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Economic Impact of State Paid Family Leave Policies on Caregivers with Older and Disabled Adults

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Abstract

This study examines the impact of the state paid family leave mandates on working-age individuals residing with older and/or disabled adults. When facing the dual demands of employment and taking care of family members with serious illness or disability, potential caregivers in states with paid leave policies have access to benefits. These benefits can help improve labor attachment after the impacted caregivers are able to take time off to provide care. Using the difference-in-difference approach to analyze American Time Use and CPS data, this study found that the paid family leave laws were associated with a higher probability of providing family caregiving, higher labor attachment, and less probability of working part-time voluntarily. Although the study found some evidence of a reduction in work hours in some cases, there was little evidence of an adverse impact on wages and earnings. The paid family leaves also reduced reliance on social welfare benefits, which suggests better economic security and the potential to improve retirement security among caregivers.

Keywords: Paid Family Leave, Elder Caregivers, Employment, Income Security

1.Introduction/ Literature Review

In 2018, nearly forty-one million Americans provided unpaid care to individuals aged 65 and older. A majority of these unpaid or family caregivers (roughly 61 percent) were also working in addition to providing care, and more than half of the employed caregivers had full-time jobs (DOL, 2019). The predictable increase in paid and unpaid eldercare demand as the population ages and trends away from institutional care requires further support from work places. Public policies that are more responsive to diverse family needs are also crucial to reduce the burden of dual work-care responsibilities and ensure leave from work when intensive caregiving is needed.

The 1993 Family and Medical Leave Act (FMLA) is the current federal leave policy in the United States. It offers 12 weeks of unpaid job-protected leave for eligible workers to care for newborns or family members with severe health conditions. While this protection covers 60 percent of the workforce, 46 percent of those eligible report not being able to afford to take unpaid time off work (Health Policy Brief, 2019). In the absence of federal paid leave programs, a growing number of states have enacted state paid leave policies. To date, four states have fully implemented their paid family leave (PFL) policies. Another five other states and the District of Columbia have also enacted PFL programs. However, they are not yet fully implemented and paying benefits.

A small but growing literature on the impact of state PFL policies shows positive effects on infant and mother health outcomes, the positive sharing of care responsibilities from fathers (Hamad, Modrek, and White, 2019; Choudhury and Polachek, 2019; Pihl and Basso, 2019; Lichtman-Sadotand and Pillay Bell, 2017; Klevens et al., 2016; Pal, I. 2016; Chatterji and Markowitz, S., 2008; Lamb, 2004), and positive labor attachment and a higher likelihood to return to the labor market among young mothers (Bana et al., 2019, Bartel et al., 2018, Baum and Ruhm, 2016, Stanczyk, 2016, Byker, 2016, Das and Polachek, 2015, Rossin-Slater et al., 2013). The overall findings show significant benefits of paid leave program for caregivers. However, most existing studies focus on working families with a new child as the population of interest. There is little known about the effects of state PFL mandates as related to workers with eldercare responsibility. It's essential to understand how the state family paid leave programs affect elderly caregivers, given the context of increasing demand for caregiving and the significant growing advocacy for a universal paid leave policy.

This study explored the potential effects of the PFL mandates on working caregivers by examining the impact on caregiving and employment behaviors among working individuals who reside with older and disabled adults. Using two different data sets - American Time Use Surveys (ATUS) and Current Population Surveys (CPS) with a difference–in–difference (DID) approach - the results showed that the state paid leave policies were associated with a higher probability of providing care for senior adults in and outside households. Specifically, across states, the PFL mandates increased the likelihood of giving care to family adult members (an increase by two ppts or 10 percent for California, six ppts or 84 percent for Rhode Island[1], and two ppts or 33 percent for New York. Regarding employment effects, at extensive margins, the paid family leave policies slightly increased labor participation generally by 0.2 ppts. However, the positive effect was only observed for California and New Jersey, with approximately 0.3 ppts joining the labor force following state polices[2]. At intensive margins, the DID estimates showed that workers were less likely to work part-time for non-economic reasons (i.e, voluntary part-time) following the mandates, with the larger effects revealed to be among female workers in Rhode Island and New York (a reduction by 12 and 10 percent, respectively), while male potential caregivers in New Jersey and Rhode Island experienced less working part-time voluntarily (a decline by 10 percent and six percent, respectively). Wage penalty induced by working less was only observed among male workers in Rhode Island and New York, with a small reduction of approximately two to three percent, respectively, following the mandates. Furthermore, findings from this study suggested that the PFL policies did not cause an adverse impact on workers' earnings and their household's incomes. There was little evidence of a negative impact on payroll tax contributions[3], and findings showed potentially less reliance on social welfare benefits. Indeed, the study observed a gain in payroll tax contributions among females in California and Rhode Island and males in New Jersey.

This study contributes to the related literature on paid leave policies and older adult care in several ways. First, this study provided understanding of the paid family leaves in all states that introduced the benefits since 2004 and examined the impact on both female and potential male caregivers. Recent studies (Kang et al., 2019, Saad-Lessler, 2020, and Anand et al., 2021[4]) have often focused on the California program, with the analysis centered among mid-aged female potential

[1] The estimate for Rhode Island seems to be noisy due to small number of observations.
[2] Though the estimate for NY is not statistically significant
[3] Payroll tax is defined as Social Security payroll deductions or FICA (Federal Insurance Contributions Act) taxes are both taxes and contributions to social insurance system of Social Security that includes both Social Security and Medicare taxes. The FICA taxes were collected for the first time in 1937. For additional details, visit https://www.ssa.gov/history/hfaq.html
[4] Anand et al., 2021 study the impact of PFL in California and New Jersey among potential caregivers (both female and male) whose spouses experienced a health shock or disability.

caregivers with physical limitations/disabled family members (especially spouses[5]), which potentially understated the role of men and younger women as potential caregivers. Second, unlike prior studies that employed Annual March CPS data, the use of Monthly Basic CPS data has two advantages: (1) given the short duration of paid leave benefits (usually four to eight weeks), the Monthly Basic CPS data allows us to observe short-term labor supply responses to the policies; and (2) it allows construction of an analysis sample that better captures the population of potential caregivers living with old-aged/disabled/bad health condition family members who are eligible care recipients under the PFL programs. This essentially increases the sample size compared to prior studies and therefore, provides more precise estimates. Finally, the study further examined the effects of PFL mandates on social welfare programs which are understudied in related papers. This provides an overall picture of how the PFL laws could potentially affect caregivers and their families.

1.2. Policy Background

State Paid Leave Policy Background

Aside from various programs and policies at both national and state levels that support informal unpaid caregivers[6], medical and family leave programs are critical sources of support that help working caregivers balance their work-care activities. The 1993 Federal Medical Leave Act (FMLA) grants US workers unpaid, job-protected leave to care for seriously ill family members, the arrival of a child, or self-care for qualified personal health problems. However, not all workers are covered; eligible workers must work for at least 12 months for a firm with at least 50 employees and have had 1,250 hours of service in the past year. As a result, only about 56 percent of the employees at worksites are eligible for FMLA (DOL, 2018[7]). Among those eligible for the FMLA program, only 15 percent took leave for a

[5] Data from the Caregiving in the US Surveys show that only 10 percent of employed caregivers provided caregiving for a spouse or partner in 2020 while more than 56 percent reported to care for parents and parent-in-laws (AARP, 2020)

[6] A few examples include National Family Caregiver Support Program, Medicaid and Medicare, Lifespan Respite Care Program, and Alzheimer's Disease Support Services Program, among others. These programs target both family caregivers and care recipients via financial support, training, counseling, and care services to care recipients (See Mudrazija & Johnson (2020) for detailed description of these programs).

[7] The 2018 Family and Medical Leave Act (FLMA) Surveys have been conducted by the Department of Labor in 1995, 2000, 2012, and 2018. More details can be obtained from: https://www.dol.gov/agencies/oasp/evaluation/fmla2018

qualifying FMLA reason[8] in 2018. Taking care of a family member, especially for older adults, was the least common reason. The low utilization rate of the FMLA policy is by and large because many workers are unable to afford unpaid leave.

Although there is no national family paid leave policy, many states have enacted laws providing paid leave benefits for new parents and family caregivers. Among these states, California (2004), New Jersey (2009), Rhode Island (2014), and New York (2018) implemented paid family leave programs, typically for between one-half and two-thirds of regular pay (Jorgensen and Appelbaum, 2014). Meanwhile, Colorado, Connecticut, Massachusetts, Oregon, Washington, and Washington DC passed legislation – but have not yet launched their paid leave policies (see Appendix A – Table 1 for detailed comparison). Across the four implemented programs, many leave provisions are similar in terms of covered workers, eligible family members with serious illness or newborn, qualifying leave reasons, or program financing. For example, all of them are run through the existing temporary disability programs and financed through either employee contributions, employer contributions, or a combination of employee and employer contributions. These programs differ from one to another in wage replacement rates, leave duration, and job-protection provision. For example, California and New Jersey's programs do not offer job protection, while Rhode Island and New York cover this provision under their mandates. The presence of job protection might substantially affect leave-taking and labor participating behaviors, especially for workers who are not covered under the FMLA.

Studies on the impact of state-level paid leave programs, especially with respect to care for older adults, have been limited and findings are mixed. For example, Morefield et al. 2016 found that paid leave programs in California and New Jersey had no significant impact on leave-taking, employment, or labor force participation compared to states with no paid leave programs. In contrast, more recent studies showed a positive link between paid leave provisions and labor participation in California (Saad-Lessler and Bahn, 2017; Kang et al., 2019). Perhaps, these findings reflect that the number of workers who received family paid leave for family caregiving reasons is much lower than those who took paid leave for being a new parent (Bedard and Rossin-Slater 2016; Morefield et al. 2016). Given the increasing prevalence and significance of family caregiving, it is crucial to understand how state paid

[8] Qualifying reasons under the FMLA include the employee's own serious health condition (including pregnancy); caring for an immediate family member (spouse, parent, child) with a serious health condition; caring for or bonding with a new child (birth, adoption, foster placement) in the first year; and leave related to a family member's service in the military.

leave provisions impacted family caregivers, especially in the context of an increase in state adoption of the policies and growing public support for federal paid leave benefits.

Existing Literature on Elder Informal Care and Related Policy Impact.

This study relates to two literatures: informal caregiving, work, and economic well-being; and the effects of state paid leave policies on informal caregivers in the context of the United States.

Informal care plays an invaluable role for society in reducing public and private spending on long-term care services and support (Charles and Sevak, 2005; Freeman,1996; Jette, Tennstedt and Crawford,1995). It also allows seniors and disabled individuals to remain at home. However, providing care to family members comes at economic and social costs.

Relationship between Informal caregiving and employment, work, and economic well-being.

The link between informal (unpaid) caregiving and labor supply outcomes has been extensively studied. Mixed conclusions about the direction of this relationship have been drawn. Numerous empirical studies have documented a negative association between care provision and labor market activities. However, most recent papers found relatively small effects of giving care on employment[9], in both terms of labor participation (extensive margin) and the number of hours worked (intensive margin) (Lily et al., 2007; Bauer and Sousa-Pozza, 2015; He and McHenry, 2017). Several studies showed no significant effect of giving care on labor participation (Wolf and Soldo, 1994; Stern, 1995; Kotsadam,2011; Meng, 2013; Van Houtven et al., 2013).

The small effects of informal caregiving on employment, perhaps, are due to substantial heterogeneity of the care-work relationship that varies across demographic groups, types of care, and the intensity of caregiving. Bauer and Sousa-Poza (2015) provided a comprehensive review of research on the impact of informal care on caregivers' employment. They showed that most of the studies focused on the female sample, especially women of middle-ages, since females were considered to be the primary providers of informal care. However, even when including men in the analysis samples, there were little significant differences between male and female caregivers, or even no effect among men (Ciani, 2012; Lee and Tang, 2013; Van Houtven et al., 2013; Nguyen and Connelly, 2014; Kolodziej et al., 2018). A larger association between unpaid care activities and labor outcomes was found among

[9] Several studies show larger estimates of the care-work association (Heitmueller, 2007; Bolin et al.,2008; Nguyen & Connelly (2014). For example, Bolin et al., (2008) estimates that a 10 percent increase in time spent on caregiving is associated with a 3.7 percentage points decrease in caregivers' employment probability.

intensive caregivers (i.e., providing 10 - 20 hours of weekly care) (Wolf and Soldo,1994; Stern,1995; Kotsadam, 2011; Meng, 2013; Jacobs et al.,2013) for co-residential and main caregiving (Ettner, 1996; Carmichael and Charles, 2003; Heitmueller, 2007; Casado-Marín et al., 2011; Nguyen and Connelly, 2014).

Regarding employment effects at the intensive margin, which are usually measured as worked hours- estimates from previous studies were relatively consistent. Caregivers were more likely to work fewer hours than non-caregivers, but the estimates still varied. Previous studies showed that though the overall effect sizes were small, the heterogenous effects observed appeared to be substantial (Ettner, 1995; Johnson and Lo Sasso, 2006; Berecki-Gisolf et al., 2008; Bolin et al., 2008; Carmichael et al., 2008; Lilly et al., 2010; Kotsadam, 2011; Meng, 2012, 2013; Van Houtven et al., 2013; Bauer and Sousa-Poza, 2015). For example, Johnson and Lo Sasso, 2006 used a sample of women aged 55- 67 from two waves of the Health and Retirement Study data and found that women who helped their parents over a two-year period reduced their work hours by 367 hours per year (or 41 percent) on average compared to non-caregivers. Using similar data, Van Houtven et al. (2013) concluded that any type of care provision decreased women's work hours by only three hours per week. However, the effect of intensive caregiving on women's work hours was as large as Johnson and Lo Sasso's 2006. In contrast, several studies found care provision has no significant effect on work hours (Bolin et al., 2008; Casado-Marín et al., 2011; Wolf and Soldo, 1994).

Work adjustments to accommodate care responsibilities might also have negatively impacted the caregiver's economic well-being. Ex-ante, reducing work hours due to caregiving responsibilities means lower wages for informal caregivers. In addition, giving care might have interfered with work, leading to lower work performance, potential fewer promotions, and thus a wage penalty for caregivers (Bauer and Sousa-Pozza, 2015). Further, as commented in Van Houtven et al.'s 2013 study, wage reductions might arise from caregivers' selection of jobs for which they are overqualified due to balancing work-care activities. Empirical evidence on the relationship between informal caregiving and wages confirms such a negative link, with most of the studies concluding that caregivers earn lower wages than their non-caregiver counterparts (Carmichael and Charles, 2003; Wakabayashi and Donato, 2005; Bittman et al., 2007; Heitmueller and Inglis, 2007; Bolin et al. 2008b; Van Houtven et al., 2013). Heitmueller and Inglis,2007, for instance, using the British Household Panel Survey for 1993 and 2002, found that employed carers were expected to earn about six percent less than non-carers, and the wage penalty was estimated to be 1.04 pounds/hour. The authors also showed that the wage penalty differed by gender, and females were more likely to be affected than male caregivers. In the case of the United States, Van Houtven and her coauthors estimated modest wage penalties among female caregivers (around $0.66 per hour in wages), that was driven by chore assistance. Further, several studies suggest that leaving the labor force due to care responsibilities might negatively impact caregivers' financial well-being, including a reduction in lifetime earnings, retirement savings, and later retirement income (Butrica and Karamcheva, 2014; Bolin et al., 2008; Crespo and Mira, 2014; Ettner, 1995; Favreault, 2010; Favreault and Steuerle, 2008; Pavalko and Artis,1997; Tamborini and Purcell, 2015, Van Houtven et al.,2013).

When reading the current literature on the association between informal caregiving and employment and wages, there are notable takeaways. First, the majority of studies documented the negative relationship between informal caregiving and labor market outcomes. Second, estimates were sensitive to caregiver subgroups, type of care (intra-residential vs. extra-residential caregiving, or intensive caregiving), and type of labor market responses, with a more specific focus on females of mid-life. Therefore, findings were hard to generalize (Bauer and Sousa-Pozza, 2015). Perhaps, since the samples of analysis used in most of these studies were relatively small, the samples hindered any sizable effects of informal caregiving on employment. Third, the endogeneity issue should be addressed because: (1) caregivers are likely to select themselves into the caring role; and (2) the link between giving care and employment is a reverse causation. Despite more sophisticated estimation methods employed (fixed effects/random effects, instrument variables, two-stage least square) and the greater availability of panel data, several studies raised doubts about the endogeneity of the care-work relationship (e.g., Bolin et al., 2008b; Ciani, 2012; Meng,2012, Van Houtven et al., 2013; and Nguyen and Connelly,2014). These challenge the identification of exogenous factors that might influence labor behaviors among caregivers in the absence of intervention events, such as public programs that support unpaid caregivers or family leave policies.

The Impact of State Paid Leave on Informal Caregivers.

The second strand of literature that relates to this study comprises previous studies that examined the impact of state leave policies on informal/family caregivers' outcomes, including labor and earnings outcomes. This literature is scarce, and there is little understanding about the effectiveness of these policies on family caregivers, especially senior adult care providers. Most of the recent papers focused on single state programs rather than a comprehensive picture of all states that implemented the family paid leave programs. Further, existing studies that evaluated the state family paid leave programs primarily focused on new mothers or fathers and the effects on their labor outcomes, with overall findings of positive effects on leave-taking, labor participation, and employment[10]. Limited work explored the potential effects of the paid leave laws on caregivers who are taking care of older adults. Among the first studies, Saad-Lessler and Bahn, 2017 found that following the Californian program, the labor force participation of unpaid care providers increased by eight percent in the short-run (after two years) and increased by 14 percent in the long run (after 14 years). Another recent study led by Kang (Kang et al.,2019) showed similar findings that the paid leave policy significantly increased the likelihood to work (about four percentage points) among middle-aged potential caregivers. However, the positive effects were more centered among the early middle-aged, near-poor, and those with the highest level of education.

Empirical Approach

In a simple model of work and caregiving (leisure time) with a budget constraint, a potential caregiver would reduce their labor supply (e.g., reduce work hours or switch to a part-time job) to provide informal care. They might also stay at work or even increase work hours to pay for formal care and/or medical expenses. With unpaid leave, absence from work for a short time would be costly because of the wage loss, especially for those whose family resources rely largely on labor income. Paid family leave mandates, therefore, would reduce this cost by offering partial wage replacement for the time spent taking care of family members with serious illnesses.

There are several channels through which the family paid leave policies might affect potential caregivers and their labor outcomes. First, the paid family leave policies would increase the number of workers taking short-term leave (Rossin-Slate, Ruhm, and Waldfogel, 2013; Baum and Ruhm,2013; and Bartel et al.,201) to take care of ill family members. The increase in leave-taking could cause the loss of skill-specific jobs or make returning to work more difficult. Further, these policies might induce working caregivers not to re-enter the labor market if the wage replacement rate rises or is high enough to offset the cost of quitting jobs. However, with job-protection provisions (such as the ones in New

[10] Most of the studies focus on California cases, and find positive association between the paid leave policy and leave taking (Rossin-Slater, Ruhm, and Waldfogel,2013, Baum and Ruhm, 2013, and Bartel et al.,2014); increase in labor participation (Das and Polachek,2015, Curtis, Hirsch, and Schroeder,2015, and Byker,2014); increase in employment and work hours (Baum and Ruhm,2013, and Rossin-Slater, Ruhm, and Waldfogel ,2013); and decrease in the risk of poverty (Stanczyk, 2019)

York and Rhode Island), the workers who take leave are more likely to return to the prior-leave jobs. This could potentially enhance job continuity and medium and long-term earnings.

Second, the presence of paid family leave mandates might encourage the potential working caregivers to remain in the labor force more than they would have in the absence of the policies. The ability to receive pay when leave is needed is considered as a benefit of employment, making work more attractive. This potential benefit suggests that the mandates might positively affect labor participation among potential caregivers.

Third, the availability of paid leave benefits, especially when combined with a job-protection provision, would potentially provide workers with flexibility regarding work arrangements (full time vs. part-time), job position, and workplace. For example, without taking leave, a potential caregiver often takes a lower-pay job as a tradeoff for a more flexible work schedule. Therefore, a job-protection guarantee would improve job match quality, compensation, and earnings.

Taken all together, despite the ambiguous effects of the paid family leave on labor outcomes as discussed above, it's expected that paid leave would increase the probability of individuals remaining in the labor force, reduce part-time work, improve long-term earnings, and as a result, potentially reduce the reliance on social welfare benefits.

2.Data and Methods

To estimate the causal effect of state paid family leave policies on informal care provision and labor outcomes, the study employed a generalized Difference - in - Difference (DID) (or two-way fixed effects) estimation method. The DID estimates compare changes in these outcomes between states that implemented PFL policies (i.e., California, New Jersey, Rhode Island, and New York) before and after the policies were in place. The sample of working individuals with elder parents/spouses as described above was used. For each outcome of interest, a generalized DID regression model was estimated as below:

$$Y_{ist} = \alpha + \beta PFL_{ist} + \gamma X_{ist} + \delta V_{st} + \theta_s + \vartheta_t + \varepsilon_{ist} \quad (1)$$

Where PFL_{ist} was a binary variable, it indicated 1 if a person lived in states with the paid family leave policies after leave was implemented in year t in each state; X_{ist} was a set of personal demographic characters that depend on specification for each outcome but generally include age, educational attainment, race, marital status, occupation, industry, number of members in households, whether the household had a child aged from ages six to 11, whether the household had any child aged 12 to 17, metropolitan status, and household income brackets; V_{st} was a vector of state characteristics that captures trends in the labor market and the need for eldercare including a population share of 65 years and older, state unemployment rates, state minimum wages rates, state Earned Income Tax Credit (EITC) introduction, state share of Medicaid beneficiaries, and poverty rates; θ_s and ϑ_t were state and time (month-year) fixed effects, respectively, which captured "treat" effect and "post" effect and macro effects across states and over time. Finally, εit was an idiosyncratic error term that was assumed to be independent of PFL_{ist}. The standard errors were clustered at state level (Abadie et., 2017). Sampling weights were used to account for the sampling design.

The coefficient - β - provided the evidence on state paid family leave effects on labor and income outcomes, and showed the overall average treatment effects. However, as discussed above, since states differ in their paid leave benefits, β would be small and even be null for some labor measurements due to potential heterogeneous effects across states. For instance, one would expect that the labor attachment in Rhode Island and New York would have been stronger than in California and New Jersey because the former offers job protection for leave takers while the latter does not. To address potential heterogenous effects at state level, the study estimated the DID models in which the treatment effect by states was separated as follows:

$$Y_{ist} = \alpha + \beta_1 CA_{it} * Post_{2004_i} + \beta_2 NJ_{it} * Post_{2009_i} + \beta_3 RI_{it} * Post_{2014_i} + \beta_4 NY_{it} * Post_{2018_i} + \gamma X_{ist} + \delta V_{st} + \theta_s + \vartheta_t + \varepsilon_{ist} \ (2)$$

where $Yist$ was the set of outcomes of interest for each individual over period t in the sample. $CAit$, $NJit$, $RI_{it}, and\ NY_{it}$ were indicators for whether an individual was a resident in California (CA), New Jersey (NJ), Rhode Island (RI), and New York (NY). $Post_{2004_i}$, $Post_{2009_i}$, $Post_{2014_i}$, and $Post_{2018_i}$ were indicators for whether the year of observation was after the PFL laws were in effect in each of these states; other parameters expressed in the Equation (2) were similar to those in Equation (1), including control variables and the adjusted robust clustered standard errors. The interpretation of βs is straight forward- for example, β_1 showed the effect of CA Paid Leave policy on each outcome variable after the policy implemented in 2004 in CA; β_2 presented the effect for NJ after 2009, β_3 was the coefficient estimates for RI, and β_4 was for NY. The specification as expressed in Equation (1) allows us to observe the different potential effects in the four states due to variation in paid family leave provisions. For each outcome variable, joint significance tests were performed to confirm that there was significantly heterogenous effects by states due to the difference in benefit provisions. Two joint significance tests were performed. The first test was to examine if the coefficients for each PFL state (βs in Equation (2) jointly differ from zero and the second test was to check if these coefficients were significantly different from each other[11].

To better understand whom was most affected by the paid family leave policies, the study conducted sub-group analysis of potential caregivers. The estimation results were presented by age, race, marital status, and education level. For each sub-group, the analysis was conducted and results were presented according to potential caregiver gender, given that prior work shows that family caregiving is gendered (Glauber, 2017).

To test whether the findings from the main specification were sensitive to alternative the choice of comparison states, several robustness checks were run. First, the study re-estimated Eq. (1) and Eq. (2) using states that enacted but had not yet implemented their paid leave policies as control states. These states include DC, Colorado, Connecticut, Massachusetts, Oregon, and Washington. Second, the impact of paid leave policy for each treated state was tested separately using specifications as defined in Eq. (1) and Eq. (2). The overall findings indicated robust and consistent evidence of the impact on labor outcomes as the main specification (see Table 9 and Table 10). Finally, event-study models were run to test the pre-trend assumption under the main DID models (as in Eq. (1) and Eq. (2)) and to assess the dynamic treatment effects over time:

$$y_{ist} = \alpha_0 + SPL\ [\textstyle\sum_{k=-2}^{-10} \tau_k \times 1(t - T_s = k) + \sum_{k=0}^{10} \theta_k \times 1(t - T_s = k)\ ] + \gamma X_{ist} + \delta V_{st} + \theta_s + \vartheta_t + \varepsilon_{ist} \quad (3)$$

where, for identification from state-level SPL changes, SPL equaled 1 for states which introduced the paid leave policy; $1(t - T_s = k)$ were indicator variables measuring the time relative to the state SPL introduction; k ran from -10 to 10 (10 years before and after the policy changes) and year prior to the policy changed (k= -1) was omitted; other covariates were similar to those defined in Eq. (1). The key coefficients in this model were τ_k and θ_k. Statistically insignificant supports τ_k the assumption of parallel pre-trends and θ_k measured the dynamic effects of SPLs at the state level on outcome variables over time, relative to the year prior to the policy change. Other variables were defined in the same way as in Eq. (1).

[11] For each outcome variable, the researcher ran the two tests and confirmed that they are jointly significant. Results will be provided upon request.

Results from event-study models confirmed that across key outcome variables, the general DID model assumption of pre-trend for both female and male samples was not violated, especially in years close to the year when the paid leave policies were implemented[12] (i.e, five years prior to the year of policies changed). For dynamic effects, there were two big takeaways from these event-style models. First, consistent but small positive effects on labor participation (e.g., increase in labor market participation and decline in voluntary part-time jobs) were observed, however, models revealed that female potential caregivers were more likely to be impacted right after the policies passed, while these effects on males took a longer time to show. Second, female workers were more likely to be beneficiaries of the SPL policies in terms of wage and income gains, especially within five years after the policies took in place. As a result, social welfare income declined persistently over time (see Figure 1 – 8, Appendix D). The primary data sources used in the study were the Basic Monthly Current Population Surveys (Monthly Basic CPS) and the CPS Annual Social and Economic Supplement (CPS-ASEC) from the years 2000 to 2019. The Monthly Basic CPS data provided detailed monthly labor force participation activities, demographic information, and the family relationship of the respondents and their household members. Meanwhile, the CPS-ASEC data added supplemental information on health insurance, self-reported health conditions, earnings, social program benefits, noncash benefits, and immigration. The CPS-ASEC also contained monthly basic monthly demographics and labor force information. The former data set was used to estimate the employment effects of the PFL policies, while the latter data was employed to evaluate the effects of the PFL programs on earnings. Given the short duration of leaves in all state paid leave programs (mostly four to six weeks), the CPS data was most suitable for examining the employment effects of the PFL policies.

The other data source was the American Time Use Survey (ATUS) from the years 2003 to 2019. The ATUS is a nationally representative, monthly cross-sectional survey of time use in the United States. The ATUS's respondents were randomly selected from a subset of households present at the eighth month of interviews for the Basic Monthly CPS data. Besides demographic and employment status information, the main purpose of the ATUS was to collect data on how the respondents have spent their time in the day before the interview. Time spent ranged from unpaid, nonmarket work such as unpaid childcare, eldercare, housework, volunteering for religious activities, socializing, exercising, and

[12] I acknowledge that the pre-trend assumption for SSI benefits among females is not satisfied around a few years prior to the policy. However, since the focus of the paper is to measure the effects of SPL mandates on labor outcomes, the assumption violation for SSI benefit outcome may not be a big threat to the validity of the study's specification.

relaxation. Apart from the first year of the survey that included 40, 500 households, ATUS covered roughly 26,400 households. However, since the average response rate was not high, about 50 percent of the households were not in the final sample. The ATUS data was employed to analyze the effects of the SPL laws on informal care provision.

2.1 Sample of Analysis

Sample of Analysis using ATUS data.

To understand how the SPL policies shaped unpaid/informal care behaviors among the potential caregivers, the study drew a sample consisting of working-age individuals 18 – 64 years-old from the years 2003 to 2019. Those who worked as formal/paid home care workers[13] were excluded because it is not possible to differentiate the care that these individuals provide as formal or informal (Mommaerts and Truskinvosky, 2020). As a result, the analysis sample consisted of working-age individuals from a total of over 150,000 observations.

While the ATUS data offered a unique data set identifying potential caregivers, several caveats are noted. First, as Mommaerts and Truskinvosky, 2020 discussed, identifying caregivers using time diaries means that caregiving measures are not explicit. Respondents might not acknowledge themselves as caregivers if asked directly. Therefore, caregiving measures are not likely to be consistent with those in other contexts, such as in other surveys that directly identify informal caregivers. Second, activities recorded in the ATUS are those performed in the single day prior to the interview day, which means it is likely that many potential caregivers who provide informal care on a non-regular basis will be missed. At the same time, informal caregiver activities are relatively broad and not limited to those listed in the ATUS survey questions. For example, many activities related to providing emotional, social, and psychological support are not included. Consequently, many potential caregivers might not be covered in the sample. Third, it is not possible to distinguish whether care recipients are eligible family members who are either inside or outside households; therefore, estimates using the ATUS data may be noisy, especially they are lower-bound estimates under the context of the PFL policies.

Sample of Analysis using CPS Data.

[13] Formal (paid) home care workers are defined as individuals whose occupations are reported as home health aides, personal care aides or nurse aides (Dao, 2020; Mommaerts & Truskinvosky, 2020).

Since the CPS data do not cover caregiving activities, to evaluate the state policies the study constructed a sample of analysis that captured the most of potential caregivers by including working-age individuals 18 – 64 years old who resided with household members eligible for paid leave benefits (i.e., spouse, parents, and siblings). Although the PFL policies do not require co-residency to qualify for the paid leaves, geographic proximity (living with or within close proximity) is a key determinant of care provision. In addition, adult children are more likely to live with a parent when that parent is disabled. Therefore, as previous studies have shown, most caregivers either live with or within close proximity of care recipients (Choi et al., 2015; NAC and AARP, 2015; Compton and Pollak, 2011; Wolff and Kasper, 2006). Furthermore, except for parents, other household members were further restricted to be 65 years-old and older, self-reported to be in bad health condition, or in disability conditions that limit capacity to work. This restriction allowed the best proxy for serious health conditions of eligible family members[14] (Kang et al., 2019), since CPS does not provide information on whether a family member is critically ill or in any serious health condition. In addition, individuals who were unemployed for more than 52 weeks were also excluded because they were not likely to be eligible for PFL mandates.

Furthermore, the sample only included individuals working in private sectors who were fully covered by the PFL laws. Finally, those who had a child under five years old were not in the sample because it might hinder the ability to differentiate childcare and eldercare responsibilities. Hence, the treatment population in this study was defined as individuals aged 18 to 64, residing in California, New Jersey, Rhode Island, and New York with a parent, spouse, or siblings 65 years-old and above, or having any household members who reported having a disability that limits ability to work or a bad health condition. A comparison population comprised individuals of similar characteristics but who reside in non-treatment states.

The setting of this sample could potentially raise a concern about sample selection if the PFL laws were to induce an adult child to move in with elder parents/siblings or vice versa. This affected sample would cause the estimates of the effects of SPLs on labor outcomes to be biased. However, that is not the case in this study for two reasons. First, since the state policies do not require co-residency to be eligible for the benefits, it is plausible to assume that the state PFLs are not significantly associated

[14] Despite different provisions, in most SPL policies, a serious health condition is defined relatively similarly – as an illness, injury, impairment, or physical or mental condition that may cause any type of incapacity and requires subsequent or continuing treatment by a physician or practitioner.

with co-residency behaviors. Second, as shown in Appendix C – Table 1, there is little evidence that the PFLs impacted the co-residency decision.

Key Outcome Variables.

Two set of outcome variables were measured in this study: informal care provision and labor outcomes.

Informal Care Provision.

The study constructed three measures of informal caregiving provided to household members[15]: "caring for household members", "caring for non-household members", and "any care". "Caring for household members" was an indicator that was marked as 1 if a person reported any of the activities classified as "Caring for or Helping household members". These activities included physical care such as bathing, dressing, putting to bed, feeding, walking, etc., medical care, looking after household adults, running errands, transportation, shopping, and the time associated with such caring/helping activities (see Appendix A – Table 2 for details), and 0 otherwise. Similarly, "caring for non-household members" was an indicator variable equal to 1 if a person reported any of the activities classified as caring or helping adults outside households. Otherwise, the indicator was marked as 0. Finally, "any care" was an indicator variable for whether an individual provided any informal care for any adults inside or outside household[16].

Employment, Incomes, and Social Welfare Benefit Outcomes.

The study measured employment effects by both extensive and intensive margins following the approach used in labor supply and caregiving literature. For extensive margins, labor participation was measured as indicator variable equal to 1 if a person was in the private labor force and as a variable of 0 otherwise. For intensive margins among employed potential caregivers, the study defined voluntary part-time workers as those who usually worked full-time but chose to work part-time due to non-economic reasons[17]. The usual weekly hours and a log of lagged annual wages[18] were recorded. Voluntary part-

[16] Note that this variable is not exclusive combination of the two indicators: caring for household members and caring for non-household members since a person could provide care for both household and non-household members within a day.
[17] CPS defines non-economic reasons to include illness or other health or medical limitations, childcare problems, family or personal obligations, in school or training, retirement or Social Security limits on earnings, and having a job where full-time work is less than 35 hours.
[18] In CPS-ASEC, the question on annual wage is asked for last year's information. Therefore, I construct a lagged variable to reflect the actual year when wages are earned.

time and work hours were measured using Monthly Basic CPS, while the log of lagged wages was derived from CPS-ASEC data.

In addition, the study measured the effects of the PFL policies on incomes including annual total personal income and family income. These outcome variables were derived directly from the CPS-ASEC data. Similar to the wage variable, personal and family income were measured as lagged and transformed to log forms.

For social welfare benefits, the effects of PFL policies on receiving social benefits on extensive margins were measured by creating indicators of whether a person received non-zero welfare income or Supplemental Security income (SSI). These variables were derived from income questions from welfare programs, including cash assistance/transfer[19], food stamp values, and Supplementary Security Income (SSI) benefits[20].Table 2 summarizes the sample characteristics between states with paid leave polices (PFL states) and states without such a policy (non-PFL states). It shows that across all outcome variables, PFL states and non-PFL states were quite similar during the study period (2000-2019). On average, about 70 percent of the working age individuals participated in the labor forces. Among employed workers, roughly five percent worked part-time voluntary for about 36 hours per week. Regarding wages and personal income, both SPL states and non-SPL states experienced approximately 11 percent growth annually, while family income showed a roughly 12 percent gain in both groups. Meanwhile, the share of workers who received welfare income and SSI were seven and eight percent in PFL states respectively and nine and 13 percent in non-PFL states.

Notably, there was different race decomposition found in the sample. For instance, shares of the white and black population were slightly larger in non-PFL states than in PFL states (75 percent vs. 70 percent for the white population, and 15 percent vs. 11 percent for the black population). Meanwhile, PFL states had a higher share of Hispanic workers than in non- PFL states: 37 percent compared to 19 percent. In addition, more highly educated workers (i.e., those with a college and above degree) lived in PFL states. Hence, these states had a higher share of families with an annual income of over 100,000 dollars. These differences in demographic characteristics might suggest different behavior responses to family paid leave policies.

[19] This outcome variable is derived from the "incwelfr" variable, which asked respondents the total amount received from cash assistance programs including AFDC/TANF, Aid to Dependent Children (ADC), General Assistance Program, Emergency Assistance, Cuban/Haitian Refugee, and Indian Assistance. Note that Food Stamps and SSI payments were specifically excluded.

[20] Instead of asking questions about welfare program participation, the CPS-ASEC surveys income sources including welfare income, food stamp values, SSI, among others.

3.Results

3.1 Effects on Informal Care Provision

The estimation results of the effects of the SPLs on informal caregiving provision are presented first. Table 3a reports the β coefficient estimates as specified in Equation (1), while Table 3b shows the results in Equation (2) for the three main outcome variables: any care, caring for household members, and caring for non-household members. For each table, the study used two different samples. The pooled sample included all working-age individuals from 18 to 64 years old (Panel A) and the working sample contained working-age individuals who were reported to be active in the labor force (Panel B). Because the paid leave policies potentially affected those with jobs, the discussion is focused on results presented in Panel B. Although, the estimates for both panels were found to be robustly similar.

In Table 3a, as expected, the estimates were consistent across samples. Overall, the PFL mandates were found to have led to a higher probability to provide care to older adults, with the larger impact among the working sample. It is estimated that the mandates were associated with a 0.9 percentage points (ppt),or 6 percent, increase in the likelihood of offering informal care (Column 1 - Panel A). The impact among working potential caregivers was found to be 1.3 percentage points, or an 8.5 percent, increase (Column 1 - Panel B). These effects were driven by the impact on potential caregivers who took care of family members living with them, rather than care of non-household adults.

However, the estimates diverged when the sample was split by gender. For instance, the results showed that while female workers were more likely to offer care for adult family members (at a 2.3 ppts, or 42 percent) increase after the mandates took in place, they reduced time taking care of non-reside adults by 0.2 ppts (or 18 percent). Meanwhile, among male workers, the PFL policies appeared to encourage them to provide more care to non-reside adults. The estimated result indicated a 1.3 ppts (or 14 percent) rise in the probability of providing care to non-family members. Although the ATUS data does not provide further details on care recipients, it is plausible to conclude that the PFL benefits led to more informal care for eligible family members[21], although the results are likely to be lower bound estimates.

[21] While co-resident adults are more likely eligible family members for PFL benefits, non-reside adults might also include ineligible family members. Summary data from the Eldercare module from the ATUS data in 2017 and 2018 as well as one report by the Department of Labor show that roughly 80 percent of care recipients are spouses, parents, grandparents, and related persons who are eligible family members for the PFL benefits regardless of their residency status (DOL, 2019). Hence, the researcher expects the majority of care recipients to be family members who might be inside or outside caregivers' households.

Next, the results by each paid leave states are presented in Table 3b. Like those displayed in Table 3a, the results are for both the pooled sample and working sample. Within each sample, the coefficient estimates are for the whole sample, female sample, and male sample respectively.

As exhibited in the first three columns of Table 3b – Panel B[22], across four treated states, there was relatively consistent evidence that the PFL policies had a positive effect on informal caregiving provision, especially on providing care for household adults. The impacts were sizeable. For example, it is estimated that the Paid Leave Policy led to about a 1.9 ppts (or 28 percent) increase in the probability to provide care to any household adults in California. As expected, the sizes of effects were larger in Rhode Island and New York, with a 0.4 ppts (or 83 percent)[23] and 1.8 ppts (or 33 percent) increase. However, the study did not observe robust estimates for the caregiving activities to adults living outside households. One exception was the case of Rhode Island, where informal care provision was strongly associated with the state policy across three outcome variables. Another exception was found in the state of New Jersey, with the study finding no detectable effect. Nevertheless, the general findings showed that the SPL policies would have encouraged individuals to offer care (measured as "any care").

When the sample was split by gender, no concrete pattern of the effect in both female and male samples was found. Among female workers, the results indicated strong positive effects of the PFLs on care giving to co-resident adults, while the inverse direction of the impact is observed for informal care provided for non-reside care receivers. Rhode Island is the exception in this case. Again, the study found a larger effect for New York, with a 3 ppts (or 59 percent) rise in informal care provision following the mandate. In contrast, the estimates for caregiving to non-household members showed consistent evidence of less likelihood to offer informal care to adults living outside households (except for the sample in Rhode Island). For the male sample, the findings showed significantly positive effects of the PFLs across three outcome variables for California and New York. For instance, it was estimated that the California law was associated with a 4 ppts (or 27 percent) increase in the probability of providing informal care after the policy took place in 2004. Meanwhile, no significantly positive effects were found on male workers in New Jersey and Rhode Island.

[22] Again, the study focused on working sample rather than the pooled sample
[23] The estimates for Rhode Island are quite large, with the pattern of the impact be noisy. Perhaps, it is because of its small sample size.

The heterogeneous effects across PFL states and between the female and male genders were as expected[24] since states differed in paid leave provisions, especially in regard to leave duration, job protection, and award amounts. As a result, the effects of PFL policies on informal caregiving were estimated to be larger in states with job-protection provisions like Rhode Island and New York. With respect to the gender difference, the study observed that while men were estimated to be more likely to care for non-reside adults, women were more likely to care for household members. However, it is not clear whether women were more affected by the paid leave policies than men.

Effects on Employment.

Next, the DID estimation results from the models of employment effects are presented. These results include labor participation (at extensive margins), voluntary part-time, work hours, and logged wages conditioning on working (intensive margins) using three samples: full sample, female sample, and male sample.

Extensive Margins: Labor Participation.

Tables 4a and 4b display the coefficient estimates from the linear probability model of labor force participation from the generalized DID models (as in Eq. (1)) and the segmented DID models (as in Eq. (2)) for three samples: pooled sample, female sample, and male sample. The results shown in Table 4a indicate that overall, the paid leave policies led to higher labor participation, although the estimated impacts were small in size across samples. For instance, the findings showed that female potential caregivers were more likely to join the labor force at a 0.3 ppts (or 0.4 percent) increase following the PFLs mandates. There were no detectable effects among males.

A further look at heterogenous effects by state policies, as expected, demonstrated different patterns of the effects across samples and across states. When using the pooled sample, as shown in Column 1 of Table 4b, the results implied that potential caregivers in paid leave states were more likely to stay in the labor force, except for the case of Rhode Island. However, the effects were similarly small across paid family leave states. There was roughly a 0.3 ppts increase in the likelihood of participating in

[24]Both joint significant tests confirm that coefficient estimates for each PFL states are statistically significantly different from zero and different from each other. Results will be presented upon request.

the labor force for California and New Jersey. The estimate for New York was very close to zero and statistically insignificant.

Such effect patterns were likely to be driven by male potential caregivers (Column 3 – Table 4b). The results also showed an opposite reaction to the mandates among males in California and New York and among those in Rhode Island and New York. These results might suggest the role of job protection provision in paid leave policies as a factor. In short, the extensive employment effects of the PFL laws seem to be very small in magnitude across states and for both female and male potential caregivers.

Intensive Margins: Voluntary Part-time, Hours, and Wages.

The following section presents the results estimating effects of the PFLs at intensive margins. Table 5a summarizes the coefficient estimates - β - from Eq. (1), and Table 5a shows the summary of the coefficient estimates - β_s - from Eq. (2). There are three big takeaways from Tables 5a and 5b.

First, regarding working part-time voluntarily, as expected, in both specifications, voluntary part-time labor was reduced after the paid leave programs were introduced in four states. In the generalized DID models, the results indicated that on average, the paid leave policies were associated with a three ppts (or five percent) fall in voluntary part-time jobs compared to similar workers in states without the policy (Column 1 – Table 5a). However, such an effect was only observed in New Jersey and Rhode Island and the effects were larger in these states. In particular, the DID models showed that the PFL policies led to a five ppts (or 10 percent) and eight ppts (or 10 percent) reduction in the probability of working part-time for noneconomic reasons for New Jersey and Rhode Island respectively. The estimates for California and New York were statistically insignificant.

Among potential female caregivers, with the exception of California, caretakers reduced working as part-timers following the paid family leave mandates (0.3 ppts or six percent in New Jersey; one ppt or 12 percent in Rhode Island, and 0.6 ppts or 10 percent in New York). The larger impact observed in Rhode Island and New York is consistent with the hypothesis that the job-protection provision under the paid family leave mandates might reduce participants' decision to work less when they had family obligations. Meanwhile, the impact among potential male caregivers was only detectable in New Jersey and Rhode Island. The study found that the paid leave programs were associated with less probability of working part-time due to non-economic reasons, with a 0.8 ppts (or 16 percent) reduction in New Jersey and 0.4 ppts (or six percent) reduction in Rhode Island.

Second, a theoretical expectation of reducing work hours following the PFL policies was observed only in Rhode Island, where both women and men worked less by 3.4 and 2.9 hours (or 10 percent and eight percent) respectively. The reductions are relatively sizable. In other states, no negative effects on work hours were observed. Possibly the lack of negative effects was due to the mixed effects on females and males (for California and New Jersey) or the no detectable impact for New York.

Third, there was little evidence of wage penalties resulting from the reduction in work hours. Wage reduction was observed among potential male caregivers in Rhode Island and New York as a result of working less, but the estimated effects of the PFLs were relatively small - a three percent and one percent fall in wages following the mandates, respectively. In other states, no evidence on wage penalties was found. For instance, in California, male employees reduced work hours by 0.5 hours (or roughly one percent) after the paid leave program, but their wages did not decrease as expected. One possible explanation is that the availability of paid leave encouraged potential caregivers to switch to higher compensation jobs that they would not have chosen without the paid leave benefits.

Heterogeneous Effects on Employment – Subgroup Analysis.

In this section, the employment effects of the paid family leave policies on potential caregivers by subgroups are analyzed to identify whether there are demographic groups that significantly drove the estimation results for the baseline models presented in previous sections. The PFLs were associated with (1) increase in labor participation; (2) decrease in voluntary part-time; and (3) mixed findings in work hours. The DID models that tested the impact of the PFLs by subgroups are summarized by Figure 1 a-d for the estimates by marital status, Figure 2a-d for the estimates by race/ethnicity, and Figure 3a-d for the estimates by education levels[25]. For each subgroup, the results are presented separately by gender.

Marital Status.

Regarding the heterogeneous effects by marital status, the effects on labor participation seemed to not be distinguishable between married and single individuals in each state. An increase in labor participation was observed among California females, New Jersey males, and married female New Yorkers. Yet, the magnitude of the effects was very small, ranging from 0.5 percent to a 1.4 percent increase (Figure 1a).

[25] Although it is interesting to see heterogenous effects by ages, given the literature shows that most of family caregivers are middle-aged females, the researcher did not find a clear pattern of the effects across states. Results by ages are provided in Appendix C for reference.

At intensive margins, the results suggested that married females were more responsive. In particular, except for New York, potential married female caregivers were less likely to be voluntary part-time workers. The effects were relatively sizeable at approximately a 12 – 13 percent reduction in the likelihood of working part-time due to non-economic reasons. Married female potential caregivers also experienced higher wages across four states (although the estimate for New Jersey was not statistically significant) (Figure 1b – 1d). For New York, an 18 percent decrease in voluntary part-time among single women was observed, but the estimates for their wages were statistically insignificant. Across subgroups, there was some evidence of wage penalty among Rhode Island's married males and New York's single males. There was a fall by four percent for both groups (Figure 1d).

Races/Ethnicity.

The effects of the PFL policies were decomposed by races: white only, black, Asian, and other races (those with two or more than two races) and by Hispanic status, across four key labor outcomes. It was revealed that white, black, and Hispanic potential caregivers masked the results in both female and male samples. Again, the coefficient estimates were very small, almost close to zero in some cases (Figure 2a). For example, the PFL mandates led to an increase in labor participation among white women (though the estimate for New Jersey was not statistically significant) and black women in California and New Jersey. The impacts ranged from 0.1 – 05 ppts among white females and from 0.7 – 0.9 ppts among black females. Overall, the effect sizes were small across subgroups, even very close to zero. These findings suggest that the observed positive effects of the paid leave policies on labor participation were not likely to be driven by differences in ethnicity.

Observing the intensive margins, there was a consistent finding that white and non-Hispanic groups masked the results. The PFL mandates led to a reduction in working part-time voluntarily among white females across four states, with the decline ranging from five to 20 percent. The results also indicated larger effects in Rhode Island and New York than in other states. For the non-Hispanic group, the estimates were only statistically significant for New Jersey's and Rhode Island's potential caregivers for both female and male samples (Figure 2c).

Regarding work hours and wages estimates, there was the expectation that due to the PFL mandates, the potential caregivers would have not necessarily reduced their work hours. As shown in

Figures 2c and 2d, this expectation held true across most of the sub-samples[26]. One exception was Rhode Island, where potential caregivers did work less across subgroups (with an average of one to five hours of working less than those in non-SPL states). Estimates from wage models suggest that potential caregivers in some subgroups experienced wage penalties following the paid leave mandates. For instance, study results showed the paid family leave mandates reduced wages among black female workers by three percent in California, two percent in New Jersey, and five percent in RI (Figure 3d). Meanwhile, black male workers were more likely to gain higher wages (though the estimates for California and New York are not statistically significant). For the Asian and other races subgroup, wage penalty was observed among New York's females and Rhode Island's males (with a decline by 12 percent and 13 percent, respectively). In addition, wage penalty was observed among Hispanic females in New Jersey and New York and non-Hispanic males in California and New York. Again, the size of the effects was relatively small (Figure 2d).

Education.

Given that less-advantaged/low-educated workers might have less access to or be less likely to afford unpaid leave, the study accessed the effects of the PFL policies across different levels of education: high school or less, some college (some college and associate degrees), and college and above degree. Figures 3a – d present the estimation results for the four key outcomes using female and male samples separately.

The results in Figure 1a showed that less-educated female workers (less than high school and high school graduates) were more likely to participate in the labor force by 0.1 to 0.5 ppts (except for New Jersey). They were also less likely to work part-time due to noneconomic reasons (though the estimate for California is not statistically significant). In addition, they worked more hours than those in states without paid leave benefits. For instance, except for RI, the state paid leave mandates were associated with an increase in hours worked among potential female caregivers with high school degree or less. Findings showed roughly a half of hour of working more following the paid family leave laws.

[26] There are a few exceptions NY's white female, NJ's black female, CA's male with other races, NJ's Hispanic male, and CA's non-Hispanic male). However, the effects are relatively small (roughly one hour was worked less following the mandates).

Among potential male caregivers, those with high school or less were more likely to be on the labor market after the laws were enacted in California and New Jersey. At the same time, such effects were not observed in Rhode Island and New York for these groups.

For potential male caregivers, there was little evidence of an effect on voluntary part-time across four states. One exception was that some male workers with college or associate degrees in New Jersey and Rhode Island probably did not choose to work part-time for non-economic reasons (there was approximately a two ppts decrease in the probability of working part-time for non-economic reasons following the implementation of the policies in these two states).

Regarding work hours, there was a robust estimate of the reduction in work hours among less-educated male workers. Larger effects were centered in Rhode Island and New York. There were roughly one to three fewer work hours in Rhode Island and New York, and about 0.5 fewer work hours in California. However, among potential male caregivers with less educational attainment, not all participants experienced wage penalties due to working less. For instance, California and New Jersey males reported higher wages. Meanwhile, higher-educated males seemed to experience some wage loss after the mandates were implemented (Figure 3d). Perhaps, despite working fewer hours, less-educated potential male caregivers might have higher compensated jobs than they would have otherwise due to care responsibility in the absence of the paid family leave policies.

Effects on Income and Policy Implications for Government Revenue.

Previous studies on the effects of paid parental leave[27] suggested less economic insecurity in states that provided paid family leave benefits. In this section, the estimation results of the PFL effects on total personal and household income are discussed in log form.

Effects on personal and family income.

Table 6a presents the results of the estimated effects on household and personal income as specified in Eq. (1) for three samples: full sample, female sample, and male sample. Across the samples, no detectable effects on income were observed. One exception was the estimate for the male sample, which implied a decline in household income after the mandates took place. However, the impact is very close to zero.

[27] For instance, Stancyk, 2019 and Lenhart, 2021 found that the California paid leave program was associated with a lower level of poverty and less food insecurity, especially among low-income mothers.

As mentioned earlier, the null effects of the PFL policies on income could truly hold or alternatively could result from heterogenous effects due to variation in state benefit provisions. Therefore, analysis was enhanced by estimating the Eq. (2) for the two income outcomes. Results displayed in the first column of Table 6b suggested dissimilar effects across treated states for the full sample. Personal and family incomes were estimated to fall by 0.3 ppts (or 0.2 percent) for New Jersey, 0.5 ppts (or 0.4 percent) and 0.2 ppts (or 0.2 percent) for Rhode Island. In contrast, California and New York experienced a small increase in both personal and family incomes (though the estimates for California were not statistically significant). It is estimated that both individual and family incomes went up slightly by 0.2 percent among New York workers. The results displayed in Column 2 and 3 in Table 6b also suggested that the effects were more prevalent among female workers. However, overall, the effects on income (including both total personal income and family income) were modest. In most cases, the effects were not distinguishable from zero, especially among male potential caregivers.

The estimates for wages and earnings might have an important policy implication in the context of implementing the national paid leave program. While the paid leave policy provided needed time off to carry care responsibilities, there was little evidence of a negative impact on wages and incomes among potential caregivers.

Effects on social welfare incomes

Reliance on welfare by low-income workers in the absence of paid leave policies is usually among the main support for the implementation of both national and state-level programs (Ybarra, 2013). However, the potential effect of the PFL mandates on employed caregivers is rarely explored. In this section, understanding of how PFL benefits could save states' welfare spending is supplemented by estimating the PFL effects on welfare income received. The results from the DID models are exhibited in Tables 7a and 7b. As expected, the null effects on welfare incomes across three samples (except for SSI among male workers), as shown in Table 7a, suggested heterogenous effects across states. It is most likely because of state variation in eligibility criteria for both PFL and welfare programs. Therefore, the estimates for each state (as shown in Table 7b) are useful to explore the PFL effects on welfare reliance. The results indicated that PFL mandates significantly reduced the reception of welfare benefits, except for in Rhode Island and SSI in New Jersey (see Column 1 - Table 7b). These impacts were mostly driven by the impact on female potential caregivers (see Column 2 - Table 7b). The estimates were substantially large, especially for welfare income receipts. For example, it was estimated that paid leave programs reduced the likelihood to receive welfare income among female workers by 85 percent in California, 33 percent in New Jersey, and

68 percent in New York, while the estimated impacts on SSI receipt were 51 percent reduction in Rhode Island and 33 percent decline in New York (see Column 2 – Table 7b). Perhaps, the small sample size and the small share of workers who received welfare and SSI benefits are the main challenge when investigating true effects. Nevertheless, the findings support the assumption that greater resources could be realized from the PFLs than from cash welfare (Ybarra, 2013).

4. Discussion

This study examined the impact of state paid family leave programs on labor supply/caregiving decisions and found clear evidence that state PFL mandates increased the probability of providing care for family members, especially among working individuals. The effects were sizeable across PFL states. Indeed, there was a 28 percent increase in California, an 83 percent increase in Rhode Island, and a 33 percent increase in New York.

Regarding labor supply decisions, there was also evidence of a positive (but small) impact on labor force attachment, with larger effects among white, less educated, or Hispanic potential caregivers. In addition, the paid family leave mandates were associated with a significant reduction in the probability of working part-time for non-economic reasons. The larger impact found among females in Rhode Island and New York (12 percent and 11 percent, respectively) suggests the job-protection provision under these paid leave laws played a role in reducing the mismatched job demand when females in those states faced care responsibilities. Although work hour reduction was observed among both female and potential male caregivers for some states, findings generally did not show an adverse impact on wages and earnings (except for a small fall in wages by three percent and one percent following the mandates in Rhode Island and New York, respectively, among male caregivers).

Little evidence of adverse impact on earnings found in the study suggests that supporting workers to have some time away to take care of family members under paid leave policies could potentially improve retirement security among employed caregivers, as they returned to work after a short duration of leave and continued to contribute to the Social Security fund. In fact, as shown in Table 8, payroll tax contributions among females increased in California and New Jersey, while there was a small decline in Rhode Island and New York following the mandates (though the estimate for New York is statistically insignificant).

5. Conclusion

As the US population ages, with longer life expectancies and preferences to stay in the community, many working individuals face the dual demand of employment and caregiving responsibilities. Many must care for older adult family members with a serious illness, disability, or physical limitation. Managing paid work alongside care responsibilities can be challenging for the employed when existing policies and programs do not meet their needs. Leave benefits and more flexible work hours at the workplace are critical to the balance of work-care activities.

Evidence provided in this study documented that state paid family leave programs offer workers significant time off from work to carry care responsibilities while not necessarily negative impact of their economic security (i.e., wage penalty and welfare benefit reliance). The study also demonstrated that the societal norm of the mid-aged female being more likely to be the family caregiver has changed over time. The study found evidence that younger and male potential caregivers were also impacted by the paid leave policies, suggesting they certainly play a role in providing care for family members with illness or disability. Moreover, the finding that there would be no adverse impact on earnings from paid leave policies support the argument that these policies might have a positive long-term impact on income security and retirement security for family caregivers. Perhaps, administrative data can provide more accurate estimates of the welfare effects of the paid leave policies.

There are some limitations that could hinder the ability of this study to detect the effects of PFL policies on labor outcomes for individuals responsible for older and/or disabled adults. First, this study is unable to capture the impact of paid leave mandates on participants who provide care for family members who live outside the household; therefore, it is unable to provide the whole picture of the impact. Second, this study does not observe whether individuals had prior access to paid leave through an employer, which makes it hard to isolate the effects of the state mandates from employer-based leave benefits. Third, the nature of the cross-sectional survey design of the CPS data does not allow the observation of a return to the labor force after taking leave, which is the most desired outcome to measure labor supply decisions among employed caregivers. Finally, since CPS data do not provide information on caregiving activities, the best proxy of potential caregivers as individuals who reside with old-aged or disabled and/or physically limited family members might not truly represent those who actually provided care. Therefore, the findings might understate the true effects of the paid leave benefits.

Nevertheless, this paper provides the first examination of all enacted state paid leave mandates under one study. This allows the observation of nonidentical effects across states due to different paid leave provisions. In addition, as paid leave benefits provide a short duration of leave, monthly CPS data is the most suitable to capture the changes in labor supply decisions in the short run. At the same time, the ASEC-CPS data allows the estimation of longer-term effects on earnings and social welfare benefits.

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Figure 1. SPL Effects by Marital Status

Figure 1a. SPL Effects on Labor Participation

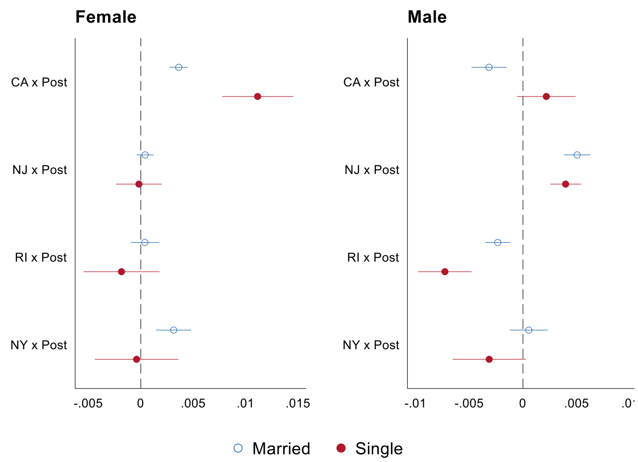


Figure 1b. SPL Effects on Voluntary Part-time

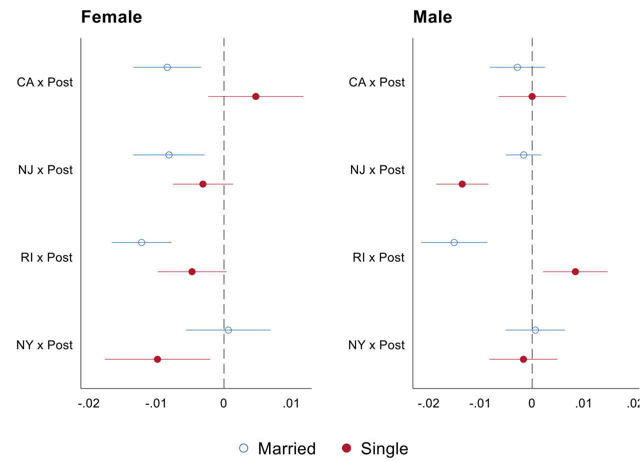


Figure 1c. SPL Effects on Work Hours

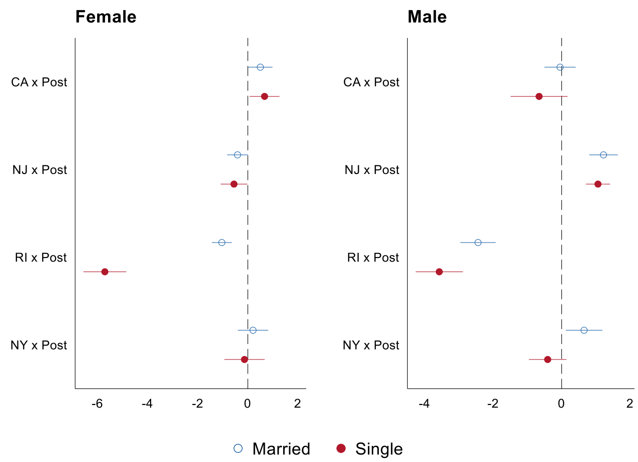
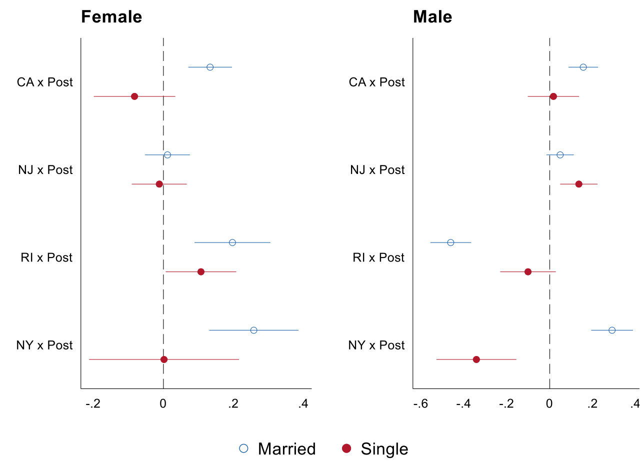


Figure 1d. SPL Effects on Wages (Log)



Notes: Each dot presents the coefficient estimate for California, New Jersey, Rhode Island, and New York after the SPL policies were implemented (i.e., βs coefficients as specified in Equation (1)) from one regression model. Outcome variables are the probability of being in labor force, the probability of working parttime for non-economic reasons, usually weekly work hours, and log of wage. The regression model runs separately for two marital statuses: married and single. All models are adjusted by age, education, race, occupation, industries, metropolitan area, household size, family income categories, whether having any child aged from six to 17, share of state population aged 65 and over, share of Federal Medicaid Assistant Programs for each state, state EITC, state unemployment rates, state minimum wages, as well as state, and month-year fixed effects that captures unobserved macroconditions over time. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. The lines present 95% confidence interval of the estimated coefficients.

<u>Figure 2</u>. PFL Effects by Races/Ethnicity

Figure 2a. PFL Effects on Labor Participation

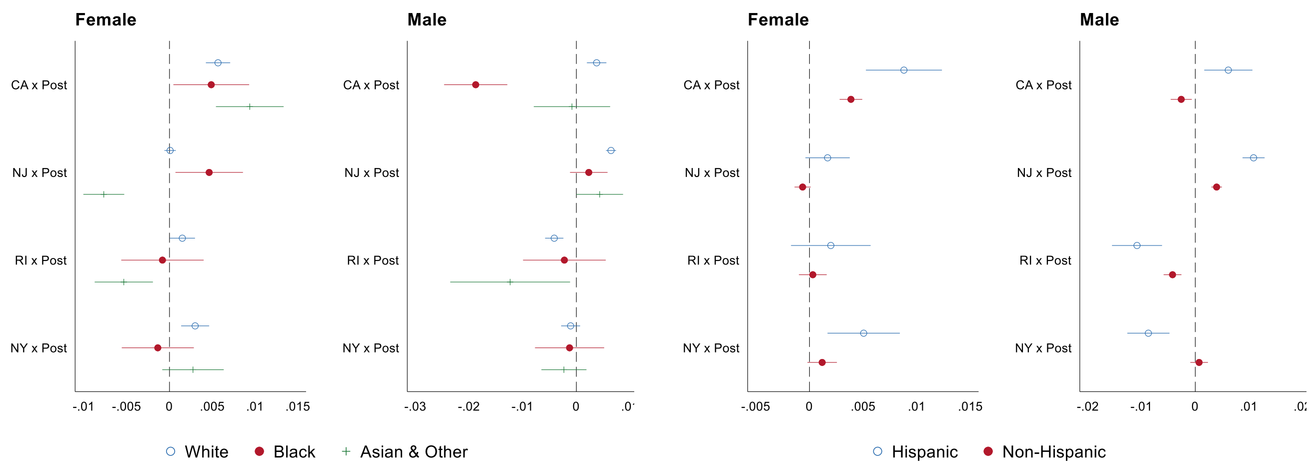


Figure 2b. PFL Effects on Voluntary Part-time

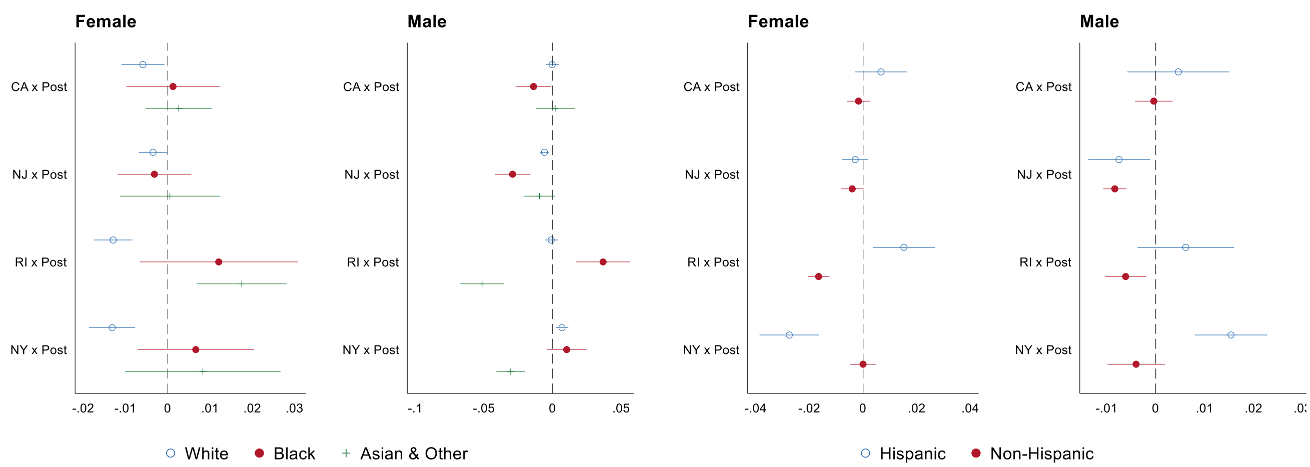


Figure 2c. PFL Effects on Work Hours

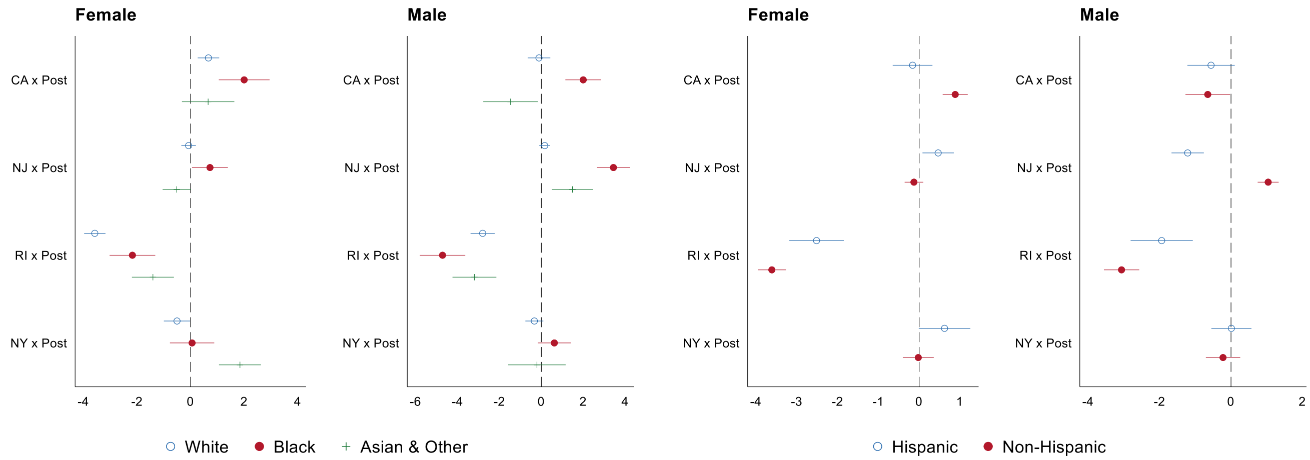
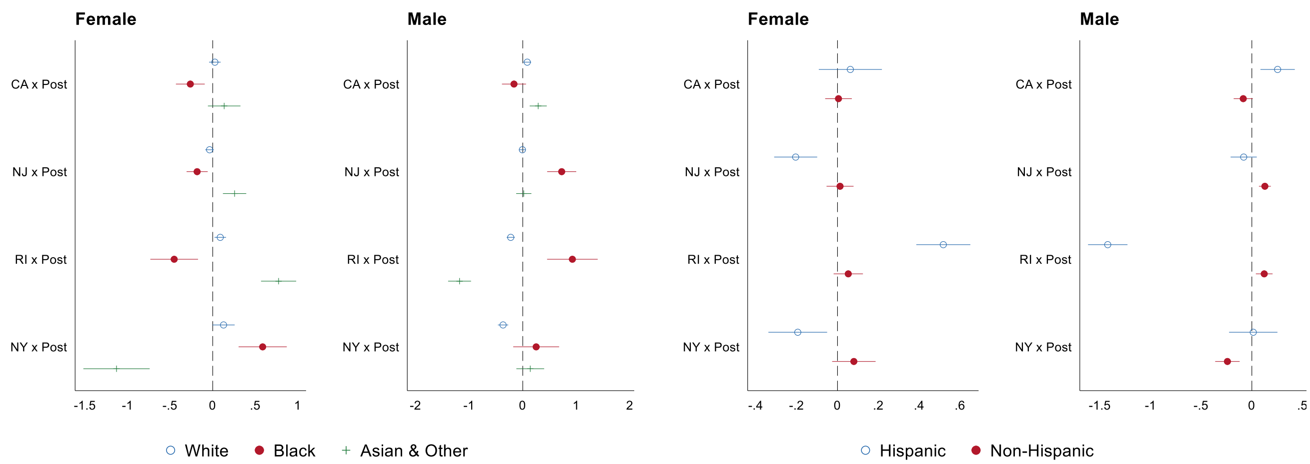


Figure 2d. PFL Effects on Wages (Log)



Notes: Each dot presents the coefficient estimate for California, New Jersey, Rhode Island, and New York after the SPL policies were implemented (i.e., βs coefficients as specified in Equation (1)) from one regression model. Outcome variables are the probability of being in labor force, the probability of working part-time for non-economic reasons, usually weekly work hours, and log of wage. The regression model runs separately for each race: Black, White, Asian and other races, Hispanic, and non-Hispanic. All models are adjusted by age, education, occupation, industries, metropolitan area, household size, family income categories, whether having any child aged from six to 17, share of state population aged 65 and over, share of Federal Medicaid Assistant Programs for each state, state EITC, state unemployment rates, state minimum wages, as well as state, month-year fixed effects that captures unobserved macroconditions over time. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. The lines present 95% confidence interval of the estimated coefficients.

<u>Figure 3</u>. PFL Effects by Educational Attainments

Figure 3a. PFL Effects on Labor Participation

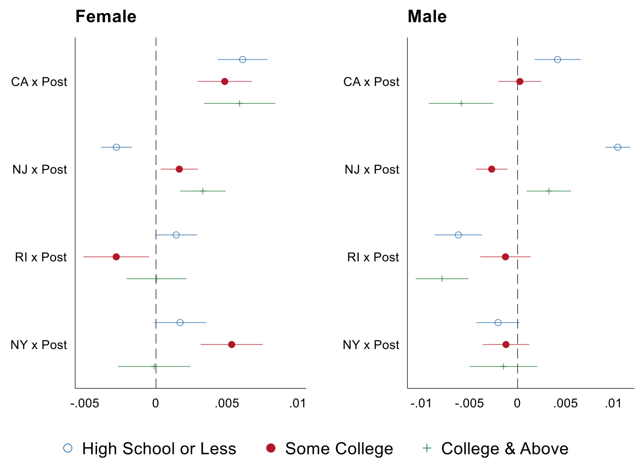


Figure 3b. PFL Effects on Voluntary Parttime

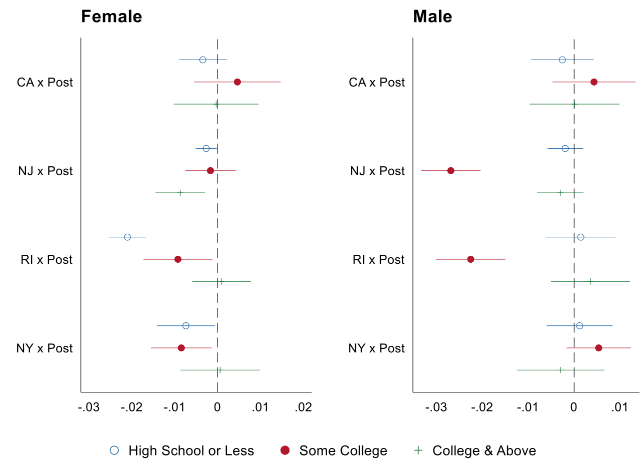


Figure 3c. PFL Effects on Work Hours

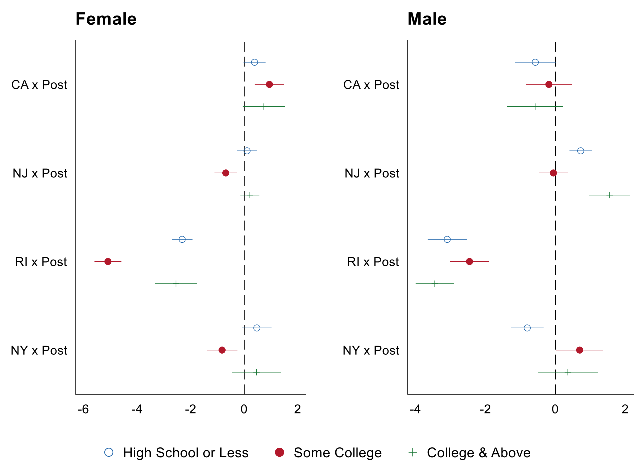
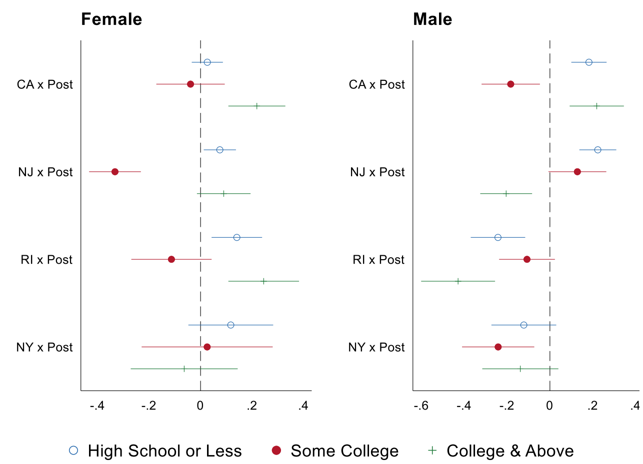


Figure 3d. PFL Effects on Wages (Log)



Notes: Each dot presents the coefficient estimate for California, New Jersey, Rhode Island, and New York after the SPL policies were implemented (i.e., βs coefficients as specified in Equation (1)) from one regression model. Outcome variables are the probability of being in labor force, the probability of working parttime for non-economic reasons, usually weekly work hours, and log of wage. The regression model runs separately for four education groups: less than high school, high school, some college, and college and above. All models are adjusted by age, education, occupation, industries, metropolitan area, household size, family income categories, whether having any child aged from six to 17, share of state population aged 65 and over, share of Federal Medicaid Assistant Programs for each state, state EITC, state unemployment rates, state minimum wages, as well as state, month-year fixed effects that captures unobserved macroconditions over time. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. The lines present 95% confidence interval of the estimated coefficients.

Table 1. ATUS - CPS Samples Statistics Summary

Sample Characteristics	PFL states				Non-PFL states			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Outcome variables								
Any Care	0.15	0.36	0	1	0.16	0.36	0	1
Caring for household members	0.07	0.25	0	1	0.07	0.25	0	1
Caring for non-household members	0.10	0.30	1	1	0.10	0.30	1	1
Demographics								
Age	39.91	13.16	18	64	40.74	13.26	18	64
Female	0.50	0.50	0	1	0.50	0.50	0	1
Married	0.53	0.50	0	1	0.56	0.50	0	1
White	0.78	0.41	0	1	0.82	0.38	0	1
Black	0.10	0.29	0	1	0.12	0.33	0	1
Asian	0.09	0.29	0	1	0.03	0.18	0	1
Other races	0.03	0.16	0	1	0.02	0.15	0	1
Living in metropolitan area	0.97	0.18	0	1	0.81	0.39	0	1
Household size	3.37	1.68	1	15	3.09	1.51	1	16
Having any child aged 6 to 12	0.20	0.40	0	1	0.19	0.39	0	1
Having any child aged 13 to 17	0.14	0.35	0	1	0.14	0.35	0	1
Educational Attainment (%)								
Less than high school	13.46				10.62			
High school graduates	24.09				30.16			
Some College	29.98				27.67			
College and above	35.48				31.55			
Family Income Brackets (%)								

Less than 30k	21.43		23.71	
30-50k	17.76		19.67	
50k-75k	18.12		20.71	
75-150k	28.92		27.06	
Over 150k	13.76		8.85	
N		27,308		120,818

Note: SPL states include California, New Jersey, Rhode Island, and New York. Non-SPL states are the rest of states and DC. Sample is constructed from the American Time Use Survey (ATUS) from 2003 to 2019, contains any person aged 18 to 64. All statistics are weighted by sample weights.

Table 2. CPS Sample Statistics Summary

Sample Characteristics	PFL states				Non-PFL states			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Outcome variables								
Labor Participation	0.67	0.47	0	1	0.66	0.48	0	1
Voluntary Parttime	0.05	0.22	0	1	0.06	0.23	0	1
Work Hours	35.33	13.39	0	160	35.16	14.60	0	173
Log of Annual Wages	9.93	1.98	0	14.15	9.93	1.87	0	14.29
Log of Annual Income	10.95	0.58	8.33	14.39	10.93	0.54	0	14.32
Log of Family Income	11.52	0.63	8.85	14.81	11.46	0.58	7.66	14.83
Received Welfare Income	0.07	0.25	0	1	0.09	0.29	0	1
Received SSI	0.08	0.28	0	1	0.13	0.33	0	1
Demographics (Working Individuals from Basic Monthly Sample)								
Age	40.84	13.59	18	64	42.42	14.00	18	64
Female	0.51	0.50	0	1	0.52	0.50	0	1
Married	0.41	0.49	0	1	0.43	0.49	0	1
Single	0.45	0.50	0	1	0.40	0.49	0	1

White	0.68	0.47	0	1	0.76	0.43	0	1
Black	0.11	0.31	0	1	0.15	0.35	0	1
Asian	0.19	0.39	0	1	0.06	0.25	0	1
Other races	0.03	0.16	0	1	0.03	0.16	0	1
Hispanic	0.34	0.47	0	1	0.17	0.37	0	1
Household size	3.93	1.82	1	16	3.45	1.55	1	16
Having any child aged 6 to 11	0.08	0.28	0	1	0.07	0.25	0	1
Having any child aged 12 to 17	0.12	0.33	0	1	0.11	0.31	0	1
Educational Attainment (%)								
Less than high school	13.46				11.50			
High school graduates	31.00				37.57			
Some Colleges & Associates Degree	29.81				30.59			
College and above	25.73				20.34			
Family Income Brackets (%)								
Less than 30k	16.88				20.54			
30-49.99k	20.61				23.66			
50k-74.99k	22.15				22.92			
75k-99.99k	16.23				14.73			
Over 100k	24.12				18.16			
N	174,184				635,413			

Note: SPL states include California, New Jersey, Rhode Island, and New York. Non-SPL states are the rest of states and DC. Employment variables (labor participation, voluntary part-time, and work hours) come from Basic Monthly CPS 2000-2019 while income variables (wages, income, welfare income, and food stamp values) come from CPS-ASEC 2000-2019. All monetary data is adjusted for inflation by 2019 dollars. All statistics are weighted by sample weights.

Table 3a. Overall Effects of the SPL policies on Informal Care Provision

	Whole Sample			Female			Male		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Any Care	Caring for household members	Caring for non-household members	Any Care	Caring for household members	Caring for non-household members	Any Care	Caring for household members	Caring for non-household members
Panel A. Pooled Sample (Working-Age Individuals 18-64)									
SPL x Post	0.0094***	0.0101***	-0.0027	-0.0011	0.0135*	-0.0181**	0.0181*	0.0054	0.0118*
	{0.0034}	{0.0025}	{0.0040}	{0.0084}	{0.0075}	{0.0072}	{0.0095}	{0.0056}	{0.0060}
Pre-Policy Mean	*0.1466*	*0.0567*	*0.100*	*0.149*	*0.056*	*0.105*	*0.145*	*0.057*	*0.095*
N	148,126	148,126	148,126	80,763	80,763	80,763	67,363	67,363	67,363
Panel B. Working Sample (In Labor Force Individuals 18-64)									
SPL x Post	0.0128*	0.0158***	-0.0012	0.0028	0.0226***	-0.0204**	0.0198	0.009	0.0130*
	{0.0074}	{0.0036}	{0.0059}	{0.0087}	{0.0066}	{0.0010}	{0.0133}	{0.0091}	{0.0068}
Pre-Policy Mean	*0.151*	*0.056*	*0.103*	*0.156*	*0.0539*	*0.111*	*0.147*	*0.058*	*0.096*
N	118,579	118,579	118,579	59,774	59,774	59,774	58,805	58,805	58,805

Notes: Each cell represents the coefficients on paid leave policies after they implemented in four states (i.e., β coefficients as specified in Equation (1)) from a separated linear probability model. All specifications control for age, gender, education, marital status, race, metropolitan area, household size, family income categories, whether having any child aged from six to 17, share of state population aged 65 and over, share of Federal Medicaid Assistant Programs for each state, state EITC, state unemployment rates, state minimum wages, as well as state, month-year fixed effects that captures unobserved macroconditions over time.

Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. Statistical significance at p<=0.10, p<=0.05, and p<=0.01 levels are indicated by *, **, and *** respectively.

<u>Table 3b</u>. Heterogenous Effects of the SPL policies on Informal Care Provision

	Whole Sample			**Female**			**Male**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Any Care	Caring for household members	Caring for non-household members	Any Care	Caring for household members	Caring for non-household members	Any Care	Caring for household members	Caring for non-household members
Panel A. Pooled Sample (Working-Age Individuals 18-64)									
CA x Post	0.0109**	0.0075**	0.0009	-0.0154**	0.0008	-0.0196***	0.0360***	0.0138***	0.0208***
	{0.0049}	{0.0028}	{0.0036}	{0.0060}	{0.00440}	{0.0040}	{0.0060}	{0.0040}	{0.0054}
Pre-Mean Policy	0.1773	0.0731	0.1175	0.1982	0.0794	0.1345	0.1558	0.0666	0.1
NJ x Post	0.0042	0.0113***	-0.0110***	0.0063	0.0284***	-0.0327***	-0.0007	-0.0065*	0.0075**
	{0.0036}	{0.0027}	{0.0025}	{0.0054}	{0.0033}	{0.0044}	{0.0051}	{0.0038}	{0.0037}
Pre-Mean Policy	*0.1563*	*0.0532*	*0.1116*	*0.1616*	*0.0553*	*0.1189*	*0.1511*	*0.0512*	*0.1045*
RI x Post	0.0345***	0.0203***	0.0236***	0.1062***	-0.0068	0.1172***	-0.0303***	0.0469***	-0.0636***
	{0.0059}	{0.0031}	{0.0042}	{0.0073}	{0.0046}	{0.0055}	{0.0092}	{0.0061}	{0.0071}
Pre-Mean Policy	*0.1253*	*0.0354*	*0.09*	*0.1106*	*0.0549*	*0.0557*	*0.1408*	*0.0149*	*0.1258*
NY x Post	0.0097	0.0111***	-0.0021	-0.0021	0.0178**	-0.0172**	0.0207**	0.0009	0.0143**
	{0.0067}	{0.0041}	{0.0051}	{0.0088}	{0.0070}	{0.0072}	{0.0097}	{0.0062}	{0.0060}
Pre-Mean Policy	*0.1393*	*0.055*	*0.0942*	*0.1374*	*0.0517*	*0.0979*	*0.1411*	*0.0584*	*0.0905*
N	148,126	148,126	148,126	80,763	80,763	80,763	67,363	67,363	67,363

Panel B. Working Sample (In Labor Force Individuals 18-64)

CA x Post	0.0193***	0.0191***	0.0025	-0.0076	0.0127***	-0.0219***	0.0412***	0.0239***	0.0230***
	{0.0047}	{0.0030}	{0.0037}	{0.0067}	{0.0047}	{0.0048}	{0.0058}	{0.0044}	{0.0051}
Pre-Mean Policy	*0.1796*	*0.0674*	*0.1205*	*0.2108*	*0.0745*	*0.1493*	*0.1533*	*0.0614*	*0.0964*
NJ x Post	-0.0066	0.0075**	-0.0169***	-0.0009	0.0328***	-0.0431***	-0.0131**	-0.0134***	0.0025
	{0.0045}	{0.0033}	{0.0029}	{0.0053}	{0.0037}	{0.0048}	{0.0058}	{0.0045}	{0.0038}
Pre-Mean Policy	*0.1653*	*0.0540*	*0.1200*	*0.1671*	*0.0547*	*0.1251*	*0.1637*	*0.0534*	*0.1156*
RI x Post	0.0646***	0.0338***	0.0419***	0.1309***	-0.0139**	0.1470***	0.006	0.0755***	-0.0503***
	{0.0063}	{0.0042}	{0.0041}	{0.0088}	{0.0069}	{0.0064}	{0.0114}	{0.0086}	{0.0073}
Pre-Mean Policy	*0.1290*	*0.0403*	*0.0887*	*0.1175*	*0.0715*	*0.0460*	*0.1386*	*0.0141*	*0.1245*
NY x Post	0.0187**	0.0182***	0.0029	0.0057	0.0286***	-0.0138	0.0276**	0.0046	0.0180**
	{0.0070}	{0.0049}	{0.0056}	{0.0106}	{0.0086}	{0.0082}	{0.0115}	{0.0074}	{0.0071}
Pre-Mean Policy	*0.1432*	*0.0551*	*0.0966*	*0.1439*	*0.0487*	*0.1037*	*0.1427*	*0.0606*	*0.0905*
N	118,579	118,579	118,579	59,774	59,774	59,774	58,805	58,805	58,805

Notes: Each cell represents the coefficients on California, New Jersey, Rhode Island, and New York after the SPL policies implemented (i.e., βs coefficients as specified in Equation (2)) from a separated linear probability model. All specifications control for age, gender, education, marital status, race, metropolitan area, household size, family income categories, whether having any child aged from six to 17, share of state population aged 65 and over, share of Federal Medicaid Assistant Programs for each state, state EITC, state unemployment rates, state minimum wages, as well as state, month-year fixed effects that captures unobserved macroconditions over time. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. Statistical significance at p<=0.10, p<=0.05, and p<=0.01 levels are indicated by *, **, and *** respectively.

Table 4a. Overall Effects of State Paid Family Leave on Labor Participation

	(1) Pooled Sample	(2) Female	(3) Male
SPL x Post	0.0021***	0.0029**	0.0011
	{0.0007}	{0.0013}	{0.0013}
Pre-Policy Mean	*0.66*	*0.60*	*0.74*
Demographics Control	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes
Month-year fixed effect	Yes	Yes	Yes
N	1,246,230	728,260	517,970

Notes: Each cell represents the coefficients on paid leave policies after they implemented in four states (i.e., β coefficients as specified in Equation (1)) from a separated linear probability model. All specifications control for age, gender, education, marital status, race, metropolitan area, household size, family income categories (less than $30k, $30-$49k, $50-$74k; and above $75k), whether having any child aged from six to 17, share of state population aged 65 and over, share of for each state, state EITC, state unemployment rates, state minimum wages, as well as state, month-year fixed effects that captures unobserved macroconditions over time. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. Statistical significance at p<=0.10, p<=0.05, and p<=0.01 levels are indicated by *, **, and *** respectively

Table 4b. Heterogenous Effects of State Paid Family Leave on Labor Participation

	(1) Full Sample	(2) Female	(3) Male
CA x Post	0.0034***	0.0055***	0.0008
	{0.0005}	{0.0005}	{0.0008}
Pre-Mean Policy	0.667	0.580	0.782
NJ x Post	0.0025***	-0.0003	0.0057***
	{0.0003}	{0.0003}	{0.0004}
Pre-Mean Policy	0.723	0.665	0.796
RI x Post	-0.0020***	0.0006	-0.0054***
	{0.0004}	{0.0005}	{0.0008}
Pre-Mean Policy	0.743	0.694	0.813
NY x Post	0.0004	0.0019***	-0.0015**
	{0.0005}	{0.0007}	{0.0007}
Pre-Mean Policy	0.650	0.598	0.715
N	1,246,230	728,260	517,970

Notes: Each cell represents the coefficients on California, New Jersey, Rhode Island, and New York after the SPL policies implemented (i.e., βs coefficients as specified in Equation (2)) from a separated linear probability model. All specifications control for age, gender, education, marital status, race, metropolitan area, household size, family income categories (less than $30k, $30-$49k, $50-$74k; and above $75k), whether having any child aged from six to 17, share of state population aged 65 and over, share of for each state, state EITC, state unemployment rates, state minimum wages, as well as state, month-year fixed effects that captures unobserved macroconditions over time. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. Statistical significance at p<=0.10, p<=0.05, and p<=0.01 levels are indicated by *, **, and *** respectively.

Table 5a. Overall Effects of State Paid Family Leave on Voluntary Parttime, Work Hours, and Wages

Outcome Variables	(1) Pooled Sample	(2) Female	(3) Male
Voluntary Part-time	-0.0025*	-0.0032*	-0.0022
	{0.0014}	{0.0016}	{0.0022}
Pre-Policy Mean	*0.05*	*0.06*	*0.05*
N	777,205	416,452	360,753
Work Hours	-0.0652	0.13171	-0.2071
	{0.1590}	{0.2164}	{0.2801}
Pre-Policy Mean	*35.52*	*34.56*	*36.54*
N	777,205	416,452	360,753
Wage (log)	0.0356**	0.004	0.0975**
	{0.0171}	{0.0386}	{0.0365}
Pre-Policy Mean	*9.58*	*9.50*	*9.67*
N	155,068	82,139	72,929

Notes: Each cell represents the coefficients of the interaction term between paid leave states and after the policies implemented (i.e., β coefficients as specified in Equation (1)) from a separated linear probability model. All specifications control for age, gender, education, marital status, race, metropolitan area, household size, family income categories (less than $30k, $30-$49k, $50-$74k; and above $75k), occupation and industry, whether having any child aged from six to 17, share of state population aged 65 and over, share of for each state, state EITC, state unemployment rates, state minimum wages, as well as state, month-year fixed effects that captures unobserved macroconditions over time. CPS-ASEC data is used for model of wage, with self-reported health conditions and private health insurance coverage are added as control variables. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. Statistical significance at p<=0.10, p<=0.05, and p<=0.01 levels are indicated by *, **, and *** respectively.

<u>Table 5b</u>. Heterogenous Effects of State Paid Family Leave on Voluntary Parttime, Work Hours, and Wages

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Full Sample			Female			Male		
	Voluntary Parttime	Weekly Hours	Wage (Log)	Voluntary Parttime	Weekly Hours	Wage (Log)	Voluntary Parttime	Weekly Hours	Wage (Log)
CA x Post	-0.0004	0.028	0.0655***	-0.0004	0.6183***	0.0402	-0.0009	-0.5202**	0.0943***
	{0.0016}	{0.1801}	{0.0195}	{0.0017}	{0.1526}	{0.0260}	{0.0021}	{0.2478}	{0.0325}
Pre-Mean Policy	*0.06*	*35.34*	*9.49*	*0.06*	*34.13*	*9.36*	*0.05*	*35.55*	*9.61*
NJ x Post	-0.0054***	0.2388**	0.0319*	-0.0033*	-0.0515	-0.0364	-0.0080***	0.5811***	0.0854***
	{0.0011}	{0.1000}	{0.0171}	{0.0017}	{0.1221}	{0.0277}	{0.0012}	{0.1147}	{0.0268}
Pre-Mean Policy	*0.06*	*36.37*	*9.64*	*0.06*	*35.30*	*9.57*	*0.05*	*37.56*	*9.70*
RI x Post	-0.0084***	-3.1734***	-0.0808***	-0.0113***	-3.3837***	0.0792**	-0.0040*	-2.8890***	-0.2445***
	{0.0017}	{0.1576}	{0.0190}	{0.0018}	{0.1498}	{0.0310}	{0.0022}	{0.2268}	{0.0335}
Pre-Mean Policy	*0.08*	*34.39*	*9.63*	*0.10*	*33.72*	*9.56*	*0.07*	*35.26*	*9.71*
NY x Post	-0.0021	-0.0877	-0.0658	-0.0059**	0.0797	0.028	0.0012	-0.1365	-0.1276***
	{0.0017}	{0.1503}	{0.0393}	{0.0026}	{0.1908}	{0.0514}	{0.00212}	{0.1857}	{0.0465}
Pre-Mean Policy	*0.05*	*35.45*	*9.61*	*0.06*	*34.58*	*9.55*	*0.05*	*36.38*	*9.68*
N	777,205	777,205	155,068	416,452	416,452	82,139	360,753	360,753	72,929

Notes: Each cell represents the coefficients on California, New Jersey, Rhode Island, and New York after the SPL policies implemented (i.e., βs coefficients as specified in Equation (1)) from a separated linear probability model. All specifications control for age, gender, education, marital status, race, metropolitan area, household size, family income categories (less than $30k, $30-$49k, $50-$74k; and above $75k), occupation and industry, whether having any child aged from six to 17, share of state population aged 65 and over, share of for each state, state EITC, state unemployment rates, state minimum wages, as well as state, month-year fixed effects that captures unobserved macroconditions over time. CPS-ASEC data is used for model of wage, with self-reported health conditions and private health insurance coverage are added as control variables. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. Statistical significance at p<=0.10, p<=0.05, and p<=0.01 levels are indicated by *, **, and *** respectively.

Table 6a. Overall Effects on Family & Personal Income

Outcome Variables	(1) Pooled Sample	(2) Female	(3) Male
Household Income (log)	-0.0017	0.0104	-0.0186*
	{0.0072}	{0.0089}	{0.0110}
Pre-Policy Mean	*11.37*	*11.34*	*11.40*
Personal Income (log)	-0.001	0.0077	-0.0124
	{0.0070}	{0.0071}	{0.0081}
Pre-Policy Mean	*10.80*	*10.76*	*10.84*
N	155,068	82,139	72,929

Notes: Each cell represents the coefficients of the interaction term between PFL states after the policies implemented (i.e., β coefficients as specified in Equation (1)) from a separated linear probability model. All specifications control for age, gender, education, marital status, race, metropolitan area, household size, occupation and industry, whether having any child aged from six to 17, self-reported health status (excellent, very good, good, fair, and poor), share of state population aged 65 and over, share of for each state, state EITC, state unemployment rates, state minimum wages, as well as state, year fixed effects that captures unobserved macroconditions over time. All outcome variables are lagged log transformation of family income, personal income, cash transfer, food stamp value, and SSI benefits. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. Statistical significance at p<=0.10, p<=0.05, and p<=0.01 levels are indicated by *, **, and *** respectively.

<u>Table 6b</u>. Heterogeneous Effects on Family & Personal Income

	(1)	(2)	(3)	(4)	(50	(6)
	Full Sample		Female		Male	
	Household Income (log)	Personal Income (log)	Household Income (log)	Personal Income (log)	Household Income (log)	Personal Income (log)
CA x Post	0.0023	0.0032	0.0034	0.0058	0.0008	0.003
	{0.0060}	{0.0044}	{0.0077}	{0.0071}	{0.0088}	{0.0088}
Pre-Mean Policy	11.27	10.75	11.26	10.70	11.29	10.79
NJ x Post	-0.0184***	-0.0206***	-0.0086	-0.0344***	-0.0321***	-0.001
	{0.0048}	{0.0039}	{0.0070}	{0.0045}	{0.0072}	{0.0067}
Pre-Mean Policy	11.43	10.83	11.40	10.79	11.46	10.87
RI x Post	-0.0462***	-0.0217***	0.017	-0.0234***	-0.1008***	-0.0283***
	{0.00939}	{0.00606}	{0.01058}	{0.00774}	{0.01014}	{0.00759}
Pre-Mean Policy	11.39	10.80	11.35	10.77	11.45	10.85
NY x Post	0.0233*	0.0237**	0.0183	0.0733***	0.0081	-0.018
	{0.0126}	{0.0093}	{0.0147}	{0.0119}	{0.0160}	{0.0115}
Pre-Mean Policy	11.39	10.82	11.36	10.78	11.43	10.85
N	155,068	155,068	82,139	82,139	72,929	72,929

Notes: Each cell represents the coefficients of the interactions between each state California, New Jersey, Rhode Island, and New York after the PFL policies implemented (i.e., βs coefficients as specified in Equation (2)) from a separated linear probability model. All specifications control for age, gender, education, marital status, race, metropolitan area, household size, occupation and industry, whether having any child aged from six to 17, self-reported health status (excellent, very good, good, fair, and poor), share of state population aged 65 and over, share of for each state, state EITC, state unemployment rates, state minimum wages, as well as state, year fixed effects that captures unobserved macroconditions over time. All outcome variables are lagged log transformation of family income, personal income, cash transfer, food stamp value, and SSI benefits. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. Statistical significance at p<=0.10, p<=0.05, and p<=0.01 levels are indicated by *, **, and *** respectively.

Table 7a. Overall Effects on Welfare Benefits Received

	(1) Pooled Sample	(2) Female	(3) Male
Welfare Income Received	-0.015	-0.0166	-0.0142
	{0.0107}	{0.0128}	{0.0095}
Pre-Mean Policy	0.033	0.040	0.026
SSI Received	-0.0142	0.0003	-0.0053**
	{0.0095}	{0.0030}	{0.0023}
Pre-Mean Policy	0.031	0.033	0.029
N	155,068	82,139	72,929

Notes: Each cell represents the coefficients of the interaction term between PFL states after the policies implemented (i.e., β coefficients as specified in Equation (1)) from a separated linear probability model. All specifications control for age, gender, education, marital status, race, metropolitan area, household size, occupation and industry, whether having any child aged from six to 17, self-reported health status (excellent, very good, good, fair, and poor), share of state population aged 65 and over, share of for each state, state EITC, state unemployment rates, state minimum wages, as well as state, year fixed effects that captures unobserved macroconditions over time. All outcome variables are lagged log transformation of family income, personal income, cash transfer, food stamp value, and SSI benefits. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. Statistical significance at p<=0.10, p<=0.05, and p<=0.01 levels are indicated by *, **, and *** respectively.

Table 7b. Heterogeneous Effects on Social Welfare Benefits

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample		Female		Male	
	Welfare Income Received	SSI Received	Welfare Income Received	SSI Received	Welfare Income Received	SSI Received
CA x Post	-0.0297***	-0.0011	-0.0350***	0.0025	-0.0261***	-0.0054**
	{0.0029}	{0.0019}	{0.0034}	{0.0025}	{0.0035}	{0.0023}
Pre-Mean Policy	0.033	0.027	0.041	0.027	0.025	0.027
NJ x Post	-0.0158***	0.0062***	-0.0091**	0.0045**	-0.0224***	0.0073***
	{0.0034}	{0.0015}	{0.0042}	{0.0019}	{0.0041}	{0.0019}
Pre-Mean Policy	0.026	0.034	0.027	0.034	0.025	0.035
RI x Post	0.0522***	-0.0103***	0.0455***	-0.0194***	0.0590***	-0.0022
	{0.0052}	{0.0014}	{0.0054}	{0.0022}	{0.0056}	{0.0023}
Pre-Mean Policy	0.031	0.032	0.036	0.038	0.024	0.024
NY x Post	-0.0201***	-0.0006	-0.0308***	-0.0134***	-0.0057	0.0101**
	{0.0065}	{0.0022}	{0.0078}	{0.0041}	{0.0068}	{0.0039}
Pre-Mean Policy	0.037	0.036	0.045	0.040	0.029	0.030
N	155,068	155,068	82,139	82,139	72,929	72,929

Notes: Each cell represents the coefficients on California, New Jersey, Rhode Island, and New York after the SPL policies implemented (i.e., βs coefficients as specified in Equation (1)) from a separated linear probability model. All specifications control for age, gender, education, marital status, race, metropolitan area, household size, occupation and industry, whether having any child aged from six to 17, self-reported health status (excellent, very good, good, fair, and poor), share of state population aged 65 and over, share of for each state, state EITC, state unemployment rates, state minimum wages, as well as state, year fixed effects that captures unobserved macroconditions over time. All outcome variables are lagged log transformation of family income, personal income, cash transfer, food stamp value, and SSI benefits. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. Statistical significance at p<=0.10, p<=0.05, and p<=0.01 levels are indicated by *, **, and *** respectively.

Table 8. Policy Implications for Tax

	(1) Full Sample	(2) Female	(3) Male
CA x Post	0.0744***	0.0886***	0.0662*
	{0.0224}	{0.0266}	{0.0364}
Pre-Mean Policy	6.84	6.67	7.01
NJ x Post	0.0516***	-0.0299	0.1259***
	{0.0170}	{0.0243}	{0.0275}
Pre-Mean Policy	7.03	6.95	7.09
RI x Post	-0.0599***	0.1160***	-0.2350***
	{0.0165}	{0.0289}	{0.0324}
Pre-Mean Policy	6.97	6.88	7.07
NY x Post	-0.04731	-0.01	-0.051
	{0.03724}	{0.0454}	{0.0433}
Pre-Mean Policy	7.02	6.95	7.10
N	133,151	70,839	62,312

Notes: Each column represents the coefficients on California, New Jersey, Rhode Island, and New York after the SPL policies implemented (i.e., βs coefficients as specified in Equation (1)) from a separated linear probability model. All specifications are adjusted by age, gender, education, marital status, race, metropolitan area, household size, occupation and industry, whether having any child aged from six to 17, self-reported health status (excellent, very good, good, fair, and poor), share of state population aged 65 and over, share of for each state, state EITC, state unemployment rates, state minimum wages, as well as state, year fixed effects that captures unobserved macroconditions over time. Outcome variables is lagged log transformation of payroll tax (or Social Security payroll tax). This variable derived from the variable "fica" (FICA tax) is defined as both taxes and contributions to the social insurance system of Social Security (also included Medicare tax) under the Federal Insurance Contributions Act which passed in 1935. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. Statistical significance at p<=0.10, p<=0.05, and p<=0.01 levels are indicated by *, **, and *** respectively.

Table 9. Robustness Check – PFL Effects using states enacted but not yet implemented paid leave as control states

	(1)	(2)	(3)	(4)	(5)	(6)
	Pooled Sample		Female		Male	
1. Labor Participation						
PFL x Post	0.0015		0.0017		0.0013	
	{0.0009}		{0.0010}		{0.0013}	
CA x Post		0.0028*		0.0041***		0.0014
		{0.0013}		{0.0010}		{0.0019}
NJ x Post		0.0033***		0.0006		0.0061***
		{0.0004}		{0.0005}		{0.0009}
RI x Post		-0.0001		0.0025***		-0.0032***
		{0.0006}		{0.0006}		{0.0009}
NY x Post		-0.0008		-0.0002		-0.0016
		{0.0009}		{0.0012}		{0.0012}
2. Voluntary Part-time						
PFL x Post	-0.0036*		-0.0057***		-0.0022	
	{0.0017}		{0.0016}		{0.0033}	
CA x Post		-0.0028		-0.0063**		-0.0001

	{0.0018}	{0.0021}	{0.0025}
NJ x Post	-0.0096***	-0.0093***	-0.0116***
	{0.0012}	{0.0026}	{0.0013}
RI x Post	-0.0086***	-0.0119***	-0.0043
	{0.0020}	{0.0030}	{0.0024}
NY x Post	0.0007	-0.0016	0.0026
	{0.0013}	{0.0023}	{0.0024}
3. Work Hours			
PFL x Post	-0.1702	-0.0665	-0.2068
	{0.2589}	{0.3648}	{0.2147}
CA x Post	0.1288	0.6754*	-0.2952
	{0.3777}	{0.3663}	{0.4318}
NJ x Post	-0.1482	-0.4838	0.2239
	{0.3187}	{0.3052}	{0.3575}
RI x Post	-3.2793***	-3.5593***	-3.0372***
	{0.3710}	{0.3680}	{0.4528}
NY x Post	-0.134	-0.0677	-0.1266
	{0.1785}	{0.3063}	{0.1831}

4. Wage (log)						
PFL x Post						
	0.0135		-0.0463		0.0547	
	{0.0283}		{0.0338}		{0.0513}	
CA x Post		0.0841***		0.0463		0.1004*
		{0.0184}		{0.0547}		{0.0460}
NJ x Post		0.0470		0.0110		0.0654
		{0.0268}		{0.0319}		{0.0563}
RI x Post		-0.0113		0.1450**		-0.1630**
		{0.0236}		{0.0469}		{0.0519}
NY x Post		-0.0964		-0.0193		-0.1365*
		{0.0542}		{0.0797}		{0.0668}

Notes: Each column represents the coefficient of the interaction states with paid leave policy (CA, NJ, RI, and NY) and year dummy indicates years after the policies implemented in each state (i.e., βs coefficients as specified in Equation (1) for Columns 1, 3, and 5; and βs coefficients as specified in Equation (2) for Columns 2, 4, and 6) from a separated linear probability model. All specifications control for age, gender, education, marital status, race, metropolitan area, household size, occupation and industry, whether having any child aged from six to 17, self-reported health status (excellent, very good, good, fair, and poor), share of state population aged 65 and over, share of for each state, state EITC, state unemployment rates, state minimum wages, as well as state, year fixed effects that captures unobserved macroconditions over time. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. Statistical significance at p<=0.10, p<=0.05, and p<=0.01 levels are indicated by *, **, and *** respectively.

Table 10. Robustness Check – Estimation Results for each PFL State

	(1)	(2)	(3)	(4)	(5)	(6)
	Specification 1			Specification 2		
	Full Sample	Female	Male	Full Sample	Female	Male
A. California						
Labor Participation	0.0037***	0.0053***	0.0017*	0.0061**	0.0068***	0.0053*
	{0.0006}	{0.0005}	{0.0010}	{0.0018}	{0.0016}	{0.0024}
Pre-Policy Mean	*0.67*	*0.58*	*0.78*	*0.67*	*0.58*	*0.78*
Voluntary Part-time	0.0002	0.0004	-0.0003	-0.0066**	-0.01033***	-0.0037
	{0.0018}	{0.0021}	{0.0024}	{0.0018}	{0.00141}	{0.0025}
Pre-Policy Mean	*0.06*	*0.06*	*0.05*	*0.06*	*0.06*	*0.05*
Work Hours	0.0779	0.8141***	-0.6301***	0.1097	0.59217**	-0.2919
	{0.1572}	{0.1684}	{0.1880}	{0.3894}	{0.23703}	{0.5125}
Pre-Policy Mean	*35.34*	*34.13*	*36.55*	*35.34*	*34.13*	*36.55*
Wage (log)	0.0767***	0.0573*	0.1061**	0.0914*	0.0637	0.1174
	{0.0248}	{0.0307}	{0.0427}	{0.0392}	{0.0599}	{0.1151}
Pre-Policy Mean	*9.92*	*9.80*	*10.02*	*9.92*	*9.80*	*10.02*
B. New Jersey						
Labor Participation	0.0030***	0.0005	0.0058***	0.0044***	-0.0001	0.0092***
	{0.0004}	{0.0004}	{0.0006}	{0.0008}	{0.0010}	{0.0020}
Pre-Policy Mean	*0.72*	*0.67*	*0.80*	*0.72*	*0.67*	*0.80*

Voluntary Part-time	-0.0042***	-0.0021	-0.0069***	-0.0126**	-0.0096*	-0.0177***
	{0.0011}	{0.0013}	{0.0014}	{0.0035}	{0.0041}	{0.0033}
Pre-Policy Mean	*0.06*	0.06	0.05	*0.06*	0.06	0.05
Work Hours	0.1123	-0.1523	0.4502***	-0.9596**	-1.2730***	-0.5707
	{0.1155}	{0.1306}	{0.1380}	{0.2902}	{0.2482}	{0.4170}
Pre-Policy Mean	*36.37*	*35.30*	*37.56*	*36.37*	*35.30*	*37.56*
Wage (log)	0.03564	-0.0323	0.1029**	0.0483	0.0951	-0.0028
	{0.02406}	{0.0369}	{0.0391}	{0.0298}	{0.0759}	{0.0677}
Pre-Policy Mean	*10.01*	*9.93*	*10.09*			
C. Rhode Island						
Labor Participation	-0.0006	0.0018**	-0.0037***	-0.0008	0.0050**	-0.0079***
	{0.0005}	{0.0007}	{0.0008}	{0.0006}	{0.0018}	{0.0017}
Pre-Policy Mean	*0.74*	*0.69*	*0.81*	*0.74*	*0.69*	*0.81*
Voluntary Part-time	-0.0054**	-0.0096***	0.0004	-0.009	-0.0203**	0.0027
	{0.0022}	{0.0025}	{0.0028}	{0.0052}	{0.0062}	{0.0077}
Pre-Policy Mean	*0.08*	*0.10*	*0.07*	*0.08*	*0.10*	*0.07*
Work Hours	-3.3641***	-3.6510***	-3.0014***	-2.5261**	-3.3094***	-1.8879*
	{0.2254}	{0.2271}	{0.2871}	{0.8008}	{0.8434}	{0.9285}
Pre-Policy Mean	*34.39*	*33.72*	*35.26*	*34.39*	*33.72*	*35.26*
Wage (log)	-0.1138***	0.0493	-0.2793***	-0.0613	-0.0506	-0.0599

	{0.0316}	{0.0534}	{0.0555}	{0.0697}	{0.0930}	{0.1124}
Pre-Policy Mean	*9.97*	*9.93*	*10.02*	*9.97*	*9.93*	*10.02*
D. New York						
Labor Participation	-0.0007	0.0005	-0.0019*	-0.0033**	-0.0027**	-0.0034*
	{0.0008}	{0.0011}	{0.0011}	{0.0010}	{0.0009}	{0.0017}
Pre-Policy Mean	*0.65*	*0.60*	*0.71*	*0.65*	*0.60*	*0.71*
Voluntary Part-time	-0.0036*	-0.0096***	0.002	0.0023	-0.0018	0.0057
	{0.0021}	{0.0026}	{0.0025}	{0.0041}	{0.0036}	{0.00612}
Pre-Policy Mean	*0.05*	*0.06*	0.05	*0.05*	*0.06*	0.05
Work Hours	-0.028	0.1553	-0.0663	-0.1813	-0.0906	0.0687
	{0.1767}	{0.2388}	{0.2429}	{0.1921}	{0.3281}	{0.46528}
Pre-Policy Mean	*35.45*	*34.58*	*36.38*	*35.45*	*34.58*	*36.38*
Wage (log)	-0.0424	0.0181	-0.0624	-0.0526	-0.054	-0.0592
	{0.0443}	{0.0538}	{0.0611}	{0.1269}	{0.1210}	{0.1590}
Pre-Policy Mean	*9.90*	9.85	9.95	9.9	9.85	9.95

Notes: Each panel presents the coefficients of the interaction of being in the state and year dummy indicates years after the policy implemented in each state for each labor outcomes. Each column represents the coefficient from a separated linear probability model. Specification 1 (Columns 1-3) use the rest of the states as control states while Specification 2 (Columns 4 – 6) uses only states that enacted but not yet implemented paid leave policies as control states that include DC, CO, CT, MA, OR, and WA. All specifications control for age, gender, education, marital status, race, metropolitan area, household size, occupation and industry, whether having any child aged from six to 17, self-reported health status (excellent, very good, good, fair, and poor), share of state population aged 65 and over, share of for each state, state EITC, state unemployment rates, state minimum wages, as well as state, year fixed effects that captures unobserved macroconditions over time. Outcome variables is lagged log transformation of payroll tax (or FICA tax). Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. Statistical significance at p<=0.10, p<=0.05, and p<=0.01 levels are indicated by *, **, and *** respectively.

Appendix A

Table 1. Paid Family Leave Enacted States

State	Timeline	Parental	Family Caregiver	Medical	Job Protection	Size of Employers Covered	Eligible Workers	Funding Method	Wage Replacement
California	Enacted 2002, effective 2004	6 weeks (8 weeks as of July 1, 2020)	6 weeks (8 weeks as of July 1, 2020)	52 weeks	No	All private employers, self-employed workers may opt in, and some public employers	Earned at least $300 in taxable income over the base period	Parental, family caregiver, and medical leave funded by workers (1%)20	60-70%; weekly maximum benefit of $1,252
New Jersey	Enacted 2008, effective 2009	6 weeks (12 weeks as of July 1, 2020)	6 weeks (12 weeks as of July 1, 2020)	26 weeks	No	All private and public employers	Earned at least $169 weekly for 20 weeks or $8,500 annually in the year before taking leave	Parental and family caregiver leave funded by workers (0.08%); medical leave funded by workers (0.17%) and employers (0.10% - 0.75%)	66%; weekly maximum benefit of $650 (85% as of July 1, 2020)

Rhode Island	Enacted 2013, effective 2014	4 weeks	4 weeks	30 weeks	Yes	All private and some public employers19	Earned at least $12,120 in Rhode Island and paid into the insurance fund in the base period	Parental, family caregiver, and medical leave funded by workers (1.1 %)	60%; weekly maximum benefit of $86724 (65% as of 2020; 70% as of 2021; 75% as of 22)
New York	Enacted 2016, effective 2018	10 weeks (12 weeks as of 2021)	10 weeks (12 weeks as of 2021)	26 weeks	Yes	Most private employers; public employers may opt-in	Employed full-time for 26 weeks or part-time for 175 days	Parental and family caregiver leave funded by workers (0.153%); medical leave (not to exceed 60 cents) funded by workers (0.5%) and employers (remaining balance)21	55%; weekly maximum benefit of $746.41 (60% as of 2020; 67% as of 2021)26
District of Columbia	Enacted 2017, effective 2020	8 weeks	6 weeks	2 weeks	No	All private employers, self-employed workers may opt in	Has been a covered employee for at least one week in the year preceding the	Parental, family caregiver, and medical leave	90%; weekly maximum benefit of $1,000

							qualifying event for leave	funded by employer (0.62%)	
Washington state	Enacted 2017, effective 2019 (premiums) and 2020 (benefits)	12 weeks	12 weeks	12 weeks	Yes	All employers, self- employed workers may opt in; firms with <50 workers are exempt; firms with 50-150 workers may receive assistance	Worked at least 820 hours during the qualifying period	Parental, family caregiver, and medical leave premium (0.4%) funded by workers (63%) and employers (37%)22	90%; weekly maximum benefit of $1,000
Massachusetts	Enacted 2018, effective 2019 (premiums) and 2021 (benefits)	12 weeks	12 weeks	20 weeks	Yes	All employers, self- employed workers and local government may opt in; firms with <25 workers are exempt	Received wages during the base period that total 30 times the weekly unemployment insurance benefit rate	Parental and family caregiver leave funded by workers (0.13%); medical leave premium (0.62%) funded by workers (40%) and employers (60%)23	80%; weekly maximum benefit of $850

Connecticut	Enacted 2019, effective 2021 (premiums) and 2022 (benefits)	12 weeks	12 weeks	12 weeks	Yes	All private sector employers; self- employed workers and local collective bargaining units may opt in	Earned at least $2,325 in the highest quarter during the base period and are employed in the 12 weeks just prior to the leave	Parental, family caregiver, and medical leave funded by workers (0.5%)	95%; maximum weekly benefit of $78027
Oregon	Enacted 2019, effective 2023	12 weeks	12 weeks	12 weeks	Yes	All employers; self- employed workers and tribal governments may opt in; firms with <25 workers are exempt, but may receive assistance	Received at least $1,000 in wages during the base year	Parental, family caregiver, and medical leave premium (1%) funded by workers (60%) and employers (40%)	100%; maximum weekly benefit of $1,21528

Source: Author's collection from state legislation webpages

Appendix B

Table 1. Caring for and Helping Adults Activities Classified in ATUS data

Caring for Adults (Household/Non-household members)	Helping Adults (Household/Non-household members)
Physical care (Ex: Bathing, cutting hair, dressing, feeding, putting to bed, walking, physical aid)	Helping adults (Ex: Helping with computer, managing bills, running errands, shopping)
Looking after adults (as a primary activity)	Organization and Planning
Providing medical care (giving medicine, bandaging)	Picking up or dropping off
Obtaining medical and care services for adults	Waiting time associated with helping activities
Waiting time associated with caring activities	Other un-classified caring activities
Other un-classified caring activities	
Caring for and Helping that are not classified elsewhere	

Source: IPUMS Time Use Documentation. More details can be obtained from https://www.atusdata.org/atus-action/time_use_variables/select_template

Table 2. Household members and non-household members classification in ATUS data

Household Persons	Non-Household Persons
Spouse	Own non-household child <18
Unmarried partner	Parents (not living in household)
Own household child	Other non-household family members 18+
Grandchild	Friends
Parent	Co-workers/colleagues/clients (non-work activities only)
Brother/Sister	Boss or manager (work activities only, 2010+)
One related person	People whom I supervise (work activities only, 2010+)
Housemate/roommate	Co-workers (work activities only, 2010+)
Roomer/boarder	Customers (work activities only, 2010+)
Other non-relative	Neighbors/acquaintances
	Other non-household children <18
	Other non-household adults 18+

Source: IPUMS Time Use Documentation. More details can be obtained from https://www.atusdata.org/atus/time_use_documentation.shtml#act

Appendix C

Table 1. The Effects of PFL mandates on co-residence

	(1)	(2)
PFL x Post	0.001	
	{0.001}	
CA x Post		0.002
		{0.001}
NJ x Post		-0.002
		{0.001}
RI x Post		0.004***
		{0.001}
NY x Post		0.001
		{0.002}
Observations	16,867,163	16,867,163

Notes: Column (1) represents the coefficient of the interaction between indicators for states with paid leave policy (CA, NJ, NY, and RI) and indicator for the time after the policy implemented in each state. Column (2) represents the coefficient of the interaction states with paid leave policy (CA, NJ, RI, and NY) and year dummy indicates years after the policies implemented in each state (i.e., βs coefficients as specified in Equation (1)) from a separated linear probability model. Outcome variable is the probability of living with parents, siblings, and other adults in the families. All specifications control for age, gender, education, marital status, race, metropolitan area, household size, occupation and industry, whether having any child aged from six to 17, self-reported health status (excellent, very good, good, fair, and poor), share of state population aged 65 and over, share of Medicaid beneficiaries for each state, state EITC, state unemployment rates, state minimum wages, state poverty rates, as well as state, year fixed effects that captures unobserved macroconditions over time. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. Statistical significance at p<=0.10, p<=0.05, and p<=0.01 levels are indicated by *, **, and *** respectively.

Table 2. Heterogenous Effects of the PFLs – By Ages

	(1)	(2)	(3)	(4)	(5)	(6)
		Female			Male	
	Age < 40	***40 <= Age <=55***	***55 < Age <65***	***Age < 40***	***40 <= Age <=55***	***55 < Age <65***
Panel A. Labor Participation						
CA x Post	0.0141***	0.0014	0.0015*	0.0001	-0.0008	-0.0012
	{0.0013}	{0.0009}	{0.0008}	{0.0013}	{0.0010}	{0.0021}
Pre-Mean Policy	*0.743*	*0.701*	*0.325*	*0.866*	*0.863*	*0.492*
NJ x Post	-0.0012	-0.0005	0.0003	0.0066***	0.0040***	0.0061***
	{0.0009}	{0.0005}	{0.0008}	{0.0007}	{0.0006}	{0.0007}
Pre-Mean Policy	*0.812*	*0.770*	*0.488*	*0.873*	*0.889*	*0.634*
RI x Post	-0.0015	0.0001	0.0008	-0.0034**	-0.0062***	-0.0051***
	{0.0013}	{0.0007}	{0.0008}	{0.0016}	{0.0008}	{0.0011}
Pre-Mean Policy	*0.816*	*0.805*	*0.517*	*0.874*	*0.896*	*0.611*
NY x Post	0.0026	0.0006	0.0020*	-0.00002	-0.0011	-0.0021
	{0.0016}	{0.0010}	{0.0011}	{0.0017}	{0.0008}	{0.0014}
Pre-Mean Policy	*0.734*	*0.723*	*0.435*	*0.813*	*0.836*	*0.576*
N	182,965	244,606	300,689	214,074	174,068	118,333
Panel B. Voluntary Part-time						
CA x Post	0.0053	0.001	-0.0174***	-0.0035	-0.0016	0.0267***
	{0.0043}	{0.0040}	{0.0050}	{0.0036}	{0.0034}	{0.0068}
Pre-Mean Policy	*0.059*	*0.060*	*0.082*	*0.055*	*0.053*	*0.040*

NJ x Post	-0.0077**	0.0005	-0.0025	-0.0157***	-0.0077***	0.0121***
	{0.0032}	{0.0027}	{0.0034}	{0.0032}	{0.0018}	{0.0030}
Pre-Mean Policy	*0.059*	*0.061*	*0.066*	*0.059*	*0.048*	*0.041*
RI x Post	0.0043	-0.0180***	-0.0207***	0.0144***	-0.0243***	-0.0039
	{0.0028}	{0.0030}	{0.0033}	{0.0039}	{0.0030}	{0.0070}
Pre-Mean Policy	*0.084*	*0.105*	*0.109*	*0.062*	*0.081*	*0.078*
NY x Post	-0.0067	-0.0119***	0.0017	-0.00004	0.0060**	-0.0049
	{0.0041}	{0.0039}	{0.0040}	{0.0042}	{0.0027}	{0.0052}
Pre-Mean Policy	*0.057*	*0.057*	*0.062*	*0.044*	*0.047*	*0.049*
N	124,368	166,297	125,787	155,322	142,360	63,071
Panel C. Work Hours						
CA x Post	1.1128***	0.6736**	0.0898	-0.3793	-0.0916	-2.0958***
	{0.2482}	{0.2744}	{0.5103}	{0.2826}	{0.2659}	{0.6616}
Pre-Mean Policy	*34.762*	*35.917*	*32.759*	*36.480*	*38.214*	*38.191*
NJ x Post	-0.5517**	1.2871***	-1.2690***	1.0090***	0.2009	0.7055**
	{0.2319}	{0.2027}	{0.2459}	{0.1505}	{0.2085}	{0.3091}
Pre-Mean Policy	*36.277*	*36.110*	*35.321*	*37.204*	*39.197*	*37.889*
RI x Post	-5.6538***	-2.7101***	-1.2354***	-3.1809***	-2.4350***	-2.1069***
	{0.3295}	{0.2430}	{0.2506}	{0.2521}	{0.3383}	{0.5031}
Pre-Mean Policy	*33.838*	*35.215*	*33.628*	*34.134*	*37.992*	*37.173*
NY x Post	-0.7934**	0.9491***	-0.1403	-0.2894	-0.0293	0.3119
	{0.3261}	{0.2584}	{0.3137}	{0.2776}	{0.2878}	{0.3652}
Pre-Mean Policy	*34.387*	*36.413*	*34.534*	*35.862*	*38.687*	*37.079*

N	124,368	166,297	125,787	155,322	142,360	63,071
Panel D. Wage (Log)						
CA x Post	0.0093	0.1541***	-0.0323	0.0763	0.1779***	0.1638
	{0.05063}	{0.0400}	{0.0504}	{0.0523}	{0.0440}	{0.1104}
Pre-Mean Policy	*9.030*	*9.583*	*9.685*	*9.294*	*9.926*	*9.995*
NJ x Post	-0.1475***	0.0022	0.1403**	0.1532***	0.0007	0.2903***
	{0.04294}	{0.03911}	{0.0562}	{0.0427}	{0.0442}	{0.0627}
Pre-Mean Policy	*9.208*	*9.735*	*9.609*	*9.086*	*10.006*	*9.988*
RI x Post	0.1646***	0.2090***	-0.165	0.0965*	-0.5538***	-0.5157***
	{0.0555}	{0.0688}	{0.1003}	{0.0510}	{0.0702}	{0.0923}
Pre-Mean Policy	*9.474*	*9.505*	*9.903*	*9.498*	*10.303*	*9.789*
NY x Post	-0.0697	0.3097***	-0.1376	-0.4411***	0.1173*	0.2870***
	{0.0788}	{0.0717}	{0.0897}	{0.0811}	{0.0691}	{0.0906}
Pre-Mean Policy	*9.116*	*9.660*	*9.628*	*9.304*	*10.089*	*9.896*
N	30,262	33,465	18,412	33,301	28,518	11,110

Notes: Each cell represents the coefficient of the interaction states with paid leave policy (CA, NJ, RI, and NY) and month-year (or year) dummy indicates years after the policies implemented in each state (i.e., βs coefficients as specified in Equation (2)) from a separated linear probability model. DID models for labor outcomes (labor participation, voluntary part-time, and work hours) use Monthly CPS data while DID models for wages use ASEC-CPS data. Depending on outcome variables, however, all models adjust for age, gender, education, race, metropolitan area, household size, family income, occupation and industry, whether having any child aged from 6 to 17, self-reported health status (excellent, very good, good, fair, and poor), share of state population aged 65 and over, share of Medicaid beneficiaries for each state, state EITC, state unemployment rates, state minimum wages, state poverty rates, as well as state, month-year (or year) fixed effects that captures unobserved macroconditions over time. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. Statistical significance at p<=0.10, p<=0.05, and p<=0.01 levels are indicated by *, **, and *** respectively.

<u>Table 3.</u> Heterogenous Effects of the PFLs – By Marital Status

	(1)	(2)	(3)	(4)
	Female		Male	
	Married	***Single***	***Married***	***Single***
Panel A. Labor Participation				
CA x Post	0.0036***	0.0112***	-0.0032***	0.0022
	{0.0004}	{0.0017}	{0.0008}	{0.0014}
Pre-Mean Policy	0.475	0.790	0.804	0.830
NJ x Post	0.0004	-0.0002	0.0051***	0.0040***
	{0.0004}	{0.0011}	{0.0006}	{0.0007}
Pre-Mean Policy	*0.588*	*0.800*	0.838	0.830
RI x Post	0.0004	-0.0019	-0.0024***	-0.0073***
	{0.0007}	{0.0018}	{0.0006}	{0.0012}
Pre-Mean Policy	*0.598*	*0.833*	0.813	0.849
NY x Post	0.0031***	-0.0004	0.0006	-0.0031*
	{0.0008}	{0.0020}	{0.0009}	{0.0017}
Pre-Mean Policy	0.536	0.750	0.767	0.788
N	423,969	174,821	208,733	232,722
Panel B. Voluntary Part-time				
CA x Post	-0.0084***	0.0047	-0.0029	-0.00001
	{0.0025}	{0.0035}	{0.0027}	{0.0032}
Pre-Mean Policy	0.068	0.058	0.050	0.052
NJ x Post	-0.0082***	-0.0031	-0.0017	-0.0135***
	{0.0026}	{0.0022}	{0.0017}	{0.0025}
Pre-Mean Policy	0.066	0.052	0.046	0.056
RI x Post	-0.0122***	-0.0047*	-0.0151***	0.0084***
	{0.0022}	{0.0025}	{0.0032}	{0.0031}
Pre-Mean Policy	0.101	0.090	0.073	0.071
NY x Post	0.0006	-0.0099**	0.0006	-0.0017
	{0.0031}	{0.0039}	{0.0029}	{0.00329}

Pre-Mean Policy	0.059	0.055	0.045	0.046
N	208,217	121,900	147,880	160,811
Panel C. Work Hours				
CA x Post	0.5003**	0.6679**	-0.0468	-0.6581
	{0.2403}	{0.2975}	{0.2272}	{0.4136}
Pre-Mean Policy	34.577	34.734	39.129	35.787
NJ x Post	-0.4105*	-0.5516**	1.2203***	1.0594***
	{0.2068}	{0.2642}	{0.2080}	{0.1765}
Pre-Mean Policy	35.377	36.627	39.742	36.515
RI x Post	-1.0371***	-5.7032***	-2.4393***	-3.57085***
	{0.1988}	{0.4263}	{0.2569}	{0.3429}
Pre-Mean Policy	33.592	34.311	39.268	34.001
NY x Post	0.2076	-0.1327	0.6545**	-0.4078
	{0.3016}	{0.4005}	{0.2663}	{0.2718}
Pre-Mean Policy	35.095	34.857	38.681	35.739
Observations	208,217	121,900	147,880	160,811
Panel D. Wage (Log)				
CA x Post	0.1334***	-0.0825	0.1566***	0.0174
	{0.0310}	{0.0580}	{0.0344}	{0.0596}
Pre-Mean Policy	9.477	9.011	10.049	9.227
NJ x Post	0.0116	-0.0117	0.0487	0.1359***
	{0.0319}	{0.0392}	{0.0317}	{0.0435}
Pre-Mean Policy	9.713	9.023	10.312	8.960
RI x Post	0.1971***	0.1072**	-0.4619***	-0.1013
	{0.0540}	{0.0502}	{0.0475}	{0.0646}
Pre-Mean Policy	9.547	9.601	10.319	9.471
NY x Post	0.2582***	0.0018	0.2909***	-0.3420***
	{0.0635}	{0.1066}	{0.0486}	{0.0929}
Pre-Mean Policy	9.593	9.092	10.083	9.243
N	39,548	25,472	32,684	31,084

Notes: Each cell represents the coefficient of the interaction states with paid leave policy (CA, NJ, RI, and NY) and month-year (or year) dummy indicates years after the policies implemented in each state (i.e., βs coefficients as specified in Equation (2)) from a separated linear probability model. DID models for labor outcomes (labor participation, voluntary parttime, and work hours) use Monthly CPS data while DID models for wages use ASEC-CPS data. Depending on outcome variables, however, all models adjust for age, gender, education, race, metropolitan area, household size, family income, occupation and industry, whether having any child aged from six to 17, self-reported health status (excellent, very good, good, fair, and poor), share of state population aged 65 and over, share of Medicaid beneficiaries for each state, state EITC, state unemployment rates, state minimum wages, state poverty rates, as well as state, month-year (or year) fixed effects that captures unobserved macroconditions over time. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. Statistical significance at p<=0.10, p<=0.05, and p<=0.01 levels are indicated by *, **, and *** respectively.

<u>Table 4.</u> Heterogenous Effects of the PFLs – By Race/Ethnicity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Female					**Male**				
	White	Black	Asian & Other Races	Hispanic	Non-Hispanic	White	Black	Asian & Other Races	Hispanic	Non-Hispanic
Panel A. Labor Participation										
CA x Post	0.0057***	0.0049**	0.0094***	0.0088***	0.0039***	0.0038***	-0.0188***	-0.0008	0.0062***	-0.0026**
	{0.0007}	{0.0022}	{0.0020}	{0.0018}	{0.0005}	{0.0009}	{0.0029}	{0.0036}	{0.0022}	{0.0010}
Pre-Mean Policy	*0.563*	*0.563*	*0.646*	*0.604*	*0.580*	*0.823*	*0.735*	*0.800*	*0.878*	*0.772*
NJ x Post	0.0001	0.0046**	-0.0077***	0.0017	-0.0006*	0.0065***	0.0023	0.0044*	0.0109***	0.0040***
	{0.0003}	{0.0020}	{0.0012}	{0.0010}	{0.0004}	{0.0005}	{0.0017}	{0.0022}	{0.0010}	{0.0005}
Pre-Mean Policy	*0.683*	*0.683*	*0.698*	*0.695*	*0.681*	*0.843*	*0.798*	*0.877*	*0.831*	*0.844*
RI x Post	0.0015**	-0.0008	-0.0053***	0.002	0.0003	-0.0041***	-0.0022	-0.0124**	-0.0109***	-0.00423***
	{0.0007}	{0.0024}	{0.0017}	{0.0019}	{0.0007}	{0.0009}	{0.0038}	{0.0056}	{0.0023}	{0.0008}
Pre-Mean Policy	*0.696*	*0.696*	*0.718*	*0.693*	*0.702*	*0.835*	*0.850*	*0.881*	*0.816*	*0.843*
NY x Post	0.0030***	-0.0014	0.0028	0.0051***	0.0012*	-0.0011	-0.0013	-0.0023	-0.0087***	0.0007
	{0.0008}	{0.0021}	{0.0018}	{0.0017}	{0.0007}	{0.0009}	{0.0032}	{0.0021}	{0.0020}	{0.0008}
Pre-Mean Policy	*0.618*	*0.618*	*0.599*	*0.623*	*0.631*	*0.781*	*0.729*	*0.822*	*0.800*	*0.770*

N	559,925	83,944	84,391	109,313	618,947	391,325	62,422	64,223	90,411	427,559
Panel B. Voluntary Part-time										
CA x Post	-0.0059**	0.0012	0.0026	0.0067	-0.0017	-0.0003	-0.0139**	0.0019	0.0046	-0.0004
	{0.0025}	{0.0055}	{0.0039}	{0.0049}	{0.0022}	{0.0024}	{0.0063}	{0.0071}	{0.0052}	{0.0019}
Pre-Mean Policy	*0.069*	*0.080*	*0.047*	*0.056*	*0.067*	*0.053*	*0.048*	*0.053*	*0.050*	*0.055*
NJ x Post	-0.0035**	-0.0032	0.0005	-0.0029	-0.0041*	-0.0060***	-0.0292***	-0.0096*	-0.0075**	-0.0084***
	{0.0017}	{0.0044}	{0.0059}	{0.0024}	{0.0021}	{0.0016}	{0.0065}	{0.0057}	{0.0032}	{0.0012}
Pre-Mean Policy	*0.066*	*0.051*	*0.042*	*0.053*	*0.063*	*0.053*	*0.061*	*0.038*	*0.043*	*0.054*
RI x Post	-0.0129***	0.01201	0.0175***	0.0152**	-0.0166***	-0.0011	0.0368***	-0.0515***	0.0061	-0.0062***
	{0.0023}	{0.0093}	{0.0053}	{0.0058}	{0.0020}	{0.0024}	{0.0098}	{0.0079}	{0.0049}	{0.0021}
Pre-Mean Policy	*0.105*	*0.062*	*0.060*	*0.091*	*0.100*	*0.076*	*0.030*	*0.059*	*0.047*	*0.075*
NY x Post	-0.0132***	0.0066	0.0083	-0.0275***	-0.00002	0.0068***	0.0103	-0.0306***	0.0154***	-0.004
	{0.0027}	{0.0069}	{0.0092}	{0.0055}	{0.0025}	{0.0023}	{0.0072}	{0.0052}	{0.0037}	{0.0029}
Pre-Mean Policy	*0.065*	*0.054*	*0.034*	*0.059*	*0.058*	*0.050*	*0.039*	*0.037*	*0.044*	*0.047*
N	315,163	49,646	51,643	64,785	351,667	277,021	37,488	46,244	68,953	291,800
Panel C. Work Hours										
CA x Post	0.6657***	1.9992***	0.6541	-0.1608	0.8838***	-0.1125	1.9964***	-1.4685**	-0.5578*	-0.6500**

	{0.2001}	{0.4718}	{0.4865}	{0.2424}	{0.1530}	{0.2686}	{0.4245}	{0.6489}	{0.3302}	{0.3108}
Pre-Mean Policy	*34.444*	*34.381*	*36.103*	*35.370*	*34.646*	*36.839*	*36.677*	*38.579*	*37.646*	*36.999*
NJ x Post	-0.0733	0.7231**	-0.5149*	0.4658**	-0.1274	0.1604	3.4366***	1.4825***	-1.2120***	1.0400***
	{0.1356}	{0.3326}	{0.2635}	{0.1912}	{0.1135}	{0.1292}	{0.3916}	{0.4903}	{0.2255}	{0.1463}
Pre-Mean Policy	*35.546*	*36.695*	*38.104*	*36.980*	*35.751*	*38.471*	*35.418*	*38.360*	*39.478*	*37.769*
RI x Post	-3.5731***	-2.1699***	-1.4045***	-2.5136***	-3.6083***	-2.7981***	-4.7107***	-3.1912***	-1.9386***	-3.0619***
	{0.1979}	{0.4245}	{0.3900}	{0.3326}	{0.1714}	{0.2873}	{0.5392}	{0.5204}	{0.4333}	{0.2459}
Pre-Mean Policy	*34.308*	*34.751*	*34.589*	*35.288*	*34.266*	*35.989*	*36.508*	*36.572*	*36.478*	*36.028*
NY x Post	-0.5063**	0.0563	1.8419***	0.6223*	-0.0207	-0.3338	0.6187	-0.2115	0.0109	-0.2226
	{0.2444}	{0.4116}	{0.3895}	{0.3147}	{0.1889}	{0.2136}	{0.3906}	{0.6821}	{0.2793}	{0.2394}
Pre-Mean Policy	*34.928*	*35.639*	*36.164*	*35.162*	*35.284*	*37.116*	*35.949*	*38.205*	*37.069*	*37.077*
N	315,163	49,646	51,643	64,785	351,667	277,021	37,488	46,244	68,953	291,800
Panel D. Wage (Log)										
CA x Post	0.0253	-0.2627***	0.1348	0.0629	0.0048	0.0844**	-0.1629	0.2887***	0.2544***	-0.0848*
	{0.0339}	{0.0844}	{0.0952}	{0.0770}	{0.0325}	{0.0362}	{0.1118}	{0.0794}	{0.0845}	{0.0470}
Pre-Mean Policy	*9.312*	*9.603*	*9.418*	*9.046*	*9.480*	*9.585*	*9.773*	*9.625*	*9.359*	*9.745*
NJ x Post	-0.0365	-0.1829***	0.2570***	-0.2050***	0.0124	-0.0061	0.7268***	0.0193	-0.0804	0.1286***
	{0.0251}	{0.0618}	{0.0682}	{0.0525}	{0.0330}	{0.0305}	{0.1353}	{0.0706}	{0.0643}	{0.0293}
Pre-Mean Policy	*9.515*	*9.413*	*9.653*	*9.187*	*9.552*	*9.646*	*9.077*	*10.089*	*9.358*	*9.611*

RI x Post	0.0888**	-0.4525***	0.7741***	0.5184***	0.0526	-0.2236***	0.9262***	-1.1779***	-1.4227***	0.1224***
	{0.0336}	{0.1395}	{0.1029}	{0.0659}	{0.0358}	{0.0378}	{0.2350}	{0.1063}	{0.0970}	{0.0411}
Pre-Mean Policy	*9.560*	*9.883*	*9.403*	*9.274*	*9.609*	*9.936*	*9.250*	*8.867*	*9.929*	*9.848*
NY x Post	0.1275*	0.5872***	-1.1300***	-0.1948***	0.0801	-0.3666***	0.2508	0.1405	0.0139	-0.2411***
	{0.0651}	{0.141}	{0.1940}	{0.0717}	{0.0530}	{0.0480}	{0.2130}	{0.1290}	{0.1190}	{0.0603}
Pre-Mean Policy	*9.411*	*9.436*	*9.501*	*9.254*	*9.458*	*9.678*	*9.434*	*9.843*	*9.424*	*9.697*
N	58,741	12,524	10,874	15,955	66,184	53,364	9,668	9,897	16,459	56,470

Notes: Each cell represents the coefficient of the interaction states with paid leave policy (CA, NJ, RI, and NY) and month-year (or year) dummy indicates years after the policies implemented in each state (i.e., βs coefficients as specified in Equation (2)) from a separated linear probability model. DID models for labor outcomes (labor participation, voluntary parttime, and work hours) use Monthly CPS data while DID models for wages use ASEC-CPS data. Depending on outcome variables, however, all models adjust for age, gender, education, race, metropolitan area, household size, family income, occupation and industry, whether having any child aged from six to 17, self-reported health status (excellent, very good, good, fair, and poor), share of state population aged 65 and over, share of Medicaid beneficiaries for each state, state EITC, state unemployment rates, state minimum wages, state poverty rates, as well as state, month-year (or year) fixed effects that captures unobserved macroconditions over time. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. Statistical significance at p<=0.10, p<=0.05, and p<=0.01 levels are indicated by *, **, and *** respectively.

<u>Table 5.</u> Heterogenous Effects of the PFLs – By Educational Attainment

	(1)	(2)	(3)	(4)	(5)	(6)
		Female			Male	
	High School or Less	***Some Colleges***	***Colleges and above***	***High School or Less***	***Some Colleges***	***Colleges and above***
Panel A. Labor Participation						
CA x Post	0.0061***	0.0049***	0.0059***	0.0042***	0.0002	-0.0059***
	{0.0009}	{0.0010}	{0.0013}	{0.0012}	{0.0011}	{0.0017}
Pre-Mean Policy	*0.526*	*0.659*	*0.639*	*0.805*	*0.834*	*0.804*
NJ x Post	-0.0028***	0.0016**	0.0033***	0.0104***	-0.0027***	0.0033***
	{0.0005}	{0.0007}	{0.0008}	{0.0007}	{0.0008}	{0.0012}
Pre-Mean Policy	*0.619*	*0.746*	*0.751*	*0.819*	*0.836*	*0.888*
RI x Post	0.0014*	-0.0028**	0.00004	-0.0062***	-0.0013	-0.0079***
	{0.0007}	{0.0012}	{0.0011}	{0.00122}	{0.0013}	{0.0014}
Pre-Mean Policy	*0.677*	*0.771*	*0.682*	*0.830*	*0.841*	*0.869*
NY x Post	0.0017*	0.0053***	-0.0001	-0.0020*	-0.0012	-0.0015
	{0.0009}	{0.0011}	{0.0013}	{0.0011}	{0.0012}	{0.0018}
Pre-Mean Policy	*0.548*	*0.703*	*0.699*	*0.749*	*0.791*	*0.820*
N	354,537	208,200	165,523	289,569	134,516	93,885
Panel B. Voluntary Part-time						

CA x Post	-0.0035	0.005	-0.0004	-0.0026	0.0043	0.0001
	{0.0028}	{0.0050}	{0.0049}	{0.0034}	{0.0045}	{0.0049}
Pre-Mean Policy	*0.056*	*0.072*	*0.065*	*0.052*	*0.057*	*0.049*
NJ x Post	-0.0027**	-0.0017	-0.0088***	-0.0019	-0.0269***	-0.003
	{0.0012}	{0.0029}	{0.0029}	{0.0019}	{0.0032}	{0.0025}
Pre-Mean Policy	*0.059*	*0.073*	*0.055*	*0.051*	*0.058*	*0.048*
RI x Post	-0.0211***	-0.0093**	0.0009	0.0015	-0.0225***	0.0036
	{0.0022}	{0.0040}	{0.0034}	{0.0038}	{0.0038}	{0.0043}
Pre-Mean Policy	*0.097*	*0.099*	*0.104*	*0.066*	*0.090*	*0.064*
NY x Post	-0.0074**	-0.0085**	0.0006	0.0012	0.0054	-0.0029
	{0.0034}	{0.0035}	{0.0046}	{0.0036}	{0.0035}	{0.0048}
Pre-Mean Policy	*0.056*	*0.062*	*0.058*	*0.046*	*0.049*	*0.043*
N	185,394	128,237	102,821	195,106	95,639	70,008
Panel C. Work Hours						
CA x Post	0.3811*	0.9348***	0.7265*	-0.5772*	-0.1888	-0.5808
	{0.2047}	{0.2730}	{0.3923}	{0.2905}	{0.3262}	{0.3983}
Pre-Mean Policy	*34.212*	*34.683*	*36.457*	*36.884*	*36.793*	*39.173*
NJ x Post	0.1007	-0.6930***	0.2047	0.7206***	-0.0589	1.5468***
	{0.1875}	{0.2110}	{0.1765}	{0.1603}	{0.2043}	{0.2898}
Pre-Mean Policy	*35.034*	*35.852*	*37.503*	*37.311*	*38.150*	*39.427*

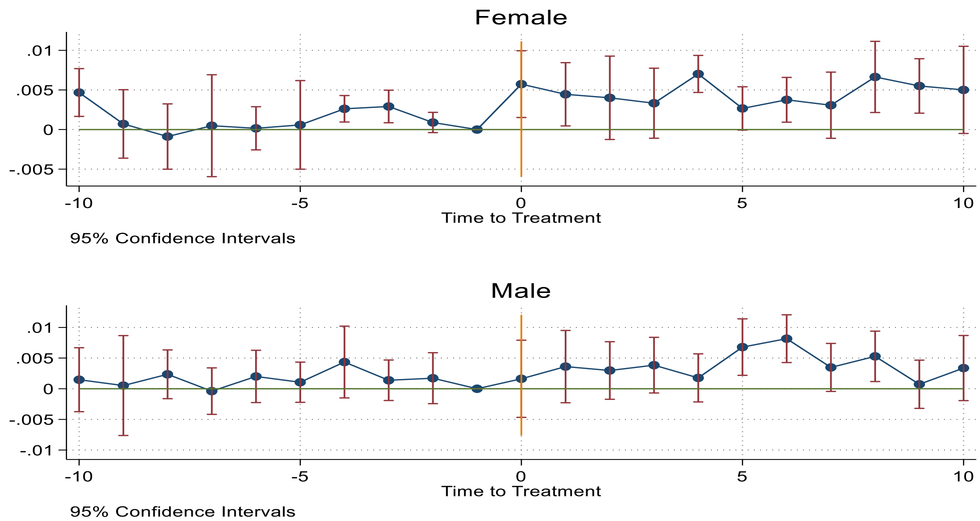
RI x Post	-2.3210***	-5.0913***	-2.5509***	-3.0950***	-2.4581***	-3.4516***
	{0.1924}	{0.2501}	{0.3901}	{0.2782}	{0.2796}	{0.2719}
Pre-Mean Policy	*33.960*	*35.023*	*34.438*	*35.795*	*35.707*	*37.292*
NY x Post	0.4653*	-0.8310***	0.453	-0.8079***	0.6915**	0.3523
	{0.2739}	{0.2845}	{0.4528}	{0.2333}	{0.3350}	{0.4281}
Pre-Mean Policy	*34.395*	*34.707*	*36.837*	*36.602*	*36.352*	*38.645*
N	185,394	128,237	102,821	195,106	95,639	70,008
Panel D. Wage (Log)						
CA x Post	0.0263	-0.039	0.2188***	0.1825***	-0.1831***	0.2190***
	{0.0301}	{0.0662}	{0.0551}	{0.0410}	{0.0679}	{0.0631}
Pre-Mean Policy	*9.037*	*9.400*	*9.928*	*9.403*	*9.663*	*10.072*
NJ x Post	0.0750**	-0.3326***	0.0901*	0.2239***	0.1284*	-0.2045***
	{0.0311}	{0.0501}	{0.0519}	{0.0430}	{0.0673}	{0.0603}
Pre-Mean Policy	*9.105*	*9.472*	*10.264*	*9.177*	*9.453*	*10.451*
RI x Post	0.1410***	-0.1132	0.2454***	-0.2428***	-0.1071	-0.4293***
	{0.0489}	{0.0777}	{0.0684}	{0.06340}	{0.0650}	{0.0861}
Pre-Mean Policy	*9.459*	*9.528*	*10.003*	*9.820*	*9.497*	*10.434*
NY x Post	0.1174	0.0257	-0.0636	-0.1219	-0.2419***	-0.1383

	{0.0821}	{0.1269}	{0.1035}	{0.0755}	{0.0840}	{0.0886}
Pre-Mean Policy	*9.205*	*9.338*	*9.987*	*9.454*	*9.474*	*10.363*
N	37,925	26,826	17,388	40,103	20,218	12,608

Notes: Each cell represents the coefficient of the interaction states with paid leave policy (CA, NJ, RI, and NY) and month-year (or year) dummy indicates years after the policies implemented in each state (i.e., βs coefficients as specified in Equation (2)) from a separated linear probability model. DID models for labor outcomes (labor participation, voluntary parttime, and work hours) use Monthly CPS data while DID models for wages use ASEC-CPS data. Depending on outcome variables, however, all models adjust for age, gender, education, race, metropolitan area, household size, family income, occupation and industry, whether having any child aged from six to 17, self-reported health status (excellent, very good, good, fair, and poor), share of state population aged 65 and over, share of Medicaid beneficiaries for each state, state EITC, state unemployment rates, state minimum wages, state poverty rates, as well as state, month-year (or year) fixed effects that captures unobserved macroconditions over time. Standard errors, clustered by state, are in parentheses. All estimates are weighted by individual sample weights. Statistical significance at p<=0.10, p<=0.05, and p<=0.01 levels are indicated by *, **, and *** respectively.

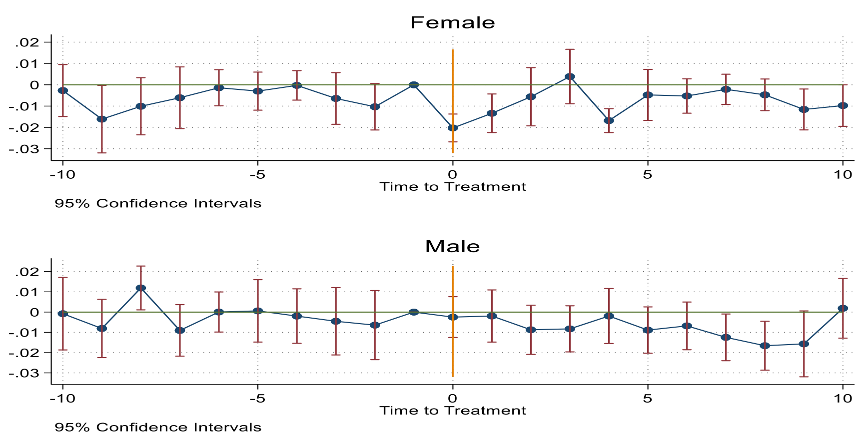
Appendix D – Event-Study Results

Figure 1. Dynamic Effects on Labor Participation



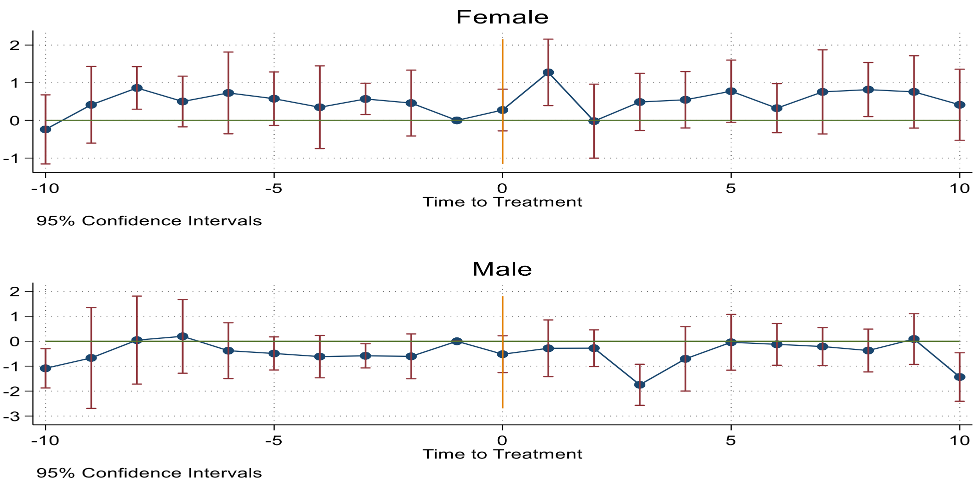
Note: Outcome variable: Labor Participation (Being on the labor force). Each dot presents each coefficient estimate of τ_k and θ_k comes the event-study model as defined in Eq. (3). The model adjusted for age, gender, education, marital status, race, metropolitan area, household size, household income categories, occupation and industry, whether having any child aged from six to 17, share of state population aged 65 and over, share of Medicaid beneficiaries for each state, state EITC introduction, state unemployment rates, state minimum wages, state poverty rate as well as state, year fixed effects that captures unobserved macroconditions over time. All estimates are weighted by individual sample weights. "Time to treatment" measures time relative to the year when the SPL implemented in each state (10 years before and after the policy changes).

Figure 2. Dynamic Effects on Voluntary Part-time



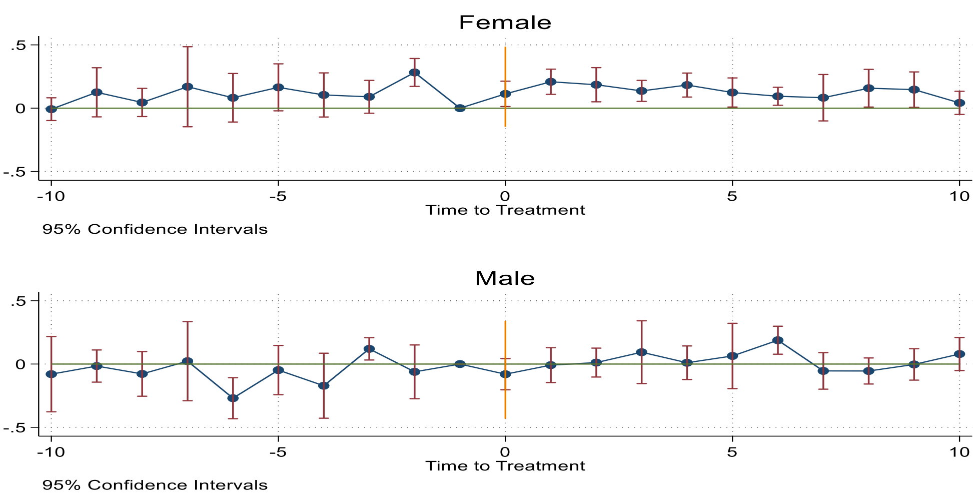
Note: Outcome variable: Voluntary Part-time. Each dot presents each coefficient estimate of τ_k and θ_k comes the event-study model as defined in Eq. (3). The model adjusted for age, gender, education, marital status, race, metropolitan area, household size, household income categories, occupation and industry, whether having any child aged from six to 17, share of state population aged 65 and over, share of Medicaid beneficiaries for each state, state EITC introduction, state unemployment rates, state minimum wages, state poverty rate as well as state, year fixed effects that captures unobserved macroconditions over time. All estimates are weighted by individual sample weights. “Time to treatment” measures time relative to the year when the SPL implemented in each state (10 years before and after the policy changes).

Figure 3. Dynamic Effects on Work Hours



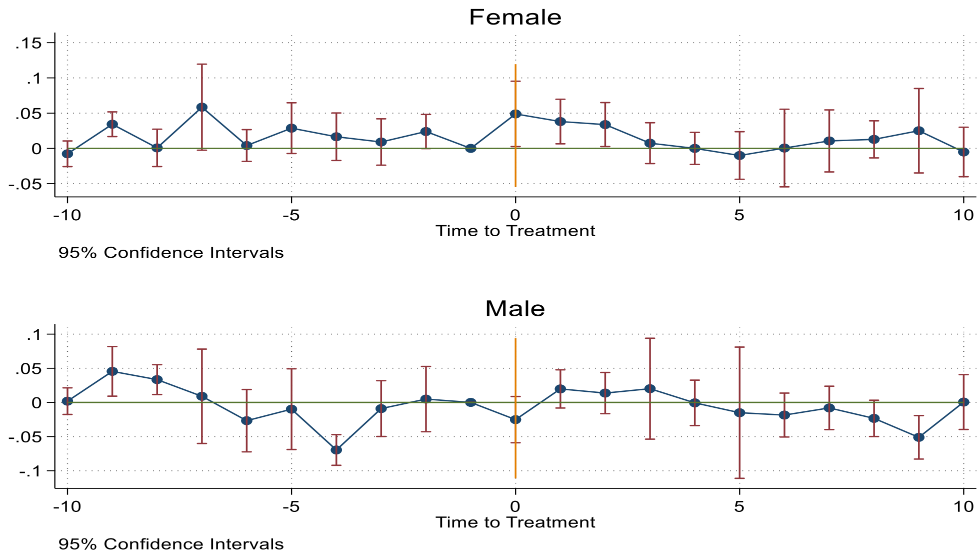
Note: Outcome variable: Weekly work hours. Each dot presents each coefficient estimate of τ_k and θ_k comes the event-study model as defined in Eq. (3). The model adjusted for age, gender, education, marital status, race, metropolitan area, household size, household income categories, occupation and industry, whether having any child aged from six to 17, share of state population aged 65 and over, share of Medicaid beneficiaries for each state, state EITC introduction, state unemployment rates, state minimum wages, state poverty rate as well as state, year fixed effects that captures unobserved macroconditions over time. All estimates are weighted by individual sample weights. “Time to treatment” measures time relative to the year when the SPL implemented in each state (10 years before and after the policy changes).

Figure 4. Dynamic Effects on Wages (Log)



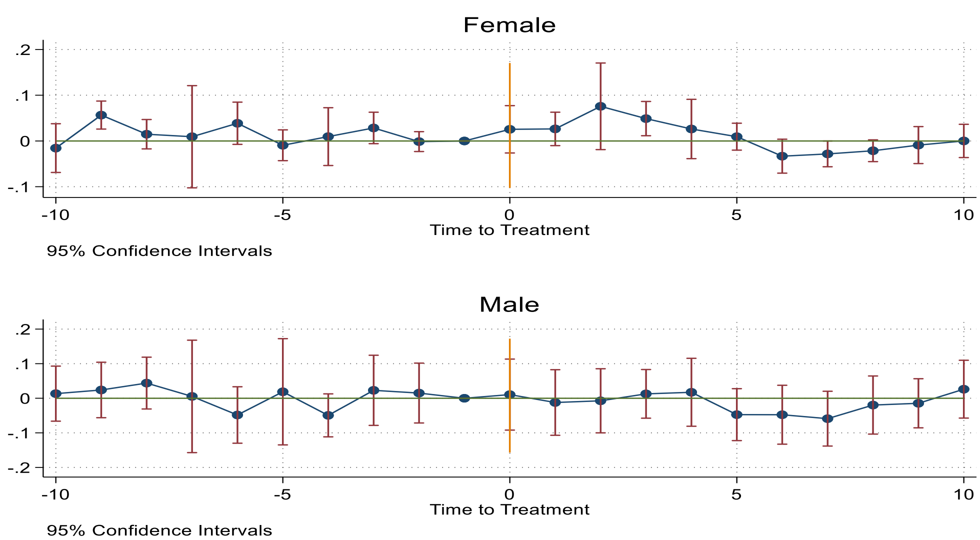
Note: Outcome variable: Wage (annually lagged log). Each dot presents each coefficient estimate of τ_k and θ_k comes the event-study model as defined in Eq. (3). The model adjusted for age, gender, education, marital status, race, metropolitan area, household size, occupation and industry, whether having any child aged from six to 17, share of state population aged 65 and over, state EITC introduction, state unemployment rates, state minimum wages, as well as state, year fixed effects that captures unobserved macroconditions over time. All estimates are weighted by individual sample weights. “Time to treatment” measures time relative to the year when the SPL implemented in each state (10 years before and after the policy changes).

Figure 5. Dynamic Effects on Personal Income (log)



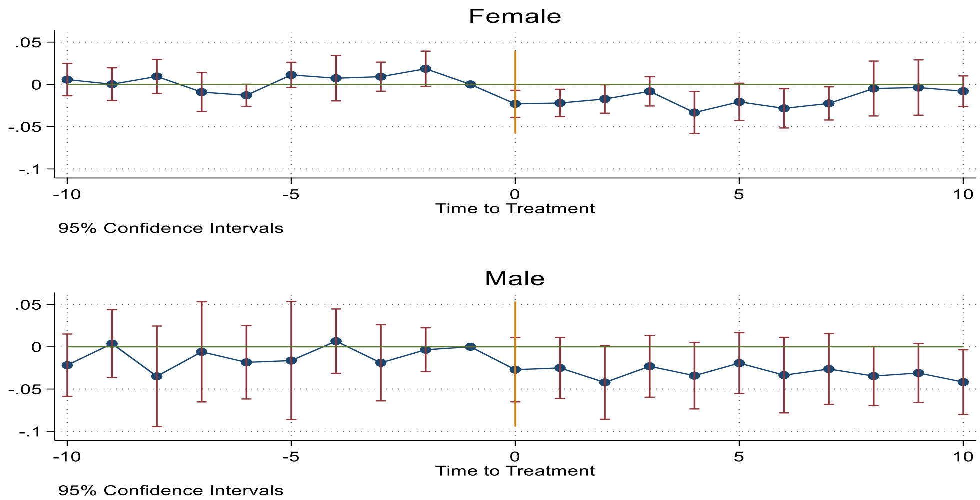
Note: Outcome variable: Personal Income (lagged log). Each dot presents each coefficient estimate of τ_k and θ_k comes the event-study model as defined in Eq. (3). The model adjusted for age, gender, education, marital status, race, metropolitan area, household size, occupation and industry, whether having any child aged from six to 17, share of state population aged 65 and over, state EITC introduction, state unemployment rates, state minimum wages, as well as state, year fixed effects that captures unobserved macroconditions over time. All estimates are weighted by individual sample weights. "Time to treatment" measures time relative to the year when the SPL implemented in each state (10 years before and after the policy changes).

Figure 6. Dynamic Effects on Family Income (log)



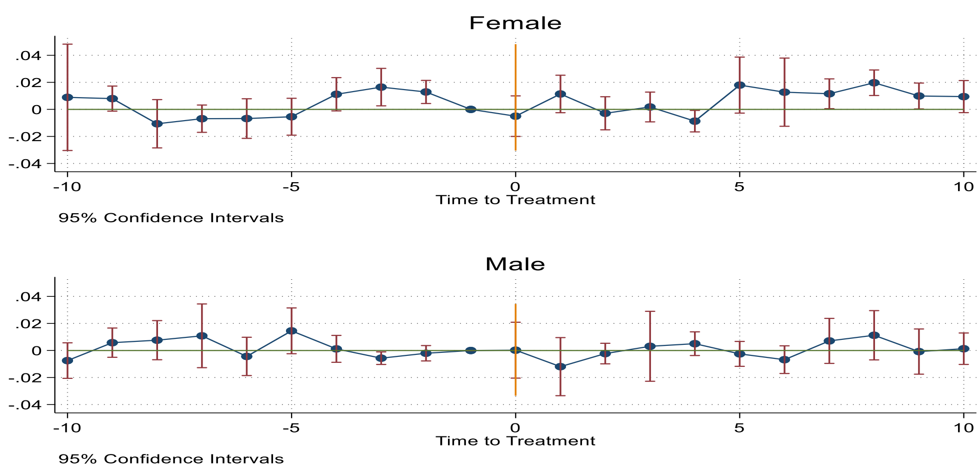
Note: Outcome variable: Family Income (lagged log). Each dot presents each coefficient estimate of τ_k and θ_k comes the event-study model as defined in Eq. (3). The model adjusted for age, gender, education, marital status, race, metropolitan area, household size, occupation and industry, whether having any child aged from six to 17, share of state population aged 65 and over, state EITC introduction, state unemployment rates, state minimum wages, as well as state, year fixed effects that captures unobserved macroconditions over time. All estimates are weighted by individual sample weights. “Time to treatment” measures time relative to the year when the SPL implemented in each state (10 years before and after the policy changes).

Figure 7. Dynamic Effects on Social Welfare Received



Note: Outcome variable: Welfare Income receipt (an indicator of whether an individual reported non-zero cash transfer or food stamp benefits). Each dot presents each coefficient estimate of τ_k and θ_k comes the event-study model as defined in Eq. (3). The model adjusted for age, gender, education, marital status, race, metropolitan area, household size, occupation and industry, whether having any child aged from six to 17, share of state population aged 65 and over, state EITC introduction, state unemployment rates, state minimum wages, as well as state, year fixed effects that captures unobserved macroconditions over time. All estimates are weighted by individual sample weights. “Time to treatment” measures time relative to the year when the SPL implemented in each state (10 years before and after the policy changes).

Figure 8. Dynamic Effects on SSI Received



Note: Outcome variable: SSI receipt (Indicator of whether an individual reported non-zero SSI benefits). Each dot presents each coefficient estimate of τ_k and θ_k comes the event-study model as defined in Eq. (3). The model adjusted for age, gender, education, marital status, race, metropolitan area, household size, occupation and industry, whether having any child aged from six to 17, share of state population aged 65 and over, state EITC introduction, state unemployment rates, state minimum wages, as well as state, year fixed effects that captures unobserved macroconditions over time. All estimates are weighted by individual sample weights. “Time to treatment” measures time relative to the year when the SPL was implemented in each state (10 years before and after the policy changes).

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