Anti-Harassment Policy and the Startup Labor Market

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March 22, 2026

Abstract

This paper examines how anti-harassment legal reforms that weaken non-disclosure agreements (NDAs) in cases of workplace sexual harassment affect startups' hiring and organizational decisions. Using a staggered difference-in-differences design and LinkedIn data on over 80,000 U.S. venture-capital-backed startups from 2014–2022, we find that NDA reforms, although intended for employee protection, reduce female hiring by about 7%, with effects concentrated among junior women, who are statistically more prone to sexual harassment, and in small or male-dominated startups. The results apply to both the intensive and extensive margins of hiring female workers. Treated entrepreneurial firms also witness more departures of male managers, promote more women, and receive less VC funding. These results suggest that while NDA-weakening laws increase firms' perceived legal risk and reduce female hiring, they also trigger internal restructuring that promotes women's advancement into leadership and may, over time, foster more accountable and inclusive organizational cultures.

JEL classification: G24, G38, H25, L26

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*For their comments and suggestions, the authors thank Anup Agrawal, Sean Cao, Elena Simintz (discussant) and seminar participants at the Chinese University of Hong Kong (Shenzhen), the University of Tennessee, the University of Alabama, and the 2026 University of Delaware/ECGI Corporate Governance Symposium. The authors are responsible for all remaining errors. Chen is with College of Business Administration, University of Illinois Chicago (chenjun@uic.edu); Ma is with Yale School of Management and NBER (song.ma@yale.edu); and Zhang is with Cox School of Business, Southern Methodist University (fengzhang@smu.edu).

1 Introduction

Gender inequality in labor markets remains one of the most persistent challenges in modern economies. Economists have long emphasized differences in human capital accumulation, occupational choice, and family responsibilities as key explanations for gender gaps in employment and wages. More recent work, however, highlights another fundamental but less visible source of inequality—workplace sexual harassment and the institutional arrangements that shape how it is handled (Folke and Rickne, 2022). Harassment not only imposes direct psychological and economic costs on victims (Welsh, 1999; McDonald, 2012; Fitzgerald and Cortina, 2018), but also deters women from entering, remaining, and advancing in certain industries and firms. In particular, startup and high-growth entrepreneurial environments are more prone to sexual harassment, and face severe gender inequality (Ewens and Townsend, 2020; Calder-Wang and Gompers, 2021).[1]

Public policies and legislation are proposed and established to protect employees against sexual harassment by empowering victims, increasing transparency, and deterring potential misconduct. One feature that has received growing attention in this context is the widespread use of non-disclosure agreements (NDAs) in employment contracts.[2] By silencing victims and concealing information, NDAs may have shielded firms from reputational damage but simultaneously allowed hostile workplace cultures to persist. In the aftermath of the #MeToo movement, beginning in 2018, a wave of U.S. states—including New York, California, and Washington—passed laws weakening or nullifying NDAs (NDA-weakening laws hereafter) that restrict disclosure of sexual harassment. These state-level initiatives culminated in the federal Speak Out Act of 2022, which made pre-dispute NDAs unenforceable nationwide for claims of sexual assault and harassment.

[1] For example, the Women in Tech 2023 survey reveals that 40% of female founders reported being sexually harassed and 65% of them had been told that they would be more likely to get funded if you were a man or had a male co-founder, while 48% of female tech workers reported being harassed. See womenwhotech.org/data-and-resources/state-women-tech-and-startups-2023.

[2] Although NDAs were originally designed to protect trade secrets and proprietary information, firms have frequently used them to prevent employees from speaking publicly about internal misconduct, including cases of sexual harassment and assault. The next section discusses in greater detail the background of NDAs and sexual harassment.

In this paper, we examine the labor-market implications of employee protection against sexual harassment in entrepreneurial firms, where gender inequality and harassment have been longstanding concerns. We leverage the passing of these state-level NDA reforms as an experiment, and study their effects on the hiring, promotion, and retention of female workers in venture-capital-backed (VC-backed) startups. This setting offers a particularly informative laboratory. Startups are disproportionately important to innovation and job creation, yet they often lack formal institutional arrangements and human resources against sexual harassment and their success depends heavily on reputation and investor confidence. They thus face a delicate balance between promoting inclusive workplaces and mitigating perceived legal and reputational risks. As a result, the NDA reforms represented a fundamental change in the risk calculus of startups: by raising the potential public and legal exposure associated with harassment cases, such laws could alter both the demand for and the composition of female employment, especially in startups with limited internal compliance capacity.

We assemble a large-scale dataset linking over 80,000 VC-backed U.S. startups from PitchBook with worker-level employment data from LinkedIn (via Revelio Labs) for the period 2014–2022. Combining these two data sources allows us to observe detailed hiring flows, job titles, seniority, and educational background for employees within each startup over time. We exploit the staggered passage of state-level NDA-weakening laws between 2018 and 2022 in a difference-in-differences (DiD) framework, comparing startups headquartered in treated states to those in untreated states before and after the reforms.

Before the enactment of state laws weakening the enforceability of nondisclosure agreements, 85% of individuals who experience sexual harassment never file a formal legal charge, and approximately 70% do not report the incident internally (Feldblum and Lipnic, 2016). The NDA-weakening state laws have encouraged employees to disclose negative internal information to the public, including incidents of sexual harassment within their firms. Holstead, Huang, and Pinto (2025) find that following the passage of such laws, firms experience an increase in media coverage, with a greater number of news articles citing employees as sources. Moreover, the tone of these articles becomes significantly more negative, suggest-

ing that employees are increasingly willing to share unfavorable internal information with journalists.

We first document a sharp decline in female hiring following the enactment of NDA-weakening laws. Startups headquartered in treated states (treated startups hereafter) hire 8% fewer women per year than startups in states that do not enact NDA-weakening laws (control startups hereafter). The effect is statistically significant at the 1 percent level across Poisson regressions. It remains robust in alternative model specifications, including stacked regressions, and after excluding the Covid-19 period and influential states (e.g., California and New York) that host a large fraction of VC-backed startups. Several additional test results support a causal interpretation of the effect. For example, we observe no divergent trends in the four years prior to NDA reforms, confirming the absence of diverging pre-trends. The negative hiring effect appears sharply in the first year after the law's passage, with persistent effects over the next several years. Moreover, we show that this effect is highly localized. A placebo analysis using startups' hiring outside their treated headquarters state reveals no change in female employment.[3] The absence of any response in non-treated geographies underscores that the observed patterns are driven by legal exposure rather than unobserved startup characteristics or coincident macroeconomic or technological shocks that may affect the startup.

Next, we disentangle the effect into intensive and extensive margins, showing that the negative effect applies to both margins. On the intensive margin, conditioning on the hiring of female workers, the number of women hired per startup declines by 3%. In terms of the extensive margin, the likelihood that a startup hires any female worker at all within a year falls by nearly five percentage points in the four years following NDA reforms. These patterns jointly imply that the new laws reduce both the breadth and depth of female participation in the startup workforce.

[3] In a legal sense, NDA laws apply based on the governing law specified in the employment contracts. However, in practice, courts and legislatures often treat the employee's physical work location as the controlling jurisdiction for public-policy reasons. For instance, California Labor Code § 925 prohibits employers from requiring California employees to agree to out-of-state choice-of-law or forum clauses as a condition of employment, see `https://leginfo.legislature.ca.gov/faces/codes_displaySection.xhtml?lawCode=LAB&sectionNum=925.`

The effect is highly heterogeneous across worker types—the decline is largely concentrated among junior female workers. This is consistent with prior studies documenting that junior women are more likely to be victims of sexual harassment (Cortina and Berdahl, 2008). Hiring of senior females, by contrast, remains largely unchanged following the NDA-weakening laws. This pattern suggests that firms respond to increased harassment-related legal risks by cutting back primarily on early-career women, potentially substituting toward male or senior female employees perceived as less risky from a legal compliance standpoint.

NDA-weakening reforms increase startups' expected costs associated with incidences of sexual harassment—both through higher litigation risk and potential public scrutiny—even if they do not immediately lower the underlying incidence of harassment. Startups with limited internal safeguards, therefore, are expected to reduce their exposures to potential risk, particularly among junior women who interact closely with male supervisors.

Further analysis supports this interpretation. We observe that the effects are stronger among firms with weaker internal employee protections against sexual harassment. Small startups and those with lower pre-existing female representation, which we use as a measure of weaker protocols to protect women, exhibit much larger declines in female hiring following NDA reforms. In contrast, women-friendly or larger startups—those more likely to have formal human resource policies or inclusive cultures—show weaker or no response. These differences are consistent with a demand-side mechanism: firms that lack the institutional capacity to prevent or manage harassment risk adjust by limiting their exposure to potential female hires.

It is possible that a state was more likely to adopt NDA-weakening laws if women in the state were more aware of sexual harassment in the workplace following the nationwide debate, which started in 2017, of Harvey Weinstein's sexual harassment cases. Increased awareness could lower women's willingness to work. We observe evidence inconsistent with the predictions of this supply-based mechanism. The supply-based mechanism implies lower female hires by VC-backed startups in the states that adopted NDA-weakening laws (i.e., the treated states) than in the control states before the treatment. However, we observe

parallel trends in female hires between the treated and control states. The supply-based mechanism also implies that the treatment effect shrinks over time as the level of awareness of sexual harassment converges among women across treated and control states. In contrast to the prediction, the treatment effect does not abate over time. In addition, compared to VC-backed startups in the treated states, startups headquartered in the control states significantly reduced their female hires after the enactment of the federal Speak Out Act in 2022. These results are inconsistent with a supply-based mechanism, although it is difficult to completely rule out the possibility of supply-side effects.

The consequences of the NDA-weakening reforms extend beyond workforce composition to firm outcomes. Startups headquartered in treated states experience a decline in their likelihood of raising new venture capital rounds by about 3 percentage points per year and a reduction in the number of VC financing rounds. These effects suggest that legal reforms impose frictions on startup operations and may heighten investor concerns about governance and litigation risk.

The silver lining is that we observe significant organizational adjustments following NDA-weakening reforms that may have long-term positive impacts. Startups promote more women to managerial positions after NDA-weakening laws take effect, and more male managers leave startups. These findings suggest that startups, perceiving higher legal risks, respond not only by hiring fewer women but also by reconfiguring internal hierarchies—removing potential sexual harassers from managerial positions and elevating female employees to leadership roles.

Together, these results paint a nuanced picture. NDA-weakening laws help protect women from sexual harassment and encourage startups to promote more women, which in turn, could attract more women to join and stay in the workplace. On the other hand, such laws may discourage startups from hiring women, potentially only in the short term, because they increase startups' legal compliance costs. Our findings suggest that the negative effects on the demand for women outweigh the potential positive effects on the supply of female workers, resulting in fewer female hires.

Our study relates to several strands of research on gender inequality, labor regulation, corporate governance, and entrepreneurial firms. A growing body of literature highlights the workplace environment and culture as important determinants of gender gaps in labor markets. Beyond differences in human capital and occupational choice (Goldin, 2014; Blau and Kahn, 2017), recent work points to sexual harassment and power asymmetries as critical barriers to women's labor market participation decisions (Cortina and Berdahl, 2008; McLaughlin, Uggen, and Blackstone, 2017). Harassment deters entry, drives attrition, and perpetuates under-representation, particularly in male-dominated and high-growth institutions. Scholars have also shown that organizational silencing mechanisms, such as confidentiality and arbitration clauses, limited whistle-blower protection, discourage reporting and allow misconduct to persist (Hersch, 2015; Folke and Rickne, 2022). We contribute to this literature by studying how legal reforms that weaken NDAs—a key institutional form of organizational silencing—affect firms' actual employment and promotion of women at scale.

Our work also adds to research on the unintended consequences of labor-market regulations. Acemoglu and Angrist (2001) find that the Americans with Disabilities Act (ADA), which aims to protect disabled workers from discrimination, actually reduces the employment of disabled workers. Doleac and Hansen (2020) document that the "Ban-the-Box" laws, which prevent employers from asking about job applicants' criminal records until late in the hiring process, reduce the employment of workers they intend to protect. Well-intentioned labor protection regulations can *decrease* rather than increase the employment of the workers they intend to protect, because firms respond to such regulations by internalizing higher expected costs of legal compliance. Related theoretical frameworks (Lazear, 1990; Autor, III, and Schwab, 2006) emphasize that hiring declines when employment protection increases downside risk without improving monitoring. Unlike the ADA and the "Ban-the-Box" laws, NDA-weakening laws enhance the transparency of incidents of sexual harassment by allowing victims to disclose information about the harassment to the public. Enhanced transparency heightens firms' exposure to reputational costs and legal risks. Our study extends this unintended consequences literature to the domain of gender and harassment protection.

In addition, we add to the literature on how firms respond to labor-related laws and regulations. Bena, Ortiz-Molina, and Simintzi (2022) find that firms invest more on cost-saving production technologies in response to state-level legal changes that raise labor dismissal costs. The increase in such investment is greater in industries with a large share of labor costs in total costs. In 2006, Denmark enacted a law that requires firms to disclose gender-disaggregated wage statistics and detailed employee-employer administrative data. Bennedsen, Simintzi, Tsoutsoura, and Wolfenzon (2022) show that the law shrinks the gender pay gap, primarily by slowing male workers' wage growth.

A fourth relevant line of research examines corporate governance, internal compliance, and diversity. Prior studies show that stronger governance and gender diversity improve monitoring and firm performance (Adams and Ferreira, 2009; Gompers, Mukharlyamov, and Xuan, 2016; Levi, Li, and Zhang, 2014; Tate and Yang, 2015; Huang and Kisgen, 2013). Conversely, weak internal oversight fosters ethical lapses and misconduct (Dyck, Morse, and Zingales, 2010). We show that the effects of NDA-weakening reforms are concentrated in small, male-dominated startups, likely firms with weaker internal governance. Our results thus complement evidence on how institutional strength mediates the effectiveness of transparency and accountability policies (Hutton, Jiang, and Kumar, 2015; Kedia and Rajgopal, 2011).

Finally, this paper contributes to the literature on entrepreneurial finance and diversity. Research on venture capital and startup ecosystems documents persistent gender disparities in founding and hiring (Calder-Wang and Gompers, 2021; Guzman and Stern, 2020), as well as gender-based differences in the extent to which fundamental frictions in venture capital markets can be mitigated (Howell and Nanda, 2024). We add a legal dimension, showing that labor-market regulation interacts with financing frictions: startups exposed to NDA-weakening laws not only hire fewer women but also raise less venture funding afterward. The evidence links workplace regulation to capital-market outcomes, bridging insights from labor economics, entrepreneurial finance, and law and economics.

2 Sexual Harassment and NDA Reforms

2.1 Sexual Harassment In the Workplace

Sexual harassment and assault are rampant in the U.S. A national survey in 2019 reveals that 81% of women and 43% of men reported experiencing some form of sexual harassment or assault in their lifetime, and 38% of women and 14% men reported sexual harassment or assault in the workplace (Kearl, Johns, and Raj, 2019). Other surveys reveal a similar picture: 42% of women and 24% of men working in the high-technology industry reported experiencing sexual harassment.[4]

Sexual harassment and assault in the workplace are forms of sex discrimination that violate Title VII of the Civil Rights Act of 1964. However, the super majority of victims of workplace sexual harassment do not report the harassment, and even fewer of them file a formal complaint within their institutions (Cortina and Berdahl, 2008). Their reluctance to report the experience of sexual harassment is attributable to fears of blame, disbelief, and retaliation. About two-thirds of victims who report the experience of sexual harassment experience some form of retaliation, and the reporting is often followed by organizational indifference and inaction (Cortina and Berdahl, 2008).[5]

Most victims of sexual harassment are women. 78.2% of sexual harassment charges over the 2018–2021 period were filed by women, according to the 2022 EEOC report. Harassers of female workers are usually the worker's colleagues, supervisors, and senior managers (Feldblum and Lipnic, 2016).

[4] https://womenwhotech.org/data-and-resources/state-women-tech-and-startups-2023

[5] Formal charges alleging sexual harassment and retaliation are often linked. 43.5% of the 27,291 sexual harassment charges filed between 2018 and 2021 were concurrently filed with a retaliation charge according to the 2022 report of the U.S. Equal Employment Opportunity Commission (EEOC), an organization that enforces Title VII of the Civil Rights Act of 1964. See: `https://www.eeoc.gov/data/sexual-harassment-our-nations-workplaces`

2.2 NDAs, NDA Reforms, and Sexual Harassment

To prevent reputation damage in the public, firms typically require new employees to sign NDAs before they start working at the firm. NDAs originated in the 1940s as contractual tools designed to protect firms' trade secrets and other proprietary information.[6] They later became prevalent among fast-growing technology companies such as IBM, which relied on NDAs to safeguard its intellectual property and competitive advantage over peers.

The increasingly broad scope of NDAs, along with their associated misuses, has raised concerns. Originally, NDA clauses were intended to protect a firm's intellectual property and proprietary knowledge. Over time, firms extended the scope of NDAs to any information besides intellectual property and know-hows, leading to instances of abuses of NDAs.[7] Such abuses typically take two forms.[8] First, employers may impose pre-dispute NDAs as a condition of employment, requiring workers to forfeit the right to speak publicly about discrimination, harassment, and other violations of their rights. Second, employers may use post-dispute NDAs to pressure their victims into signing confidentiality clauses as part of settlements, thereby concealing workplace misconduct, impeding collective action among workers, and shielding perpetrators and firms from accountability. A prominent example involves film producer Harvey Weinstein, who for years used secret settlements to silence victims of sexual harassment and assault.[9] Abuses of NDAs prevented the victims of sexual harassment from speaking out and encouraged Harvey Weinstein to continue his misconduct for years.

The confidential nature of employee contracts makes it challenging to accurately gauge the prevalence of NDAs in practice. Anecdotal evidence suggests that NDAs are widely adopted, particularly among fast-growing, high-tech startups that must protect their intellectual property and proprietary knowledge.[10] In particular, VC funds typically require

[6] https://www.cjr.org/special_report/nda-agreement.php
[7] https://hbr.org/2018/01/ndas-are-out-of-control-heres-what-needs-to-change
[8] https://nwlc.org/wp-content/uploads/2020/04/NDA-Factsheet-4.27.pdf
[9] https://www.newyorker.com/news/news-desk/harvey-weinsteins-secret-settlements
[10] https://www.lexagle.com/blog-en-sg/non-disclosure-agreements-ndas-in-the-startup-ecosystem-pitfalls-and-best-practices)

startups to sign NDAs with their employees. For example, the National Venture Capital Association (NVCA), the U.S. VC industry's trade association, provides a model term sheet that includes an NDA clause, recommending that startups enter into NDA agreements with their employees:[11]

> [Non-Disclosure and Developments Agreement:] Each current and former Founder, employee and consultant will enter into a non-disclosure and proprietary rights assignment agreement in a form reasonably acceptable to the Investors.

[Insert Table 1 Here.]

In the wake of the #MeToo movement beginning in 2017, the misuse of NDAs has triggered a national reckoning. Investigations into major firms and public figures—most notably, Harvey Weinstein's extensive use of NDAs to conceal sexual misconduct—drew intense scrutiny to their role in enabling and perpetuating toxic workplace cultures. In response, many U.S. states enacted legislation between 2018 and 2022 to limit or void NDAs that restrict disclosure of sexual harassment, assault, or discrimination claims. Early adopters include California (2018), New York (2018), New Jersey (2019), and Washington (2018). State laws vary in their content, but all of them weaken or nullify NDAs. Some states prohibit NDAs in settlement agreements involving sexual assault or harassment (e.g., California and New York), while others prohibit employers from requiring NDAs as a condition of employment (e.g., Washington). By the end of 2022, when the federal Speak Out Act (2022) was passed, 14 states had passed their own NDA-weakening laws (see Table 1 for a list of the states and the time of their NDA-weakening laws).

The likelihood of enacting NDA-weakening laws depends on various factors, including the salience of the #MeToo movement in the state, the state's "worker-protection" policy orientation, and the strength of the lobbying of women's rights organizations versus that of employer associations. State legislators more inclined to protect female workers are more likely to adopt other women-protective policies, which would benefit female workers and

[11] `https://nvca.org/document/nvca-2020-term-sheet-4/`

enhance their employment. In other words, these factors make it more difficult for us to observe the significant negative effects of NDA-weakening state laws on the hiring of female workers. Additionally, we observe parallel trends in the hiring of female workers between VC-backed startups headquartered in states that enacted NDA-weakening laws before 2022 and those in other states, further alleviating the concern that our results are driven by factors other than NDA-weakening laws.

The NDA-weakening state laws are a major shock to the strength of protection against workplace sexual harassment. They encourage victims of sexual harassment to speak out, and have led to an increase in negative news coverage of employers—particularly reports of legal issues—arising from employee disclosures (Holstead, Huang, and Pinto, 2025). They also expose firms to greater reputation damage and legal compliance costs when sexual harassment occurs within the firm, incentivizing firms to address cases of sexual harassment more proactively.

3 Sample Construction and Summary Statistics

3.1 Data

We construct a sample of VC-backed startups over the 2014–2022 period based on the PitchBook database, a comprehensive venture capital database that has been widely used in prior studies of VC-backed startups. The coverage of PitchBook has been strong since 2002, thanks to the extensive availability of Form D filings on the Securities and Exchange Commission (SEC) website (e.g., Babina et al., 2025). Our main analysis focuses on the 2014–2022 period, a nine-year window surrounding the enactment of state-level legislation that weakened non-disclosure agreements starting in 2018. Our sample starts in 2014 to have at least four years before and after the first wave of state-level legislation concerning NDAs (Table 1). Our sample ends in 2022, the year in which the federal government enacted NDA-weakening laws.[12]

[12] The Congress passed the Speak Out Act on Nov. 16, 2022, and President Biden signed it into Law on Dec. 7. The Act limits the enforceability of pre-dispute non-disclosure and non-disparagement clauses

We measure startups' employment and hiring using individual-level résumé data provided by Revelio Labs. This dataset aggregates over one billion online profiles, primarily from LinkedIn, and offers broad coverage of the U.S. workforce. The Revelio Labs data are especially representative of professional, managerial, and technical occupations (Hampole, Papanikolaou, Schmidt, and Seegmiller, 2025), which align closely with the composition of the workforce in our sample of VC-backed startups. The Revelio Labs data cover approximately 90% of white-collar workers in the U.S. and 70% of the whole U.S. labor force (Hampole et al., 2025; Revelio Labs, 2022).

Recent studies have used and validated the quality and coverage of the Revelio Labs data. For example, Ahn, Hoitash, Hoitash, and Krause (2025) employ the Revelio Labs data to examine career trajectories and racial and gender promotion gaps in Big Four accounting firms. Lin, Shen, Shi, and Zeng (2025) use the Revelio Labs data to investigate the effects on women's job mobility of state-level adoptions of Targeted Regulation of Abortion Providers (TRAP) laws, which restrict women's access to abortion. Gao, Ma, and Xu (2025) cross-check their main findings based on the Revelio Labs data with results based on the U.S. Census LEHD data, showing that the Revelio Labs data produce robust results. Note that we employ the Revelio Labs data rather than the U.S. Census LEHD data for two reasons. First, the Revelio Labs data provides a richer set of employee characteristics that are essential for our analysis, including the employee's gender, educational background, skill sets, and job title. Second, we rely on firm name and firm webpage in the Revelio Labs data to merge with VC-backed startups in the PitchBook database.

3.2 Sample Construction

To construct our sample, we start with the universe of 85,588 U.S. startups in the PitchBook database that have received at least one round of VC funding and have non-missing founding year information. We then link these startups to firms in the Revelio Labs database using two identifiers: their world wide website URLs (e.g., "www.xyz.com") and

related to sexual assault and sexual harassment claims.

their LinkedIn webpage URLs (e.g, "www.linkedin.com/company/xyz/"). Both identifiers are available in both the PitchBook and Revelio Labs datasets (there are missing values). Among U.S. VC-backed startups founded between 2009 and 2022 in the PitchBook dataset, 97.4% have a world wide website and 73.7% maintain a LinkedIn webpage. Consequently, only 2.2% of the startups in the PitchBook database lack both identifiers. Because the startups' world wide website URLs have fewer missing values than their LinkedIn URLs, we prioritize the use of the former when merging the PitchBook and Revelio Labs databases.[13] We are able to merge 66,107 VC-backed startups in the PitchBook database to the Revelio Labs database through their world wide website URLs and an additional 5,406 startups through their LinkedIn webpage URLs.

We construct a startup-year panel spanning the period from 2014 to 2022. A startup enters the sample when it is between age zero (its founding year) and age five. It exits the panel once it is older than five years or when it becomes bankrupt, is acquired or goes public through an IPO, as reported by PitchBook. The final sample consists of 52,607 unique VC-backed startups and 207,469 startup-year observations.

3.3 Sample Description and Summary Statistics

Table 2 presents summary statistics for the characteristics of VC-backed startups in our sample and their hiring of new workers in the first five years after founding. The average startup is 2.3 years old, has approximately one round of VC financing per year, and raises $6.8 million annually. Approximately 59% of the 207,469 startup-years correspond to VC-backed startups located in the fourteen states that enacted NDA-weakening laws from 2018–2022. This fraction is reasonable because California, New York, and Washington, which host large numbers of VC-backed startups, enacted laws that weaken NDAs.

The key variable of interest for our staggered difference-in-differences (DiD) analysis, $NDAWeaken_{it}$, takes a value of one if startup i's headquarters state enacted NDA-weakening laws in or after year t, and zero otherwise. This variable has a mean of 0.3, indicating that

[13] The results are nearly identical when we prioritize the use of LinkedIn URLs in the matching.

30% of the 207,469 startup-years correspond to the years post the enacting of NDA-weakening laws and are for startups whose headquarters are located in the fourteen states.[14]

[Insert Table 2 Here.]

The number of employees has a skewed distribution: the average startup has 12.8 employees, while the median startup has only 4. The average startup hires 2.93 workers in the headquarters state per year, among whom 1.12 (34%) are women. The numbers indicate that young startups typically hire a few workers and gradually add more to their payrolls as they grow. We focus on the startup's hiring in the headquarters state for two reasons. First, aggregating the startup's hires across different states would impair our identification strategy, which exploits state laws that weaken NDAs. Second, young startups mostly hire in their headquarters states and rarely expand into other states in the first few years after founding.

We also examine the types of female workers that startups hire, with a specific focus on their skill and seniority levels. We first divide female hires into high- and low-skilled female workers based on their highest education degree and job occupation code, respectively. Using the highest education degree provided by the Revelio Labs database, we classify high-skilled female workers as those holding a bachelor's degree or higher, and low-skilled workers as those with lower educational attainment. Using job occupation code, we classify high-skilled workers as those with an O*NET code (provided by the U.S. Department of Labor) corresponding to occupations that require medium, considerable or extensive preparation (Job Zones 3-5) (see e.g., Belo, Li, Lin, and Zhao, 2017; Dey, Haslag, Sensoy, and White, 2025), and low-skilled workers as those in occupations requiring little or some preparation (Job Zones 1 and 2).

On average, a startup hires 0.84 high-skilled women and 0.12 low-skilled women when skill is based on educational background, and 0.88 high-skilled women per year and 0.12 low-skilled women when skill is based on job occupation code. These findings reveal that

[14] Virginia changed its NDA-weakening law after the end of our sample period in 2022 and is therefore classified as a never-treated state in our analysis.

VC-backed startups mostly hire high-skilled female workers, who are crucial for the startup's growth and success.

We further categorize newly hired female workers (1.12 hires per year) into two categories, junior and senior, depending on the employee's age and job seniority, respectively. Following prior literature (e.g., Kogan, Makarov, Niessner, and Schoar, 2024; Agarwal et al., 2025), we define junior (senior) workers as those younger (older) than 35 years. LinkedIn users do not disclose their age. We estimate a worker's age based on the worker's education history in the Revelio Labs database, and are able to do so for about 50% of the workers in our sample. We also measure the seniority of a worker based on her job positions provided by the Revelio Labs database. Specifically, we categorize workers with entry- or junior-level positions as juniors, and those with associate, manager, director, executive, or senior executive positions as seniors. On average, a startup hires 0.47 junior female workers per year and 0.09 senior female workers, measured by employee age, and 0.66 junior women and 0.47 senior women based on job positions.[15]

4 Female Hiring After NDA-Weakening Laws

4.1 Baseline Results

As discussed above, six states adopted laws that weaken or nullify NDAs in 2018, three in 2019, three in 2020, and another two in 2022. We employ a staggered DiD model to investigate the effects of these state NDA-weakening laws on VC-backed startups' hiring of female workers:

$$Y_{it} = \beta NDAWeaken_{it} + \theta Log\ Firm\ Age_{it} + \alpha_i + \tau_t + \epsilon_{it}. \quad (1)$$

The dependent variable is the number or fraction of female workers hired in year t by a startup i. $NDAWeaken_{it}$ is an indicator that takes the value of one if the startup's

[15] The sum of 0.49 and 0.08 is smaller than the average number of female workers hired per year because of missing values in estimated worker age.

headquarters state enacted NDA-weakening laws before or in year t, and zero otherwise. The coefficient β is an estimate of the average treatment effect of NDA-weakening laws. We control for the startup's age as well as startup fixed effects and year fixed effects, and cluster standard errors by startup headquarters state.

[Insert Table 3 Here.]

Table 3 presents the Poison regression results of model (1) for the startup's annual number of female hires over the 2014–2022 period. Poisson pseudo–maximum likelihood (PPML) estimates are consistent under general conditions and can accommodate heteroskedasticity, zero outcomes, and high-dimensional fixed effects (Silva and Tenreyro, 2006). The only exception is column (5), which reports OLS regression results for the continuous dependent variable of the startup's fraction (rather than the count) of female hires in the year.

The results in Table 3 reveal that startups hire fewer women after the headquarters state adopts NDA-weakening laws. Specifically, the coefficient on $NDAWeaken$ is -0.081 and statistically significant at the 1% level in column (1), in which we do not control for startup age. The coefficient remains -0.081 and statistically significant at the 1% level in column (2), which additionally controls for startup age. Compared to startups in the states that do not enact NDA-weakening laws, startups in treated states hire 7.8% ($= e^{-0.081} - 1$) fewer women per year after the enactment of NDA-weakening laws. This effect is economically meaningful, corresponding to approximately 0.09 (=0.078*1.12) fewer female hires per startup per year (see Table 2).

The effect of 7.8% fewer female hires per year is material for small startups younger than 5 years, for which labor force and capital growth are crucial, and the upside of joining a young, promising startup is significant. The annual effect accumulates to 39% ($= 0.078 * 5$) fewer female hires over five years, which we hypothesize will make a difference for a small startup's prospectus. The average fraction of women hired by VC-backed startups, which is only 34%, will further drop because of NDA-weakening laws. Consistent with our hypothesis, we observe that NDA-weakening state laws also lower the likelihood that startups secure venture capital funding.

The baseline results remain qualitatively unchanged when we extend the sample period to include the first seven years after the startup's founding year rather than five years (column (3) of Table 3), and when we exclude from the sample the years before the startup starts to hire any employees (column (4)).

The reduced number of female hires by affected startups is unlikely to be caused by NDA-weakening laws if it is accompanied by a similar reduction in male hires by these startups. We therefore examine whether NDA-weakening laws affect the fraction of female hires by affected startups in column (5) of Table 3. To do so, we replace the dependent variable with the fraction of women among the startup's total number of workers hired in the year. The coefficient on $NDAWeaken$ is -0.011 and statistically significant at the 5% level. Compared to control startups, the fraction of female hires among treated startups drops by 1.1 percentage points after the enactment of NDA-weakening laws. The drop represents a 3.3% decline relative to the sample average of 34%.

We also separately count the numbers of male and female workers hired for each startup-year, stack the expanded startup-years, and estimate an extended version of model (1) by adding the interaction variable between $NDAWeaken$ and an indicator variable $Female$, which takes the value of one for startup-years corresponding to female hires and zero otherwise. The regression results showcased in Table IA.1 in the Internet Appendix reveal that the coefficient on this interaction variable is negative and statistically significant at the 1% level (see the first two columns). In terms of the economic magnitude, treated startups hire approximately 5% fewer female workers per year than male workers after the enacting of NDA-weakening laws. The result remains qualitatively unchanged when we exclude from the sample the years before the startup starts to hire any employees (the last two columns of Table IA.1). Taken together, these results and those in Table 3 indicate that treated startups hire fewer women after the enactment of NDA-weakening laws.

The baseline results remain robust in stacked regressions for the staggered difference-in-differences analysis, as shown in Table IA.2 in the Internet Appendix. Stacked regressions help address the concern of heterogeneous treatment effects over time or across groups (e.g.,

Baker, Larcker, and Wang, 2022; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Adhikari, Agrawal, and Sharma, 2026). To implement the stacked regression, we construct cohort-specific event-time panels, include only never-treated units as controls, and stack these panels across cohorts (Cengiz, Dube, Lindner, and Zipperer, 2019; Baker et al., 2022). This approach mitigates possible contamination from already-treated units serving as controls, yielding more reliable estimates. The stacked regression results in Table IA.2 reveal that the coefficient on $NDAWeaken$ remains statistically significant and is about -0.090, which is close to the estimate of -0.081 in the first two columns of Table 3. The stacked regression results in the last three columns of Table IA.2 are also qualitatively unchanged from those in the last three columns of Table 3.

The baseline results are not driven by the COVID-19 outbreak in early 2020: they remain robust when we exclude the COVID-19 period (i.e., after 2019) from the sample period, as shown in the first two columns of Table 10 in the Internet Appendix. This finding is unsurprising, as COVID-19 affected startups across all states. The baseline results also remain robust when we exclude states that host large fractions of VC-backed startups and enacted NDA-weakening laws in 2018, including California and New York (see the last two columns of Table 10). This result suggests that our main results are not driven by a few influential states.

We also assess the parallel trends assumption by estimating the dynamic treatment effects in each of the nine years around the enactment of NDA-weakening laws within the stacked regression framework. The estimation results, plotted in Figure 1, show economically small and statistically insignificant differences in female hiring between treated and control startups in the four years preceding NDA reforms, suggesting no diverging pre-trends and supporting the validity of the identification strategy. On the other hand, the estimated coefficients turn negative and economically significant in all four years after the enactment of NDA-weakening laws. On balance, the NDA reforms in our study appear to be exogenous and the estimated effects can be interpreted as causal.

[Insert Table 4 Here.]

In Table 4, we examine whether the baseline results concentrate in high- or low-skilled female employees or both. We first divide female workers into two categories based on whether they have a bachelor's degree or higher in Panel A, and observe that the coefficient on $NDAWeaken$ is negative and statistically significant at the 1% level when the dependent variable is the number of female workers with a bachelor's degree or higher (the first two columns) or the number of female workers with lower educational attainment (the last two columns). In Panel B, we classify workers with O*NET job codes in Job Zone above three as high-skilled workers and the remaining workers as low-skilled ones. The regression results in Panel B reveal that the coefficient on $NDAWeaken$ remains negative and statistically significant. These results indicate that VC-backed startups hire fewer high- and low-skilled female workers after the enactment of NDA-weakening laws.

4.2 Placebo Test in Non-Headquarters States

In this subsection, we conduct a placebo test to further investigate whether reduced female hiring in VC-backed startups is attributable to NDA-weakening laws. The above analysis focuses on VC-backed startups' female hiring in their headquarters states for a clean identification of the effects of NDA-weakening state laws. The key variable $NDAWeaken$ takes a value of one if the startup's headquarters state has enacted NDA-weakening laws by the year. Since NDA-weakening laws are adopted at the state level, they should not affect the VC-backed startup's female hiring in states other than its headquarters state.

We thus conduct a placebo test by replacing the dependent variable of model (1) with the number of female workers hired by the VC-backed startup in its non-headquarters states that did not adopt NDA-weakening laws. The coefficient on $NDAWeaken$ is expected to become insignificant in the placebo test if the reduced female hiring documented above is attributable to NDA-weakening laws adopted by the startup's headquarters state. The regression results, presented in Table 5, reveal that the coefficient on $NDAWeaken$ becomes statistically insignificant.

[Insert Table 5 Here.]

The placebo test results suggest that reduced female hiring in VC-backed startups is attributable to NDA-weakening state laws. These results also alleviate the concern that the baseline results are due to unobserved startup heterogeneity; such unobserved heterogeneity would have also affected the startup's female hiring in its non-headquarters states.

4.3 Extensive Margin Analysis

The results so far indicate that VC-backed startups hire fewer female workers after the enactment of NDA-weakening laws. Because the number of female hires reflects both extensive and intensive margins, these findings may capture effects along both dimensions. In this subsection, we focus on the extensive margin to investigate whether NDA-weakening laws also influence the likelihood that startups begin hiring female workers.

We implement the extensive margin analysis as follows. In each year in which at least one state enacted NDA-weakening laws, we assemble a sample of VC-backed startups that satisfy the following two criteria. First, the startup is headquartered in the state(s) that enacted NDA-weakening laws in the year or was located in a state that had never enacted NDA-weakening laws. Second, the startup had not hired a female worker prior to the treatment year, i.e., the year when the NDA-weakening law became effective.

We then stack the samples for each of the treatment years, and estimate the following model:

$$Y_{i,[t,t+n]} = \beta NDAWeaken_{it} + \theta Frac\ Women_{s,t} + Firm\ Age_g + \tau_t + \epsilon_{it}. \tag{2}$$

The dependent variable is a dummy variable, which takes the value of one if the startup starts to hire female workers over the n years after the enactment of NDA-weakening laws and zero otherwise. We control for treatment year fixed effects (τ_t), firm age fixed effects ($Firm\ Age_g$), and the fraction of startups in the state that had hired any female workers up to the treatment year ($Frac\ Women_{s,t}$). We consider four values of n ranging from one to four, and report the linear probability regression results for the four time windows in the four columns of Table 6.

[Insert Table 6 Here.]

The coefficient in $NDAWeaken$ is negative throughout the four columns. It is statistically significant at the 5% level in column (1), where the time window is one year after the enactment of NDA-weakening laws, and significant at the 1% level in the last three columns, where the time window ranges from two to four years. In terms of the economic magnitude, the likelihood that a VC-backed startup starts to hire female workers is 2.8% lower in the first year after the enactment of NDA-weakening laws for treated startups compared to control startups. The likelihood is 4.0% lower for treated startups over the two years after treatment, 4.7% lower over the three years after treatment, and 4.9% over the four-year window.

These extensive margin results are consistent with the baseline results discussed above. Together, the results indicate that VC-backed startups hire fewer women and are less likely to start hiring women after the enactment of NDA-weakening laws.

4.4 Mechanisms

To understand the mechanisms behind our findings above, consider three groups of people: a female worker in a startup, her male supervisor, and the startup's top executives. For simplicity, we assume that the victim is a female in the example. Suppose she is sexually harassed by her supervisor and is not sure whether to report the case within the startup and/or sue the advisor and the startup. The additional protection afforded by state laws, which could weaken or nullify the NDA she signed at the time of joining the startup, may encourage her to report the case within the startup or sue the harasser and the startup.

From the startup's perspective, NDA-weakening laws can lower its demand for female workers because the laws make sexual harassment more costly. The effect on firm demand for female workers is expected to be larger for firms with weaker internal protection of victims of sexual harassment: public disclosures of cases of sexual harassment are more costly for these firms. In this subsection, we conduct additional tests related to the effects of NDA-weakening laws on startups' demand for female workers. These tests shed additional light on

the mechanisms through which NDA-weakening laws affect firm demand for female workers.

4.4.1 Demand-Based Mechanism Test 1: Seniority of Female Workers

We first examine NDA-weakening laws' effects on VC-backed startups' hiring of junior versus senior female workers. Junior women are more likely to be targeted by harassers because sexual harassers are often their senior male colleagues, as discussed above. We hypothesize that VC-backed startups are more likely to cut their demand for junior women, who are more likely to be victims of sexual harassment, in response to the enactment of NDA-weakening laws.

[Insert Table 7 Here.]

To test the hypothesis, we construct two proxies for the seniority of female workers based on employee age and job positions, respectively, and estimate regression (1) separately for the startup's hiring of junior and senior female workers. The regression results reported in Table 7 reveal that the reduction in female hires concentrates among junior female workers and becomes statistically insignificant for senior female workers. Table IA.3 further confirms this pattern by showing that the difference in the estimated coefficients on $NDAWeaken$ across seniority levels is statistically significant. These results are consistent with the hypothesis, indicating that the state laws reduce startups' demand for junior female workers.

4.4.2 Demand-Based Mechanism Test 2: Strength of Internal Employee Protection

In the second test of the demand-based mechanism, we exploit cross-sectional variations in the firm's institutional strength of employee protection against sexual harassment. NDA-weakening laws protect victims of sexual harassment through ex post law enforcement, while internal institutional arrangements within the firm can prevent sexual harassment from occurring in the first place. After the occurrence of sexual harassment, firms with strong internal safeguards against sexual harassment could also promptly take appropriate actions

so that the victim does not need to disclose the case to the public or sue the harasser or the firm. Such institutional arrangements include but are not limited to employee trainings that enhance the awareness of sexual harassment as well as departments and staff that review and investigate reports of harassment. We hypothesize that firms with stronger internal employee protection against sexual harassment are less affected by the state laws, *ceteris paribus*, and will experience a smaller reduction in female hiring after the enactment of NDA-weakening state laws.

To test the hypothesis, we construct two proxies for the strength of internal employee protection against sexual harassment. The first proxy is firm size: smaller startups usually lack the resources to establish and maintain safeguards against sexual harassment. The second proxy is the fraction of female employees within the startup based on the idea that women-friendly VC-backed startups, which offer strong protection of women against sexual harassment, attract more female workers.

[Insert Table 8 Here.]

Table 8 presents the estimation results of model (1) separately for small and large startups. In Panel A, we categorize startups as either large or small based on their total number of employees. Large startups are those with the total employment in the top third; small startups are those in the bottom two-thirds. The coefficient on $NDAWeaken$ is around -0.047 and statistically significant at the 5% level in the first two columns, which correspond to large startups with more employees. The coefficient is about -0.140 and statistically significant at the 1% level in columns (3)–(4) that correspond to small startups with fewer employees. In the last two columns, we add the interaction variable between $NDAWeaken$ and an indicator for large startups to the regressions and observe that the coefficient on this interaction variable is positive and statistically significant at the 1% level.

Panel B of Table 8 is the same as Panel A except that we now classify large/small startups based on their total employment of female workers rather than the employment of all workers. The estimation results are similar to those in Panel A. Both results reveal that the reduction in female hiring after the enactment of NDA-weakening state laws is greater

in smaller startups, which have less internal resource to establish and maintain safeguards against sexual harassment and thus are more exposed to the adoption of NDA-weakening state laws.[16]

[Insert Table 9 Here.]

Table 9 presents the estimation results of model (1) for women-friendly startups versus other startups. Women-friendly startups are those with the fraction of female employees in the top third. We observe that the coefficient on $NDAWeaken$ is around -0.007 and statistically insignificant in the first two columns corresponding to women-friendly startups. The coefficient is about -0.114 and statistically significant at the 1% level in columns (3)–(4) that correspond to startups with low fractions of female workers. In the last two columns, we add the interaction variable between $NDAWeaken$ and an indicator for women-friendly startups to the regressions and observe that the coefficient on this interaction variable is positive and statistically significant at the 5% level.[17]

On balance, the cross-sectional test results in Tables 8 and 9 indicate that the effects of NDA-weakening laws on female hiring concentrate in startups with weaker internal protection against sexual harassment. They are consistent with the demand-based mechanism discussed above, through which NDA-weakening state laws reduce VC-backed startups' female hiring.

4.4.3 Test of a Supply-Based Mechanism: The Federal Speak Out Act

As discussed in the introduction, a state might be more likely to enact NDA-weakening laws if the state's women were more aware of sexual harassment in workplace. Increased

[16] The results in Table IA.4 in the Internet Appendix continue to show that the negative effects of NDA-weakening laws on female hires concentrate in small VC-backed startups with fewer than ten employees. The effects are economically small and less statistically significant in larger VC-backed startups. The effects are also insignificant in a sample of publicly listed tech firms (see Table IA.8 in the Internet Appendix), which are supposed to have more resources to protect female workers from sexual harassment.

[17] We also investigate whether the negative effects of NDA-weakening laws on female hires are affected by the gender of the startup's founder. One may argue that female founders can better protect female employees against internal sexual harassment and thus are less likely to reduce female hiring post the enactment of NDA-weakening laws. Table IA.9 in the Internet Appendix reveals that these state laws have significant negative effects on female hires regardless of whether the startup has a female founder or not.

awareness could reduce women's willingness to work in a male-dominated workplace. Although this supply-based mechanism is consistent with reduced female hiring after the enactment of NDA-weakening laws we document, it is inconsistent with other evidence. It implies lower female hires by VC-backed startups in treated states before the treatment and that the treatment effect shrinks over time as the level of awareness of sexual harassment converges across states. However, we observe parallel trends in female hires before treatment, and that the treatment effect does not abate and rather remains stable over the years after the enactment of NDA-weakening laws.

In this subsection, we further test the supply-side mechanism by exploiting the 2022 federal Speak Out Act, which weakens NDAs in the states that had not enacted NDA-weakening laws by 2022 but does not change NDA legislation in other states. In particular, we estimate a model that is the same as model 1 except that $NDAWeaken$ is replaced with $NDAWeakenFed$, which takes the value of one for the states that had not enaced NDA-weakening laws before 2022 and zero otherwise.

[Insert Table 11 Here.]

Table 11 presents the Poisson regression results using VC-backed startups over the 2020–2024 period. The coefficient is approximately -0.15 and statistically significant at the 5% level. The coefficient estimate is barely changed in column (4) where we exclude from the regression Hawaii and Maine, which adopted NDA-weakening laws in 2022, as well as in column (3) where we exclude New Mexico and Oregon that enacted NDA-weakening laws shortly after 2020. These results are inconsistent with the supply-based mechanism.

4.5 Startup Performance After Reduced Female Hiring

[Insert Table 12 Here.]

We investigate the effect of NDA-weakening laws on VC-backed startup performance in Table 12. The outcome variable in the first two columns is an indicator that takes the value of one if the startup receives any VC funding in the year, and zero otherwise. In the last two

columns, the dependent variable is replaced with the number of VC financing rounds the startup receives in the year. We observe that the coefficient on $NDAWeaken$ is negative and statistically significant at the 1% level through the four columns. In terms of the economic magnitudes, NDA-weakening laws reduce the likelihood of receiving any VC funds in the year by 2.8% per year, corresponding to a 9% decline relative to the sample mean of 31%. Similarly, NDA-weakening laws decrease the number of VC financing rounds per year by approximately 12% ($= e^{-0.129} - 1$). The results in Table 12 suggest that NDA-weakening laws hinder the performance of VC-backed startups, indicating that legal compliance costs could constrain startup performance.

5 Organizational Changes After NDA-Weakening Laws

So far, we have focused our analysis on the effects of NDA-weakening laws on VC-backed startups' female hiring. The findings indicate that such laws had negative consequences on female employment. Our findings are consistent with Acemoglu and Angrist (2001), who show that the 1991 Americans with Disabilities Act reduced the employment of disabled workers, although the act is intended to protect disabled employees and prevent discrimination against the disabled in wage determination, hiring, and firing. Doleac and Hansen (2020) find that "ban the box" (BTB) policies, which prevent employers from asking about job applicants' criminal records until late in the hiring process, worsened rather than alleviated statistical discrimination against demographic groups that include more ex-offenders. These findings suggest that laws intended to protect certain groups of workers can reduce rather than increase their employment.

In this section, we extend our analysis to the effects of NDA-weakening laws on broader organizational changes—the promotion of women, the structuring of leadership in general, and the female labor market participation rates. By protecting women from workplace sexual harassment, NDA-weakening laws are expected to induce women to join, stay, and rejoin the labor force. Our finding of reduced female hiring in VC-backed startups after the enactment of NDA-weakening laws does not necessarily imply that the laws do not enhance the supply

of female workers.

In the tests detailed in this section below, we observe that, although startups hire fewer women after the enactment of NDA-weakening laws, they promote more women to managerial positions. This finding, when viewed in conjunction with the finding of more departures of male managers, suggests that NDA-weakening laws contribute to creating a more women-friendly workplace and help women break the glass ceiling. In other words, our findings suggest that NDA-weakening laws could have positive effects on women's economic and social welfare over the very long horizon.

5.1 Promotion of Female Workers

Prior studies have documented barriers that prevent women from advancing to senior leadership roles, often referred to as the glass ceiling (Azmat, Cuñat, and Henry, 2025). These barriers include career aspiration gaps, socialized gender norms, and opaque promotion systems. After decades of research, however, we know little about how to help women break the glass ceiling in the workplace, and previous studies have emphasized the importance of firm-level policies and organizational culture as key mechanisms to improve gender equity.

In this subsection, we add to this literature by testing whether NDA-weakening state laws, which protect women from workplace sexual harassment, affect the likelihood that women are promoted to managerial positions. Additionally, our focus on fast-growing startups complements the existing literature, which largely centers on large public firms.

NDA-weakening laws could affect the promotion of female workers for several reasons. First, as shown below, more male managers leave startups after the enactment of NDA-weakening laws. The departure of male managers creates more manager positions for female workers. Second, startups can lower the potential costs of sexual harassment by promoting women to managerial positions because women are less likely to sexually harass their junior colleagues. Third, victims of sexual harassment often experience depression, other mental problems, and worse performance (Cortina and Berdahl, 2008). A safer, harassment-free working environment can enhance female workers' performance, make them more willing to

stay, and thus more likely to be promoted to managerial positions.

[Insert Table 13 Here.]

We test whether NDA-weakening laws affect the promotion of female workers within VC-backed startups to managerial positions by replacing the dependent variable of model (1) with the fraction of female workers who are promoted in the year (relative to all workers promoted in the year). We separately examine the promotion to manager- or director-level positions versus promotions to non-manager positions at the junior, or associate level.

The regression results, reported in Table 13, indicate that VC-backed startups are more likely to promote female workers to senior managerial positions after the enactment of NDA-weakening laws (columns (3)-(4)). In contrast, the effect of promoting female workers to junior positions is statistically insignificant (columns (1)-(2)). These results suggest that NDA-weakening laws enhance the likelihood of women being promoted to senior managerial positions.

5.2 Labor Market Participation of Women

By creating a safer, more harassment-free working environment, NDA-weakening laws are expected to raise women's labor market participation rate because women prefer a safer workplace that is free of sexual harassment (Cortina and Berdahl, 2008). Women who chose to be unemployed because of their aversion to workplace sexual harassment may rejoin the labor force after the enactment of NDA-weakening laws. On the other hand, such laws raise VC-backed startups' costs of coping with cases of sexual harassment, reducing their hiring of women as shown above. Their reduced demand for female workers will make it more difficult for women to rejoin the workforce. The opposite effects of such laws on women's labor market participation make it an empirical question about the net effect.

[Insert Table 14 Here.]

We investigate whether VC-backed startups hire more female workers who have been unemployed for a certain period after the enactment of NDA-weakening laws. In particular,

we re-estimate model (1) and replace the dependent variable with the number of female workers hired by the startup in the year who have been unemployed for at least two years. The regression results, presented in the first two columns of Table 14, reveal that VC-backed startups hire fewer women who have been unemployed for at least two years. The coefficient on $NDAWeaken$ is about -0.087, close to the coefficient of -0.081 in column (2) of Table 3, where the dependent variable is the startup's total number of women hired in the year. The coefficient is statistically significant at the 1% level in column (1) and at the 5% level in column (2). The results remain qualitatively unchanged in columns (3)–(4) of Table 14, which are the same as the first two columns except that the woman must have been unemployed for at least one year, rather than two years, before rejoining the workforce.

Our findings indicate that NDA-weakening laws' negative effects on startups' demand for women rejoining the labor force dominate their potential positive effects on the supply of women rejoining the labor force. To reiterate, the findings do not imply that NDA-weakening laws do not raise women's willingness to rejoin the labor force.

Our findings add to the literature on women's reentry to labor market, which has emphasized that their reentry is hindered by a combination of structural, cultural, and institutional barriers. As Deshpande et al. (2023) summarizes in their review of this literature, implicit bias, family-related constraints, and a lack of employer support make it difficult for women to rejoin the labor force. We contribute to this literature on three aspects. First, we highlight sexual harassment as an important factor affecting women's reentry to the labor market, which complements prior studies that center on cultural or household explanations for women's labor market reentry decisions. Second, unlike existing studies, we focus on fast-growing VC-backed startups that are crucial for employment and innovation. Lastly, our finding of reduced demand for women reentering the labor market because of legal compliance costs has meaningful policy implications for lawmakers.

5.3 Departure of Male Managers

Our next test focuses on the demand for male managers among VC-backed startups. This focus is motivated by the fact that sexual harassers are often male managers. By protecting victims of sexual harassment, NDA-weakening laws make it more costly for managers to harass their junior colleagues. Past and potential harassers are thus more likely to leave startups in a state after that state enacts NDA-weakening laws. In addition, startups may also prevent sexual harassment by firing managers who might harass their junior colleagues. Therefore, we hypothesize that male managers are more likely to leave the VC-backed startup after the state enacts NDA-weakening laws.

[Insert Table 15 Here.]

To test the hypothesis, we calculate the fraction of male managers among all managers (both male and female) who leave the startup in a given year. Managers are defined as employees holding a job position at the manager or director level at the time of departure, as classified by Revelio Labs. We then replace the dependent variable of model (1) with the fraction of male managers among all departing managers in the year, and present the regression results in the last two columns of Table 15. We observe that the coefficient on $NDAWeaken$ is 0.027 and statistically significant.

We also conduct a similar analysis for less senior workers departing the startup each year, defined as workers holding entry, junior, or associate-level positions. In the first two columns of Table 15, we replace the dependent variable with the fraction of male non-managerial workers among all departing non-managerial workers in the year, and observe that the coefficient on $NDAWeaken$ becomes economically small (-0.001) and statistically insignificant.

The results in Table 15 are consistent with the hypothesis that male managers are more likely to leave the startup after its headquarters state enacts NDA-weakening laws, making it more costly for male managers to harass their female junior workers. Note that the results are also consistent with the view that male managers may be more fearful of mentoring women after the enactment of NDA-weakening state law.

Altogether, our results are consistent with the view that VC-backed startups respond to the NDA-weakening laws by hiring fewer female workers and promoting more women to managerial positions. Meanwhile, male managers are more likely to leave the startups. In a nutshell, the state laws seem to affect VC-backed startups' demand for both female and male employees and lead to profound organizational changes within startups.

6 Conclusions

This paper examines the labor market consequences of recent state laws that have weakened non-disclosure agreements (NDAs) in cases of workplace sexual harassment. Using a staggered difference-in-differences design and linked data on over 80,000 venture-capital-backed startups from 2014–2022, we document that the NDA-weakening state laws had an unintended negative impact on female employment: they led to a significant decline in female hiring, driven by reductions among junior and high-skilled women and concentrated in small, male-dominated startups. Startups with weaker internal employee protection against sexual harassment respond most strongly, while those with stronger internal protection are largely unaffected. The evidence suggests a demand-side response: as the potential reputational and legal costs of harassment increase, firms with limited internal safeguards reduce their exposure by hiring fewer women.

We also document important internal organizational adjustments. Following NDA reforms, startups experience higher male-manager turnover and promote more women to managerial positions, suggesting that some startups respond by restructuring leadership to mitigate compliance risk and demonstrate accountability. It appears that NDA-weakening laws help women break the glass ceiling, an important issue for the labor market. At the same time, affected startups raise less venture capital in the years after reform, consistent with investors internalizing new forms of legal and governance risk.

The combined results highlight the complexity of translating legal protections into equitable labor market outcomes: policies that enhance accountability and transparency, though potentially beneficial in the very long run, can simultaneously depress female representation,

particularly in environments with weak internal mechanisms for employee protection.

One broader implication is that effective workplace regulation requires more than legal prohibition—it also depends on the organizational ability to implement and internalize these norms. Future research could extend this analysis by examining the equilibrium in the very long run: whether the initial contraction in female hiring gives way to sustained improvements in workplace safety, diversity, and productivity as firms adapt. More generally, our findings underscore that the interaction between law, firm governance, and labor market behavior remains a central empirical question for understanding how social policies and cultural movements reshape organizational and labor market dynamics in the economy.

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Figure 1: Dynamic Effect on Female Hires

This figure plots the coefficient estimates and their 95% confidence intervals from a dynamic version of model (1), in which the treatment variable, $NDAWeaken$, is interacted with relative-year indicators around the enactment of the NDA-weakening law. The dependent variable is the number of female workers hired by the startup in the year. The sample period is over 2014–2022. The omitted (base) year is the year immediately preceding the effective year of the law. Estimates are obtained using the stacked regression estimator with cohort-specific startup and year fixed effects. Standard errors are clustered by startup headquarters state.

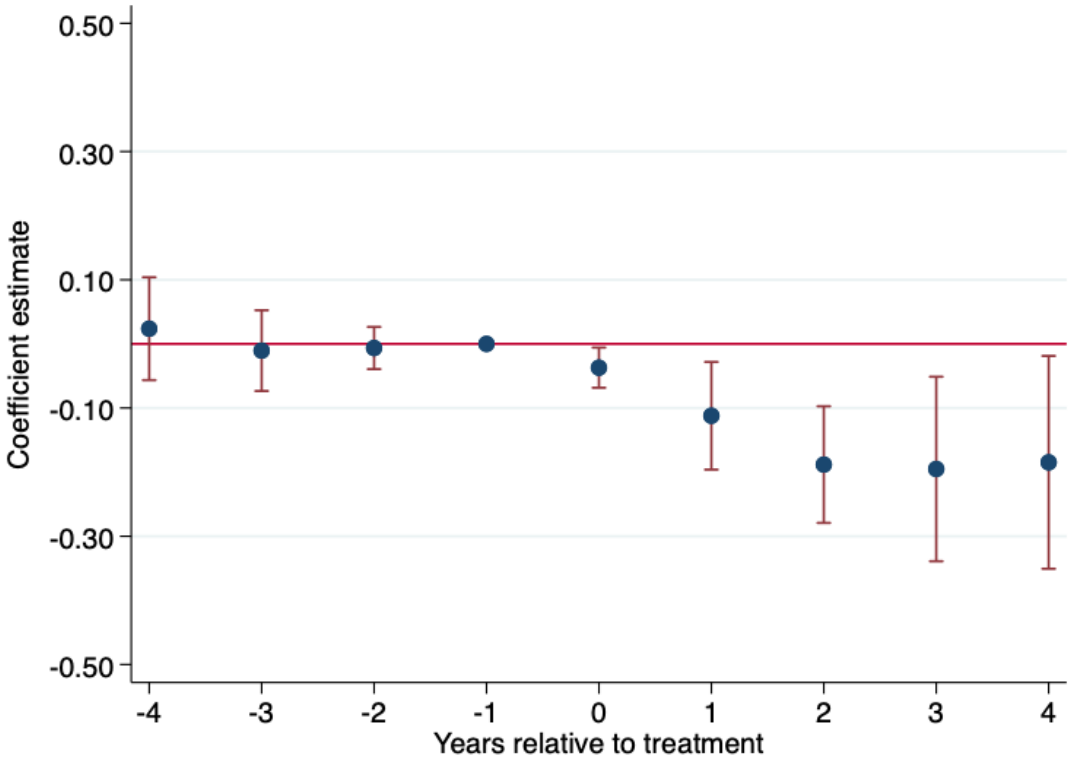


Table 1: State-level NDA-weakening laws

This table lists the U.S. states that enacted laws weakening or nullifying NDAs related to sexual harassment, along with the corresponding statutes and their effective dates. Virginia enacted its NDA-weakening law after the end of our sample period in 2022 and is therefore classified as a never-treated state in our analysis.

State	NDA-weakening Law	Effective Date
TN	Tenn. Code Ann. § 50-1-108	2018/5/15
WA	SB 5996	2018/6/7
NY	NYS Bill	2018/7/1
VT	Act No. 183 (H. 707)	2018/7/1
AZ	Ariz. Rev. Stat. Ann. § 12-720	2018/8/3
MD	Disclosing Sexual Harassment in the Workplace Act	2018/10/1
CA	STAND (Stand Together Against Non-Disclosure) Act	2019/1/1
NJ	S-121	2019/3/18
NV	Assembly Bill No. 248 (AB 248)	2019/7/1
IL	Public Act 101-0221 (SB 75)	2020/1/1
NM	Laws 2020, ch. 16, § 1	2020/5/20
OR	Workplace Fairness Act (Senate Bill 726)	2020/10/1
HI	H.B. No. 2495	2022/7/12
ME	Nondisclosure Agreements in Employment, 26 M.R.S. § 599-C	2022/8/8
*VA**	Virginia Code § 40.1-28.01	2023/7/1

Table 2: Summary Statistics

This table presents summary statistics for the variables used in the main analyses at the startup-year level. The sample period is from 2014 to 2022. *No. Hires* is the total number of workers (both male and female) hired by a startup in a year; *No. Female Hires* is the number of female workers hired by a startup in a year; *Frac Female Hires* is the fraction of female workers hired by a startup (out of all workers hired) in a given year; *NDAWeaken* equals one if the startup's headquarters state has enacted a law weakening NDAs by a given year, and zero otherwise; *Located in Treated States* is an indicator equal to one if a startup is headquartered in a state that enacted NDA-weakening laws during the sample period; *No. Employees (Firm Size)* is the cumulative number of employees a startup has hired up to a given year; *No. VC Rounds* is the number of VC funding rounds a startup raises in a given year.

	N	Mean	Std. Dev.	5-%ile	25-%ile	50-%ile	75-%ile	95-%ile
No. Hires	207,469	2.93	9.47	0.00	0.00	1.00	3.00	12.00
No. Female Hires	207,469	1.12	4.44	0.00	0.00	0.00	1.00	5.00
Frac Female Hires	113,288	0.34	0.36	0.00	0.00	0.27	0.54	1.00
No. High-skill Female Hires (edu)	207,469	0.84	3.29	0.00	0.00	0.00	1.00	4.00
No. High-skill Female Hires (job)	207,469	0.88	3.38	0.00	0.00	0.00	1.00	4.00
No. Low-skill Female Hires (edu)	207,469	0.12	0.67	0.00	0.00	0.00	0.00	1.00
No. Low-skill Female Hires (job)	207,469	0.12	1.10	0.00	0.00	0.00	0.00	1.00
No. Junior Female Hires (age)	207,469	0.47	1.93	0.00	0.00	0.00	0.00	2.00
No. Junior Female Hires (job)	207,469	0.66	2.95	0.00	0.00	0.00	0.00	3.00
No. Senior Female Hires (age)	207,469	0.09	0.62	0.00	0.00	0.00	0.00	1.00
No. Senior Female Hires (job)	207,469	0.47	2.19	0.00	0.00	0.00	0.00	2.00
NDAWeaken	207,469	0.30	0.46	0.00	0.00	0.00	1.00	1.00
Located in Treated States	207,469	0.59	0.49	0.00	0.00	1.00	1.00	1.00
Firm Age	207,469	2.29	1.67	0.00	1.00	2.00	4.00	5.00
No. Employees (Firm Size)	207,469	12.78	49.55	0.00	1.00	4.00	11.00	46.00
No. VC Rounds	207,469	0.96	1.06	0.00	0.00	1.00	1.00	3.00

Table 3: Effects of NDA-Weakening Laws on Female Hires

This table presents regression results using the startup-years over the 2014–2022 period. Our sample includes the first five years after the founding of each startup. All columns except column (5) present Poisson regression results where the dependent variable is the number of female workers hired by a VC-backed startup in a year, while column (5) reports OLS specification where the dependent variable is the fraction of female workers hired by a startup (out of all workers hired) in a given year. Column (3) extends the sample to include the first seven years after the founding of the startup, while column (4) restricts the sample to startup-years after a startup starts to hire (i.e., *active*). *NDAWeaken* equals one if the startup's headquarters state has enacted a law weakening NDAs by a given year, and zero otherwise. *Startup FE* and *Year FE* denote startup and year fixed effects. Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	No. Female Hires				Frac
Model:	Poisson				OLS
Sample:	Full	Full	7 y.o.	Active	Full
	(1)	(2)	(3)	(4)	(5)
NDAWeaken	−0.081***	−0.081***	−0.071***	−0.060***	−0.011**
	(0.024)	(0.023)	(0.025)	(0.022)	(0.004)
Log Firm Age		0.949***			
		(0.032)			
Observations	207,469	207,469	250,432	152,964	113,288
Adj./Pseudo R^2	0.560	0.564	0.600	0.552	0.238
Startup FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y

Table 4: Female Hires by Employee Skill Level

This table presents Poisson regression results using the startup-years over the 2014–2022 period. Our sample includes the first five years after the founding of each startup. The dependent variable is the number of high- or low-skilled female workers hired by a VC-backed startup in a year. In Panel A, high-skilled workers are those with a bachelor's degree or higher and low-skilled workers are those without a bachelor's degree. In Panel B, high-skilled workers are those with O*NET job codes in Job Zone 3-5 and low-skilled workers have O*NET codes in Job Zone 1-2. *NDAWeaken* equals one if the startup's headquarters state has enacted a law weakening NDAs by a given year, and zero otherwise. All regressions include startup and year fixed effects (not shown to conserve space). Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Skill proxied by educational attainment

Dependent variable:	No. Female Hires			
Skill:	Bachelor or Higher		No Bachelor	
	(1)	(2)	(3)	(4)
NDAWeaken	−0.066***	−0.064***	−0.123***	−0.127***
	(0.024)	(0.023)	(0.038)	(0.038)
Log Firm Age		1.024***		0.620***
		(0.041)		(0.031)
Observations	207,469	207,469	207,469	207,469
Pseudo R^2	0.520	0.525	0.263	0.265

Panel B. Skill proxied by job occupation classification

Dependent variable:	No. Female Hires			
Skill:	High Skill		Low Skill	
	(1)	(2)	(3)	(4)
NDAWeaken	−0.069***	−0.068***	−0.148**	−0.145**
	(0.022)	(0.022)	(0.066)	(0.060)
Log Firm Age		0.920***		1.515***
		(0.032)		(0.078)
Observations	207,469	207,469	207,469	207,469
Pseudo R^2	0.516	0.519	0.441	0.448

Table 5: Placebo Test: Female Hires in Non-Headquarters States

This table reports the results for a placebo test of the baseline results using female hires at startups' non-headquarters states. It presents Poisson regression results using startup-years over the 2014–2022 period. The sample includes the first five years after the founding of each startup. The dependent variable in columns (1)-(2) is the count of female hires in a startup's non-headquarters states, while in columns (3)-(4) it is the count of female hires in the startup's non-headquarters states that have never enacted NDA-weakening laws. *NDAWeaken* equals one if the startup's headquarters state has enacted a law weakening NDAs by a given year, and zero otherwise. *Startup FE* and *Year FE* denote startup and year fixed effects. Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	No. Female Hires			
Job location:	Non-HQ States		Never-treated States	
	(1)	(2)	(3)	(4)
NDAWeaken	0.023	0.026	0.018	0.023
	(0.060)	(0.065)	(0.066)	(0.071)
Log Firm Age		0.818***		0.808***
		(0.116)		(0.118)
Observations	207,469	207,469	207,469	207,469
Pseudo R^2	0.690	0.692	0.653	0.654
Startup FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 6: Extensive Margin Analysis

This table presents extensive margin analyses examining VC-backed startups' likelihood of hiring a female worker following the passage of NDA-weakening state laws, at the startup level. The dependent variable equals one if a startup hires a female worker within the indicated time window after treatment—one year (column 1), two years (column 2), three years (column 3), or four years (column 4)—and zero otherwise. For each treatment year (i.e., 2018, 2019, 2020, and 2022), the sample includes startups that (i) are headquartered either in treated states with the corresponding treatment year or in never-treated states, and (ii) had not hired a female worker prior to the treatment year. We then stack the samples across the four treatment years (i.e., 2018, 2019, 2020, and 2022). *NDAWeaken* equals one if the startup is headquartered in a state that enacted NDA-weakening laws, and zero otherwise. All regressions include treatment year and firm age fixed effects. *Frac Women* is the fraction of VC-backed startups in the same state-age group with at least one female worker prior to treatment. Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Likelihood to Hire Female			
Post window:	1 yr	2 yrs	3 yrs	4 yrs
	(1)	(2)	(3)	(4)
NDAWeaken	−0.028**	−0.040***	−0.047***	−0.049***
	(0.011)	(0.012)	(0.012)	(0.013)
Frac Women	0.488***	0.548***	0.583***	0.598***
	(0.048)	(0.070)	(0.084)	(0.087)
Observations	28,644	28,644	28,644	28,644
Adj. R^2	0.043	0.065	0.085	0.097
Treatment Year FE	Y	Y	Y	Y
Firm Age FE	Y	Y	Y	Y

Table 7: Female Hires by Employee Seniority

This table presents Poisson regression results using the startup-years over the 2014–2022 period. Our sample includes the first five years after the founding of each startup. The dependent variable is the number of junior or senior female workers hired by a VC-backed startup in a year. In Panel A, junior (senior) workers are younger (older) than 35 years. In Panel B, junior workers are those holding entry, or junior level positions, while senior workers hold associate, manager, director, executive, or senior executive level positions. *NDAWeaken* equals one if the startup's headquarters state has enacted a law weakening NDAs by a given year, and zero otherwise. All regressions include startup and year fixed effects (not shown to conserve space). Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Seniority measured by employee age

Dependent variable:	No. Female Hires			
Seniority:	Junior		Senior	
	(1)	(2)	(3)	(4)
NDAWeaken	−0.095***	−0.092***	−0.028	−0.029
	(0.026)	(0.026)	(0.032)	(0.034)
Log Firm Age		1.212***		0.341***
		(0.059)		(0.048)
Observations	207,469	207,469	207,469	207,469
Pseudo R^2	0.441	0.447	0.223	0.224

Panel B. Seniority measured by job classification

Dependent variable:	No. Female Hires			
Seniority:	Junior		Senior	
	(1)	(2)	(3)	(4)
NDAWeaken	−0.102***	−0.098***	−0.044	−0.044
	(0.027)	(0.027)	(0.032)	(0.032)
Log Firm Age		1.530***		0.366***
		(0.054)		(0.026)
Observations	207,469	207,469	207,469	207,469
Pseudo R^2	0.520	0.529	0.402	0.403

Table 8: Female Hires by Firm Size

This table presents Poisson regression results using the startup-years over the 2014–2022 period. Our sample includes the first five years after the founding of each startup. The dependent variable is the number of female workers hired by a small or large VC-backed startup in a year. In Panel A, large (small) startups are those whose total employment are in the top third (the bottom two thirds) of the sample distribution. In Panel B, large (small) startups are those whose total female employment are in the top third (the bottom two thirds) of the sample distribution. *NDAWeaken* equals one if the startup's headquarters state has enacted a law weakening NDAs by a given year, and zero otherwise. All regressions include startup and year fixed effects. Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Firm size proxied by total employment

Dependent variable:	No. Female Hires					
Sample:	Large Startup		Small Startup		Full	
	(1)	(2)	(3)	(4)	(5)	(6)
NDAWeaken × Large Startup					0.086***	0.094***
					(0.033)	(0.031)
NDAWeaken	−0.046**	−0.048**	−0.132***	−0.147***	−0.132***	−0.143***
	(0.023)	(0.022)	(0.026)	(0.027)	(0.026)	(0.026)
Log Firm Age		0.479***		0.772***		0.550***
		(0.067)		(0.067)		(0.044)
Observations	69,063	69,063	138,406	138,406	207,469	207,469
Pseudo R^2	0.565	0.566	0.129	0.133	0.587	0.588
Startup FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Panel B. Firm size proxied by total female employment

Dependent variable:	No. Female Hires					
Sample:	Large Startup		Small Startup		Full	
	(1)	(2)	(3)	(4)	(5)	(6)
NDAWeaken × Large Startup					0.104**	0.106**
					(0.046)	(0.045)
NDAWeaken	−0.022	−0.024	−0.126***	−0.138***	−0.126***	−0.131***
	(0.027)	(0.026)	(0.037)	(0.037)	(0.037)	(0.037)
Log Firm Age		0.235***		0.709***		0.319***
		(0.088)		(0.062)		(0.065)
Observations	66,086	66,086	141,383	141,383	207,469	207,469
Pseudo R^2	0.554	0.554	0.079	0.082	0.598	0.599
Startup FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Table 9: Female Hires by the Startup's Level of Friendliness to Women

This table presents Poisson regression results using the startup-years over the 2014–2022 period. Our sample includes the first five years after the founding of each startup. The dependent variable is the number of female workers hired by a *High Female* or *Low Female* VC-backed startup in a year. *High Female* firms are those with the fraction of female employees (out of all employees) in the top third of the sample distribution, while *Low Female* firms comprise the remainder. *NDAWeaken* equals one if the startup's headquarters state has enacted a law weakening NDAs by a given year, and zero otherwise. All regressions include startup and year fixed effects. Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	No. Female Hires					
Sample:	High Female		Low Female		Full	
	(1)	(2)	(3)	(4)	(5)	(6)
NDAWeaken × High Female					0.109**	0.104**
					(0.047)	(0.049)
NDAWeaken	−0.007	−0.008	−0.116***	−0.111***	−0.116***	−0.113***
	(0.024)	(0.024)	(0.039)	(0.040)	(0.039)	(0.039)
Log Firm Age		0.259***		1.316***		0.676***
		(0.080)		(0.052)		(0.031)
Observations	55,877	55,877	116,748	116,748	172,625	172,625
Pseudo R^2	0.602	0.603	0.510	0.516	0.574	0.576
Startup FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Table 10: Excluding the Post-Covid Period and Major Tech Hubs

This table reports robustness checks for the baseline results in Table 3. Columns 1-2 restrict the sample to the pre-Covid period (2014–2019), while columns 3-4 exclude startups headquartered in California and New York, two major venture capital hubs that have enacted laws weakening NDAs. *NDAWeaken* equals one if the startup's headquarters state has enacted a law weakening NDAs by a given year, and zero otherwise. *Startup FE* and *Year FE* denote startup and year fixed effects. Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	No. Female Hires			
Excluded:	Post-Covid Period		CA and NY	
	(1)	(2)	(3)	(4)
NDAWeaken	−0.030*	−0.035**	−0.127***	−0.132***
	(0.017)	(0.017)	(0.041)	(0.040)
Log Firm Age		0.970***		0.924***
		(0.041)		(0.056)
Observations	132,115	132,115	111,330	111,330
Pseudo R^2	0.583	0.587	0.510	0.514
Startup	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 11: Effects of Federal NDA-Weakening Law over 2020–2024

This table reports robustness checks for the baseline results in Table 3 using the federal NDA-weakening law over the post-Covid period (2020–2024). *NDAWeakenFed* equals one if the startup is headquartered in a state that had *not* enacted a law weakening NDAs by 2020, i.e., the first year of the sample period, and zero otherwise. *Post* equals one for observations after 2022, the year in which the federal NDA-weakening law became effective. Column 3 excludes startups headquartered in two states—New Mexico and Oregon—that enacted NDA-weakening laws in mid-2020, after the start of the sample period. Column 4 excludes startups headquartered in Hawaii and Maine, which passed NDA-weakening laws in 2022, the same year as the federal reform. *Startup FE* and *Year FE* denote startup and year fixed effects. Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	No. Female Hires			
Sample:	Full	Full	Ex. NM & OR	Ex. HI & ME
	(1)	(2)	(3)	(4)
NDAWeakenFed × Post	−0.151**	−0.164**	−0.154**	−0.151**
	(0.070)	(0.075)	(0.070)	(0.071)
Log Firm Age		0.847***		
		(0.070)		
Observations	113,301	113,301	112,109	112,990
Pseudo R^2	0.682	0.684	0.682	0.682
Startup FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 12: VC Funding Outcomes

This table presents OLS (Columns (1)-(2)) or Poisson (Columns (3)-(4)) regression results using the startup-years over the 2014–2022 period. Our sample includes the first five years after the founding of each startup. The dependent variable is a dummy variable equal to one if the startup raised a VC funding round in a given year and zero otherwise (Columns (1)-(2)), or the number of VC funding rounds raised by the startup in that year (Columns (3)-(4)). *NDAWeaken* equals one if the startup's headquarters state has enacted a law weakening NDAs by a given year, and zero otherwise. All regressions include startup and year fixed effects. Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	New VC Round		No. VC Rounds	
Model:	OLS		Poisson	
	(1)	(2)	(3)	(4)
NDAWeaken	−0.028***	−0.028***	−0.129***	−0.137***
	(0.008)	(0.008)	(0.031)	(0.032)
Log Firm Age		0.322***		1.247***
		(0.009)		(0.041)
Observations	207,469	207,469	207,469	207,469
Adj./Pseudo R^2	0.007	0.021	0.081	0.088
Startup FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 13: Promotions of Female Workers

This table reports analyses examining the impact of state NDA-weakening laws on promotions of female workers. It presents OLS regression results using the startup-years over the 2014–2022 period. Our sample includes the first five years after the founding of each startup. The dependent variable is the fraction of female workers who are promoted in the year (out of all promoted workers), i.e., whose job position is changed to a more senior position within the same startup. Columns (1)-(2) focus on promotions to junior, or associate levels (after promotion), while columns (3)-(4) focus on promotions to manager or director levels. *NDAWeaken* equals one if the startup's headquarters state has enacted a law weakening NDAs by a given year, and zero otherwise. All regressions include startup and year fixed effects. Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Frac Female Promotion			
Seniority after promotion:	Manager Below		Manager	
	(1)	(2)	(3)	(4)
NDAWeaken	0.032	0.033	0.030*	0.031*
	(0.028)	(0.028)	(0.017)	(0.017)
Log Firm Age		0.176**		0.051
		(0.068)		(0.057)
Observations	10,525	10,525	14,109	14,109
Adj. R^2	0.209	0.210	0.200	0.200
Startup FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 14: Hiring of Women Rejoining the Labor Market

This table presents Poisson regression results using the startup-years over the 2014–2022 period. Our sample includes the first five years after the founding of each startup. The dependent variable is the annual number of female workers hired by a VC-backed startup who have been unemployed for at least two years (columns 1-2) or one year (columns 3-4). *NDAWeaken* equals one if the startup's headquarters state has enacted a law weakening NDAs by a given year, and zero otherwise. All regressions include startup and year fixed effects. Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	No. Female Hires			
Unemployment spells:	2 yrs		1 yr	
	(1)	(2)	(3)	(4)
NDAWeaken	−0.088***	−0.087**	−0.097***	−0.096***
	(0.034)	(0.034)	(0.033)	(0.033)
Log Firm Age		0.748***		0.863***
		(0.040)		(0.032)
Observations	207,469	207,469	207,469	207,469
Pseudo R^2	0.325	0.327	0.395	0.397
Startup FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 15: Departures of Male Managers

This table reports analyses examining the impact of state NDA-weakening laws on the departure of male workers. It presents OLS regression results using the startup-years over the 2014–2022 period. Our sample includes the first five years after the founding of each startup. The dependent variable is the fraction of male workers departing the startup in a year (out of all workers who departed). Columns (1)-(2) focus on departing workers holding entry, junior, or associate level job positions at the time of departure, while columns (3)-(4) focus on departing workers holding manager or director level job positions. *NDAWeaken* equals one if the startup's headquarters state has enacted a law weakening NDAs by a given year, and zero otherwise. All regressions include startup and year fixed effects. Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Frac Male Departure			
Seniority before departure:	Manager Below		Manager	
	(1)	(2)	(3)	(4)
NDAWeaken	−0.001	−0.001	0.027***	0.027***
	(0.007)	(0.007)	(0.009)	(0.009)
Log Firm Age		−0.009		0.007
		(0.022)		(0.023)
Observations	76,455	76,455	47,239	47,239
Adj. R^2	0.212	0.212	0.162	0.162
Startup FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Internet Appendix

A Additional Figures and Tables

Table IA.1: Difference in Female and Male Hires

This table presents analyses examining the difference in female vs. male hires at VC-backed startups following the passage of NDA-weakening state laws. It presents Poisson regression results using the startup-years over the 2014–2022 period. Our sample includes the first five years after the founding of each startup. The first two columns use the full sample, while the last two columns restrict the sample to startup-years after a startup starts to hire (i.e., *active*). The dependent variable is the annual number of male or female workers hired by a VC-backed startup. *Female* is an indicator variable that takes the value of one if the dependent variable is the number of female hires and zero if it is the number of male hires. *NDAWeaken* equals one if the startup's headquarters state has enacted a law weakening NDAs by a given year, and zero otherwise. All regressions include startup and year fixed effects. Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	No. Hires			
Sample:	Full		Active	
	(1)	(2)	(3)	(4)
NDAWeaken × Female	−0.047***	−0.049***	−0.059***	−0.060***
	(0.011)	(0.012)	(0.012)	(0.012)
NDAWeaken	−0.034	−0.031	−0.001	−0.001
	(0.025)	(0.025)	(0.024)	(0.024)
Log Firm Age		0.569***		0.254***
		(0.027)		(0.035)
Observations	414,938	414,938	305,928	305,928
Pseudo R^2	0.566	0.567	0.558	0.559
Startup FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table IA.2: Stacked Regressions

This table reports a robustness check for the main results in Table 3 using stacked regressions. Specifically, for each treatment year/cohort (i.e., 2018, 2019, 2020, and 2022), we construct a panel that includes startups headquartered either in treated states with the corresponding treatment year or in never-treated states. We then stack these panels across the four treatment years and estimate regressions based on the combined sample. All columns except column (5) present Poisson regression results where the dependent variable is the number of female workers hired by a VC-backed startup in a year, while column (5) reports OLS specification where the dependent variable is the fraction of female workers hired by a startup (out of all workers hired) in a given year. Column (3) extends the sample to include the first seven years after the founding of the startup, while column (4) restricts the sample to startup-years after a startup starts to hire (i.e., *active*). *NDAWeaken* equals one if the startup's headquarters state has enacted a law weakening NDAs by a given year, and zero otherwise. *Startup FE* and *Year FE* denote startup and year fixed effects. Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	No. Female Hires				Frac
Model:	Poisson				OLS
Sample:	Full	Full	7 y.o.	Active	Full
	(1)	(2)	(3)	(4)	(5)
NDAWeaken	−0.092***	−0.088**	−0.097***	−0.064**	−0.015***
	(0.035)	(0.035)	(0.028)	(0.031)	(0.005)
Log Firm Age		0.915***			
		(0.044)			
Observations	459,706	459,706	557,665	407,515	237,356
Adj./Pseudo R^2	0.535	0.539	0.572	0.564	0.222
Startup FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y

Table IA.3: Differences in Female Hiring Across Skill and Seniority Levels

This table reports regression estimates testing for differences in the effect of NDA-weakening laws on female hiring across skill and seniority levels. Specifically, each column presents the difference in the estimated coefficients on *NDAWeaken*, along with the corresponding standard errors, between columns 1 and 3 within each of the four panels of Tables 4 and 7. All specifications include startup and year fixed effects. Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	No. Female Hires			
Heterogeneity:	Skill		Seniority	
Proxy:	Edu	Job	Age	Job
	(1)	(2)	(3)	(4)
Coef Diff	0.057	0.079	−0.067*	−0.059*
	(0.039)	(0.062)	(0.038)	(0.034)
Observations	414,938	414,938	414,938	414,938
Pseudo R^2	0.507	0.515	0.420	0.476
Startup FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table IA.4: Female Hires by Firm Size Brackets

This table presents Poisson regression results using the startup-years over the 2014–2022 period, separately for startups in four size brackets measured by their total employment. Our sample includes the first five years after the founding of each startup. The dependent variable is the annual number of female workers hired by a VC-backed startup. *NDAWeaken* equals one if the startup's headquarters state has enacted a law weakening NDAs by a given year, and zero otherwise. All regressions include startup and year fixed effects. Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	No. Female Hires			
Firm size:	[1,10]	[11,20]	[21,40]	+40
	(1)	(2)	(3)	(4)
NDAWeaken	−0.116***	−0.036	−0.053	−0.075*
	(0.029)	(0.037)	(0.054)	(0.045)
Observations	119,574	25,223	15,511	12,317
Pseudo R^2	0.148	0.238	0.294	0.642
Startup FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table IA.5: Post-Departure Job Characteristics of Male Managers

This table provides robustness checks for Table 15 by examining the characteristics of male workers' subsequent jobs following departure from the startup. In Panel A, the dependent variable is the fraction of departing male workers who move to jobs with lower salary relative to their previous positions (out of all such workers). In Panel B, the dependent variable is the fraction of departing male workers who move to jobs with lower seniority. In Panel C, the dependent variable is the fraction of departing male workers who find a job following an unemployment spell longer than the sample median. In each panel, columns (1)-(2) focus on departing workers holding entry, junior, or associate level job positions at the time of departure, while columns (3)-(4) focus on departing workers holding manager or director level job positions. All regressions include startup and year fixed effects. Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Transition to a lower-salary job

Dependent variable:	Frac Male Departure			
Seniority before departure:	Manager Below		Manager	
	(1)	(2)	(3)	(4)
NDAWeaken	−0.017	−0.017	0.035**	0.036**
	(0.012)	(0.012)	(0.017)	(0.017)
Log Firm Age		−0.027		−0.042
		(0.034)		(0.045)
Observations	35,503	35,503	24,510	24,510
Adj. R^2	0.171	0.171	0.144	0.144

Panel B. Transition to a lower-seniority job

Dependent variable:	Frac Male Departure			
Seniority before departure:	Manager Below		Manager	
	(1)	(2)	(3)	(4)
NDAWeaken	−0.010	−0.009	0.038*	0.039*
	(0.022)	(0.022)	(0.022)	(0.022)
Log Firm Age		0.045		−0.040
		(0.040)		(0.047)
Observations	20,159	20,159	23,752	23,752
Adj. R^2	0.164	0.164	0.139	0.139

Panel C. Transition following a longer unemployment spell

Dependent variable:	Frac Male Departure			
Seniority before departure:	Manager Below		Manager	
	(1)	(2)	(3)	(4)
NDAWeaken	−0.006	−0.006	0.051***	0.051***
	(0.006)	(0.006)	(0.018)	(0.018)
Log Firm Age		−0.015		0.005
		(0.025)		(0.037)
Observations	49,170	49,170	22,393	22,393
Adj. R^2	0.177	0.177	0.127	0.127
Startup FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table IA.6: Post-Departure Job Characteristics of Male Managers (For Ourselves)

Panel A. The age of departing male managers

Dependent variable:	Med Age of Departing Male Workers			
Seniority before departure:	Manager Below		Manager	
	(1)	(2)	(3)	(4)
NDAWeaken	0.005	0.005	−0.015	−0.015
	(0.005)	(0.005)	(0.010)	(0.010)
Log Firm Age		0.008		0.020
		(0.009)		(0.022)
Observations	43,230	43,230	20,678	20,678
Adj. R^2	0.222	0.222	0.230	0.229

Panel B. Move to a never-treated state

Dependent variable:	Frac Male Departure			
Seniority before departure:	Manager Below		Manager	
	(1)	(2)	(3)	(4)
NDAWeaken	−0.023**	−0.023**	0.044	0.044
	(0.009)	(0.009)	(0.033)	(0.033)
Log Firm Age		0.050		0.003
		(0.064)		(0.065)
Observations	27,704	27,704	10,828	10,828
Adj. R^2	0.177	0.177	0.123	0.123

Table IA.7: Employee Reviews

Model:	Poisson			OLS	
Dependent variable:	No. Reviews	No. Neg Reviews	No. Neg Reviews (sexual harassment)	Overall Rating	Culture Rating
	(1)	(2)	(3)	(4)	(5)
NDAWeaken	−0.016	−0.080	−0.676**	0.035	0.061
	(0.056)	(0.080)	(0.342)	(0.053)	(0.052)
Observations	207,469	207,469	207,469	12,644	12,210
Adj./Pseudo R^2	0.513	0.401	0.219	0.270	0.287
Startup FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y

Table IA.8: Female Hires at Public Tech Firms

This table presents Poisson regression results using the firm-years over the 2014–2022 period. Our sample includes publicly traded tech firms, which are defined based on industry classification following Goldschlag and Miranda (2020, Table 7). The dependent variable is the number of female workers hired by the firm in a year. The first two columns use the full sample, while the last two restrict the sample to firm-year observations after a firm begins hiring (i.e., *active*). *NDAWeaken* equals one if the firm's headquarters state has enacted a law weakening NDAs by a given year, and zero otherwise. All regressions include firm and year fixed effects. Standard errors in parentheses are clustered by firm headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	No. Female Hires			
Sample:	Full		Active	
	(1)	(2)	(3)	(4)
Weaken NDA	0.018	0.017	0.019	0.017
	(0.070)	(0.049)	(0.071)	(0.049)
Log Firm Age		−0.078*		−0.090*
		(0.046)		(0.046)
Log Firm Size		0.387***		0.389***
		(0.046)		(0.045)
Observations	10,362	10,314	9,485	9,444
Pseudo R^2	0.911	0.917	0.910	0.916
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table IA.9: Female Hires by Founder Gender

This table presents Poisson regression results using the startup-years over the 2014–2022 period, estimated separately for startups with female founders (columns (1)-(2)) and male founders (columns (3)-(4)). Our sample includes the first five years after the founding of each startup. The dependent variable is the number of female workers hired by the startup in a year. *NDAWeaken* equals one if the startup's headquarters state has enacted a law weakening NDAs by a given year, and zero otherwise. All regressions include startup and year fixed effects. Standard errors in parentheses are clustered by startup headquarters state. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	No. Female Hires					
Sample:	Female Founder		Male Founder		Full	
	(1)	(2)	(3)	(4)	(5)	(6)
NDAWeaken × Female Founder					−0.033	−0.061
					(0.061)	(0.064)
NDAWeaken	−0.103*	−0.115*	−0.070**	−0.064**	−0.070**	−0.065**
	(0.058)	(0.059)	(0.028)	(0.027)	(0.028)	(0.027)
Log Firm Age		0.491***		1.064***		0.958***
		(0.088)		(0.037)		(0.032)
Observations	24,466	24,466	183,003	183,003	207,469	207,469
Pseudo R^2	0.592	0.594	0.555	0.559	0.561	0.565
Startup FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y