The Price of Health: Paid Sick Leave Mandates, Skilled Labor, and Corporate Innovation*

August 2024

*

The Price of Health: Paid Sick Leave Mandates, Skilled Labor, and Corporate Innovation

Abstract

We observe a significant decline in corporate innovation following the staggered implementation of state-level paid sick leave (PSL) mandates. Further analysis identifies two mechanisms. First, firms anticipating increased labor costs due to PSL mandates significantly reduce the hiring of inventors, especially when they are financially constrained. Second, increased absences due to PSL mandates has an amplified negative impact on inventor productivity by disrupting inventor coordination. Our findings demonstrate that government policy can have varying impacts on skilled labor versus ordinary workers.

Keywords: PSL mandates, skilled labor, paid sick leave, corporate innovation, inventors, financial constraints, inventor coordination

JEL Classification: G38, J63, O31

Skilled labor is more crucial than ever in today's economy. A growing body of literature shows that government policy can significantly impacts skilled labor and corresponding corporate decisions (e.g., Marx, Strumsky, and Fleming, 2009; Acharya, Baghai, and Subramanian, 2013; Chen, Hsieh, and Zhang, 2021, 2024;). However, to date, we have only limited evidence on whether and how government policy may have consequences on skilled labor that deviate from its intended purpose for ordinary workers. In this paper, we aim to shed light on this overlooked yet important question by examining the effect of paid sick leave (PSL) mandates on corporate innovation and inventors.

PSL is a crucial component of social welfare programs, providing job protection and prevents wage losses for employees when they are absent due to illness or caring for sick family members. The United States remains the only developed country that does not provide universal access to PSL. As a result, twelve US states have taken it upon themselves to implement paid sick leave (PSL) mandates starting from 2008. There are concerns that PSL mandates may significantly increase labor costs for businesses, including direct and indirect costs of salary expenses, replacement workers, and absence management.[1] However, academic studies find little evidence that PSL mandates negatively impact wages and employment (Pichler and Ziebarth, 2020; Wething, 2022; Al-Sabah and Ouimet, 2023). Additionally, Chunyu, Volpin, and Zhu (2024) document enhanced labor productivity for US firms after the adoption of PSL mandates.

While the existing literature studies the impact of PSL mandates on general labor outcomes, we investigate their effect on corporate innovation, a critical skilled labor output and driver of

[1] For example, Michigan Manufacturers Association argues that "If [the mandate] increases the cost of employing people and increases the cost of the administrative burdens, it makes it much more difficult and more expensive to operate a Michigan location compared to companies in other states and, frankly, other nations." (https://www.michiganradio.org/economy/2018-05-31/michigan-manufacturers-say-paid-sick-leave-mandate-could-hurt-job-growth).

economic growth. On one hand, PSL mandates could negatively impact inventors and corporate innovation for two reasons. First, compared to ordinary workers, inventors are more costly, and their output is less tangible.[2] As a result, when managers expect rising labor costs, they may reduce the hiring of inventors to maintain more tangible operations.[3] This phenomenon could be more pronounced if firms are financially constrained. Second, innovation often requires collaboration among highly specialized inventors (e.g., Jaravel, Petkova, and Bell 2018; Baghai, Silva, and Ye, 2023). Unlike typical employees, finding a temporary replacement for an absent inventor can be especially challenging, thereby delaying the progress of the entire team. As a result, the impact of reduced work hours on inventor productivity can be amplified due to disruptions in coordination. On the other hand, PSL mandates could positively impact inventors and corporate innovation if they impact skilled labor similarly to ordinary workers.

Using a large sample of U.S. public firms between 2004 and 2019, we employ a difference-in-differences (DiD) methodology, leveraging the staggered implementation of state-level PSL mandates.[4] The dependent variable is corporate innovation, measured by patent applications and truncation-adjusted future citations of the patents (Hall, Jaffe and Trajtenberg, 2001, 2005). The main independent variable is *PSL*, which is a dummy variable that equals one for the treated states after the years of PSL mandate implementation, and zero otherwise. We control for firm characteristics including firm size, cash holdings, leverage, capital expenditures, PPE, ROA, R&D expenditures, and book-to-market ratio, as well as firm and year fixed effects.

Our DiD regression analyses reveal a significant *decrease* in corporate innovation after the

[2] See, for example, Manning (2003), Dolfin (2006), and Blatter, Muehlemann, and Schenker (2012) for the evidence that it is particularly costly to search for, hire, and train high-skill employees.
[3] Besides the labor costs directly associated with PSL itself, managers may view the implementation of PSL as a sign of potential future regulations imposing additional labor costs.
[4] We end our sample period in 2019 because of the outbreak of COVID-19 pandemic in 2020 and the introduction of FFCRA that provides universal PSL to employees for COVID-19 related reasons from April 2020.

implementation of PSL mandates. For example, patent filings experience a 6.3% standard deviation decrease following the implementation of PSL mandates, Additionally, we find a significant decline in patent quality, as measured by the average patent citations and the number of breakthrough patents, after the adoption of PSL mandates. These results remain consistent across an extensive set of robustness tests based on alternative sample constructions or alternative empirical approaches such as two-way fixed effects (TWFE) estimates (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). These results, along with the existing literature, reveal a differential impact of PSL mandates on inventors compared to ordinary workers.

The passage of PSL mandates could be associated with local economic factors such as strong economic growth. However, these economic factors would bias against finding our results of a negative impact on corporate innovation. We nevertheless conduct several analyses to alleviate concerns that our findings are driven by local factors. First, we conduct a placebo test by assigning a pseudo-adoption of PSL mandates to a randomly selected neighboring state that did not adopt such mandates. We find no significant impact of pseudo-adoptions. Second, since most of the event states are democratic states, we conduct subsample analysis and find that the decline in innovation after PSL mandates exists in both Democratic and Republican event states. We also conduct a pseudo-event analysis by assigning the adoption of PSL mandates to a neighboring blue state without PSL mandates, and the results remain similar.

We further alleviate the concerns about local factors by employing a failed attempt to adopt a PSL mandate in Orange County, Florida. During the summer of 2012, an Orange County coalition gathered enough signatures from registered voters to place an PSL mandate on the ballot, with up to 56 PSL hours per year. This proposal is likely to be passed according to the poll. Consequently, the Florida Governor signed House Bill 655 which prohibits political subdivisions

from mandating employers to provide specific benefits, effectively ending the pursuit of PSL mandates in Orange County. Contrary to the successful implementation of PSL mandates, we observe no decline in innovation in firms located in Orange County relative to control firms in other counties in Florida. Taken together, these results suggest that local factors are unlikely to drive our results.

We further validate the impact of PSL mandates by conducting two cross-sectional analyses. First, the event of PSL mandates is defined based on a firm's headquarters state and therefore only covers the firm's employees in that state. We predict and find that the decline in patent filings is concentrated in patents from inventors located in the headquarters states of the event firms. Secondly, we also expect that the effect of PSL mandates will be more pronounced for firms in industries with lower voluntary access to PSL. Our results also support this prediction.

Next, we directly investigate the impact of PSL mandates on inventor employment and productivity. Regarding inventor employment, we find that firms' net inventor hiring declines by over one-third after the adoption of PSL mandates, driven by recruiting fewer inventors rather than experiencing increased departures. In contrast, we find no decline in total employment for event firms, consistent with the existing literature showing a non-negative effect of PSL mandates on ordinary workers (Al-Sabah and Ouimet, 2023). Furthermore, consistent with our prediction, we find that the negative impact of PSL mandates on inventor hiring and innovation is more pronounced among financially constrained firms.

We further examine inventor productivity, particularly whether the impact of PSL-related inventor absences on inventor productivity is amplified by disruptions in inventor coordination. While we do not directly observe PSL-related inventor absences, we use inventor gender and age as proxies for potential absences resulting from PSL mandates, as previous studies show that

female or older employees more frequently utilize PSL due to illness or caring for sick family members.[5] Consistent with the reduced productivity due to PSL-related inventor absences, we find that the negative impact of PSL mandates on corporate innovation is more pronounced among firms with higher proportion of female inventors and older inventors.

Additionally, we investigate the mechanism of disruptions in inventor coordination using three proxies for disrupted coordination due to inventor absences. The first proxy is the proportion of patents filed by team inventors (rather than individual inventors) for a firm. We expect the disruptions in coordination to be more severe among firms with a higher proportion of team inventors. The second proxy is the diversity of inventor backgrounds for a firm. Disruptions in coordination could be more severe for firms with more diversified inventor background, as it is more difficult for these firms to find temporary replacements for absent inventors. The last proxy is a firm's flexibility for employees to work from home. Firms with less work-from-home flexibility requires more face-to-face coordination, leading to more disruptions due to sick absences. Our results show that, consistent with the mechanism of coordination disruptions, firms with more team inventors, more diverse inventor backgrounds, and less work-from-home flexibility experience a significantly larger decrease in innovation after PSL mandates.

Our study contributes to the growing literature on skilled labor, particularly how government policy may have opposite impacts on skilled labor and ordinary workers. Existing research has demonstrated that skilled labor can have substantial influence on firms' stock returns, corporate policies, and financial disclosure (e.g., Belo et al., 2017; Call et al., 2017; Ghaly, Dang, and Stathopoulos, 2017; Baghai et. al., 2021; Chen, Hshieh, and Zhang, 2021, 2024). We extend

[5] See, e.g., Kim (1998), Sandberg (1999), Bierla, Huver, and Richard (2013) and Frick and Malo (2008). Since the data on inventor age is unavailable, we use inventor tenure as a proxy. We defined inventor tenure as the number of years since an inventor filed her first patent up to the current year.

this literature by highlighting that the unique attributes of high-skill employees, such as elevated costs and specialized skills, could result in distinct employment and productivity shocks compared to average employees.

Our study also shed light on potential unintended consequences of PSL mandates. As the demand for a national paid sick leave policy in the United States continue to rise, it becomes increasingly important to understand the complexities and potential impacts of such a policy. Existing literature suggests that PSL mandates positively impact employment and labor productivity (Chunyu, Volpin, and Zhu, 2024; Al-Sabah and Ouimet, 2023).[6] Our findings reveal a negative impact of PSL mandates on inventors and corporation innovation, thereby calling for a more comprehensive consideration of the full spectrum of effects of such policies on the broader economy.

Finally, our paper contributes to literature on corporate innovation. Since innovation is a key driver of economic growth, previous studies have investigated and documented the effects of financial report quality, patent disclosure quality and various regulations such as corporate disclosure, bank deregulation, tax policies, intellectual protection, labor protection, and bankruptcy codes on corporate innovation.[7] Our paper extends this literature by documenting that health-related policies can also lead to significant consequences on corporate innovation, inventor employment, and inventor productivity.

2. DATA AND SAMPLE CONSTRUCTION

We start with all firms in the CRSP-Compustat merged database with the available stock

[6] We replicate the results in these two papers using their measures of productivity and profitability.

[7] See, for example, Acharya and Subramanian (2009), Lerner (2009), Acharya, Baghai, and Subramanian (2013, 2014), Amore, Schneider, and Žaldokas (2013), Spulber (2013), Williams (2013), Atanassov and Liu (2016), Dechezleprêtre et al. (2016), Cerqueiro et al. (2017), Laux and Stocken (2018), Lück et al. (2020), Li, Ma and Shevlin (2021), Bena, Ortiz-Molina, and Simintzi (2022) for the effects of regulations on corporate innovation.

and accounting data, excluding utility (SIC codes from 6000 to 6999) and financial firms (SIC codes from 4900 to 4999). We start our sample period from 2004, four years before the first state-level PSL mandate in 2008. We end our sample period in 2019 because the introduction of the Federal-level Families First Coronavirus Response Act (FFCRA) on April 1, 2020 provides universal PSL to employees for COVID-19 related reasons (U.S. Department of Labor, 2020).

During our sample period, twelve states adopted PSL mandates, including DC, Connecticut, California, Massachusetts, Oregon, Vermont, Arizona, Washington, Maryland, Rhode Island, New Jersey, and Michigan.[8] Figure 1 plots the cumulative number of states that have adopted PSL mandates over our sample period, which shows a graduate PSL adoption over time. Typically, PSL mandates require firms to provide one hour of paid sick leave for every 30-40 hours worked, with a cap on the total hours that can be accrued in a year. Paid sick leave usually covers both full-time and part-time employees and applies to most or all firms headquartered in the state, with different annual caps based on employee size. Some states exempt the smallest firms from providing PSL to their employees, such as those with less than five employees. Table B1 of Appendix B provides detailed information on the paid sick leave policy for the twelve states, which shows that majority of these states have a cap of 40 hours.

We obtain information on the historical headquarters locations of sample firms from the University of Notre Dame's 10-X Header Data based on 10-K filings.[9] Several cities and counties implement separate PSL mandates during our sample period. We exclude all firms headquartered in these cities or counties. Robustness tests, which include firms headquartered in these cities and counties, yield similar results (see Section 3.3). We obtain the patent data from the United States

[8] Without PSL, sick employees would have to use unpaid leave under the Family and Medical Leave Act of 1993 (FMLA), which provides the right to unpaid leave for workers who are employed by a firm with 50 or more employees and have worked for the employer for a year and a minimum of 1,250 hours.
[9] The dataset can be accessed at https://sraf.nd.edu/sec-edgar-data/10-x-header-data/.

Patent and Trademark Office (USPTO), and the inventor data from the PatentsView database. We match the patent data to sample firms using Professor Noah Stoffman's Patent and Citation File (KPSS database, 2022 version).[10] Our final sample consists of 37,726 firm-years from 2004 to 2019.

Table 1 presents the summary statistics from 2004 to 2019. To account for outliers, all firm-level continuous variables are winsorized at the 1st and 99th percentiles. About 10% of sample firm-years are covered by PSL mandates. The sample firm-years on average have R&D expenditures (scaled by total assets) of 0.07, leverage of 0.21, ROA of -0.05, and book-to-market ratio of 0.54. Around 24% of patents are filed by individual inventors rather than inventor teams. The underrepresentation of female inventors is evident, as female inventors only account for 11% of all inventors. Detailed variable definitions are provided in Appendix A.

3. PSL MANDATES AND CORPORATE INNOVATION

3.1 Methodology

To examine the impact of PSL mandates on firm innovation, we use a difference-in-differences (DiD) methodology. Specifically, we compare firms' innovation in states with and without PSL mandates before and after the implementation, based on a staggered implementation of state-level paid sick leave. The regression model is as follows:

$$Innovation_{i,t}=\beta\times PSL + \gamma'\times X_{i,t-1} + \eta_i + \Theta_t + \varepsilon_{i,t} \qquad (1)$$

where the dependent variable, $Innovation_{i,t}$, is one of the two measures of innovation for firm i in year t. The first measure is the number of patent applications filed by the firm in year t (*Patent*). The second measure is the truncation-adjusted future citations of the patents filed by the firm in

[10] We thank the authors of Kogan, Papanikolaou, Seru, and Stoffman (2017) for making this dataset available at https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.

year *t* (*Citation*). Since recent studies highlight the potential biases that arise from taking the logarithm of count variables (Cohn, Liu, and Wardlaw, 2022; Chen and Roth, 2024), we use the raw counts of patents and citations as independent variables in our analysis. To mitigate the impact of outliers, we winsorize them at the 95th percentile.[11]

The main independent variable is *PSL*, which is a dummy variable that equals one for the treated states after the years of PSL mandate implementation, and zero otherwise. We follow the literature and control for firm characteristics including firm size, cash holdings, leverage, capital expenditures, PPE, ROA, R&D expenditures, and book-to-market ratio in the previous year.[12] We further include firm and industry-year fixed effects to control for firm and industry-year level time-invariant characteristics that may affect corporate innovation.[13] We calculate t-statistics using robust standard errors adjusted for heteroskedasticity and clustered at the state level.

3.2 DiD Regression Analysis

We conduct the DiD regressions as specified in Equation (1) and report the results in Panel A of Table 2. In Column (1), we regress patent applications on *PSL* and control variables. We also include firm and year fixed effects. Column (2) is similar to Column (1) except that we include firm and industry-year fixed effects (instead of year fixed effects). We find that the coefficient of PSL is negative and significant in both models, suggesting that PSL mandates have a significantly negative impact on firms' patent applications. This result is also economically significant. For example, the coefficient in Column (2) indicates that the number of patent applications decreases by 0.597 after the adoption of PSL mandates, which is equivalent to a 6.3% standard deviation

[11] Our results are robust when we use logged values or winsorize at alternative thresholds such as 99th percentile.
[12] We follow the literature and set a firm's R&D to zero if the data is missing. Our regression results remain similar when we further control for a dummy variable accounting for missing R&D values.
[13] The industry fixed effects are based on four-digit SIC classifications.

decrease in patent application. Columns (3) and (4) of Panel A present the regressions of truncation-adjusted patent citations. In both regressions, the coefficient of *PSL* is negative and significant at the 1% level. These results are economically significant as well. For instance, the coefficient of -0.974 in Column (4) indicates that the adoption of PSL mandates leads to an 8.1% standard deviation decrease in firms' patent citations.

In Panel B of Table 2, we examine two measures of average patent quality. The first measure, *Average Citation*, is the average truncation-adjusted patent citations across patents filed by a firm in the year. The second measure, *Breakthrough Patent*, is the number of breakthrough patents filed by a firm in the year, where breakthrough patents are defined as those with forward citation counts being in the top 5% of all patents in the same application year and technology class (Singh and Fleming, 2010). The coefficient of *PSL* is significantly negative in all four models, which confirms a reduction of patent quality after the implementation of PSL mandates. These results are also economically large. For example, the coefficient in Column (4) indicates that the number of breakthrough patent decreases by 0.055 following the implementation of PSL mandates, which is equivalent an 7.6% standard deviation decrease in breakthrough patents. To summarize, the results in Table 2 provide strong evidence that there is a significant decline in corporate innovation following the implementation of PSL mandates.

3.3 Robustness Tests

We conduct a large number of robustness tests using alternative sample constructions or empirical methods. First, we exclude firms with no patents during our sample period and repeat the analysis in Panel A of Table 3, where the coefficient of PSL remains significantly negative in all regressions.

Second, recent studies have shown that staggered DiD estimates may be prone to potential

biases caused by differential treatment timing and treatment effects (e.g., Callaway and Sant'Anna 2021; Sun and Abraham 2021; Baker, Larcker, and Wang 2022). To address these concerns, we conduct robust tests using two alternative approaches proposed by Callaway and Sant'Anna (2021) and Sun and Abraham (2021) that obtain two-way fixed-effect (TWFE) estimates. Both approaches aim to correct for potential estimation bias by focusing on the average treatment effects on the treated (ATT) that accounts for differential treatment timing and heterogeneity in treatment effects based on the time of adoption.

Panel B of Table 3 presents the results of TWFE estimators. Following Callaway and Sant'Anna (2021), we estimate the aggregated group-time ATT where groups are cohorts of firms that are treated in the same year (Columns (1) to (4)). We find that the coefficient of PSL remains negative and significant in all regressions (t-statistics -2.99 to -3.39). These results suggest that our findings in the baseline DiD analysis remain robust after considering the heterogeneity in treating timing and effects.

A crucial assumption for the consistency of the DiD estimator is that treated and control firms have parallel trends in the absence of PSL mandates. To examine this assumption and explore the dynamics of the treatment effects, we follow the approach proposed by Sun and Abraham (2021). Their method provides unbiased interaction-weighted estimators by estimating regression coefficients on event-study leads and lags using the TWFE approach. We present the results in Columns (5) and (6) of Table 3 Panel B, where the independent variables consist of lead and lag dummy variables. PSL^{-2}, PSL^{-3}, and PSL^{-4} are dummy variables representing two, three, and four or more years before implementation of PSL mandates, respectively.[14] PSL^{0} is a dummy variable for the PSL implementation year. PSL^{+1}, PSL^{+2}, PSL^{+3}, and PSL^{+4} are dummy variables

[14] PSL^{-1} serves as the reference point and is omitted from the regression.

representing one, two, three, and four or more years after the implementation of PSL mandates, respectively.

In both models, we find that the coefficients on PSL^{-2}, PSL^{-3}, and PSL^{-4} are statistically indistinguishable from zero, while all the coefficients after the PSL implementation are negative and significant. We display these results in Figure 2 to provide a visual representation of these regression coefficients. The figure shows little change in firm innovation in the pre-event period and a noticeable decline in firm innovation in the post-event period. These findings confirm that the parallel trend assumption holds in our analysis, supporting the validity of our DiD estimates.

Third, as mentioned in Section 2, we exclude firms headquartered in cities or counties with separate PSL mandates from our sample.[15] To test the robustness of our results to this exclusion, we include these firms in the sample and report the regression results in Panel A of Table 4. Fourth, we exclude observations in the implementation years of PSL mandates as part of the innovation activity in the implementation year occurs before PSL implementation. We present the results of this robustness test in Panel B of Table 4. Fifth, we address the concerns that the observed decline in firm innovation may be driven by the period of global financial crisis. We exclude observations during the global financial crisis (2007 to 2009) and report the results in Panel C of Table 4. Fourth, we exclude the states with PSL adoptions in 2018 or 2019 as these adoptions are close to the end of the sample period (Panel D of Table 4). We find that our baseline results remain robust in these alternative settings.

Finally, we repeat the regression analysis except the independent variable is PSL hours instead of the PSL dummy. PSL hours represents the maximum number of paid sick leave hours that can be accrued in a year in states that have implemented PSL mandates, and is set to zero for

[15] Table B2 of Appendix B provides details about the content and implementation dates of PSL mandates in these cities and counties.

states without PSL mandates.[16] Table B3 of Appendix B presents the regression results, where we find the coefficient of PSL hours remains negative and significant in all models.

3.4 Do Local Factors Explain the Decline in Corporate Innovation?

It is possible that the enactment of PSL mandates be associated with local factors that correlate with corporate innovation. For example, states experiencing or anticipating stronger economic growth might be more inclined to implement welfare-related policies such as PSL mandates. This concern, however, is alleviated by the fact that such economic factors would likely bias against finding our results of a *negative* impact on corporate innovation. This is because stronger economic conditions should theoretically foster, rather than hinder, corporate innovation. Additionally, to investigate the possibility that PSL mandates coincide with significant regulatory changes, particularly in economic policies, we conduct a news search around the times of PSL mandate enactments and find little evidence to support this possibility. In this subsection, we nevertheless conduct several tests to further alleviate the concerns about local factors.

3.4.1 Pseudo-Event Analysis Using Neighboring States

We first conduct a placebo test based on the assumption that neighboring states have local factors in common with the event states. Specifically, when a state adopts PSL mandates, we instead assign the adoption event to a randomly selected neighboring state without PSL mandates. We then repeat the DiD regressions and report the results in Panel A of Table 5. We find no significant impact of pseudo-adoptions on firm innovation, which suggests that it is the adoption of PSL mandates, rather than some local factors, that drives our findings.

3.4.2 Democratic and Republican States

[16] We exclude firms headquartered in the state of Washington from this analysis, as the state of Washington does not enforce an annual cap on PSL hours.

As the majority of the PSL mandates occurred in Democratic states, we conduct two analyses to examine if our findings are driven by the differences between Democratic and Republican states. We classify US states into Democratic ("blue state", won by Obama/Biden) and Republican ("red state", won by McCain/Palin) using the results of the 2008 United States presidential election, as the first state-level PSL mandates were adopted in 2008. Among the twelve event states, the only red state is Arizona.

We present a subsample analysis using treated Democratic and Republican states, with untreated states, in Panels B and C of Table 5, respectively. The coefficient of *PSL* is significantly negative across the two subsamples, suggesting that our results are not driven by the political leanings of the event states. In Panel D of Table 5, we conduct a pseudo-event analysis as in Panel A, except that we assign the adoption of PSL mandates to a neighboring *blue* state that has not adopted PSL mandates. We observe no decline in innovation after these pseudo-events, which confirms that the effect of PSL mandates is not driven by the political alignment of the states.

3.4.3 A Failed Attempt to Adopt PSL Mandate by Orange County

We further alleviate the concerns about local factors by employing a failed attempt to adopt a PSL mandate in Orange County, Florida. During the summer of 2012, a coalition named 'Citizens for a Greater Orange County' gathered 50,000 signatures from registered voters in Orange County, aiming to place an initiative called 'Earned Sick Time' on the ballot (to secure a spot on the ballot, the group needed to collect more than 43,605 signatures). The proposed legislation stipulated that businesses with more than 15 employees offer PSL with a maximum of 56 hours per year for each employee. This proposal is likely to be passed, as a 2013 poll from Public Policy Polling (PPP) shows that 80% of likely Florida voters support the 'Earned Sick Time' initiative.

In September 2012, the Orange County commissioners voted not to include the initiative

on the November 2012 ballot, citing the concerns that the language of the initiative was ambiguous. However, in February 2013, a three-judge panel ordered Orange County to include the initiative on the ballot. Finally, on June 14, 2013, the Florida Governor signed House Bill 655 which prohibits political subdivisions from mandating employers to provide specific benefits, including PSL, effectively ending the pursuit of PSL mandates in Orange County.

If the observed decline in corporate innovation is associated with local factors rather than the PSL mandates, then we expect a similar decline in corporate innovation in Orange County despite the failed attempt to adopt PSL mandate. We repeat the DiD analysis, designating event firms as those headquartered in Orange County and control firms as those headquartered in other counties in Florida. We set 2013 as the event year. In Panel E of Table 5, we find no decline in innovation in firms located in Orange County compared to the control firms. This result suggests that it is the PSL mandates, rather than local factors, that drive the observed decline in innovation.

3.5 Cross-Sectional Analyses

In this section, we aim to further validate the impact of PSL mandates on firm innovation by conducting two cross-sectional analyses based on investor locations and voluntary PSL access.

3.5.1 Cross-Sectional Analysis Based on Inventor Locations

Our DiD analysis examines PSL adoptions in the sample firms' headquarters states. It is worth noting that the PSL mandates in a firm's headquarters state cover only employees who work in that state. Therefore, if the decline in firm innovation that we observe is driven by PSL mandates, we would expect the decline to be more pronounced for patents filed by invention teams with headquarters' inventor participation.

To test this prediction, we obtain inventor locations from the PatentsView database and construct two measures to quantify innovation at company headquarters. The first measure,

Headquarter Patent, is the number of patents filed with at least one inventor based at the firm's headquarters.[17] The second measure, *Headquarter Citation*, counts the total number of truncation-adjusted citations received by the patents filed by at least one inventor based at the firm's headquarters. We then define *Non-Headquarter Patent* and *Non-Headquarter Citation* similarly, except they are constructed using patents where none of the inventors are based at the firm's headquarters.

We then conduct the DiD regressions and present the results in Panel A of Table 6. In columns (1), we regress *Headquarter Patent* on PSL, and find that the coefficient of PSL is significantly negative (t-statistics -2.56). In column (2), we regress *Non-Headquarter Patent* on PSL, and the coefficient is statistically insignificant. In columns (3) and (4), we regress *Headquarter Citation* and *Non-Headquarter Citation* on PSL, respectively. The coefficient of PSL is significantly negative in column (3) but insignificant in column (4). These results show that, consistent with our prediction, the decline in corporate innovation following the adoption of PSL mandates is concentrated in the event firms' headquarters states.

3.5.2 Cross-Sectional Analysis Based on Voluntary Access to PSL

Firms in the states without PSL mandates can provide paid sick leave to their employees on a voluntary basis. If the observed decline in firm innovation is driven by PSL mandates, we would expect a larger decline in innovation in the post-event period for firms in industries with a lower proportion of voluntary access to PSL prior to the PSL mandates. To test this prediction, we obtained industry-level data (2-digit NAICS) on PSL access from the National Compensation Survey, conducted by the U.S. Bureau of Labor Statistics and published in March 2008. Since the

[17] In untabulated analysis, we define a patent as headquarter patent if *all* filing inventors are located in the firm's headquarters state, and find similar results.

first state-level PSL mandate becomes effective in November 2008 (the District of Columbia), the PSL access in this database results from voluntary access by employers.

We construct a dummy variable for low voluntary PSL access, *Low Access*, which equals one if a firm belongs to an industry with industry-level PSL access that is below the sample median, and zero otherwise. We then conducted DiD regressions that include an interaction term between *Low Access* and the PSL dummy. In Panel B of Table 6, we find that the coefficient of the interaction is negative and significant in all models (t-statistics -2.21 to -2.92). These results demonstrate that, consistent with our prediction, the negative effect of PSL mandates on firm innovation is more pronounced for firms with low voluntary PSL access prior to PSL mandates.

4. PSL MANDATES AND INVENTOR EMPLOYEMENT

With the recognition of a significantly negative impact of PSL mandates on corporate innovation, our focus shifts towards exploring the role of inventor employment in this unintended consequence. Specifically, we investigate whether managers, when faced with increased labor costs due to PSL mandates, reduce the hiring of inventors to cut costs and maintain the more tangible functions of their companies.

4.1 PSL Mandates and the Net Hiring of Inventors

We follow the literature (e.g., Marx, Strumsky, and Fleming, 2009; Chemmanur, Kong, Krishnan, and Yu, 2019) and define an inventor as having changed employers if she files two successive patent applications with different companies. In this case, the inventor is considered to leave the first firm and join the second firm in the year of the latter patent application.[18] We then calculate inventor inflows for a firm-year as the total number of newly hired investors and inventor

[18] For example, if an inventor A files two successive patents, one with Company X in 2006 and the other with Company Y in 2010, then she is identified as leaving Company X and joining Company Y in 2010.

outflows as the total number of inventors leaving the firm. Finally, we calculate net inventor hiring as the difference between inventor inflows and inventor outflows.

Columns (1) and (2) in Panel A of Table 7 present the DiD regression of net inventor hiring on PSL mandates. We find that the coefficient of PSL is significantly negative in both models, suggesting that the net hiring of inventors decreases after the adoption of PSL mandates. This result is also economically significant as the coefficient in column (1) indicates that the PSL mandates leads to a decrease of 0.708 in the net inventor hiring, representing over a one-third decline from the mean.[19]

Next, we analyze inventor inflows (columns (3) and (4)) and outflows (columns (5) and (6)) separately. The results show that, consistent with our prediction, the decrease in net inventor hiring is primarily driven by a reduction in the hiring of inventors, rather than the departure of existing inventors, as the coefficient of *PSL* is significantly negative in columns (3) and (4). In contrast, the coefficient of *PSL* is much smaller and only marginally significant in columns (5) and (6).[20]

To compare skilled labor with ordinary workers, we conduct DiD regressions of the firm's total number of employees and present the results in Panel B of Table 7. Interestingly, the coefficient of PSL is either insignificant or significantly positive (t-statistics 0.69 and 2.01). This result shows that firm's total number of employees does not significantly decrease after the adoption of PSL mandates.[21] The contrasting effects of PSL mandates on inventors and ordinary workers provide further evidence that firms reduce the hiring of inventors to maintain the more

[19] We winsorize the number of inventors and inventor flow variables at the 95th percentile, similar as the patent measures. Since an average sample firm has a total of 24.8 inventors, this decline in net inventor flows corresponds to a 3% decrease in the total number of inventors at a sample firm, which is economically significant.
[20] The negative coefficient in the *Outflow* regression is consistent with fewer inventors leaving their firms after having the access to PSL.
[21] On average, our sample firms have 24.8 inventors out of 6,530 total employees.

tangible operations.

4.2 Financial Constraints and the Reduction in Inventor Hiring

If firms reduce inventor hiring due to the expected increase in labor costs from PSL mandates, this reduction will be more pronounced among financially constrained firms (Campello, Kankanhalli, and Muthukrishnan, 2024). In this subsection, we examine the interactive effects of financial constraints and PSL mandates on inventor hiring.

Due to concerns about traditionally used financial constraint measures (e.g., Bodnaruk, Loughran, and McDonald, 2015; Farre-Mensa and Ljungqvist, 2016), we follow Hoberg and Maksimovic (2015) and utilize the text-based measure of financial constraints (henceforth HM measure). The measure is derived from financial constraint-related words extracted from the capitalization and liquidity subsection of the MD&A section of the 10-K filings.[22] We estimate DiD regressions that include an interaction term between *PSL* and *Financial Constraint*, where *Financial Constraint* is a dummy variable equals one if the text-based financial constraint measure for the firm in the previous year is above the annual sample median, and zero otherwise. Due to the availability of the HM measure, the sample period for this analysis ends in 2015.

In Panel A of Table 8, Columns (1) and (2) present regressions of net inventor hiring, where the coefficient of the interaction term is significantly negative. Additionally, the coefficient is significant negative in the regressions of inventor inflows (Columns 3 and 4) but insignificant in the regression of inventor outflows (Columns 5 and 6). These results suggest that the reduction in net inventor hiring following PSL mandates is significantly larger for financially constrained firms, and due to financially constrained firms hiring fewer inventors. In Panel B of Table 8, we further

[22] We thank Professors Hoberg and Maksimovic for making their constraint measure available at https://faculty.marshall.usc.edu/Gerard-Hoberg/MaxDataSite/index.html.

examine the interactive effect of financial constraints and PSL mandates on corporate innovation. We find that the coefficient of the interaction term is significantly negative in all regressions of patent filings and citations. These results align with the observed interactive effect on net inventor hiring in Panel A.

We conduct robustness tests using several alternative financial constraints measures. First, HM show that their equity-focused constraint score also effectively captures financial constraints. Therefore, we conduct a robustness test using this alternative text-based constraint measure. Second, using the HM measure as the training sample, Linn and Weagley (2024) construct a mapping between firm-level accounting variables and HM measures using machine learning, generating a financial constraints measure dataset from 1972 to 2021.[23] This dataset also has a broader coverage, as the measure construction for a firm does not require a liquidity subsection of the MD&A in the 10-K filings. We conduct robustness tests using Linn and Weagley's financial constraints measures.[24] For brevity, we present these robustness tests in Table B4 of Appendix B, which show that our results are robust using these alternative measures.

5. PSL MANDATES AND INVENTOR PRODUCTIVITY

While existing literature suggests that PSL mandates positively impacts the overall labor productivity for US firms (Chunyu, Volpin, and Zhu, 2024), such impact may be more negative for the productivity of inventors compared to ordinary workers. Specifically, inventorship is a unique profession that heavily relies on effective team coordination and the collaboration of individuals with specialized skills. For example, Singh and Fleming (2010) report that about 90% of patents are filed by an invention team than single inventors. Moreover, compared to ordinary

[23] The financial variables used include all 19 financial variables in the traditionally used financial constraint proxies (the KZ, HP, and WW measures).
[24] We thank the author for providing the data at https://www.danielweagley.com/data.html.

workers, securing a temporary replacement for an inventor on PSL can be particularly challenging, given that each inventor in a team may possess distinct specializations. Therefore, if an inventor within a team takes sick leave, it could potentially delay the progress of the entire team. This interruption of coordination may amplify the negative impact of sick absences on inventor productivity.

In this section, we first examine the impact of PSL-related inventor absences on corporate innovation. Next, we investigate whether the disruptions in inventor coordination amplify the impact of PSL mandates on corporate innovation.

5.1 PSL-Related Inventor Absences and Corporate Innovation

When employees have access to paid sick leave, they may take more time off from work due to illness or other qualifying reasons. Since we do not directly observe inventor absences, we conduct cross-sectional analyses based on inventor characteristics that are associated with variations in PSL-related inventor absences.

Our first analysis is centered on female inventors. Within families, females tend to spend more time caring for children, as well as the sick or elderly family members (Land, 1978). Given that PSL mandates generally cover care for family members, female workers are likely to utilize this leave more frequently to care for sick family members compared to male employees.[25] Therefore, we expect the negative impact of PSL mandates on corporate innovation is more pronounced in firms with higher participation of female inventors.

We obtain inventor gender data from the PatentsView database and calculate the proportion of female inventors for a firm-year as the firm's number of female inventors scaled by its total

[25] Previous research has documented that female employees tend to utilize family leave more frequently than their male counterparts (e.g., Kim, 1998; Sandberg, 1999).

number of inventors in the year.[26] We construct a firm-level dummy variable, *High Female Inventor*, which equals one if the proportion of female inventors for the firm in the previous year is above the annual sample median, and zero otherwise.[27] We then perform the baseline DiD regressions that include an interaction term between *High Female Inventor* and *PSL*. In Panel A of Table 9, we find that the coefficient of the interaction term is significantly negative in all four models. These results are in line with our prediction, demonstrating the impact of PSL mandates on corporate innovation is more pronounced among firms with a higher proportion of female inventors.

We further use inventor age as a proxy for the PSL-related inventor absences. Previous studies show that with advancing age, employees are more likely to be absent from work due to unavoidable circumstances such as illness and family obligations (e.g., Bierla, Huver, and Richard 2013; Frick and Malo 2008). Therefore, PSL is likely to be utilized more by older employees compared to younger employees. Since we do not have direct access to an inventor's age, we utilize inventor tenure as a proxy, under the assumption that inventors with longer tenures are likely to be older. Inventor tenure is defined as the number of years between the year of an inventor's first patent filing and the current year. We then construct a firm-level dummy variable, *High Senior Inventor*, which equals one if the average inventor tenure of a firm in the previous year is above the annual sample median, and zero otherwise. In Panel B of Table 9, we include an interaction term between the *High Senior Inventor* and the PSL dummy into the DiD regressions. We find that the coefficient of the interaction is negative and significant in all models. Overall, the results in

[26] When we calculate a firm's proportion for year t, we assume an inventor works for the firm in year t if the most recent patent filed by the inventor up to that year is with the firm.
[27] For the two analyses in this subsection using female inventors and inventor age, we exclude firms with no patents because their inventor characteristics are unavailable.

Table 9 provide evidence the PSL-related inventor absences negatively impact inventor productivity and in turn corporate innovation.

5.2 Disruptions in Inventor Coordination

To examine whether disruptions in inventor coordination amplify the negative impact of PSL mandates on corporate innovation, we conduct cross-sectional analyses using three proxies associated with disruptions in inventor coordination.

First, we predict that PSL-related disruptions in inventor coordination will be more pronounced among firms whose patents are developed by team inventors rather than single inventors. When a patent is developed by team inventors rather than a single inventor, inventor absences can potentially slow the progress of the entire team. We classify a patent as team-developed if it is filed by a team of more than one inventor, and then construct a dummy variable, *High Inventor Team*, which equals one if the proportion of patents filed by team inventors for the firm in the previous year is above the annual sample median, and zero otherwise.

We conduct DiD regressions that include an interaction between *High Inventor Team* and the *PSL* dummy. In Panel A of Table 10, we find that the coefficient of the interaction term is negative in all models and significant in three of the four models. These results suggest that, consistent with our prediction based on the interruption of coordination, the negative impact of PSL mandates on corporate innovation is more pronounced in firms with a higher proportion of patents filed by team inventors, rather than single inventors.

5.2.2 Inventor Buffer

Our second cross-sectional analysis is based on the buffer for absent inventors. Specifically, if a firm's inventors possess similar backgrounds and skill sets, it becomes easier to find a replacement inventor to assume the responsibilities of the absent inventor. Conversely, if a firm's

inventors have diverse backgrounds and skill sets, finding such replacement becomes more challenging. Therefore, we expect that the decline in corporate innovation following the implementation of PSL mandates is more pronounced among firms with more diverse innovation (i.e., less inventor buffer).

To test this prediction, we first calculate the Herfindahl index (HHI) based on the three-digital technology class-share of a firm's patents in a year. We then construct a firm-level dummy variable, *Low Inventor Buffer*, which equals one if the firms' HHI in the previous year is below or equal to the annual sample median, and zero otherwise.[28] Panel B of Table 10 presents the DiD regressions that include an interaction term between *Low Inventor Buffer* and *PSL*. We find that the coefficient of the interaction term is significantly negative in all models (t-statistics -3.10 to -6.00). Therefore, consistent with the coordination prediction, the negative effect of PSL mandates on corporate innovation is significantly larger in firms with less inventor buffer.

5.2.3 Work from Home

Our third cross-sectional analysis on disrupted coordination is based on the proportion of a company's jobs that can be done at home. If a firm has few jobs that can be done at home, then sick absences will have a larger impact on the routine face-to-face coordination. To test this prediction, we obtain the data on industry-level proportion of jobs that can be done at home from Dingel and Neiman (2020), which is constructed based on the survey data.[29] The authors obtain occupation-level survey data relevant to work from home from ONET and then aggregate it to the industry level. We then construct a firm-level dummy variable, *Low WFH*, which equals one if the

[28] For the analysis on inventor buffer, we exclude firms with no patents in the construction period. We require a firm to have at least two patents in the construction period to calculate the Herfindahl index.

[29] These two surveys were conducted by ONET, a program supported by the Department of Labor, to gain a better understanding of the nature of work and the workforce in the U.S. These surveys primarily ask questions about interpersonal relationships, physical work conditions, and work output in the workplace.

firm is in an industry whose percentage of jobs that can work from home is below the sample median, and zero otherwise.

Panel C of Table 10 presents the DiD regressions of innovation that include an interaction term between *Low WFH* and *PSL*. We find that the coefficient of the interaction term is significantly negative in all models. Therefore, consistent with the mechanism of disrupted inventor coordination, the negative effect of PSL mandates on corporate innovation is significantly larger among firms whose employees have less flexibility of working from home.

Overall, the results in Table 10 suggest that the disruptions in coordination amplifies the effect of work hour losses on inventor productivity after the implementation of PSL mandates.

6. CONCLUSION

This paper studies the differential policy impact on skilled labor and ordinary workers by investigating the impact of paid sick leave (PSL) mandates on corporate innovation and inventors. We utilize the staggered implementation of state-level PSL mandates in twelve US states from 2008 to 2019, and conduct a difference-in-differences analysis.

Our results reveal a notable *decrease* in corporate innovation in terms of patent filings and citations after the implementation of PSL mandates. For example, firms' patent filings experience a 6.3% standard deviation decrease post the adoption of PSL mandates. Similarly, we observe a significant decline in patent quality measured by the average patent citations and the number of breakthrough patents. These findings remain consistent through an extensive set of robustness tests, and are unlikely to be explained by local factors.

Next, we directly examine the impact of PSL mandates on inventor employment and productivity. Regarding inventor employment, we find a significant reduction in the recruitment of new inventors following PSL mandates, while the employment of ordinary workers remains

stable. Additionally, the reduced inventor hiring is more pronounced in financially constrained firms, consistent a crowd-out of inventors to maintain more tangible operations.

Regarding inventor productivity, we examine if disruptions in inventor coordination magnify the negative impact of PSL-related inventor absences on inventor productivity. We find that the decline in corporate innovation post-PSL mandates is more pronounced for firms with a higher proportion of female inventors and older inventors, where PSL-related inventor absences are likely to be higher. Consistent with the impact of coordination disruptions, we find that firms with more team inventors, more diverse inventor backgrounds, and less work-from-home flexibility experience a larger decrease in corporate innovation after the adoption of PSL mandates.

Our study offers fresh insights into the interplay between government policy and skilled labor. Our findings emphasize the heterogeneity within labor forces and highlight the need for a comprehensive evaluation of the potential effects labor policies can exert on skilled labor and the broader economy.

REFERENCES

Acharya, Viral V., and Krishnamurthy V. Subramanian, 2009, Bankruptcy codes and innovation, *Review of Financial Studies* 22, 4949-4988

Acharya, Viral V., Ramin P. Baghai, and Krishnamurthy V. Subramanian, 2013, Labor laws and innovation, *Journal of Law and Economics* 56, 997-1037.

Acharya, Viral V., Ramin P. Baghai, and Krishnamurthy V. Subramanian, 2014, Wrongful discharge laws and innovation, *Review of Financial Studies* 27, 301-346.

Al-Sabah, Turk, and Paige Ouimet, 2023, For better or worse? The economic implications of paid sick leave mandates, Working Paper.

Amore, Mario Daniele, Cedric Schneider, and Alminas Žaldokas, 2013, Credit supply and corporate innovation, *Journal of Financial Economics* 109, 835-855.

Atanassov, Julian, and Xiaoding Liu, 2016, Corporate income taxes, pledgeable income and innovation, Working Paper.

Baghai, Ramin P, Rui C. Silva, Viktor Thell, and Vikrant Vig, 2021, Talent in distressed firms: Investigating the labor costs of financial distress, *Journal of Finance* 76, 2907-2961.

Baghai, Ramin P., Rui C. Silva, Luofu Ye, 2023, Teams and bankruptcy, Working Paper.

Baker, Andrew C., David F. Larcker, and Charles CY Wang, 2022, How much should we trust staggered difference-in-differences estimates?, *Journal of Financial Economics* 144, 370-395.

Belo, Frederico, Jun Li, Xiaoji Lin, and Xiaofei Zhao, 2017, Labor-force heterogeneity and asset prices: The importance of skilled labor, *Review of Financial Studies* 30, 3669-3709.

Bena, Jan, Hernán Ortiz-Molina, and Elena Simintzi, 2022, Shielding firm value: Employment protection and process innovation, *Journal of Financial Economics* 146, 637-664.

Bierla, Ingrid, Benjamin Huver, and Sébastien Richard, 2013, New evidence on absenteeism and presenteeism, *International Journal of Human Resource Management* 24, 1536-1550.

Blatter, Marc, Samuel Muehlemann, and Samuel Schenker, 2012, The costs of hiring skilled workers, *European Economic Review* 56, 20-35.

Bodnaruk, Andriy, Tim Loughran, and Bill McDonald, 2015, Using 10-K text to gauge financial constraints, *Journal of Financial and Quantitative Analysis* 50, 623-646.

Call, Andrew C., John L. Campbell, Dan S. Dhaliwal, and James R. Moon Jr, 2017, Employee quality and financial reporting outcomes, *Journal of Accounting and Economics* 64, 123-149.

Callaway, Brantly, and Pedro HC Sant'Anna, 2021, Difference-in-differences with multiple time periods, *Journal of Econometrics* 225, 200-230.

Campello, Murillo, Gaurav Kankanhalli, and Pradeep Muthukrishnan, 2024, Corporate hiring under covid-19: Financial constraints and the nature of new jobs, *Journal of Financial and Quantitative Analysis*, Forthcoming.

Cerqueiro, Geraldo, Deepak Hegde, María Fabiana Penas, and Robert C. Seamans, 2017, Debtor rights, credit supply, and innovation, *Management Science* 63, 3311-3327.

Chemmanur, Thomas J., Lei Kong, Karthik Krishnan, and Qianqian Yu, 2019, Top management human capital, inventor mobility, and corporate innovation, *Journal of Financial and*

Quantitative Analysis 54, 2383-2422.

Chen, Jiafeng and Jonathan Roth, 2024, Logs with zeros? Some problems and solutions, *Quarterly Journal of Economics*, Forthcoming.

Chen, Jun, Shenje Hshieh, and Feng Zhang, 2021, The role of high-skilled foreign labor in startup performance: Evidence from two natural experiments, *Journal of Financial Economics* 142, 430-452.

Chen, Jun, Shenje Hshieh, and Feng Zhang, 2024, Hiring high-skilled labor through mergers and acquisitions, *Journal of Financial and Quantitative Analysis*, Forthcoming.

Chunyu, Liangrong, Volpin, Paolo F., and Xingchen Zhu, 2024, Do paid sick leave mandates increase productivity?, Working Paper.

Cohn, Jonathan B., Zack Liu, and Malcolm I. Wardlaw, 2022, Count (and count-like) data in finance, *Journal of Financial Economics* 146, 529-551.

Dechezleprêtre, Antoine, Elias Einiö, Ralf Martin, Kieu-Trang Nguyen, and John Van Reenen, 2016, Do tax incentives for research increase firm innovation? An RD design for R&D, Working Paper.

Dolfin, Sarah, 2006, An examination of firms' employment costs, *Applied Economics* 38, 861-878.

Farre-Mensa, Joan, and Alexander Ljungqvist, 2016, Do measures of financial constraints measure financial constraints?, *Review of Financial Studies* 29, 271-308.

Frick, Bernd, and Miguel Á. Malo, 2008, Labor market institutions and individual absenteeism in the European union: The relative importance of sickness benefit systems and employment protection legislation, *Industrial Relations: A Journal of Economy and Society* 47, 505-529.

Ghaly, Mohamed, Viet Anh Dang, and Konstantinos Stathopoulos, 2017, Cash holdings and labor heterogeneity: The role of skilled labor, *Review of Financial Studies* 30, 3636-3668.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg, 2001, The NBER patent citation data file: Lessons, insights and methodological tools, Working Paper.

Hall, Bronwyn H., Adam Jaffe, and Manuel Trajtenberg, 2005, Market value and patent citations, *RAND Journal of Economics* 36, 16-38.

Hoberg, Gerard, and Vojislav Maksimovic, 2015, Redefining financial constraints: A text-based analysis, *Review of Financial Studies* 28, 1312-1352.

Jaravel, Xavier, Neviana Petkova, Alex Bell, 2018, Team-specific capital and innovation, *American Economic Review* 108, 1034-1073.

Kim, Soonhee, 1998, Toward understanding family leave policy in public organizations: Family leave use and conceptual framework for the family leave implementation process, *Public Productivity & Management Review*, 71-87.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, 2017, Technological innovation, resource allocation, and growth, *Quarterly Journal of Economics* 132, 665-712.

Land, Hilary, 1978, Who cares for the family?, *Journal of Social Policy* 7, 257-284.

Laux, Volker, and Phillip C. Stocken, 2018, Accounting standards, regulatory enforcement, and innovation, *Journal of Accounting and Economics* 65, 221-236.

Lerner, Josh, 2009, The empirical impact of intellectual property rights on innovation: Puzzles and clues, *American Economic Review* 99, 343-348.

Li, Qin, Mark Shuai Ma, and Terry Shevlin, 2021, The effect of tax avoidance crackdown on

corporate innovation, *Journal of Accounting and Economics* 71, 101382.

Linn, Matthew, and Daniel Weagley, 2024, Uncovering financial constraints, *Journal of Financial and Quantitative Analysis*, forthcoming.

Lück, Sonja, Benjamin Balsmeier, Florian Seliger, and Lee Fleming, 2020, Early disclosure of invention and reduced duplication: An empirical test, *Management Science* 66, 2677-2685.

Manning, Alan, 2003, The real thin theory: Monopsony in modern labour markets, *Labour Economics* 10, 105-131.

Marx, Matt, Deborah Strumsky, and Lee Fleming, 2009, Mobility, skills, and the Michigan non-compete experiment, *Management Science* 55, 875-889.

Oi, Walter Y, 1962, Labor as a quasi-fixed factor, *Journal of Political Economy* 70, 538-555.

Pichler, Stefan, and Nicolas R. Ziebarth, 2020, Labor market effects of US sick pay mandates, *Journal of Human Resources* 55, 611-659.

Sandberg, Joanne C., 1999, The effects of family obligations and workplace resources on men's and women's use of family leaves, *Research in Sociology of Work*, 261-281.

Singh, Jasjit, and Lee Fleming, 2010, Lone inventors as sources of breakthroughs: Myth or reality? *Management Science* 56, 41-56.

Spulber, Daniel F., 2013, How do competitive pressures affect incentives to innovate when there is a market for inventions?, *Journal of Political Economy* 121, 1007-1054.

Sun, Liyang, and Sarah Abraham, 2021, Estimating dynamic treatment effects in event studies with heterogeneous treatment effects, *Journal of Econometrics* 225, 175-199.

Wething, Hilary, 2021, Does paid sick leave affect job turnover?, Working Paper.

Williams, Heidi L., 2013, Intellectual property rights and innovation: Evidence from the human genome, *Journal of Political Economy* 121, 1-27.

Figure 1
Cumulative Number of States that Adopt PSL Mandates

This figure shows the cumulative number of states that have adopted PSL mandates from 2008 to 2019.

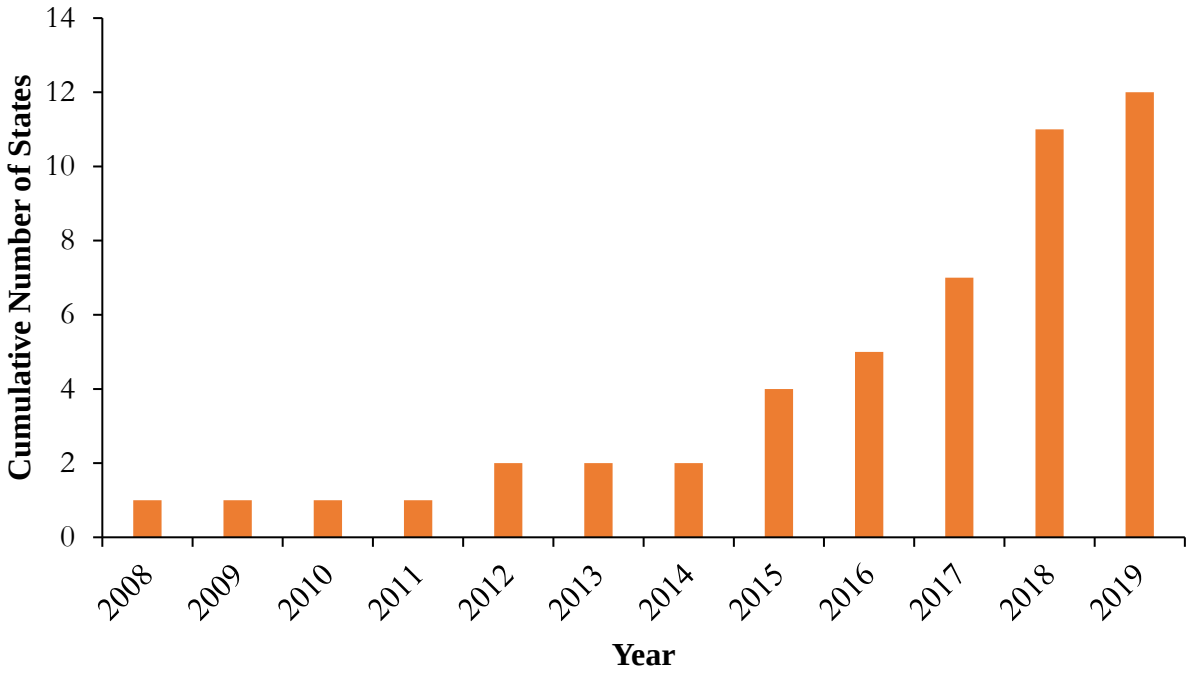
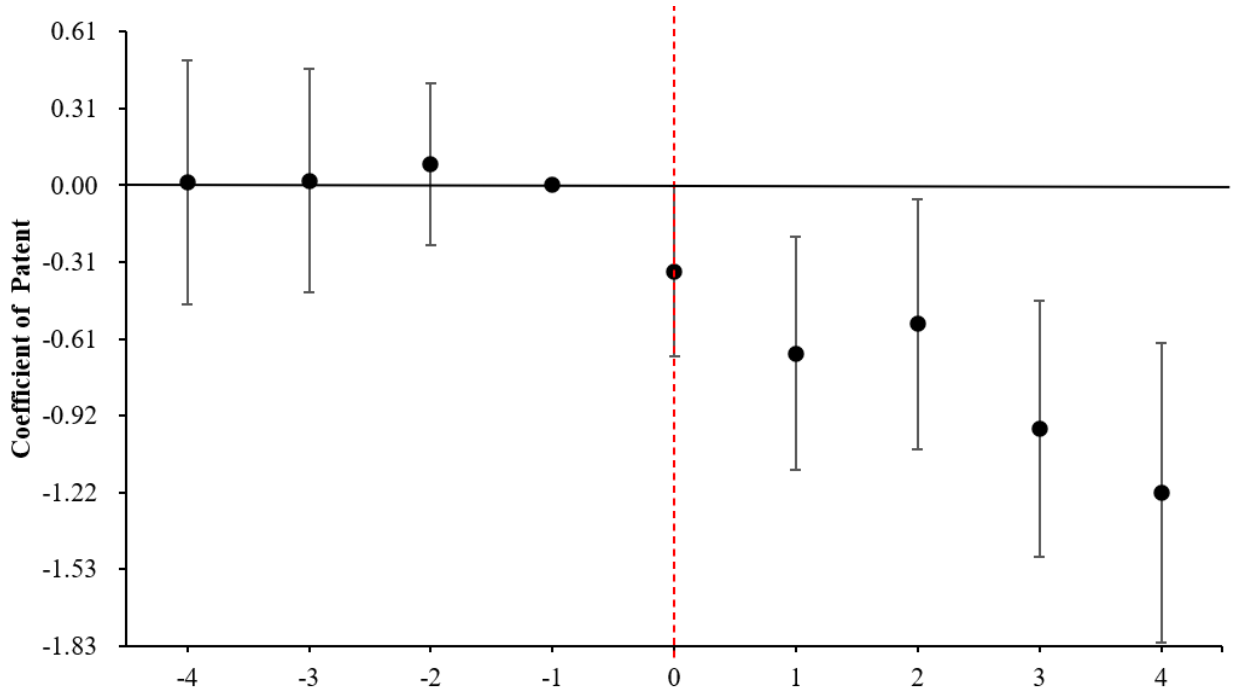


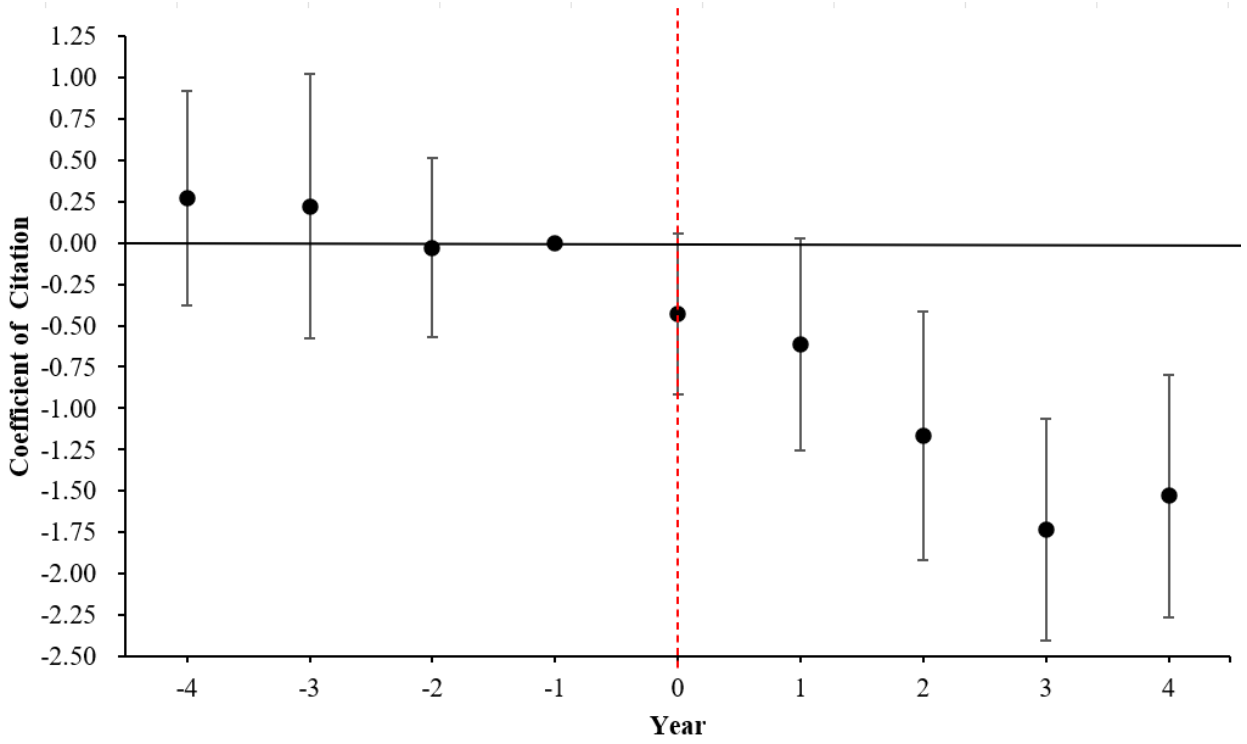
Figure 2
The Dynamic Impact of PSL Mandates on Corporate Innovation

This figure presents the dynamic impact of PSL mandates on corporate innovation using the TWFE DiD event study proposed by Sun & Abraham (2021). In Panel A, the dependent variable is *Patent*, which is defined as the number of patent applications filed. The independent variables are PSL^{-4}, PSL^{-3}, PSL^{-2}, PSL^{-1}, PSL^{0}, PSL^{+1}, PSL^{+2}, PSL^{+3} and PSL^{+4}. PSL^{-4}, PSL^{-3}, and PSL^{-2} are dummy variables that equal one if a firm is headquartered in a state that will adopt PSL mandates in four or more years, three years, or two years, respectively, and zero otherwise. PSL^{0} is a dummy variable that equals one if a firm headquartered in a state that has adopted PSL mandates in the current year and zero otherwise. PSL^{+1}, PSL^{+2}, PSL^{+3}, and PSL^{+4} are similarly defined, except that they equal one if a firm is headquartered in a state that have adopts PSL mandates one, two, three, or four or more years after the implementation year, respectively. The solid dots represent the estimated coefficients with one year prior to the mandate (t=-1) as the reference, while the solid vertical line segments present two-sided 95% confidence intervals. Control variables including total assets, cash holdings, financial leverage, capital expenditure, PPE, ROA, R&D, and book-to-market ratio in the previous year are defined in Appendix A. Panel B is similar to Panel A, except that the dependent variable is *Citation*, which is the firm's truncation-adjusted future citations. Panel C is similar to Panel A, except that the dependent variable is *Net Hiring*, which is the difference between the number of inventors who join a firm in the year and the number of inventors who leave a firm in the year. All models include firm and industry-year fixed effects, and t-statistics are clustered at the state level.

Panel A: The Dynamic Impact of PSL Mandates on Patent Applications



Panel B: The Dynamic Impact of PSL Mandates on Adjusted Citations



Panel C: The Dynamic Impact of PSL Mandates on Net Inventor Hiring

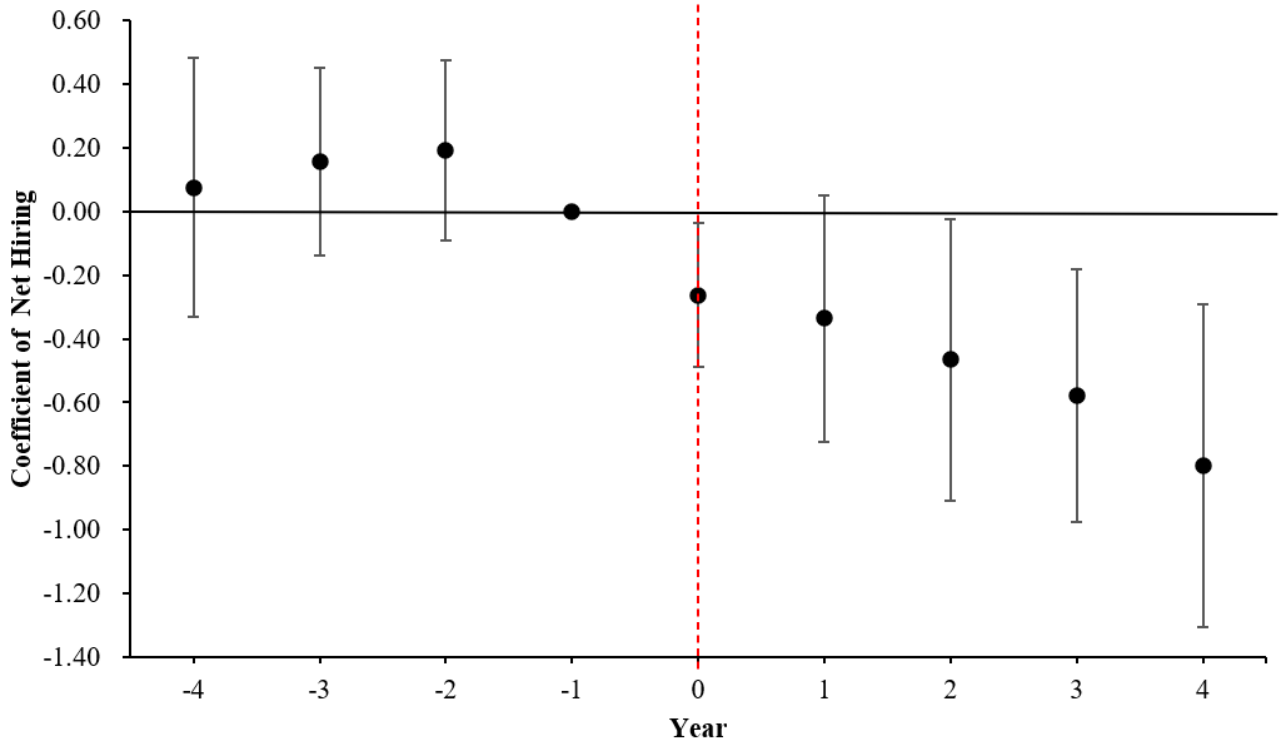


Table 1
Summary Statistics

This table reports summary statistics for sample firms from 2004 to 2019. *PSL* is a dummy variable that equals one for the state and the period after the adoption of the PSL mandate, and zero otherwise. *Patent* is the total number of patent applications filed by the firm in the year. *Citation* is the firm's truncation-adjusted future citations of patents filed in the year. *Average Citation* is the average truncation-adjusted patent citations across patents filed by a firm in the year. *Breakthrough Patent* is the number of breakthrough patents filed by a firm in the year. *R&D* is research and development expenditures scaled by total assets. *ln(Asset)* is the natural logarithm of total assets. *Cash* is cash scaled by total assets. *Leverage* is total debt scaled by total assets. *Capx* is capital expenditures scaled by total assets. *PPE* is net property, plant, and equipment scaled by total assets. *ROA* is net income scaled by total assets. *B/M* is book equity scaled by market value. *Total Employees* is the total number of employees in thousand for a firm in the year. *Delaycon* is the text-based measure of financial constraint by Hoberg and Maksimovic (2015). *Female Participation* is the percentage of females among all inventors. *Average Inventor Tenure* is the average tenure of inventors who file patents for a firm in a given year. Inventor tenure is defined as the number of years since an inventor filed her first patent up to the current year. *Single Invento*r is the percentage of patent that filed by one inventor for a firm in a year. *Inventor Buffer* is the Herfindahl index (HHI) based on the three-digital technology class-share of a firm's patents in the year. *WFH* is the percentage of jobs that can be done at home in each 2-digit NAICS from Dingel and Neiman (2020). *Inflow* is the number of inventors who join a firm in the year. *Outflow* is the number of inventors who leave a firm in the year. *Net Hiring* is the difference between *Inflow* and *Outflow*.

Variables	Obs.	Mean	SD	P10	P25	P50	P75	P90
PSL	37,726	0.10	0.30	0.00	0.00	0.00	0.00	0.00
Patent	37,726	3.81	9.52	0.00	0.00	0.00	1.00	13.00
Citation	37,726	4.49	12.02	0.00	0.00	0.00	0.46	14.76
Average Citation	37,726	0.28	0.56	0.00	0.00	0.00	0.22	1.19
Breakthrough Patents	37,726	0.23	0.72	0.00	0.00	0.00	0.00	1.00
R&D	37,726	0.07	0.13	0.00	0.00	0.00	0.07	0.20
ln(Asset)	37,726	6.08	2.03	3.39	4.58	6.06	7.50	8.74
Cash	37,726	0.23	0.25	0.01	0.04	0.13	0.33	0.64
Leverage	37,726	0.21	0.22	0.00	0.01	0.17	0.34	0.51
Capx	37,726	0.05	0.06	0.01	0.01	0.03	0.06	0.11
PPE	37,726	0.24	0.24	0.02	0.06	0.16	0.36	0.65
ROA	37,726	-0.05	0.27	-0.34	-0.06	0.03	0.08	0.12
B/M	37,726	0.54	0.52	0.10	0.24	0.44	0.74	1.13
Total Employees	37,425	6.53	11.54	0.07	0.24	1.39	6.34	21.7
Delaycon	22,484	-0.01	0.09	-0.13	-0.08	-0.01	0.05	0.11
Female Participation	15,637	0.11	0.13	0.00	0.00	0.08	0.16	0.26
Average Inventor Tenure	15,637	8.85	4.03	4.00	6.10	8.49	11.1	14.00
Single Inventor	10,282	0.24	0.27	0.00	0.00	0.18	0.33	0.56
Inventor Buffer	13,638	0.62	0.35	0.16	0.30	0.56	1.00	1.00
WFH	37,507	0.43	0.20	0.22	0.36	0.36	0.37	0.80
Net Hiring	37,726	1.99	5.28	0.00	0.00	0.00	0.00	8.00
Inflow	37,726	2.48	6.15	0.00	0.00	0.00	0.00	9.00
Outflow	37,726	0.49	1.26	0.00	0.00	0.00	0.00	2.00

Table 2
The Effect of PSL Mandates on Firm Innovation

This table examines the effect of PSL mandates on firm innovation. Panel A presents firm-level DiD regressions of firm innovation from 2004 to 2019. The dependent variable is the number of patent applications filed by a firm in year *t* (Models (1) and (2)), or the truncation-adjusted future citations for patents filed by the firm in year *t* (Models (3) and (4)). The main independent variable is *PSL*, which is a dummy variable that equals one for the state-years after the adoptions of PSL mandates, and zero otherwise. Control variables including total assets, cash holdings, financial leverage, capital expenditure, PPE, ROA, R&D, and book-to-market ratio in the previous year are defined in Appendix A. Panel B is similar to Panel A, except that the dependent variable is the average citations for patents filed by the firm in year t (Models (1) and (2)) or the number of breakthrough patents filed by the firm in year t (Models (3) and (4)). Breakthrough patents are defined as those with forward citation counts in the top 5% of all patents of the same application year and technology class. We control for firm and year fixed effects, or firm and industry-year fixed effects in some models. T-statistics using robust standard errors adjusted for heteroscedasticity and clustered at the state level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A: DiD Regressions of Firm Innovation

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL	**-0.946***** **(-4.36)**	**-0.597**** **(-2.10)**	**-1.600***** **(-3.85)**	**-0.974***** **(-3.11)**
ln(Asset)	0.783*** (4.23)	0.752*** (4.05)	0.791*** (4.17)	0.775*** (4.11)
Cash	-0.043 (-0.12)	-0.052 (-0.14)	0.710 (1.43)	0.349 (0.74)
Leverage	-0.913*** (-3.21)	-0.764*** (-3.64)	-1.172** (-2.03)	-1.172*** (-2.93)
Capx	-0.381 (-1.10)	0.752 (1.46)	-0.339 (-0.72)	1.248 (1.23)
PPE	0.349 (0.83)	0.114 (0.32)	0.868 (1.54)	-0.215 (-0.39)
ROA	-0.265 (-1.23)	-0.109 (-0.55)	-0.105 (-0.43)	0.152 (0.64)
R&D	1.006*** (3.25)	1.044*** (3.28)	1.897** (2.06)	2.184** (2.32)
B/M	-0.154** (-2.28)	-0.188*** (-3.02)	-0.130** (-2.03)	-0.180** (-2.49)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Adj. R^2	0.861	0.862	0.813	0.814
Observations	37,100	36,015	37,100	36,015

Panel B: DiD Regressions of Patent Quality

Dep. Var.	Average Citation		Breakthrough Patent	
	(1)	(2)	(3)	(4)
PSL	**-0.066*****	**-0.031***	**-0.090*****	**-0.055*****
	(-3.03)	**(-1.82)**	**(-3.44)**	**(-3.24)**
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Adj. R^2	0.581	0.580	0.704	0.704
Observations	37,100	36,015	37,100	36,015

Table 3

Robustness Tests: Alternative Sample Constructions or Empirical Methods

This table presents robustness tests for our baseline DiD analysis. In Panel A, we exclude firms without patents during the sample period. The dependent variable is the number of patent applications filed in year t (Columns (1) and (2)), or the truncation-adjusted future citations for patents filed in year t (Columns (3) and (4)). The independent variable *PSL* is a dummy variable that equals one for the state and time period after the adoption of PSL mandate, and zero otherwise. Panel B reports the two-way fixed-effect (TWFE) estimates using the approaches proposed by Callaway and Sant'Anna (2021) and Sun and Abraham (2021). In Columns (1), (2), and (5), the dependent variable is the number of patent applications filed in year t. In Columns (3), (4), and (6), the dependent variable is the truncation-adjusted future citations for patents filed in year t. The independent variable is PSL in Models (1) to (4). PSL is a dummy variable that equals one for the state and time period after the adoption of PSL mandate, and zero otherwise. The independent variables in Models (5) and (6) are PSL^{-4}, PSL^{-3}, PSL^{-2}, PSL^{0}, PSL^{+1}, PSL^{+2}, PSL^{+3} and PSL^{+4}. PSL^{-4}, PSL^{-3}, and PSL^{-2} are dummy variables that equal one if a firm headquartered in a state that will adopt PSL mandates in four or more years, three years, or two years, respectively, and zero otherwise. PSL^{0} is a dummy variable that equals one if a firm headquartered in a state that has adopted PSL mandates in the current year and zero otherwise. PSL^{+1}, PSL^{+2}, PSL^{+3}, and PSL^{+4} are dummy variables that equal one if a firm headquartered in a state that adopts PSL mandates one, two, three, or four or more years after the implementation year, respectively. All models include the same firm-level control variables as in Table 2, and their coefficients are not reported for brevity. We control for firm and year fixed effects, or firm and industry-year fixed effects in some models. T-statistics using robust standard errors adjusted for heteroscedasticity and clustered at the state level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A: Exclude Firms Without Patents During the Sample Period

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL	**-1.881***** **(-3.09)**	**-1.728*** **(-1.92)**	**-3.088***** **(-3.24)**	**-2.418**** **(-2.13)**
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Adj. R^2	0.866	0.865	0.823	0.823
Observations	18,112	16,699	18,112	16,699

Panel B: Two-Way Fixed-Effect (TWFE) Estimates

	Callaway & Sant'Anna				Sun & Abraham	
Dep. Var.	Patent		Citation		Patent	Citation
	(1)	(2)	(3)	(4)	(5)	(6)
PSL	**-0.767*** (-3.24)**	**-0.860*** (-3.39)**	**-1.153*** (-3.09)**	**-1.289*** (-2.99)**		
PSL^{-4}					**0.011 (0.04)**	**0.270 (0.84)**
PSL^{-3}					**0.018 (0.08)**	**0.221 (0.55)**
PSL^{-2}					**0.084 (0.52)**	**-0.028 (-0.11)**
PSL^{0}					-0.342** (-2.03)	-0.428* (-1.76)
PSL^{+1}					-0.668*** (-2.89)	-0.614* (-1.92)
PSL^{+2}					-0.552** (-2.24)	-1.167*** (-3.10)
PSL^{+3}					-0.969*** (-3.83)	-1.735*** (-5.22)
PSL^{+4}					-1.221*** (-4.12)	-1.529*** (-4.18)
Firm Controls	No	Yes	No	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	No	No
Industry-Year FE	No	No	No	No	Yes	Yes

Table 4
Additional Robustness Tests: Alternative Samples

This table presents the additional robustness tests using alternative sample selection criteria or fixed effects. The dependent variable is the number of patent applications filed in year t (Columns (1) and (2)), or the truncation-adjusted future citations for patents filed in year t (Columns (3) and (4)). The independent variable *PSL* is a dummy variable that equals one for the state and time period after the adoption of PSL mandate, and zero otherwise. In Panel A, we include firms that are headquartered in cities or counties with separate PSL mandates into the sample. In Panel B, we exclude observations in the year of the implementation of PSL mandates. In Panel C, we exclude observations during the financial crisis (2007 to 2009). In Panel D, we exclude the states with adoptions in 2018 or 2019. Control variables including total assets, cash holdings, financial leverage, capital expenditure, PPE, ROA, R&D, and book-to-market ratio in the previous year are defined in Appendix A. Their coefficients are not reported for brevity. We control for firm and year fixed effects, or firm and industry-year fixed effects in some models. T-statistics using robust standard errors adjusted for heteroscedasticity and clustered at the state level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A: Include Firms Headquartered in Cities or Counties with Separate PSL Mandates

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL	**-0.934*****	**-0.592****	**-1.516*****	**-0.881*****
	(-4.71)	**(-2.56)**	**(-3.93)**	**(-3.08)**
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Adj. R^2	0.879	0.894	0.835	0.855
Observations	41,474	40,530	41,474	40,530

Panel B: Exclude Observations in the Implementation Year of PSL Mandates

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL	**-1.101*****	**-0.740****	**-1.833*****	**-1.197*****
	(-5.37)	**(-2.45)**	**(-3.99)**	**(-3.35)**
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Adj. R^2	0.878	0.895	0.837	0.859
Observations	36,294	35,194	36,294	35,194

Panel C: Exclude Observations During the Financial Crisis

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL	**-1.051*****	**-0.648****	**-1.671*****	**-1.011*****
	(-4.68)	**(-2.52)**	**(-4.03)**	**(-3.74)**
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Adj. R^2	0.880	0.897	0.837	0.859
Observations	29,541	28,663	29,541	28,663

Panel D: Exclude States with Adoptions in 2018 and 2019

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL	**-1.062*****	**-0.667****	**-1.753*****	**-0.996****
	(-6.13)	**(-2.00)**	**(-4.72)**	**(-2.67)**
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Adj. R^2	0.873	0.890	0.830	0.852
Observations	33,750	32,574	33,750	32,574

Table 5
Do Local Factors Explain the Decline in Corporate Innovation?

This table presents the analyses that address the concerns that the decline in corporate innovation is driven by local factors that correlate with the passage of PSL mandates. The test design is similar as our baseline analysis (Panel A of Table 2). Panel A presents the pseudo-event test by assigning PSL mandate to a neighboring state that has not adopted PSL. Panel B presents the analysis using the subsample of blue event states (DC, Connecticut, California, Massachusetts, Oregon, Vermont, Washington, Maryland, Rhode Island, New Jersey, and Michigan) and states that have not adopted PSL mandates. Panel C presents the analysis using the subsample of red event state (Arizona) and states that have not adopted PSL mandates. Panel D presents the pseudo-event test similar as Panel A except that we assign PSL mandate to a neighboring *blue* state that has not adopted PSL. Panel E presents the pseudo-event analysis using a case of failed attempt to adopt PSL mandates in Orange County, FL. In 2013, Orange County considered a local PSL mandate that would provide up to 56 hours of PSL a year. However, a Florida preemptive bill was signed into law, halting the enactment of Orange County's PSL mandate. The pseudo-event firms are designated as those headquartered in Orange County, and control firms as those headquartered in other counties in Florida. We set 2013 as the pseudo-event year. We control for firm and year fixed effects, or firm and industry-year fixed effects in some models. T-statistics using robust standard errors adjusted for heteroscedasticity and clustered at the state level in Panels A to D, and clustered at the firm level in Panel E, are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A: Pseudo-Event Analysis Based on Neighboring States

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL	**-0.147**	**0.052**	**-0.019**	**0.215**
	(-0.43)	**(0.22)**	**(-0.04)**	**(0.70)**
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Adj. R^2	0.878	0.894	0.835	0.857
Observations	37,100	36,015	37,100	36,015

Panel B: The Subsample of Blue Event States

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL	**-0.937*****	**-0.567***	**-1.632*****	**-0.950*****
	(-4.10)	**(-1.92)**	**(-3.83)**	**(-2.94)**
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Adj. R^2	0.861	0.862	0.813	0.814
Observations	36,571	35,465	36,571	35,465

Panel C: The Subsample of Red Event State

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL	**-0.872*** **	**-1.022*** **	**-0.622*** **	**-1.028*** **
	(-6.09)	**(-3.29)**	**(-4.03)**	**(-3.16)**
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Adj. R^2	0.853	0.868	0.798	0.812
Observations	23,014	21,764	23,014	21,764

Panel D: Pseudo Events Using Blue States

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL	**-0.136**	**0.088**	**-0.005**	**0.204**
	(-0.37)	**(0.30)**	**(-0.01)**	**(0.51)**
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Adj. R^2	0.878	0.894	0.835	0.857
Observations	37,100	36,015	37,100	36,015

Panel E: Pseudo Event Using Failed PSL Attempt by Orange County, FL

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL	**0.053**	**-0.007**	**0.044**	**0.082**
	(0.71)	**(-0.08)**	**(0.36)**	**(0.70)**
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Adj. R^2	0.801	0.903	0.811	0.909
Observations	1,636	932	1,636	932

Table 6
Cross-Sectional Tests: Inventor Locations and Voluntary PSL Access

This table reports the cross-sectional analysis of the effect of PSL mandates on firm innovation. Panel A presents the cross-sectional analysis based on inventor locations. *PSL* is a dummy variable that equals one for the state and time period after the adoption of PSL mandate, and zero otherwise. *Headquarter Patent* or *Headquarter Citation* is the total number of patents filed or truncation-adjusted citations received by invention teams that contain at least one inventor located at the firm's headquarters. *Non-Headquarter Patent* and *Non-Headquarter Citation* are defined similarly to *Headquarter Patent* and *Headquarter Citation*, except they are the total number of patents and citations where none of the inventors in the invention team are located at the headquarters. Panel B presents the cross-sectional analysis based on voluntary PSL access, where we include the interaction of *PSL* and *Low Access*. *Low Access* is a dummy variable that equals one if a firm belongs to an industry (2-digit NAICS) with a ratio of voluntary PSL access below or equal to the sample median, and zero otherwise. We control for firm and year fixed effects, or firm and industry-year fixed effects in some models. T-statistics using robust standard errors adjusted for heteroscedasticity and clustered at the state level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A: Headquarters Inventor Participation

Dep. Var.	Headquarter Patent	Non-Headquarter Patent	Headquarter Citation	Non-Headquarter Citation
	(1)	(2)	(3)	(4)
PSL	**-0.342****	**-0.047**	**-0.576*****	**-0.134**
	(-2.56)	**(-0.50)**	**(-4.31)**	**(-1.35)**
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.879	0.871	0.828	0.817
Observations	36,015	36,015	36,015	36,015

Panel B: Voluntary PSL Access

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL×Low Access	**-1.649*****	**-1.539*****	**-2.390****	**-2.278****
	(-2.90)	**(-2.92)**	**(-2.21)**	**(-2.22)**
PSL	0.260	0.140	0.110	0.003
	(0.89)	(0.52)	(0.22)	(0.01)
Firm controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.875	0.876	0.833	0.834
Observations	34,214	34,214	34,214	34,214

Table 7
PSL Mandates and Inventor Employment

This table presents that the effect of PSL mandates on inventor employment at the firm level. Panel A examines the effect of PSL mandates on inventor inflows. The dependent variables are net inventor inflow *(Net Hiring)* in Models (1) and (2), inventor inflow *(Inflow)* in Models (3) and (4), and inventor outflow *(Outflow)* in Models (5) and (6), respectively. *Inflow* is the number of inventors who join a firm in a given year, while *Outflow* is the number of inventors who leave the firm in that year. *Net Hiring* is the difference between *Inflow* and *Outflow*. The main independent variable *PSL* is a dummy variable that equals one for the state and time period after the adoption of PSL mandate, and zero otherwise. Control variables including total assets, cash holdings, financial leverage, capital expenditure, PPE, ROA, R&D, and book-to-market ratio in the previous year are defined in Appendix A. Panel B is similar to Panel A but examines the effect of PSL mandates on the total number of employees. We control for firm and year fixed effects, or firm and industry-year fixed effects in some models. T-statistics using robust standard errors adjusted for heteroscedasticity and clustered at the state level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A: PSL Mandates and Inventor Inflows

Dep. Var.	Net Hiring		Inflow		Outflow	
	(1)	(2)	(3)	(4)	(5)	(6)
PSL	**-0.708*****	**-0.417****	**-0.770*****	**-0.471****	**-0.062***	**-0.054***
	(-3.87)	**(-2.10)**	**(-4.22)**	**(-2.50)**	**(-1.91)**	**(-1.81)**
ln(Asset)	0.373***	0.341***	0.429***	0.399***	0.056***	0.059***
	(4.96)	(4.66)	(5.08)	(4.78)	(3.78)	(3.44)
Cash	0.087	-0.008	0.014	-0.065	-0.073	-0.057
	(0.42)	(-0.04)	(0.06)	(-0.27)	(-0.94)	(-0.85)
Leverage	-0.643***	-0.534**	-0.655***	-0.533**	-0.011	0.000
	(-3.67)	(-2.64)	(-3.72)	(-2.45)	(-0.34)	(0.01)
Capx	-0.031	0.899	-0.253	0.677	-0.222**	-0.222**
	(-0.07)	(1.34)	(-0.72)	(1.11)	(-2.20)	(-2.11)
PPE	0.476	0.197	0.450	0.184	-0.026	-0.013
	(1.41)	(0.47)	(1.41)	(0.49)	(-0.45)	(-0.19)
ROA	-0.144	0.010	-0.154	-0.017	-0.010	-0.027
	(-0.99)	(0.07)	(-1.18)	(-0.13)	(-0.42)	(-1.15)
R&D	0.323*	0.416*	0.590***	0.599***	0.267*	0.183*
	(1.74)	(1.93)	(2.83)	(2.72)	(1.86)	(1.69)
B/M	-0.068	-0.104*	-0.069	-0.115*	-0.001	-0.010
	(-1.44)	(-1.75)	(-1.43)	(-1.95)	(-0.14)	(-1.03)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes	No	Yes
Adj. R^2	0.710	0.714	0.785	0.789	0.777	0.778
Observations	37,100	36,015	37,100	36,015	37,100	36,015

Panel B: PSL Mandates and Total Employment

Dep. Var.	Total Employees	
	(1)	(2)
PSL	**0.124**	**0.325****
	(0.69)	**(2.01)**
Firm Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	No
Industry-Year FE	No	Yes
Adj. R^2	0.956	0.961
Observations	36,800	35,712

Table 8
Financial Constraints and Crowd-Out of Innovation

This table presents the effect of financial constraint on firm's inventor hiring and innovation. In Panel A, the dependent variables are net inventor inflow (*Net Hiring*) in Models (1) and (2), inventor inflow (*Inflow*) in Models (3) and (4), and inventor outflow (*Outflow*) in Models (5) and (6), respectively. *Inflow* is the number of inventors who join a firm in a given year, while *Outflow* is the number of inventors who leave the firm in that year. *Net Hiring* is the difference between *Inflow* and *Outflow*. The independent variable is the interaction of *PSL* and *Financial Constraint*, where *Financial Constraint* is a dummy variable that equals one if the overall text-based constraint score in Hoberg and Maksimovic (2015) for the firm in the previous year is above the annual sample median, and zero otherwise. Control variables including total assets, cash holdings, financial leverage, capital expenditure, PPE, ROA, R&D, and book-to-market ratio in the previous year are defined in Appendix A. Panel B is similar to Panel A except the dependent variables is the number of patent applications in Models (1) and (2), or the truncation-adjusted future citations in Models (3) and (4). We control for firm and year fixed effects, or firm and industry-year fixed effects in some models. T-statistics using robust standard errors adjusted for heteroscedasticity and clustered at the state level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A: Financial Constraints and Inventor Hiring

Dep. Var.	Net Hiring		Inflow		Outflow	
	(1)	(2)	(3)	(4)	(5)	(6)
PSL× Financial Constraint	**-0.676*****	**-0.758***	**-0.726*****	**-0.759***	**-0.050**	**-0.000**
	(-3.56)	**(-1.89)**	**(-3.53)**	**(-1.89)**	**(-1.16)**	**(-0.01)**
PSL	-0.143	0.060	-0.165	0.001	-0.022	-0.059
	(-0.64)	(0.18)	(-0.92)	(0.00)	(-0.42)	(-1.30)
Financial Constraint	-0.030	-0.025	-0.041	-0.039	-0.011	-0.014
	(-0.47)	(-0.38)	(-0.68)	(-0.61)	(-0.99)	(-1.15)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes	No	Yes
Adj. R^2	0.734	0.732	0.808	0.806	0.779	0.774
Observations	21,832	20,812	21,832	20,812	21,832	20,812

Panel B: Financial Constraints and Innovation

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL× Financial Constraint	**-1.009*****	**-1.059*****	**-1.975*****	**-2.085*****
	(-2.87)	**(-4.20)**	**(-3.81)**	**(-4.88)**
PSL	-0.013	0.048	0.497	0.457
	(-0.08)	(0.19)	(1.36)	(0.94)
Financial Constraint	-0.079	-0.090	-0.090	-0.127
	(-1.43)	(-1.35)	(-0.96)	(-1.16)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Adj. R^2	0.900	0.914	0.859	0.879
Observations	21,832	20,812	21,832	20,812

Table 9
PSL-Related Inventor Absences and Corporate Innovation

This table examines the varying effect of PSL mandates on corporate innovation across firms with different levels of female inventors, or average tenure of inventors. The regression design is similar to our baseline regressions in Table 2, except we further include the interaction of *PSL* and the inventor characteristics. In Panel A, the independent variable is the interaction of *PSL* and *High Female Inventor*, where *High Female Inventor* is a dummy variable that equals one if the percentage of female inventors for the firm in the previous year is above the annual sample median, and zero otherwise. Panel B is similar to Panel A except we include the interaction of PSL and *High Senior Inventor*, where *High Senior Inventor* is a dummy variable that equals one if the average inventor tenure for the previous year is above the annual sample median, and zero otherwise. We control for firm and year fixed effects, or firm and industry-year fixed effects in some models. T-statistics using robust standard errors adjusted for heteroscedasticity and clustered at the state level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A: Female Inventor Participation

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL× High Female Inventor	**-3.272*****	**-3.207*****	**-3.939*****	**-3.690*****
	(-4.99)	**(-3.47)**	**(-7.49)**	**(-2.87)**
PSL	-0.203	-0.116	-0.980	-0.518
	(-0.28)	(-0.10)	(-1.09)	(-0.34)
High Female Inventor	1.874***	2.147***	2.110**	2.018**
	(2.78)	(2.84)	(2.69)	(2.42)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Adj. R^2	0.869	0.868	0.825	0.825
Observations	15,525	14,257	15,525	14,257

Panel B: Senior Inventor Participation

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL× High Senior Inventor	**-4.081*****	**-4.944*****	**-4.219*****	**-5.250*****
	(-4.30)	**(-6.68)**	**(-3.29)**	**(-4.16)**
PSL	0.049	0.754	-1.028	0.271
	(0.07)	(0.63)	(-0.82)	(0.17)
High Senior Inventor	-2.517***	-2.989***	-1.686**	-2.007*
	(-4.11)	(-3.68)	(-2.04)	(-1.93)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Adj. R^2	0.870	0.869	0.825	0.826
Observations	15,525	14,257	15,525	14,257

Table 10

Cross-Sectional Analyses: Team Inventors, Inventor Buffer, and Work From Home

This table examines the varying effect of PSL mandates on corporate innovation based on *team inventors*, *inventor buffer*, or *work from home*. The regression design is similar to our baseline regressions in Table 2, except we further include the interaction of *PSL* and *High Inventor Teams* (Panel A), *Low Inventor Buffer* (Panel B), or *WFH* (Panel C). We classify a patent as team-developed if it is filed by a team of more than one inventor. *High Inventor Team* is a dummy variable that equals one if the proportion of patents filed by team inventors in the previous year is above the annual sample median, and zero otherwise. For inventor buffer, we first calculate the Herfindahl index based on the three digital technology class-share of granted patents for the firm in the previous year, and define *Low Inventor Buffer* as a dummy variable that equals one if HHI is below or equal to the annual sample median, and zero otherwise. *WFH* is the percentage of jobs that can be done at home in each 2-digit NAICS from Dingel and Neiman (2020). *Low WFH* is a dummy variable that equals one if the WFH measure is below the sample median, and zero otherwise. Coefficients of control variables are not reported for brevity. We control for firm and year fixed effects, or firm and industry-year fixed effects in some models. T-statistics using robust standard errors adjusted for heteroscedasticity and clustered at the state level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A: Inventor Teams

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL× High Inventor Teams	**-1.723**	**-2.287***	**-3.120****	**-3.816****
	(-1.08)	**(-1.80)**	**(-2.30)**	**(-2.14)**
PSL	-1.132	1.165	-1.626	1.855
	(-0.63)	(0.45)	(-0.83)	(0.60)
High Inventor Teams	-1.418*	-1.224	-1.303	-0.536
	(-1.88)	(-1.61)	(-1.44)	(-0.54)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Adj. R^2	0.887	0.893	0.847	0.854
Observations	10,050	8,962	10,050	8,962

Panel B: Inventor Buffer

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL×Low Inventor Buffer	**-3.889*****	**-3.414*****	**-5.760*****	**-4.552*****
	(-5.44)	**(-3.63)**	**(-6.00)**	**(-3.10)**
PSL	0.045	0.443	-0.260	0.222
	(0.06)	(0.38)	(-0.29)	(0.14)
Low Inventor Buffer	3.041***	3.067***	4.152***	4.250***
	(8.15)	(8.42)	(5.92)	(6.01)
Firm controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Adj. R^2	0.875	0.874	0.834	0.834
Observations	13,515	12,218	13,515	12,218

Panel C: Work From Home

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL×Low WFH	**-1.557*****	**-1.522*****	**-2.316****	**-2.280****
	(-2.79)	**(-2.96)**	**(-2.18)**	**(-2.28)**
PSL	0.217	0.155	0.100	0.053
	(0.77)	(0.61)	(0.21)	(0.12)
Firm controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.859	0.861	0.811	0.812
Observations	36,896	36,896	36,896	36,896

Appendix A
Variable Definitions

Variable	Definition
PSL	Dummy variable that equals one for the state and the period after the adoption of the PSL mandate, and zero otherwise.
PSL hours	The maximum number of paid sick leave hours that can be accrued in a year in states that have implemented PSL mandates, and is set to zero for states without PSL mandates.
Industry Access	The percentage of access to voluntary PSL in each 2-digit NAICS sector.
Patent	The number of patent applications filed by the firm in the year.
Citation	The firm's truncation-adjusted future citations of patents filed in the year. We adjust the truncation by dividing patent citations by the mean number of citations filed in that year and in the same three digital technology class.
Average Citation	The average citations for patents filed by the firm in year t.
Breakthrough Patent	The number of breakthrough patents filed by a firm in the year. Breakthrough patents are defined as those with forward citation counts being in the top 5% of all patents in the same application year and technology class.
R&D	Research and development expenditures, scaled by total assets.
ln(Asset)	The natural logarithm of total assets.
Cash	Cash scaled by total assets.
Leverage	Total debt, scaled by total assets.
Capx	Capital expenditures, scaled by total assets.
PPE	Net property, plant, and equipment scaled by total assets.
ROA	Net income, scaled by total assets.
B/M	Book equity scaled by market value.
Total Employees	Total number of employees in thousand for a firm in a given year.
Female Participation	The percentage of females among all inventors.
Inventor Tenure	The number of years since an inventor filed her first patent up to the current year.
Delaycon	The text-based financial constraint measure based on Hoberg and Maksimovic (2015).
Team Inventors	Patents that filed by more than one inventor.
WFH	The percentage of jobs that can work from home in each 2-digit NAICS sector.
Inventor Buffer	The Herfindahl index (HHI) based on the three-digital technology class-share of a firm's patents in year t.
Headquarter Patent	The total number of patents filed by invention teams that contain at least one inventor located at the firm's headquarters.
Non-Headquarter Patent	The total number of patents where none of the inventors in the invention team are located at the headquarters.

Variable	Definition
Headquarter Citation	The total number of truncation-adjusted citation received by invention teams that contain at least one inventor located at the firm's headquarters.
Non-Headquarter Citation	The total number of truncation-adjusted citation where none of the inventors in the invention team are located at the headquarters.
Inflow	Number of inventors who join a firm in the year.
Outflow	Number of inventors who leave a firm in the year.
Net Hiring	The difference between Inflow and Outflow.

Appendix B
Additional Data Description and Results

Table B1
State-Level Paid Sick Leave Mandates

State	Effective Date	Annual Cap
Washington, DC	Nov 13, 2008	<24 employees: 24 hours 24 to 99 employees: 40 hours ≥100 employees: 56 hours
Connecticut	Jan 1, 2012	40 hours
California	July 1, 2015	24 hours
Massachusetts	July 1, 2015	40 hours
Oregon	Jan 1, 2016	40 hours
Vermont	Jan 1, 2017	2018: 24 hours 2019 and after: 40 hours
Arizona	July 1, 2017	<15 employees: 24 hours ≥15 employees: 40 hours
Washington	Jan 1, 2018	no explicit cap
Maryland	Feb 11, 2018	≥15 employees: 40 hours
Rhode Island	July 1, 2018	≥18 employees: 2018: 24 hours 2019: 32 hours 2020 and after: 40 hours
New Jersey	Oct 28, 2018	40 hours
Michigan	Mar 28, 2019	≥50 employees: 40 hours

Table B2
City/County Level Paid Sick Leave Mandates

City	Effective Date	Annual Cap
San Francisco	February 5, 2007	<10 employees: 40 hours ≥10 employees: 72 hours
Seattle	September 1, 2012	<50 employees: 40 hours 50 to 249 employees: 56 hours ≥250 employees: 72 hours
Portland	January 1, 2014	>5 employees: 40 hours
New York	April 1, 2014	≥5 employees: 40 hours
Newark	June 21, 2014	<10 employees: 24 hours ≥10 employees: 40 hours
Philadelphia	May 13, 2015	≥10 employees: 40 hours
Oakland	March 2, 2015	<10 employees: 40 hours ≥10 employees: 72 hours
Montgomery	October 1, 2016	<5 employees: 32 hours ≥5 employees: 56 hours
Cook	July 1, 2017	
Minneapolis	July 1, 2017	>5 employees: 48 hours
Saint Paul	July 1, 2017	48 hours
Tacoma	January 1, 2018	40 hours
Austin	October 1, 2018	<16 employees: 48 hours ≥16 employees: 64 hours

Table B3
The Effect of PSL Mandates on Firm Innovation: PSL Hours

This table examines the effect of PSL mandates on firm innovation. The regression design is similar to Table 2 in the paper, except that the independent variable is *PSL hours*, which is defined as the maximum number of paid sick leave hours that can be accrued in a year in states that have adopted PSL mandates, and zero for states that have not adopted PSL mandates. T-statistics using robust standard errors adjusted for heteroscedasticity and clustered at the state level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Dep. Var.	Patent		Citation	
	(1)	(2)	(3)	(4)
PSL hours	**-0.029*****	**-0.017****	**-0.045*****	**-0.025*****
	(-3.46)	**(-2.23)**	**(-2.93)**	**(-3.02)**
ln(Asset)	0.786***	0.754***	0.798***	0.777***
	(4.05)	(3.89)	(4.08)	(4.07)
Cash	-0.084	-0.112	0.623	0.227
	(-0.23)	(-0.28)	(1.14)	(0.46)
Leverage	-0.953***	-0.777***	-1.232**	-1.209***
	(-3.23)	(-3.67)	(-2.10)	(-3.16)
Capx	-0.361	0.794	-0.257	1.391
	(-1.02)	(1.48)	(-0.52)	(1.34)
PPE	0.396	0.101	0.832	-0.350
	(0.91)	(0.27)	(1.45)	(-0.61)
ROA	-0.266	-0.116	-0.132	0.138
	(-1.16)	(-0.55)	(-0.51)	(0.57)
R&D	1.140***	1.149***	2.188***	2.514***
	(4.21)	(3.65)	(2.76)	(3.00)
B/M	-0.166**	-0.195***	-0.137**	-0.182**
	(-2.42)	(-3.00)	(-2.17)	(-2.47)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Industry-Year FE	No	Yes	No	Yes
Adj. R^2	0.862	0.863	0.814	0.815
Observations	36,574	35,471	36,574	35,471

Table B4
Robustness Tests: Alternative Text-Based Financial Constraint Measures

This table presents the effect of financial constraint on firm's inventor hiringand innovation. In Panel A, the dependent variables are net inventor inflow (*Net Hiring*) in Model (1), inventor inflow (*Inflow*) in Model (2), inventor outflow (*Outflow*) in Model (3), the number of patents filed (*Patent*) in Model (4), and the truncation adjusted future citation (*Citation*) in model (5), respectively. *Inflow* is the number of inventors who join a firm in a given year, while *Outflow* is the number of inventors who leave the firm in that year. *Net Hiring* is the difference between *Inflow* and *Outflow*. The independent variable is the interaction of *PSL* and *Financial Constraint* in the previous year, where *Financial Constraint* is a dummy variable that equals one if the equity-focused constraint score in Hoberg and Maksimovic (2015) for the firm in the previous year is above the annual sample median, and zero otherwise. Control variables including total assets, cash holdings, financial leverage, capital expenditure, PPE, ROA, R&D, and book-to-market ratio in the previous year are defined in Appendix A. Panel B is similar to Panel A except *Financial Constraint* is constructed using the equity-focused constraint score in Linn and Weagley (2024) using the full model. Panel C is similar to Panel A except *Financial Constraint* is constructed using the equity-focused constraint score in Linn and Weagley (2024) using the primitive model. We control for firm and year fixed effects, or firm and industry-year fixed effects in some models. T-statistics using robust standard errors adjusted for heteroscedasticity and clustered at the state level are reported in parentheses. *, **, and *** denote statistical significance at 10%, 5%, and 1% level, respectively.

Panel A: Equity-Focused Constraint Score (Hoberg and Maksimovic, 2015)

Dep. Var.	Net Hiring	Inflow	Outflow	Patent	Citation
	(1)	(2)	(3)	(4)	(5)
PSL×Financial Constraint	**-0.797*****	**-0.881*****	**-0.084****	**-1.536****	**-2.125****
	(-3.42)	**(-3.78)**	**(-2.21)**	**(-2.41)**	**(-2.27)**
PSL	0.077	0.061	-0.016	0.288	0.470
	(0.31)	(0.24)	(-0.37)	(0.68)	(0.63)
Financial Constraint	0.100*	0.078	-0.021*	0.030	0.061
	(1.73)	(1.44)	(-1.71)	(0.50)	(0.58)
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.740	0.813	0.772	0.914	0.879
Observations	20,812	20,812	20,812	20,812	20,812

Panel B: Equity-Focused Constraint Score Using Full Model (Linn and Weagley, 2024)

Dep. Var.	Net Hiring	Inflow	Outflow	Patent	Citation
	(1)	(2)	(3)	(4)	(5)
PSL×Financial Constraint	**-0.582****	**-0.578****	**0.004**	**-0.963*****	**-1.440*****
	(-2.62)	**(-2.52)**	**(0.17)**	**(-3.34)**	**(-3.01)**
PSL	-0.137	-0.168	-0.032	-0.058	-0.221
	(-0.57)	(-0.72)	(-1.11)	(-0.18)	(-0.67)
Financial Constraint	0.051	0.042	-0.009	-0.026	0.033
	(0.99)	(0.84)	(-0.87)	(-0.33)	(0.26)
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.729	0.790	0.754	0.896	0.859
Observations	34,767	34,767	34,767	34,767	34,767

Panel C: Equity-Focused Constraint Score Using Primitive Model (Linn and Weagley, 2024)

Dep. Var.	Net Hiring	Inflow	Outflow	Patent	Citation
	(1)	(2)	(3)	(4)	(5)
PSL× Financial Constraint	**-0.351****	**-0.337****	**0.015**	**-0.707****	**-0.846****
	(-2.46)	**(-2.19)**	**(0.46)**	**(-2.45)**	**(-2.48)**
PSL	-0.256	-0.293	-0.037	-0.202	-0.532
	(-1.08)	(-1.30)	(-1.03)	(-0.66)	(-1.56)
Financial Constraint	0.049	0.029	-0.020***	-0.011	-0.026
	(0.84)	(0.51)	(-3.03)	(-0.16)	(-0.29)
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.729	0.790	0.754	0.896	0.859
Observations	34,767	34,767	34,767	34,767	34,767