國立政治大學應用經濟與社會發展英語碩士學位學程

International Master’s Program of Applied Economics and Social Development

College of Social Sciences
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碩士論文
Master’s Thesis

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Acknowledgments

I would like to first and foremost thank my advisor, Professor Tzu-Ting Yang, for taking me on as his advisee and believing in me. I am also immensely indebted to the members of my thesis committee, Professor Po-Chun Huang and Professor Terry Cheung, for their time, valuable suggestions, and constructive criticisms. 我想向我的政治大學足球教練林貴彬表達我的感激之情，感謝他在我足球生涯中的支持。Lastly, I am grateful to my parents and brother Alex for their support and encouragement from halfway across the world.

Abstract

This paper analyzes the effects of the New York Paid Family Leave (NY-PFL) on fertility and leave-taking rates. First, using a difference-in-differences strategy, I discover that NY-PFL increased the fertility rate of New York mothers by 2.9 percent where Black and women in their 40s were most sensitive to the policy. Next, I employ a difference-in-difference-in-differences design to find that New York mothers are 10.8 percent more likely to be on leave following the NY-PFL. The effects were largest for disadvantaged women, namely Black and non-college-educated women, followed by college-educated and Asian women. In addition, the increases were primarily driven by older women in theirs 30s and 40s.
Keywords: paid leave, fertility, mother's labor supply, New York reform

本文分析紐約提帶薪育嬰假（NY-PFL）對生育率和休假率的影響。首先，使用差異中差異法，我發現NY-PFL將紐約母親的生育率提高了2.9%，其中黑人和40多歲的女性受到政策的影響最大。接下來，我發現NY-PFL實施後，紐約母親休假的可能性增加了10.8%。影響最大的是弱勢女性，即黑人和非大學教育的女性，其次是大學教育和亞洲女性。最後，我也發現30-40歲的女性在改革後較容易休假。
關鍵詞**:** 育嬰津貼, 生育, 婦女勞動, 紐約州改革

Contents

1 Introduction

The U.S. still remains the only advanced country to not offer a mandated national paid family leave (PFL) despite its benefits such as promoting gender equality and improving the health of both the mother and child [Waldfogel, 1998; Tanaka, 2005; Pronzato, 2009; Burtle and Bezruchka, 2016]. As a result, New York became only the fourth state to enact a state-level PFL in 2018 following California, New Jersey, and Rhode Island. The New York Paid Family Leave (NY-PFL) is currently the most generous paid leave plan in the U.S. in terms of duration and unlike some states, offers job protection for all employees.

This paper looks at the effects of the NY-PFL on two outcomes, fertility and leave-taking rates, which is important for a few reasons. First, fertility rates have been in a state of decline throughout developed countries for many decades. Along with low fertility rates come an ageing population, a strain on government resources, and shrinking labor force which if left unresolved, can have dire consequences [Nagarajan et al., 2016; McDonald and Kippen, 2001]. By understanding the fertility behaviors in response to paid leave implementations, the policy could potentially serve as a pro-natal strategy in order to mitigate the falling fertility rate. Second, as both paid and unpaid maternity leave are associated with numerous benefits, analyzing leave-taking utilization can help determine whether the policies are achieving their intended goals such as increased access to leave. However, research shows that the current family leave law in the U.S. may not be proportionately utilized across subgroups. Han et al. (2009) present evidence that the Family and Medical Leave Act (FMLA), the national unpaid leave in the U.S., have greater leave-taking usage by college-educated and married mothers. A monthly review[1] by the U.S. Bureau of Labor Statistic also finds that Hispanic workers have much lower rates of access when compared to White non-Hispanic workers. The results from this paper may guide policymakers in other states that have yet to enact PFL by providing evidence on how it affects fertility and leave utilization.

In this paper, I use multiple econometric methods to find the effects of NY-PFL on fertility rates and mother's leave-taking rates. I first begin with a difference-in-difference model to compare the fertility rates in New York compared to the other states before and after the policy implementation. As a robustness check, I employ the synthetic control method with the same data but using a longer time period as it benefits from longer pre-treatment periods. Finally, I use a difference-in-difference-in-differences (triple differences) strategy to compare the leave-taking rates of mothers of infants to mothers of 1-3 year olds in New York versus the control states before and after 2018.

The effects of paid leave on fertility and leave-taking have been a widely explored topic and the subject of many papers, especially in Europe. However, due to the lack of paid leave availability in the U.S., research on the topic within the country has been sparse. In addition, responses to the policy may significantly differ between the U.S. and other countries as the latter typically offer a longer and more comprehensive plan. Cultural differences such as ethic diversity and work culture are also major differences. Presently, existing studies in the U.S. mainly focus on California's PFL as it is the oldest and before NY-PFL was an-

[1] https://www.bls.gov/opub/mlr/2019/article/racial-and-ethnic-disparities-in-access-to-and-use-of-paid-family-and-medical-leave.htm

nounced, most generous in terms of duration and benefit amount. By studying the effects of New York, this paper adds to limited research surrounding the effects of paid leave in the U.S.

2 Background

Paid family leave (PFL) is a measure which allows employees compensated time away from work to care for a newborn child or sick family member. There is extensive research and evidence showing the benefits of PFL including greater overall health to the infant and mother as well as the promotion of equality across genders and socioeconomic status [Waldfogel, 1998; Tanaka, 2005; Pronzato, 2009; Burtle and Bezruchka, 2016]. As such, while governments are motivated to offer paid family leave for multiple reasons, the two major factors are often to raise the female labor supply and encourage fertility [Thévenon, 2011].

In addition, most developed nations have implemented some form of paid family leave policy with the exception of the United States. For instance, Spain, France, Germany, and Finland allow for a maximum of over 150 weeks of job-protected leave while many countries including Japan, Canada, and Sweden provide at least 50 weeks of paid leave. Meanwhile, the U.S. only offers 12 weeks of national unpaid leave. For the states that do have paid family leaves, only some are job-protected while the majority have a leave duration of 10 weeks or less.

2.1 Paid Family Leave in the United States

In the United States, the Family and Medical Leave Act (FMLA) of 1993 is unpaid and currently the only national maternity leave available to employed mothers. It allows eligible employees 12 weeks of unpaid time off work during any 12-month period and does not offer financial compensation. However, in addition to the financial strain associated with an unpaid leave, more than 40%[2] of employees are estimated to be ineligible due to the strict requirements such as 12-months of work with the current employer along with at least 1,250 hours worked during this time. Many states have therefore passed policies and programs to supplement the FMLA to assist mothers in managing both work and family.

In 2004, California became the first state to introduce a statewide paid family leave followed by New Jersey and Rhode Island in 2009 and 2014, respectively. Despite being the first state, California had the most extensive coverage of the three allowing both mothers and fathers six weeks (eight weeks from 2020) of benefits and up to 55% of wages covered. Though not provided by the policy, employees may qualify for job protection if taken in tandem with FMLA.

New York first announced its paid leave in 2016 with an effective date of January 2018. Following a schedule, it offered 50% of average weekly wages (AWW) for 8 weeks in 2018, 55% of AWW for 10 weeks in 2019, 60% of AWW for 10 weeks in 2020, and ending with 67% of AWW for 12 weeks in 2021. The policy is funded via deductions in employee payrolls and is accompanied with job protection. Eligibility is more relaxed

[2] https://www.dol.gov/sites/dolgov/files/OASP/legacy/files/FMLA-2012-Technical-Report.pdf

when compared to the FMLA with full-time employees being eligible after working for 26 consecutive weeks for at least 20 hours per week. Once eligible, mothers are able to take their leave any time before and up to the child's first birthday.

2.2 Fertility

The ongoing concern in recent times for many developed countries has been the persistent decline in fertility rates. A low fertility rate is typically followed by an ageing population triggering negative impacts on economic growth in the form of increased public expenditure, decreased human capital, and changing patterns in consumptions and savings [Nagarajan et al., 2016; McDonald and Kippen, 2001; Grant et al., 2006] A total fertility rate (TFR) of 2.1 is the level at which a population replaces itself and neither grows nor shrinks but most developed countries rest far below this replacement level. In 2022, the TFR fell to 1.5 in the European Union and reached as low as 1.2 in Taiwan and 0.8 in South Korea. The United States, too, has not been able to escape declining fertility behaviors reaching a record low TFR of 1.64 in 2020 and increasing slightly to 1.66 in 2021, the first rise in seven years[3].

Under the economic framework presented by Becker (1960), children are likened to a durable good that generate income and is constrained by income and costs. It follows the utility maximization curve where increases in income and reductions in expenses positively influence the demand for children [McDonald, 2006; Gauthier, 2007]. Paid leave, on the other hand, reduces the opportunity costs of time off work to care for

[3]https://www.cdc.gov/nchs/data/vsrr/vsrr020.pdf

a child as well as lower the overall cost of having a child [Luci-Greulich and Thévenon, 2013]. Additionally, disadvantaged mothers who are more financially constrained are less likely to utilize paid leave when the wage replacement rate is low.

Bergsvik et al. (2020) provide evidence that policies which had the greatest effect on fertility were cash transfers but the results of paid leave were ambiguous primarily due to the difficulty in policy evaluation. A study by Gauthier (2007) also finds the impacts on fertility to be conflicting depending on the data and policies. Australia showed no overall significant increase after implementing pro-natal policies, except for mothers who initially intended to have children [Bassford and Fisher, 2020] and in Slovenia, family policy measures had no positive impact [Stropnik and Šircelj, 2008]. However, fertility in countries such as Germany and Sweden have all shown large increases [Hoem, 2005; Cygan-Rehm, 2016]. Additionally, in the state of California, another highly populated state similar to New York, overall fertility significantly increased following the state paid leave policy [Golightly and Meyerhofer, 2022].

2.3 Leave-taking

After the birth of a child, mothers do not always take extended breaks from work. Reasons include financial constraints from long periods without pay, career advancement goals, and even social stigma. In addition, a study conducted by the California Field Poll in 2015 showed that, more than 10 years after the PFL implementation, only 36% of voters were aware that such policies existed[4].

[4]DiCamillo, M. & Field, M. (2015) The California Field Poll. California Center for Research on Women and Families.

In the labor supply framework, women with higher income will return to work sooner and those who have invested more "firm-specific human capital" have a greater incentive to keep their current position. [Klerman and Leibowitz, 1994]. Searching for a new job will likely result in lower wages and come with additional job searching costs. If the family leave is unpaid, the duration of leave will be limited by the mother's financial circumstance. For the group of mothers who would have quit and accepted a lower wage because of the less preferred duration or compensation of the current leave, a paid leave would increase their job continuity [Klerman and Leibowitz, 1999].

Current literature has largely been consistent when observing job continuity and leave-taking after paid leave goes into effect. A study analyzing nine European countries found that both short-term (three months) and long-term (nine months) leave increased job continuity amongst mothers, and mothers with higher work capital return to work sooner than mothers who have greater family income [Pronzato, 2009]. Moreover, paid and unpaid leaves in the U.S. have also shown to increase overall leave-taking although responses between subgroups have differed. The enactment of FMLA, an unpaid leave policy, resulted in a greater increase in leave-taking rates for college-educated, married women, but insignificant effects for less educated women [Han et al., 2009]. The California paid leave policy had a larger impact on disadvantaged groups or non-college educated, Black, and Hispanic mothers [Rossin-Slater et al., 2013]. Whereas educated mothers are more likely to be able to withstand longer periods without income, disadvantaged mothers may simply not have the financial resources to forego compensation. As evidenced by existing research, allowing greater opportunities of paid leave access through financial compensation may reduce the disparity of leave-taking rates between subgroups.

3 Data

I gather data from two primary sources. I use birth data from the National Vital Statistics System (NVSS) by the U.S. Centers for Disease Control and Prevention and microdata from the American Community Survey (ACS), the largest survey conducted by the U.S. Census Bureau, to analyze the effects on fertility rates and leave-taking rates, respectively.

The NVSS birth data provides information of every birth in the U.S. and detailed descriptions for both the infant and mother's background. I first restrict the data to ages 20-44 as these are the prime childbearing years. Then, the fertility rate is calculated as total births of women ages 20-44 divided by the total population of women ages 20-44 multiplied by 1,000 which represents the fertility rate per 1,000 women. Population sources are obtained from U.S. Census Bureau, Population Division. It is important to note that NVSS does not offer data at the individual level[5] but rather presents aggregated data to protect the privacy of the individuals. Consequently, because the analysis does not use the mother's characteristics as control variables, population data from the Surveillance, Epidemiology, and End Results (SEER) program by the National Cancer Institute (NCI) is used to control for state-year age and race proportions. SEER has yet to release data for the year 2021 and therefore, the sample years of the fertility analysis is limited to 2011-2020. Lastly, I

[5]Individual level data is only offered with the state variable omitted.

include the state-year educational attainment percentages from the U.S. Census Bureau.

Next, the ACS microdata is sent to roughly 3.5 million addresses per year or 1% of the population which includes questions such as demographic, employment and educational attainment characteristics. The key variable from the dataset asks respondents whether they were absent from work one week prior from the survey date. Although the questionnaire does not differentiate the reason for the absence such as maternity leave versus vacation leave, any type of leave taken by mothers of infants (where youngest child is equal to 0) is sufficient for the analysis as we cannot observe the exact reason for the time off work. Then, I include from the dataset the variables age, race, education, age of youngest child, number of children, Hispanic origin, foodstamp recipient and marital status to control for individual characteristics. I then subset the data to all mothers between the ages of 20 and 44 with infants age 3 years or younger. The sample of females is restricted to ages between 20 and 44 as these are the prime childbearing years and are the most responsive to a paid leave. I do not condition on employment as changes in the labor force participation rate or hiring discriminations against women would bias the results. Finally, the years of the analysis are 2011-2021. The data is at the individual level and the dependent variable (whether an individual is on leave at the time of survey) indicates the likelihood of a mother to be on leave for a given state in a given year.

To control for state-year economic conditions for both the fertility and leave-taking analysis, I use the National Welfare Data provided by the University of Kentucky Poverty Research Center which contains state-year panel data covering domains such as population, unemployment and welfare. The variables of interest include average income, poverty rate, state minimum wage, unemployment rate, indicator for a democratic governor, population density, and maximum allotment benefit for a 4-person family.

In March of 2020, COVID-19 was declared a national emergency in the U.S. followed by statewide lockdowns and work-from-home mandates where each state had the jurisdiction over the handling of the epidemic resulting in widely differing responses between states. The disparity in employment and business closure policies as well as the uncertainty of the disease itself likely influenced decisions in having a child. Therefore, to control for the varying degrees in response by each state, I use the "Oxford COVID-19 Government Response Tracker" (OxCGRT) dataset[6] which tracks policy measures by each state government. From the dataset, I use the "Stringency index" which is a score aggregating government responses for schools, workplaces, outdoor movement, and travel.

4 NY-PFL Effects on Fertility Rate

4.1 Methodology

I use a difference-in-difference framework to estimate the effect of the NY-PFL on fertility rates. I compare the fertility rate, calculated as total births from females ages 20-44 divided by the female population ages 20-44, of New York before and after the paid leave implementation to

[6] https://github.com/OxCGRT/covid-policy-tracker

the other states[7]. As such, the regression model takes the form of

$$Y_{st} = \beta_3 NY_s \cdot Post_t + \psi X_{st} + \delta Z_{st} + \alpha_s + \gamma_t + \epsilon_{st} \tag{1}$$

where Y_{st} is equal to the fertility rate in state s in year t, X_{st} is a vector of state-year demographic proportions, Z_{st} is a vector of state-year economic conditions and demographic controls, α_s is state fixed effects, γ_t is year fixed effects, and ϵ_{st} is the error term. $NY_s \cdot Post_t$ is an interaction term between NY_s, a dummy variable equal to one if the state is New York, and $Post_t$, a dummy variable equal to one if the year is 2018 or after, and captures the effects of the NY-PFL on the fertility rate. However, NY_s and $Post_t$ are not included in the regression as they are absorbed by state fixed effects and year fixed effects, respectively.

Identification for a difference-in-difference model relies on a parallel trend assumption. For it to be valid, the estimator requires that the fertility rate trend between New York and the control group would have been fixed in the absence of the NY-PFL. Though this is fundamentally untestable, one method of supporting this assumption is to compare the outcome variables prior to the treatment. In addition, there should be no shocks affecting New York or any other states in the control group during the sampled years. First, since California, New Jersey, Rhode Island, and Washington have already implemented state-wide paid family leaves that have been active during the analysis period, they are removed from the control group. Next, because COVID-19 had unprecedented impacts on the factors affecting both paid leave eligibility as well as childrearing decisions such as social distancing measures, work-from-

[7] California, New Jersey, Rhode Island and Washington are excluded.

home mandates, and widespread layoffs, the analysis controls for state responses to COVID using a "stringency index".

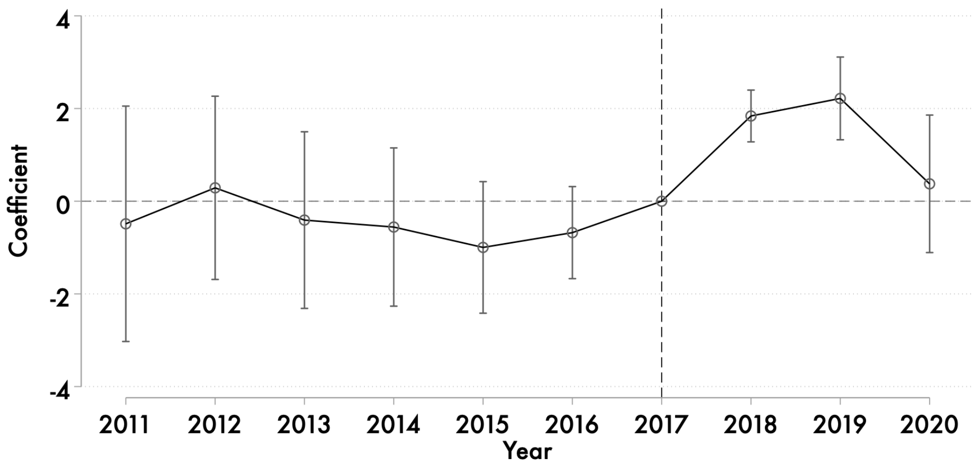
To support the common trend assumption, Equation 1 is transformed to a dynamic DD model (event study) as follows:

$$Y_{st} = \sum_{k\neq 1} \beta_k \cdot \mathbf{I}[t - L_i = k] + \sum_{k\neq 1} \gamma_k \cdot NY_s \times \mathbf{I}[t - L_i = k] \qquad (2)$$
$$+ \delta Z_{st} + \alpha_s + \gamma_t + \epsilon_{st}$$

where the $Post_t$ dummy variable is replaced with time to event dummies $\mathbf{I}[t - L_i = k]$. L_i represents the year of when the leave was introduced and $\mathbf{I}[t - L_i = k]$ is k years from the policy enactment. As the dynamic DD model uses a balanced panel of 7 years prior and 2 years after the enactment year, k denotes event time dummies such that $k = -7, -6, -5, -4, -3, -2, 0, 1, 2$. The baseline year where $k = -1$ is removed so that the coefficient measurements are relative to one year before the policy date. The interaction term between $\mathbf{I}[t - L_i = k]$ and NY_s is used for identification and coefficient γ_k indicates the difference in fertility rate between the treatment and control group in the k^{th} year before and after the policy enactment. As such, Figure 1 presents the event study plot of the fertility rate of New York vs the other states from 2011 to 2020.

In Figure 2, a line graph of the fertility rate of New York and the control group is shown. While the fertility rate continued in a downward trend for the control group during the post-treatment period, New York saw a sharp rise for the first year. In the second year, the fertility rate of New York had an overall decrease but was still greater relative to the

Figure 1: Event study: Effect of NY-PFL on fertility rates



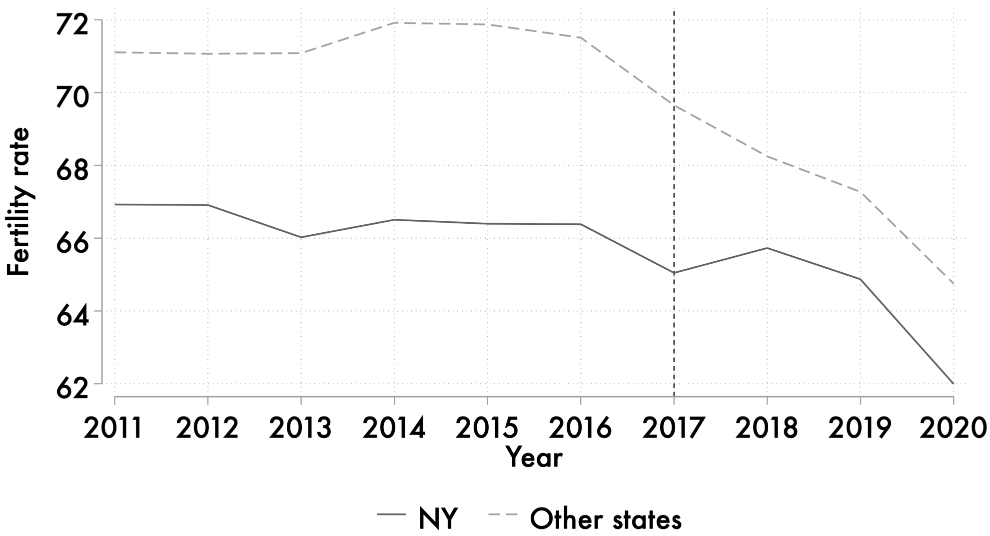
Notes: The figure plots the coefficients and 95% confidence intervals for the effects on the fertility rate.

control group. By 2020, the third year, New York had a sharper drop reversing the increases from the first two years.

4.2 Results

Table 1 shows the effect of the NY-PFL on fertility. Each column has state and year fixed effects and is clustered by state. The first column is a basic DD equation without controlling for any variables. Then in column two, state economic and demographic control variables are added. Column three adds the COVID-19 control representing the full DD model. Lastly, column four omits year 2020 which also removes the COVID control. Under the main model specification (column 3), the NY-PFL led to 1.9 more births which translates to a 2.9 percent increase. Current research show similar results with the California paid leave leading to a 3.5 percent increase and job protected paid leave in OECD countries leading

Figure 2: Fertility rate in NY vs. other states



Notes: The figure presents the fertility rate in New York compared with average fertility rate in the control group states.

to a 2.3 percent in fertility rates [Golightly and Meyerhofer, 2022; Shim, 2014].

As revealed in the event study plot, 2020 was the only year which had insignificant effects on fertility. This is likely attributed to the economic and political shocks arising from the COVID-19 pandemic which had profound impacts for both employment and childrearing. In addition, Voicu et al. (2020) construct a theoretical framework hypothesizing the negative impact COVID-19 has on fertility. They argue that the health policies such as social distancing as well as the economic response had a direct negative impact while gender roles and social values played a indirect role. Thus, column 4 omits year 2020 which consequently shows a greater effect of a 3.8 percent (2.5 births) increase.

Table 1: Effect of NY-PFL on fertility rates

	DD			
	(1)	(2)	(3)	(4)
NY*post	2.301***	2.128**	1.901**	2.499***
	(0.450)	(0.847)	(0.791)	(0.708)
Pre-treatment mean	66.313	66.313	66.313	66.313
Observations	470	470	470	423
Economic controls	No	Yes	Yes	Yes
Demographic controls	No	Yes	Yes	Yes
Covid controls	No	No	Yes	No
2020 included	Yes	Yes	Yes	No

Notes: The table shows the effect of NY-PFL on fertility in New York using the 2011-2020 NVSS Natality data. Robust standard errors are in parentheses and all specifications include state and year fixed effects. Economic controls include average income, poverty rate, state minimum wage, unemployment rate, indicator for a democratic governor, population density, and maximum allotment benefit for a 4-person family, demographic controls include state-year age proportions, race proportions, and eduational attainment, and the control for COVID-19 is a stringency index. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

4.3 Robustness

To check for robustness, I complement my findings using the synthetic control method (SCM) as proposed by Abadie et al (2010). Similar to difference-in-differences, SCM allows for causal inference when there is one treatment group and many control groups. SCM constructs a 'synthetic' New York by selecting units from a pool of similar states and assigning weights so that the difference between pre-intervention characteristics of NY and synthetic NY are minimized. Subsequently, the difference between the treatment group and the counterfactual post-treatment represents the impact of the policy.

For states $i = 1, ..., J + 1$ and periods $t = 1, ..., T$, let state $i = 1$ (New York) when exposed to the intervention at $T_0 + 1$ where T_0 is the pre-intervention period such that $1 \leq T_0 < T$. Next, let Y_{it}^I denote the fertility rate when state i at time t is exposed to PFL and Y_{it}^N in its absence. Assuming the intervention has no effect on the outcome variable before the policy is implemented, $Y_{it}^I = Y_{it}^N$. If $\alpha_{it} = Y_{it}^I - Y_{it}^N$ and D_{it} is a binary variable that takes a value of 1 when state i is exposed to intervention at time t and equals zero otherwise, the observed outcome is given by $Y_{it}^I = Y_{it}^N + \alpha_{it} D_{it}$. We want to estimate $(\alpha_{1T_0+1}, ..., \alpha_{1T})$ given by $\alpha_{1t} = Y_{1t} - Y_{1t}^N$ for $t \in T_0 + 1, ..., T$. Since Y_{it}^N is unobserved, suppose it is estimated by the model:

$$Y_{1t}^N = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \varepsilon_{it} \tag{3}$$

where:

δ_t - unknown time-dependent factor;
Z_i - vector of observed pre-intervention covariates;

θ_t - vector of unknown parameter;
λ_t - vector of unknown common factors;
μ_i - vector of unknown factor loadings;
ε_{it} - error term with zero mean.

If a vector of weights $W = (w_2, ..., w_{J+1})$ is generated where $\{w_i \geq 0 | j = 2, ..., J+1\}$ and $\sum_{j=2}^{J+1} w_j = 1$, then each vector W is a weighted average of control states representing synthetic New York. Now, suppose $(w_2^*, ..., w_{J+1})$ exists such that $\sum_{j=2}^{J+1} w_j^* Z_j = Z_1$ and $\sum_{j=2}^{J+1} w_j^* Y_{jt} = Y_{1t}, t = 1, ..., T_0$. If T_0 is large relative to ε_{it}, then an approximately unbiased estimator of α_{1t} is given by

$$\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \tag{4}$$

I use the same NVSS data and the control variables to construct the SCM model but extend the sample years to 2007 as the SCM benefits from long pre-treatment periods. The pre-intervention characteristics to be minimized are shown in Table 2 which present the average values of the matched variables for New York and synthetic New York and the closeness of values between the two indicate a good pre-treatment fit.

Table 3 shows the calculated weights and states from the donor pool that make up synthetic New York. The main contributors are Massachusetts and Maryland and are in many ways both very similar to New York. Figure 3 then shows the fertility rate of New York versus synthetic New York constructed using these weights where the dotted vertical line indicates the year of policy enactment. Under the SCM, the fertility rate increased by 2.1 and 1.8 births in the first and second year, respectively,

Table 2: Predictor means (2007-2017)

	New York	
Variable	Treated	Synthetic
Fertility rate (2015)	66.396	66.464
Fertility rate (2010)	67.492	67.070
Fertility rate (2007)	69.221	69.639
Educational attainment	33.645	36.925
State minimum wage	7.809	7.856
Unemployment rate	6.600	5.776
Average income	54.118	53.186
Povery rate	14.700	11.222
Population density	159.595	414.476
Governor is Democrat	1.000	0.677
Average benefit for 4-person family	627.182	640.745
Black	0.183	0.179
White	0.721	0.728
Asian	0.085	0.070
Hispanic	0.444	0.448
Age 20-24	0.071	0.072
Age 25-29	0.073	0.072
Age 30-34	0.068	0.067
Age 35-39	0.065	0.065
Age 40-44	0.067	0.067

Notes: All variables except lagged fertility rate variables are averaged for the 2007-2017 period. Average income and average benefit for 4-person family is in USD, average income is the annual income per individual in thousands of USD, the population density represents population per square kilometer, and the remaining variables are percentages.

and dropped down to 1.0 births in the third year or the year of COVID-19. Table 4 presents these estimates along with the p-values which is calculated by individually applying the SCM to all states in the control group and then ranking them by the ratio of the post- and pre-treatment root mean squared prediction error (RMSPE). The findings are similar to DD as revealed in Figure 1 that indicate a rise in births by 1.8, 2.2, and 0.4 for the first three years, respectively. As a result, this analysis provides further evidence of a positive fertility effect in New York women.

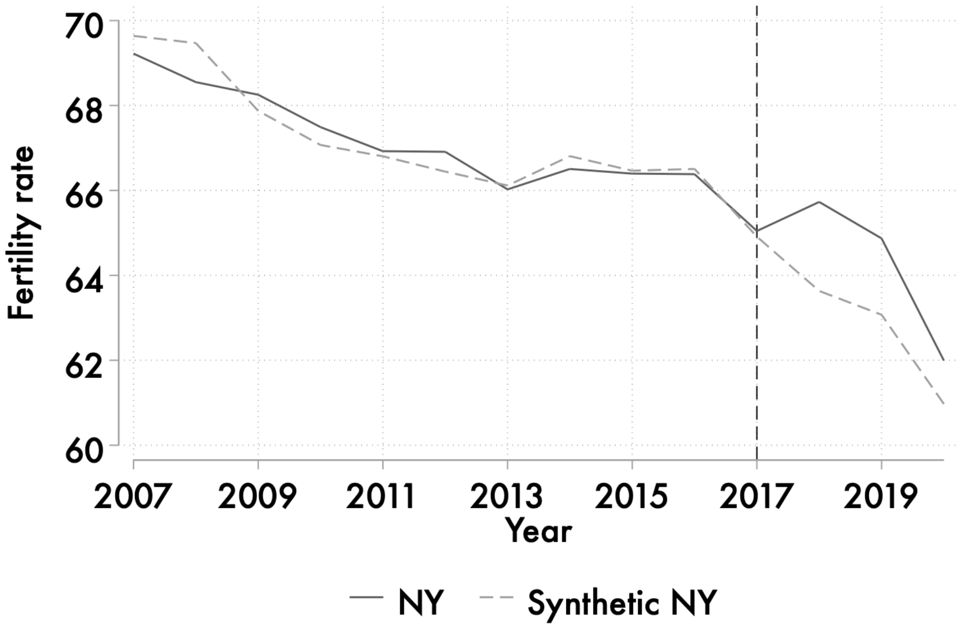
Table 3: Weight composition of synthetic New York

State	Weight
Alaska	.031
Colorado	.041
District of Columbia	.054
Hawaii	.023
Maryland	.328
Massachusetts	.344
Oklahoma	.116
Vermont	.043
Virginia	.020

4.4 Heterogeneity

Due to data limitations, heterogeneous effects are only analyzed for race and age. In Table 5, Black mothers saw the greatest surge in fertility at an increase of 4.9 births (7.7 percent) per 1000 women age 20-44 and though not as large, White mothers also saw a sizeable increase of 2.8 births (4.1 percent). Meanwhile, fertility decreased for Asian mothers but with insignificant results. When analyzing by age group in Table 6,

Figure 3: New York vs. Synthetic New York



Notes: The figure compares the fertility rate of New York compared to synthetic New York using the 2007-2022 NVSS Natality data.

Table 4: SCM post-treatment results

	Effect	P-value
2018	2.10	.000
2019	1.80	.054
2020	1.02	.432

Notes: P-values are calculated by ranking New York relative to the states in the control group when ordered by the ratio of post- and pre-treatment RMSPE.

though fertility increased for mothers of all ages, mothers in their 40s had the largest percentage growth at 10 percent due to a smaller fertility rate pre-treatment mean. Mothers in their 20s and 30s saw a rise of 3 percent.

Existing literature that show heterogeneous effects for fertility in response to changes in maternity leave structure are few. However, Golightly (2020) found that Black mothers, mothers with some college degree, and mothers in their 30s had the greatest increases in fertility after the California paid leave went into effect. On the other hand, compared to disadvantaged women, married and college-educated were more sensitive to the introduction of an unpaid, job-protected leave [Baker and Milligan, 2008; Han et al., 2009].

With the introduction of NY-PFL, women who otherwise could not afford childbirth due to the lack of wage replacement in the absence of work could now balance both work and family. Also, as NY-PFL comes with job protection, older women who tend to have more time invested into their careers and greater work capital could be incentivized towards motherhood or additional children. Furthermore, greater constraints in achieving financial and professional goals have caused women to delay childbirth in a post-Recession era [Guzzo and Hayford, 2023]. While a paid leave gives disadvantaged women the opportunity to have children while employed, the included job protection gives older, career-oriented women an option to take time off work without the fear of losing their job.

Lastly, along with the fact that Asian mothers in the U.S. tend to be more educated than mothers of other races, Myong et. al (2021) find

Table 5: Effect of NY-PFL on fertility by race

	Race		
	(1) White	(2) Black	(3) Asian
NY*post	2.760***	4.899**	−0.151
	(0.940)	(2.164)	(3.409)
Pre-treatment mean	67.605	63.436	69.981

Notes: The table shows the effect of NY-PFL on fertility in New York by mother's race using the 2011-2020 NVSS Natality data. Robust standard errors are in parentheses and all specifications include state fixed effects, year fixed effects and economic, demographic, and COVID controls. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

that pro-natal policies in East Asian societies had little influence over fertility behavior among educated women. As a result, the insignificant results for Asian mothers may partly be attributed to social norms.

Table 6: Effect of NY-PFL on fertility by age

	Age		
	(1) 20-29	(2) 30-39	(3) 40-44
NY*post	2.396**	2.556***	1.495***
	(1.117)	(0.648)	(0.333)
Pre-treatment mean	72.554	84.263	15.647

Notes: The table shows the effect of NY-PFL on fertility in New York by mother's age using the 2011-2020 NVSS Natality data. Robust standard errors are in parentheses and all specifications include state fixed effects, year fixed effects and economic, demographic, and COVID controls. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

5 NY-PFL Effects on Mother's Leave-taking

5.1 Methodology

To identify the effects of NY-PFL on mothers leave-taking, I begin with a difference-in-difference model. The treatment group is mothers of infants (age of youngest child is equal to 0) in New York and the control group is mothers of infants in other states[8]. The DD model is a linear regression

$$Y_{ist} = \beta_3 NY_s \cdot Post_t + \psi X_{ist} + \delta Z_{st} + \alpha_s + \gamma_t + \epsilon_{st}$$

where Y_{ist} is equal to one if the mother i in state s in year t is absent from work one week before the week of the survey. NY_s is a dummy variable equal to one if the mother resides in New York, $Post_t$ is a dummy variable equal to one if the mother was surveyed after the NY-PFL implementa-

[8] California, New Jersey, Rhode Island and Washington are excluded

tion, and $NY_s \cdot Post_t$ is the interaction term of the two. X_{ist} is a vector of individual characteristics and controls: age in groups (20-24, 25-29, 30-34, 35-39, 40-44), race (white, black, Asian, other), educational attainment (less than high school, high school, some college, bachelor's and higher), number of children, food stamp recipiency, Hispanic origin, and marital status. Z_{st} is a vector of state-year economic conditions: state average income, poverty rate, minimum wage, unemployment rate, population density, indicator if the governor is a democrat, and maximum food stamp benefit for a four person family. α_s is state fixed effects which absorbs NY_s, γ_t is year fixed effects which absorbs $Post_t$, and ϵ_{st} is the error term.

The validity of the DD estimator relies on the assumption that in the absence of NY-PFL, the trend of New York and the control group would have been the same. This assumption would be violated if there were any events or policies that affected leave-taking of either New York or the control group but not both. To address this potential issue, the treatment group is also compared to a different control group, mothers of 1-3 year olds in New York, as mothers of infants older than one are ineligible for the paid leave so their leave-taking rate should not be affected. Using an identical structure as Equation 2, event-study plots are shown for both models in Figure 4 and 5 to validate the parallel trends prior to the paid leave.

Finally, I use a difference-in-difference-in-differences, or triple differences, strategy that compares both sets of control groups by combining the two DD models. By taking the difference of two difference-in-difference estimators, the bias will be removed assuming both equations are equally biased.

The model compares mothers of infants to mothers of 1-3 year olds in New York versus the other states before and after 2018. I estimate the DDD equation in a linear regression as

$$\begin{aligned} Y_{ijst} = {} & \beta_4 NY_s \cdot Post_t + \beta_5 NY_s \cdot Infant_j + \beta_6 Post_t \cdot Infant_j \\ & + \beta_7 NY_s \cdot Post_t \cdot Infant_j + \psi X_{ijst} + \delta Z_{st} + \phi_j + \alpha_s + \gamma_t + \epsilon_{ijst} \end{aligned} \tag{5}$$

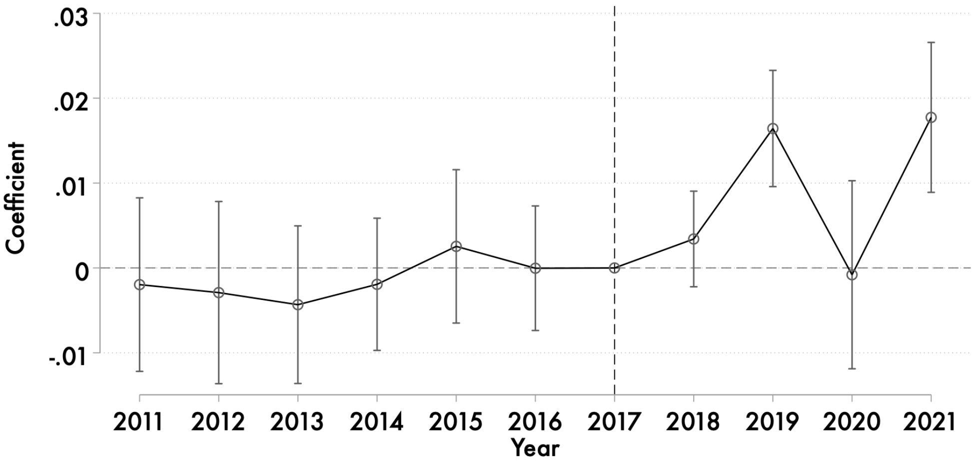
where Y_{ijst} is equal to one if individual i in state s with infant j was absent from work one week before survey week in year t. $Infant_j$ is equal to one if the mother's youngest child is less than one year old and otherwise equal to zero. X_{ijst} is a vector of individual characteristics and controls; Z_{st} is a vector of state-year economic controls; ϕ_j are dummies for age of youngest child; α_s and γ_t are respectively state and year fixed-effects.

Though a triple difference estimator is the difference between two difference-in-differences, a parallel trend assumption is necessary for only one of the difference-in-difference model. It requires that the relative outcome of mothers of infants in New York and mothers of 1 to 3 year olds in New York follows the same trend as the relative outcome of mothers of infants in the control states and mothers of 1 to 3 year olds in the control states.

5.2 Results

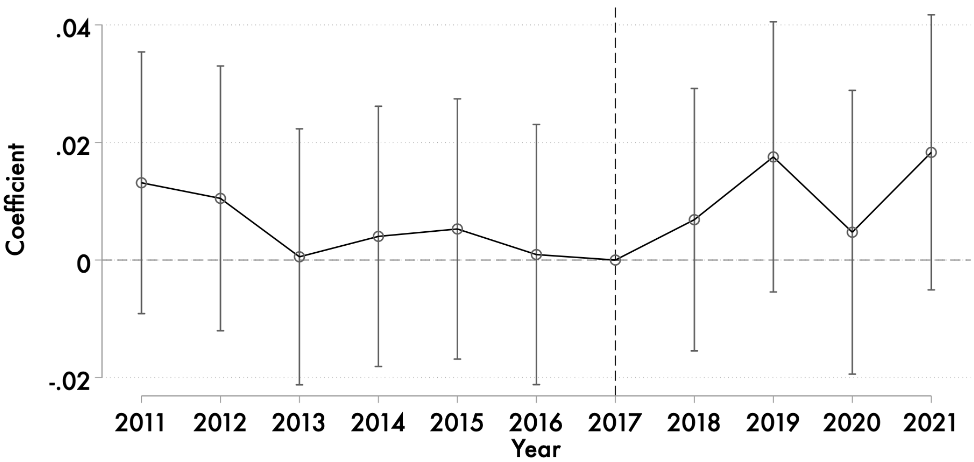
The summary statistics on Table 7 compare the means of the treatment group and control groups during the pre-treatment period for our sam-

Figure 4: Event study: Mothers of infants in NY vs. other states



Notes: The figure plots the coefficients and 95% confidence intervals for the effects on leave-taking with mothers of infants in other states as the comparison group.

Figure 5: Event study: Mothers of infants vs. 1-3 year olds in NY



Notes: The figure plots the coefficients and 95% confidence intervals for the effects on leave-taking with mothers of 1-3 year olds in New York as the comparison group.

ple. Mothers of infants in New York generally have higher leave-taking rates as well as higher labor force participation rates when compared to other states. New York mothers are less likely to be a US citizen or White when compared to mothers from other states but more likely to be Black or Asian due to the state's higher racial diversity. Lastly, New York mothers tend to be slightly older and more educated.

Table 8 presents the effects of the NY-PFL on leave-taking rates for mothers of infants in New York. The first column shows the estimate for a basic DD model with state and year fixed effects but does not include individual or state economic controls and is compared against mothers of infants in other states. Column two adds individual and state controls and column three then excludes year 2020. Column four shows the DD estimate against mothers of children ages 1 to 3 in New York which includes individual controls but omits year 2020. Lastly, the DDD estimate in column 5 uses both set of control groups and is the main specification which is used for the remainder of the study. An increase of 1.0 percentage point from a baseline of 10.8 percent suggests that the NY-PFL has raised leave-taking rates by 10.8 percent.

The preferred model specification (column 5) omits year 2020 because the ACS dataset for year 2020 utilizes experimental weighting to compensate for the effects of COVID-19 and advises against comparing with other sample years. As a result, I only include year 2020 in the first two columns and the event studies but is excluded from the remainder of the estimates.

Whereas NY-PFL had a large significant effect on fertility rates from the first year as evidenced from the event study, large significant effects

Table 7: Pre-treatment summary statistics

	(1) NY Infants	(2) Other states Infants	(3) NY 1-3YO
Absent	0.108	0.076	0.022
Labor force	0.656	0.644	0.685
US citizen	0.853	0.906	0.848
Married	0.740	0.724	0.723
Number of children	2.141	2.107	2.115
Hispanic background	0.156	0.146	0.177
Foodstamp recipient	0.238	0.258	0.240
Age			
20-24	0.135	0.186	0.089
25-29	0.248	0.303	0.198
30-34	0.338	0.315	0.314
35-39	0.214	0.155	0.273
40-44	0.065	0.042	0.127
Education			
Less than HS	0.099	0.090	0.103
HS	0.192	0.197	0.193
Some college	0.248	0.329	0.267
Bachelor+	0.460	0.385	0.437
Race			
White	0.699	0.780	0.662
Black	0.110	0.105	0.128
Asian	0.092	0.043	0.098
Other race	0.100	0.072	0.112
N	11,471	147,390	29,377

Notes: Data is from ACS and averaged for the pre-treatment period for the years 2011 to 2017. The columns are ordered as the treatment group, control group of mothers of infants in other states, and control group of mothers of children age 1 to 3 in New York. All variables except "Number of children" are dummy variables and represent the percentage of the sample.

on leave-taking only emerged from the second year. Though more research is required, one possible explanation is that mothers have timed the utilization of the paid leave. Since the benefits increased gradually for the first four years of the policy and also because mothers can take leave any time before the child's first birthday, mothers may have waited until the second year to gain an additional two weeks of paid time off as well as 5% more pay.

Table 8: Effect of NY-PFL on mother's leave-taking

	DD				DDD
	(1) Infants in other states	(2) Infants in other states	(3) Infants in other states	(4) 1-3 year-olds in NY	(5)
NY*post	0.008***	0.012***	0.012***		
	(0.001)	(0.002)	(0.003)		
post*infant				0.009	
				(0.006)	
NY*post*infant					0.010***
					(0.001)
Pre-treatment mean	0.108	0.108	0.108	0.108	0.108
Observations	239,901	239,225	222,430	57,253	792,938
Individual Controls	No	Yes	Yes	Yes	Yes
State Controls	No	Yes	Yes	No	Yes
2020 included	Yes	Yes	No	No	No

Notes: The table shows the effect of NY-PFL on the probability of being on leave during the week of the survey for mothers of infants in New York. Robust standard errors are in parentheses and all specifications include state fixed effects (minus column 4) and year fixed effects. Specifications across states, columns 1 through 3 and column 5, use state-level cluster-robust standard errors. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

When compared with existing literature, the magnitude of the increase in New York is relatively small. The CA-PFL is estimated to have increased mothers leave-taking by roughly 113 percent and fathers leave-taking by 46 percent [Rossin-Slater et al., 2013; Bartel, 2017]. One possible explanation for the large discrepancy could be that the treatment group in these analysis is conditioned on employment. However, if the NY-PFL induced mothers towards employment or hiring discriminations towards women were present, conditioning on employment would bias the results and so I provide the lower bound estimates. Additionally, I only include 3 years of post-treatment periods which may not reflect the true causal effect if the effects emerge a few years after the implementation. Therefore, future research should consider investigating the long-term effects of the NY-PFL on mother's labor supply.

5.3 Robustness

States in the East Coast of the U.S., where New York is situated, are highly dense and generally smaller than states in the west. Movement and even commutes across state borders are not uncommon. Therefore, it is possible that the NY-PFL induced migration from other states and if so would be endogenous. To evaluate potential migration patterns, I remove New York's bordering states, Vermont, Massachusetts, Pennsylvania, and Connecticut (New Jersey already removed from main specification), from the control group. Next, the NY-PFL only affects employed mothers but the main analysis includes unemployed mothers due to possible endogeneity resulting from behavioral changes in employment. I therefore test the sensitivity of the results by restricting the data to mothers currently in the labor force as this should not have a large change on the results. The test is restricted to labor force rather than employment because women on maternity leave are still considered a part of the labor force as they are temporarily absent from work and are expected to return after a certain period. Lastly, though I consider the prime childbearing ages to be between 20 and 44, I extend the analysis to include the age of mothers from 15 to 49. Table 9 presents the regression table using the main specification (column 5 of Table 8) and reveal comparable results.

Table 9: Effect of NY-PFL on mother's leave-taking

	Robustness		
	(1) Remove bordering states	(2) Restrict to labor force	(3) Extend to age 15-49
NY*post*infant	0.010***	0.010***	0.010***
	(0.001)	(0.002)	(0.001)
Pre-treatment mean	0.108	0.162	0.105
Observations	726,558	535,217	817,483

Notes: The table shows DDD estimates of the probability of being on leave. Specification from Table 8 column 5 is used for each regression. Cluster robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

5.4 Heterogeneity

Previous literature show that the decision to take maternity leave differs across subgroups with the two main factors being financial constraints and work capital. Firstly, it is harder for disadvantaged women, namely Black and non-college-educated mothers, to take long, unpaid time away from work to care for their child, as evidenced in California [Rossin-Slater et al., 2013]. Next, women who have a greater investment in their career have greater opportunity costs when choosing between family and work, especially in the absence of job protection. With the availability of a job-protected paid leave, women who are more educated

— and thus receive a higher wage — are more likely to take advantage of the policy. Lastly, findings reveal that mothers in the U.S. often delay motherhood until their 30s and 40s which is caused by a lack of a paid family leave program [Olivetti and Petrongolo, 2017]. In addition, mothers have been shifting the timing of their births due to a decreased likelihood of achieving prior goals [Guzzo and Hayford, 2023].

When analyzing the effect by educational attainment as shown on Table 10 the largest increase came from non-college-educated mothers which grew by 10 percent. Likewise, educated mothers with at least a bachelor's degree have seen a similarly large and significant increase of 8 percent. This is surprising as current research show that college-educated women are not as sensitive compared to their less educated counterparts when a paid leave is introduced. One explanation may be that women who are more educated have greater work capital and thus take shorter leaves. However, because the NY-PFL comes with job-protection, they may be more willing to take advantage of the available leave.

Next, Table 11 shows the effect by race where leave-taking increased for mothers of all races. Black mothers (32 percent increase) had the greatest increase which is expected and supported by literature whereas Asian mothers, on the other hand, also had an unexpected significant rise (14 percent). Although there is not much research showing the effects of paid leave on Asian mothers, on average, they tend to be more educated which aligns with the results from leave-taking by education. Lastly, leave utilization for White mothers grew by 9 percent.

Table 12 shows heterogeneous effects by age group. The increase in leave utilization were mainly driven by mothers in their 30s (15 percent) and 40s (18 percent). On the other hand, leave-taking significantly shrank for mothers in their 20s. Larger effects for older women may have two possible explanations. Older women tend to have greater work capital on average due to a longer time in the labor force which amplifies the opportunity costs associated with switching jobs. With job protection, they can take leave with the assurance that the current job will still be available upon their return. Next, as mothers have delayed childbirth due to the reduced likelihood of achieving prior goals, a paid leave encourages these women towards childrearing by lessening the economic costs of childbirth.

Table 10: Effect of NY-PFL on mother's leave-taking by education

	Educational Attainment	
	(1) Less than Bachelor	(2) Bachelor+
NY*post*infant	0.008***	0.011***
	(0.001)	(0.002)
Pre-treatment mean	0.083	0.137
Observations	482,876	310,062

Notes: The table shows DDD estimates of the probability of being on leave by educational attainment. Specification from Table 8 column 5 is used for each regression. Cluster robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table 11: Effect of NY-PFL on mother's leave-taking by race

	Race		
	(1) White	(2) Black	(3) Asian
NY*post*infant	0.010***	0.033***	0.014***
	(0.001)	(0.004)	(0.005)
Pre-treatment mean	0.111	0.102	0.100
Observations	602,550	83,950	39,429

Notes: The table shows DDD estimates of the probability of being on leave by race. Specification from Table 8 column 5 is used for each regression. Cluster robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

Table 12: Effect of NY-PFL on mother's leave-taking by age

	Age		
	(1) 20-29	(2) 30-39	(3) 40-44
NY*post*infant	−0.008***	0.018***	0.017***
	(0.002)	(0.002)	(0.005)
Pre-treatment mean	0.092	0.120	0.094
Observations	307,034	425,283	60,621

Notes: The table shows DDD estimates of the probability of being on leave by age. Specification from Table 8 column 5 is used for each regression. Cluster robust standard errors are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.10

6 Conclusion

This paper examines the effects of the New York Paid Family Leave on fertility rates and mothers' leave-taking rates. Fertility in New York rose by 2.9 percent with the largest effects from Black mothers and mothers age 40-44. The results are strikingly similar to those found in California where fertility increased by 2.8 percent and driven by older and low socioeconomic status mothers [Golightly and Meyerhofer, 2022]. Though more research is required, it also aligns with research that women postpone having children due to prior unachieved goals which is offset by paid leave [Guzzo and Hayford, 2023]. On the other hand, mothers' leave-taking in New York increased by 10.8 percent while disadvantaged women, namely Black and non-college-educated mothers, were most sensitive to the policy and to a lesser extent, college-educated and Asian mothers. In addition, leave usage was largely driven by older mothers in their 30s and 40s. Not only do the results corroborate findings from California as well as other countries which show that paid leave utilization disproportionately increases for disadvantaged women, it is also consistent with outcomes following the provisioning of an unpaid, job-protected leave [Han et al., 2009; Salvanes et al., 2010; Rossin-Slater et al., 2013]. As NY-PFL comes with job protection, college-educated and older women who have invested more into their work capital may be more likely than before to take leave. Overall, my findings reveal the effectiveness of a paid leave in positively influencing fertility behavior and improving leave utilization.

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