicator variable that takes the value of 1 if the firm has *Leverage (Year* 1 + 2) above the sample median and 0 otherwise. *Leverage (Year* 1 + 2) is calculated as follows. The leverage ratio is calculated as short-term plus long-term bank debt (plus corporate bonds, if any) divided by total assets; this ratio is winsorized at the 1% and 99% levels. *Leverage (Year* 1 + 2) is the average of the leverage ratios for the first two years that a firm is in the sample. Data from *Serrano*.

(*Continued*)

Table A.I—*Continued*

Variable	Definition
Join	A dummy variable that takes the value of 1 in the year an employee joins a given employer. A worker's "employer" in a given year is the firm that provides an individual with the most labor income in a given calendar year. We identify "joiners" by verifying whether the main source of labor income changed vis-à-vis the previous year. Data from LISA.
Jumped the queue	A dummy variable that takes the value of 1 in year t if a worker is no longer at the same employer in year $t + 1$ (because the worker becomes unemployed or changes jobs); this separation event must deviate from the job separation order implied by the last-in-first-out (LIFO) rule (based on the tenure of workers at the firm in year t). The variable is set to 0 if (i) the worker is no longer at the same employer in year $t + 1$ but the separation is consistent with the LIFO rule, or (ii) the worker collects unemployment insurance benefits in the year of the separation or the next. Data from LISA.
Leave	A dummy variable that takes the value of 1 in the year a worker leaves an employer, and 0 otherwise. A worker's "employer" in a given year is the firm that provides an individual with the most labor income in a given calendar year. To better capture voluntary turnover, the variable is also 0 when a worker leaves and collects unemployment benefits during the year of departure or the next. We identify "leavers" by verifying whether the main source of labor income changes in the next year. Data from LISA.
Leverage	Short-term plus long-term bank debt (plus corporate bonds, if any) divided by total assets; winsorized at 1% and 99%. Data from *Serrano*.
Ln(Assets)	The natural logarithm of (one plus) total assets; winsorized at 1% and 99%. Data from *Serrano*.
Ln(Exports)	The natural logarithm of (one plus) a firm's total exports in SEK. Export data are provided by Statistics Sweden and are available for the period 2000 to 2011.
Ln(Years of education)	The natural logarithm of an individual's years of schooling. Because the actual years of schooling are unavailable, we proxy this number using 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: 12 years for a high school graduate, 15 years for an individual with a bachelor's degree, and so on. Data from LISA.
Ln(Wage)$_{t-1}$	The natural logarithm of the gross wage paid by the main employer in a given year, in 100 SEK and lagged by one year. The "main" employer is the employer that, according to LISA, has provided the individual with the largest amount of labor income during the current year. Data from LISA.
Number of employees	Number of employees during a calendar year; we count only workers for whom a given firm is the "main employer" (the employer that, according to LISA, has provided the individual with the largest amount of income during the current year). Data from LISA.
Number of test-takers	The number of workers with their main source of labor income from the firm (according to LISA) that have nonmissing observations for both the cognitive and the noncognitive test scores. Military test scores are from the Military test database.

(*Continued*)

Table A.I—*Continued*

Variable	Definition
Other municipality	Indicator variable that is equal to 1 if a worker resides in a different municipality in year t compared to year $t-1$ (whether or not s/he changes employment). Data from LISA.
Placebo close	Indicator variable that, for firms in the *bankruptcy* group, takes the value of 1 in years $t-6$, $t-5$, and $t-4$ relative to the corporate bankruptcy filing (which is at $t0$) and 0 in the years $t-7$ and $t-8$. For firms in the *nonbankruptcy* group, it takes the value of 1 in years $t-6$, $t-5$, and $t-4$ relative to the matching year (which is at $t-5$) and 0 in years $t-7$ and $t-8$. Information on the corporate bankruptcy filing year comes from *Serrano*.
Profitability	EBITDA divided by total assets; winsorized at 1% and 99%. Data from *Serrano*.
Short tenure	Indicator variable that is equal to 1 if a worker's tenure is below the median for all workers in the sample firms. Tenure is calculated as the total number of years that the employee has worked for the current employer. This variable is censored due to the start of available employment histories in LISA in 1990.
Short tenure share	Average, by firm and year, of the variable *Short tenure*.
Talent concentration	The fraction of the total combined cognitive and noncognitive skills in a firm-year that are held by the top 5% of workers within that firm-year. Specifically, for each firm and year, we rank workers based on their combined cognitive and noncognitive ability scores; we identify the workers in the top 5th percentile ("top 5% workers"; see the procedure described for the variable *Top talent*). We then sum the cognitive and noncognitive ability scores for the top 5% workers and divide this number by the total sum of the cognitive and noncognitive ability scores of all workers in that firm-year. This ratio is then multiplied by the factor (0.05/share of workers in the top 5% of talent distribution), which ensures that this variable does not mechanically capture a firm size effect. The resulting number is the variable *Talent concentration*. Both the cognitive ability score and the noncognitive ability score range from one to nine on the Stanine scale and are obtained from the Military test database.
Tangibility	Property, plant, and equipment divided by total assets; winsorized at 1% and 99%. Data from *Serrano*.
Top talent	Indicator variable that is equal to 1 if an individual has a combined cognitive ability and noncognitive ability test score in the top 5% of the distribution of such scores at the firm-year level; it takes the value of 0 if the worker's score is below the top 5th percentile. In cases in which the top 5th percentile cannot be unambiguously determined (because a firm has fewer than 20 workers who took the military tests, or because the top scores are shared by more than 5% of the workers), *Top talent* takes the value of 1 for all workers who share the top score. The firm-year distribution of scores is based on all workers for whom the given firm is the main source of labor income in a given calendar year. Both the cognitive ability score and the noncognitive ability score range from one to nine on the Stanine scale and are obtained from the Military test database.
Unemployed	Indicator variable that takes the value of 1 if a worker leaves a firm and collects unemployment insurance benefits in the switching year or the year thereafter. Data from LISA.

Table A.II

Summary Statistics: Comparing Exporters

This table compares firms in the sample underlying regression models examining the effects of exchange rate shocks on exporters (Table VIII). Panel A presents summary statistics for exporting firms with above- and below-median leverage, respectively, where leverage is the average leverage ratio (variable *Leverage*) of an exporter in the first two sample years. Panel B presents summary statistics for firms with above- and below-median exports, respectively, where exports are the average *Ln(Exports)* of an exporter in the first two sample years. Finally, Panel C focuses on firms with above-median exports (where exports are the average *Ln(Exports)* of an exporter in the first two sample years); within this subsample, we present summary statistics for firms with above- and below-median leverage, respectively

Panel A: Characteristics of Exporters with High and Low Leverage

	Low Leverage			High Leverage			Difference
	Observations (1)	Mean (2)	*SD* (3)	Observations (4)	Mean (5)	*SD* (6)	t-Test (p-Value) (7)
Ln(Assets)	31,930	10.960	1.533	32,449	10.410	1.308	0.000
Profitability	31,930	0.119	0.160	32,449	0.111	0.128	0.000
Leverage	31,928	0.036	0.094	32,449	0.206	0.183	0.000
Number of employees	31,930	199.515	884.586	32,449	80.837	439.307	0.000
Tangibility	31,930	0.152	0.173	32,449	0.230	0.198	0.000
Firm age	31,930	33.032	22.753	32,449	28.794	19.346	0.000
Average skills	31,895	10.480	1.426	32,417	9.953	1.341	0.000
Average wage	31,930	3,179.538	1,103.616	32,449	2,707.467	780.780	0.000
Average age	31,930	41.168	4.992	32,449	40.659	4.890	0.000
Short tenure share	31,930	0.335	0.179	32,449	0.345	0.172	0.000
Average experience in industry	31,930	10.116	2.894	32,449	10.001	2.813	0.000
Average education years	31,930	11.802	1.213	32,449	11.307	0.949	0.000
Talent concentration	31,895	0.071	0.008	32,417	0.072	0.009	0.000
Number of test-takers	31,930	83.783	367.657	32,449	33.430	142.434	0.000
Avg. skills in top 5%	31,895	14.750	1.729	32,417	14.175	1.827	0.000
Ln(Exports)	31,930	14.596	3.412	32,449	14.555	2.887	0.099

(*Continued*)

Table A.II—*Continued*

Panel B: Characteristics of Exporters with High and Low Exports

	Low Exports			High Exports			Difference
	Observations (1)	Mean (2)	*SD* (3)	Observations (4)	Mean (5)	*SD* (6)	*t*-Test (*p*-Value) (7)
Ln(Assets)	28,797	10.186	1.360	35,582	11.084	1.396	0.000
Profitability	28,797	0.115	0.146	35,582	0.115	0.144	0.557
Leverage	28,797	0.129	0.174	35,580	0.116	0.164	0.000
Number of employees	28,797	97.434	451.149	35,582	173.902	846.881	0.000
Tangibility	28,797	0.192	0.202	35,582	0.191	0.180	0.268
Firm age	28,797	27.391	18.471	35,582	33.732	22.801	0.000
Average skills	28,767	10.260	1.484	35,545	10.178	1.343	0.000
Average wage	28,797	2,915.251	1,081.630	35,582	2,962.924	895.460	0.000
Average age	28,797	40.449	5.264	35,582	41.286	4.642	0.000
Short tenure share	28,797	0.369	0.184	35,582	0.317	0.165	0.000
Average experience in industry	28,797	9.727	2.893	35,582	10.326	2.794	0.000
Average education years	28,797	11.587	1.178	35,582	11.525	1.062	0.000
Talent concentration	28,767	0.070	0.008	35,545	0.073	0.009	0.000
Number of test-takers	28,797	40.020	184.370	35,582	73.282	336.066	0.000
Avg. skills in top 5%	28,767	14.200	1.927	35,545	14.671	1.665	0.000
Ln(Exports)	28,797	12.373	2.644	35,582	16.358	2.299	0.000

(Continued)

Table A.II—*Continued*

Panel C: Characteristics of Firms with High versus Low Leverage (Subsample of High-Export Firms)

	Low Leverage			High Leverage			Difference
	Observations (1)	Mean (2)	*SD* (3)	Observations (4)	Mean (5)	*SD* (6)	t-Test (p-Value) (7)
Ln(Assets)	17,714	11.377	1.478	17,868	10.793	1.243	0.000
Profitability	17,714	0.123	0.157	17,868	0.107	0.130	0.000
Leverage	17,712	0.034	0.089	17,868	0.197	0.181	0.000
Number of employees	17,714	249.248	1060.077	17,868	99.205	550.442	0.000
Tangibility	17,714	0.161	0.169	17,868	0.220	0.185	0.000
Firm age	17,714	36.779	24.429	17,868	30.712	20.623	0.000
Average skills	17,693	10.387	1.362	17,852	9.970	1.291	0.000
Average wage	17,714	3,163.937	958.350	17,868	2,763.644	778.805	0.000
Average age	17,714	41.643	4.615	17,868	40.931	4.642	0.000
Short tenure share	17,714	0.307	0.165	17,868	0.326	0.164	0.000
Average experience in industry	17,714	10.463	2.816	17,868	10.190	2.765	0.000
Average education years	17,714	11.723	1.128	17,868	11.328	0.953	0.000
Talent concentration	17,693	0.072	0.008	17,852	0.073	0.009	0.000
Number of test-takers	17,714	105.877	439.701	17,868	40.969	176.481	0.000
Avg. skills in top 5%	17,693	14.911	1.580	17,852	14.432	1.712	0.000
Ln(Exports)	17,714	16.536	2.500	17,868	16.181	2.066	0.000

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.