The Impact of Paid Family Leave on Employers: Evidence from New York *

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October 4, 2021

Abstract

We designed and fielded a survey of small firms in New York and Pennsylvania to study the impacts of New York's 2018 Paid Family Leave policy on employer outcomes. We match each NY firm to a comparable PA firm and use difference-in-difference models to analyze within-match-pair changes in outcomes. Contrary to common concerns about the burdens of PFL on employers, we find no evidence that PFL had any adverse impacts on employer ratings of employee performance in terms of attendance, commitment, cooperation, productivity, and teamwork. Instead, we observe an improvement in employers' rating of their ease of handling long employee absences, concentrated in the first policy year. We also find an increase in employee leave-taking in the second policy year, driven by the smallest firms in our study.

JEL classification: J21, J23, J32, I38

Keywords: paid family leave, employers, worker absences

*We thank Junying Fang and Jett Pettus for excellent research assistance. We thank participants at APPAM and AEA conferences for helpful feedback. We gratefully acknowledge funding for this research from Pivotal Ventures, Washington Center for Equitable Growth, Russell Sage Foundation, and Ford Foundation, and support from the Columbia Population Research Center which is funded by the National Institute for Child Health and Human Development (NICHD) through grant P2CHD058486.

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1 Introduction

The vast majority of Americans are supportive of Paid Family Leave (PFL), a policy that provides workers with paid time off while they care for newborn children or seriously ill family members.[1] Yet the United States remains the only high-income country without a national PFL policy, and only nine states and Washington, D.C., have implemented or passed PFL legislation. Although the economic and health benefits of PFL for workers and their families have been documented in an expansive literature (see Olivetti and Petrongolo, 2017; Rossin-Slater, 2018; Rossin-Slater and Uniat, 2019; Rossin-Slater and Stearns, 2020 for some overviews), the lack of policy action in the U.S. partially reflects concerns about the potential burden that PFL imposes on employers. While most federal PFL proposals and nearly all current state-level policies use employee payroll taxes as financing mechanisms, employers—especially small ones—may face other costs and challenges associated with having to manage their workers' absences.

Thus, evidence on the impacts of PFL on employers is necessary to inform the policy debate, but this research has been limited. Existing survey and administrative data sets do not contain information about employers' experiences with managing employee absences, which are key to understanding the potential burden of PFL on firms.[2] In this paper, we collect survey data from small firms, and use a natural experiment research design to provide novel evidence on the causal impacts of PFL on employers.

Specifically, we study the introduction of New York's PFL policy, which was the fourth state-level PFL policy implemented in the U.S. (following California, New Jersey, and Rhode Island), taking effect in January 2018. We designed and fielded a survey over the years 2016 to 2019, using a representative sample of firms with 10 to 99 employees in New York and

[1] For evidence on public support of PFL, see, e.g.: `https://www.forbes.com/sites/marybethferrante/2020/02/20/80-of-americans-support-paid-family-and-medical-leave-yet-less-than-20-have-access/#49e231673d9b`. See also: `http://www.nationalpartnership.org/our-work/resources/economic-justice/paid-leave/state-paid-family-leave-laws.pdf`.

[2] Recent studies using administrative data from California and Rhode Island have examined the impacts of paid leave policies in these two states on a range of outcomes of the workers and their families (Bana et al., 2020; Campbell et al., 2017). Another study using California administrative data shows that firms play an important role in determining the take-up of leave benefits, but does not shed light on the impacts of the program on employer outcomes (Bana et al., 2018). Related, Kamal et al. (2020) use data from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) and analyze the impact of a negative labor demand shock on employee composition for firms that are and are not covered by the provisions of the federal Family and Medical Leave Act.

Pennsylvania, a neighboring state without a PFL policy. Our survey asked employers to rate their employees' performance, as well as the ease of coordinating work schedules and handling employee absences of various durations. We also gathered data on the incidence of employee leave-taking for purposes of caring for newborn children or family members with serious illness; on the rates of employee quits and absences without advance notice during the past year; and on the shares of employees who are female and who work part-time.

To estimate policy impacts on employer outcomes, we first use the pool of PA firms to select a matched control for each NY firm in our data based on industry sector, location in a metro area, firm size, county unemployment rate, and the county average weekly wage. Then, we estimate difference-in-differences and event-study models to compare changes in outcomes in NY firms from before to after the policy was implemented, relative to the changes in outcomes in PA firms over the same period. Our specifications include match-pair-by-year fixed effects, so we obtain *within-match-pair* differences in outcome changes, controlling flexibly for match-pair-specific trends.

Our results show that New York's PFL policy does not impose large burdens on firms. We find no statistically significant or economically meaningful adverse impacts on employer ratings of employee performance in terms of attendance, commitment, cooperation, productivity, and teamwork. In fact, our estimates allow us to rule out that NY PFL reduces these outcomes by more than 0.11, 0.02, 0.02, 0.18, and 0.16 of a standard deviation (SD), respectively.

When examining employers' experiences with their employees' absences, we similarly find no evidence of damaging effects. If anything, it appears that employers find it easier to deal with their workers' absences: we show a 0.27 SD increase in employers' average rating of their ease of handling workers' absences longer than four weeks in duration. While our data do not allow us to isolate the exact mechanism driving this change, it is possible that the existence of a standardized universal program in the state makes it easier for firms to handle situations when workers need extended time off (which they previously may have had to manage on a case-by-case basis, e.g., by piecing together other benefits such as sick days or vacation).

We also observe that, in the second year of the policy, there is a 19.5 percentage point (50 percent relative to the pre-policy mean) increase in the incidence of employee leave-taking. This impact reflects increases in both female and male employees taking parental leaves, as

well as male employees taking leaves to care for severely ill family members. When we examine heterogeneity in impacts by firm size, we find that the increases in employee leave-taking take place in firms with 10 to 49 workers. This finding is consistent with employers with fewer than 50 workers not being covered by the federal Family and Medical Leave Act, which provides 12 weeks of job-protected unpaid leave. Thus, for firms with fewer than 50 employees—which constitute two-thirds of the employers in our study—New York's PFL program provides the first experience of employees being able to use government-provided job-protected leave.[3]

Lastly, we find no significant changes in the share of employees who quit or are absent without advance notice, or who are female or employed part-time. These results suggest that our estimated impacts on employers are not driven by changes in employee composition.

Our paper contributes to a small set of studies that have analyzed employers in the context of PFL. Eileen Appelbaum and Ruth Milkman pioneered the research on employers with a survey of 250 California firms, which was conducted four to five years after California's first-in-the-nation PFL program was implemented. A central finding from this work is that 90 percent of California employers reported that the PFL policy had either a positive or a neutral effect on employee productivity, morale, and costs (Milkman and Appelbaum, 2013; Appelbaum and Milkman, 2011). Another study of 18 employers in New Jersey indicates that businesses do not report adverse impacts of NJ's second-in-the-nation PFL program on profitability or employee productivity (Lerner et al., 2014). Most recently, Goodman et al. (2020) examine the impacts of San Francisco's Paid Parental Leave Ordinance, which was implemented in 2017 and is the first U.S. policy that mandates that employers provide fully paid leave to workers.[4] The authors surveyed employers in San Francisco and surrounding Bay Area counties in 2018, and show that employers report minimal negative impacts and high support for the policy. While these studies break new ground in collecting data on employer outcomes, they are limited by a lack of baseline data on pre-PFL outcomes, do not have control groups that can

[3]As we note in Section 2, New York has a Temporary Disability Insurance program, which provides 6 to 8 weeks of partially paid leave to birthing mothers for the purposes of preparing for and recovering from childbirth. However, this leave is not job protected and the maximum wage payment received during the leave is low.

[4]Specifically, the ordinance requires that employers in San Francisco supplement the state-level PFL policy by providing workers with 100% wage replacement during leave.

be followed over time, and do not use representative samples of firms.[5] Our survey indicates that employers have high ratings on these types of outcomes even in the years *before* the policy, suggesting limited scope of measurable improvements along these dimensions, and that pre-PFL data is essential for assessing the impacts that can be attributed to the policy.

Lastly, four recent studies using administrative data from Europe have analyzed the impacts of employee leave-taking on outcomes among employers. Brenøe et al. (2020) use Danish data, and find no impacts of a female employee taking parental leave on firm output, profitability, or survival. By contrast, Gallen (2019) indicates that a Danish reform that expanded fully-compensated parental leave by 22 weeks did have a negative effect on firm survival and the retention of mothers. Ginja et al. (2020) study a parental leave expansion in Sweden, and demonstrate that firms respond to this reform by hiring additional workers and increasing incumbent workers' hours, and thus incur additional wage costs. Huebener et al. (2020) analyze a German parental leave reform, and find impacts on firms' subsequent hiring decisions. However, the dramatic differences in statutory leave duration, labor market characteristics, and broader policy environments between these European countries and the United States make it challenging to infer lessons from this evidence for the U.S. setting.

2 New York's Paid Family Leave Act

Before 2018, some workers in New York had access to government-provided job-protected unpaid leave through the federal Family and Medical Leave Act (FMLA) of 1993, which covers workers who meet various eligibility requirements, such as working at an employer with 50 or more employees. In addition, since the 1978 Pregnancy Discrimination Act, birth mothers have been eligible for approximately 6 to 8 weeks of partially paid disability leave under NY's Temporary Disability Insurance (TDI) program to prepare for and recover from childbirth. TDI provides a wage replacement rate of 50 percent of the average weekly wage for the last eight weeks worked, but only up to a current (as of 2021) maximum benefit of $170 per week,

[5] Bartel et al. (2016) analyze the impact of Rhode Island's third-in-the-nation PFL program on employers with a survey of small and medium-sized food services and manufacturing businesses in Rhode Island, Connecticut, and Massachusetts. They collected data both before and after the program went into effect, and report no statistically significant impacts on a wide range of outcomes. However, small sample sizes generate concerns for statistical power, and limit the conclusions that could be drawn from this analysis.

and the leave is not job protected.[6]

In January 2018, New York state implemented the Paid Family Leave Act (PFLA), thus becoming the fourth state to provide job-protected paid leave for new parents and employees caring for a severely ill family member. The program covers all private sector workers and has been implemented gradually over 2018 to 2021. In 2018, workers were able to claim 8 weeks of leave with a wage replacement rate equal to 50 percent of the employee's average weekly wage (AWW), up to a maximum benefit set at 50 percent of the state-level AWW. In 2019 and 2020, workers could claim leave for 10 weeks, with wage replacement rates of 55 and 60 percent of their AWW, up to 55 and 60 percent of the state AWW, respectively. In 2021, the fully phased-in policy provides 12 weeks of leave, with 67 percent of the worker's AWW replaced, up to 67 percent of the state AWW (corresponding to a $971.61 maximum weekly benefit). Similar to many other state-level PFL programs, New York's program is funded through a payroll tax on employees.[7]

3 Data

Survey design. We surveyed a representative sample of firms with 10 to 99 employees in NY and PA in each fall (September to December) of 2016, 2017, 2018, and 2019.[8] The survey was approved by the Institutional Review Board (IRB) at Columbia University and conducted by the Office for Survey Research (OSR) at Michigan State University (whose IRB also approved). We identified employers in each state using data from Survey Sampling Inc., and drew random samples within three firm size and 16 North American Industry Classification System (NAICS) code categories. Thus, within each state, approximately one third of the surveyed employers have 10 to 19 employees, a third have 20 to 49 employees, and a third have 50 to 99 employees.

The initial contact with employers was made by mail, with follow-ups conducted by mail, e-mail, and phone. In each firm, we asked either the owner or manager to complete the survey, as these individuals are likely to be knowledgeable about employee performance, the ease of managing employee absences, as well as employee composition and the incidence of employee

[6] Women who experience childbirth complications are eligible for longer leaves, with doctor certification. The maximum amount of leave under the TDI program is 26 weeks.

[7] See: `https://paidfamilyleave.ny.gov/employees` for more details.

[8] We also surveyed firms in New Jersey but do not use them in this analysis for reasons discussed below.

leave-taking.

In the first survey year (2016), we had a response rate of 46 percent in both states, resulting in a sample of 1,207 firms from each state. In Year 2 (2017), we attempted to re-survey as many firms as possible from the preceding year. We obtained responses from 1,599 of these firms, and recruited 820 new firms to generate a total of 2,419 firms (1,215 from NY and 1,204 from PA). We repeated this process in subsequent years, generating a final sample of 4,573 unique firms that participated in the survey in at least one year.

The survey questionnaire covered multiple domains. First, we obtained data on firm size and employee characteristics, including the share of female employees and the share of employees who work part-time. We also obtained information on the share of employees who quit in the last 12 months and who had been absent without providing notice or with less than 24 hours of notice in the prior month.[9] Second, we asked employers to rate employees' performance on a scale of 1 to 10 (with 1 representing "very poor" and 10 representing "excellent") along the following dimensions: attendance, commitment to the job, cooperativeness to get the job done, productivity, and teamwork. Third, we asked employers to rate their ability to coordinate work schedules and deal with employee absences of various durations (less than two weeks, two to four weeks, and more than four weeks) on a scale of 1 to 10 (with 1 representing "very difficult" and 10 representing "very easy"). Fourth, we asked whether employers had any employee who took time off work in the past year because they had or adopted a child, or had a family member with a serious illness. We also inquired about the employee's gender and the reason for leave (i.e., parental or serious family illness).[10]

As noted previously, we select our control firms from the state of Pennsylvania, which has a lengthy border with NY and has never had a PFL law. We also collected data from another neighboring state, New Jersey, which we hoped could serve as another pool of control firms that have been "always treated", since New Jersey has had a PFL program since 2009.

[9] We asked employers to report the number of employees who are currently on payroll, including full-time, part-time, and temporary workers. We also asked them about the number of employees who are female, the number of employees who work part-time (less than 35 hours), the number of employees who voluntarily left the firm in the past year, and the number of employees who were absent without notice or with less than 24 hours notice in the past month. We used these variables from the first year of data in which we observe each firm to calculate the shares.

[10] For firms that had multiple employees to take leave, we asked about the gender and reason for leave of the most recent leave-taker. We do not have information on employees who had children or had a family member with a serious illness but did not take any leave.

However, in the middle of our data collection, New Jersey substantially expanded its PFL program, making its firms unsuitable controls.[11]

Key outcomes. To study employer ratings of employee performance and the ease of coordinating schedules and dealing with absences, we generate standardized $z-$scores by subtracting the analysis sample mean and dividing by the sample standard deviation. Thus, coefficients in regressions that use these outcomes as dependent variables can be interpreted in SD units.

We also create five indicator variables capturing employee leave-taking. These include binary variables set to 1 for employers who report that any employee has taken any leave for any family-related reason in the past year, and 0 otherwise, as well as separate indicators for employers who report having at least one: female employee taking parental leave; male employee taking parental leave; female employee taking leave to care for a seriously ill family member; and male employee taking leave to care for a seriously ill family member.

Finally, we study changes in employee composition by using as outcomes the shares of workers who quit in the past year, who were absent without advance notice in the past month, who are female, and who work part-time.

4 Empirical Analysis

Our goal is to estimate the causal effect of the NY PFL policy on employer outcomes. We use a difference-in-differences (DD) strategy, comparing the change in outcomes of NY firms to the change in outcomes of control firms, from before to after the policy went into effect. The DD approach relies on the standard assumption that outcomes in the treatment and control firms would have followed parallel trends in the absence of program implementation. Since we only have two pre-policy years of data (2016 and 2017), we are limited in our ability to comprehensively assess the validity of this assumption by analyzing long pre-treatment trends; however, we do examine changes in outcomes between these two years to obtain some indication of whether such trends exist.

To select our control firms, we use the PA data and select a match for each NY firm using

[11] New Jersey elected a new Democratic governor in 2018, who had promised to expand the PFL program. The expansion was signed into law in 2019.

a nearests-neighbor algorithm. Our algorithm makes an exact match on industry sector (one of 16 categories) and an indicator for whether the firm is located in a metro area based on the 2013 Rural-Urban Continuum Code.[12] Then, we conduct a "fuzzy" match (with replacement) using the following variables: number of employees in the firm in the first year available in the data, the 2016 county unemployment rate, and the 2016 county average weekly wage.[13] This process yields a sample consisting of a total of 2,364 matched pairs of firms (2,364 NY firms and their 655 PA matches).

Appendix Table A1 reports the means of county-level characteristics used in the matching process. We report the means for all NY and PA firms in the first two columns, and in the NY and PA firms in the matched pair sample in the following two columns. We also report the difference in means of these variables between firms in NY and PA before the match, along with the mean within-match-pair difference after the match. The table shows that the magnitudes of the differences in these variables decline after matching, indicating that the matched firms from PA more closely resemble firms in NY than when using the full sample of PA firms.

After constructing our matched pair sample, we estimate DD and event-study models that include match-pair×year fixed effects. These models compare changes in the outcomes of NY firms to changes in the outcomes of PA firms within each matched pair. Our DD model takes the following form:

$$Y_{ipst} = \beta_0 + \beta_1 NY_s + \beta_2 Post_t + \beta_3 NY_s \times Post_t + \gamma' X_i + \theta_{pt} + \epsilon_{ipst} \tag{1}$$

for each firm i in matched pair p in state s observed in year t. NY_s is an indicator for firms located in New York, and $Post_t$ is an indicator set to 1 in the post-implementation years (2018 and 2019). X_i is a vector of baseline firm-level control variables measured in the first year the firm is observed in the survey that includes the number of employees, the proportion of employees who: work part-time, are female, have worked for the firm for more than one year,

[12] These codes were obtained from `https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/`.

[13] County-level characteristics are obtained from the 2016 Quarterly Census of Employment and Wages.

quit in the past 12 months, and were absent without advanced notice in the past month.[14] θ_{pt} are interactions between matched pair and survey year fixed effects, allowing us to make comparisons of changes in outcomes within matched pairs of firms. The key coefficient of interest is β_3, which measures the impact of the NY PFL program on the outcome of interest, relative to the change in the matched PA firm over the same time period.

We also estimate event-study models, which replace the single $Post_t$ indicator in equation (1) with indicators for each survey year (while keeping all of the other variables the same). The interactions between the NY_s indicator and the survey year indicators in these event-study models allow us to examine differential trends in outcomes in NY relative to PA firms, both before and after the law. We omit the 2016×NY interaction term, so the other coefficients measure differential trends relative to the first survey year.

Lastly, since we analyze a large set of outcomes, we address concerns with multiple hypothesis testing by using the Romano-Wolf correction. We report the Romano-Wolf $p-$value associated with our key coefficients of interest for each outcome.[15]

Descriptive statistics. Appendix Table A2 reports the means of our key variables in our sample of matched pairs of firms, separately for PA and NY firms, before and after the policy. There are several take-aways from this table. First, average employer ratings of employee performance are consistently high in both states and in all years. In particular, across all five dimensions, and for firms in all categories (PA, NY, pre- and post-policy), the mean rating is higher than 8 on a scale of 1 to 10. This suggests that there is not much scope for improvements to be measured along these dimensions. It is noteworthy that high ratings are observed in both the pre-policy years and in PA, which does not have a PFL policy, suggesting that high ratings on these variables are unlikely to be attributed to the PFL policy.

Second, employer ratings of the ease of coordinating work schedules and dealing with worker absences are considerably lower. Absences longer than four weeks (and to a lesser

[14] We exclude these firm-level baseline controls when analyzing employee characteristics (share of employees who: are female, work part-time, quit in the past year, and were absent without notice in the past month) as outcomes. We also find that our results for other outcomes are similar if we exclude these controls (results available upon request).

[15] The Romano-Wolf correction controls for the familywise error rate, which is the probability of rejecting at least one true null hypothesis among a family of hypotheses under a test. We treat each set of outcomes in each table panel as a family. See Romano and Wolf (2005a), Romano and Wolf (2005b), Romano et al. (2010), Romano and Wolf (2016), Clarke et al. (2020).

extent those between two and four weeks) appear to present particular challenges for many employers. Third, we observe no large changes in employee composition, quit rates, or rates of absences without advance notice in either NY or PA firms. Fourth, although the incidence of leave-taking increases over time in both states, the magnitude of the increase is larger among NY firms.

5 Results

Table 1 reports results on the impacts of the NY PFL policy on employer ratings of employee performance. Panel A presents the estimates of the β_3 coefficients from equation (1), while estimates of the coefficients from the event-study models are in Panel B. As noted above, in addition to reporting heteroskedasticity-robust standard errors, we also display Romano-Wolf p-values that adjust for multiple hypothesis testing. In Panel A, we find no statistically significant impacts on any of the five dimensions of employer ratings of employee performance. The 95% confidence intervals allow us to rule out that NY PFL reduces employer ratings of employee attendance, commitment, cooperation, productivity, and teamwork by more than 0.11, 0.02, 0.02, 0.18, and 0.16 of a standard deviation, respectively. In Panel B, we see a marginally significant improvement in employers' ratings of employee commitment in the first year of the policy, which appears to disappear in the second year.

Table 2 presents the analogous results for employer ratings of the ease of coordinating work schedules and dealing with employee absences of different durations. As with the outcomes in Table 1, we find no evidence of any adverse impacts. If anything, it appears that there are improvements in employers' ability to handle employee absences. Panel A, which presents results from our DD models, shows that the NY PFL policy leads to a 0.27 SD increase in employers' assessment of the ease of dealing with employee absences longer than 4 weeks. The event-study estimates in Panel B indicate that there are no significant pre-trends in these outcomes, and that the positive impacts are large and statistically significant in the first year after implementation, becoming insignificant in the second year. Specifically, in the first year of the policy, PFL is estimated to reduce the difficulty of dealing with absences of 4 weeks or more by 0.32 SD and of dealing with absences 2–4 weeks long by 0.38 SD. There is also some

suggestive evidence of an improvement in the ease of coordinating work schedules in the first year, but we note that this result is not robust to multiple hypothesis adjustments, and may in part reflect the continuation of a pre-policy trend (i.e., the coefficient on the interaction term between NY and 2017, the year immediately before the policy, is also fairly large and positive, albeit insignificant).

Next, we analyze employee leave-taking variables in Table 3. While none of the coefficients is statistically significant in the DD models in Panel A, we do find that the effects on leave-taking materialize in the second year of the policy in the event-study models in Panel B. Specifically, we find a 19.5 percentage point (50 percent at the pre-policy mean) increase in the likelihood of any employee using any leave in the second year post-law. This impact appears to be driven by increases in the likelihood of female employees taking parental leave, male employees taking parental leave, and male employees using leave to care for ill family members.

In Table 4, we check whether the effects on employers' ratings of the ease of dealing with employee absences are heterogeneous across firms with and without any recent experience with workers taking leave by including an interaction with the indicator for whether a firm has any employee taking any leave in the past 12 months. While the results are not statistically significant once we account for multiple hypothesis testing, the large positive coefficients on the interaction terms are consistent with the improvement in the ease of dealing with employee absences being concentrated among firms that have had at least one employee take leave.

Lastly, Table 5 reports the results for the employee attributes (share part-time, share female, etc.) from our DD and event-study models. We do not see any statistically significant impacts on any of these outcomes. These results suggest that the previously discussed findings on employer experiences with dealing with worker absences and on employee leave-taking rates are not driven by changes in firm composition.

We explore heterogeneity in our findings by firm size in Appendix Tables A3 through A5. We split our sample into larger firms with 50 or more employees and smaller firms with 10 to 49 employees, reflecting FMLA eligibility for the former but not the latter sub-group. Interestingly, the increase in employee leave-taking occurs exclusively among the smaller firms, which is consistent with workers at these firms previously not having any access to government-

provided job-protected leave. The impacts on the ease of handling employee absences are positive in both smaller and larger firms in our sample, with bigger point estimates for larger employers, although none of these effects is statistically significant due to small sample sizes.

6 Discussion

Opposition to government-provided paid family leave in the United States largely rests on an argument that this policy will impose large burdens on businesses, especially small businesses. Accordingly, business community leaders, trade groups such as the National Federation of Independent Business, and the U.S. Chamber of Commerce have repeatedly expressed concerns with proposed PFL legislation.[16] However, empirical evidence supporting these arguments has been lacking, largely due to data constraints.

We bring new data and empirical analysis to inform this discussion, finding that PFL does not appear to impose large burdens on firms. We study New York's PFL program, which went into effect in 2018, and analyze outcomes among firms with 10—99 employees, using a survey that we conducted over a four-year period from 2016 to 2019. We match each NY firm with a PA firm on observable characteristics, and then estimate difference-in-differences models within matched pairs to compare changes in outcomes in NY firms from before to after the policy was implemented relative to changes in similar firms in PA during the same time period.

Our analysis generates strong evidence that New York's PFL policy has *not* had adverse impacts on the employer outcomes measured in our survey. There are no statistically significant or economically meaningful adverse impacts on employer ratings of employee performance in terms of attendance, commitment, cooperation, productivity, and teamwork. Our regression estimates allow us to rule out that NY PFL reduces these outcomes by more than 0.11, 0.02, 0.02, 0.18, and 0.16 of an SD, respectively. We also find no indication that NY PFL has made it harder for employers to deal with workers' absences. Instead, we find a 0.27 SD increase in employers' rating of their ease of handling workers' absences longer than four

[16] For more discussion of the opposition of PFL in the business community, see, for example: `https://www.npr.org/sections/itsallpolitics/2015/07/15/422957640/lots-of-other-countries-mandate-paid-leave-why-not-the-us`.

weeks in duration. It seems plausible that employers—who previously may have managed their employees' needs for extended time off on a case-by-case basis—find it easier to use a standardized state PFL program instead.

We also find a large increase in the incidence of employee leave-taking in the second year post-policy, concentrated among firms whose employees were previously not eligible for FMLA leave. Lastly, we do not observe any changes in the shares of female or part-time workers, quit rates, or the rates of absences without advance notice, suggesting that the impacts on employers' ease of dealing with absences and employee leave-taking are not driven by changes in employee composition.

While our study delivers some of the first estimates of the causal impacts of PFL on employer outcomes, important questions remain. As noted above, the New York program gradually expanded in generosity through 2021, and more research is needed to shed light on how changes in program parameters influence employers. More generally, our data reflect a phase-in period when employers (and employees) were still learning about the program. Qualitative comments from firms in our study indicate that some of them lacked adequate understanding of program details, a problem likely more significant for smaller firms who may not have access to professional human resources staff and support. More follow-up, especially with the smallest firms in our sample, may be necessary to understand how employers learn about and implement state-level PFL programs.

It is also important to note that in 2017, the year before NY PFL went into effect, New York state initiated a gradual minimum wage policy targeting a $15 minimum wage, with the exact schedule varying by region and firm size.[17] This policy may have also influenced employer outcomes, although it is unlikely to have had a direct impact on their ease of managing employee absences. That said, the initiation of the minimum wage policy may help explain some of the "pre-trend" coefficients for employer ratings of employee performance.[18]

Further, the COVID-19 pandemic has significantly disrupted business operations and underscored the importance of paid leave for workers who get sick, must take care of ill family

[17] For more details, see: `https://labor.ny.gov/stats/minimum_wage.shtm`.

[18] We do not have information on employee wages in our data, preventing us from directly analyzing firms with employees who were likely affected by the minimum wage policy. That said, we have examined heterogeneity across firms in industries with more and fewer minimum wage workers based on information from the American Community Survey data, finding no evidence that these firms were differentially affected by NY PFL.

members, or lack childcare due to closures of schools and daycares. Our most recent follow-up survey from fall 2020 will provide more evidence on the implications of New York's PFL program for businesses during COVID-19.

Finally, our pre-PFL period only includes two years of data collection, which limits our ability to comprehensively assess outcome pre-trends. We also note that our matching algorithm selected only a subset of the Pennsylvania firms as suitable controls for the New York firms, indicating important differences in employer characteristics between the two states. As a growing number of states are planning to implement PFL programs in the coming years, researchers may consider collecting baseline data from other states for future analyses of PFL impacts on employer outcomes.

References

Appelbaum, Eileen and Ruth Milkman, "Leaves that Pay: Employer and Worker Experiences with Paid Family Leave in California," report, Center for Economic and Policy Research 2011.

Bana, Sarah H, Kelly Bedard, and Maya Rossin-Slater, "The impacts of paid family leave benefits: regression kink evidence from California administrative data," *Journal of Policy Analysis and Management*, 2020, *39* (4), 888–929.

Bana, Sarah, Kelly Bedard, Maya Rossin-Slater, and Jenna Stearns, "Unequal use of social insurance benefits: The role of employers," Working Paper 25163, National Bureau of Economic Research 2018.

Bartel, Ann, Maya Rossin-Slater, Christopher Ruhm, and Jane Waldfogel, "Assessing Rhode Island's Temporary Caregiver Insurance Act: Insights from a Survey of Employers," Report, US Department of Labor, Chief Evaluation Office 2016.

Brenøe, Anne A, Serena P Canaan, Nikolaj A Harmon, and Heather N Royer, "Is Parental Leave Costly for Firms and Coworkers?," Working Paper 26622, National Bureau of Economic Research 2020.

Campbell, Z., I. Chin, E. Chyn, and J. Hastings, "The impact of paid leave: Evidence from temporary disability insurance in Rhode Island," 2017. Brown University, unpublished manuscript.

Clarke, Damian, Joseph P Romano, and Michael Wolf, "The Romano–Wolf multiple-hypothesis correction in Stata," *The Stata Journal*, 2020, *20* (4), 812–843.

Gallen, Yana, "The effect of parental leave extensions on firms and coworkers," 2019. University of Chicago, unpublished manuscript.

Ginja, Rita, Arizo Karimi, and Pengpeng Xiao, "Employer responses to family leave programs," Discussion Paper 13833, IZA 2020.

Goodman, Julia M, Holly Elser, and William H Dow, "Employer-Reported Access to Paid Parental Leave: A study of San Francisco's Paid Parental Leave Ordinance," *SSM-population health*, 2020, *11*, 100627.

Huebener, Mathias, Jonas Jessen, Daniel Kuehnle, and Michael Oberfichtner, "A Firm-Side Perspective on Parental Leave," 2020. DIW Berlin, unpublished manuscript.

Kamal, Fariha, Asha Sundaram, and Cristina J Tello-Trillo, "Family-Leave Mandates and Female Labor at US Firms: Evidence from a Trade Shock," Working Paper CES-20-25, Center for Economic Studies 2020.

Lerner, Sharon, Eileen Appelbaum et al., "Business as usual: New Jersey employers' experiences with family leave insurance," Report 2014-12, Center for Economic and Policy Research (CEPR) 2014.

Milkman, Ruth and Eileen Appelbaum, *Unfinished Business: Paid Family Leave in California and the Future of U.S. Work-Family Policy*, Cornell University Press, 2013.

Olivetti, Claudia and Barbara Petrongolo, "The economic consequences of family policies: lessons from a century of legislation in high-income countries," *Journal of Economic Perspectives*, 2017, *31* (1), 205–30.

Romano, Joseph P and Michael Wolf, "Exact and approximate stepdown methods for multiple hypothesis testing," *Journal of the American Statistical Association*, 2005, *100* (469), 94–108.

_ **and** _ , "Stepwise multiple testing as formalized data snooping," *Econometrica*, 2005, *73* (4), 1237–1282.

_ **and** _ , "Efficient computation of adjusted p-values for resampling-based stepdown multiple testing," *Statistics & Probability Letters*, 2016, *113*, 38–40.

_ **, Azeem M Shaikh, and Michael Wolf**, "Hypothesis testing in econometrics," *Annu. Rev. Econ.*, 2010, *2* (1), 75–104.

Rossin-Slater, Maya, "Maternity and Family Leave Policy," in Susan L. Averett, Laura M. Argys, and Saul D. Hoffman, eds., *Oxford Handbook of Women and the Economy*, New York: Oxford University Press, 2018.

_ **and Jenna Stearns**, "Time On with Baby and Time Off from Work.," *Future of Children*, 2020, *30* (2).

_ **and Lindsey Uniat**, "Paid family leave policies and population health," *Health Affairs Health Policy Brief*, 2019.

7 Tables

Table 1: DD and Event-Study Estimates of the Effects of NY Paid Family Leave on Employer Ratings of Employee Performance

	(1) Attendance	(2) Commitment	(3) Cooperation	(4) Productivity	(5) Teamwork
A. DD Models					
Post × NY	0.039	0.134	0.147	-0.017	0.008
	[0.077]	[0.081]	[0.083]	[0.081]	[0.083]
Romano-Wolf p-value	0.972	0.505	0.495	0.986	0.986
B. Event-Study Models					
2017 × NY	-0.032	0.098	0.238	0.228	0.196
(pre-policy)	[0.121]	[0.129]	[0.133]	[0.126]	[0.132]
Romano-Wolf p-value	0.956	0.956	0.956	0.585	0.731
2018 × NY	0.115	0.311*	0.375	0.225	0.217
(post-policy)	[0.112]	[0.118]	[0.123]	[0.122]	[0.125]
Romano-Wolf p-value	0.327	0.082	0.122	0.327	0.327
2019 × NY	-0.068	0.060	0.165	-0.024	0.001
(post-policy)	[0.108]	[0.114]	[0.121]	[0.118]	[0.121]
Romano-Wolf p-value	0.625	0.663	0.715	0.303	0.473
Firm/Year Observations	9186	9188	9192	9181	9170

Notes: All dependent variables are expressed as $z-$scores. Panel A reports the β_3 coefficients from equation (1), while Panel B reports the coefficients from the event-study version of equation (1), separately for each dependent variable. Heteroskedasticity robust standard errors are in brackets, while Romano-Wolf p-values adjusted for multiple hypothesis testing are reported in the rows below the standard errors. Significance levels (based on Romano-Wolf p-values): * p<0.1 ** p<0.05 *** p<0.01.

Table 2: DD and Event-Study Estimates of the Effects of NY Paid Family Leave on Employer Ratings of the Ease of Coordination and Handling of Employee Absences

	(1) Coordination	(2) Handling Absences <2 Weeks	(3) Handling Absences 2-4 Weeks	(4) Handling Absences >4 Weeks
A. DD Models				
Post × NY	0.158	0.115	0.194	0.266**
	[0.086]	[0.085]	[0.086]	[0.086]
Romano-Wolf p-value	0.268	0.268	0.170	0.032
B. Event-Study Models				
2017 × NY	0.147	0.055	0.005	-0.121
(pre-policy)	[0.132]	[0.132]	[0.135]	[0.137]
Romano-Wolf p-value	0.926	0.926	0.611	0.158
2018 × NY	0.293	0.206	0.381***	0.316**
(post-policy)	[0.125]	[0.122]	[0.126]	[0.129]
Romano-Wolf p-value	0.246	0.246	0.006	0.034
2019 × NY	0.173	0.082	0.018	0.094
(post-policy)	[0.119]	[0.120]	[0.121]	[0.123]
Romano-Wolf p-value	0.996	0.996	0.615	0.996
Firm/Year Observations	9148	9117	9030	9047

Notes: All dependent variables are expressed as $z-$scores. Panel A reports the β_3 coefficients from equation (1), while Panel B reports the coefficients from the event-study version of equation (1), separately for each dependent variable. Heteroskedasticity robust standard errors are in brackets, while Romano-Wolf p-values adjusted for multiple hypothesis testing are reported in the rows below the standard errors. Significance levels (based on Romano-Wolf p-values): * p<0.1 ** p<0.05 *** p<0.01.

Table 3: DD and Event-Study Estimates of the Effects of NY Paid Family Leave on Employee Leave-Taking

	(1) Any Employee, Any Leave	(2) Female Employee, Parental	(3) Male Employee, Parental	(4) Female Employee, Serious Fam. Illness	(5) Male Employee, Serious Fam. Illness
A. DD Models					
Post × NY	0.061	0.041	0.028	-0.010	0.034
	[0.042]	[0.032]	[0.030]	[0.029]	[0.026]
Romano-Wolf p-value	0.755	0.767	0.767	0.798	0.767
B. Event-Study Models					
2017 × NY	0.075	0.023	-0.010	0.049	0.066
(pre-policy)	[0.062]	[0.044]	[0.042]	[0.040]	[0.033]
Romano-Wolf p-value	0.944	0.944	0.942	0.864	0.942
2018 × NY	0.002	0.003	-0.039	0.025	0.032
(post-policy)	[0.059]	[0.045]	[0.042]	[0.040]	[0.036]
Romano-Wolf p-value	0.555	0.800	0.555	0.884	0.800
2019 × NY	0.195**	0.103	0.085	0.005	0.104
(post-policy)	[0.059]	[0.043]	[0.040]	[0.041]	[0.036]
Romano-Wolf p-value	0.046	0.178	0.124	0.705	0.178
Pre-Policy Dep. Var. Mean	0.390	0.158	0.128	0.111	0.080
Firm/Year Observations	9226	9227	9227	9226	9227

Notes: Panel A reports the β_3 coefficients from equation (1), while Panel B reports the coefficients from the event-study version of equation (1), separately for each dependent variable. Heteroskedasticity robust standard errors are in brackets, while Romano-Wolf p-values adjusted for multiple hypothesis testing are reported in the rows below the standard errors. Significance levels (based on Romano-Wolf p-values): * p<0.1 ** p<0.05 *** p<0.01.

Table 4: Differential Effects of NY Paid Family Leave on Employer Ratings of the Ease of Coordination and Handling of Employee Absences, by Whether Firms Have Any Leave-Takers

	(1) Coordination	(2) Handling Absences <2 Weeks	(3) Handling Absences 2-4 Weeks	(4) Handling Absences >4 Weeks
Post × NY	0.025	-0.056	0.046	0.040
	[0.134]	[0.132]	[0.137]	[0.138]
Romano-Wolf p-value	0.990	0.990	0.990	0.990
Any Leave-Takers × Post × NY	0.332	0.411	0.369	0.565
	[0.245]	[0.247]	[0.249]	[0.253]
Romano-Wolf p-value	0.443	0.427	0.443	0.228
Firm/Year Observations	9147	9116	9029	9046

Notes: All dependent variables are expressed as $z-$scores. This table reports the coefficients from estimating an augmented version of equation (1), which includes an indicator for whether a firm/year observation has at least one employee who has taken any leave in the past 12 months, as well as an interactions between this indicator and the NY_s indicator, the $Post_t$ indicator, and the triple interaction with $NY_s \times Post_t$. Models are estimated separately for each dependent variable. Heteroskedasticity robust standard errors are in brackets, while Romano-Wolf p-values adjusted for multiple hypothesis testing are reported in the rows below the standard errors. Significance levels (based on Romano-Wolf p-values): * p<0.1 ** p<0.05 *** p<0.01.

Table 5: DD and Event-Study Estimates of the Effects of NY Paid Family Leave on Employee Attributes

	(1) Share Part-Time	(2) Share Female	(3) Share Quit	(4) Share Absent w/out Notice
A. DD Models				
Post × NY	0.014	0.007	0.003	0.017
	[0.018]	[0.019]	[0.021]	[0.009]
Romano-Wolf p-value	0.892	0.958	0.958	0.407
B. Event-Study Models				
2017 × NY	0.028	0.120	-0.004	-0.023
(pre-policy)	[0.027]	[0.027]	[0.037]	[0.013]
Romano-Wolf p-value	0.968	0.118	0.968	0.196
2018 × NY	0.035	0.081	0.009	0.005
(post-policy)	[0.026]	[0.027]	[0.026]	[0.012]
Romano-Wolf p-value	0.904	0.904	0.904	0.904
2019 × NY	0.022	0.059	-0.007	0.006
(post-policy)	[0.025]	[0.026]	[0.025]	[0.012]
Romano-Wolf p-value	0.982	0.966	0.966	0.741
Pre-Policy Dept. Var. Mean	0.294	0.459	0.194	0.088
Firm/Year Observations	9759	9751	9533	9358

Notes: Panel A reports the β_3 coefficients from equation (1), while Panel B reports the coefficients from the event-study version of equation (1), separately for each dependent variable. Heteroskedasticity robust standard errors are in brackets, while Romano-Wolf p-values adjusted for multiple hypothesis testing are reported in the rows below the standard errors. Significance levels (based on Romano-Wolf p-values): * p<0.1 ** p<0.05 *** p<0.01.

For Online Publication

The Impact of Paid Family Leave on Employers: Evidence from New York's 2018 Policy

Bartel, Rossin-Slater, Ruhm, Slopen, and Waldfogel (2021)

Table A1: Pre- and Post-Match Variable Means, NY and PA Firms, 2016–2019

	All Firms		Matched Firms		Pre-Match	Post-Match
	NY	PA	NY	PA	Diff.	Diff.
County Unemployment Rate, 2016	4.593	5.575	4.593	4.748	-0.981	-0.154
County Average Weekly Wage, 2016	1200.34	1025.37	1200.34	1063.47	174.964	136.86
Number of Employees at Baseline	36.680	36.002	36.680	36.281	0.678	0.407
Number Unique Firms	2364	2198	2364	655		

Notes: The first two columns report means for all NY and PA firms in our data, respectively. The next two columns report means for NY and PA firms in the matched-pair sample, respectively. The second-to-last column ("Pre-Match Diff.") reports the difference between mean characteristics in NY and PA firms before the match. The last column ("Post-Match Diff.") provides the mean within-matched-pair difference. County-level characteristics are from the 2016 Quarterly Census of Employment and Wages. Firms are also matched on exact NAICS industry code and an indicator for whether the firm is in a metro area.

Table A2: Means of Key Outcome Variables, Matched Pair Sample

	PA Firms		NY Firms	
	Pre	Post	Pre	Post
A. Employer Ratings of Employee Performance				
Attendance	8.11	8.08	8.05	8.08
Commitment	8.14	8.11	8.17	8.26
Cooperation	8.30	8.21	8.29	8.38
Productivity	8.05	8.11	8.15	8.21
Teamwork	8.01	8.15	8.21	8.29
B. Employer Ratings of Ease of Coordination and of Handling Absences				
Ease of Coordination	7.44	7.39	7.33	7.39
Ease of Handling Absences < 2 Weeks	6.80	6.57	6.71	6.58
Ease of Handling Absences $2 - 4$ Weeks	5.35	4.70	5.16	4.87
Ease of Handling Absences > 4 Weeks	4.48	3.51	4.13	3.70
C. Incidence of Employee Leave in Past 12 Months				
Female Employee—Parental	0.17	0.20	0.14	0.21
Male Employee—Parental	0.13	0.17	0.12	0.15
Female Employee—Serious Family Illness	0.10	0.14	0.12	0.17
Male Employee—Serious Family Illness	0.08	0.11	0.07	0.14
Any Employee Taking Leave	0.38	0.47	0.38	0.53
D. Employee Attributes				
Share Part-time	0.29	0.27	0.30	0.28
Share Female	0.45	0.49	0.46	0.49
Share Quit in the Past Year	0.18	0.16	0.21	0.17
Share Absent Without Notice	0.09	0.08	0.08	0.09
Number of Unique Firms	461	473	1624	1638

Notes: This table presents the means of the matched sample of firms in the pre- and post-policy periods (2016-2017 and 2018-2019, respectively). Panel A presents employer ratings of employee performance, while Panel B presents employer ratings of the ease of coordination and of handling employee absences, on a scale of 1 to 10, with 1 being the most negative rating and 10 being the most positive rating. Panel C provides the proportion of firms with at least one employee using leave by gender and type of leave. Panel D provides the proportion of employees in a firm by attribute.

Table A3: DD Estimates of the Effects of NY Paid Family Leave on Employer Ratings of Employee Performance and Ease of Coordination and Handling of Employee Absences, by Firm Size

A. Employer Ratings of Employee Performance

	(1) Attendance	(2) Commitment	(3) Cooperation	(4) Productivity	(5) Teamwork
Firms with 50–99 Employees					
Post × NY	-0.139	0.141	0.049	0.000	0.031
	[0.138]	[0.153]	[0.162]	[0.150]	[0.155]
Romano-Wolf p-value	0.856	0.856	0.986	0.992	0.986
Firm/Year Observations	3103	3100	3102	3096	3102
Firms with 10–49 Employees					
Post × NY	0.153	0.113	0.189	-0.032	-0.025
	[0.099]	[0.098]	[0.099]	[0.102]	[0.102]
Romano-Wolf p-value	0.571	0.715	0.465	0.944	0.944
Firm/Year Observations	6083	6088	6090	6085	6068

B. Employer Ratings of Ease of Coordination and of Handling Absences

	(1) Coordination	(2) Handling Absences <2 Wks	(3) Handling Absences 2-4 Wks	(4) Handling Absences >4 Wks
Firms with 50–99 Employees				
Post × NY	0.391	0.274	0.798	1.085
	[0.294]	[0.303]	[0.358]	[0.409]
Romano-Wolf p-value	0.523	0.523	0.230	0.138
Firm/Year Observations	3078	3054	3036	3024
Firms with 10–49 Employees				
Post × NY	0.175	0.119	0.131	0.339
	[0.211]	[0.240]	[0.261]	[0.265]
Romano-Wolf p-value	0.844	0.874	0.874	0.723
Firm/Year Observations	6070	6063	5994	6023

Notes: All dependent variables are expressed as $z-$scores. The table reports the β_3 coefficients from equation (1), separately for each dependent variable, and for each sub-sample. Heteroskedasticity robust standard errors are in brackets.

Table A4: DD Estimates of the Effects of NY Paid Family Leave on Employee Leave-Taking, by Firm Size

	(1) Any Employee, Any Leave	(2) Female Employee, Parental	(3) Male Employee, Parental	(4) Female Employee, Serious Fam. Illness	(5) Male Employee, Serious Fam. Illness
Firms with 50–99 Employees					
Post × NY	-0.078	-0.012	-0.019	-0.048	-0.021
	[0.074]	[0.067]	[0.063]	[0.056]	[0.052]
Romano-Wolf p-value	0.938	0.982	0.982	0.956	0.982
Pre-Policy Dep. Var. Mean	0.434	0.215	0.140	0.116	0.101
Firm/Year Observations	3113	3114	3114	3113	3114
Firms with 10–49 Employees					
Post × NY	0.148	0.075	0.061	0.010	0.061
	[0.054]	[0.038]	[0.035]	[0.037]	[0.031]
Romano-Wolf p-value	0.160	0.359	0.359	0.908	0.359
Pre-Policy Dep. Var. Mean	0.366	0.127	0.122	0.109	0.068
Firm/Year Observations	6113	6113	6113	6113	6113

Notes: The table reports the β_3 coefficients from equation (1), separately for each dependent variable, and for each sub-sample. Heteroskedasticity robust standard errors are in brackets.

Table A5: DD Estimates of the Effects of NY Paid Family Leave on Employee Attributes, by Firm Size

	(1) Share Part-Time	(2) Share Female	(3) Share Quit	(4) Share Absent w/out Notice
Firms with 50–99 Employees				
Post × NY	0.028	0.016	-0.013	0.026
	[0.033]	[0.030]	[0.019]	[0.012]
Romano-Wolf p-value	0.872	0.872	0.872	0.275
Pre-Policy Dep. Var. Mean	0.282	0.485	0.167	0.069
Firm/Year Observations	3392	3394	3261	3158
Firms with 10–49 Employees				
Post × NY	0.007	0.003	0.015	0.011
	[0.024]	[0.026]	[0.032]	[0.013]
Romano-Wolf p-value	0.976	0.976	0.974	0.930
Pre-Policy Dep. Var. Mean	0.301	0.445	0.209	0.098
Firm/Year Observations	6367	6357	6271	6200

Notes: The table reports the β_3 coefficients from equation (1), separately for each dependent variable, and for each sub-sample. Heteroskedasticity robust standard errors are in brackets.