

Employee Flight Risk and Capital Structure Decisions*

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Abstract:

We examine how employee flight risk—the risk that a firm will suffer productivity losses and incur significant search and training costs when some of its mobile workers leave—affects capital structure decisions. We proxy for this risk with the ex-ante cross-industry labor mobility of a firm’s workers using a novel dynamic textual measure for this mobility derived from network centrality. The results from a battery of tests validate the use of our measure. To alleviate omitted variable and functional form bias concerns, we report estimates using the double machine learning (DML) estimator. Higher employee flight risk compels firms to adopt more conservative capital structures. This effect is stronger for firms with limited access to external capital, that are in labor-intensive industries, or with a larger number of workers who are skilled or in managerial occupations. Conversely, the effect is weaker for firms in strongly performing industries and after exogenous increases in the supply of labor or workers’ costs of switching employers. Our evidence implies that employee flight risk, which can be especially acute during financial distress, leads to more cautious financial choices because it increases a firm’s expected costs of financial distress.

Keywords: Capital structure, indirect costs of financial distress, employee flight risk, labor mobility, skilled workers, textual analysis, network analysis

JEL Classification: G31, G32, G35, J24, J61, J62

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1. Introduction

Human capital is a critical asset for all firms (Zingales (2000)), and the risk of voluntary employee departures is therefore a major corporate concern (e.g., Oi (1962), Diamond (1982), Pissarides (1990), and Bolton, Wang, and Yang (2019)). Firms can experience substantial productivity and value losses when employees who are important to firm success leave, and the costs of searching for and training replacement workers can be significant (Becker (1962), Staw (1980), and Ton and Huckman (2008)). Prior work estimates that the total costs associated with an employee's departure amount to approximately 6 to 30 months of the employee's annual wages (Mobley (1982), Dolfen (2006), and Dube, Freeman, and Reich (2010)).

In this paper, we examine how the risk of experiencing productivity losses and incurring large employee replacement costs from unexpected employee departures, which we refer to as employee flight risk, affects firms' financial decisions. Our focus differs from prior research that emphasizes the risk that departing employees could transmit proprietary information to rival firms and the implications of such risks for financing choices (e.g., Conti (2014) and Klasa, Ortiz-Molina, Serfling, and Srinivasan (2018)). To isolate employee flight risk from concerns about trade secret leakage, we study workers' mobility to jobs at non-rival firms, where disclosure of proprietary information does not pose a competitive threat.

This approach is motivated by the observation that employee job changes most frequently involve moves across industries rather than within industries. We show that this pattern holds not only for the average worker, but also for high-skilled employees and workers in managerial positions, who are often especially costly to replace. Focusing on cross-industry mobility therefore allows us to capture employee flight risk while abstracting from direct product market competition between origin and destination firms when workers switch jobs.

Our main hypothesis, which we refer to as the employee flight risk hypothesis, is that firms optimally choose lower debt ratios when they face greater employee flight risk. This hypothesis follows from the static tradeoff theory of capital structure and is consistent with evidence suggesting that employee flight risk increases firms' indirect costs of financial distress and therefore their total expected costs of financial distress. Specifically, prior work

shows that an increase in default risk can trigger employee departures and impair firms' ability to recruit new workers, as employees seek to avoid the job insecurity, low prospects of wage growth, and potential reputational costs associated with employment at a financially distressed firm (Brown and Matsa (2016) and Baghai, Silva, Thell, and Vig (2021)). In our paper, rather than focusing on ex post worker departures resulting from firm default risk, we examine how firms anticipate and proactively mitigate employee flight risk through ex-ante conservative capital structure choices.

To examine the effect of employee flight risk on capital structure decisions, we construct a new dynamic measure of cross-industry labor mobility, referred to as CIM. A higher value of CIM indicates greater cross-industry labor mobility in a given industry. The underlying assumption behind CIM is that when the products or services offered in two industries are more related, the workers in each industry have some expertise in the products or services in the other industry. This can enable the workers to more easily find employment in the other industry, which results in higher employee flight risk. For example, an employee working in the communications equipment industry will have a skill set that can make it easier to get a job in the computer and electronics industry (which sells related products), where her expertise in communication systems can be used to produce or sell electronics and computer products.

We measure product similarity between a given three-digit SIC industry and all other three-digit SIC industries using textual analysis of firms' business descriptions from their 10-K filings. Following Hoberg and Phillips (2016), we identify the unique words used in these descriptions and their assumption that these words proxy for unique products. We build on their approach to use this set of unique words, i.e., unique products, to calculate the similarity of products across industries¹ Three examples of industry pairs with high product similarity and hence greater labor mobility between them are (i) SIC 272 (Periodicals) & SIC 731 (Advertising), (ii) SIC 873 (Research and testing services) & SIC 382 (Measuring and

¹ We calculate CIM for three-digit SIC industries rather than for FIC or TNIC 10-K text-based industries because in our tests we make use of different datasets based on SIC or NAICS industries, such as National Income and Product Accounts and Industry Economic Accounts from the BEA, Occupation Employment Statistics data from the BLS, and IPUMS-CPS survey and Occupation Employment Statistics data. However, it is not possible to map NAICS or SIC codes to FIC or TNIC industries. In Section 2.2 we provide further discussion on this issue.

controlling devices), and (iii) SIC 208 (Beverages) & SIC 514 (Groceries).

To compute CIM, we conduct network analysis to identify industries that occupy more central positions in a network of industries connected through product similarity. Specifically, we measure an industry’s centrality using closeness centrality. This allows for CIM to account for the breadth of workers’ outside labor options beyond only industries to which they have direct skill transferability. This breadth of workers’ outside options further raises a firm’s employee flight risk. Importantly, our approach allows CIM to reflect not only the extent of potential cross-industry labor mobility, but also how that mobility evolves over time as industries’ product offerings change. Approximately 30% of the total variation in CIM arises from within-industry variation over time, enabling analyses that exploit changes in employee flight risk within industries.²

Before examining the relation between cross-industry labor mobility and capital structure decisions, we validate CIM in a multivariate setting using worker-level data from IPUMS-CPS, a monthly U.S. household survey conducted jointly by the U.S. Census Bureau and the Bureau of Labor Statistics. Supporting its use as a measure of cross-industry labor mobility, CIM is positively associated with the likelihood that a worker switches jobs and moves to a different industry. In contrast, CIM is not associated with the overall likelihood of a worker changing jobs.

If CIM reliably proxies for the mobility of workers across industries, its relation with actual cross-industry job moves should be accentuated when workers have greater incentives to leave their current industry for other industries where their skills are transferable, which we refer to as transfer industries. To measure these incentives, we consider relative industry sales performance and assume that employees in strongly performing industries should be less likely to move to an industry with weaker performance. We find that when sales growth in an industry is high relative to that in transfer industries, this indeed leads to a less pronounced

² Donangelo (2014) examines whether cross-industry labor mobility is priced in firms’ stock returns. The novel measure for cross-industry mobility he constructs is largely time invariant as it focuses on the extent to which the occupations in an industry tend to be occupations that make the industry’s workers generalists in that they have general skills found in many different industries.

effect of CIM on the likelihood a worker changes jobs to one in a different industry.

Further, CIM's association with actual across-industry job switches should be impacted by the number of jobs in an industry relative to that in transfer industries. When this ratio is high there should be relatively fewer cross-industry employment opportunities for the workers in the industry. Consistent with expectations, when the value for this ratio is larger this mitigates the positive effect of CIM on the likelihood that a worker switches industries.

Importantly, CIM also captures mobility among workers whose departure is likely to be particularly costly for firms. The positive association between CIM and cross-industry job switching is more pronounced for workers in managerial positions and for workers whose jobs require higher skill levels and longer training periods.

Having established that CIM reliably proxies for employee flight risk, we next examine its relation with firms' capital structure decisions using a broad sample of Compustat industrial firms. In our tests, in addition to OLS panel regressions, we report estimates using the double machine learning (DML) estimator, which offers a useful approach to alleviate omitted variable and functional form bias concerns by leveraging the strong predictive power of machine learning methods (Belloni and Chernozhukov (2013) and Chernozhukov et al. (2018)). In doing so, we follow recent studies in economics and finance that use the Random Forests method that accounts for non-linearities and two-way or higher interactive effects between explanatory variables (e.g. Dube, Jacobs, Naidu, and Suri (2020), Hansen and Siggard (2024), and Feigenbaum, Palmer, and Schneer (2025)).

Our use of machine learning methods also enables us to include a multitude of control variables in the DML-related analyses, beyond the standard ones used in capital structure tests. For instance, in addition to controlling for further firm-level financial variables, we also control for firm- and industry-level measures of product market competition intensity, union bargaining power, monitoring by large institutional investors, and a firm's information environment, proxied for with analyst coverage.

Providing empirical support for the employee flight risk hypothesis, CIM is negatively associated with firms' debt ratios. A one-standard deviation increase in CIM is associated with

an approximately 12% reduction in financial leverage. This relation is robust across alternative leverage definitions, including book, market, net, and long-term leverage.³ Further, firms in high CIM industries hold more cash and pay less dividends, consistent with more conservative financial policies in response to heightened employee flight risk.

According to the employee flight risk hypothesis, the importance of a lower debt ratio to avoid indirect costs of financial distress is larger for firms with more limited access to external capital, who typically face a higher likelihood of experiencing financial distress. Supporting this prediction, across different measures for access to external capital, the negative relation between leverage and CIM is accentuated for firms with worse access to external capital.

Next, we conduct a multitude of analyses that specifically test whether labor mechanisms are likely to lead to the negative association between CIM and financial leverage. Importantly, if omitted variables were responsible for this association then they would need to also explain the cross-sectional results we find relating to labor mechanisms.

A key implication of the employee flight risk hypothesis is that the advantages from maintaining a lower debt ratio in high CIM industries are greater for firms in industries in which labor costs make up larger fractions of firms' total costs. Using measures constructed with Bureau of Economic Analysis labor data, we find that the negative relation between CIM and leverage is indeed stronger in more labor-intensive industries.

Subsequently, we investigate whether the negative effect of CIM on leverage is more pronounced in industries with more skilled workers or workers in managerial occupations. Such workers are generally more costly and difficult to replace, implying larger potential productivity losses when employee departures occur. As a result, firms operating in such industries should be particularly sensitive to employee flight risk. Consistent with this argument, the negative association between CIM and leverage is more pronounced in

³ Agrawal and Matsa (2013) and Kim (2020) argue that firms choose higher leverage when the costs for workers of becoming unemployed due to financial distress-related layoffs are lower, because lower costs of layoffs reduce the wage premium firms must pay their workers for bearing the risk of such events. Higher labor mobility across industries could reduce the expected costs of layoffs for workers and thus incentivize borrowing, but our findings in the opposite direction suggest that in our context firms' concerns about employee flight risk likely dominate.

industries in which a greater fraction of workers are skilled or in managerial positions.

If the workers in an industry tend to be in occupations that make them specialists because they have skills that are specialized for their industry and not in high demand outside of the industry this should reduce firms' concern about employee flight risk. Thus, we also run tests in which we use the measure created by Donangelo (2014), which captures the extent to which an industry's occupations produce specialist workers. Supporting the employee flight risk hypothesis, we find that the negative association between CIM and leverage is mitigated in industries with a higher prevalence of specialist occupations.

We next conduct two tests that consider how workers' switching costs to alternative jobs shape the relationship between employee flight risk and capital structure. Conceptually, lower switching costs amplify employee flight risk and increase firms' incentives to hold less debt. We first use annual data on county- and state-level house prices to examine the effect of exogenous shocks to workers' switching costs if they were to change employers and move to another region. When house prices are higher in a worker's home region relative to that in regions where the worker has job mobility, the worker is expected to face lower switching costs from changing jobs and moving to another region. In these situations, firms are likely to be more concerned about potential employee departures and respond by reducing leverage. Consistent with this notion, when relative house prices in a worker's county or state are higher this leads to a more pronounced negative association between CIM and leverage.

Switching costs should also be lower when transfer industry jobs are geographically close. We measure this by considering the relative presence of firms in transfer industries within a firm's county or state. Providing further support to our prediction relating to switching costs, the negative effect of CIM on leverage is stronger for firms located in counties or states with a greater relative number of nearby transfer-industry firms.

Finally, we consider the effect of an exogenous shock to the supply of workers. In 2005, Hurricane Katrina caused large population movements from New Orleans to Houston, substantially increasing the supply of workers in the Houston metropolitan area (McIntosh (2008)). Given the sudden increase in the Houston worker population, we expect firms in

industries with high cross-industry labor mobility located in Houston to be less concerned about the mobility of their workers to other industries after the hurricane, as the cost of searching for new workers would be lower compared to the case prior to the hurricane. Further, the greater supply of workers in the Houston area would likely increase competition between workers for available jobs and reduce the likelihood workers would try to leave their current job. Supporting this intuition and providing additional support to the employee flight risk hypothesis, the negative effect of CIM on debt ratios becomes less pronounced for firms situated in Houston after Hurricane Katrina compared to that for propensity-score-matched control firms.

Our paper builds on the evidence in Eisfeldt and Papanikolaou (2013), Donangelo (2014), Brown and Matsa (2016), and Baghai, Silva, Thell, and Vig (2021) that bring to light the importance of indirect costs of financial distress that result from interactions between finance and labor. Specifically, we bring attention to how indirect costs of financial distress arising from employee flight risk — distinct from costs related to the loss of trade secrets to rivals — can have significant effects on firms’ financial policy decisions. Because we only consider these costs in the context of cross-industry job moves, the estimates from our analyses can be viewed as a lower bound on the effect of these costs on capital structure decisions.

More broadly, we also contribute to the literature on what determines firms’ capital structures (e.g., Titman (1984), Titman and Wessels (1988), Rajan and Zingales (1995), Leary and Roberts (2005), Lemmon, Roberts, and Zender (2008)). We do so by highlighting that when firms decide on their optimal level of debt financing, they trade off benefits of this financing with indirect costs of financial distress resulting from employee flight risk

Our study also complements prior work which shows how labor market frictions resulting from issues such as union bargaining power (Matsa (2010)), workers’ risk of becoming unemployed (Agrawal and Matsa (2013)), employment protection legislation (Simintzi, Vig, and Volpin (2014)), firms’ needs for skilled workers (Ghaly, Dang, and Stathopoulos (2017)), the risk that departing mobile workers will divulge a firm’s trade secrets to rival firms (Klasa et al. (2018) and Sanati (2025)), and labor market power (Bai, Massa, Wan, and Wang (2025))

affect their financial policy decisions.

Finally, we contribute by introducing a new dynamic measure of cross-industry labor mobility, which proxies for employee flight risk. We show that CIM reliably proxies for the mobility of workers to jobs in other industries. The introduction of CIM provides an avenue for future research that could examine how cross-industry labor mobility relates to a multitude of different corporate decisions.

2. Sample selection and construction of CIM

2.1 Main sample selection

Financial and accounting data are from the CRSP-Compustat-Merged dataset where firms are publicly traded on NYSE, NASDAQ, or AMEX without missing values for sales and total assets over the fiscal years 1996 to 2020. Firms in financial or utility industries (SIC codes 6000-6999 or 4900-4999) are excluded from the sample. Importantly, we also drop all industries classified as “miscellaneous”, “not classified elsewhere”, or industries with a “9” in the third digit of their SIC code as these industries do not represent an actual industry. Further, we delete all firm-year observations with missing values for any of the variables used as a control variable in the leverage regressions. All variables are defined in the Internet Appendix and Table A1 reports descriptive statistics for these variables. The final sample comprises 78,321 firm-year observations with 8,228 unique firms.

2.2 Construction of CIM

We construct our measure of cross-industry labor mobility (CIM) at the three-digit SIC industry level. We focus on SIC industries rather than text-based industry definitions (e.g., FIC or TNIC) for several reasons. FIC industries are designed to maximize within-industry product similarity, which by construction minimizes cross-industry product similarities, making them less suitable for our purpose. TNIC industries, on the other hand, assign each firm to multiple overlapping industry groups, creating ambiguity when defining cross-industry moves. Also, there are mapping tables that can be used to convert to SIC codes the industry classifications used in most large-scale labor-related economic datasets. However, there are no

such mapping tables for TNIC or FIC industries.

Conceptually, product similarity is a compelling proxy for cross-industry labor mobility because industries that produce similar products often demand comparable technical skills, managerial expertise, and specialized knowledge. Unlike occupational similarity measures that just focus on job titles or narrow tasks, product similarity captures broader functional and technological overlap, which is particularly relevant for the mobility of many types of workers. This approach builds on prior evidence that words in product descriptions meaningfully reflect firms' activities and technological orientation (Hoberg and Phillips (2016)).

To construct CIM, we first collect “10-K”, “10-K405”, “10KSB”, and “10KSB40” filings from EDGAR for 1996–2020 and extract each firm's product description section. Using natural language processing, we identify and retain non-common nouns and proper nouns to represent product keywords, following Hoberg and Phillips (2016). We convert words to singular form and remove those appearing too frequently across firms to capture product-specific content.

For each firm-year, we generate a Boolean vector indicating the presence of each product word. Firms with fewer than 20 unique product words are excluded to ensure sufficient description granularity. We then aggregate these vectors to form an industry-level representative vector, reflecting the average presence of each product word among all firms in the same three-digit SIC industry.

Using these vectors, we compute pairwise product similarity scores between industries each year, creating an $N \times N$ similarity matrix. To focus on meaningful connections, we identify significant industry pairs with normalized similarity scores above the 1% threshold ($z > 2.576$) and set non-significant similarities to zero. These "transfer industries" represent alternative sectors where workers may plausibly move, given comparable product expertise.

The last step in creating CIM is to conduct network analysis and determine the centrality of each industry based on the final matrix of industry pairs' product similarity. We calculate the closeness centrality of each industry in a network of industries connected via

product similarity and set industries' CIM values equal to their value for closeness centrality.⁴ Doing so enables us to account for the breadth of workers' outside work options beyond only the industries to which they have direct skill transferability. This breadth of workers' outside employment options further increases a firm's employee flight risk. Because we assume greater similarity of products across industries suggests more transferable labor skills, a higher value for CIM implies that the workers in an industry can more easily move across industries. Noteworthy, CIM also captures how the cross-industry mobility of workers in a particular industry changes over time as the products sold in their industry evolve. Therefore, the use of CIM enables us to conduct analyses that exploit within-industry variation over time for cross-industry labor mobility.

Table A1 in the Internet Appendix documents that CIM is slightly left skewed with mean (median) sample values of 0.208 (0.250) and a standard deviation of 0.147. Table A2 reports the findings from an ANOVA analysis of CIM that show approximately 71% of the total variation in CIM is due to across-industry variation in CIM and the remaining 29% of this variation comes from within-industry variation in CIM over time. Thus, the use of CIM allows us to conduct analyses in which we can exploit both of these sources of variation in CIM.

3. Validation of CIM as a measure for cross-industry labor mobility

Table 1 reports the results of tests for whether CIM is a useful measure for cross-industry labor mobility. In these tests we use IPUMS-CPS survey data. The CPS is a monthly nationally representative U.S. household survey conducted jointly by the U.S. Census Bureau and the Bureau of Labor Statistics that gathers information on education, labor force status, and other aspects of the U.S. population. In this survey, individuals are interviewed for four months and following a gap of eight months, they are interviewed for another four months. We limit the sample to individuals who are part of the March Annual Social and Economic Supplement to obtain individuals' wages. Also, we exclude individuals who are less than 18 or greater than 65 years old, interviewed less than two times in a year, or are in a financial or

⁴ In Tables A3-A5 in the Internet Appendix, we show our results are robust to the use of other network centrality measures to construct CIM.

utility industry. We compare each of the individuals' interviews with the next interview to identify workers who changed their job to a job in another industry. We also use the individual's occupation to identify those who are high-skilled workers or work in managerial positions. The final sample based on IPUMS-CPS survey data from 1995 to 2020 has 5,612,016 individual-month observations for 633,122 unique individuals.

In Panel A of Table 1, we first report univariate statistics for the extent to which job changes are due to moves within or across industries. Based on the three-digit SIC classification, we find that 61.56% of job moves are across industry and 38.44% of job moves are within the same industry. Thus, the majority of job moves are across-industry. In the second and third columns of Panel A, we show that the finding that the majority of job moves are cross-industry moves holds if only high-skilled workers or those in managerial positions are considered.

In Panel B of Table 1 we report the results of tests that validate CIM as a measure for cross-industry labor mobility. The dependent variable in models 1 to 5 is an indicator equal to one if the person changes the industry where she works between the current and the next interview, and zero otherwise. The dependent variable in model 6 is an indicator equal to one if the person changes her employer between the current and the next interview, disregarding if she also changes her industry, and zero otherwise. In all six models, we control for workers' characteristics that could affect the probability that a worker changes her job. We also control for year fixed effects and the number of months between interviews.

The results for model 1 in Panel B show that CIM is positively associated with the likelihood that a worker changes her job to one in another industry. This effect is economically important. Relative to the unconditional likelihood that a worker changes the industry where she works, a one-standard-deviation increase in CIM would lead to a 9.54% increase in the likelihood that the worker changes her industry of employment. This is strong support that CIM is a useful proxy for cross-industry labor mobility.

In contrast, the results for model 6 show that CIM is not associated with the overall likelihood that an individual changes employers between interviews, regardless of whether

she moves to a different industry or remains within the same industry. Consequently, the positive association between CIM and the likelihood a worker moves to a job in another industry is not simply driven by a general tendency for individuals in high-CIM industries to change jobs more frequently.

If CIM is a valid proxy for the mobility of workers across industries, its relation with actual across industry job moves should be more pronounced when workers have greater incentives to leave their industry for other industries where they can easily transfer their skills and find employment. To measure these incentives, we consider relative industry sales performance. Employees in strongly performing industries should be less likely to move to an industry with lower sales performance. This leads to the prediction that the positive relation between CIM and the mobility of workers across industries should be less pronounced for workers in industries with higher relative sales performance. We report the results of a test of this prediction in model 2 of Panel B in Table 1. For this test the sample size is reduced as we only consider industries with at least one transfer industry.⁵

In model 2 of Panel B we interact CIM with an indicator variable for whether relative industry sales growth is in the top quartile of this measure across all industries in that year. Relative industry sales growth is total industry sales growth minus average total sales growth across transfer industries. The coefficient estimates from model 2 imply that for employees who are in industries with high relative industry sales growth, a one-standard-deviation rise in CIM would result in a 5.13% lower increase in the likelihood a worker changes her industry compared to that for employees in other industries.⁶

CIM's association with actual across industry job switches should also be impacted by the number of jobs in an industry relative to that in transfer industries. In instances when this ratio is large there should be fewer cross-industry employment opportunities for the workers in the industry. In model 3 we test this prediction and proxy for the number of jobs in an industry with industry size. We interact CIM with an indicator for whether total sales in a

⁵ Connections between industries with significant product similarity are discussed in Section 2.2.

⁶ The results are very similar if relative industry sales growth is measured over the prior three years.

worker's industry of employment relative to average sales in transfer industries is in the top quartile of this measure across all industries in that year. The negative coefficient on the interaction term in model 3 shows that, as expected, workers in high CIM industries are less likely to leave their industry when it has a greater number of jobs compared to that in transfer industries. The coefficient estimates from model 3 indicate that for employees who are in industries with a large number of jobs relative to that in transfer industries, a one-standard-deviation rise in CIM would lead to a 13.59% lower increase in the probability that a worker changes her industry compared to that for employees in other industries.

For our tests related to firms' leverage decisions, it is important for CIM to measure the cross-industry mobility of workers in managerial positions or whose job requires more skills and longer training given that the loss of such workers could be particularly costly for a firm. To investigate this issue, we use Occupational Employment Statistics (OES) data from the Bureau of Labor Statistics to construct measures for workers' skill levels and if they are in a managerial position. In model 4 we interact CIM with an indicator for whether a worker has a high skill level. The coefficient on the interaction term is positive and significant, which shows that CIM has incremental power in predicting the mobility of high-skilled workers across industries. We estimate that for workers with a high skill level, a one-standard-deviation rise in CIM would lead to an increase in the probability that a worker changes her industry that is 3.30% higher than it is for other employees.

Model 5 interacts CIM with an indicator for whether the employee's job is in a managerial occupation. Here too, the coefficient on the interaction variable is positive and significant, implying that CIM has incremental power in predicting the mobility of employees in managerial occupations across industries. The coefficient estimates from this model imply that for employees who are in a managerial occupation, a one-standard-deviation increase in CIM would result in an increase in the probability that a worker changes her industry that is 6.16% higher than it is for other employees. Overall, the Table 1 findings help to validate the use of CIM as a proxy for cross-industry labor mobility.

4. CIM and financial policy decisions

4.1 Model specification

Next, we test the study’s main prediction of a negative effect of employee flight risk on firms’ debt ratios. In our tests our basic OLS regression model is as specified below:

$$y_{i,t} = \beta_1 CIM_{j,t} + \gamma_1 X_{it} + \alpha_j + \delta_t + \varepsilon_{i,t}, \quad (1)$$

where, $y_{i,t}$ is book or market leverage for firm i in year t and $CIM_{j,t}$ is Cross-Industry Labor Mobility of firm i located in industry j in year t . The vector X_{it} consists of control variables for firm i in year t (*Log (book assets)*, *Market-to-book assets*, *ROA*, *Cash flow volatility*, *Dividend payer*, *R&D/sales*, *Asset tangibility*, *State IDD adoption*). The first seven control variables are standard controls included in financial leverage models. With respect to the State IDD adoption indicator, prior work shows that the recognition of the IDD by the courts in a firm’s state significantly reduces the mobility of workers to rival firms, i.e., firms within the same industry. To ensure that the effect of CIM on firms’ leverage is due to the mobility of workers across industries, and not somehow affected by the likelihood of mobility of workers to rival firms and the risk of losing trade secrets to these rivals, we control for whether the IDD has been recognized in a firm’s state. We also include industry fixed effects (α_j) and year fixed effects (δ_t) in all regressions. Because CIM is constructed for three-digit SIC industries, the industry fixed effects are two-digit SIC fixed effects so that we can exploit both within-industry time-series variation in CIM and across-industry variation in CIM values in our analyses. Finally, in all regression models we cluster the standard errors at the three-digit SIC level.

4.2 Use of the DML estimator

An important empirical consideration in estimating Equation (1) is that firms’ operating environments and workforce characteristics are inherently complex and may be related to leverage in nonlinear ways. While our baseline OLS specifications control for a rich set of firm- and industry-level characteristics, concerns may remain that restrictive functional form assumptions or the existence of high-dimensional relationships between control variables (e.g., two- or three-way interactions) could lead to biased estimates. To address these issues,

we complement our OLS analyses with estimates obtained using the double machine learning (DML) estimator developed by Chernozhukov et al. (2018). The DML framework is designed to deliver reliable inferences on a parameter of interest in the presence of complex functional forms and high-dimensionality of control variables. In our use of the DML procedure, we follow Chernozhukov et al. (2018) and estimate the partially linear model appearing below:

$$Y = X\theta_0 + g_0(Z) + \epsilon, \quad E[\epsilon|Z, X] = 0 \quad (2)$$

$$X = m_0(Z) + \nu, \quad E[\nu|Z] = 0 \quad (3)$$

where Y is the outcome variable (financial leverage), X is the regressor of interest (CIM), Z is the vector of potentially high-dimensional control variables, g_0 and m_0 are unknown nuisance functions, ϵ and ν are disturbance terms, and θ_0 is the coefficient on CIM. Importantly, while equation (2) focuses on the potential impact of CIM on financial leverage, equation (3) accounts for the various effects of the control variables on CIM, thereby helping to reduce omitted variable bias. Although the nuisance functions are not of immediate interest, they are needed to obtain correct model specification, e.g., to fully capture the relevant non-linear relations in the data and the existence of high-dimensional relationships between control variables so that model misspecification can be minimized.

The estimation procedure follows in two steps. First, we use the machine learning method, Random Forests, to estimate $g_0(Z)$ and $m_0(Z)$, which allows us to use equations (2) and (3) to calculate the residuals of Y and X . In the second step, we estimate the effect of CIM on financial leverage using OLS by regressing the residual of Y on the residual of X . As such, in the second step we are using versions of Y and X that are purged from the potential confounding high-dimensional or non-linear influences of the control variables in Z .

Random Forests, which we use to estimate the nuisance functions, is an ensemble method that fits a large number of decision trees on resampled versions of the data and averages their predictions. This averaging reduces variance and helps to limit overfitting. Because the trees are constructed via recursive splits that partition the covariate space into many regions, Random Forests can flexibly accommodate nonlinear relationships between the controls and the outcome (including patterns consistent with quadratic or other higher-order

nonlinearities) without requiring us to pre-specify a particular functional form. Likewise, Random Forests can capture interaction effects among controls, such as two-way, three-way, or higher order interactions, because recursive splits within trees can depend on different variables at different levels of the trees. Importantly, the algorithm adaptively emphasizes the combinations of variables that improve predictive performance, rather than requiring the researcher to specify interaction terms in advance.

We use the `sklearn.ensemble.RandomForestRegressor` module from Scikit-learn (sklearn), a widely used, free, open-source Python machine learning library, to estimate the nuisance functions. We estimate the nuisance functions using `RandomForestRegressor` with 100 trees (`n_estimators = 100`). Consistent with common practice in applied DML implementations, we set the remaining hyperparameters to the scikit-learn defaults and rely on cross-fitting to mitigate overfitting concerns in the construction of the orthogonalized residuals. We also set a fixed random seed (`random_state`) to ensure replicability of the nuisance-function estimates and the resulting cross-fitted residuals.⁷

4.2.1 Cross-fitting and estimation

Following prior work using DML procedures, we employ cross-fitting to mitigate overfitting bias that can arise when the same data are used both to estimate the nuisance functions and to generate predictions from them. Specifically, we implement five-fold cross-fitting by partitioning the sample into five equally sized folds. For each fold, we hold that fold out as a test set and estimate the nuisance models on the remaining four folds. Using two separate Random Forests, we estimate the nuisance functions $g_0(Z)$ and $m_0(Z)$, which predict financial leverage and CIM, respectively. We then use these fitted nuisance functions to generate out-of-sample predictions for the held-out fold and construct the corresponding residuals for Y and X . We repeat this procedure four more times so that each fold serves as the

⁷ Random Forests involve stochastic elements through bootstrap resampling of observations and random feature selection at each split. Setting a fixed random seed (`random_state`) fixes the underlying pseudo-random number generator, ensuring the same bootstrap samples and split-variable draws are used across runs. As a result, the fitted nuisance functions, cross-fitted predictions, and the resulting residuals are exactly reproducible given the same data and hyperparameters.

held-out sample exactly once.

After completing cross-fitting, we pool the residuals across all folds and estimate the effect of CIM on financial leverage by regressing the residuals from Equation (2) on the residuals from Equation (3). Thus, the second-stage regression uses residuals that are purged of the influence of controls using cross-fitted Random Forest predictions. In our tables, we report significance levels for these regression estimates that are calculated using standard errors clustered at the three-digit SIC industry level.

4.2.2 Controls used in DML analyses

The set of control variables used in the DML-related analyses includes the eight control variables listed in equation (1). Further, to leverage the predictive power from using machine learning methods, we include an additional ten control variables. First, because investment by a firm in capital could affect both its financial leverage and its demand for workers we control for capital expenditures/assets and acquisition/assets. Likewise, a firm’s short-term liquidity position could be related to both financial leverage and workers’ incentives to stay at their job. Hence, we include net-working-capital/assets as an additional control.

To account for the intensity of product market competition a firm faces, we further include as controls product market fluidity from Hoberg, Phillips, and Prabhala (2014), the industry four-firm concentration ratio calculated by the U.S. Census, and firm age. To consider the extent to which a firm is monitored by external investors, we include controls for total institutional ownership and institutional ownership concentration. Likewise, we control for a firm’s information environment with an indicator for whether the firm is covered by at least one equity analyst. Finally, we control for union bargaining power with a firm’s three-digit SIC industry unionization rate.

When estimating equations (2) and (3), we account for fixed effects in the same manner as in Equation (1) by removing two-digit SIC industry fixed effects and year fixed effects from all variables (i.e., demeaning by industry and year). The Random Forest nuisance models are estimated using these fixed-effect-adjusted variables. Hence, the DML estimates are identified from the remaining within-industry and within-year variation in the data.

4.2.3 DML and cross-sectional analyses

We also conduct cross-sectional tests using DML in which we interact CIM with other variables. Using S as notation for the variable which is interacted with CIM, we extend the partially linear model as follows:

$$Y = (X \times S)\delta_0 + X\delta_1 + S\delta_2 + g_0(Z) + \epsilon, \quad E[\epsilon|Z, X, S] = 0 \quad (4)$$

In these specifications, the interaction term $X \times S$ and its constituent variables X and S are treated as regressors of interest. We continue to account for two-digit SIC industry fixed effects and year fixed effects by demeaning all variables prior to estimating the nuisance functions. Employing five-fold cross-fitting with Random Forests, we estimate separate nuisance functions for Y , $X \times S$, X , and S using the same set of baseline and extended controls Z . We then use the residualized (orthogonalized) versions of Y , $X \times S$, X , and S in the second-stage regression to estimate δ_0 , with standard errors clustered at the three-digit SIC level.

4.3 Main effect results

Table 2 reports our main findings for the effect of CIM on firms' financial leverage. The dependent variables in models 1 to 5 are book leverage, market leverage, net book leverage, net market leverage, and long-term leverage (book), respectively. The results for the first two models in Panel A of Table 2 show that CIM is negatively associated with book and market leverage. From the OLS estimates, we estimate that a one-standard-deviation increase in CIM would result in book and market leverage which would be, respectively, 12.22% and 13.24% lower relative to the sample means for these variables. The findings for models 3 to 5 in this table show that if we alternatively consider net leverage or long-term leverage that we continue to find that CIM has a negative effect on leverage.

The last row of Panel A reports estimates obtained with the DML estimator using Random Forests, described in Section 4.2. As already discussed, these estimates are computed using an augmented set of control variables for additional firm financial characteristics, product market competition intensity, union bargaining power, monitoring by institutional investors, and a firm's information environment. The findings using DML are similar to those using OLS, suggesting that the negative association between CIM and leverage is not driven

by functional form assumptions or by high-dimensional relationships between control variables.⁸

As discussed in Section 2.2, CIM is constructed using product-based industry connections that are statistically significant at the 1% level, and some industries therefore have no significant connections to other industries. Panel B of Table 2 re-estimates the models from Panel A using a restricted sample of firms operating in industries that have at least one significant connection. The OLS and DML results in Panel B closely mirror those in Panel A, indicating that the main findings are not driven by industries with no meaningful product-based connections to other industries.

In Tables A3 to A5 of the Internet Appendix, we further assess robustness by replacing CIM with alternative network centrality measures that capture different aspects of cross-industry connectivity. Specifically, Degree measures the number of industries directly connected to a given industry. Strength captures both the number and the intensity of industry connections. Finally, Linked is an indicator equal to one if a three-digit SIC industry has at least one significant connection to another industry. The OLS and DML findings show that across all three measures, we continue to find a negative association between cross-industry labor mobility and leverage. Taken together, these results indicate that the main findings reflect both variation in the intensity of cross-industry mobility among connected industries and differences between industries that are connected versus isolated.

Finally, if employee flight risk increases firms' expected indirect costs of financial distress, it should also affect other financial policies. The OLS and DML findings reported in Table A6 of the Internet Appendix show that CIM, Degree, Strength, and Linked are positively associated with corporate cash holdings and negatively associated with the likelihood that a firm pays dividends. These findings are further evidence consistent with firms in high-CIM

⁸ We note that the reported coefficients using the DML procedure are typically larger in magnitude than the corresponding coefficients from the OLS estimations. This may occur if the linear OLS specifications do not adequately capture nonlinear and interactive relationships between the controls and both CIM and leverage. In that case, residual confounding may remain after linear partialling-out, potentially biasing the OLS estimate toward zero. By using flexible machine learning methods to partial out these nuisance components and cross-fitting to reduce overfitting bias, DML can yield a less attenuated estimate of the effect of CIM on leverage.

industries adopting more conservative financial policies in response to elevated employee flight risk.

4.4 Cross-sectional variation in the impact of employee flight risk

We next examine cross-sectional variation in the impact of CIM on firms' debt ratios. These tests provide insights on the economic mechanisms that lead to the negative effect of CIM on financial leverage. Further, this analysis is useful in assessing whether our results have a causal interpretation. This is because if a variable omitted from our benchmark regression model were to drive the negative association between CIM and financial leverage, then not only would that variable need to be uncorrelated with all of the control variables in that model, but it would also have to explain all of the cross-sectional results we find for the effect of CIM on financial leverage. As in the baseline analysis, we report both OLS and DML estimates for all cross-sectional specifications; the corresponding DML estimates for interaction variables is reported in the last row of each table.

4.4.1 Access to external capital

Our hypothesis predicts that the importance of keeping a lower debt ratio to avoid indirect costs of financial distress is larger for firms with more limited access to external capital, who generally face a higher likelihood of experiencing financial distress. Accordingly, we expect the effect of CIM on firms' leverage to be more pronounced for such firms.⁹

We test this prediction using several commonly used measures for access to external capital and report the results in Table 3. Specifically, firms are classified as having more limited access to external capital if they do not have a bond rating, are not dividend payers, or have values for the Hadlock and Pierce (2010) index or the Whited and Wu (2006) index above the annual sample median.

In Table 3, the dependent variable in models 1 to 4 is book leverage, and in models 5 to 8 it is market leverage. Across all specifications, the OLS and DML results show that the

⁹ While constrained firms may not be able to fully adjust their capital structures, they may still act more conservatively when setting debt levels ex ante to avoid costly future adjustments and distress.

coefficients on the interactions between CIM and the indicators for limited access to external capital are negative and statistically significant. From the OLS specifications, we estimate that a one-standard-deviation increase in CIM would result in about 6.5% - 13.3% larger decreases in financial leverage for firms with worse access to external capital compared to that for other firms. These findings are strong support for the study’s main hypothesis.

4.4.2 Labor-intensive industries

Next, we conduct a series of analyses that specifically test whether labor mechanisms are likely to lead to the negative association between CIM and financial leverage. We report the results of these analyses in Sections 4.4.2-4.4.6. First, we consider that firms in more labor-intensive industries should have larger concerns about employee flight risk-related costs. This is because in these industries, a higher share of value creation comes directly from labor rather than from physical or intangible capital. Consequently, losing workers can significantly disrupt operations, reduce output, and lead to high replacement and training costs.

In Table 4 we consider this issue. We follow Palacios (2013) and use data from Bureau of Economic Analysis (BEA) to calculate the share of labor in the production of an industry, which is the ratio of compensation of employees over the value added by the industry. The value added of an industry, also referred to as gross domestic product (GDP)-by-industry, is the contribution of an industry to overall national GDP. The components of value added consist of compensation of employees, taxes on production and imports less subsidies, and gross operating surplus. The industry classification used to calculate value added is based on three-digit NAICS codes. We use mapping tables to convert NAICS to three-digit SIC codes.

In models 1 and 4 of Table 4, we interact CIM with an indicator for whether an industry’s labor share based on total compensation is in the top quartile across all industries. The significant negative coefficients on the interactions in the OLS and DML specifications indicate that the negative association between CIM and leverage is stronger in more labor-intensive settings, as predicted. Specifically, the OLS estimates from model 1 imply that a one-standard-deviation increase in CIM results in an approximately 8.0% larger decrease in book leverage for firms in high labor share industries relative to other firms. In models 2 and 5, we

refine the labor share measure to focus on total salaries (excluding benefits and perks), and find results in line with those in models 1 and 4. Finally, in models 3 and 6, we use the number of employees scaled by industry value added as an alternative proxy for labor intensity. Again, the results consistently show that the negative effect of CIM on leverage is amplified when labor intensity is higher. Overall, the Table 4 findings are persuasive evidence that employee flight risk drives the negative effect of CIM on leverage.

4.4.3 High-skilled and managerial workers

The employee flight risk hypothesis further predicts that the benefits of maintaining lower debt ratios in high-CIM industries are greater for firms whose workforce consists of more high-skilled workers or workers in managerial occupations. Skilled workers are often difficult to replace, and their departure can lead to substantial productivity losses. Along the same lines, managers frequently have many years of experience in their positions, and it can be quite hard to replace such workers who are vital for a firm's success.

Table 5 examines whether the negative effect of CIM on debt ratios is more pronounced in industries with more skilled or managerial workers. Panel A focuses on skilled employees and reports three interaction specifications based on: an indicator for industries with a high proportion of skilled workers, an indicator for industries that pay skilled workers relatively high wages, and an indicator for industries with high average skill levels. In each case, CIM is interacted with an indicator equal to one if the industry is in the top quartile of the relevant measure in a given year. Panel B follows a similar structure for managerial occupations, interacting CIM with indicators for industries with a high proportion of managers and industries with high average managerial compensation.

Across both panels, the OLS and DML results consistently show that the negative association between CIM and leverage is stronger in industries with more skilled workers or managers. For example, the model 1 OLS estimate in Panel A indicates that a one-standard-deviation increase in CIM is associated with an additional 9.30% decrease in book leverage for firms operating in industries with a high proportion of skilled workers. Similarly, the model 1 OLS estimate in Panel B implies that a one-standard-deviation increase in CIM is associated

with an additional 5.95% decrease in book leverage for firms in industries with a high proportion of managers. These results support the argument that firms in industries more exposed to worker mobility, especially among high-skilled and managerial employees, face stronger incentives to reduce leverage in order to mitigate employee flight risk. Put together, the Table 5 results are further evidence consistent with our study’s main hypothesis.

4.4.4 Specialized industry skills

Conceptually, if the workers in an industry are mostly in occupations that make them specialists because they have skills that are specialized for their industry and in low demand outside of the industry this should reduce firms’ concern about employee flight risk. Thus, we also run tests in which we use the measure created by Donangelo (2014) for whether the workers in an industry tend to be specialists, as a result of the occupations in that industry. We expect that if the occupations in an industry make the workers specialists this will lower firms’ in high CIM industries concern about employee flight risk and mitigate the extent to which they would hold less debt.

In Table 6, in models 1 and 3, we interact CIM with the continuous measure from Donangelo (2014) that captures the extent to which workers in an industry are specialists. In models 2 and 4, we interact CIM with an indicator for firms operating in industries with low labor specialization, defined as those in the bottom quartile of the specialization distribution. The OLS and DML estimates for the interaction terms are positive and significant in models 1 and 3, and negative and significant in models 2 and 4. The OLS coefficient estimates from model 2 imply that a one-standard deviation increase in CIM would result in about a 9.3% greater decrease in book leverage for firms in industries with workers who are more likely generalists compared to that for other firms. These findings support the argument that when the workers in an industry are more likely specialists (generalists) this lessens (accentuates) firms’ concerns about employee flight risk and therefore lowers (heightens) the negative impact of CIM on financial leverage. As such, this further increases confidence that employee flight risk drives the negative effect of CIM on financial leverage.

4.4.5 Workers' switching costs from changing jobs

Workers' switching costs from changing employers can materially affect firms' exposure to employee flight risk. When workers face higher switching costs from changing jobs, employee flight risk is reduced, lowering firms' incentives to maintain conservative capital structures, even when cross-industry labor mobility is high. In contrast, when workers' switching costs are low, the negative effect of CIM on leverage is expected to be more pronounced.

We first test these predictions by considering the effect of exogenous shocks to workers' switching costs from changing employers and relocating across counties or states. We use variation in county- and state-level residential real estate prices to capture plausibly exogenous changes in these switching costs. Higher residential house prices in a worker's home location can reduce the effective cost of selling a home and purchasing housing elsewhere, thereby lowering the cost of relocating to accept a job in another county or state. As a result, higher local housing prices are expected to increase employee flight risk and strengthen firms' incentives to reduce leverage.

We collect county- and state-level residential house price indices from the Federal Housing Finance Agency for the period 1996 to 2020. In Table 7, we report regressions that examine whether local housing prices impact the negative effect of CIM on leverage. The dependent variable in models 1 and 2 (3 and 4) is book (market) leverage. In each specification, we interact CIM with an indicator equal to one if the residential house price index (HPI, normalized to 100 in 2000) in the county or state where the firm is headquartered is in the top quartile of the respective distribution in that year.

Consistent across all specifications, the OLS and DML estimates for the interaction terms are negative and statistically significant, indicating that when residential house prices are high, the negative association between CIM and leverage is more pronounced. Economically, the OLS estimates from model 1 (2) imply that for firms headquartered in counties (states) with housing prices in the top quartile, a one-standard-deviation increase in CIM leads to an additional 5.73% (5.60%) decrease in book leverage relative to other firms.

This evidence from exogenous changes to workers' switching costs is further support for the employee flight risk hypothesis.

To test the predictions relating to switching costs, we also consider that in regions where workers are more likely to find nearby alternative employment in industries to which they are mobile, the workers should have lower switching costs from changing jobs. As a result, the negative effect of CIM on leverage is expected to be stronger for firms located in such regions.

Table 8 examines whether the negative effect of CIM on leverage is stronger in regions where the relative presence of firms in transfer industries is greater. Specifically, we calculate the ratio of the number of firms in transfer industries located in a firm's county or state to the number of such firms located elsewhere in the United States. In models 1 to 4 of Table 8 we interact CIM with indicators for whether these ratios are in the top quartiles of their respective distributions in that year. The dependent variable in models 1 and 2 (3 and 4) is book (market) leverage.

The OLS and DML estimates for the interaction terms between CIM and these measures are negative and statistically significant in models 1, 2, and 3. In model 4 although the OLS and DML coefficients on the interaction variables are negative, they are not statistically significant. The OLS coefficient estimates from models 1 and 2 indicate that for firms headquartered in counties or states with a high relative presence of firms in transfer industries a one-standard-deviation increase in CIM leads to an identical additional 6.55% decrease in book leverage relative to other firms.

Overall, the results in Table 8 are further evidence consistent with the employee flight risk hypothesis. When workers face lower switching costs due to abundant nearby employment alternatives, employee flight risk is amplified, and firms respond by adopting more conservative capital structures

4.4.6 Exogenous shock to the supply of workers

Based on CPS survey data, McIntosh (2008) documents that Hurricane Katrina in 2005 led to large population movements from New Orleans to Houston, increasing the population of

the Houston metropolitan area by approximately 3.1%. Using this exogenous shock, McIntosh (2008) examines the effect of Hurricane Katrina evacuees on the Houston metropolitan area labor market. Other researchers also use this shock to study a variety of issues. For example, De Silva, McComb, Moh, Schiller, and Vargas (2010) use Hurricane Katrina as a natural experiment to look at the effect of immigration on workers' earnings, while Ghaly et al. (2017) use Hurricane Katrina to study labor adjustment costs.

We exploit this exogenous labor supply shock to assess whether our main findings are consistent with a labor-market channel linking employee flight risk to leverage. The results are reported in Table 9. We use firms' headquarter zip codes obtained from 10-K filings to assign each firm to a metropolitan area. Firms headquartered in the Houston metropolitan area (Houston-Baytown-Sugar Land, TX) constitute the treated group, and firms headquartered in the Dallas–Fort Worth metropolitan area serve as the control group. Using the Dallas-Fort Worth metropolitan area to identify control firms helps account for state-level and broader regional factors affecting labor markets in both areas. We further use propensity-score matching to identify comparable control firms, matching on year, two-digit SIC industry, and the set of firm characteristics used as controls in Table 9.

In Table 9, *Treated* is an indicator equal to one for firms headquartered in the Houston metropolitan area and zero for firms headquartered in the Dallas–Fort Worth metropolitan area. *Post Katrina* is an indicator equal to one for the year after the hurricane (2006) and zero for the year before the hurricane (2004). Panel A first reports specifications without additional controls to mitigate concerns that some controls might themselves be affected by the shock. Models 1 and 5 show that CIM is negatively related to leverage when leverage is measured using book or market definitions, consistent with our main results. In models 2 and 6, we interact CIM with the *Treated* indicator to test for differences across locations, while in models 3 and 7 we interact CIM with the *Post Katrina* indicator to test for differences between the pre- and post-periods. There is no evidence that the relationship differs across the two dimensions.

The key specifications are the difference-in-difference-in-differences estimations in

models 4 and 8. The positive and statistically significant coefficients on the triple interaction term indicate that, following Hurricane Katrina, the negative association between CIM and leverage becomes significantly less pronounced for firms headquartered in Houston relative to matched firms headquartered in Dallas-Fort Worth. Panel B shows that the results are similar when control variables are included.¹⁰

Figure 1 plots the year-by-year dynamics of the coefficient estimates on $\text{CIM} \times \text{Treated} \times \text{year}$ indicators from 2002 to 2007, along with 90% confidence intervals. The figure is based on specifications analogous to models 4 and 8 in Table 9, Panel B, but estimated over a longer window using year indicators (with 2002 as the omitted year). The estimates show that the attenuation in the CIM-leverage relation emerges only after Hurricane Katrina, providing support for the parallel trends assumption and indicating that differential pre-trends are unlikely to explain the results.

Taken together, the evidence in Table 9 and Figure 1 is consistent with the view that the exogenous increase in the local labor supply in Houston reduced firms' exposure to employee flight risk. The sudden influx of workers expanded the pool of potential replacement employees, lowering firms' search and hiring costs, while at the same time increasing competition among workers for available jobs and reducing workers' incentives to leave their current employers. As a result, Houston firms operating in industries with high cross-industry labor mobility became less sensitive to employee flight risk following Hurricane Katrina. This mechanism aligns closely with the observed post-Katrina attenuation of the negative relation between CIM and leverage for firms headquartered in Houston relative to the matched Dallas-Fort Worth control group. Overall, these results support the prediction of employee flight risk having a causal effect on leverage.

¹⁰ We do not use DML in Table 9, Panel A because these analyses do not include control variables. We also do not apply DML in Panel B because the sample used for the Hurricane Katrina-related tests is small (342 observations) and cross-fitting would leave limited training data per fold, making nuisance-function estimates using Random Forests unstable and resulting second-stage inferences imprecise.

5. Conclusion

We study whether employee flight risk influences firms' financial policy decisions. To proxy for employee flight risk, we develop a new dynamic, text-based measure of cross-industry labor mobility based on network centrality, which we refer to as CIM. The construction of this measure rests on the idea that workers in industries with greater product similarity with other industries possess skills that are more transferable across industry boundaries and therefore enjoy greater cross-industry job mobility. We provide empirical evidence that strongly supports the use of CIM as a measure for cross-industry labor mobility and also show that it is unrelated to the mobility of a firm's workers to rival firms.

In our tests of the effect of employee flight risk on capital structure decisions, in addition to OLS panel regressions, we report estimates using the double machine learning estimator, which helps to alleviate concerns due to restrictive functional form assumptions or the existence of high-dimensional relationships between control variables. Our central finding is that when firms face a higher risk of employee departures to firms in other industries, they maintain more conservative capital structures. The results from an array of cross-sectional tests confirm that this risk indeed explains our empirical findings. To alleviate endogeneity concerns, we rely on the exogenous shocks to workers' switching costs emanating from changes in house prices and on the exogenous increase in the supply of workers in the Houston metropolitan area after Hurricane Katrina.

Put together, our results provide strong support for the empirical prediction that when a firm's employee flight risk is greater it maintains a lower debt ratio. Our findings align conceptually with the evidence in Brown and Matsa (2016) and Baghai, Silva, Thell, and Vig (2021), who show that financial distress can prompt workers to leave and impede hiring. However, instead of focusing on ex post worker departures resulting from increases to a firm's default risk, we investigate how firms anticipate and proactively reduce such risks through ex ante conservative capital structure choices. In a nutshell, the introduction of CIM enables us to directly quantify the impact of employee flight risk on capital structure decisions.

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Figure 1

Dynamic Effect Around Hurricane Katrina of Cross-Industry Labor Mobility on Leverage

The figure plots the estimated effect of Cross-Industry Labor Mobility (CIM) on leverage for firms located in the Houston metropolitan area relative to matched control firms located in the Dallas metropolitan area during each of the individual years within the period 2002-2007 (year 2002 is the left-out reference period) as well as the associated 90% confidence intervals based on standard errors clustered at the three-digit SIC code level. The coefficients are those on $\text{CIM} \times \text{Treated} \times \text{Year}$ dummies from models similar to models (4) and (8) in Panel B of Table 9, except that the Post Katrina indicator is replaced with year indicators.

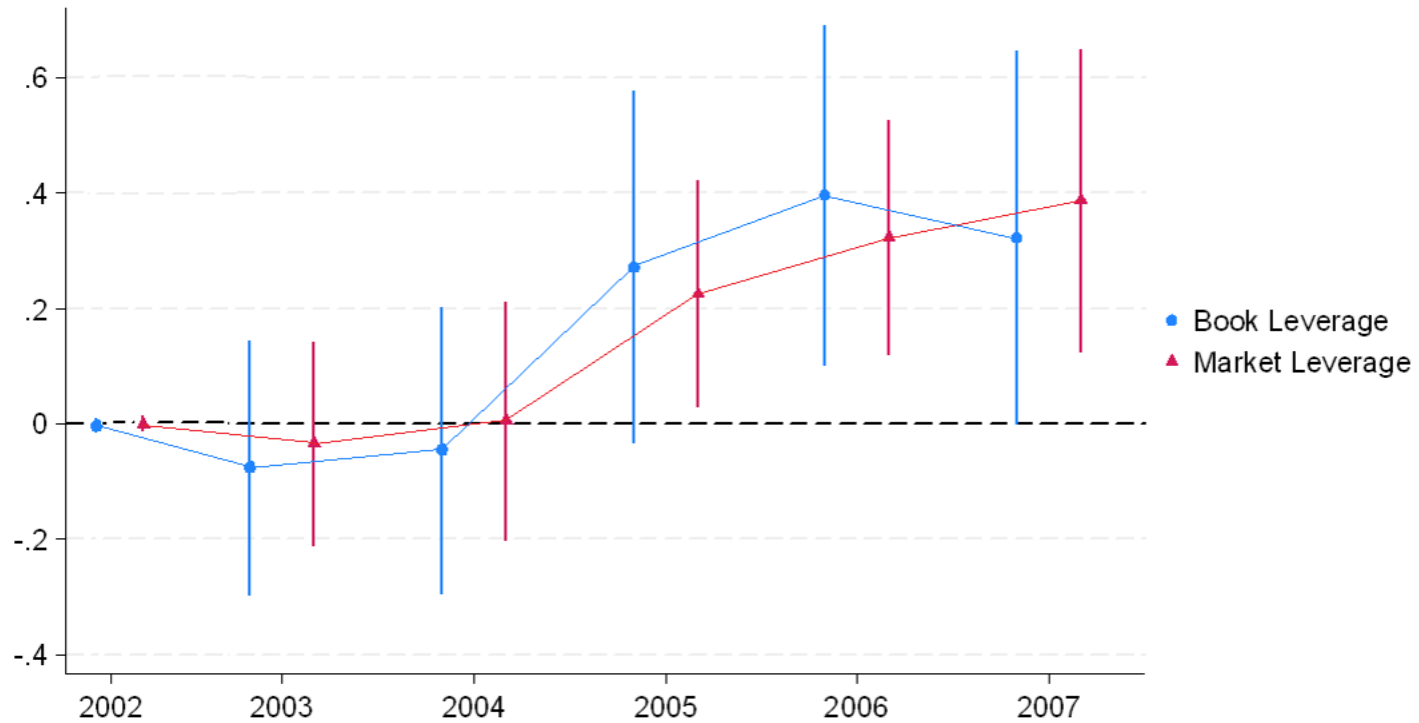


Table 1
Validation Tests of the Cross-Industry Labor Mobility Measure (CIM)

This table presents evidence from the analysis of labor mobility using IPUMS-CPS survey data for the period 1995–2020. The sample construction for this analysis is detailed in Section 3. Panel A reports the distribution of job moves across and within industries (at the three-digit SIC level). Cross-industry labor mobility refers to the share of job changes involving a move to a different industry, while within-industry labor mobility refers to moves within the same industry. These percentages are reported separately for (i) all employees, (ii) employees with high skill position (defined as those in Job Zones 5), and (iii) employees in managerial occupations. Panel B presents OLS estimates of whether an individual switches industries between two consecutive interviews regressed on Cross-Industry Labor Mobility (CIM) and its interactions with various industry-level and individual-level characteristics. All dependent variables in columns (1) to (5) are indicators equal to one if the worker changes industries between interviews and zero otherwise (i.e. Industry switch). Column (6) reports the unconditional relationship between CIM and the probability of switching employers, regardless of industry change (i.e. Employer switch). “High-” indicators equal one if the corresponding variable is in the top quartile of its distribution across industries in a given year. Industry-level relative measures are computed as the difference between an industry’s value and that of the average across all transfer industries (transfer industries are defined in Section 2.2). Individual-level controls include age, sex, education status (in-school indicator variable), log weekly working hours, and log wage. High-skill position is defined as a job in Job Zone 5, and managerial position is based on occupational classification. All regressions include year fixed effects and control for the number of months between interviews. Standard errors are heteroskedasticity-robust and clustered at the three-digit SIC level. p-values are reported in parentheses.

Panel A – Percentage of labor mobility that is within- and cross-industry			
	All employees	Employees with high skill position	Employees in managerial occupations
	(1)	(2)	(3)
Cross-industry labor mobility (SIC3)	61.56 %	65.83 %	66.65 %
Within-industry labor mobility (SIC3)	38.44 %	34.17 %	33.35 %

Panel B – Relative industry performance						Unconditional
	Industry switch					Any employer switch
	(1)	(2)	(3)	(4)	(5)	(6)
CIM	0.1331 (0.000)	0.1940 (0.000)	0.2872 (0.000)	0.1149 (0.000)	0.1190 (0.000)	-0.0016 (0.553)
High Relative industry sales growth		0.0157 (0.064)				
CIM × High Relative industry sales growth		-0.0616 (0.046)				
High Relative industry sales			-0.0191 (0.200)			
CIM × High Relative industry sales			-0.1881 (0.025)			
High Skill position				-0.0080 (0.024)		
CIM × High Skill position				0.0396 (0.016)		
Managerial position					-0.0056 (0.202)	
CIM × Managerial position					0.0739 (0.000)	
Age	-0.0035 (0.000)	-0.0033 (0.000)	-0.0001 (0.311)	-0.0035 (0.000)	-0.0035 (0.000)	-0.0003 (0.000)
Sex	0.0009 (0.885)	-0.0116 (0.148)	-0.0116 (0.230)	0.0012 (0.853)	0.0012 (0.857)	-0.0036 (0.000)
In-school	0.0117 (0.002)	0.0031 (0.248)	-0.0121 (0.020)	0.0118 (0.002)	0.0119 (0.002)	-0.0033 (0.004)
Log (weekly working hours)	-0.0020 (0.422)	0.0037 (0.445)	-0.0128 (0.001)	-0.0019 (0.445)	-0.0019 (0.412)	-0.0040 (0.000)
Log (wage)	-0.0258 (0.000)	-0.0293 (0.000)	-0.0067 (0.141)	-0.0253 (0.000)	-0.0259 (0.000)	-0.0040 (0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,612,016	2,223,123	2,223,123	5,612,016	5,612,016	5,612,016
Adjusted R-squared	0.0306	0.0330	0.0149	0.0307	0.0307	0.0030

Table 2
Cross-Industry Labor Mobility and Leverage

This table examines the effect of Cross-Industry Labor Mobility (CIM) on firms' leverage over the 1995–2020 period. The dependent variables are book leverage in model (1), market leverage in model (2), net book leverage in model (3), net market leverage in model (4), and long-term leverage (book) in model (5). Panel A includes all industries. Panel B restricts the sample to industries with at least one transfer industry connection. All regressions control for industry fixed effects defined at the two-digit SIC level. Standard errors are heteroskedasticity-robust and clustered at the three-digit SIC level. p-values are reported in parentheses. Double Machine Learning (DML) estimates using the Random Forests method for the coefficient on CIM are reported in the last row of the table panels. Section 4.2 provides details on our use of the DML estimator and also lists the ten additional control variables that are used in the DML-related analyses.

Panel A – Sample includes all industries					
The dependent variable is:	Book leverage	Market leverage	Net book leverage	Net market leverage	Long-term leverage (book)
	(1)	(2)	(3)	(4)	(5)
CIM	-0.1727 (0.000)	-0.1285 (0.000)	-0.3738 (0.000)	-0.2424 (0.000)	-0.1470 (0.000)
Log (book assets)	0.0279 (0.000)	0.0164 (0.000)	0.0423 (0.000)	0.0278 (0.000)	0.0286 (0.000)
Market-to-book assets	-0.0060 (0.005)	-0.0226 (0.000)	-0.0339 (0.000)	0.0013 (0.822)	-0.0042 (0.014)
ROA	-0.0945 (0.000)	-0.0764 (0.000)	0.0833 (0.004)	0.0282 (0.291)	-0.0507 (0.044)
Cash flow volatility	0.1060 (0.000)	0.0126 (0.496)	0.0899 (0.064)	0.0002 (0.996)	0.0830 (0.003)
Dividend payer	-0.0421 (0.000)	-0.0430 (0.000)	-0.0191 (0.180)	-0.0362 (0.000)	-0.0408 (0.000)
R&D/sales	-0.0046 (0.000)	-0.0025 (0.000)	-0.0167 (0.000)	-0.0063 (0.000)	-0.0027 (0.000)
Asset tangibility	0.2332 (0.000)	0.2013 (0.000)	0.5472 (0.000)	0.3712 (0.000)	0.2082 (0.000)
State IDD adoption	0.0186 (0.000)	0.0117 (0.000)	0.0419 (0.000)	0.0272 (0.000)	0.0230 (0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	78,321	78,321	78,315	78,315	78,321
Adjusted R-squared	0.2710	0.3832	0.4574	0.3811	0.2771
DML using Random Forests	-0.1969 (0.000)	-0.1625 (0.000)	-0.4751 (0.000)	-0.3032 (0.000)	-0.1709 (0.000)

Panel B – Sample includes only industries with at least one transfer industry					
The dependent variable is:	Book leverage	Market leverage	Net book leverage	Net market leverage	Long-term leverage (book)
	(1)	(2)	(3)	(4)	(5)
CIM	-0.2078 (0.000)	-0.1064 (0.020)	-0.4669 (0.000)	-0.2720 (0.001)	-0.1865 (0.000)
Log (book assets)	0.0267 (0.000)	0.0156 (0.000)	0.0407 (0.000)	0.0269 (0.000)	0.0275 (0.000)
Market-to-book assets	-0.0054 (0.014)	-0.0193 (0.000)	-0.0329 (0.000)	0.0061 (0.243)	-0.0038 (0.028)
ROA	-0.0937 (0.001)	-0.0611 (0.000)	0.0775 (0.017)	0.0419 (0.138)	-0.0541 (0.039)
Cash flow volatility	0.1124 (0.000)	0.0216 (0.200)	0.1216 (0.007)	0.0262 (0.375)	0.0887 (0.002)
Dividend payer	-0.0321 (0.002)	-0.0325 (0.000)	0.0009 (0.961)	-0.0209 (0.042)	-0.0320 (0.001)
R&D/sales	-0.0045 (0.000)	-0.0022 (0.000)	-0.0154 (0.000)	-0.0056 (0.000)	-0.0029 (0.000)
Asset tangibility	0.2469 (0.000)	0.1913 (0.000)	0.6406 (0.000)	0.3949 (0.000)	0.2053 (0.000)
State IDD adoption	0.0197 (0.000)	0.0119 (0.001)	0.0446 (0.000)	0.0280 (0.000)	0.0245 (0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	59,382	59,382	59,381	59,381	59,382
Adjusted R-squared	0.2549	0.3501	0.4418	0.3605	0.2662
DML using Random Forests	-0.2919 (0.000)	-0.2520 (0.000)	-0.7594 (0.000)	-0.5506 (0.000)	-0.2733 (0.000)

Table 3

Cross-Industry Labor Mobility and Financially Constrained Firms

This table examines the effect of Cross-Industry Labor Mobility (CIM) on firms' leverage for financially constrained firms over the 1995–2020 period. The dependent variable is book leverage in models (1) to (4) and market leverage in models (5) to (8). Firms are classified as financially constrained if they lack a bond rating, are not dividend payers, or have an HP-index or WW-index above the annual median for these measures across all firms. All regressions include industry fixed effects defined at the two-digit SIC level. Standard errors are robust to heteroskedasticity and clustered at the three-digit SIC level. p-values are reported in parentheses. Double Machine Learning (DML) estimates using the Random Forests method for the coefficient on the interaction variables are reported in the last row of the table. Section 4.2 provides details on our use of the DML estimator and also lists the ten additional control variables that are used in the DML-related analyses.

The dependent variable is:	Book leverage				Market leverage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CIM	-0.0459 (0.211)	-0.0941 (0.016)	-0.1029 (0.001)	-0.1101 (0.001)	-0.0468 (0.198)	-0.0436 (0.176)	-0.0830 (0.007)	-0.0600 (0.072)
No bond rating	-0.1120 (0.000)				-0.0676 (0.000)			
CIM × No bond rating	-0.1491 (0.000)				-0.0973 (0.000)			
Not a dividend payer		0.0654 (0.000)				0.0681 (0.000)		
CIM × Not a dividend payer		-0.1292 (0.008)				-0.1397 (0.000)		
High HP-Index			-0.0334 (0.001)				-0.0149 (0.054)	
CIM × High HP-Index			-0.1200 (0.001)				-0.0816 (0.001)	
High WW-Index				-0.0249 (0.002)				0.0050 (0.434)
CIM × High WW-Index				-0.0865 (0.001)				-0.1146 (0.000)
Dividend payer	-0.0457 (0.000)		-0.0215 (0.010)		-0.0451 (0.000)		-0.0301 (0.000)	
Log (book assets)	0.0078 (0.002)	0.0280 (0.000)			0.0041 (0.007)	0.0165 (0.000)		
Market-to-book assets	-0.0048 (0.014)	-0.0058 (0.005)	-0.0059 (0.005)	-0.0079 (0.002)	-0.0219 (0.000)	-0.0224 (0.000)	-0.0226 (0.000)	-0.0237 (0.000)
ROA	-0.0745 (0.002)	-0.0983 (0.000)	-0.0599 (0.008)	-0.0508 (0.008)	-0.0642 (0.000)	-0.0804 (0.000)	-0.0553 (0.000)	-0.0580 (0.002)
Cash flow volatility	0.0759 (0.013)	0.1072 (0.000)	0.0209 (0.536)	0.0556 (0.024)	-0.0059 (0.783)	0.0139 (0.446)	-0.0380 (0.128)	-0.0137 (0.465)
R&D/sales	-0.0042 (0.000)	-0.0047 (0.000)	-0.0045 (0.000)	-0.0051 (0.000)	-0.0023 (0.000)	-0.0026 (0.000)	-0.0025 (0.000)	-0.0029 (0.000)
Asset tangibility	0.2298 (0.000)	0.2331 (0.000)	0.2388 (0.000)	0.2363 (0.000)	0.1992 (0.000)	0.2012 (0.000)	0.2050 (0.000)	0.2007 (0.000)
State IDD adoption	0.0124 (0.002)	0.0182 (0.000)	0.0133 (0.001)	0.0148 (0.000)	0.0079 (0.004)	0.0114 (0.000)	0.0087 (0.002)	0.0090 (0.001)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	78,321	78,321	78,321	78,321	78,321	78,321	78,321	78,321
Adjusted R-squared	0.3187	0.2725	0.2442	0.2372	0.4138	0.3864	0.3668	0.3602
DML using Random Forests	-0.2996 (0.000)	-0.1631 (0.000)	-0.1615 (0.000)	-0.1126 (0.000)	-0.2189 (0.000)	-0.1414 (0.000)	-0.1381 (0.000)	-0.1196 (0.000)

Table 4

Cross-Industry Labor Mobility and Industry Labor Intensity

This table examines the effect of Cross-Industry Labor Mobility (CIM) on firms' leverage in industries where labor accounts for a large share of the total production of the industry over the 1995–2020 period. The dependent variable is book leverage in models (1) to (3) and market leverage in models (4) to (6). Industry labor share is measured in three ways: In models (1) and (4), by total compensation paid to employees over industry value added. In models (2) and (5), by total salaries paid to employees over industry value added. In models (3) and (6), by the number of full-time employees over industry value added. “High-” indicates the variable is an indicator equal to one if the corresponding labor share measure is in the top quartile across industries in a given year. Industry labor share data are sourced from BEA-National Income and Product Accounts (employment, salaries, compensation) and BEA-Industry Economic Accounts (value added). All regressions include industry fixed effects defined at the two-digit SIC level. Standard errors are heteroskedasticity-robust and clustered at the three-digit SIC level. p-values are reported in parentheses. Double Machine Learning (DML) estimates using the Random Forests method for the coefficient on the interaction variables are reported in the last row of the table. Section 4.2 provides details on our use of the DML estimator and also lists the ten additional control variables that are used in the DML-related analyses.

The dependent variable is:	Book leverage			Market leverage		
	(1)	(2)	(3)	(4)	(5)	(6)
CIM	-0.1483 (0.000)	-0.1472 (0.000)	-0.1562 (0.000)	-0.1131 (0.001)	-0.1138 (0.001)	-0.1154 (0.000)
High Industry labor share by compensation	0.0119 (0.390)			0.0071 (0.485)		
CIM × High Industry labor share by compensation	-0.1134 (0.008)			-0.0712 (0.019)		
High Industry labor share by salaries		0.0168 (0.199)			0.0082 (0.379)	
CIM × High Industry labor share by salaries		-0.1262 (0.002)			-0.0710 (0.011)	
High Industry labor share by the number of employees			0.0327 (0.100)			0.0106 (0.386)
CIM × High Industry labor share by the number of employees			-0.1338 (0.037)			-0.0768 (0.050)
Log (book assets)	0.0280 (0.000)	0.0280 (0.000)	0.0279 (0.000)	0.0165 (0.000)	0.0165 (0.000)	0.0164 (0.000)
Market-to-book assets	-0.0059 (0.004)	-0.0059 (0.004)	-0.0061 (0.004)	-0.0225 (0.000)	-0.0226 (0.000)	-0.0226 (0.000)
ROA	-0.0969 (0.000)	-0.0970 (0.000)	-0.0945 (0.000)	-0.0779 (0.000)	-0.0779 (0.000)	-0.0766 (0.000)
Cash flow volatility	0.1055 (0.000)	0.1053 (0.000)	0.1069 (0.000)	0.0122 (0.504)	0.0121 (0.508)	0.0135 (0.461)
Dividend payer	-0.0422 (0.000)	-0.0423 (0.000)	-0.0423 (0.000)	-0.0430 (0.000)	-0.0431 (0.000)	-0.0431 (0.000)
R&D/sales	-0.0047 (0.000)	-0.0047 (0.000)	-0.0046 (0.000)	-0.0026 (0.000)	-0.0026 (0.000)	-0.0026 (0.000)
Asset tangibility	0.2327 (0.000)	0.2330 (0.000)	0.2338 (0.000)	0.2010 (0.000)	0.2011 (0.000)	0.2009 (0.000)
State IDD adoption	0.0183 (0.000)	0.0183 (0.000)	0.0186 (0.000)	0.0116 (0.000)	0.0116 (0.000)	0.0117 (0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	78,321	78,321	78,321	78,321	78,321	78,321
Adjusted R-squared	0.2724	0.2725	0.2716	0.3842	0.3841	0.3840
DML using Random Forests	-0.1821 (0.000)	-0.1907 (0.000)	-0.1469 (0.000)	-0.1250 (0.000)	-0.1284 (0.000)	-0.0813 (0.000)

Table 5

Cross-Industry Labor Mobility and Industries with a Higher Share of Skilled Employees or Managers

This table examines whether the effect of Cross-Industry Labor Mobility (CIM) on firms' leverage is more pronounced in industries with a higher share of skilled employees or managerial employees over the 1995–2020 period. Panel A focuses on skilled employees. The dependent variable is book leverage in models (1) to (3) and market leverage in models (4) to (6). The proportion of skilled employees in an industry is defined as the ratio of pay to employees in Job Zones 4 and 5 relative to total pay in the industry. Industry pay to skilled employees is defined as the natural logarithm of annual pay to skilled workers. Industry average skill is the weighted average of job zone levels, with weights based on pay within each zone. Panel B focuses on employees in managerial positions. The dependent variable is book leverage in models (1) to (2) and market leverage in models (3) to (4). The proportion of managers is defined as the ratio of pay to employees in managerial occupations relative to total pay in the industry. Industry pay to managers is defined as the natural logarithm of annual managerial pay. “High-” indicates that the variable equals one if the industry value is in the top quartile of its distribution in a given year. The sample is based on Occupational Employment Statistics (OES) data from 1999 to 2020. All regressions include industry fixed effects defined at the two-digit SIC level. Standard errors are robust to heteroskedasticity and clustered at the three-digit SIC level. p-values are reported in parentheses. Double Machine Learning (DML) estimates using the Random Forests method for the coefficient on the interaction variables are reported in the last row of the table panels. Section 4.2 provides details on our use of the DML estimator and also lists the ten additional control variables that are used in the DML-related analyses.

Panel A – Skilled employees						
The dependent variable is:	Book leverage			Market leverage		
	(1)	(2)	(3)	(4)	(5)	(6)
CIM	-0.1566 (0.000)	-0.1121 (0.002)	-0.0998 (0.004)	-0.1143 (0.000)	-0.0909 (0.006)	-0.0803 (0.003)
High Proportion of skilled employees in industry	0.0227 (0.319)			0.0095 (0.552)		
CIM × High Proportion of skilled employees in industry	-0.1314 (0.057)			-0.0929 (0.064)		
High Industry pay to skilled employees		-0.0017 (0.884)			-0.0039 (0.693)	
CIM × High Industry pay to skilled employees		-0.0886 (0.026)			-0.0592 (0.058)	
High Industry average skill			0.0045 (0.687)			0.0037 (0.714)
CIM × High Industry average skill			-0.0984 (0.024)			-0.0731 (0.075)
Log (book assets)	0.0280 (0.000)	0.0289 (0.000)	0.0289 (0.000)	0.0165 (0.000)	0.0173 (0.000)	0.0172 (0.000)
Market-to-book assets	-0.0059 (0.005)	-0.0037 (0.113)	-0.0038 (0.108)	-0.0225 (0.000)	-0.0212 (0.000)	-0.0212 (0.000)
ROA	-0.0958 (0.000)	-0.0863 (0.006)	-0.0862 (0.006)	-0.0777 (0.000)	-0.0698 (0.000)	-0.0697 (0.000)
Cash flow volatility	0.1063 (0.000)	0.1048 (0.000)	0.1039 (0.000)	0.0126 (0.493)	0.0148 (0.466)	0.0142 (0.493)
Dividend payer	-0.0425 (0.000)	-0.0429 (0.000)	-0.0425 (0.000)	-0.0434 (0.000)	-0.0447 (0.000)	-0.0444 (0.000)
R&D/sales	-0.0047 (0.000)	-0.0045 (0.000)	-0.0045 (0.000)	-0.0026 (0.000)	-0.0024 (0.000)	-0.0024 (0.000)
Asset tangibility	0.2319 (0.000)	0.2394 (0.000)	0.2421 (0.000)	0.1998 (0.000)	0.2125 (0.000)	0.2150 (0.000)
State IDD adoption	0.0185 (0.000)	0.0172 (0.000)	0.0174 (0.000)	0.0117 (0.000)	0.0121 (0.000)	0.0122 (0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59,876	59,876	59,876	59,876	59,876	59,876
Adjusted R-squared	0.2717	0.2694	0.2691	0.3844	0.3948	0.3943
DML using Random Forests	-0.0828 (0.000)	-0.1591 (0.000)	-0.1609 (0.000)	-0.0515 (0.000)	-0.1046 (0.000)	-0.0962 (0.000)

Panel B – Managers				
	Book leverage		Market leverage	
The dependent variable is:	(1)	(2)	(3)	(4)
CIM	-0.1339 (0.002)	-0.1418 (0.000)	-0.0930 (0.006)	-0.1105 (0.000)
High Proportion of managers in industry	0.0072 (0.419)		0.0043 (0.518)	
CIM × High Proportion of managers in industry	-0.0841 (0.030)		-0.0566 (0.048)	
High Industry pay to managers		0.0116 (0.354)		0.0079 (0.423)
CIM × High Industry pay to managers		-0.1388 (0.022)		-0.1057 (0.018)
Log (book assets)	0.0289 (0.000)	0.0289 (0.000)	0.0168 (0.000)	0.0173 (0.000)
Market-to-book assets	-0.0038 (0.102)	-0.0037 (0.101)	-0.0205 (0.000)	-0.0211 (0.000)
ROA	-0.0889 (0.004)	-0.0889 (0.004)	-0.0669 (0.000)	-0.0718 (0.000)
Cash flow volatility	0.1070 (0.000)	0.1049 (0.000)	0.0160 (0.395)	0.0148 (0.470)
Dividend payer	-0.0428 (0.000)	-0.0428 (0.000)	-0.0387 (0.000)	-0.0446 (0.000)
R&D/sales	-0.0044 (0.000)	-0.0046 (0.000)	-0.0023 (0.000)	-0.0024 (0.000)
Asset tangibility	0.2399 (0.000)	0.2363 (0.000)	0.1913 (0.000)	0.2103 (0.000)
State IDD adoption	0.0174 (0.000)	0.0176 (0.000)	0.0110 (0.000)	0.0124 (0.000)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	59,876	59,876	59,876	59,876
Adjusted R-squared	0.2691	0.2698	0.3987	0.3952
DML using Random Forests	-0.1314 (0.001)	-0.1430 (0.000)	-0.0859 (0.000)	-0.0670 (0.000)

Table 6
Cross-Industry Labor Mobility and Industries with Specialized Occupations

This table examines whether the effect of Cross-Industry Labor Mobility (CIM) on firms' leverage varies by the level of occupational specialization within an industry over the 1995–2020 period. The dependent variable is book leverage in models (1) to (2) and market leverage in models (3) to (4). The variable Industry Specialization captures the extent to which occupations in an industry are concentrated within that industry (i.e., less commonly observed across other industries). It is constructed following Donangelo (2014). Specifically, we first compute an occupation-level concentration index based on the interindustry distribution of workers across occupations. We then aggregate this to the industry level using the occupation's employment share in the industry as weights, producing a measure of how specialized a given industry's occupational mix is. Low Industry Specialization is an indicator equal to one if an industry falls in the bottom quartile of the specialization distribution in a given year, and zero otherwise. All regressions include industry fixed effects defined at the two-digit SIC level. Standard errors are robust to heteroskedasticity and clustered at the three-digit SIC level. p-values are reported in parentheses. Double Machine Learning (DML) estimates using the Random Forests method for the coefficient on the interaction variables are reported in the last row of the table. Section 4.2 provides details on our use of the DML estimator and also lists the ten additional control variables that are used in the DML-related analyses.

The dependent variable is:	Book leverage		Market leverage	
	(1)	(2)	(3)	(4)
CIM	-0.1542 (0.000)	-0.1443 (0.000)	-0.1194 (0.000)	-0.1175 (0.000)
Industry Specialization	-0.0138 (0.020)		-0.0078 (0.178)	
CIM × Industry Specialization	0.0534 (0.013)		0.0414 (0.041)	
Low Industry Specialization		0.0263 (0.007)		0.0181 (0.012)
CIM × Low Industry Specialization		-0.1296 (0.010)		-0.0783 (0.041)
Log (book assets)	0.0287 (0.000)	0.0287 (0.000)	0.0171 (0.000)	0.0172 (0.000)
Market-to-book assets	-0.0038 (0.102)	-0.0038 (0.100)	-0.0212 (0.000)	-0.0213 (0.000)
ROA	-0.0874 (0.005)	-0.0872 (0.005)	-0.0708 (0.000)	-0.0705 (0.000)
Cash flow volatility	0.1051 (0.000)	0.1052 (0.000)	0.0146 (0.475)	0.0153 (0.448)
Dividend payer	-0.0422 (0.000)	-0.0421 (0.000)	-0.0441 (0.000)	-0.0442 (0.000)
R&D/sales	-0.0044 (0.000)	-0.0045 (0.000)	-0.0023 (0.000)	-0.0023 (0.000)
Asset tangibility	0.2414 (0.000)	0.2415 (0.000)	0.2142 (0.000)	0.2148 (0.000)
State IDD adoption	0.0176 (0.000)	0.0179 (0.000)	0.0125 (0.000)	0.0126 (0.000)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	59,876	59,876	59,876	59,876
Adjusted R-squared	0.2688	0.2689	0.3941	0.3940
DML using Random Forests	0.0889 (0.000)	-0.1144 (0.000)	0.0667 (0.000)	-0.0745 (0.000)

Table 7
Cross-Industry Labor Mobility and Nearby Residential House Prices

This table examines whether the relation between Cross-Industry Labor Mobility (CIM) and firms' leverage is affected by nearby residential house prices over the 1995–2020 sample period. The dependent variable in models (1) and (2) is book leverage and in models (3) and (4) it is market leverage. High County (State) HPI is an indicator equal to one if the HPI (with a base of 100 in 2000) in the county (state) where the firm is headquartered is in the top quartile of this measure across all counties (states) in that year. All models include industry fixed effects defined at the two-digit SIC code level. Standard errors are corrected for heteroskedasticity and clustering at the three-digit SIC code level. Significance levels for whether estimated coefficients are different from zero are in parentheses. Double Machine Learning (DML) estimates using the Random Forests method for the coefficient on the interaction variables are reported in the last row of the table. Section 4.2 provides details on our use of the DML estimator and also lists the ten additional control variables that are used in the DML-related analyses.

The dependent variable is:	Book leverage		Market leverage	
	(1)	(2)	(3)	(4)
CIM	-0.1389 (0.000)	-0.1316 (0.000)	-0.1087 (0.000)	-0.1010 (0.000)
High County HPI	-0.0065 (0.574)		-0.0051 (0.561)	
CIM × High County HPI	-0.0802 (0.023)		-0.0567 (0.034)	
High State HPI		-0.0022 (0.807)		-0.0004 (0.961)
CIM × High State HPI		-0.0783 (0.009)		-0.0658 (0.006)
Log (book assets)	0.0295 (0.000)	0.0296 (0.000)	0.0168 (0.000)	0.0169 (0.000)
Market-to-book assets	-0.0057 (0.011)	-0.0060 (0.013)	-0.0220 (0.000)	-0.0223 (0.000)
ROA	-0.0974 (0.000)	-0.0922 (0.001)	-0.0755 (0.000)	-0.0737 (0.000)
Cash flow volatility	0.1122 (0.000)	0.1111 (0.000)	0.0134 (0.441)	0.0135 (0.413)
Dividend payer	-0.0439 (0.000)	-0.0435 (0.000)	-0.0436 (0.000)	-0.0435 (0.000)
R&D/sales	-0.0044 (0.000)	-0.0046 (0.000)	-0.0024 (0.000)	-0.0024 (0.000)
Asset tangibility	0.2444 (0.000)	0.2429 (0.000)	0.2013 (0.000)	0.1984 (0.000)
State IDD adoption	0.0086 (0.031)	0.0114 (0.003)	0.0056 (0.039)	0.0086 (0.001)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	69,148	67,276	69,148	67,276
Adjusted R-squared	0.2713	0.2720	0.3683	0.3692
DML using Random Forests	-0.1439 (0.000)	-0.1344 (0.000)	-0.0830 (0.000)	-0.0932 (0.000)

Table 8

Cross-Industry Labor Mobility and Nearby Job Opportunities

This table examines whether nearby job opportunities in transfer industries affect the relation between Cross-Industry Labor Mobility (CIM) and firms' leverage over the 1995–2020 sample period. We proxy for nearby employment opportunities using the number of nearby firms in transfer industries. Relative within-county job opportunities in transfer industries are defined as the ratio of the number of firms in transfer industries that are in the same county to the number of firms in transfer industries that are in a different county. Relative within-state job opportunities are defined analogously using state borders. “High-” indicates that the variable is an indicator equal to one if the variable is in the top quartile of its distribution across all industries in a given year. In models (1) and (2), the dependent variable is book leverage, and in models (3) and (4), it is market leverage. All models include industry fixed effects defined at the two-digit SIC code level. Standard errors are corrected for heteroskedasticity and clustering at the three-digit SIC code level. Significance levels for whether estimated coefficients are different from zero are in parentheses. Double Machine Learning (DML) estimates using the Random Forests method for the coefficient on the interaction variables are reported in the last row of the table. Section 4.2 provides details on our use of the DML estimator and also lists the ten additional control variables that are used in the DML-related analyses.

The dependent variable is:	Book leverage		Market leverage	
	(1)	(2)	(3)	(4)
CIM	-0.1702 (0.000)	-0.1730 (0.000)	-0.1044 (0.006)	-0.0999 (0.015)
High Relative within county job opportunities in transfer industries	0.0136 (0.329)		-0.0000 (0.997)	
CIM × High Relative within county job opportunities in transfer industries	-0.1239 (0.004)		-0.0562 (0.061)	
High Relative within state job opportunities in transfer industries		0.0158 (0.443)		-0.0022 (0.884)
CIM × High Relative within state job opportunities in transfer industries		-0.1212 (0.053)		-0.0461 (0.337)
Log (book assets)	0.0283 (0.000)	0.0276 (0.000)	0.0161 (0.000)	0.0159 (0.000)
Market-to-book assets	-0.0051 (0.033)	-0.0052 (0.028)	-0.0189 (0.000)	-0.0190 (0.000)
ROA	-0.0951 (0.001)	-0.0935 (0.001)	-0.0594 (0.000)	-0.0599 (0.000)
Cash flow volatility	0.1173 (0.000)	0.1157 (0.000)	0.0231 (0.125)	0.0224 (0.142)
Dividend payer	-0.0308 (0.000)	-0.0312 (0.000)	-0.0309 (0.000)	-0.0319 (0.000)
R&D/sales	-0.0042 (0.000)	-0.0041 (0.000)	-0.0019 (0.000)	-0.0020 (0.000)
Asset tangibility	0.2678 (0.000)	0.2569 (0.000)	0.2022 (0.000)	0.1961 (0.000)
State IDD adoption	0.0118 (0.006)	0.0081 (0.157)	0.0069 (0.015)	0.0041 (0.289)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Observations	52,733	54,844	52,733	54,844
Adjusted R-squared	0.2651	0.2620	0.3557	0.3526
DML using Random Forests	-0.1050 (0.000)	-0.1169 (0.000)	-0.0625 (0.000)	-0.0731 (0.168)

Table 9

Evidence from Hurricane Katrina on the Effect of Cross-Industry Labor Mobility on Leverage

This table uses Hurricane Katrina as an exogenous shock to the worker population in the Houston metropolitan area. Hurricane Katrina struck the Gulf Coast of the U.S. in August 2005, causing large-scale population displacement from New Orleans to Houston. Post Katrina is an indicator equal to one for the year 2006 and zero for 2004. Treated is an indicator equal to one for firms headquartered in the Houston metropolitan area (Houston-Baytown-Sugar Land, TX) and zero for matched firms in Texas that were unaffected by the hurricane, i.e., located in the Dallas–Fort Worth metropolitan area. Firms in the control group are matched based on industry (2-digit SIC), year, and the control variables used in the regression. Panel A reports baseline OLS results without firm-level controls. Panel B includes firm-level control variables: log of book assets, market-to-book assets, return on assets (ROA), cash flow volatility, dividend payer, R&D intensity, and asset tangibility. The dependent variable is book leverage in models (1) to (4) and market leverage in models (5) to (8). All regressions include year fixed effects. Standard errors are robust to heteroskedasticity and clustered at the three-digit SIC code level. p-values are reported in parentheses.

Panel A – Without control variables								
The dependent variable is:								
	Book leverage				Market leverage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CIM	-0.3191 (0.002)	-0.3394 (0.034)	-0.2864 (0.005)	-0.1391 (0.387)	-0.2613 (0.003)	-0.2784 (0.029)	-0.2613 (0.008)	-0.1873 (0.200)
Treated		-0.0246 (0.469)		-0.0070 (0.838)		-0.0242 (0.459)		-0.0132 (0.721)
CIM × Treated		0.0356 (0.874)		-0.2995 (0.164)		0.0289 (0.866)		-0.1488 (0.414)
CIM × Post Katrina			-0.0688 (0.622)	-0.4209 (0.038)			-0.0001 (0.999)	-0.1932 (0.241)
Treated × Post Katrina				-0.0453 (0.081)				-0.0273 (0.259)
CIM × Treated × Post Katrina				0.7019 (0.015)				0.3744 (0.060)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	342	342	342	342	342	342	342	342
Adjusted R-squared	0.0389	0.0425	0.0394	0.0549	0.0506	0.0567	0.0506	0.0625

Panel B – Control variables included								
The dependent variable is:								
	Book leverage				Market leverage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CIM	-0.1139 (0.196)	-0.1072 (0.459)	-0.0911 (0.390)	0.0758 (0.613)	-0.0878 (0.239)	-0.0926 (0.338)	-0.1000 (0.242)	-0.0140 (0.898)
Treated		-0.0037 (0.875)		0.0040 (0.874)		-0.0062 (0.725)		-0.0023 (0.925)
CIM × Treated		-0.0164 (0.938)		-0.3519 (0.096)		0.0078 (0.954)		-0.1810 (0.199)
CIM × Post Katrina			-0.0484 (0.683)	-0.3796 (0.017)			0.0257 (0.764)	-0.1611 (0.211)
Treated × Post Katrina				-0.0223 (0.396)				-0.0110 (0.639)
CIM × Treated × Post Katrina				0.6827 (0.003)				0.3835 (0.011)
Log (book assets)	0.0158 (0.020)	0.0157 (0.025)	0.0159 (0.018)	0.0165 (0.016)	0.0136 (0.042)	0.0134 (0.044)	0.0136 (0.042)	0.0138 (0.035)
Market-to-book assets	-0.0263 (0.013)	-0.0263 (0.012)	-0.0261 (0.014)	-0.0262 (0.011)	-0.0501 (0.000)	-0.0502 (0.000)	-0.0503 (0.000)	-0.0504 (0.000)
ROA	-0.4515 (0.000)	-0.4483 (0.000)	-0.4521 (0.000)	-0.4547 (0.000)	-0.3404 (0.000)	-0.3380 (0.000)	-0.3401 (0.000)	-0.3412 (0.000)
Cash flow volatility	-0.3054 (0.137)	-0.3109 (0.122)	-0.3071 (0.134)	-0.3038 (0.135)	-0.2477 (0.062)	-0.2479 (0.067)	-0.2469 (0.064)	-0.2417 (0.079)
Dividend payer	-0.0315 (0.259)	-0.0315 (0.281)	-0.0317 (0.253)	-0.0332 (0.239)	-0.0364 (0.141)	-0.0358 (0.152)	-0.0363 (0.142)	-0.0366 (0.136)
R&D/sales	0.0070 (0.802)	0.0092 (0.773)	0.0061 (0.824)	0.0078 (0.785)	0.0027 (0.906)	0.0040 (0.874)	0.0032 (0.892)	0.0040 (0.869)
Asset tangibility	0.2234 (0.000)	0.2231 (0.000)	0.2233 (0.000)	0.2193 (0.000)	0.1426 (0.004)	0.1424 (0.004)	0.1427 (0.004)	0.1404 (0.004)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	342	342	342	342	342	342	342	342
Adjusted R-squared	0.2789	0.2791	0.2791	0.2919	0.3870	0.3874	0.3871	0.3945

Employee Flight Risk and Capital Structure Decisions

Internet Appendix

Variable Definitions

[I] Labor Mobility Variables

General construction

Let W_t be the $N_t \times N_t$ weighted matrix of pairwise product similarity between industries in year t , with typical element $W_{ij,t} \geq 0$ and $W_{ij,t} = 0$.

Let A_t be the corresponding adjacency matrix with $a_{ij,t} = 1\{W_{ij,t} \geq \tau_t\}$, where τ_t is the year-specific threshold described in Section 2.2. All network measures below are computed at the industry–year level.

CIM

Cross-Industry Labor Mobility (CIM) is our baseline measure of the ease with which employees in industry i can reallocate across industries in year t . Operationally, CIM captures how *close* industry i is to the rest of the network formed by W_t . Higher CIM indicates shorter (weighted) distances to other industries and therefore a thicker set of plausible outside options for workers. In our baseline, CIM is computed as a normalized (weighted) closeness measure on W_t ; details are provided in Section 2.2.

Degree

Degree is the number of industries to which industry i has a *significant* product-similarity link in year t :

$$Degree_{i,t} = \sum_{i \neq j} a_{ij,t}$$

This counts immediate neighbors in the product-similarity network.

Strength

Strength (weighted degree) sums the magnitudes of industry i 's similarity links:

$$Strength_{i,t} = \sum_{i \neq j} w_{ij,t} \cdot a_{ij,t}$$

Strength rises with both the number of links and the intensity of each link.

Linked

Linked is an indicator equal to 1 if industry i has at least one significant link in year t and 0 otherwise:

$$Linked_{i,t} = 1\{Degree_{i,t} > 0\}$$

[II] Skill- and Occupation-Based Measures

Data sources and classification

We use the BLS Occupational Employment Statistics (OES) to obtain the number of employees and the average annual wage for each occupation–industry–year. Industry codes follow SIC through 2002 and NAICS thereafter; occupations follow the 2000 SOC from 1999–2009 and the 2010 SOC from 2010 onward (prior to 1999, OES used its own occupation system). Occupational skill levels come from the Dictionary of Occupational Titles (DOT, 4th ed., rev. 1991), which reports Specific Vocational Preparation (SVP), the time typically required to achieve average performance. ONET's Job Zone classification maps SVP into five ordered levels: Job Zone 1 (SVP<4), Zone 2 (4≤SVP<6), Zone 3 (6≤SVP<7), Zone 4 (7≤SVP<8), and Zone 5 (SVP≥8). We merge OES with DOT/ONET using the SOC–DOT crosswalk to identify each occupation's Job Zone in the OES data. Following the SOC Policy Committee, occupations in major group “11-0000” are classified as managerial.

Unless otherwise noted, measures based on OES and Job Zones are constructed for 1999–2020, when SOC-based coding is available. “High-” indicators equal one if the underlying continuous measure is in the top quartile across industries in year t.

Notation

Let o index occupations, i industries, and t years.

$emp_{o,i,t}$ is employment and $wage_{o,i,t}$ is the average annual wage from OES.

Define total pay for occupation o in industry i and year t as:

$$pay_{o,i,t} = emp_{o,i,t} \times wage_{o,i,t}$$

Industry-year total pay is $Pay_{i,t} = \sum_o pay_{o,i,t}$.

Let $Z_{4,5}$ denote Job Zones 4 and 5 and M denote managerial occupations (SOC “11-0000”).

High-Skill Position (occupation-level)

Indicator equal to 1 if an occupation is in Job Zone 5, and 0 otherwise.

Managerial Position (occupation-level)

Indicator equal to 1 if an occupation’s SOC code belongs to the “11-0000” managerial major group, and 0 otherwise.

Proportion of Skilled Employees in Industry

Share of industry pay going to skilled workers (Job Zones 4–5):

$$SkilledShare_{i,t} = (\sum_{o \in Z_{4,5}} pay_{o,i,t} / Pay_{i,t})$$

High Proportion of Skilled Employees in Industry is an indicator equal to 1 if $SkilledShare_{i,t}$ is in the top quartile across industries in year t, and 0 otherwise.

Industry Pay to Skilled Employees (log)

Natural logarithm of annual pay to skilled workers:

$$\ln PaySkilled_{i,t} = \ln (\sum_{o \in Z_{4,5}} pay_{o,i,t})$$

High Industry Pay to Skilled Employees is an indicator equal to 1 if $\ln PaySkilled_{i,t}$ is in the top quartile across industries in year t.

Industry Average Skill

Weighted average Job Zone level in an industry–year using pay weights:

$$AvgSkill_{i,t} = \sum_{z=1}^5 z \times (\sum_{o: JobZone(o)=z} pay_{o,i,t} / Pay_{i,t})$$

High Industry Average Skill is an indicator equal to 1 if $AvgSkill_{i,t}$ is in the top quartile across industries in year t.

Proportion of Managers in Industry

Share of industry pay going to managerial occupations:

$$ManagerShare_{i,t} = (\sum_{o \in M} pay_{o,i,t} / Pay_{i,t})$$

High Proportion of Managers in Industry is an indicator equal to 1 if $ManagerShare_{i,t}$ is in the top quartile across industries in year t.

Industry Pay to Managers (log)

Natural logarithm of annual managerial pay:

$$\ln PayManagers_{i,t} = \ln \left(\sum_{o \in M} pay_{o,i,t} \right)$$

High Industry Pay to Managers is an indicator equal to 1 if $\ln PayManagers_{i,t}$ is in the top quartile across industries in year t.

Industry Labor Share by Compensation (BEA)

$$LaborShareComp_{i,t} = Total\ Compensation_{i,t} / Value\ Added_{i,t}$$

High Industry Labor Share by Compensation is an indicator equal to 1 if $LaborShareComp_{i,t}$ is in the top quartile across industries in year t.

Industry Labor Share by Salaries (BEA)

$$LaborShareSal_{i,t} = Total\ Salaries_{i,t} / Value\ Added_{i,t}$$

High Industry Labor Share by Salaries is an indicator equal to 1 if $LaborShareSal_{i,t}$ is in the top quartile across industries in year t.

Industry Labor Share by Number of Employees (BEA)

$$LaborShareEmp_{i,t} = Number\ of\ Full\ Time\ Employees_{i,t} / Value\ Added_{i,t}$$

High Industry Labor Share by Number of Employees is an indicator equal to 1 if $LaborShareEmp_{i,t}$ is in the top quartile across industries in year t.

Industry Specialization

Degree to which an industry's occupational mix is concentrated within that industry (i.e., less common in other industries), constructed following Donangelo (2014). We first compute an occupation-level concentration index from the inter-industry distribution of workers and then aggregate to the industry level using the occupation's employment share in the industry as weights to obtain $IndustrySpecialization_{i,t}$.

Low Industry Specialization

Indicator equal to 1 if $IndustrySpecialization_{i,t}$ is in the bottom quartile across industries in year t, and 0 otherwise.

[III] Capital Structure, Firm Controls, and Other Variables

Notation

Let f index firms, i industries (three-digit SIC, unless noted), and t years.

Book assets = AT, Long-term debt = DLTT, Debt in current liabilities = DLC, Cash and short-term investments = CHE, Shares outstanding = CSHO, Price = PRCC_F, Common equity = CEQ, Sales = SALE, R&D = XRD, Common dividends = DVC, Purchases of stock = PRSTKC, Net PPE = PPENT, Operating income before depreciation = OIBDP, Interest expense = XINT, Taxes = TXT, Current assets = ACT, Current liabilities = LCT, Capital expenditures = CAPX, and Acquisition expenditures = AQC.

Unless otherwise noted, all ratios use book assets in the denominator and are measured at the firm-year level.

Book leverage

$$BookLeverage_{f,t} = (DLTT_{f,t} + DLC_{f,t}) / AT_{f,t}$$

Market leverage

$$MarketLeverage_{f,t} = (DLTT_{f,t} + DLC_{f,t})/MVA_{f,t}$$

$$MVA_{f,t} = CSHO_{f,t} \times PRCC_{f,t} + AT_{f,t} - CEQ_{f,t}$$

Net book leverage

$$NetBookLeverage_{f,t} = (DLTT_{f,t} + DLC_{f,t} - CHE_{f,t})/AT_{f,t}$$

Net market leverage

$$NetMarketLeverage_{f,t} = (DLTT_{f,t} + DLC_{f,t} - CHE_{f,t})/MVA_{f,t}$$

Long-term leverage (book)

$$LTLeverage_{f,t} = DLTT_{f,t}/AT_{f,t}$$

Market-to-book assets

$$MTB_asset_{f,t} = MVA_{f,t}/AT_{f,t}$$

Log (book assets)

$$\log(AT_{f,t})$$

ROA

$$ROA_{f,t} = OIBDP_{f,t}/AT_{f,t}$$

Cash flow volatility

Standard deviation of ROA over the previous five fiscal years (minimum of three non-missing observations required).

Dividend payer

Indicator equal to 1 if $DVC_{f,t} > 0$, and 0 otherwise.

R&D/sales

$$XRD_{f,t}/SALE_{f,t}$$

Asset tangibility

$$PPENT_{f,t}/AT_{f,t}$$

No bond rating

Indicator equal to 1 if the firm has no S&P long-term credit rating in year t and 0 otherwise.

Not a dividend payer

Indicator equal to 1 if $DVC_{f,t} = 0$

High HP-Index

Indicator equal to 1 if the **HP-index** (Hadlock and Pierce, 2010) is above the annual median, where

$$HP_{f,t} = -0.737 \times Size_{f,t} + 0.043 \times Size_{f,t}^2 - 0.040 \times Age_{f,t}$$

$Size_{f,t} = \log(AT_{f,t})$ and $Age_{f,t}$ is firm age in years.

High WW-Index

Indicator equal to 1 if the **WW-index** (Whited and Wu, 2006) is above the annual median, where

$$WW_{f,t} = -0.091 \times CashFlow_{f,t} - 0.062 \times DividendDummy_{f,t} + 0.021 \times LongTermDebt_{f,t} - 0.044 \times Size_{f,t} \\ + 0.102 \times IndustrySalesGrowth - 0.035 \times SalesGrowth$$

$Size_{f,t} = \log(AT_{f,t})$, $IndustrySalesGrowth_{i,t}$ is year-over-year growth in industry total sales, and $SalesGrowth_{f,t}$ is year-over-year growth in firm sales.

Cash/assets

$$CHE_{f,t}/AT_{f,t}$$

Dividend/assets

$$DVC_{f,t}/AT_{f,t}$$

Cash flow/assets

$$(OIBDP_{f,t} - XINT_{f,t} - TXT_{f,t} - DVC_{f,t})/AT_{f,t}$$

NWC/assets

$$(ACT_{f,t} - LCT_{f,t} - CHE_{f,t})/AT_{f,t}$$

(net working capital **excluding** cash and short-term investments, scaled by assets).

CAPX/assets

$$CAPX_{f,t}/AT_{f,t}$$

Acquisition/assets

$$AQC_{f,t}/AT_{f,t}$$

Log (firm age)

$$\log(Age_{f,t})$$

where $Age_{f,t}$ is computed from the firm's first Compustat year with non-missing AT.

Industry cash flow risk

For each firm-year, compute the standard deviation of **Cash flow/assets** over the previous 10 years (minimum of three observations). **Industry cash flow risk** in industry *iii* and year *t* is the cross-firm average of these firm-level standard deviations within industry *i*.

State IDD adoption

Indicator equal to 1 if the Inevitable Disclosure Doctrine (IDD) has been adopted by courts in the firm's headquarters state as of year t (Klasa et al., 2018), and 0 otherwise.

Product market fluidity

10-K text-based measure from Hoberg-Phillips Data Library (<https://hobergphillips.tuck.dartmouth.edu/>). Product market fluidity is a competitive threat measure based on changes in product vocabulary usage by rival firms.

Union coverage percentage

Industry-level union coverage from Union Membership Database (unionstats.com) based on CPS data. Percentage of workers covered by union contracts in 3-digit SIC industry. Mapped using 5 CIC vintage crosswalks (CIC1990, CIC2002, CIC2007, CIC2012, CIC2017).

Institutional ownership (IO) ratio

Proportion of shares held by institutions from Thomson Reuters 13F filings.
Proportion of outstanding shares held by institutional investors.

Institutional ownership concentration (HHI)

Herfindahl index of institutional ownership from Thomson Reuters 13F filings
Concentration measure of institutional ownership. $HHI = \text{sum of squared ownership shares}$.

Analyst coverage dummy

Is an indicator equal to 1 if a firm is covered by at least one analyst, else 0, from I/B/E/S (Institutional Brokers' Estimate System) data.

Four-firm concentration ratio

Market share of 4 largest firms from U.S. Census Bureau Economic Census (1997, 2002, 2007, 2012, 2017, 2022). Calculated at the three-digit SIC level. Mapped from NAICS using Census crosswalks.

[IV] Relative industry and geographic shifters**General construction**

For any industry-level metric $X_{i,t}$ define its **relative** version as

$$Relative\ X_{i,t} = X_{i,t} - \frac{1}{|\tau(i,t)|} \cdot \sum_{j \in \tau(i,t)} X_{j,t}$$

Where $\tau(i,t)$ is the set of the industry's **transfer (linked) industries** defined in Section 2.2. And $\frac{1}{|\tau(i,t)|} \cdot \sum_{j \in \tau(i,t)} X_{j,t}$ is the average X across all linked industries. “High-” indicates a dummy equal to 1 if the relative measure is in the top quartile across industries in year t .

High Relative industry sales

Indicator equal to 1 if Relative industry sales is in the top quartile in year t . Industry sales is total sales aggregated across firms in industry i .

High Relative industry sales growth

Indicator equal to 1 if Relative industry sales growth is in the top quartile in year t . Industry sales growth is the year-over-year change in industry total sales; the relative version subtracts the average growth across transfer industries.

Relative within-county job opportunities in transfer industries

$$\frac{\text{number of firms in transfer industries located *in* the same county}}{\text{number of firms in transfer industries located *outside* the county}}$$

with a “High-” indicator equal to 1 if this ratio is in the top quartile across industries in year t .

Relative within-state job opportunities in transfer industries

$$\frac{\text{number of firms in transfer industries located *in* the same state}}{\text{number of firms in transfer industries located *outside* the state}}$$

with a “High-” indicator equal to 1 if this ratio is in the top quartile across industries in year t .

High County HPI

Indicator equal to 1 if the county-level HPI (base 2000=100) for the firm’s headquarters county is in the top quartile across counties in year t .

High State HPI

Indicator equal to 1 if the state-level HPI for the firm’s headquarters state is in the top quartile across states in year t .

Post Katrina

Indicator equal to 1 for 2006 and 0 for 2004.

Treated

Indicator equal to 1 for firms headquartered in the Houston–Baytown–Sugar Land, TX metropolitan area and 0 for matched firms in Dallas–Fort Worth, TX (matched on two-digit SIC, year, and the regression control set).

Table A1
Descriptive Statistics

This table reports the number of observations, mean, standard deviation, minimum, 25th percentile, median (50th percentile), 75th percentile of each variable. The sample period spans 1995–2020. Firms in the financial (SIC 6000–6999) or utility (SIC 4900–4999) industries are excluded. Industries classified as "Miscellaneous," "Not Elsewhere Classified," or with a nine in the third digit of their SIC code are also excluded. Book leverage, market leverage, net book leverage, net market leverage, long-term leverage (book), log assets, market-to-book, ROA, cash flow volatility, R&D/sales, asset tangibility, cash/assets, dividend/assets, cash flow/assets, industry cash flow risk, CAPX/assets, NWC/assets, acquisitions/assets are winsorized at the 1st and 99th percentiles. Variable definitions are provided in the Internet Appendix. Industries are defined at the three-digit SIC level in all tables.

Variables	N	Mean	Std	P25	Median	P75
CIM	78,321	0.2081	0.1474	0.0137	0.2501	0.3358
Degree	78,321	0.0917	0.0934	0.0123	0.0566	0.1687
Strength	78,321	5.9104	5.9163	1.0000	4.0000	11.000
Linked	78,321	0.7377	0.4399	0.0000	1.0000	1.0000
Book leverage	78,321	0.2119	0.2121	0.0130	0.1685	0.3364
Market leverage	78,321	0.1456	0.1630	0.0053	0.0938	0.2269
Net book leverage	78,315	-0.0124	0.3774	-0.2617	0.0328	0.2578
Net market leverage	78,315	0.0302	0.2403	-0.1048	0.0170	0.1743
Long-term leverage ratio	78,321	0.1758	0.1974	0.0010	0.1181	0.2862
Firm size (log assets)	78,321	6.1451	2.0943	4.5847	6.0210	7.5820
Market-to-book assets	78,321	2.2510	1.8511	1.1753	1.6273	2.5595
ROA	78,321	0.0585	0.2152	0.0337	0.1068	0.1655
Cash flow volatility	78,321	0.0618	0.0934	0.0143	0.0324	0.0682
Dividend payer	78,321	0.3316	0.4708	0.0000	0.0000	1.0000
R&D/sales	78,321	0.5196	2.7086	0.0000	0.0073	0.1102
Asset tangibility	78,321	0.2577	0.2390	0.0727	0.1711	0.3758
State IDD adoption dummy	78,321	0.4264	0.4946	0.0000	0.0000	1.0000
Cash/assets	78,315	0.2249	0.2396	0.0386	0.1303	0.3407
Dividend/assets	78,321	0.0098	0.0236	0.0000	0.0000	0.0089
Cash flow/assets	78,321	0.0133	0.2057	0.0078	0.0667	0.1098
Industry cash flow risk	78,300	0.1063	0.0813	0.0480	0.0816	0.1331
CAPX/assets	77,859	0.0547	0.0610	0.0166	0.0346	0.0687
NWC/assets	78,315	0.0549	0.1804	-0.0486	0.0369	0.1584
Acquisition/assets	78,321	0.0240	0.0607	0.0000	0.0000	0.0116
Firm age (log)	78,321	2.1059	0.8855	1.6094	2.1972	2.7726
Product market fluidity	68,013	6.7665	3.4940	4.1819	6.0927	8.7086
Union coverage percentage	78,279	9.0146	9.0176	3.0927	5.4267	11.578
Institutional ownership (IO) ratio	66,218	0.5399	0.3147	0.2614	0.5801	0.8190
IO concentration (HHI)	66,218	0.1482	0.1855	0.0448	0.0721	0.1675
Analyst coverage dummy	78,321	0.5394	0.4985	0.0000	1.0000	1.0000
Four-firm concentration ratio	78,255	38.721	13.821	30.572	36.941	46.300

Table A2
One-way analysis of variance for CIM

This table presents results from a one-way analysis of variance (ANOVA) for Cross-Industry Labor Mobility (CIM) at the three-digit SIC level over the 1995–2020 sample period. Panel A reports the source of variation, decomposing the total variance in CIM into between-industry and within-industry components. Panel B reports the corresponding estimated standard deviations. Industries are defined at the three-digit SIC code level.

Panel A – Source of the variation					
Source	SS	DF	MS	F	Prob > F
Between industry	52.2476	205	0.2548	48.80	0.0000
Within industry	21.1170	4043	0.0052		
Total	73.3646	4248	0.0172		

Panel B – Estimated standard deviation	
	SD
Estimated Standard Deviation of Industry Effect	0.1100
Estimated Standard Deviation within the Industry	0.0722

Table A3
Cross-Industry Labor Mobility and Leverage – Degree centrality

This table shows the effect of Degree centrality on firms' leverage over the 1995–2020 sample period. Degree centrality is defined as the total number of industries directly connected to the industry. Across both panels, the dependent variables in models (1) to (5) are book leverage, market leverage, net book leverage, net market leverage, and long-term leverage (book), respectively. Panel A examines the effect of CIM on firms' leverage across all industries. Panel B restricts the sample to industries that have connections with at least one transfer industry. All models include industry fixed effects defined at the two-digit SIC code level. Standard errors are corrected for heteroskedasticity and clustering at the three-digit SIC code level. Significance levels for whether estimated coefficients are different from zero are in parentheses. Double Machine Learning (DML) estimates using the Random Forests method for the coefficient on Degree are reported in the last row of the table panels. Section 4.2 provides details on our use of the DML estimator and also lists the ten additional control variables that are used in the DML-related analyses.

Panel A – Sample includes all industries					
The dependent variable is:	Book leverage	Market leverage	Net book leverage	Net market leverage	Long-term leverage (book)
	(1)	(2)	(3)	(4)	(5)
Degree	-0.2658 (0.000)	-0.2158 (0.000)	-0.5512 (0.000)	-0.4142 (0.000)	-0.2299 (0.000)
Log (book assets)	0.0278 (0.000)	0.0163 (0.000)	0.0420 (0.000)	0.0277 (0.000)	0.0285 (0.000)
Market-to-book assets	-0.0060 (0.004)	-0.0226 (0.000)	-0.0340 (0.000)	0.0013 (0.817)	-0.0043 (0.011)
ROA	-0.0916 (0.000)	-0.0743 (0.000)	0.0899 (0.002)	0.0322 (0.218)	-0.0481 (0.054)
Cash flow volatility	0.1016 (0.000)	0.0095 (0.615)	0.0801 (0.111)	-0.0055 (0.872)	0.0793 (0.007)
Dividend payer	-0.0410 (0.000)	-0.0424 (0.000)	-0.0166 (0.258)	-0.0352 (0.000)	-0.0399 (0.000)
R&D/sales	-0.0047 (0.000)	-0.0026 (0.000)	-0.0169 (0.000)	-0.0065 (0.000)	-0.0028 (0.000)
Asset tangibility	0.2353 (0.000)	0.2023 (0.000)	0.5527 (0.000)	0.3728 (0.000)	0.2099 (0.000)
State IDD adoption	0.0187 (0.000)	0.0117 (0.000)	0.0423 (0.000)	0.0271 (0.000)	0.0231 (0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	78,321	78,321	78,315	78,315	78,321
Adjusted R-squared	0.2705	0.3838	0.4561	0.3824	0.2769
DML using Random Forests	-0.2767 (0.000)	-0.2222 (0.000)	-0.6306 (0.000)	-0.4342 (0.000)	-0.2455 (0.000)

Panel B – Sample includes only industries with at least one transfer industry					
The dependent variable is:	Book leverage	Market leverage	Net book leverage	Net market leverage	Long-term leverage (book)
	(1)	(2)	(3)	(4)	(5)
Degree	-0.1693 (0.004)	-0.1294 (0.002)	-0.4041 (0.008)	-0.3178 (0.001)	-0.1476 (0.002)
Log (book assets)	0.0266 (0.000)	0.0156 (0.000)	0.0404 (0.000)	0.0268 (0.000)	0.0274 (0.000)
Market-to-book assets	-0.0054 (0.013)	-0.0193 (0.000)	-0.0328 (0.000)	0.0061 (0.233)	-0.0038 (0.027)
ROA	-0.0920 (0.001)	-0.0601 (0.000)	0.0813 (0.012)	0.0444 (0.113)	-0.0526 (0.045)
Cash flow volatility	0.1093 (0.000)	0.0202 (0.236)	0.1148 (0.014)	0.0226 (0.447)	0.0859 (0.004)
Dividend payer	-0.0317 (0.002)	-0.0326 (0.000)	0.0015 (0.932)	-0.0210 (0.040)	-0.0316 (0.001)
R&D/sales	-0.0045 (0.000)	-0.0022 (0.000)	-0.0155 (0.000)	-0.0056 (0.000)	-0.0029 (0.000)
Asset tangibility	0.2472 (0.000)	0.1913 (0.000)	0.6412 (0.000)	0.3950 (0.000)	0.2055 (0.000)
State IDD adoption	0.0199 (0.000)	0.0119 (0.001)	0.0450 (0.000)	0.0279 (0.000)	0.0247 (0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	59,382	59,382	59,381	59,381	59,382
Adjusted R-squared	0.2540	0.3507	0.4409	0.3619	0.2653
DML using Random Forests	-0.1895 (0.000)	-0.1471 (0.000)	-0.3911 (0.000)	-0.3159 (0.000)	-0.1637 (0.000)

Table A4
Cross-Industry Labor Mobility and Leverage – Strength centrality

This table shows the effect of Strength on firms' leverage over the 1995–2020 sample period. Strength is a network analysis measure that quantifies the importance of a node within a network based on the sum of the weights of its connections to other nodes. In other words, Strength considers both the number of connections and the magnitude of connectedness. Across both panels, the dependent variables in models (1) to (5) are, respectively, book leverage, market leverage, net book leverage, net market leverage, and long-term leverage (book). Panel A examines the effect of Cross-Industry Labor Mobility (CIM) on firms' leverage across all industries. Panel B considers only industries that have connection with at least one transfer industry. All models include industry fixed effects defined at the two-digit SIC code level. Standard errors are corrected for heteroskedasticity and clustering at the three-digit SIC code level. Significance levels for whether estimated coefficients are different from zero are in parentheses. Double Machine Learning (DML) estimates using the Random Forests method for the coefficient on Strength are reported in the last row of the table panels. Section 4.2 provides details on our use of the DML estimator and also lists the ten additional control variables that are used in the DML-related analyses.

Panel A – Sample includes all industries					
The dependent variable is:	Book leverage	Market leverage	Net book leverage	Net market leverage	Long-term leverage (book)
	(1)	(2)	(3)	(4)	(5)
Strength	-0.0056 (0.000)	-0.0044 (0.000)	-0.0119 (0.000)	-0.0087 (0.000)	-0.0048 (0.000)
Log (book assets)	0.0278 (0.000)	0.0163 (0.000)	0.0420 (0.000)	0.0276 (0.000)	0.0285 (0.000)
Market-to-book assets	-0.0061 (0.003)	-0.0227 (0.000)	-0.0342 (0.000)	0.0012 (0.832)	-0.0043 (0.010)
ROA	-0.0916 (0.000)	-0.0743 (0.000)	0.0897 (0.003)	0.0321 (0.224)	-0.0482 (0.055)
Cash flow volatility	0.1030 (0.000)	0.0105 (0.579)	0.0831 (0.100)	-0.0035 (0.919)	0.0805 (0.006)
Dividend payer	-0.0416 (0.000)	-0.0427 (0.000)	-0.0178 (0.218)	-0.0360 (0.000)	-0.0404 (0.000)
R&D/sales	-0.0047 (0.000)	-0.0026 (0.000)	-0.0169 (0.000)	-0.0065 (0.000)	-0.0028 (0.000)
Asset tangibility	0.2341 (0.000)	0.2016 (0.000)	0.5498 (0.000)	0.3711 (0.000)	0.2089 (0.000)
State IDD adoption	0.0186 (0.000)	0.0117 (0.000)	0.0420 (0.000)	0.0270 (0.000)	0.0230 (0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	78,321	78,321	78,315	78,315	78,321
Adjusted R-squared	0.2713	0.3841	0.4574	0.3835	0.2775
DML using Random Forests	-0.0049 (0.000)	-0.0037 (0.000)	-0.0108 (0.000)	-0.0078 (0.000)	-0.0042 (0.000)

Panel B – Sample includes only industries with at least one transfer industry					
The dependent variable is:	Book leverage	Market leverage	Net book leverage	Net market leverage	Long-term leverage (book)
	(1)	(2)	(3)	(4)	(5)
Strength	-0.0038 (0.003)	-0.0027 (0.002)	-0.0093 (0.004)	-0.0069 (0.001)	-0.0033 (0.001)
Log (book assets)	0.0265 (0.000)	0.0156 (0.000)	0.0404 (0.000)	0.0268 (0.000)	0.0274 (0.000)
Market-to-book assets	-0.0054 (0.012)	-0.0193 (0.000)	-0.0330 (0.000)	0.0060 (0.240)	-0.0039 (0.025)
ROA	-0.0919 (0.001)	-0.0600 (0.000)	0.0816 (0.012)	0.0446 (0.114)	-0.0526 (0.045)
Cash flow volatility	0.1105 (0.000)	0.0210 (0.218)	0.1175 (0.012)	0.0246 (0.409)	0.0869 (0.003)
Dividend payer	-0.0321 (0.002)	-0.0328 (0.000)	0.0006 (0.974)	-0.0216 (0.033)	-0.0319 (0.001)
R&D/sales	-0.0045 (0.000)	-0.0022 (0.000)	-0.0154 (0.000)	-0.0056 (0.000)	-0.0029 (0.000)
Asset tangibility	0.2468 (0.000)	0.1911 (0.000)	0.6404 (0.000)	0.3945 (0.000)	0.2053 (0.000)
State IDD adoption	0.0198 (0.000)	0.0119 (0.001)	0.0447 (0.000)	0.0278 (0.000)	0.0246 (0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	59,382	59,382	59,381	59,381	59,382
Adjusted R-squared	0.2546	0.3510	0.4420	0.3629	0.2658
DML using Random Forests	-0.0037 (0.000)	-0.0029 (0.000)	-0.0080 (0.000)	-0.0064 (0.000)	-0.0032 (0.000)

Table A5
Cross-Industry Labor Mobility and Leverage – Linked measure

This table shows the effect of Linked on firms' leverage over the 1995–2020 sample period. Linked is an indicator equal to one when an industry has a significant connection to another industry—that is, it is connected to at least one transfer industry—and zero otherwise. The dependent variables in models (1) to (5) are, respectively, book leverage, market leverage, net book leverage, net market leverage, and long-term leverage (book). All models include industry fixed effects defined at the two-digit SIC code level. Standard errors are corrected for heteroskedasticity and clustering at the three-digit SIC code level. Significance levels for whether estimated coefficients are different from zero are in parentheses. Double Machine Learning (DML) estimates using the Random Forests method for the coefficient on Linked are reported in the last row of the table. Section 4.2 provides details on our use of the DML estimator and also lists the ten additional control variables that are used in the DML-related analyses.

The dependent variable is:	Book leverage	Market leverage	Net book leverage	Net market leverage	Long-term leverage (book)
	(1)	(2)	(3)	(4)	(5)
Linked	-0.0315 (0.001)	-0.0286 (0.001)	-0.0726 (0.000)	-0.0492 (0.000)	-0.0253 (0.004)
Log (book assets)	0.0278 (0.000)	0.0163 (0.000)	0.0420 (0.000)	0.0276 (0.000)	0.0285 (0.000)
Market-to-book assets	-0.0062 (0.004)	-0.0227 (0.000)	-0.0343 (0.000)	0.0011 (0.851)	-0.0044 (0.011)
ROA	-0.0925 (0.000)	-0.0753 (0.000)	0.0874 (0.003)	0.0306 (0.250)	-0.0489 (0.055)
Cash flow volatility	0.1015 (0.000)	0.0098 (0.613)	0.0806 (0.113)	-0.0056 (0.870)	0.0790 (0.008)
Dividend payer	-0.0400 (0.000)	-0.0418 (0.000)	-0.0149 (0.305)	-0.0336 (0.000)	-0.0389 (0.000)
R&D/sales	-0.0046 (0.000)	-0.0025 (0.000)	-0.0167 (0.000)	-0.0063 (0.000)	-0.0027 (0.000)
Asset tangibility	0.2378 (0.000)	0.2036 (0.000)	0.5562 (0.000)	0.3765 (0.000)	0.2124 (0.000)
State IDD adoption	0.0194 (0.000)	0.0122 (0.000)	0.0435 (0.000)	0.0282 (0.000)	0.0237 (0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	78,321	78,321	78,315	78,315	78,321
Adjusted R-squared	0.2674	0.3809	0.4525	0.3764	0.2739
DML using Random Forests	-0.0474 (0.000)	-0.0403 (0.000)	-0.1183 (0.000)	-0.0712 (0.000)	-0.0396 (0.000)

Table A6

Cross-Industry Labor Mobility and Other Financial Policies

This table reports the results from OLS regressions of cash holdings and dividend payments on cross-industry labor mobility (CIM) over the 1995–2020 sample period. The dependent variable in models (1) to (4) is cash holdings over book assets, and in models (5) to (8) it is an indicator for whether a firm pays a dividend in that year. The control variables in models (1) to (4) are defined following Bates, Kahle, and Stulz (2009). Panel A includes all industries. Panel B restricts the sample to industries with at least one transfer industry. This table includes specifications using all four labor mobility measures—CIM, Degree, Strength, and Linked—to capture different facets of labor mobility across industries. All models include industry fixed effects defined at the two-digit SIC code level. Standard errors are corrected for heteroskedasticity and clustering at the three-digit SIC code level. Significance levels for whether estimated coefficients are different from zero are in parentheses. Double Machine Learning (DML) estimates using the Random Forests method for the coefficient on CIM are reported in the last row of the table panels. Section 4.2 provides details on our use of the DML estimator and also lists the ten additional control variables that are used in the DML-related analyses.

Panel A – Sample includes all industries								
The dependent variable is:					Dividend payer			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CIM	0.0682 (0.018)				-0.3433 (0.000)			
Degree		0.1040 (0.063)				-0.4302 (0.001)		
Strength			0.0024 (0.045)				-0.0093 (0.001)	
Linked				0.0136 (0.064)				-0.0883 (0.000)
Industry cash flow risk	0.2961 (0.000)	0.3088 (0.000)	0.3018 (0.000)	0.3066 (0.000)	-0.6398 (0.000)	-0.7245 (0.000)	-0.6998 (0.000)	-0.6622 (0.000)
Market-to-book assets	0.0204 (0.000)	0.0204 (0.000)	0.0205 (0.000)	0.0204 (0.000)	0.0086 (0.005)	0.0085 (0.006)	0.0083 (0.007)	0.0086 (0.005)
Log (book assets)	-0.0131 (0.000)	-0.0130 (0.000)	-0.013 (0.000)	-0.013 (0.000)	0.0759 (0.000)	0.0759 (0.000)	0.0758 (0.000)	0.0758 (0.000)
Cash flow/assets	-0.0938 (0.000)	-0.0948 (0.000)	-0.0951 (0.000)	-0.094 (0.000)				
NWC/assets	-0.3669 (0.000)	-0.3669 (0.000)	-0.3663 (0.000)	-0.3679 (0.000)				
CAPX/assets	-0.0666 (0.011)	-0.0683 (0.010)	-0.0673 (0.010)	-0.0666 (0.011)				
Book leverage	-0.2631 (0.000)	-0.2631 (0.000)	-0.2626 (0.000)	-0.2646 (0.000)				
R&D/sales	0.0099 (0.000)	0.0100 (0.000)	0.0100 (0.000)	0.0099 (0.000)				
Dividend payer	-0.0300 (0.000)	-0.0303 (0.000)	-0.0301 (0.000)	-0.0305 (0.000)				
Acquisition/assets	-0.4021 (0.000)	-0.4032 (0.000)	-0.4028 (0.000)	-0.4039 (0.000)				
Log (firm age)					0.0796 (0.000)	0.0794 (0.000)	0.0795 (0.000)	0.0795 (0.000)
ROA					0.1802 (0.001)	0.1862 (0.001)	0.1864 (0.001)	0.1806 (0.001)
Asset tangibility	-0.2904 (0.000)	-0.2904 (0.000)	-0.2902 (0.000)	-0.2912 (0.000)	0.1180 (0.005)	0.1218 (0.004)	0.1205 (0.005)	0.1200 (0.003)
State IDD adoption	-0.0135 (0.001)	-0.0135 (0.001)	-0.0135 (0.001)	-0.0137 (0.000)	0.0283 (0.001)	0.0290 (0.001)	0.0288 (0.001)	0.0292 (0.001)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	77,831	77,831	77,831	77,831	77,831	77,831	77,831	77,831
Adjusted R-squared	0.6160	0.6160	0.6161	0.6156	0.3171	0.3156	0.3161	0.3161
DML using Random Forests	0.2319 (0.000)	0.2790 (0.000)	0.0057 (0.000)	0.0623 (0.000)	-0.5232 (0.000)	-0.5521 (0.000)	-0.0113 (0.000)	-0.1557 (0.000)

Panel B – Sample includes only industries with at least one transfer industry						
The dependent variable is:	Cash/assets			Dividend payer		
	(1)	(2)	(3)	(4)	(5)	(6)
CIM	0.1224 (0.003)			-0.2567 (0.018)		
Degree		0.1126 (0.052)			-0.2396 (0.063)	
Strength			0.0026 (0.031)			-0.0053 (0.058)
Industry cash flow risk	0.2333 (0.004)	0.2439 (0.003)	0.2353 (0.004)	-0.6126 (0.000)	-0.6341 (0.000)	-0.6168 (0.000)
Market-to-book assets	0.0204 (0.000)	0.0204 (0.000)	0.0204 (0.000)	0.0060 (0.025)	0.0060 (0.026)	0.0059 (0.028)
Log (book assets)	-0.0122 (0.000)	-0.0121 (0.000)	-0.0121 (0.000)	0.0708 (0.000)	0.0707 (0.000)	0.0706 (0.000)
Cash flow/assets	-0.0819 (0.000)	-0.0832 (0.000)	-0.0834 (0.000)			
NWC/assets	-0.3992 (0.000)	-0.3983 (0.000)	-0.3979 (0.000)			
CAPX/assets	-0.0664 (0.023)	-0.0691 (0.021)	-0.0679 (0.021)			
Book leverage	-0.2810 (0.000)	-0.2812 (0.000)	-0.2808 (0.000)			
R&D/sales	0.0092 (0.000)	0.0092 (0.000)	0.0092 (0.000)			
Dividend payer	-0.0373 (0.000)	-0.0374 (0.000)	-0.0373 (0.000)			
Acquisition/assets	-0.4482 (0.000)	-0.4506 (0.000)	-0.4502 (0.000)			
Log (firm age)				0.0725 (0.000)	0.0722 (0.000)	0.0722 (0.000)
ROA				0.166 (0.001)	0.1683 (0.001)	0.1684 (0.001)
Asset tangibility	-0.3638 (0.000)	-0.3629 (0.000)	-0.3633 (0.000)	0.1260 (0.013)	0.1254 (0.014)	0.1256 (0.015)
State IDD adoption	-0.0138 (0.004)	-0.0139 (0.004)	-0.0138 (0.004)	0.0322 (0.000)	0.0323 (0.000)	0.0322 (0.000)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59,044	59,044	59,044	59,044	59,044	59,044
Adjusted R-squared	0.6062	0.6061	0.6063	0.2932	0.2931	0.2933
DML using Random Forests	0.3700 (0.000)	0.1607 (0.000)	0.0033 (0.000)	-0.5011 (0.000)	-0.2070 (0.000)	-0.0047 (0.000)