The Employee Clientele of Corporate Leverage: Evidence from Family Labor Income Diversification

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Abstract

Consistent with theories on the equilibrium matching between capital structure and employee job risk aversion, we find a robust, positive association between a firm's leverage and its employees' family labor income diversification. Higher-leverage firms also recruit new employees with greater income diversification. For identification, we exploit two policy shocks that exogenously change employee income diversification and firm leverage, respectively. Individual employee-level tests further reveal that workers with differential risk attitudes adjust their job choices and household labor income portfolios in response to significant shifts in their employers' leverage. Finally, human bankruptcy costs contribute to the general level of corporate risk-taking.

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I. Introduction

Classical tradeoff theories predict that firms choose optimal capital structures by balancing tax savings and bankruptcy costs. However, direct bankruptcy costs have been found to be too small to explain the observed lack of debt usage (e.g., Warner (1977), and Haugen and Senbet (1978)). Consequently, the literature has started to explore indirect bankruptcy costs, especially the human costs of bankruptcy for employees, such as unemployment and reduced worker welfare (Titman (1984) and Titman and Wessels (1988)).[1] In particular, Berk, Stanton, and Zechner (2010) develop a theory in which firms with employees who are more averse to unemployment risk will use less debt, and lower-levered firms will hire employees who are more risk-averse towards their jobs. Ultimately, this "clientele effect" gives rise to an equilibrium matching between corporate leverage and employee *job* risk preferences.

Motivated by this literature, researchers have found novel evidence that lower unemployment costs due to exogenous state- or region-level shocks prompt affected firms to increase their financial leverage (e.g., Agrawal and Matsa (2013) and Kim (2020)). However, such a unilateral causal relation is only a necessary but not a sufficient condition for the existence of a two-sided firm-level matching between corporate leverage and employee job risk aversion.[2] A comprehensive analysis of such matching necessitates a firm-level measure of

[1] Previous studies have documented that unemployment causes substantial and long-lasting losses to employees, both financially and psychologically (e.g., Di Tella, MacCulloch, and Oswald (2001), Helliwell (2003), Layard (2005), David and von Wachter (2011), Giroud and Mueller (2017), (2019), and Graham, Kim, Li, and Qiu (2023)).

[2] For example, even if firms with different levels of leverage hire employees with the same job risk preference (i.e., no cross-firm matching in equilibrium), we may still observe an increase in leverage after an exogenous decrease in unemployment costs for these firms as along as such costs play a role in capital structure decisions.

employee job risk aversion, whose cross-sectional relation to firm leverage can then be examined. To the best of our knowledge, however, such a measure has not been developed in the literature, primarily due to the challenges of observing and quantifying an employee's risk attitude towards a job. Hence, despite rich theoretical predictions, there has been sparse empirical evidence on the cross-firm matching between financial leverage and employee job risk aversion. Our study attempts to overcome this empirical hurdle by exploiting the granular person/family-level information from the U.S. Census Bureau.

Our approach is motivated by the literature showing that higher household income diversification makes an economic agent more tolerant of labor income risk. For example, Weller and Wenger (2015) show that individuals with more diversified household income are more likely to be entrepreneurs, a career choice shown to reflect risk tolerance (Hvide and Panos (2014)). Hence, we measure an employee's risk tolerance towards her job using her family labor income diversification (*FamilyDiverse*), defined as one minus the ratio of her income from the focal firm to her total family labor income. The larger this measure, the greater the share of her family labor income accounted for by other income sources, thereby reducing the employee's concern about the human cost of bankruptcy from her employer. We then aggregate *FamilyDiverse* across all employees in a firm-year and link it to the firm's capital structure.

FamilyDiverse differs from innate (i.e., genetically determined) risk attitudes, which describe people's attitudes towards the *same* amount of risk or loss. In contrast, *FamilyDiverse* quantifies the magnitude of the labor income risk (monetary losses due to unemployment) faced by each employee and thus allows us to focus on the effect of human costs of bankruptcy from a given job, as analyzed by the theory. Moreover, while innate risk attitudes are difficult to *quantify* in practice, family income diversification is economically motivated and can be accurately computed using our granular data.[3]

As theory suggests, the influence of employee risk aversion on capital structure is mainly achieved through labor market interactions. Therefore, employees just need to have a general idea of their employers' bankruptcy risk rather than directly observing their employers' leverage (Matsa (2018)).[4] Brown and Matsa (2016) find that job applicants, as outsiders, can accurately perceive firms' financial risk, indicating that current employees as insiders are also likely to be aware of their employers' financial conditions. Further, existing studies find that rank-and-file employees can predict their firms' future performance (Babenko and Sen (2016), Agrawal, Hacamo, and Hu (2021), and Green, Huang, Wen, and Zhou (2019)). Similarly, the equilibrium matching does not require managers to know employees' family income diversification, because such personal attributes have been incorporated into employees' job application/departure behaviors, which in turn influence managers' debt policies.

We use the Longitudinal Employer-Household Dynamics (LEHD) data of the U.S. Census Bureau, which contains employee wage records that their employers submit to state unemployment insurance (UI) offices. One crucial advantage of the LEHD data is that it covers all the paid jobs a given individual has in a state. In addition, the LEHD program identifies each person's household using tax return information (primarily the 1040 tax forms) and residential

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[3] Innate risk aversion, if at work at all, will likely bias us against finding the theory-driven positive relation between leverage and *FamilyDiverse*, because individuals with higher innate risk aversion will likely work for firms with lower leverage and in the meantime increase their family income diversification to reduce household income uncertainty.

[4] As pointed out by Matsa (2018), "…the impact of leverage on unemployment risk is likely to be manifest in informative signals from coworkers, management, the media, and from other aspects of the economic environment."

address data, which allows us to calculate the separate contribution of each family member towards household labor income. We merge the LEHD data with Compustat to obtain a sample of about 2,800 unique U.S. public firms, covering approximately 10,500 firm-years from 2000 to 2008.[5]

Our baseline analysis regresses a firm's leverage on its *FamilyDiverse* after controlling for a broad set of firm characteristics and employee characteristics, as well as industry×year and state×year fixed effects.[6] The results show that, consistent with the equilibrium matching between employee risk aversion and corporate leverage, firms with higher employee family income diversification use significantly more debt in their capital structure in terms of both book leverage and market leverage. Further, our results continue to hold when we examine the wage-weighted average measures of employee family income diversification and when we account for employees' family sizes in the regressions. Finally, our results hold across a number of robustness tests, such as accounting for risk levels of different labor income sources, controlling for employee characteristics at the individual level, using alternative fixed effects, excluding employees who are likely part-time workers or job hoppers, using alternative measures for corporate leverage, and excluding firms with zero leverage.

Next, we conduct cross-sectional analyses since the employee clientele effect is expected to be stronger for firms whose employees have more outside job opportunities. If employees do not have the option of selecting jobs in their local areas, their personal risk preferences will be

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[5] The numbers are rounded to the nearest hundred due to the disclosure requirement of the Census Bureau.

[6] While our main analysis excludes firm fixed effects to provide cross-firm evidence that is more relevant to the theoretically-predicted equilibrium matching than within-firm evidence, our results are robust to including firm fixed effects (see Section III.B.3).

less relevant. Furthermore, we expect the clientele effect to be stronger for firms that rely more on human capital and those with higher financial distress risk where employees are more concerned about the human costs of bankruptcy. Consistent with these predictions, we find that the positive relation between leverage and employee family income diversification is more pronounced for firms located in regions with more outside job opportunities, those with higher labor intensity, and those with a greater probability of bankruptcy.

It is worth noting that our main purpose is to test the two-way equilibrium matching between employee job risk attitudes and leverage across firms, rather than to identify a causal effect in either direction. As such, our major identification challenge comes from omitted variables rather than reverse causality. We mitigate the omitted variable concern by employing various layers of fixed effects and conducting cross-sectional tests based on employee outside opportunities, labor intensity, and distress risk. Nevertheless, we further address this concern by analyzing the unique setting of the California Paid Family Leave Legislation (CA-PFL). This legislation, enacted in 2004, allows employees in California to take paid leaves to care for newborn/adopted children and thus promotes the labor market participation of female workers. Moreover, the policy does not directly impact employers' cash flows because it is funded by the California State's tax revenues rather than the employers.

Since CA-PFL is a one-time policy shock that could potentially be confounded by other contemporaneous events, we exploit the cross-sectional variation in the impact of CA-PFL on Californian firms with varying employee compositions and conduct a triple difference-in-differences (DiD) analysis. Specifically, we expect the effect of CA-PFL to be stronger among firms with a higher proportion of male workers in their fertile age because such employees' spouses are more likely to benefit from CA-PFL and take on additional jobs. Consistent with this prediction, we find that the positive effect of CA-PFL on the corporate leverage of Californian firms relative to other firms is significantly larger when such firms have a higher fraction of fertile-age males among their employees. This result suggests that plausibly positive shocks to a firm's employee job risk tolerance can allow the firm to take on more debt.[7]

To test the other direction of the two-way equilibrium matching, we examine whether firms with lower leverage attract and recruit more risk-averse employees. We find that new employees hired by a lower-levered firm tend to have lower family income diversification. This result suggests that employees who are less equipped to deal with labor income losses prefer to work for (and are chosen by) firms with less debt. To draw causal inference, we exploit an exogenous shock to firms' financial leverage caused by the SFAS 123(r) accounting rule change (Lian and Ma (2021)). The SFAS 123(r) rule, effective in 2006, mandates that US public firms include option compensation expenses in operating expenses, thereby reducing firms' *reported* EBITDA. Lian and Ma (2021) show that, for firms subject to existing earnings-based constraints (EBCs) such as EBITDA-based loan covenants, the reduction in reported earnings tightens these constraints and forces such firms to reduce debt issuance. Moreover, SFAS 123(r) is only an accounting rule change that does not directly impact firms' operations or cash positions, making it plausibly exogenous to firm fundamentals. The theory of equilibrium matching predicts that this sudden reduction in debt usage will enable affected firms to hire more risk-averse employees. Consistent with this prediction, we find that firms subject to EBCs, relative to those

[7] We verify two important premises for this triple DiD analysis. First, we find that CA-PFL has a positive causal effect on firms' family income diversification but does not significantly alter their other labor-related outcomes such as average wage level, wage growth, or operating leverage. Second, we confirm the parallel trends assumption holds.

without EBCs, hire new employees with lower family labor income diversification after the SFAS 123(r) rule change, and this effect only concentrates among firms with high pre-existing option compensation expenses.[8] Taken together, the above new-hire tests provide strong evidence for the *two-way* equilibrium matching between financial leverage and employee job risk preference.

We also use our granular individual-level data to examine how a firm's workforce composition and its employees' intra-household labor allocations respond to large leverage changes. We expect that following a large increase in leverage, firms will become more attractive to risk-tolerant job seekers, resulting in higher family income diversification among newly hired employees. Conversely, such an increase in firm leverage will make the firm less attractive to its current employees who are more risk averse, leading to lower family labor income diversification among those who decide to leave ("leavers") because risk-averse (i.e., less diversified) employees tend to leave the firm when leverage increases substantially. Finally, a large increase in leverage will increase family labor income diversification for employees who stay at the firm ("stayers") since these employees, who may be unable or unwilling to leave, are incentivized to diversify their family labor income to cope with their employer's increased bankruptcy risk. We run person-level regressions for these three types of employees (i.e., new-hires, leavers, and stayers) separately and find evidence consistent with the above predictions.

Finally, we illustrate a broader implication of our study for future corporate finance research. While the theory of equilibrium matching focuses on financial leverage, its underlying

[8] Similar to the CA-PFL analysis, we verify two important premises for this triple DiD test. First, we find that the SFAS 123(r) rule change has a negative causal effect on firms' leverage but does not significantly affect firms' investments or worker compensation. Second, we confirm that the parallel trends assumption holds.

mechanism suggests that firm managers may also consider human costs of bankruptcy when making other risky corporate decisions. Consistent with this prediction, we find that firms with higher employee family income diversification exhibit greater corporate risk-taking measured by operating performance volatility, stock return volatility, and the probability of default. These results suggest that the impact of human bankruptcy costs on firms' risk-taking could go beyond leverage and have important implications for other corporate outcomes that have been underexplored in this context.

Our paper makes several contributions to the finance literature. While previous research provides valuable insights by establishing the groundwork for the equilibrium matching between employee risk preferences and firm leverage (e.g., Agrawal and Matsa (2013), Serfling (2015), Brown and Matsa (2016), Kim (2020), and Baghai, Silva, Thell, and Vig (2021)), it only explores either *one* direction of the matching or *state-level* (i.e., across-the-board) changes in employee risk attitudes.[9] Our paper extends this literature by simultaneously presenting *firm-level* evidence on the *two-way* equilibrium matching between employee job risk attitudes and corporate leverage. To this extent, our findings add to the large literature on the determinants of

[9] For example, while Brown and Matsa (2016) show that distressed firms attract fewer job applicants, they do not analyze how firm leverage affects the job risk attitudes of the employees currently employed by these firms or document the impact of employees' risk attitudes on firms' risk-taking. Similarly, using Swedish employer-employee matched data, Baghai et al. (2021) find that high-talent employees tend to leave firms approaching financial distress. However, like Brown and Matsa (2016), they do not examine how changes in employee job risk aversion affect firms' capital structure decisions. For another example, while Agrawal and Matsa (2013) present novel evidence that higher unemployment benefits lead to increased corporate leverage, their study examines only a necessary, but not sufficient, condition for the equilibrium matching, i.e., the impact of state-level changes in employee risk attitudes on firms' leverage.

capital structure (e.g., Berger, Ofek, and Yermack (1997), Harford, Li, and Zhao (2008), Harford, Klasa, and Walcott (2009), and Chen, Harford, and Kamara (2019)).

Second, we are also among the first to provide *individual-level* evidence on how workers with different risk attitudes adjust their job choices and actively manage their household labor income portfolios in response to changes in their employers' financial risk. These findings shed new light on an under-explored channel underlying the equilibrium matching between employee risk attitudes and corporate leverage, namely, how a firm's risk-taking actions influence its employees' intra-household labor allocations and the consequent workforce composition.

Third, we propose a novel *firm-level* measure of employee job risk aversion based on individual workers' family labor income diversification. While existing studies examine human bankruptcy costs at the state or industry level (e.g., Titman and Wessels (1988) and Agrawal and Matsa (2013)), our firm-level (as well as worker-level) measure of such costs is economically motivated and easily quantifiable. This measure has significant potential to inform future research on the interplay between labor market considerations and corporate/household financial decisions.[10]

Fourth, our findings suggest that employee job risk aversion could have a broad impact on firms' corporate policies by shaping corporate risk-taking behaviors in various dimensions other than debt usage. From this broader perspective, our paper significantly extends the literature that investigates the role of labor in corporate finance (e.g., Atanassov and Kim (2009), Bae, Kang, and Wang (2011), Tate and Yang ((2015), (2024)), Simintzi, Vig, and Volpin (2015),

[10] For example, future researchers can use our measure of family income diversification to analyze individuals' or household's labor supply together with their financial decisions, potentially contributing to the household finance or labor economics literature.

Lin, Schmid, and Xuan (2018), Dore and Zarutskie (2023), Ellul, Wang, and Zhang (2023), and Ouimet and Tate (2023)).

Last but not least, while a large literature suggests that managerial preferences have a considerable impact on corporate policies (e.g., Graham and Narasimhan (2004), Hartzell, Ofek, and Yermack (2004), Harford and Li (2007), Schoar (2007), Malmendier and Tate (2005), (2008), Xuan (2009), Malmendier, Tate, and Yan (2011), Gormley and Matsa (2016), and Pan, Siegel, and Wang (2020)), our findings indicate that the preference of *rank-and-file employees* can also significantly influence corporate financial policies such as capital structure decisions, suggesting a non-trivial interaction between labor market dynamics and capital market outcomes.

II. Data, Sample Selection, and Summary Statistics

A. Data and Sample Selection

We combine data on individual employees' job history and their family members with data on their employers using two unique datasets maintained by the U.S. Census Bureau. The first dataset contains individual worker-level data from the LEHD program, which consists of quarterly worker-specific earnings records that employers submit to the unemployment insurance (UI) offices of their states. These quarterly earnings records, contained in the Employment History File (EHF), are submitted to the LEHD program along with establishment-level datasets collected as part of the Quarterly Census of Employment and Wages (QCEW), which provides information about the employers themselves. Moreover, the Individual Characteristics File (ICF) provides data on worker gender, age, race, and education. Overall, the LEHD data covers over

95% of the employment in the private sector.[11] Our LEHD data covers 26 US states that agree to share their data with our project, which is comparable to the number of states available to other non-Census researchers.[12]

The second dataset is the Longitudinal Business Database (LBD), which reports the name, address, number of employees, and total payroll for each business establishment in the U.S. as well as the identifier of the firm to which this establishment belongs. This dataset is updated annually. To link the Census datasets to Compustat records, we first improve and update the Compustat-SSEL bridge file provided by the Census to link LBD firms to Compustat. We then use the Business Register Bridge (BRB), another internal link file from the Census, to match the LBD establishments to the LEHD by EIN, state, and county.

After linking the two Census datasets to Compustat, we drop heavily regulated industries, i.e., financial firms (SIC codes 6000 to 6999), utilities (SIC codes 4900 to 4999), and the public administration sector (SIC codes 9100 to 9729). We also restrict the sample to employees between the age of 25 and 64 and those with at most five jobs in one year.[13] In addition, we

[11] The LEHD has two advantages relative to survey-based data. First, the administrative nature ensures that the LEHD data is less subject to the usual self-reporting bias or measurement errors. Second, the LEHD data includes all forms of monetary compensation, including gross wages and salaries, bonuses, stock options, tips and other gratuities, and meals and lodging. For a full description of the LEHD data, see Abowd, Stephens, Vilhuber, Andersson, McKinney, Roemer, and Woodcock (2009).

[12] The 26 LEHD states in our data are Arizona, California, Colorado, Delaware, Georgia, Hawaii, Idaho, Illinois, Indiana, Louisiana, Maryland, Maine, New Jersey, New Mexico, Nevada, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, Tennessee, Texas, Utah, Vermont, Washington, and Wisconsin.

[13] The cases falling outside these ranges are likely to be part-time workers or caused by incorrect assignment of social security numbers (and thus incorrect PIKs) to immigrants in state employment records.

require a sample firm to have at least 90 percent of its workforce (either by the number of employees or by total payroll in LBD) covered by its establishments in our 26 LEHD states.[14] This filter ensures that the LEHD employees used to calculate a sample firm's characteristics such as family income diversification are representative of all employees in that firm. Our financial information comes from Compustat. Our final sample includes about 10,500 firm-years, covering approximately 2,800 unique firms between 2000 and 2008.[15]

B. Variable Constructions

In order to measure employee family labor income diversification, we first calculate a person's annual household income by aggregating her and her household members' quarterly incomes in LEHD over the four quarters in a year. Next, to calculate the *FamilyDiverse* measure for firm i in year t, we calculate, for each employee of firm i, one minus the fraction of her household labor income that comes from her focal income at firm i in year t, and then average it across all employees of firm i.[16] Higher values of this measure indicate greater labor income diversification and in turn higher employee job risk tolerance, because everything else equal, employees with more labor income from their family members may be more tolerant to risky

[14] Our results remain qualitatively similar if we use cutoffs of 100%, 75%, or 50%.

[15] The numbers of observations for our sample are all rounded according to the disclosure requirements of the U.S. Census Bureau. For example, we round a number to the nearest hundred if it is between 1,000 and 10,000.

[16] To identify a person's self-employment income that is not covered by the LEHD, we use the Integrated Longitudinal Business Database (ILBD), which records the income of self-employed proprietors that do not hire other employees. We also take into account the situation where family members from a household work for the same firm by assigning the summation of their *focal incomes* in the firm to each member as the new focal income to calculate *FamilyDiverse*.

financial strategies by their employers (e.g., higher leverage).[17]

Following the literature, we examine two widely adopted measures for financial leverage. The first one is market leverage (*MktLev*), which is calculated as a firm's total debt (the sum of current liabilities and long-term debt) divided by the sum of its total debt and the market value of its equity. The second one is book leverage (*BookLev*), which is calculated as a firm's total debt divided by its total assets.

We control for a vector of variables commonly found in studies on capital structure (e.g., Rajan and Zingales (1995) and Lemmon, Roberts, and Zender (2008)), which include firm size (the natural logarithm of total assets), growth opportunities (Tobin's Q), return on total assets (*ROA*), firm age, and asset tangibility (net property, plant, and equipment scaled by total assets). Following recent work on labor and financial leverage (e.g., Matsa (2010) and Agrawal and Matsa (2013)), we also include the modified Altman's Z-score to control for a firm's probability of bankruptcy. Finally, we control for the average employee characteristics for a firm including the average wage, average employee age, average years of education, average family labor income, as well as the fractions of male employees, white employees, and married employees.[18] To ensure that outliers do not drive our results, all the continuous variables are winsorized at

[17] Since there is a large literature on managerial risk preference and corporate decisions, we exclude top-five managers (top-five highest paid employees) when constructing the employee family income diversification measures to distinguish between the risk preferences of rank-and-file employees and those of top executives. All our results hold if we include the top-five highest paid employees into the calculation of firm-level family income diversification.

[18] We define an employee to be married if her household has more than one member (with or without labor income).

their 1st and 99th percentiles. Appendix A provides detailed explanations of all the above variables.

C. Summary Statistics

Panel A of Table 1 reports the summary statistics. *FamilyDiverse* has a mean of 37.5%, suggesting that focal income accounts for the majority of an average employee's total family labor income.[19] While the average market leverage for sample firms is 15.9%, the average book leverage is 21.8%. On average, firms have log book assets (in millions of 2000 dollars) of 4.17, Tobin's Q of 2.95, log age (in years) of 2.4, ROA of -0.15, and PPE to assets ratio of 21%. Compared to the Compustat universe, our sample firms have a smaller asset base, slightly higher Tobin's Q, and lower ROA. They have broadly similar leverage ratios, firm age, and PPE-to-assets ratios to those of an average Compustat firm.

[Insert Table 1 here]

In terms of employee characteristics, the log mean wage (in thousands of 2000 dollars) is 4.18, the log number of years of education is 2.63, about 66.2% of them are white, on average about 62.2% of the sample firms' employees are male, about 76.7% of the sample firms' employees are married, and the log mean family labor income (in thousands of 2000 dollars) is 4.62. We also compare the average demographic characteristics of employees with and without working family members. As can be seen in Panel B of Table 1, the two groups have similar characteristics.

[Insert Figure 1 here]

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[19] While the Census does not allow us to disclose percentiles of variables, in untabulated analysis, we examine such statistics for *FamilyDiverse* and find that it follows an approximately normal distribution.

To understand the time trend of employee family income diversification, we plot in Figure 1 the annual average of the firm-level *FamilyDiverse* measure for 2000-2008. As can be seen, *FamilyDiverse* varies with economic conditions and shows an overall declining trend. To validate our *FamilyDiverse* measure, we obtain public data on family-level employment from the Bureau of Labor Statistics and calculate the ratio of the number of U.S. families that have two working members to the number of families with either one or two working members for each year in our sample period. Figure 1 shows a high correlation between the time trend of this ratio and that of the *FamilyDiverse* measure, suggesting that *FamilyDiverse* effectively captures family-level labor income diversification in our sample period.

III. Baseline Empirical Analysis

A. Relation between Financial Leverage and Employee Family Income Diversification

To test the clientele effect of corporate leverage with respect to employees, we run the following OLS regression:

(1) $Leverage_{i,t} = \alpha + \beta FamilyDiverse_{i,t} + \gamma FirmControls_{i,t} + \lambda EmployeeControls_{i,t} + Fixed\ Effects + \varepsilon_{i,t},$

where the dependent variable is either the market leverage or the book leverage of firm *i* in year *t*. The key independent variable, *FamilyDiverse*, is the firm-level employee family labor income diversification measure. $FirmControls_{i,t}$ is a vector of time-varying firm characteristics, and $EmployeeControls_{i,t}$ is a vector of control variables for average employee characteristics. We also include industry×year fixed effects (at the two-digit SIC level) and state×year fixed effects (based on headquarters states). The heteroskedasticity-robust standard errors are clustered at the firm level.

[Insert Table 2 here]

Table 2 presents the regressions of market leverage (columns 1 and 2) and book leverage (columns 3 and 4). We examine both a parsimonious specification (without any control variables other than fixed effects) and a full specification that controls for firm and employee characteristics. The coefficient estimate of *FamilyDiverse* is significantly positive in all models, consistent with employee labor income diversification being positively associated with firm leverage. The effect is also economically significant. For example, the coefficient of 0.108 in the full specification (column 2) indicates that a one standard deviation increase of *FamilyDiverse* is associated with 1.33 percentage point (=0.108×0.123×100) higher market leverage, or an increase in market leverage by 8.4% relative to its mean. This magnitude is similar to the effect of an increase in state corporate taxes on firm leverage, as documented by Heider and Ljungqvist (2015).[20]

The coefficients on other control variables show that larger firms, more profitable firms, firms with more fixed assets, and firms with higher modified Altman's Z-score have lower leverage, which is consistent with the existing literature (e.g., Titman and Wessels (1988)).[21] Tobin's Q is negatively associated with market leverage likely because market value of equity is in the numerator of Tobin's Q but in the denominator of market leverage. Tobin's Q is positively associated with book leverage, suggesting that firms with greater growth potential takes on more

[20] To the extent that employee innate risk aversion is an omitted variable, the OLS coefficient of *FamilyDiverse* is downwardly biased because innate risk aversion tends to be negatively related to leverage but positively related to family income diversification. After controlling for innate risk aversion, the economic magnitude of the correlation between leverage and *FamilyDiverse* should be larger.

[21] The family wage is significantly negative, but one should be careful when interpreting this coefficient since family wage is used to calculate family income diversification and highly correlated with an employee's own focal firm wage.

debt. Additionally, we find a significantly negative relationship between leverage and average employee wage, implying that the ex-post bargaining effect of leverage (e.g., Matsa (2010) and Michaels, Page, and Whited (2019)) seems to dominate the ex-ante compensation premium effect (e.g., Chemmanur, Cheng, and Zhang (2013)).

B. Robustness Tests

Our results hold across a number of robustness tests.[22] First, we perform several analyses to show that our findings are mainly driven by the variation in the continuous measure of family income diversification rather than the mere difference between multiple-earner and single-earner families. Next, we conduct robustness tests using alternative measures, alternative sample constructions, and alternative model specifications.

1. Single-earner vs. Multiple-earner Families

Employees from single-earner families have zero family income diversification but those from multiple-earner families have positive family income diversification. Hence, we perform several analyses to investigate whether our findings are driven by the variation in the continuous measure of family income diversification or simply the difference between multiple-earner families and single-earner families.

For the first analysis, we construct a dummy variable, *MultiEarner*, defined as the fraction of a firm's employees from families with multiple earners, and zero otherwise. Columns 1 and 2 of Table 3 show that the coefficient of *FamilyDiverse* remains significantly positive after controlling for *MultiEarner*, suggesting that the effect of family income diversification on firm leverage is not driven by the difference between multiple-earner and single-earner families.

[22] Some of these tests are not tabulated due to the disclosure rules of the Census Bureau.

[Insert Table 3 here]

Next, we divide employees from multiple-earner families into two subgroups based on the median of family income diversification. We then construct *HighFDRatio* (*LowFDRatio*) as the number of employees in the top (bottom) group divided by the total number of employees in a firm-year. Columns 3 and 4 of Table 3 report the regressions of firm leverage on these two measures, in which the coefficient of *HighFDRatio* is large and significantly positive, while that of *LowFDRatio* is small and insignificant. The F-tests for the difference between the coefficients of *HighFDRatio* and *LowFDRatio* are significant at the 1% or 5% level.

Finally, we construct a measure, *HighFDMultiEarn*, as the fraction of employees with high family income diversification among those from multiple-earner families (i.e., *HighFDRatio* / (*HighFDRatio* + *LowFDRatio*)). We then repeat the baseline regressions replacing *FamilyDiverse* with *HighFDMultiEarn.* In columns 5 and 6 of Table 3, the coefficient of *HighFDMultiEarn* is significantly positive. Taken together, the results in Table 3 suggest that consistent with the theory of equilibrium matching, our findings are mainly driven by the level of income diversification rather than the difference between single-earner and multiple-earners.

2. Alternative Measures of Family Income Diversification

We further conduct robustness tests using several alternative measures of family income diversification. First, instead of assigning an equal weight to each individual employee, we construct a wage-weighted diversification measure to account for the fact that higher-ranked employees might better perceive their employer's financial risk or exert greater influence on the capital structure decisions. Panel A of Table 4 presents the regressions using the wage-weighted measure, which show that the association between employee labor income diversification and financial leverage continues to be significantly positive, with coefficient estimates slightly larger than those in Table 2.

[Insert Table 4 here]

Second, we examine two modified family income diversification measures that consider the risk levels of income sources. The first modified measure, *FamilyDiverse_VolAdj*, uses industry volatility to capture the risk level of an income source. The second modified measure, *FamilyDiverse_SizeAdj*, uses firm size to capture the risk level of an income source (i.e., incomes from larger employers are assumed to have a lower level of risk). We provide details of these measure constructions in Section B1 of Appendix B. Panel B of Table 4 reports the regressions using these two modified labor income diversification measures. We find that both measures remain significantly positive in the regressions.

Third, we incorporate the industry correlations of an employee's focal income with her family income sources into the labor income diversification measure (see Section B2 of Appendix B for details on constructing this alternative measure). We find that this alternative family labor income diversification measure has a very high correlation with the original measure and that the (untabulated) results of leverage regressions using this alternative measure are almost identical to our baseline results in terms of both magnitudes and statistical significance.

Fourth, we exploit our granular data and control for the associations between an employee's characteristics and her labor income diversification at the individual level. Specifically, we obtain residuals from the individual-level regression of an employee's family labor income diversification on her characteristics, namely, education, race, wage, age, gender, marital status, and family total wage. We then calculate the average residual measure at the firm level (*FamilyDiverse_Residual*). Panel C of Table 4 presents this robustness test, in which the residual diversification measure remains significantly positive.

3. Alternative Fixed Effects

To examine the sensitivity of our results to alternative fixed effects, we include industry×state×year fixed effects into our baseline regressions to control for time-varying characteristics of a given industry in a given state. We also use alternative industry definitions based on three-digit or four-digit SIC codes to construct fixed effects. Additionally, we include firm fixed effects to control for time-invariant firm characteristics. The results in Panel D of Table 4 confirm that our findings remain robust using these alternative fixed effects.

4. Other Robustness Tests

In untabulated analyses, we verify that our results are robust when we (1) examine the alternative sample of full-time rank-and-file employees who work for a firm in all four quarters of a year (i.e., exclude potential part-time/seasonal workers or job hoppers); (2) use an alternative way of constructing our *FamilyDiverse* measure by using the annual average of *quarterly* family income diversification of each employee; (3) examine alternative measures of corporate leverage including net debt ratio (total debt minus cash holdings divided by total assets) and net debt issuance (Frank and Goyal (2003)); and (4) drop firms with zero-leverage to address concerns for nonlinearity.

C. Cross-Sectional Analysis

1. Local Employment Opportunities

When employees have fewer outside options, their risk aversion will matter less for their employers' decisions due to their lower bargaining power. Therefore, we expect the positive relation between firm leverage and employee family labor income diversification to be stronger for firms located in areas with more local employment opportunities.

To test this prediction, we construct two measures for local employment opportunities. The first measure, *HighNLocalEstab*, is a dummy variable that equals one if the number of business establishments operating in the same industry (at the six-digit NAICS level) and the same commuting zone as the focal firm is above the cross-sectional median, and zero otherwise. A larger number of local industry peers indicates more employment opportunities for the focal firm's employees. The second measure, *HighNLocalEmp*, is a dummy variable that equals one if the total number of employees working for the establishments in the same industry and same commuting zone of the focal firm is above the cross-sectional median, and zero otherwise.[23] We then regress firm leverage on the interaction between *FamilyDiverse* and each measure. In Panel A of Table 5, the interaction terms are significantly positive in all regression models, suggesting that, consistent with our prediction, the employee clientele effect of corporate leverage is more pronounced when workers have more outside employment opportunities.[24]

[Insert Table 5 here]

2. Labor Intensity

[23] For a focal firm with multiple establishments, we calculate the measure for each establishment and then derive a value-weighted mean across all establishments, using the number of employees at each establishment as the weight.

[24] We acknowledge that, in addition to the size of local job market, the financial leverage of local firms might also influence employees' local job opportunities. For example, if local firms have high financial leverage, their job opportunities may not be attractive to risk-averse employees. However, we are unable to accurately measure the financial leverage of local firms, as the vast majority of them are privately held.

Firms using more human capital in their operations would naturally care more about their employees' preferences when making financial decisions because employees of these firms have greater bargaining power against the management. Hence, we expect a stronger employee clientele effect of corporate leverage for more labor-intensive firms.

To test this prediction, we create two proxies for labor intensity following the spirit of Dewenter and Malatesta (2001): total wages over assets and the number of employees over assets.[25] We then regress firm leverage on the interaction between *FamilyDiverse* and *HighWageAsset* (*HighEmpAsset*), a dummy variable that equals one if a firm's total wages over assets (number of employees over assets) is above the cross-sectional median. In Panel B of Table 5, the coefficient of the interaction term is significantly positive in both the regressions of *MktLev* and *BookLev*, which indicates that, consistent with our prediction, the positive correlation between corporate leverage and employee labor income diversification is more pronounced among firms with higher labor intensity.

3. Financial Distress

Employees are more likely to know their employer's capital structure or financial risk when the firm is closer to financial distress because such an undesirable situation is more likely to be covered by media/intermediaries and discussed among employees. As a result, to prevent talented workers from "jumping the sinking ship", the distressed firm has to cater its financial policy more to its employees' risk attitudes. Therefore, the relation between employee income diversification and financial leverage should be more pronounced for firms with higher bankruptcy risk.

[25] Our results are qualitatively similar if we measure labor intensity using total wages or number of employees divided by sales.

To test this prediction, we estimate a firm's probability of default following Bharath and Shumway (2008), and regress firm leverage on the interaction between *FamilyDiverse* and *HighProbD*, a dummy variable that equals one if the firm's probability of default is above the cross-sectional median, and zero otherwise.[26] The results in Panel C of Table 5 show that, consistent with our prediction, the interaction is significantly positive.

D. Exogenous Shock Based on The California Paid Family Leave Legislation

While we focus on testing the equilibrium matching between financial leverage and employee job risk aversion, this section attempts to alleviate the concerns for omitted variable biases in our baseline OLS analysis. Our cross-sectional analyses in the previous section alleviate such concerns because for omitted variables to drive our results, their effects on financial leverage would also need to covary with local employment opportunities, labor intensity, and financial distress in the anticipated directions, which is a high hurdle to overcome. Nevertheless, in this section, we exploit the unique setting of California Paid Family Leave Legislation (CA-PFL) to further investigate the causal effect of family income diversification on financial leverage.

1. Institutional Background

In 1993, the Family and Medical Leave Act (FMLA) came into place, which guaranteed up to 12 weeks of *unpaid* leave for qualified employees at eligible firms following the birth or adoption of a child. However, due to its stringent requirement on firm size and employee work history, FMLA had a limited coverage of the population of US workers, especially those in the private sector. California became the first state in the United States to implement a paid family

[26] Our results continue to hold if we use accounting measures of bankruptcy risk such as the Altman's Z-score.

leave program in 2004. The California Paid Family Leave Legislation (CA-PFL) enables qualified employees to take a maximum 6-week leave to care for newborn babies or adopted children while receiving 55 percent of the pay.[27] CA-PFL is financed through payroll taxes levied on all the employees in California and collected by the California State Disability Insurance Program.

CA-PFL provides a unique setting for our analysis. On the one hand, it affects family labor income diversification through two possible channels. First, CA-PFL can increase male workers' family labor income diversification during the years when their working spouses give births. Second and more importantly, as documented by the existing literature, CA-PFL can increase the labor market participation by non-working females in single-earner (usually male-led) families.[28] On the other hand, an employee's paid leave is treated similarly as disability, and funded by the California State's tax revenues rather than her employer, so it does not directly affect the employer's tax expenses, cash flows, or other fundamentals.[29] Hence, we expect that CA-PFL led to an exogenous increase in family labor income diversification for Californian

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[27] The maximum amount was $728 per week in 2004, which gradually increased to $1,104 per week in 2015.

[28] Prior literature has found that CA-PFL had a sudden and substantial economic impact on female labor market participants, especially female employees. Rossin-Slater, Ruhm, and Waldfogel (2013) provide evidence that CA-PFL significantly increased both weekly work hours and wages of employed mothers with 1- to 3-year-old children. Baum and Ruhm (2016) further show that CA-PFL led to greater employment probabilities and higher work hours and wages for female workers. Byker (2016) finds that CA-PFL increased labor force attachment of women who otherwise would have exited the labor market after their childbirths.

[29] Previous studies (e.g., Bedard and Rossin-Slater (2016)) find no evidence that firms with higher rates of leave-taking exhibit higher wage costs or employee turnover. CA-PFL does not affect the tax expenses of Californian firms either since the corporate tax rate of California did not increase around 2004.

firms, which allows us to examine the causal effect of a firm's employee labor income diversification on its capital structure.

2. Triple Difference-in-differences Analysis

We acknowledge that the CA-PFL setting can be affected by confounding events or the differences in fundamentals between Californian and non-Californian firms. To address this concern, we exploit the heterogeneous treatment effect of CA-PFL across firms whose employee family income diversification, rather than other characteristics, is differentially exposed to the policy shock. Specifically, we expect the treatment effect to be stronger among firms with more male workers in fertile age because such employees' spouses are more likely to benefit from CA-PFL and thus be willing to take on additional jobs. We therefore conduct a triple DiD analysis based on the fraction of a firm's employees who are fertile-age males (i.e., male workers with age between 25 and 45), which specifically captures its exposure to CA-PFL through the family income diversification channel.[30]

Specifically, we estimate the following regression:

$$(2)\quad Leverage_{i,t} = \alpha + \beta_1 Californian_i \times Post_t \times HighFertileMale_i + \beta_2 Californian_i \times Post_t + \beta_3 Californian_i \times HighFertileMale_i + \beta_4 Post_t \times HighFertileMale_i + \beta_5 Californian_i + \beta_6 HighFertileMale_i + \gamma FirmControls_{i,t} + \lambda EmployeeControls_{i,t} + Fixed\ Effects + \varepsilon_{i,t},$$

where the dependent variable is one of the two leverage measures of firm *i* in year *t*. The key independent variable is the triple interaction of *Californian*, *Post*, and *HighFertileMale*. *Californian* is a dummy variable that equals one if a firm is headquartered in California during

[30] The fraction of fertile-age male employees follows an approximately normal distribution with a reasonably-valued (unreported) mean and standard deviation.

the pre-event period (i.e., 2000-2003) and zero otherwise.[31] *Post* is a dummy variable that equals one for the post-event period (i.e., 2005 to 2008) and zero for the pre-event period. *HighFertileMale* is a dummy variable that equals one if a firm's average fraction of fertile-age male employees in the pre-event period is above the sample median and zero otherwise. We include the same controls and fixed effects as in our baseline regression (Table 2). Following the previous literature that uses state-level legal changes as identification strategies (e.g., Heider and Ljungqvist (2015), Agrawal and Matsa (2013), and Serfling (2015)), we cluster standard errors by the headquarters state.

Panel A of Table 6 shows that the triple interaction between *Californian*, *Post*, and *HighFertileMale* is significantly positive for both *MktLev* and *BookLev*, whereas *Californian*×*Post* is insignificant. These results indicate that, consistent with our prediction, Californian firms increase their leverage to a greater extent than other firms after the implementation of CA-PFL, and this significant treatment effect concentrates in firms with a high fraction of fertile-age male employees. According to the estimates in column 1, for firms with a high fraction of fertile-age male employees, those in California have a 2.2 (= (0.038-0.016) × 100) percentage point higher increase in market leverage after the implementation of CA-PFL than those not in California, which is approximately 10% of the standard deviation of market leverage in this sample of firms. By contrast, the treatment effect of CA-PFL on market leverage for firms with a low fraction of fertile-age male employees is negative and insignificant.

[31] Ideally, we would like to use firms with all employees working in California. However, the U.S. Census Bureau does not allow the disclosure of test results involving workers from a single state. We find that approximately 80% of the employees of our CA-headquartered sample firms actually work in California, which alleviates the concern for using headquarters to define our treatment group.

In all, these results lend support to the hypothesis that an exogenous increase in the legal protection for paid family leave can encourage female participation in the labor force and increase a firm's employee family income diversification, which in turn allows the firm to take on more debt.[32]

[Insert Table 6 here]

Next, we conduct several tests to check the key premises of our triple-DiD setting. First, we examine whether the implementation of CA-PFL indeed causes a sizable increase in employee family labor income diversification (i.e., our hypothesized channel through which the CA-PFL affects corporate leverage). To this end, we estimate regressions similar to that of equation (2) but replace the dependent variable with *FamilyDiverse*. In Panel B of Table 6, column 1 shows that the coefficient of *Californian*×*Post*×*HighFertileMale* is significantly positive, indicating that the implementation of CA-PFL increases the employee family labor income diversification of Californian (i.e., treated) firms significantly more when they have a high fraction of fertile-age males than when they have a low fraction of such workers.[33] In untabulated analysis, we also conduct a robustness test by examining firms' employee family income diversification constructed solely based on their Californian employees and find similar results (with considerably larger magnitudes).

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[32] *Californian*×*Post* and *Californian* are not absorbed by the state×year fixed effects since *Californian* is defined by a firm's headquarters in the pre-event period, which may change during the post-event period. We find similar results when defining *Californian* by a firm's headquarters location in each year.

[33] The effect is also economically sizable: For firms with a high fraction of fertile-age male employees, those in California have a 4.4 (=(0.011+0.033)×100) percentage-point higher increase in employee family income diversification after the implementation of CA-PFL than those not in California, which is approximately 43.6% of the standard deviation of *FamilyDiverse* in our sample.

An alternative explanation for our finding is that CA-PFL might decrease Californian firms' labor costs due to an increased supply of female labor, which in turn allows such firms to take on more debt because of lowered operating leverage or improved financial condition. This concern is largely alleviated by our triple-DiD framework, as it is unclear why the effect of CA-PFL through these alternative mechanisms should systematically vary with a firm's fraction of fertile-age male workers. Nevertheless, we directly examine this alternative explanation by conducting a placebo test. Specifically, we estimate regressions similar to that of equation (2) but replace the dependent variable with the natural logarithm of a firm's average wage (*LnWage*), wage growth (*ChgLnWage*), or operating leverage (*OpLev*). Columns 2 to 4 of Table 6 Panel B show that the coefficient of the triple interaction is small and insignificant in all three models, indicating that our findings are unlikely to be driven by changes in these alternative labor-related outcomes.

Second, we conduct a dynamic triple DiD analysis to examine the parallel trends assumption. Specifically, we decompose the triple interaction term in equation (2) into eight components for each year during our sample period. Panel A of Table 7 shows that the yearly triple interaction terms are insignificant in the pre-event period but significantly positive in the post-event period, suggesting that our findings are not driven by any trends in the pre-event period.

[Insert Table 7 here]

Third, we perform a placebo test to further examine the parallel trends assumption. Specifically, we conduct the triple-difference analysis using a pseudo-event dummy (*SPost*) rather than the actual post event dummy (*Post*). *SPost* is a dummy variable that equals one for the pseudo-post-event period (i.e., 2002 to 2003) and zero for the pseudo-pre-event period (i.e., 2000 to 2001). Panel B of Table 7 shows that the new triple interaction term in the placebo test is small and statistically insignificant. This result again shows that there are no observable diverging trends in corporate leverage between treatment and control firms before the policy shock.

Fourth, we perform a robustness test by refining the definition of a firm's exposure to the CA-PFL shock based on its employee characteristics. Given that CA-PFL primarily affects households of married males, we define *HighMarriedFertileMale* as a dummy variable that equals one if a firm's average fraction of married fertile-age male employees (with age between 25 and 50) in the pre-event period is above the sample median and zero otherwise. As shown in columns 1 and 3 of Table 7 Panel C, the baseline CA-PFL analysis is robust to this alternative definition of exposed firms.

Finally, to control for time-invariant firm characteristics that might affect the results, we include firm fixed effects in addition to industry×year and state×year fixed effects in the CA-PFL analysis. As shown in columns 2 and 4 of Table 7 Panel C, our results are robust to the inclusion of firm fixed effects.[34]

IV. Analysis of New Hires

Berk et al. (2010) propose a self-reinforcing dynamic equilibrium, where risk-averse employees push for lower leverage, and in the meantime firms with lower leverage attract more risk-averse employees. In this section, we use both an OLS analysis and a triple-difference approach to examine whether lower-leverage firms indeed attract and hire more employees with

[34] While we increase the upper bound of fertile age from 45 to 50 when conducting the above two robustness tests to comply with the Census Bureau's disclosure requirements, all our results hold if we define fertile age to be between 25 and 45.

higher job risk aversion.

A. Corporate Leverage and New Hires: OLS Analysis

We first estimate the following OLS regression:

(3) $NewHireFamilyDiverse_{i,t} = \alpha + \beta\, Leverage_{i,t} + \gamma FirmControl_{i,t} + \lambda EmployeeControls_{i,t} + \delta NewHireControls_{i,t} + \varepsilon_{i,t}$,

where the dependent variable is *NewHireFamilyDiverse,* defined similarly as *FamilyDiverse* in the previous sections but calculated using the sample of newly hired employees. We define an employee to be a new hire in year *t* if she receives labor income from firm *i* in year *t* but not in year *t-1*. Furthermore, to ensure that this employee is not a part-time or seasonal worker, we also require that she must receive wages from firm *i* in all four quarters in year *t+1*. We include the same controls and fixed effects as in the baseline analysis (Table 2). To better control for the characteristics of the *new hires*, we further include in equation (4) $NewHireControls_{i,t}$, the *new hires*' characteristics (i.e., age, race, gender, education, wage, marital status, and family wage).[35]

Table 8 presents the regression results, where columns 1 and 3 control for firm and average employee characteristics, while columns 2 and 4 further control for the characteristics of new hires. The coefficient of *Leverage* is significantly positive in all models, suggesting that firms with a higher existing level of leverage hire new employees who are more risk tolerant. These results provide supporting evidence of the self-reinforcing equilibrium modeled in Berk et al. (2010).

[Insert Table 8 here]

[35] Both *NewHireFamilyDiverse* and *NewHireControls* are constructed using information from year *t+1* since it is the first year that newly hired employees receive full-year wages from their employers.

B. Corporate Leverage and New Hires: SFAS 123(r) Rule Change

To take a step further for causal inference, we exploit an exogenous shock to firms' financial leverage, namely, the SFAS 123(r) rule change (Lian and Ma, 2021). SFAS 123(r), issued by the Financial Accounting Standard Board (FASB) in 2004 and implemented in 2006, requires US public firms to include option compensation expenses in their reported operating expenses. As a result, firms with higher option compensation expenses would experience a larger decrease in their *reported* earnings before interest, taxes, depreciation, and amortization (EBITDA) after this rule change. Lian and Ma (2021) find that, in the presence of earnings-based borrowing constraints (EBCs), a decrease in firms' reported EBITDA would tighten these constraints and reduce firms' debt usage.[36] More importantly, this reduction in debt is likely to be exogenous to firm fundamentals since SFAS 123(r) is an accounting rule change that does not directly affect firms' cash flows or operations.

Following Lian and Ma (2021), we obtain the data of corporate loans and loan covenants from DealScan, the data of corporate bonds and bond covenants from Fixed Income Securities Database (FISD), and the data of option compensation expenses from Compustat.[37] We then estimate the following triple DiD regression:

(4) $NewHireFamilyDiverse_{i,t+1} = \alpha + \beta_1 HighXOPT_i \times EBC_i \times Post2006_t + \beta_2 HighXOPT_i \times EBC_i + \beta_3 HighXOPT_i \times Post2006_t + \beta_4 EBC_i \times Post2006_t + \beta_5 HighXOPT_i + \beta_6 EBC_i + \gamma FirmControls_{i,t} + \lambda EmployeeControls_{i,t} + \delta NewHireControls_{i,t} + Fixed\ Effects + \varepsilon_{i,t}$,

where $NewHireFamilyDiverse_{i,t+1}$ is new hires' family labor income diversification in year $t+1$

[36] EBCs, typically in the form of loan or bond covenants, restrict the total debt level of a firm such as requiring the firm's total debt not to exceed a multiple of reported EBITDA. See Lian and Ma (2021) for a detailed discussion.

[37] We merge the DealScan data to Compustat using the linking table provided by Chava and Roberts (2008).

when they join firm *i* in year *t*. *HighXOPT* is a dummy variable that equals one if a firm's average option compensation expenses scaled by lagged total assets in the pre-event period (i.e., years 2002 to 2004) is above the sample median, and zero otherwise. *EBC* is a dummy variable that equals one if a firm has earnings-based constraints in the pre-event period, and zero otherwise. *Post2006* is a dummy variable that equals one for the post-event period (i.e., years 2006 to 2008), and zero for the pre-event period.[38] We include the controls of firm characteristics, employee/new-hire characteristics, and fixed effects as before. Following Lian and Ma (2021), we cluster standard errors at the two-digit SIC industry level.

[Insert Table 9 here]

Panel A of Table 9 shows that the coefficient of *HighXOPT×EBC×Post2006* is significantly negative, indicating that firms subject to EBCs hire new employees with lower family labor income diversification than those without EBCs after the SFAS 123(r) rule change, and this effect is significantly stronger among firms with higher pre-existing option compensation expenses. For firms with high option expenses, those with EBCs hire new employees with a 0.7 (= (0.035-0.028) × 100) percentage point larger decrease in family income diversification after the SFAS 123(r) rule change than those without EBCs, which is approximately 6% of the standard deviation of *NewHireFamilyDiverse* in this sample of firms.

We conduct several additional tests to strengthen the interpretation of our results. First, we verify the impact of SFAS 123(r) on corporate leverage by estimating a regression similar to that of equation (4) but replace *NewHireFamilyDiverse* with *Leverage*. As shown by columns 1 and 2 in Panel B of Table 9, the coefficient of *HighXOPT×EBC×Post2006* is significantly

[38] Following Lian and Ma (2021), we exclude the year 2005 since the SFAS 123(r) rule change was announced in 2004 and implemented in 2006.

negative, indicating that both the market leverage and book leverage of firms subjecting to EBCs decrease significantly more after SFAS 123(r) when they have higher pre-existing option compensation expenses, which echoes the findings of Lian and Ma (2021).

Second, the SFAS 123(r) rule change, by tightening firms' financial constraints, might lead to reductions in investments or employee compensation and in turn corporate leverage. To address this concern, we run regressions similar to equation (4) but replace leverage with the following variables: 1) capital expenditures scaled by sales (*CAPX*), 2) research and development expenses scaled by sales (*R&D*), 3) acquisition expenses scaled by sales (*Acq*), 4) the natural logarithm of average employee wage (*LnWage*), and 5) the natural logarithm of average new hires' wage (*NewHireLnWage*). Columns 3 to 7 in Panel B of Table 9 show that none of the coefficients of *HighXOPT×EBC×Post2006* is significant, suggesting that the SFAS 123(r) rule change does not materially affect firm investment or worker compensation.

Third, similar to our CA-PFL analysis, we conduct several robustness tests for the analysis based on the SFAS 123(r) rule change. The first is a dynamic triple DiD test for each year in our sample period. Panel A of Table 10 shows that the triple interaction terms are either insignificant or marginally *positive* in the pre-event years, while significantly negative in most of the post-event years. The second analysis is a placebo test similar to that for the CA-PFL analysis (Panel B of Table 7), where we perform the triple DiD analysis around a pseudo-event year (i.e., 2002) instead of the actual event year of 2005. Panel B of Table 10 shows that the triple interaction term involving the pseudo-event dummy is not significant. These results indicate that the parallel trends assumption likely holds for this setting. Finally, we include firm fixed effects in addition to industry×year and state×year fixed effects in the analysis. As reported in Panel C of Table 10, the SFAS 123(r) analysis is robust to the inclusion of firm fixed effects.

[Insert Table 10 here]

V. Family Income Diversification after Large Changes in Leverage: Individual Employee-Level Analyses

To complement our firm-level analyses, we exploit our granular data to conduct individual employee-level analyses on the interplay between employee family income diversification and firm leverage. Specifically, we investigate the impact of a large change in corporate leverage on a firm's workforce composition and its employees' family income diversification.

Under the hypothesis of equilibrium matching, we expect that a significant increase (decrease) in a firm's leverage will make it more (less) attractive to risk-tolerant job seekers, thereby resulting in *higher* (*lower*) family income diversification of newly hired employees. Conversely, such an increase (decrease) in firm leverage may make the firm less (more) attractive to current employees who are more risk averse, leading to *lower* (*higher*) family labor income diversification among newly departed employees ("leavers"). This is because risk-averse (risk-tolerant), i.e., less (more) diversified employees tend to leave the firm when leverage increases (decreases) substantially. Finally, the family labor income diversification of those employees who remain with the firm ("stayers") is expected to increase (decrease) due to the heightened (reduced) risk associated with their employer, which incentivizes them to diversify (concentrate) their family labor income to mitigate the increased (take advantage of the decreased) unemployment risk.

We present the corresponding regression results in Table 11. Column 1 of Panel A presents the regression analysis for new hires, where the dependent variable is new hires' adjusted family income diversification in year t+1.[39] The key explanatory variable, *ChgMktLev*, is an indicator of large changes in firms' market leverage. This variable quals one if the change in market leverage from year t-1 to year t exceeds the sample 90th percentile, negative one if the change is below the sample 10th percentile, and zero otherwise. We find that the coefficient of *ChgMktLev* is significantly positive, indicating a positive association between large changes in leverage and the family labor income diversification for new hires.

[Insert Table 11 here]

Column 2 of Panel A present a similar analysis for leavers, where the dependent variable is the leaver's adjusted family income diversification in t-1.[40] The coefficient of *ChgMktLev* is significantly negative, suggesting a negative association between large changes in leverage and leavers' *ex-ante* family income diversification. Column 3 of Panel A presents the regression of the *changes* in family income diversification for stayers from year t to t+1 to examine their household labor allocation responses to large changes in leverage.[41] We find a positive association between large changes in firm leverage and stayers' changes in family income diversification. Therefore, the results in Panel A are consistent with our predictions regarding the varying effects of a significant change in leverage on different types of employees. For robustness, we report the regressions using large changes in book leverage (rather than market

[39] We adjust a new hire's family income diversification by subtracting from it the firm's time-series average employee family income diversification. The purpose of this adjustment is to focus on the "abnormal" family income diversification of a new hire when her employer has a large change in leverage compared to that in normal times.

[40] An employee is defined as a leaver in year t if she receives labor income from her employer in t but not t+1. Similarly, she must receive income from the firm in all four quarters of *t-1*.

[41] An employee is defined as a stayer if she receives income from her employer in all quarters of t and t+1.

leverage) and find similar results in Panel B of Table 11.[42]

VI. Broader Implication: Corporate Risk-Taking

While the theory of equilibrium matching focuses on corporate leverage as a specific form of financial risk-taking, the underlying mechanism is that firms consider human costs of bankruptcy when making various risk-taking decisions. Therefore, this logic can be applied to a wide range of risk-taking behaviors beyond the usage of debt. In this subsection, we explore whether employee job risk tolerance is associated with firms' risk-taking in a broader sense, which can shed further light on the implication of equilibrium matching for corporate policies.

We estimate regressions similar to that specified by equation (1) but replace *Leverage* with one of the following risk-taking measures: 1) ROA volatility (*ROAvol*), 2) ROIC (return on invested capital) volatility (*ROICvol*), 3) stock return volatility (*RetVol*), 4) idiosyncratic stock return volatility (*IdioVol*), and 5) probability of default (*ProbD*). The regression results in Table 12 show that, consistent with our prediction, *FamilyDiverse* is positively and significantly (at the 1% level) associated with all the dependent variables. The economic magnitudes are also non-trivial. For example, a one standard-deviation increase in *FamilyDiverse* is associated with a 9.4% standard-deviation increase in *ROAvol* and a 4.3% standard-deviation increase in *ROICvol*. These results not only support the underlying mechanism of equilibrium matching, but also show

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[42] In untabulated analysis, we also examine the interactive effect of firm leverage and family labor income diversification on employee wages at the individual level. Consistent with the equilibrium matching hypothesis, we find that after a firm's significant increase (decrease) in corporate leverage, it will offer a higher (lower) salary to risk-averse new hires (i.e., those with less diversified family income) in response to the increased (decreased) human bankruptcy costs.

that employee job risk tolerance matters for firms' overall risk levels captured by performance volatility or default probability.[43]

[Insert Table 12 here]

VII. Conclusion

Using the Longitudinal Employer-Household Dynamics (LEHD) data from the U.S. Census Bureau, we offer direct evidence on the "employee clientele" of corporate leverage as predicted by theories. Consistent with the clientele effect, we find that a firm has lower financial leverage when its employees are more risk-averse towards their jobs due to a lack of family income diversification. This relation is more pronounced for firms with more local employment opportunities, higher labor intensity, and higher bankruptcy risk. Further, we find that firms with lower leverage recruit new employees with lower family income diversification. To address concerns for omitted variables, we exploit the quasi-natural experiments of the California Paid Family Leave Legislation and the SFAS 123(r) rule change.

Leveraging our granular employee-level data, we also investigate the reactions of different subgroups of employees (i.e., new hires, leavers, stayers) to significant shifts in their firms' leverage and find evidence supporting the notion that employees take human bankruptcy risk into account when making their own career choices and intra-household labor allocation decisions. Furthermore, we find that firms with higher employee family income diversification also engage in riskier activities as evidenced by their higher performance volatility and probability of default, suggesting that the impact of human bankruptcy costs on corporate risk-

[43] We also find that the equilibrium matching between employee job risk aversion and debt usage could contribute to the well-known puzzle of persistent leverage (Lemmon et al. (2008)), and present the analysis in Appendix C for brevity.

taking may go beyond financial leverage.

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Figure 1: Time Trends of Family Labor Income Diversification

This figure plots the time trends of average *FamilyDiverse* based on the sample of U.S. listed firms that are covered by the Longitudinal Employer-Household Dynamics (LEHD) program from 2000 to 2008. It also plots the percentage of double-income families based on the public data on family level employment from the Bureau of Labor Statistics on the right vertical axis. The percentage is calculated as the ratio of the number of U.S. families that have two working members to the number of the families with either one or two working members. Definitions of variables are in Appendix A.

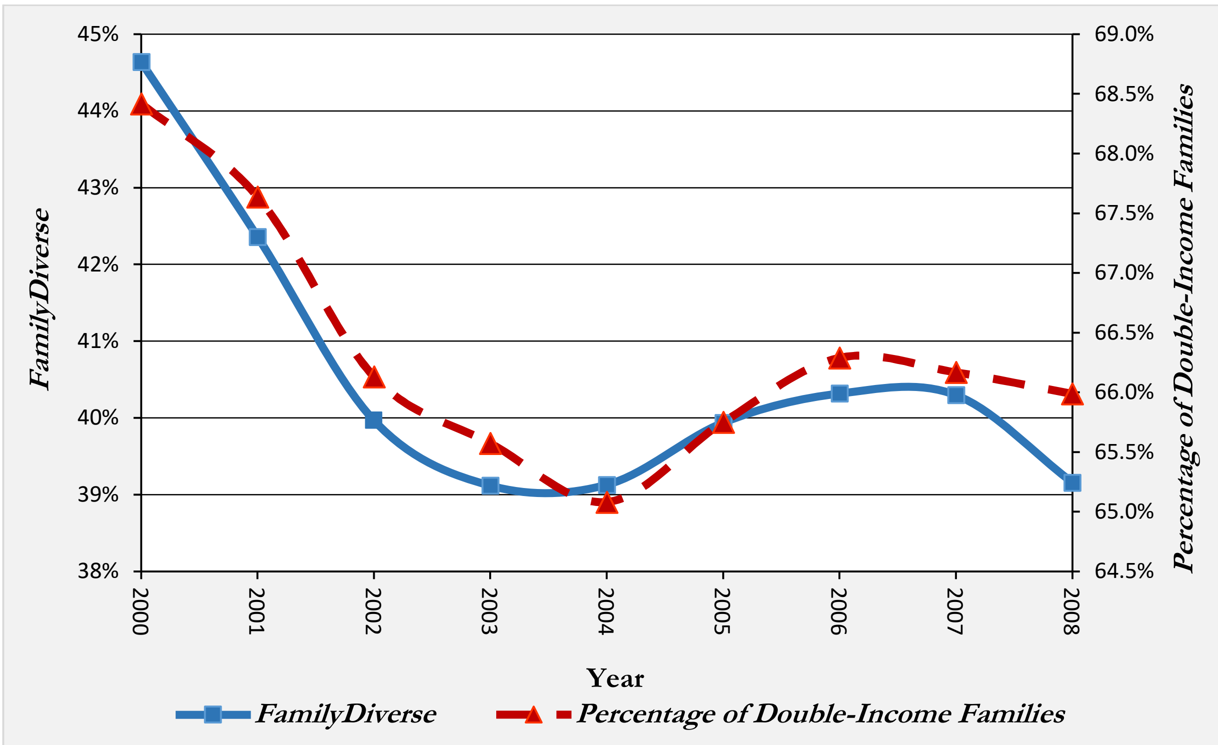

Table 1: Summary Statistics

Panel A reports the summary statistics for variables constructed based on the sample of U.S. listed firms that are covered by the Longitudinal Employer-Household Dynamics (LEHD) program from 2000 to 2008. The numbers are rounded according to the disclosure requirements of the U.S. Census Bureau. Panel B reports univariate results to compare the mean demographic characteristics of employees with working family members (i.e., from multi-earner families) and those without (i.e., from single-earner families). *Family* is a dummy variable that equals one if an employee has other working family members, and zero if her family does not have other labor income. All the other variables are defined in Appendix A. The last column reports the t-statistics for a two-sample T-test to compare the means in columns 1 and 2. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Summary Statistics for Firm Characteristics

Variable	Mean	S.D.	Firm-Years
FamilyDiverse	0.375	0.123	10,500
MktLev	0.159	0.232	10,500
BookLev	0.218	0.349	10,500
LnAsset	4.169	1.999	10,500
ROA	-0.146	0.516	10,500
PPEAsset	0.210	0.221	10,500
TobinQ	2.951	3.272	10,500
AZModified	-3.134	10.390	10,500
LnAge	2.398	0.682	10,500
LnEducation	2.628	0.047	10,500
WhiteRatio	0.662	0.189	10,500
LnWage	4.180	0.579	10,500
LnEmpAge	3.716	0.089	10,500
MaleRatio	0.622	0.156	10,500
MarriedRatio	0.767	0.089	10,500
LnFamilyWage	4.620	0.446	10,500

Panel B: Comparison of Employee Demographics with and without Working Family Members

Variables	*Family=0*	*Family=1*	*Difference*	*T-stat*
	(1)	(2)	(3)	(4)
White	0.694	0.616	0.078	210.5^{***}
Age (in years)	41.950	40.780	1.966	143.2^{***}
Male	0.670	0.602	0.068	180.7^{***}
Education (in years)	13.590	13.540	0.050	23.4^{***}
Observations	2,184,000	5,807,000		

Table 2: Regression of Firm Leverage on Employee Family Labor Income Diversification
This table presents the OLS regressions of firm leverage on employee family labor income diversification. Definitions of the variables are in Appendix A. The key independent variable is *FamilyDiverse*, the average of family income diversification of a firm's employees, calculated as the proportion of an employee's family income that is not accounted for by her income from the firm. Each regression includes industry×year fixed effects (at the two-digit SIC level) and state×year fixed effects. Standard errors are corrected for heteroskedasticity and within-firm clustering. We report t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dep. Var.	***MktLev***		***BookLev***	
	1	2	3	4
FamilyDiverse	0.119***	0.108***	0.362***	0.129**
	(3.64)	(3.21)	(6.42)	(2.43)
LnAsset		0.013***		0.017***
		(4.66)		(4.42)
ROA		0.053***		0.067**
		(4.10)		(2.50)
PPEAsset		0.250***		0.318***
		(8.17)		(6.97)
TobinQ		-0.015***		0.013***
		(-14.84)		(5.19)
AZModified		-0.008***		-0.018***
		(-10.60)		(-11.94)
LnAge		-0.004		0.005
		(-0.64)		(0.53)
LnEducation		-0.132		-0.020
		(-1.40)		(-0.11)
WhiteRatio		0.051**		0.082**
		(2.02)		(2.26)
LnWage		-0.035***		-0.038***
		(-3.91)		(-2.98)
LnEmpAge		0.320***		0.284***
		(6.08)		(3.46)
MaleRatio		0.037		0.030
		(1.22)		(0.69)
MarriedRatio		-0.024		-0.010
		(-0.55)		(-0.13)
LnFamilyWage		-0.046***		-0.070***
		(-4.01)		(-3.94)
Ind×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Observations	10,500	10,500	10,500	10,500
R-squared	0.255	0.378	0.121	0.387

Table 3: Family Characteristics, Family Labor Income Diversification, and Firm Leverage

This table reports the tests on the relationship between employee family characteristics, family labor income diversification, and firm leverage. Columns 1 and 2 report the baseline regressions controlling for the fraction of employees from families with more than one earner (*MultiEarnerRatio*). Columns 3 and 4 report the regressions of firm leverage on *HighFDRatio*, defined as the fraction of a firm's employees who are from multi-earner families and whose family labor income diversification is above the sample median, and on *LowFDRatio*, defined as the fraction of a firm's employees who are from multi-earner families and whose family labor income diversification is below the sample median. In addition, we report the F-statistics and the associated p-values for the difference between the coefficients of *HighFDRatio* and *LowFDRatio*. Columns 5 and 6 report the regressions of firm leverage on *HighFDMultiEarn*, defined as the fraction of a firm's multi-earner-family employees whose family labor income diversification is above the sample median, and on *MultiEarnerRatio*, defined as the fraction of a firm's employees from families with more than one earner. Each regression includes industry ×year fixed effects (at the two-digit SIC level) and state ×year fixed effects. Standard errors are corrected for heteroskedasticity and within-firm clustering. We report t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dep. Var.	***MktLev***	***BookLev***	***MktLev***	***BookLev***	***MktLev***	***BookLev***
	1	2	3	4	5	6
FamilyDiverse	0.100***	0.100***				
	(2.97)	(2.86)				
HighFDRatio			0.210***	0.126*		
			(3.49)	(1.87)		
LowFDRatio			0.072	0.010		
			(1.08)	(0.13)		
HighFDMultiEarn					0.083***	0.073*
					(2.73)	(2.05)
MultiEarnerRatio	0.132**	0.045			0.160***	0.073
	(2.19)	(0.66)			(2.67)	(1.09)
F-statistics			7.388	4.167		
P-value			0.007	0.041		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ind×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,500	10,500	10,500	10,500	10,500	10,500
R-squared	0.380	0.389	0.380	0.344	0.380	0.344

Table 4: Robustness Tests Using Alternative Measures of Family Labor Income Diversification or Alternative Fixed Effects

This table presents the robustness tests using alternative measures of family labor income diversification or alternative fixed effects. Panel A presents robustness tests using *WavgFamilyDiverse*, the wage-weighted mean of a firm's employees' family income diversification. Panel B reports regressions using alternative measures of employee family labor income diversification that account for risk levels of income sources. Panel C reports regressions using residual employee family labor income diversification as the main independent variable, where the residual measure is first obtained from an employee-level regression of an individual's family income diversification measure on her characteristics, and then averaged at the firm level. Each regression in Panels A, B, and C includes industry×year fixed effects (at the two-digit SIC level) and state×year fixed effects. Panel D reports the baseline regressions with alternative fixed effects. Columns 1 and 5 include industry×state×year fixed effects (at the two-digit SIC level). Columns 2 and 6 include industry×year fixed effects (at the three-digit SIC level) and state×year fixed effects. Columns 3 and 7 include industry×year fixed effects (at the four-digit SIC level) and state×year fixed effects. Columns 4 and 8 include firm and year fixed effects. Other regression settings are similar to our baseline regressions in Table 2. Standard errors are corrected for heteroskedasticity and within-firm clustering. We report t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Wage-weighted Family Income Diversification

Dep. Var.	***MktLev***	***BookLev***
	1	2
WavgFamilyDiverse	0.120***	0.132***
	(3.02)	(2.04)
Controls	Yes	Yes
Ind×Year FE	Yes	Yes
State×Year FE	Yes	Yes
Observations	10,500	10,500
R-squared	0.378	0.387

Panel B: Family Income Diversification after Adjusting for Risk Levels of Income Sources

Dep. Var.	***MktLev***	***BookLev***	***MktLev***	***BookLev***
	1	2	3	4
FamilyDiverse_VolAdj	0.092***	0.081**		
	(3.27)	(2.46)		
FamilyDiverse_SizeAdj			0.080**	0.090**
			(2.07)	(2.31)
Controls	Yes	Yes	Yes	Yes
Ind×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Observations	10,500	10,500	10500	10500
R-squared	0.359	0.296	0.359	0.296

Panel C: Residual Employee Family Labor Income Diversification

Dep. Var.	*MktLev*	*BookLev*
	1	2
FamilyDiverse_Residual	0.199***	0.146***
	(4.42)	(3.29)
Firm controls	Yes	Yes
Employee controls	No	No
Ind×Year FE	Yes	Yes
State×Year FE	Yes	Yes
Observations	10,500	10,500
R-squared	0.257	0.379

Panel D: Baseline Regressions with Alternative Fixed Effects

Dep. Var.	*MktLev*				*BookLev*			
	1	2	3	4	5	6	7	8
FamilyDiverse	0.122***	0.095***	0.072**	0.079***	0.137**	0.116**	0.109*	0.100*
	(3.23)	(2.90)	(2.12)	(2.84)	(2.23)	(2.10)	(1.91)	(1.91)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SIC2×State×Year FE	Yes	No	No	No	Yes	No	No	No
SIC3×Year FE	No	Yes	No	No	No	Yes	No	No
SIC4×Year FE	No	No	Yes	No	No	No	Yes	No
State×Year FE	No	Yes	Yes	No	No	Yes	Yes	No
Firm FE	No	No	No	Yes	No	No	No	Yes
Year FE	No	No	No	Yes	No	No	No	Yes
Observations	10,500	10,500	10,500	10,500	10,500	10,500	10,500	10,500
R-squared	0.575	0.475	0.533	0.780	0.536	0.451	0.492	0.759

Table 5: Cross-sectional Analyses Based on Local Employment Opportunities, Labor Intensity, and Distress Risk

This table reports cross-sectional analyses based on local employment opportunities, labor intensity, and financial distress risk. The regression design is similar to our baseline analysis (Table 2). In Panel A, we interact *FamilyDiverse* with two measures of local employment opportunities. *HighNLocalPlant* is a dummy variable that equals one if the number of business establishments operating in the same industry (at the six-digit NAICS level) and the same commuting zone as the focal firm is above the cross-sectional median, and zero otherwise. *HighNLocalEmp* is a dummy variable that equals one if the total number of employees working for the local and same-industry establishments of the focal firm is above the cross-sectional median, and zero otherwise. In Panel B, we interact *FamilyDiverse* with two measures of labor intensity. *HighWageAsset* is a dummy variable that equals one if the ratio of total wages to total book assets of a firm is above the cross-sectional median, and zero otherwise. *HighEmpAsset* is a dummy variable that equals one if the ratio of the number of employees to total book assets of a firm is above the cross-sectional median, and zero otherwise. In Panel C, we interact *FamilyDiverse* with *HighProbD*, a dummy variable that equals one if a firm's probability of default estimated using Bharath and Shumway's (2008) model is above the cross-sectional median, and zero otherwise. Definitions of other variables are in Appendix A. Each regression includes the full set of control variables as in Table 2, industry×year fixed effects (at the two-digit SIC level), and state×year fixed effects. Standard errors are corrected for heteroskedasticity and within-firm clustering. We report t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Cross-sectional Analysis Based on Local Employment Opportunities

Dep. Var.	***MktLev***	***BookLev***	***MktLev***	***BookLev***
	1	2	3	4
FamilyDiverse×HighNLocalEstab	0.092**	0.241**		
	(2.43)	(1.97)		
FamilyDiverse×HighNLocalEmp			0.139**	0.163**
			(2.40)	(2.15)
HighNLocalEstab	-0.024*	-0.094*		
	(-1.67)	(-1.90)		
HighNLocalEmp			-0.050**	-0.068**
			(-2.37)	(-2.31)
FamilyDiverse	0.049**	0.137	0.043	0.044
	(2.09)	(1.35)	(1.14)	(0.73)
Controls	Yes	Yes	Yes	Yes
Ind×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Observations	10,500	10,500	10500	10500
R-squared	0.356	0.304	0.356	0.388

Panel B: Cross-sectional Analysis Based on Labor Intensity

Dep. Var.	***MktLev***	***BookLev***	***MktLev***	***BookLev***
	1	2	3	4
FamilyDiverse×HighWageAsset	0.113**	0.325***		
	(2.41)	(3.84)		
FamilyDiverse×HighEmpAsset			0.094*	0.219***
			(2.20)	(2.63)
HighWageAsset	-0.049***	-0.152***		
	(-2.70)	(-4.74)		
HighEmpAsset			-0.014	-0.047
			(-0.84)	(-1.44)
FamilyDiverse	0.047	-0.012	0.066*	0.058
	(1.25)	(-0.21)	(1.68)	(0.93)
Controls	Yes	Yes	Yes	Yes
Ind×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Observations	10,500	10,500	10,500	10,500
R-squared	0.386	0.387	0.322	0.321

Panel C: Cross-sectional Analysis Based on Distress Risk

Dep. Var.	***MktLev***	***BookLev***
	1	2
FamilyDiverse×HighProbD	0.118***	0.257***
	(2.80)	(3.63)
HighProbD	0.144***	0.128***
	(8.90)	(4.49)
FamilyDiverse	-0.02	-0.093*
	(-0.64)	(-1.89)
Controls	Yes	Yes
Ind×Year FE	Yes	Yes
State×Year FE	Yes	Yes
Observations	10,500	10,500
R-squared	0.499	0.392

Table 6: Triple DiD Estimation Based on the California Paid Family Leave Legislation (CA-PFL)
Panel A presents the triple difference-in-differences (DiD) analysis of CA-PFL on corporate leverage. *Californian* is a dummy variable that equals one if a firm is headquartered in California during the pre-event period (i.e., 2000-2003) and zero otherwise. *Post* is a dummy variable for the post-event period (i.e., 2005 to 2008). *HighFertileMale* is a dummy variable for firms with a high fraction of fertile-age male employees. Panel B presents the triple DiD tests of CA-PFL on family income diversification, wage level, wage growth, and operating leverage. *LnWage* is the natural logarithm of a firm's average employee wage. *ChgLnWage* is the change in *LnWage* from year *t-1* to *t*. *OpLev* is operating leverage, defined as a firm's selling, general, and administrative expenses (SG&A) scaled by lagged total assets. Definitions of other variables are in Appendix A. Each regression includes industry×year fixed effects (at the two-digit SIC level) and state×year fixed effects. Standard errors are adjusted for heteroskedasticity and clustering by headquarters state. We report t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Financial Leverage

Dep. Var.	***MktLev***	***BookLev***
	1	2
Californian×Post×HighFertileMale	0.038**	0.071***
	(2.34)	(2.95)
Californian×Post	-0.016	0.058
	(-0.24)	(0.65)
Californian×HighFertileMale	0.002	0.001
	(0.19)	(0.09)
Post×HighFertileMale	-0.02	-0.036*
	(-1.30)	(-1.72)
Californian	-0.006	-0.02
	(-0.08)	(-0.35)
HighFertileMale	-0.008	-0.01
	(-0.66)	(-0.57)
Controls	Yes	Yes
Ind×Year FE	Yes	Yes
State×Year FE	Yes	Yes
Observations	8,600	8,600
R-squared	0.385	0.394

Panel B: Employee Family Labor Income Diversification, Wage, and Operating Leverage

Dep. Var.	*FamilyDiverse*	*LnWage*	*ChgLnWage*	*OpLev*
	1	2	3	4
Californian×Post×HighFertileMale	0.011**	-0.015	-0.005	-0.023
	(2.17)	(-0.53)	(-0.45)	(-0.41)
Californian ×Post	0.033	-0.036	0.019	0.135
	(0.85)	(-0.39)	(0.35)	(0.74)
Californian ×HighFertileMale	-0.003	-0.012	0.017*	0.045
	(-0.99)	(-0.51)	(1.70)	(0.67)
Post×HighFertileMale	-0.013**	0.058**	-0.005	-0.007
	(-2.21)	(2.48)	(-0.47)	(-0.32)
Californian	-0.002	0.02	0.009	-0.051
	(-0.10)	(0.22)	(0.22)	(-0.48)
HighFertileMale	-0.004	-0.013	0.001	-0.025
	(-0.84)	(-0.60)	(0.09)	(-0.52)
Controls	Yes	Yes	Yes	Yes
Ind×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Observations	8,600	8,600	8,200	7,500
R-squared	0.472	0.724	0.137	0.401

Table 7: Additional Tests for the CA_PFL Analysis

Panel A presents the dynamic triple difference-in-differences (DiD) analysis that examines the effect of the California Paid Family Leave Legislation (CA-PFL) on corporate leverage. *Californian* is a dummy variable that equals one if a firm is headquartered in California during the pre-event period (i.e., 2000-2003) and zero if it is a non-Californian firm. *Year200X* is a dummy variable that equals one for observations in year 200X and zero otherwise. *HighFertileMale* is a dummy variable that equals one if a firm's average fraction of fertile-age male employees in the pre-event period is above the sample median and zero otherwise. The fraction of fertile-age male employees is calculated as the number of male workers with age between 25 and 45 divided by the total number of employees in a firm. *Californian*, *HighFertileMale*, the year dummies, and the double interactions between the variables are included in the regressions but not reported. Panel B presents a placebo test for the effect of CA-PFL on corporate leverage. *SPost* is a dummy variable that equals one for the pseudo-post-event period (i.e., 2002 to 2003) and zero for the pseudo-pre-event period (i.e., 2000 to 2001). Each regression in Panels A and B includes industry ×year fixed effects (at the two-digit SIC level) and state ×year fixed effects. Panel C presents the regressions with alternative definitions of exposed firms and alternative fixed effects. *HighMarriedFertileMale* is a dummy variable that equals one if a firm's average fraction of married fertile-age male employees (with age between 25 and 50) in the pre-event period is above the sample median and zero otherwise. Columns 1 and 3 include industry ×year fixed effects (at the two-digit SIC level) and state ×year fixed effects. Columns 2 and 4 include firm fixed effects in addition to industry ×year fixed effects and state ×year fixed effects. Definitions of other variables are in Appendix A. Standard errors are adjusted for heteroskedasticity and clustering by headquarters state. We report t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Dynamic Triple Difference-in-differences Estimation

Dep. Var.	***MktLev***	***BookLev***
	1	2
Californian×HighFertileMale×Year2000	0.004	-0.005
	(0.22)	(-0.39)
Californian×HighFertileMale×Year2001	-0.005	0.006
	(-0.20)	(0.34)
Californian×HighFertileMale×Year2002	-0.001	0.001
	(-0.05)	(0.03)
Californian×HighFertileMale×Year2003	-0.001	0.008
	(-0.05)	(0.35)
Californian×HighFertileMale×Year2005	0.023	0.040*
	(1.04)	(1.70)
Californian×HighFertileMale×Year2006	0.029	0.054*
	(1.13)	(1.70)
Californian×HighFertileMale×Year2007	0.059**	0.084***
	(2.21)	(3.32)
Californian×HighFertileMale×Year2008	0.042	0.100***
	(1.35)	(3.98)
Controls	Yes	Yes
Ind×Year FE	Yes	Yes
State×Year FE	Yes	Yes
Observations	8,600	8,600
R-squared	0.386	0.37

Panel B: Placebo Test

Dep. Var.	***MktLev***	***BookLev***
	1	2
Californian×SPost×HighFertileMale	0.002	-0.012
	(0.12)	(-0.50)
Californian×SPost	-0.018*	-0.021
	(-1.74)	(-1.57)
Californian×HighFertileMale	0.002	0.011
	(0.14)	(0.77)
SPost×HighFertileMale	-0.01	0.012
	(-0.55)	(0.46)
Californian	-0.008	0.010
	0.002	-0.013
HighFertileMale	-0.003	-0.019
	(-0.18)	(-1.34)
Controls	Yes	Yes
Ind×Year FE	Yes	Yes
State×Year FE	Yes	Yes
Observations	5,100	5,100
R-squared	0.402	0.415

Panel C: Alternative Definitions of Affected Firms and Alternative Fixed Effects

Dep. Var.	***MktLev***		***BookLev***	
	1	2	3	4
Californian×Post×HighMarriedFertileMale	0.053***	0.025*	0.116***	0.095***
	(3.82)	(1.72)	(5.54)	(2.96)
Californian×Post	-0.022	0.056	0.035	0.099
	(-0.31)	(1.25)	(0.38)	(0.81)
Post×HighMarriedFertileMale	-0.023	-0.009	-0.033*	-0.031
	(-1.67)	(-0.92)	(-1.78)	(-0.95)
Californian×HighMarriedFertileMale	-0.020*		-0.062***	
	(-1.88)		(-3.76)	
Californian	0.007		0.016	
	(0.09)		(0.28)	
HighMarriedFertileMale	0.009		0.017	
	(0.66)		(1.02)	
Controls	Yes	Yes	Yes	Yes
Ind×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Observations	8,600	8,600	8,600	8,600
R-squared	0.403	0.830	0.405	0.811

Table 8: Regression of New Hires' Family Income Diversification on Corporate Leverage

This table presents the OLS regressions of new hires' employee family labor income diversification (*NewHireFamilyDiverse*) on corporate leverage. Columns 1 and 3 include firm characteristics and average employee characteristics as control variables. Columns 2 and 4 include average characteristics of new hires in addition to firm and employee characteristics. Each regression includes industry×year fixed effects (at the two-digit SIC level) and state×year fixed effects. Standard errors are corrected for heteroskedasticity and within-firm clustering. We report t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dep. Var.	***NewHireFamilyDiverse***			
	1	2	3	4
MktLev	0.019**	0.016***		
	(2.05)	(2.76)		
BookLev			0.015**	0.009**
			(2.16)	(2.00)
Firm controls	Yes	Yes	Yes	Yes
Employee controls	Yes	Yes	Yes	Yes
New hire controls	No	Yes	No	Yes
Ind×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes
Observations	7,800	7,800	7,800	7,800
R-squared	0.351	0.718	0.351	0.718

Table 9: Triple DiD Estimation Based on the SFAS 123(r) Rule Change

Panel A presents the triple difference-in-differences (DiD) analysis that examines the effect of the SFAS 123(r) rule change on new hires' employee family labor income diversification. *HighXOPT* is a dummy variable that equals one if a firm's average option compensation expenses scaled by lagged total assets in the pre-event period (i.e., years 2002 to 2004) before the issuance of SFAS 123(r) is above the sample median, and zero otherwise. *EBC* is a dummy variable that equals one if a firm has earnings-based constraints during the pre-event period, and zero otherwise. *Post2006* is a dummy variable that equals one for the post-event period (i.e., years 2006 to 2008), and zero for the pre-event period (i.e., years 2002 to 2004). Panel B presents the triple DiD analysis that examines the effect of the SFAS 123(r) rule change on corporate leverage, firm investment, and employee wages. *Capex* is capital expenditures (CAPX) scaled by sales. *R&D* is research and development expenses (XRD) scaled by sales. *Acq* is acquisition expenses (ACQ) scaled by sales. *LnWage* is the natural logarithm of a firm's average annual wage (thousand in 2000 dollars). *NewHireLnWage* is the natural logarithm of the average annual wage (thousand in 2000 dollars) of a firm's newly hired employees. Definitions of the other variables are in Appendix A. Each regression includes firm controls, employee (new hire) controls, industry×year fixed effects (at the two-digit SIC level), and state×year fixed effects. Standard errors are corrected for heteroskedasticity and within-industry clustering. We report t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: New Hires' Family Income Diversification

Dep. Var.	***NewHireFamilyDiverse***
	1
HighXOPT×EBC×Post2006	-0.035***
	(-2.91)
HighXOPT×EBC	0.017**
	(2.19)
HighXOPT×Post2006	0.024*
	(1.96)
EBC×Post2006	0.028***
	(2.82)
HighXOPT	-0.019**
	(-2.64)
EBC	-0.020***
	(-2.79)
Firm controls	Yes
Employee controls	Yes
New hire controls	Yes
Ind×Year FE	Yes
State×Year FE	Yes
Observations	4,500
R-squared	0.690

Panel B: Financial Leverage, Firm Investment, and Employee Wages

Dep. Var.	*MktLev*	*BookLev*	*Capex*	*R&D*	*Acq*	*LnWage*	*NewHireLnWage*
	1	2	3	4	5	6	7
HighXOPT×EBC×Post2006	-0.079***	-0.106***	-0.033	0.149	-0.005	0.025	0.027
	(-2.90)	(-2.77)	(-0.98)	(1.53)	(-1.21)	(0.59)	(0.95)
HighXOPT×EBC	0.003	0.056	0.005	-0.233**	-0.001	0.014	0.003
	(0.14)	(1.58)	(0.25)	(-2.05)	(-0.25)	(0.35)	(0.07)
HighXOPT×Post2006	0.101***	0.136***	-0.001	-0.129	0.002	-0.041	-0.035
	(4.72)	(3.19)	(-0.02)	(-1.16)	(1.02)	(-1.05)	(-1.23)
EBC×Post2006	0.063**	0.098***	0.044	-0.194	0.001	-0.031	-0.009
	(2.16)	(2.70)	(1.08)	(-1.56)	(0.47)	(-1.07)	(-0.30)
HighXOPT	-0.095***	-0.122***	0.030*	0.199*	0.005***	0.085***	0.064**
	(-5.17)	(-4.34)	(1.79)	(2.00)	(2.98)	(3.61)	(2.51)
EBC	0.027	-0.025	-0.042**	0.014	0.002	-0.052*	-0.017
	(1.24)	(-0.71)	(-2.19)	(0.34)	(0.90)	(-1.71)	(-0.56)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employee controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
New hire controls	No	No	No	No	No	No	Yes
Ind×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,200	5,200	5,200	5,200	5,200	5,200	4,500
R-squared	0.390	0.386	0.444	0.436	0.145	0.751	0.837

Table 10: Additional Tests for the SFAS 123(r) Analysis

Panel A presents the dynamic triple difference-in-differences (DiD) analysis that examines the effect of the SFAS 123(r) rule change on new hires' employee family labor income diversification. *HighXOPT* is a dummy variable that equals one if a firm's average option compensation expenses scaled by lagged total assets in the pre-event period (i.e., years 2002 to 2004) before the issuance of SFAS 123(r) is above the sample median, and zero otherwise. *EBC* is a dummy variable that equals one if a firm has earnings-based constraints during the pre-event period, and zero otherwise. *Year200X* is a dummy variable that equals one for observations in year 200X and zero otherwise. *HighXOPT*, *EBC*, the year dummies, and the double interactions between the variables are included in the regressions but not reported. Panel B presents the placebo test. *SPost2006* is a dummy variable that equals one for the pseudo-post-event period (i.e., 2003 to 2004) and zero for the pseudo-pre-event period (i.e., 2001 to 2002). Each regression in Panels A and B includes firm controls, employee controls, new hire controls, industry×year fixed effects (at the two-digit SIC level), and state×year fixed effects. Panel C reports the regression including firm fixed effects in addition to industry×year fixed effects and state×year fixed effects. Definitions of the other variables are in Appendix A. Standard errors are corrected for heteroskedasticity and within-industry clustering. We report t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Dynamic Triple Difference-in-differences Estimation

Dep. Var.	***NewHireFamilyDiverse***
	1
HighXOPT×EBC×Year2002	0.012*
	(1.74)
HighXOPT×EBC×Year2003	0.000
	(-0.03)
HighXOPT×EBC×Year2004	0.009
	(0.92)
HighXOPT×EBC×Year2006	-0.021
	(-1.57)
HighXOPT×EBC×Year2007	-0.031***
	(-2.74)
HighXOPT×EBC×Year2008	-0.047***
	(-3.76)
Firm controls	Yes
Employee controls	Yes
New hire controls	Yes
Ind×Year FE	Yes
State×Year FE	Yes
Observations	4,500
R-squared	0.642

Panel B: Placebo Test

Dep. Var.	*NewHireFamilyDiverse*
	1
HighXOPT×EBC×SPost2006	-0.006
	(-0.67)
HighXOPT×EBC	0.023**
	(2.36)
HighXOPT× SPost2006	0.002
	(0.23)
EBC× SPost2006	0.005
	(0.58)
HighXOPT	-0.019*
	(-1.84)
EBC	-0.025***
	(-2.96)
Firm controls	Yes
Employee controls	Yes
New hire controls	Yes
Ind×Year FE	Yes
State×Year FE	Yes
Observations	2,400
R-squared	0.663

Panel C: Alternative Fixed Effects

Dep. Var.	*NewHireFamilyDiverse*
	1
HighXOPT×EBC×Post2006	-0.023**
	(-2.19)
HighXOPT×Post2006	0.017**
	(2.56)
EBC×Post2006	0.021**
	(2.13)
Firm controls	Yes
Employee controls	Yes
New hire controls	Yes
Ind×Year FE	Yes
State×Year FE	Yes
Firm FE	Yes
Observations	4,500
R-squared	0.841

Table 11: Individual Employees' Family Income Diversification and Large Changes in Leverage
This table presents the individual employee-level analysis of family labor income diversification following large changes in firm leverage. In Panel A, columns 1 and 2 report the regressions of adjusted family labor income diversification on large changes in firms' market leverage for newly hired employees (column 1) or newly departed employees (column 2). The dependent variable, *AdjFamilyDiverse,* is a new hire's (leaver's) family labor income diversification in year *t+1* (year *t-1*) minus the firm's time-series average employee family labor income diversification. The main dependent variable, *ChgMktLev*, is a dummy variable that equals one if a firm's change in market leverage from year *t-1* to year *t* exceeds the sample 90th percentile, equals negative one if the change is below the sample 10th percentile, and equals zero otherwise. Column 3 reports the regressions of staying employees' changes in family labor income diversification on large changes in firms' market leverage. The dependent variable, *ChgFamilyDiverse*, is the change in a staying employee's family labor income diversification from year *t* to *t+1*. Panel B reports regressions similar to those in Panel A except that the key independent variable is large changes in firms' book leverage (*ChgBookLev*). Standard errors are corrected for heteroskedasticity and within-household clustering. We report t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Dynamics of Family Labor Diversification Following Large Changes in Market Leverage

Dep. Var.	***AdjFamilyDiverse***		***ChgFamilyDiverse***
Sample	**New Hires**	**Leavers**	**Stayers**
	1	2	3
ChgMktLev	0.009***	-0.003***	0.001***
	(12.10)	(-5.08)	(2.61)
Controls	Yes	Yes	Yes
Ind×Year FE	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes
Observations	1,243,000	1,434,000	1,535,000
R-squared	0.317	0.279	0.030

Panel B: Dynamics of Family Labor Diversification Following Large Changes in Book Leverage

Dep. Var.	***AdjFamilyDiverse***		***ChgFamilyDiverse***
Sample	**New Hires**	**Leavers**	**Stayers**
	1	2	3
ChgBookLev	0.008***	-0.002***	0.001**
	(12.64)	(-3.57)	(2.00)
Controls	Yes	Yes	Yes
Ind×Year FE	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes
Observations	1,243,000	1,434,000	1,535,000
R-squared	0.317	0.279	0.030

Table 12: Regression of Firm Risk-taking on Employee Family Labor Income Diversification

This table presents the OLS regressions of other firm risk-taking measures on employee family labor income diversification. *ROAvol* (*ROICvol*) is the standard deviation of seasonally adjusted quarterly pretax returns on assets (returns on invested capital) over the three-year period from year *t* to *t+2*, calculated following Ljungqvist, Zhang, and Zuo (2017). *RetVol* is the standard deviation of a firm's monthly stock returns during year *t* to *t+2*. *IdioVol* is the standard deviation of a firm's monthly idiosyncratic returns (estimated using the Fama-French three-factor model) during year *t* to *t+2*. *ProbD* is a firm's probability of default estimated using the Bharath and Shumway (2008) model. Each regression includes industry ×year fixed effects (at the two-digit SIC level) and state×year fixed effects. Standard errors are corrected for heteroskedasticity and within-firm clustering. We report t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dep. Var.	***ROAvol***	***ROICvol***	***RetVol***	***IdioVol***	***ProbD***
	1	2	3	4	5
FamilyDiverse	0.124***	0.091***	0.057***	0.048***	0.061***
	(5.73)	(3.05)	(4.58)	(4.58)	(2.69)
Controls	Yes	Yes	Yes	Yes	Yes
Ind×Year FE	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes
Observations	10,500	10,500	10,500	10,500	10,500
R-squared	0.618	0.531	0.529	0.527	0.351

Appendix A: Definitions of Variables

Variables	Definition
FamilyDiverse	The equal-weighted mean of a firm's employees' family income diversification, which is the ratio of labor income from other jobs and family members to total family income. For a firm-year, we first calculate, for each employee, the ratio of her annual labor income from other jobs (i.e., not from the focal firm) as well as from her family members to her family's total annual labor income, and then calculate the mean of this ratio across all employees of the firm.
MktLev	Firm *i*'s market leverage ratio, defined as total debt (the sum of current liabilities and long-term debt, DLC+DLTT) divided by the sum of total debt and market value of equity (PRCC_F×CSHO).
BookLev	Firm *i*'s book leverage ratio, defined as total debt (the sum of current liabilities and long-term debt, DLC+DLTT) divided by book value of total assets (AT).
LnAsset	The natural logarithm book value of firm *i*'s total assets (AT, Million in 2000 dollars).
ROA	Return on assets defined as operating income before depreciation (OIBDP) divided by book value of total assets (AT).
PPEAsset	Property, plant & equipment (PPENT) divided by book value of assets (AT).
TobinQ	Firm *i*'s Tobin's *Q*, defined as market value of equity (PRCC_F×CSHO) plus book value of assets (AT) minus book value of equity (CEQ) minus deferred taxes (TXDB) (set to zero if missing) divided by book value of assets.
AZModified	The modified Altman's z-score, calculated as 1.2×(working capital/ assets) + 1.4×(retained earnings/assets) + 3.3×(earnings before interests and taxes/assets) + (sales/assets).
LnAge	The natural logarithm of firm *i*' age. Age is approximated by the number of years listed on Compustat.
LnEducation	The natural logarithm of the average years of education that an employee receives in firm *i*.
WhiteRatio	The percentage of white employees in firm *i*.
LnWage	The natural logarithm of average annual wage (Thousand in 2000 dollars) for employees of firm *i*.
LnEmpAge	The natural logarithm of the average employee's age in firm *i*.
MaleRatio	The percentage of male employees in firm *i*.
MarriedRatio	The percentage of married employees in firm *i*.
LnFamilyWage	The natural logarithm of average total family labor income (Thousand in 2000 dollars) for employees of firm *i*.
White	The percentage of white employees in the employee-level sample.
Age	The average employee age in the employee-level sample.
Male	The percentage of male employees in the employee-level sample.
Education	The average years of education that an employee receives in the employee-level sample.
FamilyDiverse_VolAdj	A modified family labor income diversification measure controlling for the industry volatility of the income sources. Details are provided in the main text.

FamilyDiverse_SizeAdj	A modified family labor income diversification measure controlling for the firm size of the income sources. Details are provided in the main text.
FamilyDiverse_Residual	A modified family labor income diversification measure controlling for employee characteristics. Details are provided in the main text.
HighNLocalEstab	A dummy variable that equals one if the number of business establishments operating in the same industry (at the six-digit NAICS level) and the same commuting zone as the focal firm is above the cross-sectional median, and zero otherwise.
HighNLocalEmp	A dummy variable that equals one if the total number of employees working for the local and same-industry establishments of the focal firm is above the cross-sectional median, and zero otherwise.
HighWageAsset	A dummy variable that equals one if a firm's total wages to total book assets ratio is above the cross-sectional median, and zero otherwise.
HighEmpAsset	A dummy variable that equals one if a firm's number of employees to total book assets ratio is above the cross-sectional median, and zero otherwise,
HighProbD	A dummy variable that equals one if a firm's probability of default estimated using Bharath and Shumway's (2008) model is above the cross-sectional median, and zero otherwise.
Californian	A dummy variable that equals one if a firm is headquartered in California during 2000 and 2003, and zero if it is a non-Californian firm.
Post	A dummy variable that equals one for the post-CA-PFL period (i.e., 2005 to 2008) and zero for the pre-CA-PFL period (i.e., 2000 to 2003).
HighFertileMale	A dummy variable that equals one if a firm's average fraction of fertile-age male employees in the pre-CA-PFL period (i.e., 2000-2003) is above the sample median and zero otherwise.
NewHireFamilyDiverse	Defined similar to *FamilyDiverse* but for newly hired employees. An employee is identified as a new hire for year *t* if she is not on the payroll in year *t-1* but on the payroll in year *t* and receives wages from the firm in each quarter of year *t+1*.
HighXOPT	A dummy variable that equals one if a firm's average option compensation expenses scaled by lagged total assets in the pre-SFAS 123(r) period (i.e., years 2002 to 2004) is above the sample median, and zero otherwise.
EBC	A dummy variable that equals one if a firm has earnings-based constraints during 2002 and 2004, and zero otherwise.
Post2006	A dummy variable that equals one for the post-SFAS 123(r) period (i.e., years 2006 to 2008), and zero for the pre-SFAS 123(r) period (i.e., years 2002 to 2004).

Appendix B: Alternative Measure of Family Income Diversification

B1. Controlling for the Risks of Income Sources

We construct two modified diversification measures that adjust for the risk levels of income sources. Suppose two employees of a firm have the same measure of family income diversification. For Employee A, the non-focal income is from her spouse with a low-risk job, whereas for Employee B, the non-focal income is from her spouse with a high-risk job. Despite the same labor income diversification, A will be more risk tolerant to her focal job than B.

Our first modified measure uses industry volatility to capture the risk level of an income source. For each year in our sample, we calculate the average monthly stock return volatility of three-digit NAICS industries, and sort them into deciles based on the return volatility. Each industry is then assigned a volatility score that equals one plus the product of 0.1 and its decile number (1 for the lowest and 10 for the highest).[44] Next, we adjust a labor income source for risk by dividing the income by its firm's industry volatility score.[45] This way the labor income from industries with higher volatility is discounted to a greater degree. We then construct a modified labor income diversification measure using the discounted labor income (*FamilyDiverse_VolAdj*). Our second modified measure, *FamilyDiverse_SizeAdj*, is constructed in a similar fashion except that we capture risk by firm size, i.e., incomes from larger employers are assumed to have a lower level of risk. Panel B of Table 4 reports the regressions using these two modified labor income diversification measures. Both measures remain significantly positive in the regressions, suggesting that our results are robust to controlling for heterogeneous levels of risk across labor income sources.

B2. Controlling for the Risk Correlation Between the Industries of Employees' Focal Jobs and Those of Their Family Members

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[44] For example, the volatility score of industries in the top decile = 1 + 0.1×10 = 2, while that of industries in the bottom decile = 1 + 0.1×1 = 1.1.

[45] We use industry-level stock return volatility because labor incomes can come from private firms.

Our baseline regressions presented in Table 2 show a positive relation between employee family income diversification and employer leverage. However, since a higher correlation between an employee's focal income and other family incomes can lead to lower labor income diversification (i.e., higher job risk) than what our current measure captures, we conduct a robustness test that takes into account the risk correlation between the industries of the focal jobs and those of the other family income sources.

Specifically, for each employee of a firm-year, we first calculate the correlations of the average daily stock returns of her focal job's industry (at the two-digit SIC level) and those of her other family incomes in that year.[46] Then, for each employee with positive non-focal family income in our sample, we recalculate her family income diversification measure by replacing the employee's unweighted family labor income (in the denominator of the original measure) with the weighted sum of all family incomes. The weight for a given income source is two minus its industry correlation with the focal income and the weight for the focal income itself is one.[47] In this approach, the higher the industry correlation of a family income source with the focal income, the less weight is assigned to this income when calculating the weighted total family income. When a non-focal family income is from the same industry as that of the focal job (so that the industry correlation is one), its weight will be the minimum weight of one, which assumes that even a same-industry non-focal family income can diversify away some labor income risk the employee faces.[48]

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[46] The results are similar whether we use value-weighted or equal-weighted average industry returns.

[47] For example, suppose an employee has a focal income of \$80,000 and a spouse income of \$20,000, with the industry correlation between the two jobs being 0.5. We recalculate her total family income as 110,000 (= 80,000 + 20,000×(2-0.5)) and her family labor income diversification as 0.273 (=1-80,000/110,000). Note that this new, transformed measure cannot be directly compared to the original family labor income diversification measure because one incorporates industry correlations and the other does not, i.e., either one is internally consistent in ranking the employees but their values cannot be compared across the ranking scales.

[48] An alternative way of assigning weights to the non-focal incomes in the denominator is to set them as one (instead of two) minus the industry correlations, but this approach treats a same-industry job as offering no diversification

The untabulated results show that this alternative family labor income diversification measure has a very high correlation with the original measure, and that the results of leverage regressions using this alternative diversification measure are almost identical to our baseline results in terms of both magnitudes and statistical significances.

benefits at all (because its weight will be zero), which seems unrealistic. However, we find that our results are robust to setting the weights of non-focal incomes as one or 1.5 minus the industry correlations.

Appendix C: Employee Clientele Effect and Persistent Leverage

Lemmon et al. (2008) discover that the cross-sectional distribution of corporate leverage is surprisingly stable over time. For example, initially higher-levered firms tend to have higher leverage than initially lower-levered firms even after two decades. This puzzle has attracted tremendous attention and sparked extensive debates in the finance literature. Lemmon et al. (2008) suggest that this stable distribution could be attributed to an "unobserved time-invariant effect", but the underlying cause for this persistence remains unclear.[49] Berk et al. (2010) suggest that human bankruptcy costs can influence the persistence in the cross-section of leverage through the self-reinforcing equilibrium matching, although they do not empirically test this conjecture.[50] We therefore examine the relation between a firm's current financial leverage and its initial employee family income diversification.

We conduct regression analyses similar to those specified by equation (1) in the paper, but replace *FamilyDiverse* with *FamilyDiverse_Initial*, which is a firm's initial employee family labor income diversification (measured either at the start of our sample period or in the first year that the firm appears in our sample). We extend the sample period for this test to 2014, the latest year of Compustat annual data uploaded to our Census project space, although our LEHD data stops at 2008. Thus, our regressions only include the set of firm-level control variables as in Table 2 in the paper (i.e.*, LnAsset, ROA, PPEAsset, TobinQ, AZModified, LnAge*) because these variables are available from Compustat. As shown in Table C1, initial employee labor income diversification is a significant predictor of a firm's future market leverage and book leverage, indicating that employee risk aversion contributes to the persistence of financial leverage. While employee risk-aversion is unlikely the primary driver of the persistence in corporate

[49] Leary and Roberts (2005), for example, show that adjustment costs prevent firms from rebalancing their leverage.

[50] Both firm leverage and employee family income diversification are highly persistent over time: The autocorrelation of both market and book leverage in our sample is around 80% while that of employee family income diversification is around 70%. Besides, the within-firm standard deviation of these variables is very small.

leverage, this finding illustrates that the puzzle of persistent leverage may be attributed to economic forces that have a self-reinforcing relation with leverage.[51]

Table C1: Regression of Firm Leverage on Initial Employee Family Labor Income Diversification
This table presents the OLS regressions of firm leverage on *FamilyDiverse_Initial*, the initial employee family income diversification of a firm (measured either at the beginning of our sample period or in the first year that the firm appears in our sample). Each regression includes the set of firm-level control variables as in Table 2 (i.e., *LnAsset, ROA, PPEAsset, TobinQ, AZModified, LnAge*), industry×year fixed effects (at the two-digit SIC level), and state×year fixed effects. Standard errors are corrected for heteroskedasticity and within-firm clustering. We report t-statistics in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dep. Var.	***MktLev***	***BookLev***
	1	2
FamilyDiverse_Initial	0.106***	0.293***
	(3.40)	(3.02)
Controls	Yes	Yes
Ind×Year FE	Yes	Yes
State×Year FE	Yes	Yes
Observations	17,500	17,500
R-squared	0.291	0.400

[51] In unreported analysis, we find that the incremental R^2 of initial employee family labor income diversification in these regressions is pretty small. Since our analysis intends to illustrate that firm characteristics that have self-reinforcing relationships with corporate leverage can contribute to the persistence in leverage (rather than claiming that employee risk-aversion is the primary driver of the persistence in leverage), we focus on interpreting the sign and statistical significance of the coefficient.