

The Cost of Care: Paid Family Leave and Bank Loan Pricing*

Si Li, Jianglong Liu, Linjia (Alex) Song, and Xintong (Eunice) Zhan[†]

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Abstract

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Keywords: Bank loan cost, labor adjustment costs, employee benefits, paid family leave.

JEL classification: G21, G32, J32, M14

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[†]Si Li (sli@wlu.ca) is with Wilfrid Laurier University. Jianglong Liu (jianglongliu23@m.fudan.edu.cn) and Xintong Zhan (xintongzhan@fudan.edu.cn) are with Fudan University. Linjia Song (songlinjia@xmu.edu.cn) is with Xiamen University.

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Abstract

Exploiting staggered state-level paid family leave (PFL) laws, we find that firms in PFL-adopting states experience a 21-basis-point (9% of the sample average) increase in bank loan spreads. Firms under PFL mandates have elevated default risk, and banks with higher credit risk exposure cut lending to such firms. Our evidence suggests that labor adjustment costs play an important role in driving our results. Firms hire more temporary workers following PFL adoption, and those with greater labor reliance, PFL take-up rates, or labor adjustment frictions face steeper increases in borrowing costs. Overall, our findings highlight the unintended costs of employee benefits.

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1 Introduction

Employee welfare is a cornerstone of a thriving and sustainable workforce. By addressing employees’ physical, mental, and financial needs, welfare programs—such as health insurance, paid leave, and wellness initiatives—create a supportive environment that enhances overall well-being. According to Glassdoor’s Employment Confidence Survey, 79% of employees consider welfare programs essential to their overall well-being.¹ However, the implementation of such programs entails trade-offs for employers. While these welfare programs provide flexibility and improve work-life balance for employees, they may impose costs on employers, such as operational disruptions and labor adjustment costs. Although prior research has highlighted the benefits of employee welfare programs, including greater gender diversity and reduced employee turnover (Liu, Makridis, Ouimet, and Simintzi, 2023; Ouimet and Tate, 2023), the associated costs have been less explored.

To comprehensively understand the cost-benefit trade-offs of employee welfare programs, we exploit the staggered implementation of state-level paid family leave (PFL henceforth) in the U.S. as a quasi-natural experiment and examine its effect on firms’ bank loan financing. Since 2004, more than ten states, including California and New York, have enacted mandatory PFL policies (Appendix Table A1).² These state-level PFL mandates allow employees to take 6 to 12 weeks off work to care for newborns, newly adopted children, or sick family members while continuing to receive a portion of their regular pay. The funding for these programs typically comes from a small payroll tax on wages, which is mainly borne by em-

¹<https://www.glassdoor.com/blog/ecs-q3-2015/>

²<https://www.americanprogress.org/article/the-state-of-paid-family-and-medical-leave-in-the-u-s-in-2023/>

employees. While PFL offers greater flexibility and support for employees, it may also impose adjustment costs on employers due to increased employee absences.

Our focus on bank loan pricing is motivated by the fact that banks are crucial providers of external financing, and their informational advantage allows loan contracts to accurately reflect a firm’s potential economic costs (Sufi, 2007; Minnis and Sutherland, 2017). The effects of PFL on bank loan costs, however, are ex-ante ambiguous. On one hand, PFL may increase bank loan costs. Specifically, PFL could increase employee absences, raising employers’ costs related to securing temporary replacements (Ginja, Karimi, and Xiao, 2023; Huebener, Jessen, Kuehnle, and Oberfichtner, 2025). More frequent employee turnover can also disrupt coworker collaboration and hinder overall team efficiency. These costs can weaken firm performance and elevate default risk, leading banks to increase loan rates on affected firms.³ On the other hand, firms affected by PFL may have lower loan spreads. PFL may help attract and retain talent, improve firm performance, and ultimately reduce default risk and borrowing costs.

To answer this empirical question, we analyze 22,952 bank loans issued to 3,632 public firms from 2001 to 2020. Using the difference-in-differences (DID) approach, we find that, following the adoption of PFL, the average loan spreads of firms headquartered in treated states increase significantly. The magnitude of this effect is also economically substantial: the average loan spread for treated firms is 21 basis points (9% of the sample average loan spread) higher than that of control firms. These results remain intact after controlling for state-level

³Anecdotal evidence also indicates that firms are concerned about the PFL-associated costs. For example, CVS Health Corporation noted in its 2019 annual report: “The federal and certain state legislatures continue to consider and pass legislation that increases our costs of doing business, including increased minimum wages and requiring employers to provide paid family leave.”

characteristics, including GDP and labor market conditions (such as the unemployment rate and minimum wage).

We also conduct several robustness tests. First, to address the concern that differences in loan and firm characteristics between treated and control samples may drive our results, we repeat the analysis using a propensity-score-matched sample and an entropy-balanced sample. Second, because different states implemented their respective PFL laws in different years, the DID analysis with staggered treatment timing may yield biased model estimates in the presence of heterogeneous treatment effects (Baker, Larcker, and Wang, 2022). To tackle this concern, we follow Cengiz, Dube, Lindner, and Zipperer (2019) and employ the Stacked-DID approach to account for staggered policy adoption. Our results remain consistent with these alternative empirical methods. Furthermore, being headquartered in a particular state does not necessarily imply that a firm’s employees or establishments are concentrated in that state.⁴ We therefore construct two measures of a firm’s PFL exposure by calculating the fractions of establishments and employees located in PFL-adopting states for each firm-year observation. Both measures confirm that higher exposure to PFL is associated with more expensive loan pricing.

Having established the positive and causal effect of PFL on borrowing firms’ bank loan spreads, we next explore the underlying mechanisms. The evidence that banks charge higher loan spreads to PFL-affected firms suggests that these firms face increased default risk, which is priced in loan contracts. We provide corroborating evidence for this conjecture by investigating both the default risk metrics of borrowing firms and the lending portfolios of

⁴In our sample, an average of 28.6% of employees and 18.4% of establishments are located in the state where the company’s headquarters is based.

banks. First, we document that firms in PFL-mandated states exhibit a higher expected default frequency (EDF), a lower Altman’s Z-score, reduced cash flows, and more covenant violations compared to firms in states without PFL mandates. These findings suggest that PFL policies may be linked to a heightened corporate default risk. Second, we find that lending banks with greater ex-ante exposure to firms with elevated credit risk (measured by the proportion of outstanding loans extended to firms with high EDF or low Z-score) become more reluctant to lend to firms in PFL-mandated states, as such lending would exacerbate their risk exposure. These heterogeneous responses from lending banks confirm that firms in PFL-mandated states face increased default risk.

We take one step further to investigate whether the heightened default risk and increased borrowing costs for firms impacted by PFL are a result of higher labor adjustment costs. Although PFL is often funded through employee contributions from after-tax wages (as described Appendix Table A1), employers may incur indirect costs, such as those arising from the need to hire replacements for employees on leave. To explore this, we examine whether a firm posts more temporary positions in states with the PFL mandates. For the same firm, if it posts more temporary positions in PFL-mandated states than in non-mandated states (controlling for other characteristics), the difference is possibly driven by the need to cover for employees on leave. Our results lend support to this argument.

To further validate the link between PFL-induced labor adjustment costs and increased borrowing costs, we examine the heterogeneous effects of PFL across firms. We first consider factors that could affect firms’ exposure to PFL-related risk. Specifically, we find that borrowing costs increase more for labor-intensive firms, as they must secure more replacements

when employees take leave. Firms with a larger share of women of childbearing age, who are more likely to utilize PFL benefits also face higher costs. Across these dimensions, our results provide consistent evidence supporting the labor adjustment cost mechanism. We then consider labor adjustment frictions, i.e., the difficulty to replace employees on leave with labor or machine. Following [Ginja, Karimi, and Xiao \(2023\)](#), we consider two measures that capture the frictions of replacing with labor: internal substitutability and labor market thickness, which reflect the ease of replacing temporarily on-leave employees within the firm and in the external labor market, respectively. We find that the impact of PFL is more pronounced among firms with limited internal substitutability and thinner labor markets, both of which indicate higher labor adjustment costs. We also consider frictions in replacing labor with capital, and we find that firms with limited capacity to automate tasks or substitute labor with robotics experience a greater increase in borrowing costs.

Our results are not inconsistent with [Bennett, Erel, Stern, and Wang \(2025\)](#), who document that PFL reduces employee turnover and enhances firm profitability. Unlike equity holders, banks do not benefit from the corporate upside opportunities associated with PFL but suffer from increased default risk from firms in the left tail of the credit quality distribution. When we split the sample firms according to their ex-ante default risk, we find that our findings and those of [Bennett, Erel, Stern, and Wang \(2025\)](#) are driven by distinct subsamples. Specifically, the positive effects of PFL on profitability are concentrated among low-default-risk firms, whereas the impact of PFL on loan spreads is concentrated among high-default-risk firms. For these higher-default-risk firms, typically characterized by smaller and volatile cash flows, the costs of PFL outweigh the benefits, exacerbating default risk and

leading to higher loan spreads.

While PFL is fully funded by employees in some states, it is partially employer-financed in others (see Appendix Table A1). In states where employers share the PFL contribution costs, PFL imposes direct costs on firms, and we expect the increase in borrowing costs to be more pronounced. During our sample period, only the 2017 San Francisco Paid Parental Leave Ordinance requires employers to provide supplemental compensation to employees for new child bonding.⁵ The general PFL policy in California, however, does not have such a requirement. We thus exploit the policy variation within California to examine the borrowing costs of the firms headquartered in the state. Specifically, we define firms with at least one establishment in San Francisco as the treatment group and compare their bank loan spreads with those of firms headquartered in California but without any establishments in San Francisco.

We find that treated firms have significantly higher loan spreads, specifically 35 basis points higher, than other firms after the San Francisco PFL policy became effective. In our main sample, the average loan spread of treated firms is 21 basis points higher than that of control firms. That is, the loan-pricing effect of the PFL policy that imposes direct costs on employers is over 1.5 times greater than that of PFL policies without direct employer costs. Additionally, in this California subsample, we find that banks reduce the loan size extended to borrowers impacted by the San Francisco PFL Ordinance, suggesting that loan pricing alone may not be sufficient for banks to manage the increased default risk stemming from

⁵The PFL mandates that require employers to share the cost were all adopted after July 2020 (see Table A1 in the Appendix). Our loan-firm merged dataset spans from 2001 to April 2020, so the main analysis includes only the four states where the PFL effective date was before 2020. In these four states, PFL is 100% employee-financed.

both the indirect and direct costs of PFL.

Overall, our paper contributes to three stands of literature. First, our work supplements the nascent literature on the impact of paid family leave on corporate outcomes. Several studies provide evidence that PFL reduces labor market frictions and benefits firms. [Bennett, Erel, Stern, and Wang \(2025\)](#) find that PFL decreases labor market frictions, leading to reduced employee turnover and higher productivity. [Jin and Zhu \(2024\)](#) document that PFL policies increase innovation output for firms employing workers in PFL states. [Liu, Makridis, Ouimet, and Simintzi \(2023\)](#) find that female-friendly benefits enhance gender diversity and lead to positive three-day cumulative abnormal returns around the dates when PFL legislation was passed. While the benefits of PFL to firms are well documented, evidence on the extent to which it burdens firms remains limited, with existing studies primarily focusing on firms in European countries. For example, [Ginja, Karimi, and Xiao \(2023\)](#) find that a three-month expansion of parental leave in Sweden increases employee’s leave duration and job separations, leading firms to hire more workers and incur higher wage costs. Using data from Germany, [Huebener, Jessen, Kuehnle, and Oberfichtner \(2025\)](#) show that parental leave policies disrupt employment relationships and impose costs on firms when internal substitutes are limited. [Brenøe, Canaan, Harmon, and Royer \(2024\)](#) find similar results using data from Denmark. Our study is the first to examine how the costs of PFL impact firms’ borrowing costs in the U.S. context.

Our paper is also closely linked to the literature on how labor adjustment costs influence firms’ financing conditions. Previous studies suggest that labor market changes, such as increased labor unionization or stricter labor protection laws, can impose labor adjust-

ment costs and reduce operational flexibility (Banker, Byzalov, and Chen, 2013; Chang, Dai, Lohwasser, and Qiu, 2022; Moon and Sertsios, 2025). These labor market frictions play a critical role in shaping corporate decisions and outcomes, including capital structure (Serfling, 2016), dividend policies (He, Tian, Yang, and Zuo, 2020), M&A performance (Jang and Yehuda, 2021), and financing costs (Chen, Kacperczyk, and Ortiz-Molina, 2011; Alimov, 2015; Chino, 2021). While these studies mainly focus on the rigidity of workforce adjustment, our study highlights that employee welfare programs, such as PFL, can induce considerable labor adjustment costs, such as those associated with temporary hiring. These costs, in turn, have a significant impact on creditors' decisions.

Finally, our paper contributes to the literature on the determinants of loan spreads and other loan contract terms. Previous research has documented that various factors affect loan contracting, including stakeholder orientation (Gao, Li, and Ma, 2021), organized capital (Danielova, Francis, Teng, and Wu, 2023), political risk (Gad, Nikolaev, Tahoun, and van Lent, 2024), strategic alliance relationship (Khan, Lin, Ma, and Stice, 2024), among others. The most relevant to our study is the relationship between policy changes and corporate loan contracts. For example, Falato and Liang (2016) provide evidence that labor unionization leads to higher loan prices. Ivanov, Pettit, and Whited (2025) investigate how state corporate income tax reductions impact firm leverage and borrowing costs. Ivanov, Kruttli, and Watugala (2024) find that high-emission firms affected by cap-and-trade policies face shorter loan maturities, reduced access to bank financing, and higher interest rates. Our study broadens the scope of policies influencing loan pricing by considering employee welfare programs.

The rest of the paper is organized as follows. Section 2 describes the institutional background and develops the hypothesis. Section 3 details our data and measures. Section 4 presents the main empirical results. Section 5 discusses labor adjustment costs, the main economic mechanism. Section 6 further aligns our findings with the extant literature, and investigates the direct-cost mechanism. Section 7 concludes the paper.

2 Institutional Background and Hypothesis Development

2.1 Institutional background

Paid family leave is a policy that allows employees to take time off from work to care for a newborn, newly adopted child, or ill family member, while continuing to receive a portion of their regular salary. The purpose of paid family leave is to provide workers with financial support and job security during these significant life events. Currently, the United States is the only developed country without a nation-wide paid family leave program.

The Family and Medical Leave Act (FMLA) was signed into law in 1993, requiring covered employers with 50 or more employees to offer eligible workers up to 12 weeks of unpaid leave within a 12-month period. This leave can be used for purposes such as caring for a newborn or newly adopted child, tending to a seriously ill family member, or recuperating from a serious illness. Nevertheless, FMLA eligibility is limited by the program's design. To be eligible for FMLA leave, an employee must have worked for a covered employer for at least 12 months and have worked at least 1,250 hours during the 12-month period immediately

preceding the leave. According to the 2018 FMLA survey, only about 56 percent of the workforce is eligible for FMLA protection.⁶ Even when employees qualify for FMLA leave, they may choose not to use it due to potential income loss. In 2021, the Build Back Better Act, spearheaded by then-President Joe Biden, proposed a federally funded paid family leave program. However, during the legislative process, the bill faced challenges and underwent revisions. Ultimately, the paid family leave provision was excluded from the final version of the legislation, despite Biden’s advocacy for its inclusion.

Although there is no nationwide paid family leave law, eleven states and the District of Columbia have enacted PFL laws requiring employers to provide paid family leave benefits. California was the first to implement its PFL law in 2004, followed by other states such as New Jersey, Rhode Island, and New York, which adopted similar laws over the next decade. In recent years, an increasing number of states have accelerated the legislative process for PFL. Appendix Table A1 outlines all state-level PFL laws in the U.S. to date, along with their respective enactment dates, effective dates, and funding mechanisms. While the specifics of these state-level policies vary, all of them offer benefit for the birth, adoption, or fostering of a new child, as well as for caring for a sick family member. The duration of leave typically ranges from 6 to 12 weeks, and the wage replacement rate ranges from 50% to 90%. Funding of these programs generally comes from a small payroll tax on wages, which, in our sample, is predominantly imposed on employees.

⁶https://www.dol.gov/sites/dolgov/files/OASP/evaluation/pdf/WHF_FMLA2018PB1WhoIsEligible_StudyBrief_Aug2020.pdf.

2.2 Hypothesis development

We argue that PFL influences firms' borrowing costs by affecting their default risk. Theoretically, PFL can either increase or decrease default risk. On one hand, PFL mandates may encourage greater labor force participation, attract more talented employees, and enhance human capital quality (Jin and Zhu, 2024). Moreover, PFL may improve gender diversity and foster a more supportive corporate culture (Liu, Makridis, Ouimet, and Simintzi, 2023). If enhanced human capital quality and gender diversity lead to better firm performance and lower default risk, banks may charge lower interest rates to firms impacted by PFL.

On the other hand, PFL can heighten default risk by raising labor adjustment costs. Under paid family leave policies, employees are granted paid leave ranging from 6 to 12 weeks. Employers respond by relying on internal substitutes or hiring new workers, both of which incur additional costs. Using internal substitutes often requires overtime compensation and may reduce productivity as normal workflows are disrupted. According to a 2013 survey by the Society for Human Resource Management (SHRM), employee absences cause a 29.5% drop in co-workers' productivity and a 15.7% decline in supervisors' productivity compared to normal operations. For firms with limited capacity to find internal substitutes, employers must allocate resources for recruiting, hiring and training new workers, further increasing labor adjustment costs and negatively impacting performance (Brenøe, Canaan, Harmon, and Royer, 2024). Additionally, when human capital is highly specialized, labor replacement becomes difficult or inefficient, as suitable new hires may be scarce or less productive than the workers on leave (Ginja, Karimi, and Xiao, 2023). As state-level PFL mandates exacerbate these challenges, banks may respond by charging higher loan rates to compensate for the

increased default risk posed by underperforming borrowers.

In summary, while PFL can enhance firm performance by attracting talent and increasing labor force participation, it may also impose significant labor adjustment costs, reduce productivity, and ultimately lower firm performance. The overall impact of PFL on firm default risk—and consequently, on borrowing costs—remains an empirical question. Thus, we propose the following hypothesis:

H1: Firms subject to mandatory PFL adoption will face higher loan spreads.

During our sample period, PFL mandates are primarily funded through employee payroll contributions, although in some cases employers are required to share the costs. For example, the 2017 San Francisco Paid Parental Leave Ordinance (SF PPLO) mandates that employers provide supplemental compensation for new child bonding. We hypothesize that this direct cost burden may further strain firms’ financial stability, thereby amplifying the effect of PFL on default risk.

H2: The effect of PFL on loan spreads will be more pronounced in firms affected by the SF PPLO.

3 Data and Measures

3.1 Data sources and sample coverage

To construct our sample, we obtain bank loan data from the Loan Pricing Corporation (LPC) Dealscan and firm-level quarterly accounting data from Compustat. Following standard procedures in the literature, we remove loans with missing key items (loan spread,

amount, and maturity) and exclude bridge loans and non-fund-based loans. We drop borrowers from the financial and utility sectors (SIC codes 6000–6999 and 4900–4999) and firms lacking the necessary data to construct control variables for our empirical tests. We then merge both the bank loan data and the firm financial data with Michael Roberts’ Dealscan-Compustat link file.⁷ Our sample period spans from 2001 to 2020.⁸ Since loans are, on average, negotiated two to three months prior to their legal effective date (Murfin, 2012), we match the loan issue date with the corresponding firm financial data in Compustat using a three-month lag. Our final sample consists of 22,952 loans and 3,632 unique firms.

3.2 Key measures

3.2.1 Measures of PFL mandates

To measure PFL mandates, we manually gather information on the passage and effective dates of PFL laws from state government websites. Our sample period covers 2001 to 2020, focusing on PFL mandates in four states: California (PFL effective in 2004), New Jersey (2009), Rhode Island (2014), and New York (2018). For each loan, we introduce an indicator variable, PFL, which equals one if the borrowing firm is headquartered in a state with an effective PFL law, and zero otherwise. To identify the historical headquarters locations of each firm, we use the 10-X Header Database provided by Bill McDonald.⁹

⁷We thank Michael Roberts for providing the data on his personal webpage (<https://finance.wharton.upenn.edu/~mrrobert/research.html>).

⁸We begin our sample period in 2001, three years before the first U.S. state-level PFL became effective in 2004 in California. We end our sample period in 2020, as this is the most recent year available in the Dealscan-Compustat link file.

⁹The data is available at <https://sraf.nd.edu/sec-edgar-data/10-x-header-data/>. We thank Bill McDonald for providing this data.

3.2.2 Measures of loan pricing and control variables

To measure firm borrowing cost, we use $\log(\textit{Spread})$, which is the natural logarithm of the all-in drawn loan spread. Following prior literature (Graham, Li, and Qiu, 2008), we control for various loan and firm characteristics to sharpen the effects of PFL on loan pricing. For loan-level characteristics, we control for loan amount, maturity, whether the loan is secured, whether it is syndicated, the presence of performance-based pricing, and the number of lenders. For firm-level characteristics, we control for firm size, leverage, book-to-market ratio, cash holdings, tangibility, return on assets (ROA), Altman’s Z-Score, and sales growth. Detailed definitions of these variables are provided in the Appendix.

3.3 Sample statistics

Table 1 reports the summary statistics of the main variables used in our analysis. In our sample, 9.2% of loans are affected by PFL. The average loan spread is 233.3 basis points (bps), with a standard deviation of 149.6 bps, indicating significant variation in loan pricing. The average loan size is \$451.46 million, and the average maturity is approximately 51 months. Additionally, 59.5%, 88.0% and 41.5% of sample loans are secured, issued with syndication, and have performance pricing provisions, respectively. We also report firm-level summary statistics: the average borrowing firm has total assets of 7.161 billion, a cash ratio of 0.09, a book-to-market ratio of 0.45, an ROA of 0.006, leverage of 1.57, a Z-score of 2.349, and sales growth of 0.748.

4 PFL and Loan Pricing

4.1 Baseline results

We examine the impact of PFL on loan pricing using a staggered DID approach. Specifically, we estimate the following baseline model:

$$\log(\text{Spread})_{i,f,t} = \alpha + \beta \times PFL_{i,t-1} + \text{Loan Control}_{f,t} + \text{Firm Control}_{i,t-1} + \delta_i + \tau_t + \varepsilon_{i,f,t}. \quad (1)$$

In this regression, each observation represents loan facility f borrowed by firm i in quarter t . The dependent variable, $\log(\text{Spread})$, is the natural logarithm of the all-in drawn loan spread in bps. PFL is an indicator variable which equals one if the firm is located in a PFL-adopting state, and zero otherwise. We control for loan and firm characteristics as outlined in Section 3.2.2. In addition, we include firm fixed effects (σ_i) and quarter fixed effects (τ_t) to capture time-invariant heterogeneity across borrowers and time trends. For robustness checks, we also use firm and industry-by-quarter fixed effects as an alternative specification to account for industry-specific time trends. All continuous variables are winsorized at the 1st and 99th percentiles, and all time-variant explanatory variables are lagged by one quarter. The standard errors are clustered at the state level.

Table 2 reports our baseline regression results. In Column (1), we include only firm and quarter fixed effects, without adding any other control variables. The coefficient on PFL is 0.076 and statistically significant, suggesting that loans borrowed by firms in PFL-adopting states have an average loan spread that is 7.6% higher than those borrowed by firms from non-PFL states. In Column (2), after we include loan and firm-level controls,

the coefficient on PFL remains positive and statistically significant, with a larger magnitude of 0.09. Considering the average sample loan spread of 233.270 bps, PFL-affected loans are priced 21 bps ($233.270 \times 9\%$) higher than PFL-unaffected loans. The 21-bp change in loan spreads is economically significant, given that the sample mean and standard deviation of loan spread are 233 bps and 150 bps.

The regression result also shows that the signs of coefficients on control variables are generally consistent with the economic expectations. Loans with a larger amount, a shorter maturity, and performance pricing provisions have a lower spread. Loans with more lenders have a lower spread, possibly due to better risk-sharing among lenders. Secured loans are associated with a higher loan spread, consistent with the argument in some literature that riskier loans are more likely to require collateral (James and Kizilaslan, 2014; Saffar, Wang, and Wei, 2024). Syndication is positively correlated, possibly because of its high correlation (0.74) with another control variable, the logarithm of the number of lenders.¹⁰ In addition, larger firms and firms with higher profitability (ROA) or lower default risk (higher Z-Score) borrow from banks at a lower cost. In Column (3) and (4), we replace the quarter fixed effects with industry-by-quarter fixed effects and the results remain essentially the same. Overall, the results show that borrowing costs are higher for firms in states with PFL mandates, supporting the hypothesis that banks perceive PFL mandates as a risk factor for firms and consequently charge a premium in loan pricing.

One concern about the above regressions is that states do not adopt PFL mandates randomly. It is possible that some state-level economic and political factors drive the passage

¹⁰We find that the sign on *Syndication* becomes negative if the number of lenders is dropped. Our main result that PFL has a positive impact on loan prices remains intact when we control for *Syndication*, $\log(\text{Num.Lenders})$, or both.

of the PFL mandate, and these state-level economic factors also impact loan pricing. To address this concern, we augment the baseline model with state-year level control variables, including economic variables such as the natural logarithm of GDP, the unemployment rate, the labor force participation rate, and the female employee ratio. We also control for each state’s minimum wage level, as it is associated with firms’ labor costs and financial health (Chava, Oettl, and Singh, 2023) and may confound the effect of PFL. After adding these variables sequentially through Columns (1) to (5) in Table 3, the coefficients of *PFL* remain statistically and economically significant, suggesting that our results are robust to controlling for state-level economic factors and minimum wage policy.

It is also notable that during our sample period the four states with PFL-adoption are all Democratic-leaning, where labor-friendly policies are more likely to be proposed. Therefore, the adoption of PFL may capture a kind of broader political risk from the perspective of banks. To rule out such possibility, we control for the county-level political leaning, *Democrat*, in our regression. *Democrat* is an indicator variable equal to 1 if for each quarter and in the firm’s headquartered county, the Democrat has won in the most recent presidential election. The intuition is that county-level policies play an important role in employees welfare improvement as well as state or federal laws, and the political leaning varies among counties even within a Democrat- or Republican- dominated state. In Column (6) of Table 3, we show that our result is unchanged after *Democrat* is controlled, while the coefficient of *Democrat* is not significant, suggesting that our finding is not driven by local political risk.

We next examine whether PFL also affects non-price terms of loan contracts, such as loan

amount, maturity, covenants, and the performance pricing provision. Price and non-price attributes of contracts may complement each other, and thus lenders may adjust both terms when anticipating higher risk. On the other hand, if the loan spread adjustment adequately compensates lenders for the additional risk caused by PFL, the non-price terms may remain unchanged. Appendix Table A2 shows that PFL has negative but insignificant influences on loan amount and maturity, and a positive but insignificant influence on both the number of covenants and performance pricing. The lack of significant impact of PFL on non-price terms appears to suggest that the price change in response to PFL has sufficiently accounted for the additional risk from PFL.

4.2 Dynamic effects

The validity of the DID approach relies on the assumption that there is no pre-trend before the PFL implementation. To examine whether such a pre-trend exists before the PFL adoption, we estimate the following dynamic model:

$$\log(\text{Spread})_{i,f,t} = \alpha + \sum_{\substack{k=-10 \\ k \neq -1}}^{10} \beta_k \times PFL_{i,t-1}^k + \text{Loan Control}_{f,t} + \text{Firm Control}_{i,t-1} + \delta_i + \tau_t + \varepsilon_{i,f,t}, \quad (2)$$

where $PFL_{i,t-1}^k$ represents a set of indicator variables that are equal to 1 if borrower i is headquartered in a state that will adopt (adopted) PFL mandates in k quarters (k quarters ago) if k is positive (negative). Specifically, PFL^{+1} to PFL^{+9} represent one to nine quarters after PFL implementation, while PFL^{-1} to PFL^{-9} represent one to nine quarters before

PFL implementation. PFL^{-10} and PFL^{+10} are ten or more quarters before and after PFL implementation. PFL^{-1} serves as the reference period and is thus excluded from Equation (2). Control variables and fixed effects are the same as those in our baseline specification, which is reported in Table 2 Column (2).

Figure 1 depicts the results. Prior to the adoption of PFL, there is no significant difference in loan spreads between the treated and control groups. However, after PFL becomes effective, the loan spread for the treatment group exhibits a significant upward trend over the next four quarters. These findings confirm that the parallel trend assumption holds in our analysis and that PFL has a positive effect on loan spreads.

4.3 Robustness tests

We employ a battery of tests to verify the robustness of our baseline results. First, we apply the Propensity Score Matching (PSM) method to create more balanced treatment and control groups. Specifically, each loan in the treatment group is matched to one loan in the control group with the highest propensity scores. The propensity scores are estimated via a probit model, in which the covariates include state level GDP, female employee ratio, minimum wage, firm size, leverage, book-to-market, ROA, and sale growth, loan size, maturity, secured, syndication, performance pricing, loan type, loan purpose, and industry fixed effects. Panels B and C of Appendix Table A3 report our results of PSM diagnostic test, which confirms that after matching, the differences in loan and firm characteristics have been diminished in both magnitude and statistical significance. We then re-estimate our baseline model using this matched sample and report the PSM-DID estimation results in Columns (1)

of Appendix Table A3, Panel A. The impact of PFL on loan pricing remains significant, with both economic and statistical magnitudes similar to those found in the baseline regression.

Second, we adopt an entropy balancing approach to align the first moments of covariate distributions across the treated and control groups. The covariates used are the same as those in the PSM method. Appendix Table A3, Panel D shows that the moments of loan and firm characteristics between the treated and control groups are closely matched after entropy balancing. Column (2) of Appendix Table A3, Panel A shows that our main finding is robust to the entropy balancing approach.

Third, we also use the Stacked-DID approach to mitigate potential bias in staggered DID estimation. Recent econometrics research (Cengiz, Dube, Lindner, and Zipperer, 2019; Callaway and Sant’Anna, 2021) suggests that the staggered DID approach may produce biased outcomes in the presence of variability in treatment effects. To address the potential bias, we implement the Stacked-DID approach following Cengiz, Dube, Lindner, and Zipperer (2019). The Stacked-DID method compares treated observations with control observations from the same period, where the control group has either never been treated throughout the entire sample period or has not yet been treated during the period under analysis. For each instance when a new treatment group is introduced, we construct a sample cohort comprising the new treatment group and the corresponding control group. We then stack these cohorts and estimate the average treatment effect using an event study model, including unit-stack, time-stack, and other fixed effects as outlined in Equation (1). The estimation result, reported in Columns (3) of Appendix Table A3, Panel A, demonstrates that the effect of PFL laws on loan spreads remains robust in this Stacked-DID setting, with coefficient

magnitudes closely aligning with those in our baseline analysis. Meanwhile, Figure A1 in Appendix confirms that dynamic effects estimated in the stacked sample are similar to results estimated in the baseline sample.

Fourth, we examine the effect of firms' PFL exposure on loan spreads using establishment-level data. Since firms often operate establishments and employ workers across multiple states, a firm's headquarter location may not accurately reflect its actual exposure to PFL. To address this concern, we construct alternative PFL exposure measures using establishment-level data from Your-economy Time Series (YTS). The YTS database contains information on the location and number of employees at each establishment on an annual basis.¹¹ We first define the establishment-level $PFL_{i,e,t}$ variable as an indicator variable which equals one if the establishment e of firm i is located in a state with an effective PFL law in quarter t and after, and zero otherwise. Next, we aggregate the establishment-level data to construct the following firm-level PFL measures:

$$\%Est.PFL_{i,t} = \frac{1}{N_{i,t}} \sum_{e \in E_{i,t}} PFL_{i,e,t}, \quad (3)$$

$$\%Emp.PFL_{i,t} = \sum_{e \in E_{i,t}} \frac{Emp_{i,e,t}}{Emp_{i,t}} \times PFL_{i,e,t}. \quad (4)$$

In the above equations, $E_{i,t}$ denotes the set of all establishments of firm i in quarter t , and $N_{i,t}$ is the total number of establishments of firm i in quarter t . $Emp_{i,e,t}$ is the number of employees in establishment e and firm i in quarter t , and $Emp_{i,t}$ is the number of

¹¹The YTS database is used in recent finance studies, including Flynn Jr and Ghent (2024) and Campello, Connolly, Kankanhalli, and Steiner (2022).

employees in firm i in quarter t . Hence, $\%Est.PFL_{i,t}$ represents the proportion of firm i 's establishments affected by PFL in quarter t , and $\%Emp.PFL_{i,t}$ represents the proportion of firm i 's employees affected by PFL in quarter t .

We use these two establishment-aggregated PFL measures as independent variables and estimate the same regression as in our baseline specification. The results, reported in Appendix Table A4, show that the coefficients on $\%Est.PFL$ and $\%Emp.PFL$ are 0.081 and 0.106, respectively, and both are significant. Therefore, the effect of PFL on loan spreads is robust even when establishment-level data are used to construct more precise measures of PFL exposure.

Fifth, to better isolate the treatment effect, we restrict the time series of treated states to the three years before and five years after the mandate becomes effective. The result remains robust and is reported in Columns (1) and (2) of Appendix Table A5. In addition, in Columns (3) and (4) in Appendix Table A5, we account for lender-side effects by including lead bank fixed effects in the regression. The result confirms the robustness of our main conclusion.

4.4 Default risk

The results provided up to this point suggest that firms' borrowing costs increase significantly following the adoption of PFL. Because borrowing costs are primarily determined by firms' default risk, we further examine whether PFL is associated with elevated default risk for firms. Specifically, in this subsection, we provide both firm-level and lender-level evidence that firms affected by PFL exhibit higher default risk.

4.4.1 Firm-level evidence

To examine the effect of PFL on default risk, we estimate the following firm-level equation:

$$Default\ Risk_{i,t} = \alpha + \beta \times PFL_{i,t-1} + Firm\ Control_{i,t-1} + \delta_i + \tau_t + \varepsilon_{i,t}, \quad (5)$$

where $Default\ Risk_{i,t}$ represents firm i 's default risk at the end of quarter t . We utilize three measures of default risk: the expected default frequency (EDF) introduced by [Bharath and Shumway \(2008\)](#), [Altman \(1968\)](#)'s Z-score, and cash flow scaled by total assets. A higher EDF indicates a higher probability of default, while a lower Z-score and lower cash flow signify worse financial health and thus higher firm default risk. We also control for firm-level characteristics and include firm and time fixed effects in the regression.

Table 4 presents the regression results. In Column (1), the coefficient on PFL is 1.563 and statistically significant. That is, the expected default frequency of PFL-treated firms is 1.56% higher than that of control firms, which is economically substantial considering the sample mean of 3.24%. In Column (2), we find that the effect of PFL on Z-score is negative and statistically significant. The coefficient of -0.174 shows that following the adoption of PFL mandates, the firm's Z-score decreases by 7% ($0.174/2.426$), relative to the average sample Z-score of 2.426. In Column (3), we find that PFL mandates significantly reduce firm cash flow by 0.6% on average, relative to total assets. Overall, these findings suggest that PFL increases firms' default risk, leading banks to charge a higher loan spread.

To further validate PFL's impact on default risk, we investigate how borrowers' loan covenant violations change after PFL mandates are adopted. The rationale is that if PFL

exacerbates firms' default risk, we should observe a higher incidence of covenant violations in PFL-impacted loans. We construct a firm-quarter level sample comprising all quarters with outstanding loans of all borrowers and estimate the following model:

$$Covenant_Violation_{i,t} = \alpha + \beta \times PFL_{i,t-1} + Firm\ Control_{i,t-1} + \delta_i + \tau_t + \varepsilon_{i,t}. \quad (6)$$

We introduce an indicator variable *Covenant_Violation*, which is equal to 1 if at least one covenant is violated for any outstanding loan borrowed by firm *i* in quarter *t*, and zero otherwise. The data on loan covenants is from Dealscan. In line with the loan covenant literature (Demiroglu and James, 2010; Falato and Liang, 2016; Yang, 2025), we consider five commonly used covenants: minimum tangible net worth, minimum net worth, minimum current ratio, maximum leverage ratio, and maximum debt-to-cash flow ratio. For each quarter and each loan facility, we compute the distance between the threshold specified in the covenants and the corresponding actual data of the firm. A greater absolute value of distance indicates that the firm is further away from the threshold and has a lower risk of covenant violation. We define a covenant violation as occurring if in any covenants of any outstanding loans, the distance is negative (positive) if a positive value of this variable indicates higher (lower) default risk.

Table 5 presents the results of regressing *Covenant_Violation* on PFL. Column (1) reports the result without control variables, while Column (2) include all loan and firm controls. In both columns, the coefficients on PFL are positive and significant above the 1% level, indicating a greater likelihood of covenant violation for firms affected by PFL.

If PFL increases loan spread by heightening default risk, we should expect such effect

to be more pronounced in financially constrained firms. When employees take paid leave, employers may need to hire additional workers or pay overtime. A firm’s ability to manage these adjustments largely depends on its financial condition. Firms lacking external financing may face greater operational disruptions and thus higher default risk, prompting banks to charge higher loan prices.

To test this hypothesis, we partition the sample into two groups based on proxies for financial constraints and conduct regression analysis for each subsample. We first use the Kaplan-Zingales (KZ) index, where a higher value indicates greater financial constraints. Columns (1) and (2) of Table 6 show that the impact of PFL on loan spreads is stronger for firms in the high KZ-index sample than those in the low KZ-index sample. In Columns (3) and (4) of Table 6, we use a firm’s payout ratio as a proxy for financial constraints, with a lower payout ratio indicating greater financial constraints. The result shows that low payout firms are charged significantly higher loan spreads due to PFL, compared to high payout firms, and the difference is significant below 1% level. Overall, the results suggest that financially constrained firms experience a larger increase in borrowing costs following PFL adoption, consistent with our expectations.

4.4.2 Lender-level evidence

Our analyses thus far show that PFL mandates increase firms’ borrowing costs for bank loans, primarily due to heightened concerns about firm default risk. To further support this argument, we explore how banks’ risk exposure, when interacting with borrower’s PFL exposure, affects their lending behavior. Specifically, we hypothesize that banks with high

ex-ante loan exposure to riskier borrowers are less likely to issue new loans to PFL-affected firms, as such lending could exacerbate their risk profile.

We first calculate a lender-firm-quarter level variable, $Borrower_Share_{i,l,t}$, as the share of newly issued loans that lender l lends to borrower i in lender l 's total new lending to all borrowers in quarter t :

$$Borrower_Share_{i,l,t} = \frac{New_Issued_Loan_{i,l,t}}{\sum_{i=1}^N New_Issued_Loan_{i,l,t}} \times 100\%, \quad (7)$$

where $New_Issued_Loan_{i,l,t}$ is the amount of new loans borrowed by firm i from lender l in quarter t . $Lender_Share_{i,l,t}$ thus captures borrower i 's weight in lender l 's portfolio.

We then construct a lender-quarter level default risk exposure variable as:

$$Default_Risk_Exposure_{l,t} = \frac{\sum_{i=1}^N Outstanding_Loan_{i,l,t} \times High_Default_Risk_{i,t}}{\sum_{i=1}^N Outstanding_Loan_{i,l,t}}, \quad (8)$$

where $Outstanding_Loan_{i,l,t}$ is the amount of all unmatured loans borrowed by firm i from lender l at the end of quarter t . $High_Default_Risk_{i,t}$ is a firm-quarter level indicator for firms with higher default risk than the cross-sectional median, where default risk is proxied by EDF or a negative Z-Score. $Default_Risk_Exposure_{l,t}$ is the proportion of outstanding loans that lender l lends to firms with high default risk in quarter t . We then define $High_Default_Risk_Exposure_{l,t}$ as a lender-quarter level indicator which equals one if the lender's $Default_Risk_Exposure_{l,t}$ is greater than the cross-sectional median, and zero otherwise.

Finally, we test whether lenders with higher ex-ante exposure to high default risk borrow-

ers are less willing to lend to PFL-affected firms. We interact *High_Default_Risk_Exposure* with firm-level *PFL* and include firm-lender fixed effects and quarter fixed effects in the following model:

$$\begin{aligned}
Borrower_Share_{i,l,t} = & \alpha + \beta_1 \times High_Default_Risk_Exposure_{l,t-1} \times PFL_{i,t-1} \\
& + \beta_2 \times High_Default_Risk_Exposure_{l,t-1} + \beta_3 \times PFL_{i,t-1} \\
& + Firm\ Controls_{i,t-1} + \varphi_{i,l} + \tau_t + \varepsilon_{i,l,t}.
\end{aligned} \tag{9}$$

Table 7 reports the estimation results. In Column (1), the coefficient on *PFL* is -0.105, negative but statistically insignificant. In Columns (2) and (3), the coefficients on the interaction terms are negative and statistically significant, suggesting that lenders with higher ex-ante default risk exposure significantly reduce lending to PFL-affected firms. This result, together with our earlier findings, shows that lenders exposed to higher risk not only adjust loan pricing to account for PFL but also reduce their lending to PFL-affected firms, suggesting that PFL is an important risk factor in lending decisions.

5 Economic Mechanisms

This section explores the underlying mechanisms through which PFL affects firms' borrowing costs. We identify one main mechanism: indirect costs stemming from labor adjustments that firms make in response to PFL adoption. We find evidence that PFL-affected firms tend to hire more employees, and firms with a potentially higher PFL take-up rate or firms that find more difficult to adjust labor deployment experience a steeper increase in

loan prices, supporting the indirect cost channel.

5.1 Labor adjustments following PFL

With paid leave benefits in place, more employees are likely to take leave, and some may extend their time off, resulting in these employees being “employed but not at work.” Additionally, some employees may choose not to return to their jobs, as the enjoyment of parenting increases with time spent with infants, and prolonged absences from the labor market can make re-entry more difficult (Bailey, Byker, Patel, and Ramnath, 2025). As a result, the rise in leave rates leads to more temporary job vacancies. To fill these vacancies, firms need to hire new employees, which incurs additional labor adjustment costs. These costs can negatively affect firm performance, subsequently impacting the company’s credit risk and loan terms.

To test this hypothesis, we first verify that PFL increases firms’ labor adjustments. We use a firm’s number of temporary job openings and job postings as proxies for labor adjustments. We collect job posting information for our sample firms from RavenPack’s Job Analytics Database and focus on jobs located within the United States.¹² We specifically analyze job postings labeled as “temporary” by RavenPack, as these are more likely to reflect hiring aimed at filling vacancies due to PFL, rather than hiring new employees attracted by PFL benefits.¹³ RavenPack contains detailed job descriptions for each posting, including

¹²Campello, Kankanhalli, and Muthukrishnan (2024) verify that this job posting data is well representative of actual job creation, as it closely aligns with data from the Job Openings and Labor Turnover Survey (JOLTS) of the Bureau of Labor Statistics (BLS) and the data on job creation (the variable “Firm Job Gains”) from the U.S. Census Bureau’s Quarterly Workforce Indicators (QWI).

¹³RavenPack labels a job posting as “temporary” if its description contains keywords such as temporary employment, temp-to-hire, daily hire employment, employee leasing, internship, on-call employment, part-time employee, among others.

workplace location, which enables us to measure labor adjustments at the firm-state-quarter level. We construct two measures of labor adjustments: 1) $Temp_Job_Opening_{i,s,t}$, the number of job positions listed in firm i 's temporary job postings in state s and quarter t ; 2) $Temp_Job_Posting_{i,s,t}$, the total number of temporary job postings by firm i in state s and quarter t .¹⁴

We create a firm-state-quarter-level sample by merging job posting data with the employee data from the YTS database and our baseline sample. The final sample includes firm-state-quarter (i, s, t) observations, where firm i is a borrower in our baseline sample, has at least one temporary job posting during the entire sample period, and has job openings in state s and quarter t . The sample begins in 2008, instead of 2001 as in the baseline regression, due to the availability of job posting data only from 2008 onward. Using this sample, we conduct the following test:

$$E[Labor_Adj_{i,s,t}] = \exp(\beta \times PFL_{i,s,t-1} + \gamma \times \log(Emp)_{i,s,t-1} + Firm\ Controls_{i,t-1} + \mu_{i,s} + \tau_t). \quad (10)$$

In the equation above, $Labor_Adj_{i,s,t}$ denotes the two labor adjustments variables discussed earlier, $PFL_{i,s,t}$ indicates whether state s , where firm i has employees, has adopted PFL in quarter t , and $\log(Emp)_{i,s,t-1}$ denotes the natural logarithm of the number of firm i 's employees located in state s and quarter t . Because the dependent variables are nonnegative count variables, we use a Poisson model in Equation (10) to yield consistent and efficient estimates (Cohn, Liu, and Wardlaw, 2022). To control for possible confounders, we include the number of employees at the firm-state-quarter level and firm-state and quarter fixed

¹⁴We construct these two separate measures because a job posting may include one or more job openings.

effects in the model.

The regression results from Equation (10), as reported in Table 8, find a notable increase in temporary job postings in PFL-mandated states. On average, a company’s temporary job postings increase by approximately 90% ($\exp(0.64)-1$) in states with PFL mandates. In summary, the results in Table 8 highlight that, after the passages of state-level PFL mandates, firms hire more temporary employees to cover for those on leave, and such intensified labor adjustments could increase costs. ¹⁵

5.2 Labor intensity and PFL take-up

We have thus far demonstrated that PFL-affected firms have more labor adjustments. In this section, we argue that the impact of PFL is more significant when the marginal influence of PFL is greater, i.e., labor-intensive firms or those with employees who are more likely to take paid leave. Therefore, if PFL’s impact on borrowing costs stems from banks’ concerns about labor supply disruptions, we expect the effect to be more pronounced for firms with higher labor intensity or greater PFL take-up rates. To validate this conjecture, we introduce two measures on firms’ exposure to PFL and conduct a cross-sectional analysis based on these measures.

We measure labor intensity as the industry-level annual staff expenses, divided by total assets in the industry (Agrawal and Matsa, 2013). Firms in industries with higher staff expenses compared to total assets are more labor intensive. Moreover, although PFL applies to both male and female workers, female employees, who typically spend more time with

¹⁵In unreported analysis, we also find that temporary job postings are associated with higher loan spreads.

their children, have higher PFL take-up rates and take longer leaves (Byker, 2016; Baum and Ruhm, 2016). Thus, we anticipate a stronger effect of PFL in firms with a higher fraction of childbearing-age women. Since a firm’s demographic characteristics are not directly observable, we use the ratio of childbearing-age women to the total population at the county level as a proxy for firm-level demographics.¹⁶ As labor markets are often geographically segmented, a firm’s gender structure can be reasonably captured by the gender structure of the local labor market.

Next, for each quarter, we partition the full sample into two groups based on the aforementioned labor-related measures, and conduct panel regressions following the baseline specification for these subsamples. Panel A of Table 9 presents the results of the cross-sectional analysis. Comparing Columns (1) and (2), we observe that the impact of PFL on loan spreads is more pronounced for firms operating in industries with higher labor intensity, and the difference is both economically and statistically significant. This result suggests that the loan pricing premium associated with PFL primarily stems from firms that rely more heavily on human capital. Similarly, Columns (3) and (4) indicate a stronger positive effect of PFL on loan spreads for firms with higher ratios of childbearing-age women.

Overall, the results above suggest that in PFL states, firms characterized by high exposure to PFL are more likely to experience productivity losses and increased labor adjustment costs, leading to higher borrowing costs.

¹⁶Specifically, we use the proportion of females aged 15-44 to the total population of individuals aged 15-44 in the county where the firm is headquartered. We define childbearing-age women as those aged 15-44, and the results remain robust when we use alternative age cutoffs.

5.3 Labor adjustment frictions

To further explore the labor adjustment mechanism, we examine factors that could affect a firm’s ability to make labor adjustments. Firms could replace employees on leave with other employees or with machine. For replacement with other employees, [Ginja, Karimi, and Xiao \(2023\)](#) document that firms respond to temporary worker leave through internal replacement or external hiring in practice. Accordingly, we introduce two measures capturing labor adjustment frictions along these dimensions: internal substitutability and labor market thickness. For replacement with machine, in firms that employ workers who are not easily replaceable by capital, such as skilled labor, teamwork efficiency and firm operations may be negatively impacted by employees’ leave, leading to higher labor adjustment costs. We thus use automation potential as a proxy for firms’ labor replaceability with machine.

We first construct a measure of internal substitutability (IS) to capture how easily employees within a firm can substitute for one another following [Ginja, Karimi, and Xiao \(2023\)](#). The underlying intuition is that if more employees at a given workplace perform similar types of jobs, it is easier for the firm to replace a worker who takes leave. We define a “workplace” as the specific location or site where the firm operates. Because detailed workplace-level employment data are unavailable, we treat each city in which a firm operates as one workplace. Using employment data from Revelio Labs, we construct the IS measure as below. First, we calculate internal substitutability at the firm-workplace-year level as:

$$IS_{i,w,t} = \frac{emp_{i,w,t}^{\max}}{emp_{i,w,t}}, \quad (11)$$

where $emp_{i,w,t}^{\max}$ is the number of employees in the largest occupation category at workplace w , and $emp_{i,w,t}$ is the total number of employees of firm i at workplace w in year t . A higher value of $IS_{i,w,t}$ indicates greater occupational concentration and, therefore, higher internal substitutability in that workplace.¹⁷ Second, we aggregate the firm-workplace-year-level measure to the firm-year level by weighting each workplace's value by its employee count:

$$IS_{i,t} = \frac{\sum_w emp_{i,w,t} \times IS_{i,w,t}}{\sum_w emp_{i,w,t}}. \quad (12)$$

Columns (1) and (2) of Panel B in Table 9 present regression results comparing firms with high versus low internal substitutability. The coefficient on PFL is larger and more significant for firms with low internal substitutability, suggesting that PFL imposes a greater burden on firms that struggle to find replacements for employees on leave. This finding supports the role of labor adjustment costs in shaping loan pricing responses.

To capture external labor adjustment, we construct a measure of labor market thickness at the industry-state-year level as below.

$$\theta_{k,s,t} = \left(\frac{emp_{k,s,t}}{emp_{s,t}} \right) / \left(\frac{emp_{k,t}}{emp_t} \right), \quad (13)$$

where emp denotes the total number of employees, and k, s, t refer to industry, state, and year, respectively. For example, $emp_{k,s,t}$ is the total number of employees in industry k , state s , and year t . As a result, $\theta_{k,s,t}$ denotes the share of employees in industry k within

¹⁷In untabulated results, we also construct an alternative measure of internal substitutability using one minus the Herfindahl-Hirschman Index (HHI) of the share of employees in each occupation within each firm-city-year and find similar results.

state s relative to the national average for that industry. We define a local labor market as “thick” if $\theta_{k,s,t} > 1$ and “thin” otherwise. Column (3) and (4) of Panel B in Table 9 shows that the effect of PFL on loan spreads is positive and significant for firms operating in thin labor markets, but negative and insignificant for those in thick labor markets.

Lastly, we measure labor replaceability with machine using the automation potential measure from Knesl (2023), which is the natural logarithm of the number of employees in routine-intensive occupations in a firm divided by the firm’s capital.¹⁸ Employees in routine occupations are more easily replaced by capital through automation, thus mitigating the effect of labor shortages. Columns (5) and (6) of Panel B in Table 9 present the findings from the cross-sectional analysis based on labor automation potential. We find that PFL has a more significant impact on loan pricing for firms with a lower fraction of automation potential, which incur higher adjustment costs. These results are consistent with our labor adjustment mechanism.

6 Further Discussion

6.1 Aligning with the extant literature: the role of default risk

Our study provides evidence that PFL increases loan spreads, driven by labor adjustment costs. While this may seem at odds with prior research such as Bennett, Erel, Stern, and Wang (2025), who document that PFL reduces employee turnover and enhances firm

¹⁸Following Knesl (2023), we estimate the number of employees in routine-intensive occupations within a firm by multiplying the firm’s total number of employees, as reported in Compustat, by the proportion of routine-intensive jobs in the firm’s industry. Industry-level occupational shares are from the Occupational Employment Statistics (OES) database, and the Routine Task Intensity (RTI) measure is from the O*NET database. We thank Jiri Knesl for providing the data and code used in this analysis.

profitability, the findings are not inconsistent with each other. It is important to note that unlike equity holders, debtholders do not benefit from the corporate upside opportunities associated with PFL but suffer from increased default risk from firms in the left tail of the credit quality distribution. In fact, when we split the sample firms according to their ex-ante default risk, we find that our findings and those of [Bennett, Erel, Stern, and Wang \(2025\)](#) are driven by distinct subsamples. We detail our analysis below.

We first replicate the main results in [Bennett, Erel, Stern, and Wang \(2025\)](#) using the same sample as in their study. Column (1) in Table 10 shows that the overall effect of PFL on profitability (measured by Return on Assets, or ROA) is positive and consistent with their reported results.¹⁹ Building on the argument that default risk is the primary driver of increased loan spreads, we partition the sample by expected default frequency. Columns (2) and (3) reveal that the positive effect of PFL on ROA is significant only among firms with low default risk. [Bennett, Erel, Stern, and Wang \(2025\)](#) suggest that PFL enhances workforce stability and productivity. This effect may be attenuated for higher-risk firms, as these firms are generally less attractive to employees, smaller in size, more cash-flow volatile, and operationally less efficient. These characteristics make it more challenging to adjust labor deployment in response to temporary leave. Consequently, we observe no profitability gains from PFL among higher-risk firms (Table 10 Column 2). In contrast, lower-risk firms, typically larger and financially healthier, experience significant profitability gains from PFL, as the benefits (increased productivity from attracting talent) of PFL outweigh the associated costs (labor adjustments) (Table 10 Column 3).

¹⁹The results in Table 10 are based on annual data, consistent with [Bennett, Erel, Stern, and Wang \(2025\)](#). Unreported analyses show that these results remain largely unchanged when using quarterly data.

Next, we partition our baseline loan sample into high and low default risk groups. The findings in Column (4) through Column (6) in Table 10 show that the effect of PFL on loan spreads is more pronounced among firms with higher default risk.

To summarize, the positive effects of PFL on profitability are concentrated among low-default-risk firms, whereas the impact of PFL on loan spreads is concentrated among high-default-risk firms. This is consistent with the notion that debtholders do not capture the upside potential of PFL but instead bear the increased default risk from firms in the lower tail of the credit quality distribution.

6.2 Direct cost: compensation provision

Our sample period from 2001 to 2020 limits our analysis to PFL mandates in four states: California (PFL effective in 2004), New Jersey (2009), Rhode Island (2014), and New York (2018). Note that the PFL policies in these four states are 100% funded by employees through a payroll tax on wages, thus imposing no direct costs on employers. Our findings based on these four states support the hypothesis that, even without direct costs, firms experience an increase in labor adjustment costs, credit risk, and loan prices; that is, the indirect costs caused by the PFL are significant.

In this subsection, we explore the implications of the San Francisco Paid Parental Leave Ordinance (SF PPLO), which became effective on January 1, 2017. This mandate requires employers in the City and County of San Francisco to provide supplemental compensation to employees who receive California Paid Family Leave (CPFL) benefits. CPFL is a state-level program that compensates eligible employees at 55% of their weekly wages to support

bonding with a newborn, newly adopted, or foster child and was introduced in 2004. Under the SF PPLO, employers are obligated to provide supplemental compensation equal to the difference between normal gross weekly wages and CPFL benefits. With the SF PPLO, employees can receive up to 100% of their weekly wages for up to six weeks.

We investigate how the SF PPLO policy affects loan pricing. We hypothesize that when employers are required to fund supplemental PFL, the increase in borrowing costs will be more pronounced compared to situations where employers do not contribute to PFL. To test this hypothesis, we focus on borrowers headquartered in California and limit the sample period to three years before and after the SF PPLO’s implementation in 2017, specifically from 2014 to 2020. We then compare loan prices for firms with employees in San Francisco to those without, both before and after the SF PPLO mandate. That is, we estimate the following regression model:

$$\log(\text{Spread})_{i,f,t} = \alpha + \beta \times SF_PPLO_{i,t-1} + \text{Loan Control}_{f,t} + \text{Firm Control}_{i,t-1} + \delta_i + \tau_t + \varepsilon_{i,f,t}, \quad (14)$$

where *SF_PPLO* is an indicator variable equal to one if the firm is affected by the SF PPLO (that is, the firm has at least one establishment in San Francisco after January 1, 2017), and zero otherwise. We include loan-level and firm-level control variables as in the baseline model, and standard errors are clustered at the county level.

Column (1) of Table 11, Panel B reports the estimated results and shows that the coefficient of *SF_PPLO* is 0.156 and significant at the 5% level. This indicates that for firms with establishments in San Francisco, the loan borrowing cost is approximately 15.6% (or

35.48 basis points, given the sample mean borrowing cost of 227.44 basis points from Table 11, Panel A) higher than other California-headquartered firms after the SF PPLO mandate took effect in 2017. We also examine the effect of *SF_PPLO* on loan size in Column (2) of Table 11, Panel B. We find that loans borrowed by San Francisco firms after the SF PPLO decrease significantly in size by 21.5% (or \$161 million, based on the average sample loan size of \$748 million in Table 11, Panel B). The increase in spread and the decrease in loan size is significantly larger than in the baseline results (21 basis points from Table 2 Column (2), and \$31 million from Appendix Table A2 Column (1), with the latter being statistically insignificant).²⁰ Therefore, in addition to the indirect costs associated with labor adjustments, the imposition of direct costs on employers results in a more substantial impact on bank loans.

7 Conclusion

This study examines the impact of state-level paid family leave mandates on firms' bank loan costs. Our analysis reveals a significant increase in loan spreads for firms headquartered in states that have implemented PFL policies. The increase in borrowing costs is economically meaningful, with treated firms facing an average loan spread approximately 21 basis points higher than firms without PFL mandates. These results hold across various robustness checks, such as controlling for economic and political factors, matching and Stacked-DID methods, and alternative measures using establishment-level data.

Further analysis shows that PFL increases firms' default risk, leading to higher borrowing

²⁰The comparison of magnitudes should be interpreted with caution because the sample size for the SF PPLO analysis is considerably smaller.

costs. Banks with greater exposure to default risk are more reluctant to lend to PFL-affected firms, emphasizing PFL's impact on bank lending. Two mechanisms contribute to the heightened default risk: indirect labor adjustment costs and direct costs arising from compensating employees on leave.

For the indirect cost mechanism, we find that firms under PFL mandates experience greater demand for new hires. Moreover, firms that depend more on labor and face greater labor adjustment frictions exhibit a larger increase in borrowing costs. Regarding the direct cost mechanism, we utilize the 2017 San Francisco Paid Parental Leave Ordinance as an exogenous policy shock and show that firms required to provide supplemental compensation for employees on family leave face higher borrowing costs than firms not required to do so. Overall, the results from both mechanisms suggest that banks factor in both indirect and direct costs of PFL when pricing loans.

In summary, our study provides novel evidence of the previously under-explored consequence of paid family leave on firms' bank loan costs. Our findings contribute to the emerging literature on paid family leave and highlight the need for a broader examination of the impact of social policies on firms.

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Figure 1. Dynamic Effects of PFL on Loan Spreads

This figure presents the dynamic effect of PFL on loan spreads by estimating Equation (2). The solid dots and bars represent the estimated coefficients of each $PFL_{i,t-1}^k$ and their corresponding 95% confidence intervals. The x-axis is quarters relative to PFL adoption, from -10 to 10, and the y-axis displays the magnitude of the coefficients. The red dashed vertical line marks the PFL adoption date, and the red dashed horizontal line represents zero.

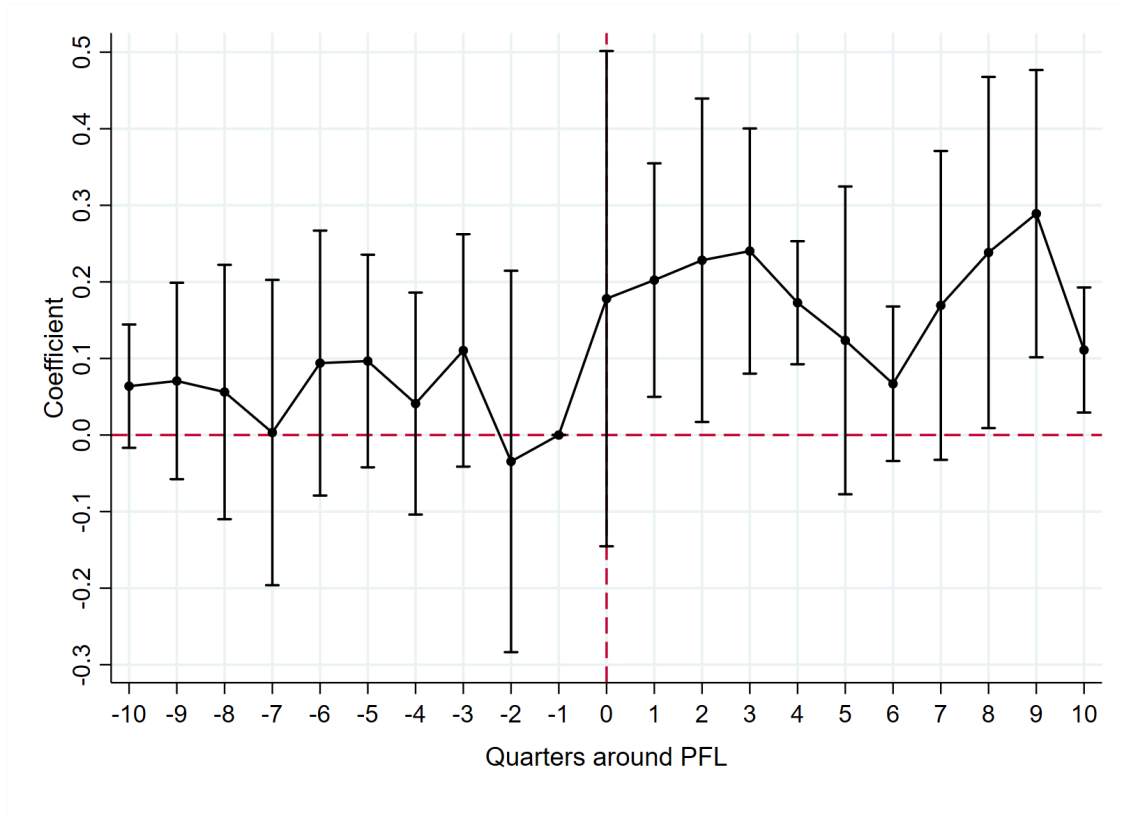


Table 1. Summary Statistics

This table presents the summary statistics for the main variables used in our analysis. The sample period is from 2001 Q2 to 2020 Q2 and consists of 22,952 firm-quarter-loan observations. All continuous variables are winsorized at the 1st and 99th percentiles. Detailed variable definitions are provided in Appendix.

Panel A: Loan-level characteristics						
Variables	Obs.	Mean	SD	P25	Median	P75
Loan Spread (bps)	22,952	233.270	149.610	17.500	125	200
log(Spread)	22,952	5.227	0.735	2.862	4.828	5.298
Loan Size (\$million)	22,952	451.460	675.694	2.045	65	200
log(Loan Size)	22,952	5.150	1.569	0.715	4.174	5.298
Maturity (number of months)	22,952	51.444	19.909	6	36	60
log(Maturity)	22,951	3.819	0.570	1.792	3.584	4.094
Secured	22,952	0.595	0.491	0	0	1
Syndication	22,952	0.880	0.325	0	1	1
Performance pricing	22,952	0.415	0.493	0	0	0
Num_lenders	22,952	8.520	7.776	1	3	6
log(Num_lenders)	22,952	1.746	0.941	0	1.099	1.792
Panel B: Firm-level characteristics						
Variables	Obs.	Mean	SD	P25	Median	P75
PFL	22,952	0.092	0.289	0	0	0
Total Asset (\$billion)	22,952	7.161	18.614	0.508	1.637	5.147
log(Total Asset)	22,949	7.365	1.760	3.061	6.203	7.375
Leverage	22,948	1.571	6.522	-34.402	0.663	1.237
Book-to-market	21,736	0.449	1.212	-8.754	0.249	0.444
Cash holding	22,949	0.092	0.111	0	0.018	0.051
Tangibility	22,904	0.292	0.239	0.011	0.104	0.218
ROA	22,932	0.006	0.034	-0.182	0.001	0.010
Z-Score	20,278	2.349	2.352	-2.266	1.087	1.886
Sales growth	21,911	0.748	6.281	-28.477	-0.296	0.493

Table 2. The Effect of PFL on Loan Pricing: Baseline Results

This table reports the effect of PFL on loan pricing using loan-level regressions. The dependent variable, $\log(\textit{Spread})$, is the natural logarithm of the all-in drawn loan spread (in basis points). The main independent variable, PFL , is an indicator variable equal to one if the firm's headquarters state has an effective PFL mandate and zero otherwise. Column (2) is the main specification used throughout the subsequent regressions. All continuous variables are winsorized at the 1st and 99th percentiles, and all time-variant explanatory variables are lagged by one quarter. t -statistics based on heteroskedasticity consistent standard errors clustered at the state level are reported in parentheses. Definitions for other variables are in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. The sample period is from 2001 Q2 to 2020 Q2.

	(1)	(2)	(3)	(4)
PFL	0.076*** (2.78)	0.090*** (3.19)	0.076*** (3.30)	0.078*** (4.31)
log(Loan Size)		-0.101*** (-11.08)		-0.090*** (-12.32)
log(Maturity)		0.171*** (10.49)		0.165*** (11.46)
Secured		0.361*** (19.91)		0.342*** (21.31)
Syndication		0.149*** (5.95)		0.156*** (4.45)
Performance pricing		-0.127*** (-8.22)		-0.130*** (-9.28)
log(Num_lenders)		-0.136*** (-13.51)		-0.144*** (-15.89)
log(Total Asset)		-0.053*** (-3.68)		-0.057*** (-4.41)
Leverage		-0.000 (-0.42)		-0.000 (-0.24)
Book-to-market		-0.002 (-0.56)		0.001 (0.17)
Cash holding		-0.027 (-0.34)		0.009 (0.11)
Tangibility		-0.086 (-0.96)		-0.061 (-0.59)
ROA		-1.243*** (-5.06)		-1.293*** (-5.58)
Z-Score		-0.029*** (-7.88)		-0.028*** (-7.70)
Sales growth		0.001 (0.85)		0.001 (0.49)
Firm FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes		
Industry×Quarter FE			Yes	Yes
Obs.	22,217	18,770	21,877	18,400
Adj. R^2	0.615	0.706	0.657	0.737

**Table 3. The Effect of PFL on Loan Pricing:
Ruling out Economic and Political Factors**

This table report the regression results on the effect of PFL on loan pricing, after controlling for state-year characteristics. The dependent variable, $\log(\textit{Spread})$, is the natural logarithm of the all-in drawn loan spread (in basis points). The main independent variable, $\textit{PFL}$, is an indicator variable equal to one if the firm’s headquarter state has an effective PFL mandate and zero otherwise. “Loan Controls” and “Firm Controls” are the same as in Table 2, Column (2). Definitions for other variables are in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles, and all time-variant explanatory variables are lagged by one quarter. t -statistics based on heteroskedasticity consistent standard errors clustered at the state level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. The sample period is 2001 Q2 to 2020 Q2.

	(1)	(2)	(3)	(4)	(5)	(6)
PFL	0.094*** (3.50)	0.092*** (3.52)	0.088*** (3.76)	0.088*** (3.87)	0.090*** (3.86)	0.091*** (3.87)
log(GDP)	-0.037* (-1.98)	-0.037* (-1.97)	-0.029 (-1.34)	-0.030 (-1.34)	-0.029 (-1.28)	-0.030 (-1.31)
Unemployment rate		0.004 (0.46)	0.004 (0.47)	0.005 (0.51)	0.004 (0.46)	0.005 (0.50)
Labor force rate			1.011* (1.79)	0.802 (1.20)	0.866 (1.39)	0.849 (1.38)
Female employee ratio				-2.787 (-0.85)	-2.882 (-0.86)	-3.165 (-0.95)
Minimum wage					-0.006 (-0.58)	-0.007 (-0.61)
Democrat						0.010 (0.44)
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	18,757	18,757	18,757	18,757	18,757	18,757
Adj. R^2	0.706	0.706	0.706	0.706	0.706	0.706

Table 4. PFL and Firm Default Risk

This table reports the results of regressing firm-level default risk on PFL. *EDF* is the expected default frequency. *Z-score* is the Altman's Z-score. *Cash Flow* is EBITDA divided by total assets. The main independent variable, *PFL*, is an indicator variable equal to one if the firm's headquarter state has an effective PFL mandate and zero otherwise. Definitions for other variables are in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles, and all time-variant explanatory variables are lagged by one quarter. *t*-statistics based on heteroskedasticity consistent standard errors clustered at the state level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. The sample period is 2001 Q2 to 2020 Q2.

	(1) EDF	(2) Z-Score	(3) Cash Flow
PFL	1.563* (1.93)	-0.174** (-2.46)	-0.006** (-2.07)
log(Total Asset)	-0.849** (-2.18)	-0.406*** (-7.99)	-0.004 (-1.12)
Leverage	-0.076* (-1.94)	-0.000 (-0.18)	0.000 (1.03)
Book-to-market	-0.300 (-0.50)	0.024* (1.72)	-0.011*** (-3.82)
Cash holding	0.681 (0.25)	5.569*** (12.83)	-0.038*** (-3.37)
Tangibility	12.702*** (4.58)	-0.689** (-2.24)	-0.010 (-0.61)
ROA	-109.363*** (-12.21)	12.472*** (18.12)	0.721*** (17.93)
Z-Score	-0.739*** (-4.51)		0.006*** (6.57)
Sales growth	-0.082** (-2.38)	0.003 (1.62)	0.000 (0.72)
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Obs.	11,147	11,948	11,416
Adj. R^2	0.381	0.711	0.632

Table 5. PFL and Loan Covenant Violation

This table reports the results of regressing firm-quarter-level covenant violations on PFL. The sample comprises all quarters with outstanding loans of all borrowers. The dependent variable is $Covenant_Violation_{i,t}$, which is an indicator equal to 1 if at least one of the five commonly used covenants is violated by firm i in quarter t , and zero otherwise. The five covenants considered include: minimum tangible net worth, minimum net worth, minimum current ratio, maximum leverage ratio, and maximum debt-to-cash flow ratio. A violation occurs when the firm's corresponding variable is above (or below) the threshold, depending on whether it indicates higher (or lower) default risk. The main independent variable, PFL , is an indicator variable equal to one if the firm's headquarter state has an effective PFL mandate and zero otherwise. "Firm Controls" are the same as in Table 4, Column (1). All continuous variables are winsorized at the 1st and 99th percentiles, and all time-variant explanatory variables are lagged by one quarter. t -statistics based on heteroskedasticity consistent standard errors clustered at the state level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. The sample period is from 2001 Q2 to 2020 Q2.

	(1) Covenant Violation	(2) Covenant Violation
PFL	0.058*** (4.38)	0.056*** (3.32)
Firm Controls		Yes
Firm FE	Yes	Yes
Quarter FE	Yes	Yes
Obs.	65,676	65,676
Adj. R^2	0.400	0.423

Table 6. PFL and Loan Pricing: The Role of Financial Constraints

This table presents the cross-sectional analysis of the effect of PFL on loan spreads. The dependent variable, $\log(\text{Spread})$, is the natural logarithm of the all-in drawn loan spread (in basis points). The main independent variable, PFL, is an indicator variable equal to one if the firm’s headquarter state has an effective PFL mandate and zero otherwise. We partition the full sample into two groups based on two financial constraint measures: the KZ (Kaplan-Zingales) index and the firm payout ratio. A higher KZ index indicates greater financial constraints. Firms are categorized into high and low KZ index subsamples based on whether the one-quarter-lagged KZ index is above or below the cross-sectional median. The payout ratio is calculated as the sum of a firm’s total dividends and repurchases divided by its market value of equity, which is the product of the number of shares outstanding and the stock price. A higher payout ratio is associated with lower financial constraints. Firms are categorized into “High” and “Low” payout ratio subsamples based on whether the one-quarter-lagged value of payout ratio is above zero or equal to zero. The table also reports the differences in the coefficients β of PFL between the high and low groups. Along with the p -values from significance tests. The p -value for the coefficient differences is derived from an empirical Fisher’s permutation test based on 1,000 resamplings. “Loan Controls” and “Firm Controls” are the same as in Table 2, Column (2). All continuous variables are winsorized at the 1st and 99th percentiles, and all time-variant explanatory variables are lagged by one quarter. t -statistics based on heteroskedasticity consistent standard errors clustered at the state level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. The sample period is 2001 Q2 to 2020 Q2.

Category variable	(1)	(2)	(3)	(4)
	KZ Index		Payout Ratio	
	High	Low	High	Low
PFL	0.090** (-2.32)	0.047 (1.43)	0.044 (0.88)	0.195*** (6.86)
Difference between β	0.043 p=0.195		-0.151*** p=0.008	
Loan Controls	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Obs.	8,981	8,779	11,764	5,450
Adj. R^2	0.670	0.740	0.732	0.622

Table 7. PFL, Lenders' Ex-ante Default Risk Exposure, and Lending Behavior

This table reports the results of regressing the borrower's share on firm-level PFL exposure, the lender's ex-ante default risk exposure, and their interactions. The dependent variable is $Borrower_Share_{i,l,t}$, which is the share of newly issued loans that lender l lends to borrower i in lender l 's total lending in quarter t . $High_Default_Risk_Exposure_{l,t}$ is a lender-quarter level indicator equal to one if the lender's $Default_Risk_Exposure_{l,t}$ is higher than the cross-sectional sample median, and zero otherwise. $Default_Risk_Exposure_{l,t}$ is the proportion of outstanding loans that lender l has lent to firms with higher default risk in quarter t . Default risk is proxied by Z -score and EDF in Columns (2) and (3) respectively. Z -score is the Altman's Z-score. EDF is the expected default frequency. PFL is an indicator variable equal to one if the firm (borrower)'s headquarter state has an effective PFL mandate and zero otherwise. "Firm Controls" are the same as in Table 4, Column (1). All continuous variables are winsorized at the 1st and 99th percentiles, and all time-variant explanatory variables are lagged by one quarter. t -statistics based on heteroskedasticity consistent standard errors clustered at the lender-state level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. The sample period is 2001 Q2 to 2020 Q2.

	(1)	(2)	(3)
Dep. Var. = Borrower_Share			
Default Risk Proxy		Z-Score	EDF
High_Default_Risk_Exposure×PFL		-0.478*** (-2.94)	-0.299* (-1.75)
High_Default_Risk_Exposure		0.369 (1.37)	0.345 (1.54)
PFL	-0.105 (-0.26)	0.134 (0.32)	0.027 (0.06)
Firm Controls	Yes	Yes	Yes
Lender×Firm FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Obs.	67,405	67,405	67,405
Adj. R^2	0.611	0.611	0.611

Table 8. PFL and New Job Postings

This table reports the result from the firm-state-quarter panel Poisson regression of temporary job openings and postings on PFL. *Temp_Job_Opening* is the number of temporary job openings posted by each firm in each state and quarter; *Temp_Job_Posting* is the number of temporary job postings posted by each firm in each state and quarter. The main independent variable, *PFL*, is an indicator equal to 1 if the state where the firm has employees has adopted PFL in that quarter. $\log(\text{Emp})$ is the natural logarithm of the total number of employees at the firm in each state and quarter. "Firm Controls" are the same as in Table 4, Column (1). All continuous variables are winsorized at the 1st and 99th percentiles, and all time-variant explanatory variables are lagged by one quarter. *t*-statistics based on heteroskedasticity consistent standard errors clustered at the state level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. The sample period is from 2008 Q1 to 2020 Q2.

	(1) Temp_Job_Opening	(2) Temp_Job_Posting
PFL	0.641*** (3.32)	0.640*** (3.29)
$\log(\text{Emp})$	0.121 (1.59)	0.119 (1.56)
Firm Controls	Yes	Yes
Firm×State FE	Yes	Yes
Quarter FE	Yes	Yes
Obs.	25,794	25,783
Pseudo R^2	0.589	0.590

Table 9. PFL and Loan Pricing: Labor Adjustment Costs

This table presents the cross-sectional analysis of the effect of PFL on loan spreads. The dependent variable, $\log(\textit{Spread})$, is the natural logarithm of the all-in drawn loan spread (in basis points). The main independent variable, $\textit{PFL}$, is an indicator equal to 1 if the state where the firm has employees has adopted PFL in that quarter. *Labor Intensity* is the annual staff expense divided by total assets at the industry level. *Female Employee Ratio* is the proportion of females aged 15-44 to the total population of individuals aged 15-44 in the county where the firm is headquartered. *Internal Substitutability* is a firm-year level variable constructed as the number-of-employees-weighted average of firm-city-year level internal substitutability, which is defined as the largest employment share of occupational category within each workplace of the firm in a given year. *Labor Market Thickness* is an industry-state-year level variable defined as the annual share of employees in a given industry within a specific state, divided by the corresponding share of employees in that industry nationwide. *Automation Potential* is the natural logarithm of the number of employees in routine-intensive occupations in a firm (calculated by multiplying the total number of employees in the firm by the percentage of jobs in routine-intensive occupations in the firm's industry), divided by the firm's capital. Firms are classified into "High" and "Low" subsamples based on whether the one-year or one-quarter-lagged value of each category variable is above or below the cross-sectional sample median (except for *Labor Market Thickness*, where a breakpoint of 1 is used). The table reports the differences in the coefficients β of PFL between the high and low groups, along with the p -values from significance tests. The p -value for the coefficient differences is derived from an empirical Fisher's permutation test based on 1,000 resamplings. "Loan Controls" and "Firm Controls" are the same as in Table 2, Column (2). All continuous variables are winsorized at the 1st and 99th percentiles, and all time-variant explanatory variables are lagged by one quarter. t -statistics based on heteroskedasticity consistent standard errors clustered at the state level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. The sample period is 2001 Q2 to 2020 Q2.

Panel A: Labor intensity and PFL take-up				
Category variable	(1)	(2)	(3)	(4)
	Labor Intensity		Female Employee Ratio	
	High	Low	High	Low
PFL	0.166*** (6.76)	-0.001 (-0.01)	0.136** (2.21)	0.058** (2.03)
Difference between β	0.167*** p=0.004		0.079* p=0.065	
Loan Controls	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Obs.	8,246	9,015	9,557	9,027
Adj. R^2	0.706	0.719	0.727	0.710

Panel B: Labor adjustment frictions						
Category variable	(1)	(2)	(3)	(4)	(5)	(6)
	Internal Substitutability		Labor Market Thickness		Automation Potential	
	High	Low	High	Low	High	Low
PFL	0.068 (1.64)	0.171*** (4.70)	-0.042 (-1.51)	0.121*** (4.00)	0.047 (1.45)	0.163** (2.60)
Difference between β	-0.103** p=0.032		-0.163*** p=0.003		-0.116** p=0.022	
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	8,101	8,823	10,362	7,047	8,030	8,081
Adj. R^2	0.664	0.736	0.711	0.733	0.708	0.740

**Table 10. PFL’s Effects on Firm Profitability and Loan Pricing:
The Role of Default Risk**

This table reports the effect of PFL on firm profitability and loan pricing, conditional on default risk. Columns (1)-(3) present the effect of PFL on Return on Assets (*ROA*), across the full Compustat firm-year universe and within the high and low default risk subsamples. Columns (4)-(6) present the effect of PFL on $\log(\textit{Spread})$ in our baseline loan sample (the same regression result as in Table 2 Column 2) and its high and low default risk subsamples. Firms are classified into “High” and “Low” subsamples based on whether their one-year or quarter-lagged Expected Default Frequency (*EDF*) is above or below the cross-sectional sample median. *ROA* is computed as income before extraordinary items divided by total assets. $\log(\textit{Spread})$ is the natural logarithm of the all-in drawn loan spread (in basis points). The main independent variable, *PFL*, is an indicator equal to 1 if the state where the firm has employees has adopted PFL in that quarter. The table reports the differences in the coefficients β of *PFL* between the high and low groups, along with the *p*-values from significance tests. The *p*-value for the coefficient differences is derived from an empirical Fisher’s permutation test based on 1,000 resamplings. “Loan Controls” and “Firm Controls” are the same as in Table 2, Column (2). All continuous variables are winsorized at the 1st and 99th percentiles, and all time-variant explanatory variables are lagged by one year/quarter. *t*-statistics based on heteroskedasticity consistent standard errors clustered at the state level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. The sample period in Column (1)-(3) is 2001 to 2020 and in Column (4)-(6) is 2001 Q2 to 2020 Q2.

	(1)	(2)	(3)	(4)	(5)	(6)
	ROA			$\log(\textit{Spread})$		
Sample	Full Sample	High Default Risk	Low Default Risk	Full Sample	High Default Risk	Low Default Risk
PFL	0.013** (2.02)	0.004 (0.40)	0.013** (2.02)	0.090*** (3.19)	0.132*** (4.11)	0.035 (0.85)
Difference between β		-0.013* p=0.087			0.097** p=0.033	
Loan Controls				Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes			
Quarter FE				Yes	Yes	Yes
Obs.	59,195	28,736	28,293	18,770	8,611	8,314
Adj. R^2	0.601	0.564	0.621	0.706	0.615	0.744

Table 11. The Effect of SF PPLO on Loan Pricing

This table examines how the San Francisco Paid Parental Leave Ordinance (SF PPLO) affects loan contracting. The sample includes loan-firm level observations for all borrowers headquartered in California between 2014 Q1 and 2020 Q2. *SF_PPLO* is a binary indicator that takes the value of one if the firm has at least one establishment in the City and County of San Francisco after January 1, 2017, and zero otherwise. Panel A reports summary statistics for key variables in the sample, and Panel B reports the results of regressing loan spread and loan size on *SF_PPLO*. $\log(\text{Spread})$ is the natural logarithm of the all-in drawn loan spread (in basis points). $\log(\text{Loan Size})$ is the natural logarithm of the loan size, which is actual amount (in \$million) of the loan facility committed by the facility's lender pool. "Loan Controls" and "Firm Controls" are the same as in Table 2, Column (2) ($\log(\text{Loan Size})$ is excluded in Panel B, Column (2)). All continuous variables are winsorized at the 1st and 99th percentiles, and all time-variant explanatory variables are lagged by one quarter. *t*-statistics based on heteroskedasticity consistent standard errors clustered at the county level are reported in parentheses in Panel B. Definitions for other variables are in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

Panel A: Summary statistics						
Variables	Obs.	Mean	SD	P25	Median	P75
SF_PPLO	433	0.176	0.381	0	0	0
Loan Spread (bps)	433	227.444	145.037	125	175	250
Loan Size (million dollar)	433	747.692	936.653	150	450	915.750
Maturity (number of months)	433	55.824	15.091	55	60	60
Panel B: Regression results						
	(1)		(2)			
	$\log(\text{Spread})$		$\log(\text{Loan Size})$			
SF_PPLO	0.156**		-0.215**			
	(2.08)		(-2.70)			
Loan Controls	Yes		Yes			
Firm Controls	Yes		Yes			
Firm FE	Yes		Yes			
Quarter FE	Yes		Yes			
Obs.	433		433			
Adj. R^2	0.704		0.570			

The Cost of Care:
Paid Family Leave and Bank Loan Pricing

Online Appendix

Variable Definition

Variable	Definition
PFL	An indicator variable equal to 1 if, in quarter t and thereafter, firm i is headquartered in a state with an effective Paid Family Leave act in that quarter and beyond, and 0 otherwise.
Loan Spread	All-in drawn spread of the loan facility (in basis points). $\log(Spread)$ is the natural logarithm of the loan spread.
Loan Size	Actual amount (in \$million) of the loan facility committed by the facility's lender pool. $\log(Loan\ Size)$ is the natural logarithm of the loan size.
Maturity	Loan maturity in months. $\log(Maturity)$ is the natural logarithm of the loan maturity.
Secured	An indicator variable equal to 1 if the loan facility is secured by assets, and 0 otherwise.
Syndication	An indicator variable equal to 1 if the loan facility involves more than one lender, and 0 otherwise.
Performance pricing	An indicator variable equal to 1 if the loan contract includes a performance pricing provision, and 0 otherwise.
$\log(\text{Num_Covenants})$	Natural logarithm of the number of covenants in a loan contract.
$\log(\text{Num_lenders})$	Natural logarithm of the number of lenders in a loan deal.
$\log(\text{Total Asset})$	Natural logarithm of total assets (in \$million).
Leverage	The ratio of total liability to book equity.
Book-to-market	The value of book equity to market equity.
Cash holding	Cash and marketable securities divided by total assets.
Tangibility	Property, plant, and equipment (PPE) divided by total assets, measured at the beginning of the fiscal quarter.
ROA	Income before extraordinary items divided by total assets.
Z-Score	Modified Altman (1968) 's Z-Score = $(1.2 \times \text{working capital} + 1.4 \times \text{retained earnings} + 3.3 \times \text{income before extraordinary items} + 0.999 \times \text{sales}) / \text{total assets}$.
Sales growth	The percentage growth rate of sales from two quarters prior to the quarter immediately before the quarter of loan inception.

Variable	Definition
%Emp.PFL	The average of the establishment-level PFL variable, weighted by the number of employees at each establishment, divided by the total number of employees in the firm.
Temp_Job_Opening	The number of job positions posted in a firm's temporary job postings in each quarter.
Temp_Job_Posting	The total number of temporary job postings made by a firm in each quarter.
log(Emp)	The natural logarithm of the number of employees at each firm in each state and each quarter.
%Est.PFL	The equal-weighted average of the establishment-level PFL variable across all of a firm's establishments.
Unemployment rate	The annual unemployment rate for each state. <i>Source</i> : U.S. Bureau of Labor Statistics.
Labor force rate	The ratio of the labor force amount to the total population for each state. <i>Source</i> : U.S. Bureau of Labor Statistics.
Minimum wage	The annual minimum hourly wage in each state. <i>Source</i> : U.S. Department of Labor.
Democrat	An indicator variable equal to 1 if in the firm's headquartered county, the Democrat has won in the most recent presidential election for each quarter. <i>Source</i> : MIT Election Data and Science Lab.
KZ Index	The Kaplan-Zingales financial constraints index = $-1.002 \times \text{Cash flow} + 0.283 \times \text{Tobin}'Q + 3.139 \times \text{Total debt} - 39.368 \times \text{Dividends} - 0.315 \times \text{Cash}$.
Payout Ratio	The ratio of a firm's total dividends and stock repurchases to its market value of equity, where the market value of equity is the product of the number of shares outstanding and the stock price.
EDF	The expected default frequency (EDF) is the implied probability of default, derived from the cumulative standard normal distribution of the negative Distance to Default (DD).
Cash Flow	Earnings before interest, taxes, depreciation, and amortization (EBITDA) divided by total assets.
Internal Substitutability	Internal substitutability at the firm-city-year level is defined as the share of employees in the largest occupational category within each city where the firm operates in a given year. Internal substitutability at the firm-year level is the firm-city-year-level internal substitutability averaged across all cities in which the company operates and weighted by the number of employees in each city.

Variable	Definition
Labor Market Thickness	Industry-state-year-level labor market thickness is defined as the annual share of employees in a given industry within a specific state, divided by the corresponding share of employees in that industry nationwide.
Female Employee Ratio	The proportion of females aged 15-44 (i.e., childbearing age) to the total population of individuals aged 15-44 in the county where the firm is headquartered.
Automation Potential	Natural logarithm of the number of a firm's employees working in routine-intensive occupations, divided by the firm's capital. Following Knesl (2023), we calculate the number of employees in routine-intensive occupations in a firm by multiplying the firm's total number of employees (from Compustat) by the proportion of routine-intensive jobs in the firm's industry.
Labor Intensity	The annual staff expense divided by total assets at the industry level (measured by two-digit SIC codes).
Covenant Violation	$Covenant_Violation_{i,t}$ is a binary variable equal to one if at least one of five loan covenants is violated for any outstanding loan borrowed by firm i in quarter t , and zero otherwise. The five covenants considered are minimal tangible net worth, minimal net worth, minimal current ratio, maximal leverage ratio, and maximal debt to cash flow. A covenant violation occurs when the firm's corresponding financial variable is either above or below the covenant threshold, indicating higher or lower default risk.
SF PPLO	An indicator variable that is equal to one if a firm has at least one establishment in the City and County of San Francisco after Jan 1, 2017, and zero otherwise.
Borrower Share	The proportion of newly issued loans a lender provides to a specific borrower, relative to the lender's total new lending to all borrowers in each quarter.
Default Risk Exposure	The proportion of outstanding loans that a lender has issued to firms with higher default risk in each quarter. Firms with higher default risk are those that have a lower Z-Score or a higher Expected Default Frequency (EDF) than the cross-sectional median.
High Default Risk Exposure	An indicator variable equal to one if a lender's $Default_Risk_Exposure$ is higher than the cross-sectional median, and zero otherwise.

Figure A1. Dynamic Effects of PFL on Loan Spreads Using Stacked Sample

This figure presents the dynamic effect of PFL on loan spreads, estimated Equation (2) in the stacked sample. The solid dots and bars represent the estimated coefficients of each $PFL_{i,t-1}^k$ and their corresponding 95% confidence intervals. The x-axis is quarters relative to PFL adoption, from -10 to 10, and the y-axis displays the magnitude of the coefficients. The red dashed vertical line marks the PFL adoption date, and the red dashed horizontal line represents zero.

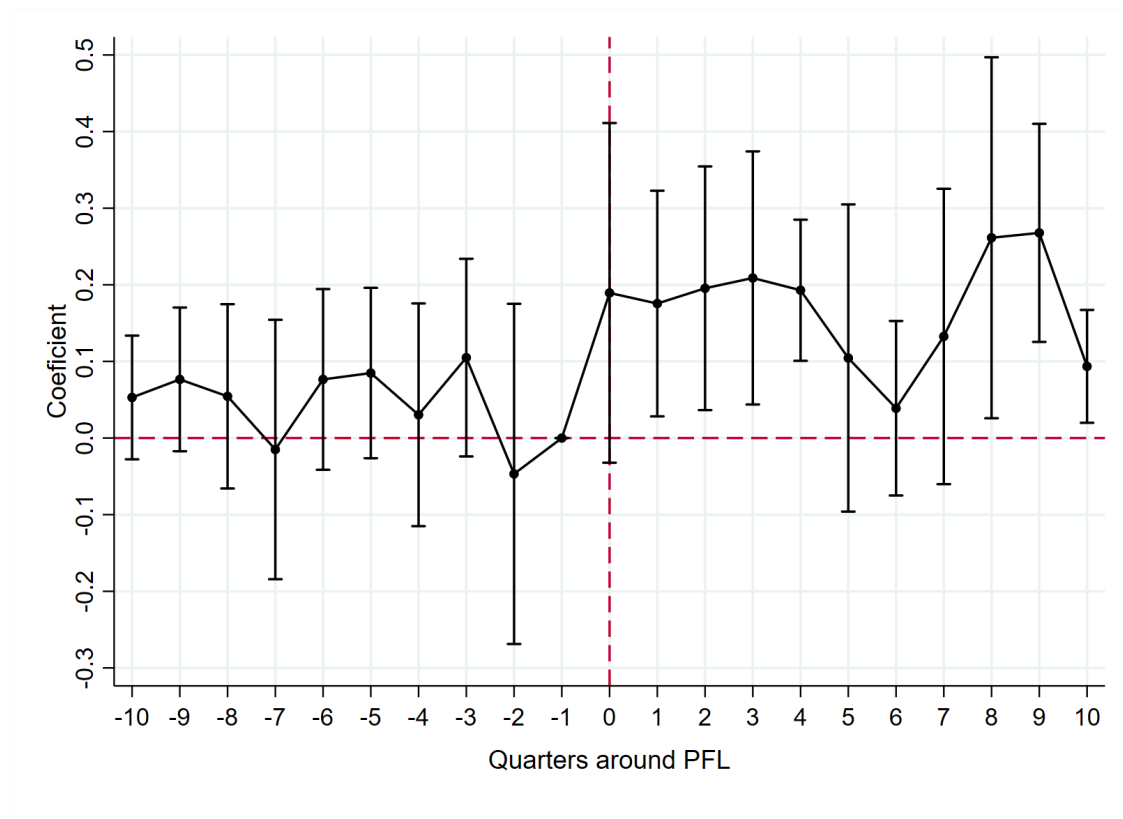


Table A1. PFL Policy Summary

The table outlines the state-level PFL laws with the respective enactment date, effective date, and funding source.

State	Enacted Date	Effective Date	Funding Source
California	February 21, 2002	July 1, 2004	100% funded by employees
New Jersey	February 28, 2008	July 1, 2009	100% funded by employees
Rhode Island	July 11, 2013	January 5, 2014	100% funded by employees
New York	April 4, 2016	January 1, 2018	100% funded by employees
Washington, D.C.	February 17, 2017	July 1, 2020	100% funded by employers
Washington	July 5, 2017	January 1, 2020	Shared. During 2022-2023, employers pay up to 27.24% and employees pay 72.76%. Since 2024, employers pay 28.57% and employees pay 71.43%.
Massachusetts	June 28, 2018	January 1, 2021	Shared, with the share determined by employers.
Connecticut	June 25, 2019	January 1, 2022	100% employees
Oregon	August 9, 2019	September 3, 2023	Shared. Employers pay 40%, and employees pay 60%.
Colorado	November 3, 2020	January 1, 2024	Shared. Employers and employees each contribute 50%.
Maryland	April 9, 2022	January 1, 2025	Shared, with the share determined by employers.
Delaware	May 11, 2022	January 1, 2026	Shared, with the share determined by employers. Employee's share is up to 50%.

Table A2. The Effect of PFL on Non-price Loan Terms

This table presents the results of regressing non-price loan terms on PFL. $\log(\text{Loan Size})$ is the natural logarithm of the loan amount (in USD millions). $\log(\text{Maturity})$ is the natural logarithm of the loan maturity (in months). $\log(\text{Num_Covenants})$ is the natural logarithm of the number of covenants in a loan contract. Performance pricing is an indicator variable equal to 1 if the loan contract has a performance pricing provision, and zero otherwise. The main independent variable, PFL, is an indicator variable equal to one if the firm's headquarters state has an effective PFL mandate and zero otherwise. "Loan Controls" and "Firm Controls" are the same as in Table 2, Column (2). All continuous variables are winsorized at the 1st and 99th percentiles, and all time-variant explanatory variables are lagged by one quarter. t -statistics based on heteroskedasticity consistent standard errors clustered at the state level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. The sample period is from 2001 Q2 to 2020 Q2.

	(1)	(2)	(3)	(4)
	$\log(\text{Loan Size})$	$\log(\text{Maturity})$	$\log(\text{Num_Covenants})$	Performance pricing
PFL	-0.069 (-1.40)	-0.030 (-1.29)	-0.017 (-0.25)	0.010 (0.34)
Loan Controls	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Obs.	18,770	18,770	18,770	18,770
Adj. R^2	0.686	0.369	0.625	0.359

Table A3. Robustness: Matching and Stacked DID Estimates

This table reports the results using matching and Stacked-DID approaches. Column (1) through Column (3) in Panel A reports the regression results of PFL on loan spread in propensity-score-matched, entropy-balanced, and stacked sample, respectively. Panels B and C report the differences in loan and firm characteristics before and after propensity score matching, respectively. We match loans in the treatment and control groups using one-to-one nearest neighbor matching. The propensity score is estimated via the probit model, using state-level, loan-level, and firm-level variables as covariates. In Panel D, we adopt an entropy balancing approach and show that the moments of loan and firm characteristics between the treated and control groups are closely matched after entropy balancing. The dependent variable, $\log(\textit{Spread})$, is the natural logarithm of the all-in drawn loan spread (in basis points). The main independent variable, PFL, is an indicator variable equal to one if the firm’s headquarter state has an effective PFL mandate and zero otherwise. “Loan Controls” and “Firm Controls” are the same as in Table 2, Column (2). Definitions for other variables are in the Appendix. All continuous variables are winsorized at the 1st and 99th percentiles, and all time-variant explanatory variables are lagged by one quarter. t -statistics based on heteroskedasticity consistent standard errors clustered at the state level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. The sample period is from 2001 Q2 to 2020 Q2.

Panel A: Matching and stacked DID regression results			
	(1) Propensity Score Matched Sample	(2) Entropy Balanced Sample	(3) Stacked Sample
PFL	0.074** (2.38)	0.088*** (2.98)	0.081*** (2.73)
Loan Controls	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	
Quarter FE	Yes	Yes	
Firm(unit) $\times$ Stack FE			Yes
Quarter(time) $\times$ Stack FE			Yes
Obs.	17,190	18,757	53,162
Adj. R^2	0.725	0.732	0.703

Panel B: Differences in loan and firm characteristics before matching						
	Treatment	Control	Difference	<i>t</i> -stat		
log(Loan Size)	5.018	5.187	0.169	6.76		
log(Maturity)	3.809	3.822	0.013	1.42		
Secured	0.604	0.593	-0.011	-1.41		
Syndication	0.847	0.890	0.043	8.27		
Performance pricing	0.402	0.418	0.016	2.09		
log(Total Asset)	7.276	7.391	0.115	4.10		
Leverage	1.332	1.638	0.306	2.95		
Book-to-market	0.441	0.452	0.010	0.51		
ROA	0.005	0.007	0.002	3.35		
Sales growth	0.617	0.786	0.169	1.67		
Panel C: Differences in loan and firm characteristics after propensity score matching						
	Treatment	Control	Difference	<i>t</i> -stat		
log(Loan Size)	5.126	5.166	0.039	1.10		
log(Maturity)	3.846	3.830	-0.016	-1.22		
Secured	0.564	0.584	0.020	1.78		
Syndication	0.892	0.885	-0.007	-0.95		
Performance pricing	0.404	0.422	0.018	1.55		
log(Total Asset)	7.371	7.379	0.008	0.19		
Leverage	1.611	1.607	-0.003	-0.02		
Book-to-market	0.451	0.445	-0.007	-0.24		
ROA	0.008	0.007	-0.001	-0.95		
Sales growth	0.663	0.811	0.148	1.06		
Panel D: Differences in loan and firm characteristics after entropy balancing						
	Treat			Control		
	mean	variance	skewness	mean	variance	skewness
log(Loan Size)	4.996	2.891	-0.388	5.176	2.402	-0.481
log(Maturity)	3.807	0.321	-1.567	3.826	0.319	-1.664
Secured	0.589	0.242	-0.361	0.584	0.243	-0.342
Syndication	0.842	0.133	-1.871	0.886	0.101	-2.433
Performance pricing	0.407	0.241	0.378	0.422	0.244	0.317
log(Total Asset)	7.258	3.484	0.024	7.388	3.087	0.012
Leverage	1.402	25.420	-0.164	1.618	40.590	-0.489
Book-to-market	0.435	1.331	-5.135	0.451	1.540	-4.598
ROA	0.006	0.001	-2.502	0.007	0.001	-2.637
Sales growth	0.559	35.040	0.717	0.803	36.050	1.349

**Table A4. The Effect of PFL on Loan Pricing:
Establishment-level Evidence**

This table reports the regression results using the establishment-level data to construct alternative PFL exposure measures. The dependent variable, $\log(\textit{Spread})$, is the natural logarithm of the all-in drawn loan spread (in basis points). The establishment-level data is from YTS. Main independent variable $\%Est.PFL$ represents the proportion of a firm's establishments affected by PFL and $\%Emp.PFL$ denotes the proportion of a firm's employees affected by PFL. "Loan Controls" and "Firm Controls" are the same as in Table 2, Column (2). All continuous variables are winsorized at the 1st and 99th percentiles, and all time-variant explanatory variables are lagged by one quarter. t -statistics based on heteroskedasticity consistent standard errors clustered at the state level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. The sample period is 2001 Q2 to 2020 Q2.

	(1)	(2)
$\%Est.PFL$	0.081* (1.85)	
$\%Emp.PFL$		0.106*** (2.72)
Loan Controls	Yes	Yes
Firm Controls	Yes	Yes
Firm FE	Yes	Yes
Quarter FE	Yes	Yes
Obs.	11,080	11,080
Adj. R^2	0.706	0.706

Table A5. Additional Robustness Checks

This table reports the results of additional robustness checks. The dependent variable, $\log(\textit{Spread})$, is the natural logarithm of the all-in drawn loan spread (in basis points). The main independent variable, $\textit{PFL}$, is an indicator variable equal to one if the firm’s headquarter state has an effective PFL mandate and zero otherwise. Columns (1) and (2) present results based on a restricted time window, covering the three years before and five years after the mandate’s effective date in treated states. Columns (3) and (4) report results from regressions that include lead bank fixed effects. “Loan Controls” and “Firm Controls” are the same as in Table 2, Column (2). All continuous variables are winsorized at the 1st and 99th percentiles, and all time-variant explanatory variables are lagged by one quarter. t -statistics based on heteroskedasticity consistent standard errors clustered at the state level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level. The sample period is 2001 Q2 to 2020 Q2.

	(1)	(2)	(3)	(4)
	Shorter Time Window for Treated States		Controlling for Lead Bank Fixed Effects	
PFL	0.101*** (4.70)	0.101*** (4.08)	0.074** (2.38)	0.067** (2.56)
Loan Controls	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Quarter FE	Yes		Yes	
Industry FE $\times$ Quarter FE		Yes		Yes
Lead Bank FE			Yes	Yes
Obs.	16,071	15,641	18,767	18,153
Adj. R^2	0.700	0.733	0.745	0.788