The Impact of Paid Family Leave Policies on Working Caregivers and Older Adults

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Abstract

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One in two older Americans needs assistance with functional limitations that affect their ability to care for themselves. Functional limitations are associated with unmet self-care and social needs, which can increase their risk of adverse events such as falls, hospitalizations, and nursing home admissions. As older adults near the end of life, an estimated 74% need help with functional limitations. In the US, access to publicly-funded programs that provide long-term care services are limited; Instead, unpaid caregivers (primarily family members) serve as the backbone of long-term care. Trends suggest a growing share of caregivers are adult children, who must often balance employment and caregiving responsibilities for an aging parent. A potentially effective policy solution is to provide working caregivers with access to paid family leave (PFL). PFL programs provide access to paid leave for three distinct needs: i) when they are expecting a new child, as parental leave; ii) when workers experience a serious health issue of their own, as medical leave; iii) when caring for a family member with serious health issues, as caregiving leave. A handful of states were early adopters of PFL, namely California, New Jersey, and Rhode Island. Since then,

the policy has spread to a total of thirteen states and the District of Columbia, as of 2025, signaling the salience of the issue for policymakers.

Despite working caregivers being a key goal of PFL policies, research on their utilization and impact as a caregiving leave benefit remains scant. Using program administrative data and the Health and Retirement Study, this dissertation evaluates the impact of PFL policies in the care of older adults by working adult children. In Aim 1, I explore trends and characteristics associated with PFL utilization in Rhode Island and Washington. In Aim 2, I examine the impact of PFL on place of residence for worker's aging parents. In Aim 3, I examine the impact of PFL on working caregivers' health and wellbeing. As the population continues to age, the results yield rigorous evidence that can guide state planning decisions and inform ways to modify program benefits to increase access to PFL benefits and support working caregivers.

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Chapter 1: Introduction

By 2034, one in four Americans will be aged 65 and older.[1] One in two older adults have functional limitations and require assistance with personal care tasks such as getting dressed, bathing, eating, and household chores.[2] Functional limitations in older adults are associated with unmet self-care and social needs,[3,4] which increases their risk of adverse events including falls, hospitalization, and nursing home admissions.[5–7] Over 60% of older adults with functional limitations received paid long-term care for their care needs.[8]

To contain rising health care costs, governments are promoting aging-at-home policies, which align with most older adults' preference to remain in their homes.[9,10] While community-based care may be cost-effective for public programs, it can shift the care burden onto families, as formal long-term care services are limited in the US. Medicare does not provide coverage for custodial care, and only 8% of Americans have private long-term care insurance.[11] As a result, older adults incur an average of $120,900 in long-term care costs after age 65, with approximately 40% of costs paid for privately.[11] Publicly-funded long-term support services are available through state Medicaid programs. However, these programs are means-tested (e.g., require low income), and most require older adults to spend down their assets to below $2000. Even when eligible, the estimated average wait time for long-term support service programs is 45 months.[12] With the passage of the One Big Beautiful Bill Act, which includes over $1T in cuts to Medicaid programs,[13] access to long-term care services will likely be further reduced.

With limited access to long-term care services for older adults aging in their homes, unpaid caregivers (hereafter, "caregivers") serve as the primary long-term care providers in the US. In 2020, there were 48 million caregivers in the US, 20% of whom provided care to an older adult with functional limitations, and 61% of whom are part of the workforce.[14]

The impact of aging on working caregivers is a salient policy issue. People under the age of 45 make up the largest share of caregivers followed by people aged between 45-64 years.[15] In addition, a quarter of working caregivers are estimated to be part of the sandwich generation of individuals caring for children at home as well as aging parents.[16]

Family and Medical Leave Policies in the US. In the US, a federal paid leave policy does not exist to support working caregivers. While the Family Medical Leave Act (FMLA) has been available since 1993, offering 12-weeks of job protected leave in a 12-month period for parental leave, personal serious illness, or family caregiving duties, only covers 50% of workers, and does not replace wages.[17] Without access to wage replacement, taking leave may not be feasible for many working caregivers, and particularly for low-income workers and families.[17–20]

To overcome the gaps left by the FMLA, several states have implemented their own PFL policies. As of 2025, thirteen states and the District of Columbia implemented a PFL program starting with California in 2004, followed by New Jersey in 2009, Rhode Island in 2014, New York in 2018, District of Columbia and Washington in 2020, Massachusetts in 2021, Connecticut in 2022, Oregon in 2023, Colorado in 2024, and Delaware, Maine, Maryland, and Minnesota to follow in 2026. Across PFL policies, states offer paid leave for three main reasons: 1) to employees who are expecting to have a new child, as parental leave, 2) to employees who experience their own serious health issues, as medical leave, and 3) to employees who care for a family member with health needs, as family leave.

Experts on informal caregivers have called for the effects of PFL to be studied on these three populations, separately.[17] Researchers have predominantly studied the impact of PFL as a parental leave policy.[21] However, as the number of older adults outpace children in the US,[18] using PFL as a mechanism to support working caregivers will become increasingly important. Research on the

impact of PFL policies for working caregivers of aging parents remains scant, as much of the empirical research on PFL has been on its use as parental leave.[21] Thus far, studies have found that implementing PFL policies have increased the amount of time working adult children spent on caregiving for parents with functional limitations and subsequently, the amount of help older adults receive from family members.[22–24] Two studies have examined the policy effects on downstream outcomes for older adults and the health effects on working caregivers. Arora and Wolf examined the impact of implementing PFL on nursing home admissions and found that its implementation significantly reduced nursing home admissions by 11%.[25] Gimm and Yang examined the impact of introducing PFL on the health of informal caregivers in CA and found that PFL did not have a significant effect on caregivers' self-reported mental or physical health.[26] While these studies used an approach that aims to generate causal estimates, because they are mostly limited to the experience of a single state, the results may be biased as there may be systematic difference when comparing PFL in California to states without PFL. In addition, none of the studies have been able to utilization of PFL benefits due to the challenge of accessing program administrative data (which are not publicly available), leaving gaps in knowledge of the profile of workers who seek PFL benefits for caregiving leave.

With an aging population, it is important to understand the ways in which PFL programs are being used, by whom, and how they are impacting the care of older adults and workers' wellbeing. Prior studies have provided important early indicators of PFL implementation leading to an increase in caregiving supply and care provision to older adults, whether programs can have downstream impact on care recipients and importantly, support the health and wellbeing of workers who face competing demands. Scholars have noted that the design of PFL benefits may create barriers to access benefits for working caregivers.[27] For example, most programs require advance

notice, and with declines in health trajectories being difficult to predict in older adults,[28,29] requesting leave in advance may not always be feasible.[27,28]

Conceptual Model

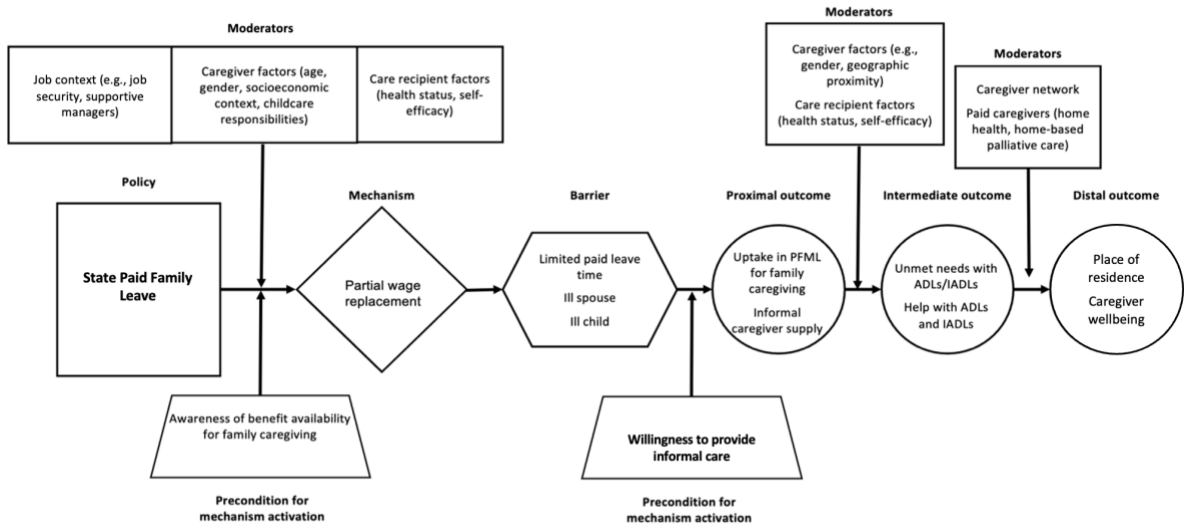


Figure 1. A conceptual model of the PFL intervention for older adults adapted from the Working Informal Caregiver Model.

The dissertation is guided by a conceptual framework on PFL for older adults that is adapted from the Working Informal Caregiver (WIC).[30] The WIC which describes the social and environmental factors that affect a working caregiver's ability to provide and engage in informal care including work participation, family and care commitments, and policies, laws, and regulations which influence the caregiver's ability to provide informal care. Further differentiations are made within social environmental factors. For example, work participation differentiates between the types of job conditions, work hours, and industry which can affect the ability to provide informal care.

In the adapted model, partial wage replacement is the main mechanism by which PFL can affect any potential outcomes in the causal pathway. Uptake of PFL leave for caregiving and

subsequently an increase in family caregiver supply among working caregivers would be the earliest indicators that PFL is supporting working caregivers. Submitting a request for paid leave to care for a family member is a necessary first step for getting approval to take leave. However, administrative burdens can pose barriers for workers to successfully access benefits and vary by state requirements. Following the pathway from early indicators of PFL could include a decrease in unmet care needs among aging parents. One way to observe whether PFL is enabling family caregivers to care for older adults is to see if older adults are receiving help with their difficulty performing ADLs and IADLs among respondents who reported having difficulty but did not receive help. Indeed, recent studies have found that after implementing PFL policies, the probability of older adults receiving help for their functional limitations increased by 34%.[23]

Place of residence is a key distal outcome of interest for policymakers. While not all residency in nursing home is preventable, delaying or reducing nursing home residency is a goal that aligns with the vast majority of older adults who wish to age at home. This is a priority that aligns with policy priorities reflected by decades of aging-in-place initiatives. Nursing home admissions can be measured in the short term and long term.[9] From a care recipient perspective, most older adults do not wish to move into a nursing home. From a payer perspective, diverting short-term and long-term nursing home stay are beneficial to public payers as 62% of resident stays are paid for by Medicaid and 13% by Medicare.[31] In the short run, it is possible that, following a health shock such as a fall or a stroke, having access to PFL can enable older adults to be discharged home instead of nursing homes, if adult children are able to take time off to support a parent during their transitional home. Since working caregivers have access to limited paid leave, using PFL benefits may be aligned better with supporting a parent following an acute hospitalization as opposed to longer-term intermittent use of benefits for caregiving duties. Using paid leave for temporary

reasons may be more economically feasible for working caregivers as they may be able to absorb the cost of foregone wages temporarily, as PFL offers partial wage replacement and not full. This may depend on their income and sense of financial security from receiving partial wage replacement.

In the process of increasing the informal care supply, ensuring that workers are able to maintain their health and wellbeing should be a key goal of PFL programs. Decades of research suggest caregiving is associated with a myriad of health outcomes. Caregivers experience worse health across a number of outcomes including depression, sleep deprivation, weight loss, loneliness, and self-reported health.[32–39] Worse mental health outcomes have been consistently found among caregivers who provide different types of support.[38] About 12% of caregivers in the US are socially isolated,[40] which may contribute to worse mental health.

In this dissertation, I examine PFL programs utilization and the impact of implementing PLF on distal outcomes for working caregivers and their aging parents. In Chapter 2, I describe trends and characteristics of PFL utilization in two states that have not been studied longitudinally, Rhode Island and Washington state. In Chapter 3, I examine the effect of implementing PFL on place of residence for parents of working children. In Chapter 4, I examine the impact of implementing PFL on how it affects the health and wellbeing of workers who support their parents with functional limitations. The dissertation contributes to the nascent area of research on PFL as a caregiving leave policy by using program administrative data to describe PFL leave beneficiaries and survey data to expand on prior research with study designs that increases generalizability of findings for states adopting PFL policies.

Chapter 2: Trends and Characteristics of Working Caregivers Using Paid Family Leave Programs in Rhode Island and Washington

Abstract

Background: Many family caregivers are part of the workforce and are integral to the well-being of older adults. State Paid Family Leave (PFL) programs offer workers partial wage replacement for caregiving leave. However, analyses of PFL program data for caregiving leave by claim status and predictors of claim approval are limited.

Objective: We examine trends in PFL applications for caregiving leave, characteristics of applicants, and predictors of applicant approval in Rhode Island (RI) and Washington (WA).

Research Design and Methods: A repeated cross-sectional study of workers who applied for caregiving leave in RI (N=14,323) from 2015-2022, and in WA State (N=85,237) from 2020-2023. Descriptive analyses and logistic regression models were used to examine associations between worker characteristics and claim approval.

Results: Overall, 82.3% of caregiving leave applications were approved in RI, and 76.0% in WA. Spousal caregiving was most common in RI (37.0%), and parental caregiving in WA (39.1%). Age, care recipient type, wage quintile, and job industry were associated with claim approval in RI and WA. The associations were most pronounced for workers with incomes in the top quintiles, compared to the bottom quintile (RI: AME=20.59pp, 95% CI=17.94 to 23.22; WA: AME=4.68pp, 95% CI: 3.56 to 5.80).

Discussion and Implications: The results provide a profile of workers who sought caregiving leave. We found large differences in claim approval by wage, with the highest probabilities of approval for higher-earning workers. Reducing administrative burden and streamlining the

application process may promote more equitable use of PFL programs, particularly among lower-earning workers.

Background

Over 37 million family caregivers provide unpaid care to older Americans.[41] Adult children are the largest share of family caregivers, many of whom are in the workforce and also have childcare responsibilities.[42,43] Despite competing demands, reliance on working adult children for caregiving support is expected to rise as the US population ages.[14,32,44] Although caregiving can be rewarding for individuals who provide eldercare, it can also lead to negative economic outcomes. Working caregivers are more likely than non-caregivers to reduce their hours on the job or leave the workforce entirely, leading to falling household incomes.[45–48] Moreover, the economic impact of eldercare is unevenly felt, as Black, female, and less-educated caregivers face the greatest likelihood of job loss and financial hardship.[45,49–52] Unsurprisingly, family caregiving is associated with financial hardship and intensive caregiving is associated with lower wealth.[47,53]

State paid family leave (PFL) programs may be an effective policy for supporting working caregivers. PFL programs are available as parental leave for workers with a new child and caregiving leave for workers who look after family members with serious health issues. Some states include medical leave for workers facing serious health issues as part of PFL programs. Much of the academic research to date has been on the impact of PFL as parental leave [21]. However, changing social and demographic patterns, including lower birth rates and an aging workforce and population, make PFL a crucial policy for working caregivers of older adults.[17,27,54,55]

Examining PFL utilization for caregiving leave has been limited as program administrative data are difficult to access for research. Early evidence using population-level survey data have found positive impacts, including an increase in the supply of family caregivers

by 1% and the probability of remaining in the workforce for women by 0.9 percentage points in California, and a decrease in the probability of reducing work hours due to caregiving by 1.6 percentage points in California and New Jersey.[22,56,57] As California was the first state to implement PFL, the extant literature on PFL for working caregivers has relied on California's experience. However, utilization of PFL benefits is likely to vary across states given the variations in program design features and state-related factors including demographics and other existing labor policies and programs. For example, lower earning workers are less likely to be eligible for state paid leave programs or to know about their eligibility.[58–60] As PFL expands to states with different socioeconomic and political compositions, studying the experience of other state PFL programs may offer new perspectives.

This paper contributes to the literature in the following ways. First, the study examines applications for PFL using program administrative data that allows us to describe workers who have applied for paid leave, which has not been widely studied. Second, we use program data from Rhode Island (RI) and Washington (WA) adding evidence from two states whose experience with PFL have not been previously reported. Third, we focus on PFL applications that were submitted for caregiving leave, a nascent area of research. Finally, in addition to describing workers who have applied for caregiving leave, we examine factors associated with application approval, which has not been examined in prior studies. To this end, the goals of the paper are three-fold: first, we describe trends of PFL applications for caregiving leave over multiple years in in RI and WA; second, we describe characteristics of workers who applied for caregiving leave among all applications and by application status; and third, we identify factors associated with approval for caregiving leave applications. Identifying the profile of workers applying for and receiving benefits can increase awareness of program reach and utilization for employers

and state programs that offer PFL and highlight subgroups for whom program benefits may fall short.

Methods

Program Description and Data

RI's program, the Temporary Caregiver Insurance (TCI) program, was implemented in 2014. As of 2024, TCI offers up to 6 weeks of paid leave. Eligible workers receive up to 60% wage replacement, with a replacement cap of $1,070 per week.[61] WA's program, WA Paid Family and Medical Leave program (WA Paid Leave) was implemented in 2020, and as of 2024, offers 12 weeks of leave and eligible workers receive up to 90% wage replacement with a replacement cap of $1,427 per week.[62] The TCI program in 2022 (the last year of data available in this study) offered up to 5 weeks of paid leave with a maximum weekly wage replacement rate of $1,007. The WA Paid Leave program in 2023 (the last year of data available in this study) provided 12 weeks of leave with a maximum weekly wage replacement rate of $1,327. In both states, the PFL programs are funded through a payroll tax and involve employee and employer contributions. In RI, eligible workers also benefit from job protection while taking leave through the TCI program whereas in WA State, eligible workers have job protection if they qualify under the Federal Medical Leave Act (FMLA). Both TCI and WA Paid Leave are funded through payroll deductions for all covered employees. In both RI and WA, workers are eligible if they earn wages in the state, regardless of residency status. In both states, workers taking caregiving leave are required to apply within 30 days after taking the first day of leave, with exceptions available. Once applications have been approved, workers are required to submit weekly claims to be paid each week.

We used administrative data from the TCI program for 2015-2022 and WA Paid Leave program for 2020-2023. The de-identified TCI data were made available through a data request to the RI Department of Labor and Training. The WA Paid Leave program data are available at the UW Data Collaborative through a data sharing agreement between the University of Washington and the WA Employment Security Department (Principal Investigator: Heather D. Hill). In RI, a claim remains open for one year. For example, if an applicant applied for caregiving leave for a child in the spring and needed to take leave to care for a parent in the fall, they would be able to reopen an existing claim. In this case, the TCI program database would capture the last record for whom leave was taken. In other words, the TCI program data reflect the last claim on record as opposed to the total claims that were sought on an annual basis. Therefore, to conduct a parallel analysis of the two programs, we restricted the WA Paid Leave program dataset to the last recorded claim submitted by workers. In summary, the datasets used in this study reflect a sample of workers who submitted at least one application for caregiving leave each year.

Measures

The main outcome measures were applications and claim status. Applications measured claims that workers submitted regardless of whether their application was approved or denied. Claim status measured whether an application was approved or denied. As covariates, we examined workers' age, sex, ethnicity (available only for WA State), wages, English as the preferred language, relationship of care recipient for whom leave was taken, and job industry. Sex and English as the preferred language were measured as binary variables. Using the sample distribution by state, annual wages were categorized into quintiles: RI = first (<$19,869), second

($19,969-$31,650), third ($31,651-$43,660), fourth ($43,661-$63,559), and fifth ($63,559+); WA = first (<$24,246), second ($24,247-$36,411), third ($36,412-$50,517), fourth ($50,518-$72,965), and fifth ($72,965+). Five care recipient categories were included: child, spouse, parent, grandparent, and other. Industry was explored using the 21 industries available in the North American Industry Classification System (NAICS).[63] Annual trends were explored with year-specific dummy variables.

Analysis

We examined the number of workers who applied for caregiving leave over the study period and their characteristics, overall, and by claim status, for each state. We then identified characteristics associated with claim approval for caregiving leave. In the logistic regression models, industries sparsely represented in the data were collapsed into "Other," along with the "Other industries" category for each state. In addition, the datasets included the following missing data: for RI, wages were missing for 2015, job industry was missing for 2019, and preferred language was missing for 2018 and 2019. As such, the regression model covered five program years with 2015, 2018, and 2019 excluded. For WA State, the following variables had missing observations, which were excluded from the logistic regression model: sex (0.6%), ethnicity (4.4%), wage (13.9%), English as preferred language (19.1%), and care recipient (0.2%). We present estimates as average marginal effects (AME) for easier interpretation of coefficients as percentage points (pp). AMEs allow coefficients from logistic regression models to be interpreted on a probability scale, instead of odds ratios, by deriving the difference in predicted probabilities of an outcome associated with a unit-change in a covariate.[64] To account for potential clustering in the datasets, robust standard errors were used. For industry, to avoid

comparing estimates to one industry, we used the method of recycled predictions to calculate adjusted percentages of claim approvals.[65] The adjusted models were run separately for RI and WA due to data storage requirements. The University of Washington Institutional Review Board determined the data do not include human subjects and therefore exempt from review. The analysis was performed using R version 4.3.2.

Results

Trends in Use of PFL for Caregiving

In RI, 14,323 workers submitted a claim between 2015-2022, 82.3% of whom had their application approved. The annual number of workers submitting caregiving claims fluctuated between 2015 and 2022, with the highest number of workers in 2020 (Figure 1a). The percentage of workers with approved claims ranged from 73.7% to 99.9%. In WA, 85,237 caregiving claims were filed between 2020-2023, 76.8% of which were approved. The annual number of workers submitting caregiving claims increased overall and peaked in 2022 (Figure 1b). The percentage of workers whose claims were approved ranged from 72.0% to 83.0%.

Characteristics of Working Caregivers and By Claim Status

Rhode Island

Table 1 includes the full set of working caregiver characteristics by claim status. In RI, the mean age (SD) of applicants at claim submission was 48.3 years (12.8) and included a female majority applicant base (64.9%). Most applicants submitted a caregiving claim to care for an ill spouse (37.0%), followed by a sick child (36.3%) and parent (25.2%). Most applicants spoke

English as their preferred language (95.1%). The top three industries of working caregivers in RI were health care (26.8%) and social assistance followed by manufacturing (10.1%) and retail trade (7.5%).

Among approved claims by characteristics, workers in their 30s (25.4%) and 60s (25.1%), caring for a spouse (39.1%), with wages in the third quintile (21.1%), and working in the health care and social assistance sector (27.7%) had the highest share of claims approved. Among denied claims by characteristics, workers in their 30s (28.4%), caring for a parent (27.5%) or a spouse (27.4%), with wages in the first quintile (35.5%), and working in the health care and social assistance sector (22.2%) had the highest share of denied claims.

Washington

The mean age (SD) of WA applicants at claim submission was 47.1 years (12.0) and primarily female (62.2%). Most applicants identified as White (57.4%) followed by Hispanic (13.8%), and Black (8.6%). Most applicants submitted a caregiving leave claim for a parent (39.3%), followed by their spouse (28.9%). Most applicants spoke English as their preferred language (89.2%). The top three industries of working caregivers in WA were health care and social assistance (18.9%) followed by retail trade (7.8%) and manufacturing (7.6%).

Among approved claims by characteristics, workers in their 40s (27.2%), White race (58.8%), caring for a parent (41.1%), with wages in the fifth quintile (20.7%), and working in the health care and social assistance sector (19.9%) had the highest share of applications approved. Among denied claims, workers in their 30s (30.0%), workers of White race (52.7%), caring for a

parent (33.4%), with wages in the first quintile (24.5%), and working in the health care and social assistance sector (15.3%) had the highest share of claims denied.

Factors Associated with Claim Approval

Rhode Island

The model results for RI workers are presented in Table 2, which show that age, care recipient type, wage quintile, job industry, and year were significantly associated with claim approval. Compared to workers in their 20s, caregivers aged 30-39 years had a higher probability of claim approval by 4.3pp (95% CI = 1.36 to 7.24). Compared to caring for a sick child, workers who cared for their spouse, parent, grandparent, or other family members all had significantly lower probabilities of claim approval. Among these, workers caring for a grandparent had the lowest probabilities (AME = -10.15pp; 95% CI = -18.46 to -1.83). Compared to workers with wages in the lowest quintile, workers with earnings in all other quintiles had higher probabilities of claim approval with the largest difference found for highest-earning workers (AME = 20.59pp; 95% CI = 17.95 to 23.22). Industries with the highest predicted approval rates were educational services, information, and public administration, with estimates ranging from 96.43% to 95.0%. In contrast, workers with jobs in accommodation and food services, transportation and warehousing, and retail trade had the lowest predicted approval rates with estimates ranging from 84.04% to 87.6%, excluding jobs collapsed under other.

Washington

The model results for WA workers are presented in Table 3. In WA, all sociodemographic characteristics were significantly associated with claim approval. Compared to workers aged 20-29 years, the probability of claim approval increased with each age decile. The largest difference was observed for workers aged 60 years and older (AME = 10.39pp, 95% CI = 8.73 to 12.05). Compared to White workers, the difference in predicted probabilities of claim approval were lowest for Hawaiian or Pacific Islanders (AME=-5.87pp; 95% CI=-8.10 to -3.46), Middle Easterners (AME=-5.13pp; 95% CI=-10.10 to -0.17), and East Asians (AME=-3.98pp; 95% CI=-6.33 to -1.63). Male working caregivers had a lower probability of claim approval compared to female workers (AME=-2.58pp; 95% CI = -3.33 to -1.83). Working caregivers who spoke English as their preferred language had a higher probability of claim approval by 2.03pp compared to workers with a different preferred language (95% CI = 0.76 to 3.31). Compared to caring for a sick child, workers who care for a spouse, a parent, or a grandparent had significantly higher probabilities of claim approval; The largest difference was observed for parents (AME 5.27pp; 95% CI = 4.41 to 6.12). Compared to workers with earnings in the lowest quintile, workers with earnings in second through fifth quintiles had higher probabilities of having their claims approved; The largest difference was observed for workers with earnings in the fourth quintile (AME=4.69pp; 95% CI = 3.60 to 5.77). Industries with the highest predicted claim approval rates were finance and insurance, public administration, and agriculture, forestry, fishing and hunting with approval rates ranging from 87.04% to 87.33%. In contrast, workers with jobs in accommodation and food services, construction, and administrative and waste services had the lowest predicted claim approval rates, aside from other, with estimates ranging from 80.29% to 82.14%.

Discussion

In this study, we accessed claims for caregiving leave in RI and WA's PFL programs, whose program data have not been described over time. In this descriptive study, we examined trends in caregiving leave and differences in worker characteristics that were associated with claims approval. We found an overall increase in the trajectory of program use with fluctuations between years. While WA's program was implemented in 2020, RI's program has been operating since 2014. During the Covid-19 pandemic, we found a spike in applications for caregiving leave. This is likely the case as RI extended program benefits to workers who were primary caregivers for family members with Covid-19.[66]

In terms of differences we found, the most striking result is the positive association between higher wages and claim approval, which was observed in both RI and WA. This finding is consistent with state annual reports and research on other types of paid leave.[67–69] In WA State, we also observed differences in claim approval by ethnicity, with workers with Hawaiian or Pacific Islanders, Middle Eastern, and East Asian ethnicities being less likely to have their applications approved, compared to White workers. Although we do not observe the reasons for denial of claims in this study, research on administrative burden suggests challenges in accessing, completing, and complying with application processes for social programs are known to be unequally distributed.[70,71] For example, a common reason denying applications for benefits in social programs is failing to provide documentation of eligibility. In the WA Paid Leave program, among the most common reasons for claim denials is insufficient documentation, often stemming from failure to provide medical certification.[68]

In the case of paid leave, workers earning lower wages or racially minoritized workers may face greater difficulty when navigating the requirements for demonstrating eligibility. For example, in RI, workers must apply within 30 days of taking leave, and upon submitting their application, workers must ask the healthcare provider of the care recipient to submit a medical certification once received in the mail. However, workers are not eligible unless they have been away from work for at least a week. These kinds of administrative processes create unequal burdens for workers during a stressful period. Sometimes administrative burdens are created by design as a form of rationing access to benefits from social programs in the US.[70,71] However, unlike social assistance programs that are means tested, PFL programs are benefits to which workers are entitled. Streamlining the application process may reduce inequitable outcomes. For example, in RI, workers with the lowest wages account for 47% of individuals contributing to the fund.[72] However, our findings suggest these individuals are least likely to have their applications approved. In the context of caregiving, workers may need caregiving leave benefits multiple times each year as illness trajectories of older adults are unpredictable, particularly towards the end of life. States can reduce the burden in applying for caregiving leave benefits by increasing flexibility such as reducing the minimum days missed from work before becoming eligible and streamlining application requirements like making the process for submitting medical certification easier.

Between RI and WA state, we found differences in claim approval by care recipient type. In RI, workers who cared for a parent were less likely to have their claims approved, compared to caring for a sick child, whereas in WA, workers caring for a parent were more likely to be approved. The difference may, in part, be explained by the fact that, in 2019, 49.8% of caregiving leave applications were from workers in their 50s and 60s, compared to 27.8% in 2020 and

26.1% in 2021 (data not shown). The reason for the decline in applications from older workers is unknown despite this group of workers being most likely to have parents with caregiving needs. A similar trend is unavailable in WA state as PFL was implemented in 2020. One possible explanation is that the change in unemployment rate following the Covid-19 pandemic was higher in RI (5.8%) than in WA (4.3%),[73] and seeking unemployment insurance and paid leave benefits simultaneously would result in denied claims. As the population continues to age, future research can continue to monitor the ways in which PFL programs are being used for caregiving needs by workers.

Finally, a small number of industries accounted for the majority of applications, with health and social care, manufacturing, and retail sectors being the top three industries in both states. Many industries had a small number of applicants, overall, even though caregiving is an issue that affects more than half of workers.[14] From prior studies, we know that awareness and understanding of benefits vary by job class[74] and that support for taking paid leave also varies by industry.[75] Future research is needed examine workers' awareness of the availability of paid leave availability and understand the barriers to accessing program benefits among workers in industries with sparse representation.

We note several limitations in how our findings should be interpreted. First, the data used in this study come from program administrative databases and represent a sample of workers who applied for PFL, and not the population of workers eligible for PFL in RI and WA State. Second, the WA and RI data include only the last submitted claim within a given year. Therefore, the samples reflect workers who applied for caregiving leave at least once each year and not the entirety of claims submitted by workers. Third, we are unable to account for clustering by individuals over time due to a lack of a longitudinal identifier in the RI dataset. Working

caregivers are likely to remain in their caregiving role for several years, which we are unable to observe with the current data. We aimed to address this limitation by using robust standard errors. Fourth, while the datasets record claim status, they do not include the reason for denying claims. Therefore, we are unable to confirm the reason for denying applications. Finally, both datasets had varying amounts of missing data. We aimed to account for some of the missingness by including it as a category, when possible.

Conclusion

We used program administrative data among working caregivers who applied for PFL benefits in RI and WA and provide a profile of workers who are applying for and receiving caregiving leave benefits. Notably, we found large differences in applicants and approval rates by income and ethnicity. Streamlining the application process may reduce inequitable outcomes. Future research is needed to understand awareness and barriers to program benefits among workers with lower wages, minoritized workers, and workers in industries that PFL programs may not be reaching. Further research is also needed to understand the impact of administrative burden on accessing benefits and its potential effects on creating inequities in accessing paid leave benefits.

Tables and Figures

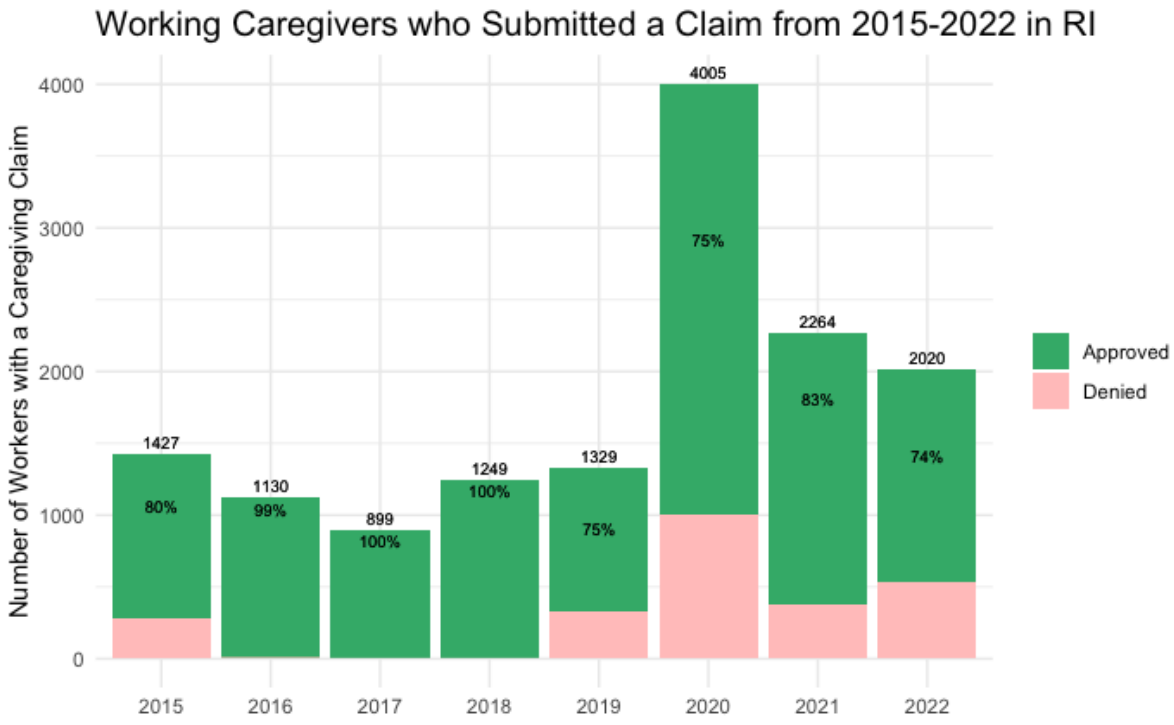


Figure 1a. Working caregivers who submitted a claim from 2015-2022 in RI.
Note: The figure shows the number of workers who submitted a claim for caregiving leave in Rhode Island's TCI program, by claim status and year.
Source: TCI program data for years 2015-2022 from the Rhode Island Department of Labor and Training.

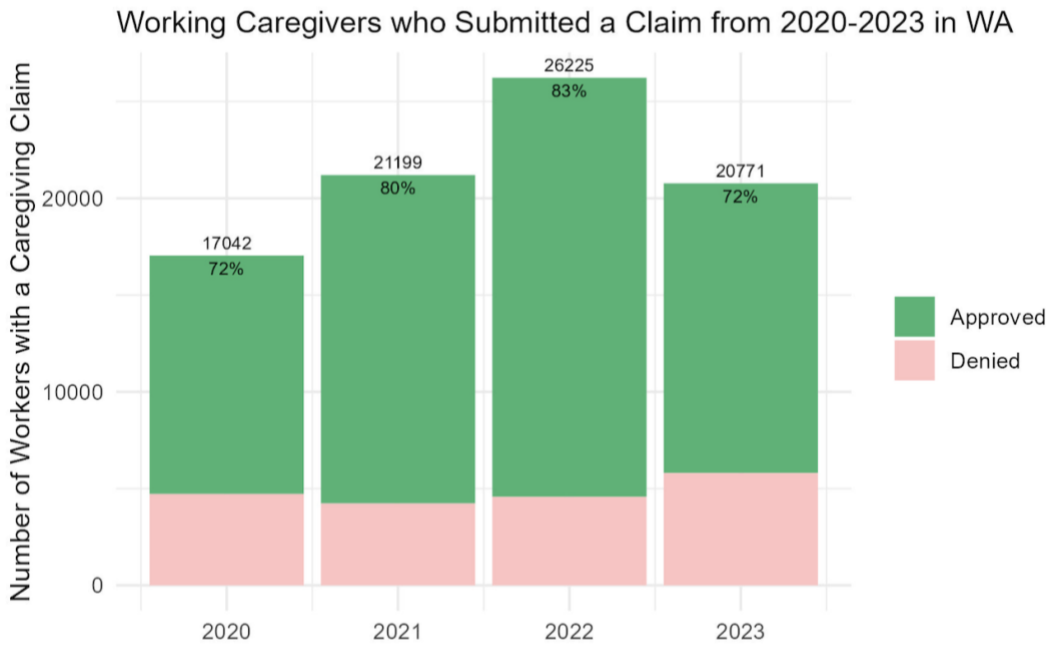


Figure 1b. Working caregivers who submitted a claim in RI from 2020-2023 in WA.
Note: The figure shows the number of workers who submitted a claim for caregiving leave in the WA Paid Leave program, by claim status and year.
Source: WA Paid Leave program data for 2020 to 2023 from the WA Employment Security Department.

Table 1. Characteristics of workers who applied for caregiving leave in Rhode Island in 2015-2022 and Washington in 2020-2023 by claim status.

	Rhode Island			Washington		
	Overall (N=14,323)	**Approved (N=11,779)**	**Denied (N=2,544)**	**Overall (N=75,739)**	**Approved (N=58,118)**	**Denied (N=17,621)**
Age (mean (SD))	48.29 (12.81)	48.80 (12.80)	45.89 (12.58)	46.89 (12.08)	47.63 (11.95)	44.44 (12.19)
Age deciles (%)						
20s	671 (4.7)	463 (3.9)	208 (8.2)	4820 (6.4)	3140 (5.4)	1680 (9.5)
30s	3716 (25.9)	2994 (25.4)	722 (28.4)	18953 (25.0)	13582 (23.4)	5371 (30.5)
40s	3556 (24.8)	2904 (24.7)	652 (25.6)	20365 (26.9)	15691 (27.0)	4674 (26.5)
50s	2958 (20.7)	2456 (20.9)	502 (19.7)	17826 (23.5)	14428 (24.8)	3398 (19.3)
60s	3422 (23.9)	2962 (25.1)	460 (18.1)	13774 (18.2)	11277 (19.4)	2497 (14.2)
Female (%)	9782 (68.3)	7986 (67.8)	1791 (70.4)	46579 (61.5)	36149 (62.2)	10449 (59.3)
Ethnicity (%)						
White				41755 (57.7)	32806 (59.1)	8949 (53.0)
AIAN[1]				508 (0.7)	371 (0.7)	137 (0.8)
East Asian				1579 (2.2)	1208 (2.2)	371 (2.2)
South Asian		N/A		1489 (2.1)	1126 (2.0)	363 (2.1)
Southeast Asian				3022 (4.2)	2350 (4.2)	672 (4.0)
Hawaiian or Pacific Islander				1546 (2.1)	1060 (1.9)	486 (2.9)
Black				6172 (8.5)	4539 (8.2)	1633 (9.7)

Hispanic				10012 (13.8)	7450 (13.4)	2562 (15.2)
Middle Eastern				303 (0.4)	209 (0.4)	94 (0.6)
Mixed				6011 (8.3)	4381 (7.9)	1630 (9.6)
English as preferred language(%)	11170 (95.1)	9102 (95.4)	2068 (93.7)	53351 (89.2)	41721 (89.5)	11630 (88.0)
Care recipient (%)						
Child	5197 (36.3)	4123 (35.0)	1074 (42.2)	17649 (23.4)	12404 (21.4)	5245 (29.8)
Spouse	5300 (37.0)	4604 (39.1)	696 (27.4)	22014 (29.1)	17357 (29.9)	4657 (26.5)
Parent	3605 (25.2)	2906 (24.7)	699 (27.5)	29537 (39.1)	23723 (40.9)	5814 (33.1)
Grandparent	130 (0.9)	91 (0.8)	39 (1.5)	1848 (2.4)	1353 (2.3)	495 (2.8)
Other	91 (0.6)	55 (0.5)	36 (1.4)	4535 (6.0)	3164 (5.5)	1371 (7.8)
Wage quintile[2] (%)						
First	2559 (20.0)	1763 (16.7)	796 (35.5)	12967 (20.0)	9645 (18.8)	3322 (24.4)
Second	2558 (20.0)	2150 (20.4)	408 (18.2)	12967 (20.0)	10154 (19.8)	2813 (20.7)
Third	2558 (20.0)	2221 (21.1)	337 (15.0)	12967 (20.0)	10365 (20.2)	2602 (19.1)
Fourth	2558 (20.0)	2215 (21.0)	343 (15.3)	12966 (20.0)	10487 (20.5)	2479 (18.2)
Fifth	2556 (20.0)	2197 (20.8)	359 (16.0)	12966 (20.0)	10591 (20.7)	2375 (17.5)
Industry (%)						

Accommodation & food services	544 (3.8)	425 (3.6)	119 (4.7)	1759 (2.3)	1274 (2.2)	485 (2.8)
Administrative & waste services	654 (4.6)	535 (4.5)	119 (4.7)	4338 (5.7)	3389 (5.8)	949 (5.4)
Agriculture, forestry, fishing & hunting	6 (0.0)	4 (0.0)	2 (0.1)	1339 (1.8)	1105 (1.9)	234 (1.3)
Arts, entertainment & recreation	60 (0.4)	45 (0.4)	15 (0.6)	374 (0.5)	290 (0.5)	84 (0.5)
Construction	281 (2.0)	233 (2.0)	48 (1.9)	3047 (4.0)	2337 (4.0)	710 (4.0)
Educational services	367 (2.6)	332 (2.8)	35 (1.4)	4488 (5.9)	3738 (6.4)	750 (4.3)
Finance & insurance	716 (5.0)	602 (5.1)	114 (4.5)	1623 (2.1)	1397 (2.4)	226 (1.3)
Health care & social assistance	3832 (26.8)	3267 (27.7)	565 (22.2)	13860 (18.3)	11247 (19.4)	2613 (14.8)
Information	153 (1.1)	138 (1.2)	15 (0.6)	632 (0.8)	533 (0.9)	99 (0.6)
Local government	426 (3.0)	368 (3.1)	58 2.3)		N/A	
Management of companies & enterprises	251 (1.8)	219 (1.9)	32 (1.3)	279 (0.4)	237 (0.4)	42 (0.2)
Manufacturing	1444 (10.1)	1242 (10.5)	202 (7.9)	5726 (7.6)	4626 (8.0)	1100 (6.2)
Mining	1 (0.0)	1 (0.0)	0 (0.0)	22 (0.0)	20 (0.0)	2 (0.0)
Other services (except public administration)	265 (1.9)	225 (1.9)	40 (1.6)	1544 (2.0)	1237 (2.1)	307 (1.7)

Professional & technical services	419 (2.9)	366 (3.1)	53 (2.1)	3354 (4.4)	2785 (4.8)	569 (3.2)
Public administration	94 (0.7)	84 (0.7)	10 (0.4)	2903 (3.8)	2477 (4.3)	426 (2.4)
Real estate, rental & leasing	107 (0.7)	89 (0.8)	18 (0.7)	785 (1.0)	631 (1.1)	154 (0.9)
Retail trade	1068 (7.5)	866 (7.4)	202 (7.9)	6097 (8.1)	4841 (8.3)	1256 (7.1)
Transportation & warehousing	309 (2.2)	245 (2.1)	64 2.5)	2680 (3.5)	2176 (3.7)	504 (2.9)
Utilities	45 (0.3)	42 (0.4)	3 (0.1)	935 (1.2)	788 (1.4)	147 (0.8)
Wholesale trade	259 (1.8)	219 (1.9)	40 (1.6)	2642 (3.5)	2122 (3.7)	520 (3.0)
NA[3]	3022 (21.1)	2232 (18.9)	790 (31.1)	17312 (22.9)	10868 (18.7)	6444 (36.6)

[1] AIAN=American Indian and Alaska Native

[2] Wage quintiles: first (<$19,869), second ($19,969-$31,651), third ($31,652-$43,660), fourth ($43,661-$63,559), and fifth ($63,559+); WA: first (<$24,246), second ($24,247-$36,410), third ($36,411-$50,517), fourth ($50,518-$72,965), and fifth ($72,965+).

[3] NA: Given the large number of missing industries, NA was included as its own category.

Note: The table displays number and percentage values of characteristics of workers who submitted a claim for caregiving leave in RI and WA by claim approval status.

Source: RI TCI program data from 2015-2022 and WA Paid Leave program data from 2020-2023.

Table 2. Characteristics associated with claim approval for workers who sought caregiving leave in Rhode Island.

	Rhode Island (N=10,211)		
	AME	**Lower 95%**	**Upper 95%**
Age bands			
20s	Ref		
30s	4.30**	1.36	7.24
40s	2.11	-0.98	5.2
50s	1.90	-1.44	5.23
60s	3.44*	0.00	6.88
Male	-0.91	-2.72	0.90
Care recipient type			
Child	Ref		
Spouse/partner	-1.24	-3.21	0.74
Parent	-5.16**	-7.24	-3.07
Grandparent	-10.15**	-18.46	-1.83
Other	-10.53**	-19.46	-1.60
Wage quintile[a]			
First	Ref		
Second	17.39**	14.88	19.9
Third	20.18**	17.67	22.7
Fourth	20.23**	17.65	22.81
Fifth	20.59**	17.95	23.22
English as preferred language	1.02	-2.09	4.12
Job industry[b]			
Accommodation & food services	84.04**	80.11	87.33
Administrative & waste services	88.94**	85.81	91.46

Construction	88.41**	83.81	91.83
Educational services	96.43**	94.10	97.86
Finance & insurance	91.92**	89.02	94.10
Health care and social assistance	91.25**	89.42	92.79
Information	95.43**	91.42	97.62
Local government	93.18**	89.98	95.41
Management of companies & enterprises	90.89**	86.56	93.92
Manufacturing	92.11**	90.03	93.79
Professional & technical services	94.28**	91.68	96.11
Public Administration	95.00**	89.54	97.69
Real estate, rental & leasing	90.55**	84.06	94.57
Retail trade	87.60**	84.79	89.96
Transportation & warehousing	86.3**	81.32	90.11
Wholesale trade	90.41**	86.14	93.47
Other[c]	86.37**	83.21	89.02
Year			
2016	Ref		
2017	0.38	-0.07	0.83
2020	-24.95**	-26.37	-23.52
2021	-16.5**	-18.21	-14.8
2022	-25.9**	-27.89	-23.91

* P-value <.05

** P-value <.01

[a] Wage quintile: first (<$19,869), second ($19,969-$31,650), third ($31,651-$43,660), fourth ($43,661-$63,559), and fifth ($63,559+).
[b] Average predicted percent of workers with an approved claim, adjusting for other covariates.
[c] Other includes agriculture, forestry, fishing and hunting, mining, and utilities due to small frequencies, as well as industries collapsed under "other services (except publication administration)", and missing.
Note: The table displays the average marginal effects of claim approval by worker characteristics in RI.
Source: RI TCI program data from 2015-2022.

Table 3. Difference in predicted probabilities of workers' characteristics on having approved claims compared to denied claims in Washington State.

	Washington (N=57,746)		
	AME	**Lower 95%**	**Upper 95%**
Age bands			
20s		Ref	
30s	4.34**	2.75	5.92
40s	8.52**	6.94	10.1
50s	10.04**	8.44	11.64
60+	10.39**	8.73	12.05
Ethnicity			
White		Ref	
AIAN[a]	-1.48	-5.46	2.51
East Asian	-3.98**	-6.33	-1.63
South Asian	-2.38*	-4.67	-0.1
Southeast Asian	0.21	-1.32	1.74
Hawaiian or Pacific Islander	-5.78**	-8.1	-3.46
Black	-1.26**	-2.4	-0.13
Hispanic	-1.05	-2.12	0.03
Middle Eastern	-5.13*	-10.1	-0.17
Mixed	-2.86**	-4.06	-1.66
Male	-2.58**	-3.33	-1.83
Care recipient type			
Child		Ref	
Spouse	4.39**	3.43	5.34
Parent	5.27**	4.41	6.12
Grandparent	3.71**	1.64	5.78

Other	-2.33**	-3.93	-0.72
Wage quintile[b]			
First		Ref	
Second	3.3**	2.26	4.33
Third	4.52**	3.47	5.58
Fourth	4.69**	3.6	5.77
Fifth	4.68**	3.56	5.8
English as preferred language	2.03**	0.76	3.31
Job industry (%)[c]			
Accommodation & food services	80.29**	77.96	82.43
Administrative & waste services	82.14**	80.83	83.38
Agriculture, forestry, fishing and hunting	87.04**	84.99	88.86
Arts, Entertainment, and Recreation	82.98**	78.15	86.92
Construction	80.95**	79.25	82.54
Educational services	86.11**	84.93	87.21
Finance & insurance	87.33**	85.4	89.03
Health care and social assistance	84.62**	83.96	85.26
Information	86.82**	83.46	89.58
Management of companies & enterprises	86.30**	81.36	90.09
Manufacturing	84.04**	82.95	85.06
Professional & technical services	85.72**	84.3	87.03
Public administration	87.21**	85.89	88.43
Real estate, rental & leasing	82.80**	79.56	85.61
Retail trade	84.50**	83.42	85.52
Transportation & warehousing	84.79**	83.24	86.21

Utilities	87.00**	84.43	89.2
Wholesale trade	83.25**	81.59	84.79
Other[d]	68.46**	67.62	69.28
Year			
2020		Ref	
2021	4.84**	3.45	6.23
2022	6.92**	5.59	8.26
2023	-1.57*	-2.96	-0.18

* P-value <.05

** P-value <.01

[a] AIAN: American Indian and Alaska Native

[b] WA: first (<$24,246), second ($24,247-$36,411), third ($36,412-$50,517), fourth ($50,518-$72,965), and fifth ($72,965+).

[c] Average predicted percent of workers with an approved claim, adjusting for other covariates.

[d] Other includes mining due to small frequencies, industries collapsed under "other services (except publication administration)", and missing.

Note: The table displays the average marginal effects of claim approval by worker characteristics in WA.

Source: WA Paid Leave program data from 2020-2023.

Chapter 3: Do Paid Family Leave Policies Impact Place of Residence for Workers' Aging Parents? Evidence from the Health and Retirement Study

Abstract

Objective: Older adults rely on unpaid caregivers, primarily their working adult children, to age at home. Several US states have implemented Paid Family Leave (PFL) policies, which may support working adult children care for aging parents. We examine the impact of PFL on parents' place of residence.

Study Setting and Design: We conducted a quasi-experimental study to examine the impact of PFL on two parent outcomes: 1) nursing home residency, and 2) any residential care setting, including nursing homes, assisted living, and retirement homes. We performed a staggered difference-in-differences analysis using variation in the timing of PFL implementation across states.

Data Sources and Analytic Sample: We used data from the Health and Retirement Study (2000–2020) to construct a cohort of respondent-parent dyad observations. The sample included adult children working full- or part-time, who lived in a state with an enacted PFL policy, and had at least one living parent during the study. Observations were assigned to the treatment group if the respondent resided in a state with an active PFL program during the study period; respondents in states that enacted but not yet implemented PFL served as the comparison group.

Principal Findings: Among 27,490 dyads, implementing PFL policies did not lead to a significant difference on nursing home residency (average treatment effect on the treated (ATT)=0.70 percentage points; 95% CI=-6.27 to 7.66) or across all residential care settings (ATT=-4.59 percentage points; 95% CI=-14.02 to 4.85), compared to the comparison group. We

also did not find any differential PFL effects by state, despite state variation in PFL benefit generosity.

Conclusion: We did not find evidence that PFL policies affect place of residence for older parents of working children. With PFL policies expanding across states, experimentation of program benefits to support workers and their aging parents are needed to increase policy effectiveness.

Background

One in two older adults over age 64 have functional limitations and require assistance with personal care tasks such as getting dressed, bathing, eating, and household chores.[2] Functional limitations in older adults are associated with unmet self-care and social needs,[3,4] which can increase their risk of adverse events including falls, hospitalization, and nursing home admissions.[5–7] Over 60% of older adults with functional limitations received paid long-term care for their care needs.[8] However, private-purchasing of long-term care services is expensive; estimates suggest older adults incur $120,900 in cumulative costs, on average, for long-term care services after turning 65, with nearly 40% of this amount estimated paid for out of pocket.[76] Publicly funded long-term support services are available through state Medicaid programs. However, these programs are means-tested (e.g., require low income) and typically require older adults to spend down their assets to below a $2000 threshold to qualify. Even when eligible, the estimated average wait time for long-term support service programs is 45 months.[12] With the passing of the One Big Beautiful Bill Act–which includes over $1T in cuts to Medicaid programs[13]–publicly funded long-term care services are expected to face steep reductions, just as the aging population enters a transformative decade in 2030.[1]

With private long-term care services being expensive and limited publicly-funded services, unpaid caregivers serve as the primary long-term care providers to older adults in the US.[77] An estimated 45 million older adults receive caregiving support in the US with the vast majority living in the community.[53] Among older adults with disability, nearly 80% receive unpaid care from a family member or friend, 50% of whom rely solely on unpaid caregivers.[78] Adult children account for the largest share of caregivers in the US, with over half remaining in the workforce while caring for their parents.[14]

While not all residency in nursing home is preventable, delaying or reducing nursing home residency is a goal that aligns with the vast majority of older adults who wish to age at home.[10] This is a priority that aligns with policy priorities reflected by decades of aging-in-place initiatives.[79] A survey of older Americans finds that over three-quarters prefer to remain in their current homes for as long as possible.[10] Among long-stay nursing home residents, Medicaid serves as the primary payer for approximately 63%,[80] highlighting the significant financial implications for state budgets. However, preventing or delaying nursing home residency depends on access to formal services and caregiving, particularly in light of the functional declines that often accompany aging.

Paid Family Leave (PFL) programs have been implemented across a growing number of states and may support working caregivers. PFL programs provide eligible workers with access to time-limited leave with partial-wage replacement. PFL programs are available as parental leave for workers with a newborn or adopted child, medical leave for workers who experience their own serious health issues, and caregiving leave for workers who look after family members with serious illness. Since PFL programs have been available, awareness and utilization of PFL programs has been greatest for new parents.[21,69] However, the US is projected to need more caregiving for aging parents than children by 2030.[1] As the population continues to age, PFL represents an important policy for supporting working caregivers manage competing demands of work and caring for parents.

Early evidence on the impact of PFL demonstrates its effectiveness for workers who balance paid work and unpaid caregiving demands. Studies have found that implementing PFL significantly increased the probability of caregivers remaining in the workforce by 0.32-1.4%.[56,81] A few studies examined caregiving supply. Across these studies, implementing PFL led

to significant increases in caregiving supply by 6-34%,[22,23] with one study finding an increase in personal care provision by working caregivers was limited to states that offer job protection.[56,82]

Research examining the impact of PFL on the care outcomes of older adults is in a nascent stage. To our knowledge, only one study has examined the impact of PFL on nursing home admissions, which reported a reduction of 11% in California.[25] Since publication of the study, PFL policies have been implemented in twelve other states and the District of Columbia as mandatory. The extent of PFL benefits for caregiving vary from six to twelve weeks, therefore, the impact on nursing home residency may not be uniform, warranting an extension on the initial study to include multiple states with PFL. Second, the rise of assisted living and memory care facilities have rapidly changed the place of residence for older adults with substantial care needs.[83–85] Many assisted living facilities offering varying levels of care for their residents and therefore offer substitutes for traditional nursing homes, warranting a broader examination on place of residence.[86]

In this paper, we examine the impact of implementing state PFL policies on place of residence for workers' parents. We expand on prior work by using a dataset that includes up to fourteen years of follow up after the oldest policies went into effect, allowing us to include multiple states with PFL thereby increasing the generalizability of our findings. Additionally, we examine place of residency across any residential care facilities. We draw on the variation in timing PFL policy implementation across states compared to states that have not yet implemented PFL programs for a robust examination of PFL program effects on place of residence.

Methods

Data Source

This study used data from the Health and Retirement Study (HRS) from 2000-2020. The HRS is sponsored by the National Institute on Aging (grant numbers NIA U01AG009740 and NIA R01AG073289) and is conducted by the University of Michigan.[87] The HRS is a longitudinal, nationally representative study of older Americans aged >50 years and their spouses.[88] The purpose of the HRS is to create a cohort that allows researchers to study aging as well as how social and policy changes affect older adults. The HRS began enrolling respondents in 1992 and conducts in person or telephone surveys biennially, with initial response rates of 79% and follow-up rates of 85% to 91%.[88] The HRS samples panel participants at the household level and selected members and their spouse are asked to participate and are followed biennially until respondents are lost to follow up or die. The study asks respondents about their socio-demographics, labor force participation, family structure, intergenerational transfers on helping children and parents, and health status, making it a rich dataset for addressing questions on intergenerational care use and health. The HRS biennial data products and the cross-wave harmonized data by RAND are publicly available.[89] To obtain variables on state of residence, we linked the harmonized RAND HRS and Family Files to the restricted geographic datafiles.

Study Population

The study population inclusion/exclusion criteria are presented in Supplementary File 1. The HRS respondents were used as working children to create respondent-parent dyads. With the inclusion of parent-in-laws, each respondent was able to contribute up to four dyads depending on whether both parents were reported alive and their marital status. Respondents are asked if

their parents, mother, or father are still living. Using these questions, we identified respondents' who reported having at least one living parent at any point in the study period to create respondent-parent dyads where an observation included respondent variables and limited parent/parent-in-law variables. Among dyads, we identified respondents who are part of the workforce, full time or part time. Respondents who worked for the federal government were excluded, as federal workers are not eligible for PFL in most states. In addition, we dropped respondents who moved states during the study period, were interviewed before treatment exposure in the policy implementation year, or lived in a state with PFL with an insufficient sample size (Supplementary File 1). Maintaining a balanced panel in this study was not feasible due to the dynamic nature of the sample, including the introduction of new cohort entrants every six years, changes in marital status affecting in-law data collection, sample attrition, and the natural aging and death of parents. To address these challenges while maximizing available information, we utilized respondent–parent dyads as repeated cross-sectional samples.

Study Design

We conducted a quasi-experimental study using Callaway and Sant'Anna's staggered difference-in-differences approach.[88,90] This is a causal framework that examines the impact of introducing PFL across states and in different years by incorporating multiple states in the treatment group. Table 1 describes states that have enacted or implemented PFL policies. States that implemented PFL policies in the study period were used to create the treatment group. To assign dyads to the treatment group, we used the interview dates of when data collection occurred. This is because for two of the three states in the treatment group, PFL policies did not take effect until July 1. If an interview coincided with a PFL implementation year, but the

interview was conducted before policy implementation date, the following interview wave was coded as the first post-PFL period. States that implemented PFL after the study period (i.e., after 2020) were used to create the comparison group. We treated the comparison group as "never treated" because these respondents were not exposed to a PFL policy during the study period. Although the states in the comparison group have since implemented PFL programs, they were implemented after the study. We focused on respondents with residency in states with PFL laws to increase the comparability between the treatment and control groups.

Measures

The HRS asks respondents about their parents' living situations. The outcome measure, place of residence, was created from the following survey item: 1) The HRS asks respondents with living parents the following: "With whom do [mother/father/parents] live -- with you, by themselves, with another child, with other relatives, in a nursing home, or what?" with the following response categories: 1) lives with the respondent; 2) by themselves; 3) with another child; 4) with other relatives; 5) in a nursing home; 6) in a retirement center including a senior housing complex, assisted care facility, assisted living facility, and adult foster care; or 7) other.

We used two versions of the outcome variable. First, a binary for nursing home residency only (1), compared to all other options (0), excluding response option 6. Second, a binary measure of nursing home, assisted living facilities, and retirement homes, compared to all other response options, which represent care settings in private home environments.

As covariates, we controlled for respondents' and parents' socio-demographic and health-related variables. For respondents, we included respondents' age, gender (male/female),

race and ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, and other), highest level of education (<high school, high school or equivalent, some college, or college and above), marital status (married or partnered/other), employment status (full time/part time), respondent's income and household wealth inflated to 2020 value, paid vacation in weeks (≤1, 2-3, ≥4) and paid sick days (0, 1-7, 8-14, and ≥15 or more), as workers often exhaust workplace benefits before using PFL benefits. Respondent's income is the total earnings reported by respondents from wages or salaries, bonuses, commissions, overtime pay, tips, second job or military reserve earnings, and professional practice or trade income. Household wealth is the sum of all wealth components net debt. For income and household wealth variables, RAND includes imputed values in their public harmonized files.[87] For parent-level variables, respondents with a living parent are also asked about the parent's demographics and health and wellbeing. As parent-level covariates, we included parents' gender, education level (high school or less/some college/college and above), marital status (married/other), needing help with personal care tasks (yes/no), co-residency with respondent (yes/no), and whether the parent can be left alone for more than an hour (binary).

Statistical Analysis

First, we used standardized mean differences to compare the sample characteristics of the treatment and comparison groups. We used a cut-off of 0.1 cut-off for interpretation of a significant difference.[91] Next, we examined the pre-trends of each outcome between the treatment and comparison groups to ensure that the evolution of the outcomes were not significantly different. The parallel-trends assumption is essential for a causal interpretation in difference-in-differences analysis, as it indicates that, in the absence of a policy change, the

outcomes for the treatment and comparison groups would have followed similar trends in the post-treatment period. To examine pre-trends, we used an event-study approach to ensure that significant differences between the treatment and comparison groups do not exist in the pre-treatment period overall after adjusting for covariates. In addition, we visually compared unadjusted outcomes over time between the treatment and control groups.

Third, we estimated our main parameters of interest, which in a staggered difference-in-differences analysis is the group-average treatment effect on the treated (G-ATT). The average treatment effect on the treated (ATT) estimates the mean treatment effects only for individuals who are exposed to a treatment. In the Callaway and Sant'Anna framework for conducting a staggered difference-in-differences analysis, ATTs are estimated for each combination of treated state at a given time point, resulting in G-ATTs.[90] G-ATTs were identified using a doubly-robust estimator, which combines propensity scores and an outcome regression model into one estimation command. [90,92] The inverse probability of treatment weight is the propensity score method used to adjust for treatment exposure based on a set of covariates, while the outcome regression model uses an ordinary least squares model for covariate adjustment. Our main effects are reported as an overall ATT, which provides a single treatment effect across G-ATT combinations. The overall ATT is derived by taking the ATT for each state, and average across the treated states. As PFL benefits vary across states, we report on ATTs by group to assess treatment heterogeneity across benefit designs. Given the multiple sources of clustering in the data, the Callaway and Sant'Anna difference-in-differences approach uses a wild bootstrapping method.[90] Cluster standard errors were used at the state level given the state-based policy implementation.

We conducted a secondary analysis to examine the impact of PFL on residency in other residential care settings, excluding parents who lived in nursing homes. This allows us to compare the impact of PFL on nursing home to residency in other formal residential care settings, whereas our primary outcome of all residential care settings includes residency in nursing homes.

Sensitivity Analyses

To test the robustness of our results, we performed sensitivity analyses using two different samples. First, we broadened the control group to include all other states without active PFL programs in the study period. Including all other states in the US increases the sample and study power. Second, we exclude respondents who work part time and re-run the analysis using full-time worker-parent dyads. This is because full-time workers are entitled to the maximum benefit amount, which allows us to compare our results against a more precise sample of respondents with access to PFL.

Results

Table 2 provides the sample characteristic of dyad-wave observations (N=27,490) by treatment (PFL states) and comparison (no PFL) groups. Comparing to the control group, respondents in the treatment group had a lower percentage of White (61.5% vs 71.8%, SMD=0.26), workers from other racial backgrounds (22.9% vs. 16.4%, SMD=0.26), and identifying as Hispanic (28.4% vs. 16.4%, SMD=0.29). Respondents in the treatment group were more likely to have less than high school education (13.7% vs. 4.3%, SMD=0.34) and conversely, less likely to have a college degree and above (35.8% vs. 42.6%, SMD=0.34).

Respondents in the treatment group were less likely to have four or more weeks of paid vacation than the control group (48.1% vs. 57.0%, SMD=0.18). No statistically significant differences pertaining to workers' parents' characteristics were observed by group.

Difference-in-Differences Model Estimates

The event-study plots with results of the pre-trends analysis, conditional on covariates, for the two outcomes are presented in Figures 1 and 2. The plot for nursing home only shows fluctuating results in the periods leading up to policy implementation (centered at zero). One period leading up to PFL implementation shows a significant difference, however, the overall pre-trends period was found to be not statistically significant (p=0.5582). The plot for all residential care facilities also shows fluctuations in the outcome leading up to policy implementation at time zero. Similarly, the period prior to zero shows a significant difference in the outcome. However, the overall pre-trends period was found to be not statistically significant (p=0.5826). A plot of the unadjusted outcomes by group also shows similar trends over time (Supplementary Figures 2 and 3).

The unadjusted results are presented in Supplementary Table 1. The staggered difference-in-differences estimates without covariates show that implementing PFL led to a non-statistically significant increase in nursing home residency by 2.57 percentage points (95% CI=-0.46 to 5.60) and a non-statistically significant increase in residency across residential care settings by 4.07 percentage points (95% CI=-0.27 to 8.40).

The staggered difference-in-differences estimates using the doubly-robust model are presented in Table 3. Implementing PFL was associated with a non-statistically significant

increase in nursing home residency by 0.70 percentage points across treated states (95% CI=-6.27 to 7.66) compared to control states. When looking across all residential care settings, implementing PFL was associated with a non-statistically significant decrease in residential care residency by 4.59 percentage points across treated states (95% CI=-14.02 to 4.85) compared to states without PFL in the study period. At a mean rate of 18.57% residency in all residential care settings in the pre-treatment period, the estimate represents a relative decrease of 24.72% in the outcome for the treatment group. The event-study plot in Figure 1 shows that estimates in the periods following PFL implementation cross zero with confidence bands between +/-0.1, suggesting no significant differences over time when examining nursing home only as the place of residence. The event-study plot in Figure 2 shows a negative trend in the periods following PFL implementation when examining all residential care settings as the outcome. However, the estimates all cross the null value of zero.

Treatment Heterogeneity by Group

PFL program benefits vary in generosity with certain states offering longer leave periods and higher wage replacement rates. In addition, given the difference in implementation year, certain states have had programs in operation for longer which may affect awareness and utilization. Therefore, examining the treatment effect by states in the treatment group may be informative.

In the unadjusted models, we found similar estimates by group to the overall ATT for nursing home residency. However, when looking across all residential care settings, we found that implementing PFL led to a significant increase in residency in nursing, retirement, and

assisted living homes combined by 5.88 percentage points (95% CI: 0.17 to 11.59). This reflects a relative increase of 33.6% at the pre-treatment mean. All ATTs by group can be found in Supplementary Table 1.

After including covariates in the doubly-robust models, we did not find any significant results. However, we do find treatment effects in the opposite direction, particularly when looking at the combination of residential care settings. Specifically, we find a non-statistically significant decrease in nursing home residency for respondents who had lived in a state with PFL in 2004 (ATT=-1.00; 95% CI=-9.79 to 7.80), and a non-statistically significant increase in nursing home residency for respondents who lived in states that implemented PFL in 2009 (ATT=7.19; 95% CI=-4.27 to 18.64), and in 2018 (ATT=4.99; 95% CI=-1.72 to 11.70). For all residential care settings, we find non-significant decreases for respondents who lived in a state with PFL in 2004 (ATT=-4.95; 95% CI=-16.77 to 6.86), in 2009 (ATT=-4.95; 95% CI=-16.77 to 6.86), and in 2018 (ATT=-5.69; 95% CI = -15.20 to 3.82). While treatment effects by group were lower, we did not find precise estimates as evidenced by the large confidence intervals (see Table 3).

We conducted a secondary analysis to isolate the effect of PFL on residency in retirement homes and assisted living facilities (Supplementary Table 2). Excluding parents who lived in a nursing home as their place of residence resulted in similar estimates with predominantly non-significant negative effects except for one state in the treatment group. For respondents who lived in a state that implemented PFL in 2018, we found a significantly lower residency in retirement homes and assisted living facilities (ATT= -10.73; 95% CI= -20.73 to -0.74).

Robustness Checks

We conducted three robustness checks to test our main results (Supplementary File 3). First, we expanded the control group to include all other states without PFL. The effect of implementing PFL on nursing home residency remained similar (ATT=-0.02; 95% CI=--3.94 to 3.90) along with the effect on residency across residential care settings (ATT=-3.89; 95% CI=-10.36 to 2.58). In the second scenario, we restricted the sample to full-time workers only. In this scenario, the implementing PFL led to a non-significant increase in nursing home residency by 2.20 percentage points (95% CI = -4.62 to 9.03) and the treatment effect for all residential care settings was attenuated but remained lower (ATT=-1.90; 95% CI = -10.93 to 7.13). None of the treatment effects were statistically significant.

Discussion

In this paper, we examined the effect of implementing PFL policies on place of residence for workers' aging parents. This work contributes to the growing evidence base on PFL policies to support working caregivers. Specifically, we extend the current evidence on the impact of PFL on place of residence by including multiple states using a methodologically rigorous study to increase the generalizability of our results, and by broadening place of residence given the shift in the nursing home landscape. We provide robust evidence that implementing PFL did not result in a significant difference on nursing home residency for workers' aging parents. This result is consistent across all models and remained robust in the sensitivity analyses. The majority of long-stay nursing home residents have high levels of care needs and cognitive impairment.[93–96] Our findings have face validity given that short-term paid leave is unlikely to prevent residency in nursing home given the level of care required by older adults with complex needs and

dementia.[97] Our results stand in contrast to prior research which reported a significant reduction in nursing home residency in California following the implementation of PFL.[82] The difference in results are likely related to several factors including a different study design, sample, study period, and outcome measurement.

Including retirement homes and assisted living facilities in the outcome definition substantially increased the number of parents classified as residing in residential care. Although the direction of treatment effects changed, estimates remained imprecise and non-statistically significant. Excluding nursing home cases when focusing on other residential care settings produced similarly null results. These findings suggest that current PFL policies are unlikely to significantly influence place of residence for aging parents of workers in a sample that includes workers over the age of 50 – a group that predominantly cares for older adults in the US. The findings highlight the importance of examining residential care settings beyond nursing homes, given the changing landscape of residence among older adults with functional limitations.[84] With expansions in both PFL policies and expansion of retirement communities and assisted living facilities across the US, ongoing research is needed using data with follow-up periods that are more frequent, longer follow up periods for states recently implementing PFL, and larger samples to measure residency in assisted living as the sector continues to expand.

Our findings carry important policy implications. First, state and federal policymakers may consider adopting PFL benefit structures to enhance their effectiveness in supporting working caregivers and their aging parents. As the population ages and the prevalence of dementia continues to rise,[98,99] the demand for nursing home care is expected to increase. Given that Medicaid is the primary payer for long-stay nursing home residents,[80] efforts to influence nursing home use may be of particular interest to state administrators seeking to manage long-

term care expenditures and improve aging-in-place options. Caring for an older adult with multiple chronic conditions and cognitive decline can be intermittent and vary in intensity over time. One way to test whether PFL benefits may be more effective for workers and their parents is by lowering the minimum threshold for missed work time. For example, Rhode Island requires workers to be absent for seven days before becoming eligible to apply for benefits whereas Washington's Paid Leave program allows workers to apply for benefits after missing 4 hours of work over two consecutive days.[61,62] Indeed, an analysis of program benefits suggests higher wages are significantly associated with PFL utilization in Rhode Island and Washington state with smaller differences found for Washington (in revision). Another consideration is for more states to offer job protection for taking leave. Recent evidence suggests PFL without job protection may be ineffective in inducing workers to provide personal care support to older adults.[82] PFL policies are relatively new in many states and experimenting with benefit design may lead to more effective programs for working caregivers.

This study has several limitations. First, this study relies on workers living in a state with PFL policies in our identification strategy and did not identify uptake of PFL among workers. Therefore, the analysis is akin to an intent-to-treat approach than an as-treated analysis. The upside to conducting an intent-to-treat analysis is the mitigation of selection bias in the sample. Second, the study was conducted as a repeated cross-sectional study, and not a panel analysis, as explained under methods. Therefore, we were unable to adjust for changes within respondent-dyads over time. Third, the Callaway-Sant'Anna approach fixes time-varying covariates at the immediate period preceding policy implementation. Therefore, potential changes in the time-varying covariates in the post-treatment period were unable to be accounted for. However, the pre-trends analysis provides no evidence of significant differences in the evolution of the

outcome between the treatment and control groups. Fourth, while our inclusion/exclusion criteria were designed to home in on a sample that is likely eligible for PFL benefits, the cohort is subject to potential nondifferential misclassification.

Conclusion

In this quasi-experimental study, we did not find evidence that PFL implementation led to a significant difference on place of residence for workers' aging parents. With PFL policies expanding across states, experimentation of program benefits to support working caregivers are needed to increase program effectiveness. Future research is needed to evaluate uptake of benefits and monitor effects as stands continue to implement and adapt PFL policies.

Tables and Figures

Table 1. Description of state paid family leave policies.

State	Effective date	Maximum weeks for family leave per 52 weeks	Maximum amount per week
California	2004	8	$1,681
Colorado	2024	12	$1,324
Connecticut	2022	12	$941
Delaware	2026	6*	$900
District of Columbia	2020	12	$1,153
Maine	2026	12	$1,144
Maryland	2026	12	$1,000
Massachusetts	2021	12	$1,150
Minnesota	2026	12	$1,372
New Jersey	2009	12	$1,081
New York	2018	12	$1,178
Rhode Island	2014	7	$1,070
Oregon	2023	12	$1,569
Washington	2020	12	$1,542

*Over a 24-month period

Source: Data from AARP with wage replacement amounts updated to reflect 2025 dollar amounts from state program websites.[100]

Table 2. Sample characteristics of respondents living in a state with and without paid family leave policies.

	Overall N=27490	**PFL N=18789**	**No PFL N=8701**	**SMD**
Age (mean (sd))	57.63 (6.30)	57.35 (6.18)	58.24 (6.53)	0.14
Female (%)	15703 (57.1)	10656 (56.7)	5047 (58.0)	0.026
Race (%)				0.262
White	17630 (64.7)	11418 (61.5)	6212 (71.8)	
Black	4192 (15.4)	2901 (15.6)	1291 (14.9)	
Other[1]	5408 (19.9)	4257 (22.9)	1151 (13.3)	
Hispanic	6754 (24.6)	5331 (28.4)	1423 (16.4)	0.29
Married or partnered (%)	18937 (68.9)	12988 (69.1)	5949 (68.4)	0.016
Education (%)				0.341
< high school	2949 (10.7)	2579 (13.7)	370 (4.3)	
High school or equivalent	6399 (23.3)	4307 (22.9)	2092 (24.1)	
Some college	7705 (28.0)	5179 (27.6)	2526 (29.1)	
College and above	10431 (38.0)	6724 (35.8)	3707 (42.6)	
Employment status (%)				0.05
Full time	22481 (81.8)	15317 (81.5)	7164 (82.3)	
Part time	5009 (18.2)	3472 (18.5)	1537 (17.7)	0.021
Paid vacation days in weeks (%)				0.18
1 or less	4150 (15.1)	2981 (15.9)	1169 (13.4)	
2 or 3	9340 (34.0)	6771 (36.0)	2569 (29.5)	
4 or more	14000 (50.9)	9037 (48.1)	4963 (57.0)	
Paid sick days (%)				0.144
0	20144 (74.2)	13550 (72.9)	6594 (77.0)	

1 to 7	2973 (11.0)	2267 (12.2)	706 (8.2)	
8 to 14	2624 (9.7)	1863 (10.0)	761 (8.9)	
15 or more	1409 (5.2)	907 (4.9)	502 (5.9)	
Income (mean (sd))	63313.44 (112618.76)	62981.29 (121381.59)	64030.67 (90860.02)	0.01
Wealth (mean (sd)	679267 (1898877)	647375 (1953219)	748134 (1774021)	0.054
Number of living children (%)				0.111
0	2926 (10.6)	2154 (11.5)	772 (8.9)	
1	3562 (13.0)	2514 (13.4)	1048 (12.0)	
2	8667 (31.5)	5706 (30.4)	2961 (34.0)	
3 or more	12335 (44.9)	8415 (44.8)	3920 (45.1)	
Number of living siblings (%)				0.117
0	1541 (5.7)	1047 (5.6)	494 (5.7)	
1	4450 (16.3)	2989 (16.0)	1461 (17.0)	
2	5854 (21.5)	3757 (20.2)	2097 (24.4)	
3 or more	15373 (56.5)	10832 (58.2)	4541 (52.8)	
Parent's age (mean (sd))	81.81 (7.67)	81.77 (7.80)	81.89 (7.36)	0.016
Parent's gender				0.007
Mother	16435 (59.8)	11283 (60.1)	5152 (59.2)	
Father	11055 (40.2)	7506 (39.9)	3549 (40.8)	0.017
Parent's marital status (%)				0.06
Single	10631 (55.4)	7314 (55.6)	3317 (54.8)	
Married, living together	6226 (32.4)	4173 (31.7)	2053 (33.9)	
Married, living separately	553 (2.9)	376 (2.9)	177 (2.9)	

Married to other	1796 (9.4)	1286 (9.8)	510 (8.4)	
Parent's education (%)				0.088
High school or less	13965 (55.7)	9805 (56.9)	4160 (53.0)	
Some college	2193 (8.7)	1406 (8.2)	787 (10.0)	
College and above	8932 (35.6)	6031 (35.0)	2901 (37.0)	
Lives with respondent (%)	954 (3.8)	731 (4.2)	223 (2.8)	0.079
Parents with personal care needs (%)	4652 (24.4)	3229 (24.8)	1423 (23.6)	0.029

Source: Health and Retirement Study waves 5-15 (2000-2020)
Notes: SD=standard deviation; PFL = paid family leave; SMD = standardized mean difference
[1] The Health and Retirement Study's race variable collapses American Indian, Alaskan Native, Asian, Native Hawaiian, and Pacific Islander into an "Other" category.
Note: The table provides the number and percentage values of worker characteristics by group. The standardized mean difference provides the absolute difference between groups relative to standard deviation.
Source: HRS data waves 5-15 representing years 2000-2020.

Table 3. Staggered difference-in-differences analyses with covariates.

	Nursing Home Only			All Residential Care Settings		
	ATT (95% CI)	**Pre-Treatment Mean (%)**	**Relative Change**	**ATT (95% CI)**	**Pre-Treatment Mean (%)**	**Relative Change**
Overall	0.70 (-6.27 to 7.66)	8.99%	7.73%	-4.59 (-14.02 to 4.85)	18.57%	-24.72%
By state implementation year						
2004	-1.00 (-9.79 to 7.80)	6.64%	-15.06%	-4.95 (-16.77 to 6.86)	17.50%	-28.29%
2009	7.19 (-4.27 to 18.64)	6.68%	107.63%	- 1.59 (-17.06 to 13.88)	17.09%	9.30%
2018	4.99 (-1.72 to 11.70)	8.73%	57.16%	-5.69 (-15.20 to 3.82)	19.40%	-29.33%
	N=11,936			N=15,571		

ATT = Average treatment effect on the treated, measures the percentage point difference from the post-policy period to before for the treatment group compared to the comparison group; 95% CI = 95% confidence intervals. Group years refer to the PFL implementation year within the treatment group. Pre-treatment mean refers to the average rate of place of residence for each care setting among respondent-dyads in the treatment group prior to PFL implementation. Nursing home only compares residency in nursing home to other non-residential care settings. All residential care setting includes nursing homes, retirement homes, and assisted living facilities. The models are adjusted for respondent's age, gender, race and ethnicity, marital status, education, employment status, income quintile, wealth quintile, paid vacation in weeks, paid sick days, number of household kids, number of living siblings, parent's age, parent's sex, parent's education attainment, parent having personal care needs, co-residency, and parent's ability to be alone for at least 1 hour.

Source: HRS data waves 5-15 representing years 2000-2020.

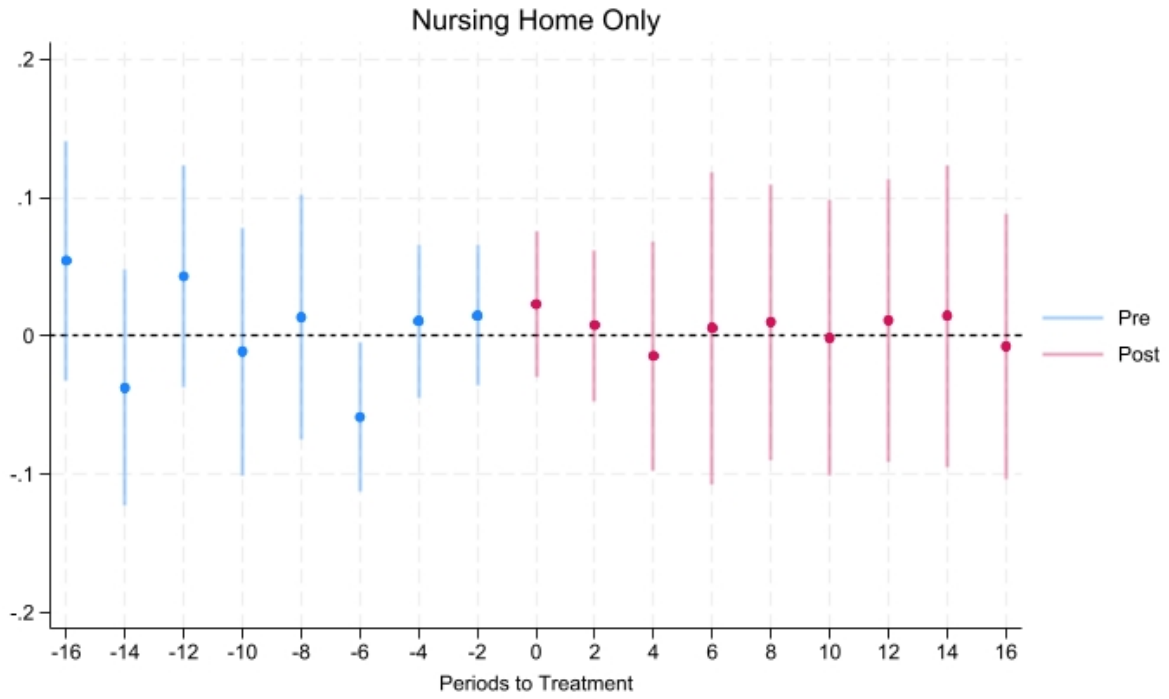


Figure 1. Event-study plot based on the staggered difference-in-differences model of nursing home residency among parents of workers living in a state with paid family leave (PFL) compared to states without PFL before and after policy implementation. The estimated treatment effect on the y-axis represents the average treatment effect on the treated. The x-axis is standardized to 0 and reflect periods (i.e. 2-year increments) leading up to and PFL implementation. The estimated treatment reflects percentage point differences in the post-PFL period to pre-PFL period for the treatment group compared to the comparison group. The error bars around the point estimates represent 95% confidence intervals. Robust standard errors were clustered at the state level.
Source: HRS data waves 5-15 representing years 2000-2020.

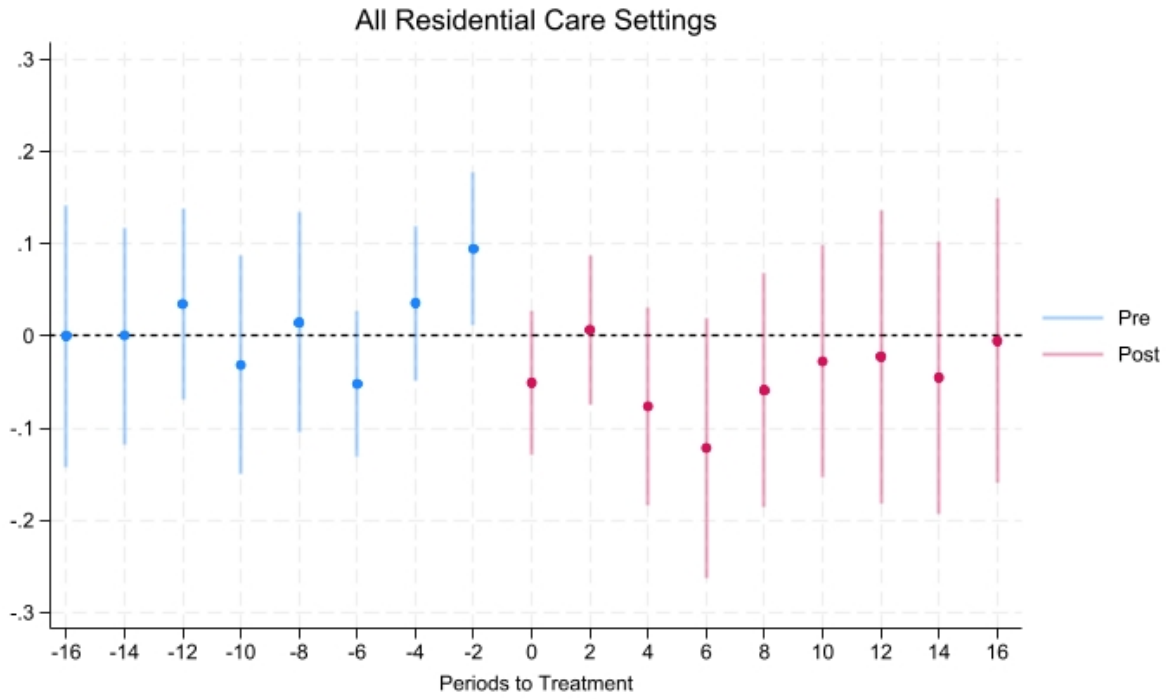
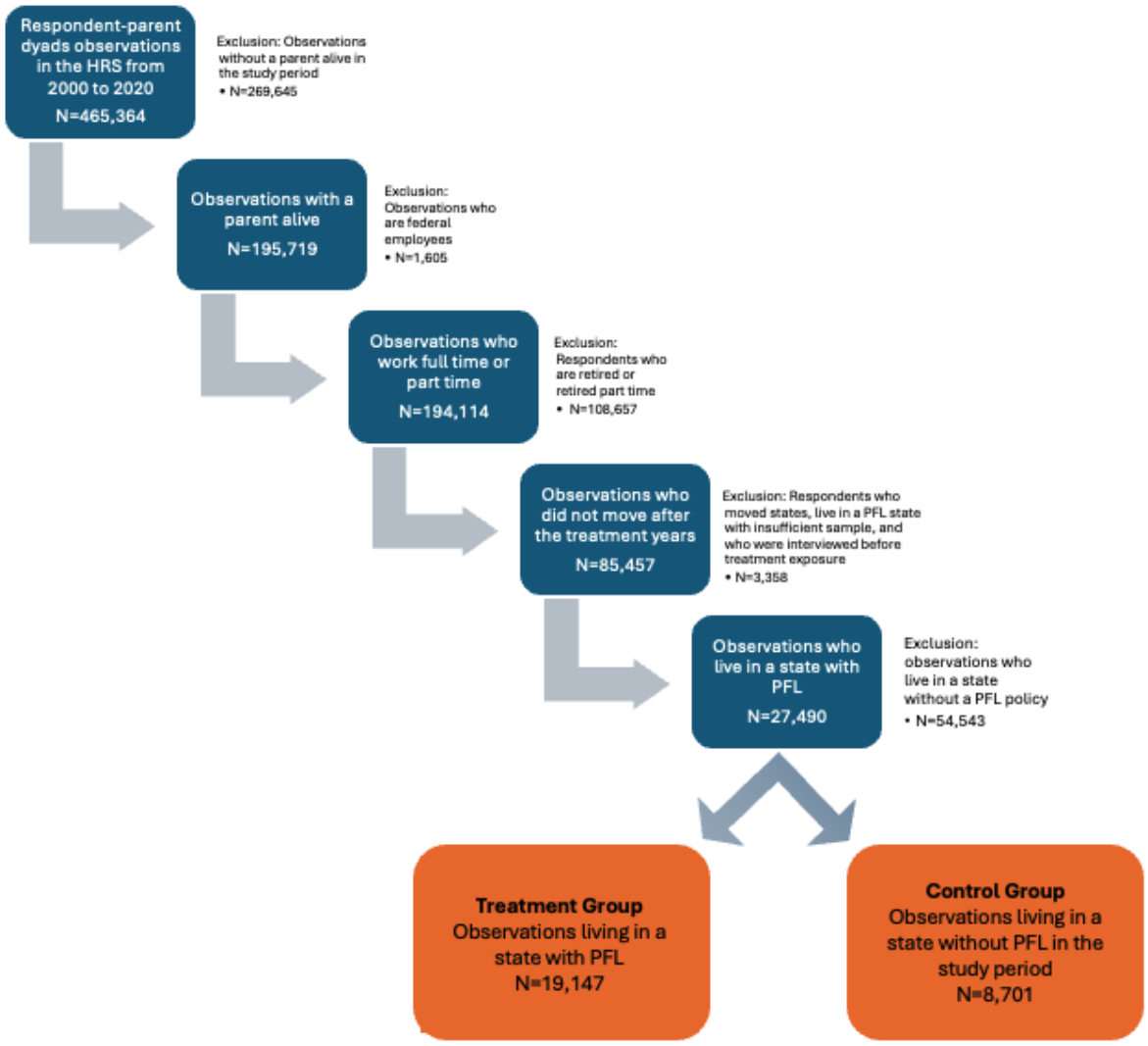
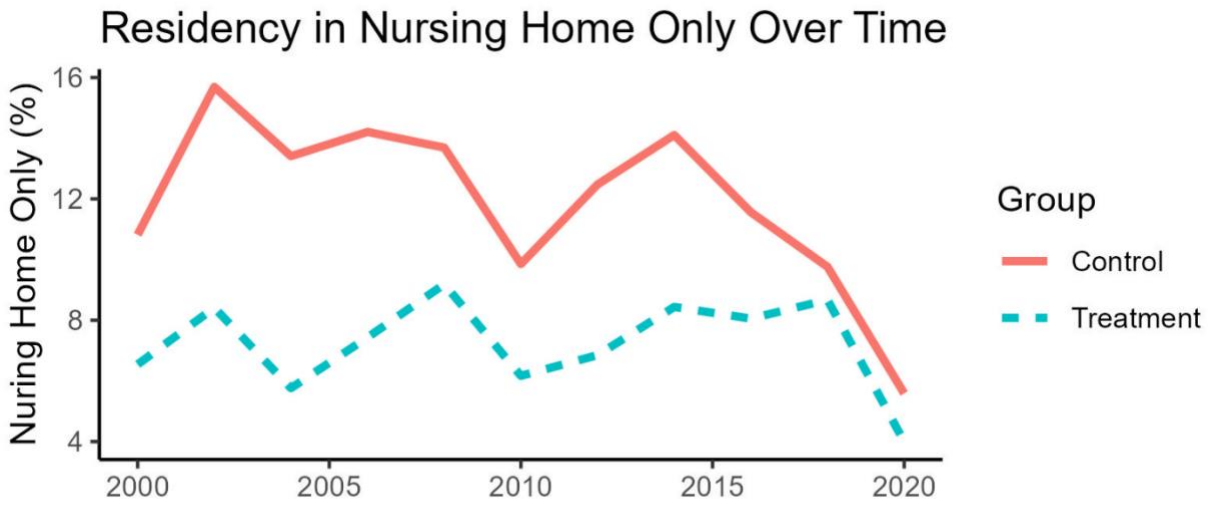


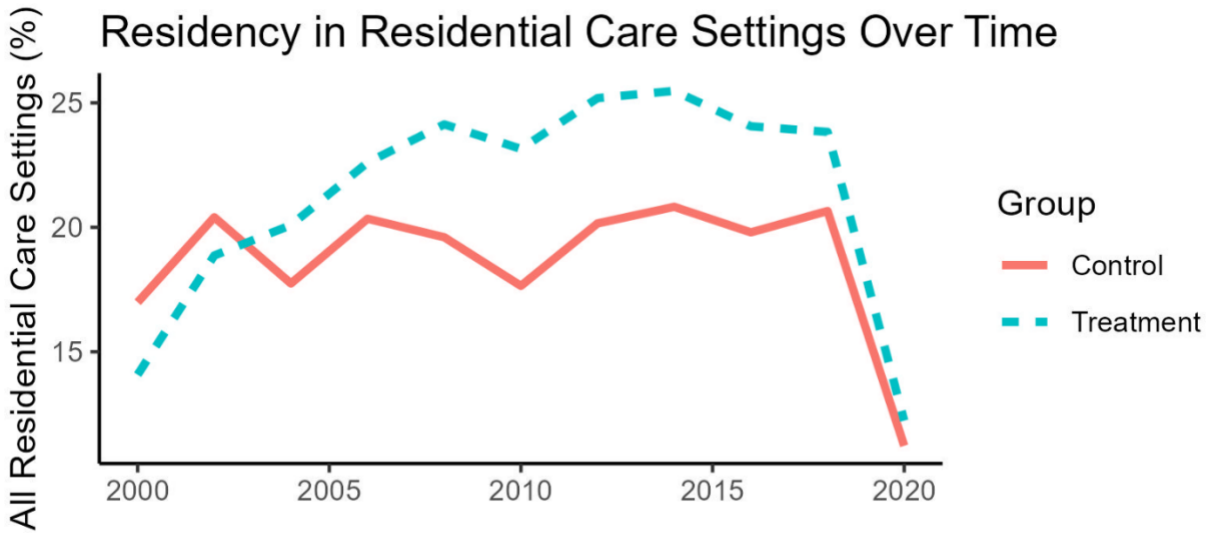
Figure 2. Event-study plot based on the staggered difference-in-differences model of residency in nursing homes and assisted living facilities among parents of workers living in a state with paid family leave (PFL) compared to states without PFL before and after policy implementation. The estimated treatment effect on the y-axis represents the average treatment effect on the treated. The x-axis is standardized to 0 and reflect periods (i.e. 2-year increments) leading up to and PFL implementation. The estimated treatment reflects percentage point differences in the post-PFL period to pre-PFL period for the treatment group compared to the comparison group. The error bars around the point estimates represent 95% confidence intervals. Robust standard errors were clustered at the state level.
Source: HRS data waves 5-15 representing years 2000-2020.

Supplementary File 1. Study population inclusion/exclusion criteria.





Supplementary Figure 2. Unadjusted trends of nursing home residency over time by group.



Supplementary Figure 3. Unadjusted trends of all residential care settings over time by group.

Supplemental Table 1. Staggered difference-in-differences analyses without covariates.

	Nursing Home Only			All Residential Care Settings		
	ATT (95% CI)	**Pre-Treatment Mean (%)**	**Relative Change**	**ATT (95% CI)**	**Pre-Treatment Mean (%)**	**Relative Change**
Overall	2.57 -0.46 to 5.60	8.99%	26.81%	4.07 (-0.27 to 8.40)	18.57%	21.92%
By state implementation year						
2004	2.55 (-1.56 to 6.65)	6.64%	38.40%	**5.88** (0.17 to 11.59)	17.50%	33.60%
2009	3.55 (-1.01 to 8.10)	6.68%	53.14%	-0.26 (-7.51 to 6.99)	17.09%	-1.52%
2018	1.58 (-1.29 to 4.45	8.73%	18.10%	-1.45 (-6.14 to 3.25)	19.40%	-7.47%
Number of observations	23,057			27,490		

ATT = Average treatment effect on the treated, measures the percentage point difference from the post-policy period to before for the treatment group compared to the comparison group; 95% CI = 95% confidence interval. Group years refer to the PFL implementation year within the treatment group. Pre-treatment mean refers to the average rate of place of residence for each care setting among respondent-dyads in the treatment group prior to PFL implementation. Nursing home only compares residency in nursing home to other non-residential care settings. All residential care setting includes nursing homes, retirement homes, and assisted living facilities.

Source: HRS data waves 5-15 representing years 2000-2020.

Supplementary File 2. Secondary analysis of PFL implementation on residency in retirement homes and assisted living facilities.

	Retirement Home and Assisted Living Facilities	
	ATT	95% CI
Overall	-2.32	-12.78 to 8.14
2004	-1.84	-15.17 to 11.48
2009	0.07	-15.41 to 16.76
2018	-10.73	-20.73 to -0.74
	N=15,590	

Supplementary File 3. Robustness checks.

Treatment Effect	S1: Using All States		S2: Full-time Workers Only	
	Nursing Home Only	**All Residential Care Settings**	**Nursing Home Only**	**All Residential Care Settings**
	ATT (95% CI)	ATT (95% CI)	ATT (95% CI)	ATT (95% CI)
Overall	- 0.02 (-3.94 to 3.90)	-3.89 (-10.36 to 2.58)	2.20 (-4.62 to 9.03)	-1.90 (-10.93 to 7.13)
By Group				
2004	-1.34 (-6.17 to 3.49)	-3.96 (-11.99 to 4.08)	1.54 (-7.00 to 10.09)	-1.72 (-13.04 to 9.59)
2009	6.39 (-2.32 to 15.10)	-2.73 (-14.75 to 9.28)	2.58 (-11.12 to 16.29)	-0.8 (-17.16 to 15.52)
2018	1.34 (-3.91 to 6.58)	-4.90 (-12.62 to 2.82)	6.89 (-0.33 to 14.11)	-4.89 (-15.47 to 5.69)
N	39,249	48,933	9,914	12,849

S1 models compare states with PFL to all other US states. S2 models restrict the sample to full-time workers. All residential care setting includes nursing homes, retirement homes, and assisted living facilities. The models are adjusted for respondent's age, gender, race and ethnicity, marital status, education, employment status, income quintile, wealth quintile, paid vacation in weeks, paid sick days, number of household kids, number of living siblings, parent's age, parent's sex, parent's education attainment, parent having personal care needs, co-residency, and parent's ability to be alone for at least 1 hour.
Source: HRS data waves 5-15 representing years 2000-2020.

Supplementary File 4. Crude differences in mean nursing home rates before and after policy implementation for respondents in treatment groups.

	Nursing home			**All Residential Care Settings**		
	Pre-treatment mean at t-1 (%)	Post-treatment mean (%)	Difference	Pre-treatment mean at t-1 (%)	Post-treatment mean (%)	Difference
Overall	8.63%	7.03%	-1.60%	20.80%	0.2311	2.31%
2004	8.17%	6.61%	-1.57%	20.65%	0.2471	4.06%
2009	6.59%	9.17%	2.58%	18.99%	0.1773	-1.26%
2018	9.59%	7.90%	-1.69%	21.32%	0.1611	-5.21%

Chapter 4: Impact of Paid Family Leave on Health and Wellbeing of Working Caregivers: A Quasi-Experimental Study of US Policies

Abstract

Objective: Most older adults rely on informal caregivers, primarily their working adult children, to age at home. Working caregivers face competing demands that put their health and wellbeing at risk. Several US states have implemented Paid Family Leave (PFL) policies, which provide working caregivers respite from work to manage caregiving responsibilities. This study examines the impact of PFL implementation on the health and wellbeing of working caregivers.

Study Setting and Design: We conducted a quasi-experimental study to examine the impact of PFL on working caregivers' self-reported health, depressive symptoms, restless sleep, and feeling lonely. We used a staggered difference-in-differences design to exploit variation in the timing of PFL implementation across states.

Data Sources and Analytic Sample: We used data from the Health and Retirement Study (1998–2020) to identify working caregivers. The sample included adult children working full or part time who provided a parent with personal care, household tasks, or financially. Respondents were assigned to the treatment group if they resided in a state with an active PFL program during the study period; working caregivers in states that had enacted but not yet implemented PFL served as controls.

Principal Findings: Among 9321 working caregivers, we found that implementing PFL policies was not associated with a significant difference on self-reported health (ATT= -2.62pp; 95% CI: -7.74 to 4.93), feeling depressed, (ATT=1.44pp; 95% CI = -4.86 to 7.73), experiencing restless sleep, (ATT=2.54pp; 95% CI=-6.35 to 11.43), feeling lonely (ATT=-1.40; 95% CI: -7.74 to 4.93), compared to states without PFL policies in the study.

Conclusion: We did not find evidence that PFL policies was associated with significant differences on the health and wellbeing of working caregivers. With PFL policies expanding across states, experimentation of program benefits to support working caregivers and their aging parents are needed to increase policy effectiveness.

Background

Over 24 million informal caregivers provide unpaid help to older Americans.[77] Informal caregivers are family and friends who provide support with personal care needs, household chores, and psychosocial support. Nearly 60% of informal caregivers are of working age who face competing time demands including paid work, other caregiving duties, childcare, and unpaid labor at home. In 2022, 40% of informal caregivers were part of the workforce, 17% of had a child below age 18 living at home, and spent an average of seventeen hours a week providing care to an older adult.[77]

Informal caregiving is associated with a myriad of health and economic outcomes. Informal caregivers experience worse health across a number of outcomes including depression, sleep deprivation, weight loss, loneliness, and self-reported health.[32–39] While early research on the health effects of caregivers were predominantly based on cross-section analyses,[101] more recent studies have used longitudinal data and found that becoming a caregiver is associated with lower depressive symptoms and self-reported health. [35,38] Worse mental health outcomes have been consistently found among informal caregivers who provide different types of support.[38] About 12% of informal caregivers in the US are socially isolated,[40] which may contribute to worse mental health. While the evidence on the effects of informal caregiving on social isolation is smaller, a systematic review consistently found positive relationships between informal caregiving and social isolation.[102]

The economic and health consequences of caregiving are correlated and it is difficult to isolate their unique effects on work and health outcomes due to selection into caregiving roles and differences in the type and intensity of care provided by adult children.[103,104] Caregivers who are in the workforce face greater competing demands leading to higher levels of burden due to perceived caregiver-work conflict among caregivers.[105] Qualitative evidence suggests informal

caregivers are more likely to forgo promotions at work, reduce hours or work part time, or leave the workforce entirely compared to non-caregivers.[30,36,45,50,55,103,105] Additional stressors may stem from caregivers being more likely to experience financial strain compared to non-caregivers.[53,104] The economic toll can span multiple generations as working caregivers to aging parents over the long-run leads to significantly lower wealth accumulation and higher probability of falling into poverty later in life.[47,103]

Supporting working caregivers is an important societal priority, both to sustain the care economy that is predominantly comprised of informal caregivers, and to improve caregivers' economic security and health outcomes. Paid Family Leave (PFL) policies have been introduced across states and represent a mechanism for improving the economic and health situation for working caregivers. PFL policies that offer benefits to eligible employees with time-limited paid leave. Based on early evidence, implementing PFL increased the supply of informal caregivers by 6-34%[22,24,106] and simultaneously a decrease the probability of workers leaving the workforce.[48,56,57,107]

Despite the early evidence that PFL policies yield positive economic outcomes, their potential to improve health and well-being remains underexplored. California was the first state to implement PFL in 2004 and early examination of the policy did not find a significant effect on worker's mental and physical health. PFL policies have now spread to seventeen states. With paid leave more accessible across the workforce, workers with caregiving responsibilities may experience better health and wellbeing through two possible mechanisms: First, temporary paid leave programs provide working caregivers respite from paid work, thereby reducing their competing demands and increasing leisure time, both of which may enhance their health and wellbeing. Second, temporary paid leave provides working caregivers partial wage replacement,

and through an improved sense of financial security, workers may report better health and wellbeing. On the contrary, temporary paid leave programs may be insufficient for improving informal caregivers' health and wellbeing. First, informal caregiving responsibilities can be strenuous and intensive, particularly as older adults have multiple health and social needs and cognitive impairments.[2,77,97] Therefore, even with respite from paid work, informal caregivers may experience poor health. Second, because most informal caregivers of older adults provide support on a long-term basis, intermittent use of or temporary paid time away from work may offer limited relief from the cumulative toll on their health and wellbeing. Third, partial wage replacement may protect higher-earning workers from experiencing financial stress but less so for lower-earning workers.[60,108] Depending on the economic situation of working caregivers, partial wage replacement may be insufficient for improving health and wellbeing.

We examine the impact of implementing state PFL policies on working caregivers' health and wellbeing. The expansion to additional states provides an opportunity to leverage the variation in timing of PFL implementation, increasing the external generalizability of results for states with PFL policies.

Methods

Data Source

This study used data from the Health and Retirement Study (HRS) from 1998-2020. The HRS is a longitudinal, nationally representative study of older Americans aged >50 years and their spouses.[88] The purpose of the HRS is to create a cohort that allows researchers to study aging as well as how social and policy changes affect older adults. The HRS began enrolling respondents in 1992 and conducts in person or telephone surveys biennially, with initial response

rates of 79% and follow-up rates of 85% to 91%.[88] The HRS samples panel participants at the household level and selected members and their spouse are asked to participate and are followed biennially until respondents are lost to follow up or die. The study asks respondents about their socio-demographics, labor force participation, family structure, intergenerational transfers on helping children and parents, and health status, making it a rich dataset for addressing questions on intergenerational caregiving. The HRS biennial data products and the cross-wave harmonized data by RAND are publicly available.[89] To obtain variables on state of residence, we linked the harmonized RAND HRS and Family Files to the restricted geographic datafiles.

Study Population

We created a cohort of working caregivers in the HRS sample by identifying respondents who are part of the workforce (full time or part time) and provided support to a parent or parent-in-law with personal care tasks, household chores, or financial support. The HRS includes the following survey questions about informal care provision: 1) whether they spent "a total of 100 or more hours since the previous interview or in the last two years helping your parents/mother/father/mother [-in-law(s)] with basic personal activities like dressing, eating, and bathing?"; 2) whether they spent a total of 100 or more hours since the previous interview or in the last two years helping your parents/mother/father/mother [-in-law(s)] with other things such as household chores, errands, transportation, etc.?" and 3) whether the respondent provided financial help to their parents/mother/father/mother [-in-law(s)] amounting to $500 or more since the previous interview or in the last two years with financial help referring to "giving money, helping pay bills, or covering specific types of costs such as those for medical care or insurance,

schooling, down payment for a home, rent, etc." We excluded respondents who were federal employees and respondents who moved states after the policy implementation period.

We conducted a quasi-experimental study using Callaway and Sant'Anna's staggered difference-in-differences approach.[88,90] This is a causal framework that examines the impact of introducing PFL across states and in different years by incorporating multiple groups in the treatment group. This flexibility allows us to assess the impact of PFL programs that were introduced in different years. Table 1 describes states that have enacted or implemented PFL policies. We used state of residence to create the treatment and control groups. We focused on states with PFL laws in the study to increase the comparability of states in the treatment and control groups. Working caregivers who lived in states that implemented PFL policies during the study period were assigned to the treatment group. Working caregivers who lived in states that implemented PFL policies after the study period were used to create the control group. For the treatment group, because of the lookback period included in the questions used to identify caregiver status, we used the wave following PFL implementation as the first wave in the post-treatment period. For example, if a state implemented PFL in 2004, the wave from 2006 would serve as the first post-treatment period. Although the states that are assigned to the control group now have PFL programs in operation, because they had not in the study period and therefore were not exposed to the policy, we used the "never-treated" approach in the study for the control group.

Measures

The study includes four outcome measures to assess health and wellbeing: self-reported health, felt depressed, restless sleep, and felt lonely. Self-reported health is a measure of one's

assessment of general health based on the following question: “Would you say your health is excellent, very good, good, fair, or poor?” We created a dichotomous measure to compare individuals who reported their health as excellent and very good, to those with good, fair, or poor self-reported health assessments. To examine depressive symptoms, feeling lonely, and experiencing restless sleep, the following items were used: “Now think about the past week and the feelings you have experienced, please tell me if each of the following was true for you much of the time during the past week. Much of the time during the past week, you felt depressed/you felt lonely/your sleep was restless. Would you say yes or no?” from the cognition module of the HRS.

As covariates, we included socio-demographics, job-related, health-related, and caregiving-related variables. As socio-demographics variables, we controlled for respondents’ age, gender (male/female), race (White, Black, other), ethnicity (Hispanic or non-Hispanic), highest level of education (<high school, high school or equivalent, some college, or college and above), marital status, number of living children, and respondent’s income and household wealth inflated to 2020 value. Respondent’s income is the total earnings reported by respondents from wages or salary, bonuses, commissions, overtime pay, tips, second job or military reserve earnings, and professional practice or trade income. Household wealth is the sum of all wealth components net debt. As job-related variables, we included labor force status (full-time, part-time), paid vacation in weeks (≤1, 2-3, ≥4) and paid sick days (0, 1-7, 8-14, and ≥15 or more), as workers often exhaust workplace benefits before using PFL benefits. We also controlled for job-related stress as it may confound the effect on health. As health-related variables, we controlled for the respondent’s number of chronic conditions, having private health insurance, and being on a public insurance plan. Measures that were used to identify informal caregiver status were used

as dichotomous variables to control for type of caregiving support (i.e., personal care, household tasks, and financial). We also included whether a respondent has a parent living within 10 miles and whether a parent can be left alone for one hour as these measures are associated with caregiving intensity.

Statistical Analysis

First, we examined the pre-trends of each outcome between the treatment and control groups to ensure that the evolution of the outcomes were not significantly different. The parallel-trends assumption is essential for a causal interpretation in difference-in-differences analysis, as it indicates that, in the absence of a policy change, the outcomes for the treatment and control groups would have followed similar trends in the post-treatment period. This allows any additional difference observed to be attributed to the implementation of PFL policy. To examine pre-trends, we used an event-study approach to ensure that significant differences between the treatment and control groups do not exist in the pre-treatment period overall. Next, we identified our main parameters of interest, which in a staggered difference-in-differences analysis is the group-average treatment effect on the treated (G-ATT). The average treatment effect on the treated (ATT) estimates the mean treatment effects only for individuals who are exposed to a treatment. In the Callaway and Sant'Anna framework for conducting a staggered difference-in-differences analysis, ATTs are estimated for each combination of treated group at a given time point, resulting in G-ATTs. G-ATTs were identified using a doubly-robust estimator, which combines propensity scores and an outcome regression model into one estimation command. [90,92] The inverse probability of treatment weight is the propensity score method used to adjust for treatment exposure based on a set of covariates, while the outcome regression model uses an

ordinary lease squares model for covariate adjustment. Our main effects are reported as an overall ATT which provides a single treatment effect across G-ATT combinations. The overall ATT is derived by aggregating the ATTs for each state, and averaging across states. As PFL benefits vary across states, we report on ATTs by group to assess treatment heterogeneity across benefit designs. Given the multiple sources of clustering in the data, the Callaway and Sant'Anna difference-in-differences approach uses a wild bootstrapping method.[90] Standard errors were clustered at the state level given the state-based policy implementation. Add that we compared treatment and control group composition using standard mean differences with a 0.1 cut-off for interpretation of a significant difference.[91]

Results

Table 1 provides the sample characteristic of working caregivers (N=9321) by treatment (PFL states) and control (no PFL) groups. The mean age of working caregivers was 56.6 years (sd=6.0) and 52.3% were female. Comparing to the control group, working caregivers in the treatment group were less likely to be White (59.7% vs 68.8 %, SMD=0.32), Black (14.6% vs. 17.9%, SMD=0.32), and more likely to belong to other racial groups (25.7% vs. 13.3%, SMD=0.32) and be Hispanic (31.9% vs. 12.8%, SMD=). Respondents in the treatment group were more like to have less than high school level education (14.6% vs. 5.6%) and conversely, less likely to have a college degree and above (32.7% vs. 40.4%, SMD=0.47). Working caregivers in the treatment group were more likely to have 1 week or less in paid vacation weeks (21.0% vs. 16.6%, SMD=0.15) and less likely to have four or more weeks (48.8% vs. 55.9%, SMD=0.15) than the control group. Working caregivers in the treatment group were less likely to help with chores or errands (63.3% vs 72.2%, SMD=0.21) and more likely to provide financial

support to a parent (54.5% vs. 45.3%, SMD=0.18) than the control group. No other significant differences were observed between the treatment and control groups.

Impact on Health and Wellbeing

The unadjusted results are presented in Supplementary Table 1. The parallel trends in the pre-implementation period were not statistically significantly different as evidenced by large p-values. The event-study plots shown in Figure 1 show that all 95% confidence-intervals cross the null value of zero in the pre-implementation period. In the unadjusted models, implementing PFL was associated with a lower share of working caregivers rating their self-reported health as good, fair, or poor by 1.29 percentage points (95% CI=8.44 to 5.87), a lower share of working caregivers reporting feeling depressed in the last week by 1.17 percentage points (95% CI: -5.26 to 2.92), and a lower share of working caregivers reporting feeling lonely in the last week by 0.73 percentage points (95% CI: -5.22 to 3.76), compared to states without PFL in the study. Following PFL implementation, a higher share of working caregivers reported experiencing restless sleep in the last week by 0.18 percentage points (95% CI= -6.54 to 6.90) compared to states without PFL in the study. None of the estimates were statistically significant.

In the doubly-robust models, the parallel trends remained statistically non-significant for for all outcomes, except when examining depressive symptoms. Adjusting for covariates, implementing PFL leave was associated with a lower share of working caregivers rating their self-reported health as good, fair, or poor by 2.62 percentage points (95% CI=-11.69 to 6.44), and a lower share of working caregivers reporting feeling lonely in the last week by 1.4 points (95% CI: -7.74 to 4.93) compared to working caregivers living in states without PFL in the study.

However, PFL implementation was associated with a higher share of working caregivers reported feeling depressed by 1.44 (95% CI = -4.86 to 7.73), and associated with a higher share of working caregivers experiencing restless sleep in the last week by 2.54 percentage points (95% CI=-6.35 to 11.43), compared to states without PFL in the study. All of the outcomes remained non-statistically significant. Figure 1 shows the event-study plots that since working caregivers became exposed to PFL implementation, the effects on health and wellbeing remain close to the null value of 0 in the post-treatment periods for the vast majority of estimates.

Impact on Health and Wellbeing by Group

The group average treatment effects on the treated (G-ATTs) by implementation year are presented in Table 3. The aggregated group G-ATTs on the treated were similar to the overall ATTs. The effect sizes for some of the G-ATT by implementation year were larger, particularly for working caregivers living in a state that implemented in 2018. However, none of the estimates were statistically significant.

Robustness Check

To test the robustness of the results, we compared the outcomes to a control group that included all other US states without PFL (see Supplementary File 2). Across outcomes, none of the results were statistically significant and the treatment effects remained largely similar to the doubly-robust models in the main analysis.

Discussion

In this quasi-experimental study, we did not find that implementing PFL was associated with the health and wellbeing of working caregivers. Research on the effects of PFL on workers' health outcomes are limited.[21] To our knowledge, two studies have examined the impact of state PFL policies on workers' mental and physical health.[26,109] Gimm and colleagues, who also focused on caregiving for aging parents, similarly found no significant difference on the physical and mental health of working caregivers following California's implementation of PFL.[26] In a more recent and complementary study, Coile and colleagues focused on caregiving for spouses or children with health shocks following implementation of PFL in California and New Jersey and found a significantly lower probability of using mental health medications.[109] The analytic sample used in our study is different from prior work in that we used a broader definition for identifying working caregivers who provided support with personal care, household chores, or financial support, and included three states with PFL in the treatment group. Our study is most similar to Gimm and Yang's paper who also used the HRS sample. In addition, our heterogeneity of treatment effect estimates by group found large effect sizes for states that implemented PFL closer to the end of our study period. Despite larger effect sizes, none of the estimates were statistically significant that crossed zero, therefore, we are unable to determine precisely whether the effect were null, small, or large. This is likely a result of smaller sample size given only one period of follow up that was available in the dataset at the time of analysis. As PFL are new policies in many states, ongoing monitoring of policy impacts with longer follow-up periods are needed to confirm our findings.

A noteworthy aspect of our sample is that over 90% of working caregivers had at least one child. While we controlled for number of living children and not specifically age of children,

given the mean age, a large portion of our sample likely reflects a population who belong to the sandwich generation of caring for children and aging parents. The dual caregiving responsibilities workers face may explain the null results observed in our study.[43] About a third of workers in the US care for both children and parents.[110] The probability of belonging to a sandwich generation peaks between ages 50-64 year, which reflects the working caregiver sample in this study.[16,43,110] Sandwiched caregivers are equally likely to provide the same about of informal care compared to caregivers who provide for older adults only, while they are more likely to be part of the workforce.[16] With the aging population, improving the health and wellbeing of working caregivers, particularly ones with multiple caregiving responsibilities, is an important priority for policy makers and employers. Informal caregivers will continue to account for providing the vast majority of long-term care to older adults in the US.[14,77,78] Research is needed to understand the reasons behind the lack of policy effectiveness and ways to change program benefits to support working caregivers.

The study results should be interpreted within the context of their limitations. First, we identified working caregivers who are living in a state that enacted PFL policies. We were unable to discern whether working caregivers used PFL benefits for their caregiving responsibilities. Therefore, the analysis conducted is akin to intent-to-treat, and not as-treated. The benefit of conducting an intent-to-treat analysis is that it minimizes selection bias by including both working caregivers who may have used or not used PFL benefits. Second, the HRS conducts interviews on a biennial basis falling on even years. However, New Jersey's PFL policy went into effect on July 1, 2009. The HRS questions that ask respondents about providing informal care to a parent include a two-year recall period or since the last interview. Given the 2-year recall period, we used wave 11 from 2012 as the first follow-up period for working caregivers

living in New Jersey, leaving data from wave 10 to include both a pre- and post-PFL exposure. Dropping wave 10 was not an option when using Callaway and Sant'Anna's staggered difference-in-differences method. Therefore, the results likely include a small number of misclassified respondents. Third, the cohort examined in the study included workers who reported helping a parent with personal care tasks, household chores, or financially. It is possible that selecting on working caregivers may have introduced endogeneity into the study design. It was not feasible to identify workers with parents who identified a need for caregiving support across measures of functional limitations. Therefore, we do not provide causal interpretation of model results in this study. Fourth, we were unable to control for parents' socio-demographic factors related to the parent who received informal care support. However, given the use of working caregiver panel, the analysis included individual and year fixed effects allowing us to control for within working-caregiver changes.

Conclusion

In this quasi-experimental study, we did not find evidence that implementing PFL was significantly associated with the health and wellbeing of working caregivers. With PFL policies expanding across states, experimentation of program benefits to support working caregivers are needed to increase program effectiveness. Access to granular and linked data are needed to conduct robust studies of PFL benefits to monitor implementation, uptake, and impact of PFL.

Tables and Figures

Table 1. Sample characteristics of working caregivers living in a state with and without paid family leave policies.

	Overall	PFL	No PFL	SMD
N	9321	5345	3976	
Age (mean (sd))	56.57 (6.00)	56.49 (6.16)	56.69 (5.77)	0.034
Female (%)	4879 (52.3)	2763 (51.7)	2116 (53.2)	0.031
Race (%)				0.317
White	5882 (63.6)	3156 (59.7)	2726 (68.8)	
Black	1478 (16.0)	770 (14.6)	708 (17.9)	
Other[1]	1885 (20.4)	1357 (25.7)	528 (13.3)	
Hispanic (%)	2211 (23.8)	1702 (31.9)	509 (12.8)	0.47
Education (%)				0.318
<HS	1002 (10.8)	781 (14.6)	221 (5.6)	
HS or GED[2]	2370 (25.4)	1366 (25.6)	1004 (25.3)	
Some college	2594 (27.8)	1449 (27.1)	1145 (28.8)	
College and above	3354 (36.0)	1749 (32.7)	1605 (40.4)	
Married or partnered (%)	7667 (82.3)	4380 (81.9)	3287 (82.7)	0.019
Employment status (%)				0.072
Full-time	6722 (83.0)	1969 (82.1)	2753 (86.3)	
Part-time	1551 (16.6)	950 (17.8)	601 (15.1)	
Weeks of vacation (%)				0.15
1 week or less	1787 (19.2)	1125 (21.0)	662 (16.6)	
2-3 weeks	2700 (29.0)	1609 (30.1)	1091 (27.4)	
4 or more weeks	4834 (51.9)	2611 (48.8)	2223 (55.9)	
Sick days (%)				0.181
0	6506 (70.8)	3707 (70.1)	2799 (71.7)	
1-7 days	1043 (11.3)	709 (13.4)	334 (8.6)	
8-14 days	1016 (11.1)	572 (10.8)	444 (11.4)	
15 or more	629 (6.8)	301 (5.7)	328 (8.4)	
Income (mean (SD))	62043.57 (79273.84)	60571.38 (75990.54)	64022.65 (83453.22)	0.043
Wealth (mean (SD))	671191.35 (1632488.24)	618679.17 (1241906.86)	741784.32 (2041160.59)	0.073
Number of household children (%)				0.056
0	870 (9.3)	508 (9.5)	362 (9.1)	
1 or 2	3930 (42.2)	2191 (41.0)	1739 (43.7)	
3 or more	4521 (48.5)	2646 (49.5)	1875 (47.2)	
Number of chronic conditions (%)				0.026
0	3330 (35.7)	1916 (35.8)	1414 (35.6)	

1	3110 (33.4)	1803 (33.7)	1307 (32.9)	
2	1905 (20.4)	1077 (20.1)	828 (20.8)	
3 or more	976 (10.5)	549 (10.3)	427 (10.7)	
Government insurance (%)	1054 (11.4)	588 (11.1)	466 (11.8)	0.022
Private insurance (%)	5557 (60.3)	3122 (59.1)	2435 (62.0)	0.059
Parents live within 10 miles (%)	1948 (22.5)	1063 (21.4)	885 (24.0)	0.061
Parents alone for 1 hour (%)	5999 (68.8)	3356 (67.0)	2643 (71.3)	0.093
Helps with personal care (%)	2287 (24.5)	1365 (25.5)	922 (23.2)	0.055
Helps with chores/errands (%)	6281 (67.4)	3381 (63.3)	2900 (72.9)	0.209
Provides financial support (%)	4715 (50.6)	2912 (54.5)	1803 (45.3)	0.183

Notes: SD = Standard deviation; PFL = Paid family leave; SMD = Standardized mean difference; HS = High school; GED = General educational development

[1] The Health and Retirement Study's race variable collapses American Indian, Alaskan Native, Asian, Native Hawaiian, and Pacific Islander into an "Other" category

Source: Health and Retirement Study waves 4-15 (1998-2020)

Table 2. Staggered difference-in-differences estimates with covariates.

Outcome	ATT (95% CI)	Parallel Trends P-value	Pre-treatment Mean (%)	Relative Change (%)	N
Self-reported Health	-2.62 (-11.69 to 6.44)	0.6850	53.50	-4.90	7837
Felt Depressed	1.44 (-4.86 to 7.73)	0.0389	11.92	12.08	7633
Restless Sleep	2.54 (-6.35 to 11.43)	0.7029	28.08	9.05	7631
Felt Lonely	-1.40 (-7.74 to 4.93)	0.5693	10.90	-12.84	7636

Notes: 95% CI = 95% confidence interval; PFL = paid family leave; ATT = Average Treatment Effect on the Treated. The ATT reports the percentage point difference in the outcome after policy implementation compared to before, for respondents in the treatment group compared to the control group. Pre-treatment Mean reports the mean outcome among respondents who live in the treated states in the pre-policy period. Covariates include age, gender, race, ethnicity, education, marital status, labor force status, number of paid sick days, paid vacation in weeks, income, wealth, number of household children, number of chronic conditions, parents living within 10 miles, whether parents can be left alone for at least 1 hour, provides support with personal care, household chores, or financial help, job stress, government health insurance, private health insurance.
Source: Health and Retirement Study waves 4-15 (1998-2020)

Table 3. Staggered difference-in-differences estimates with covariates by implementation year.

	Model 1: Self-reported Health	**Model 2: Felt Depressed**	**Model 3: Restless Sleep**	**Model 4: Felt Lonely**
By state implementation year	ATT (95% CI)	ATT (95% CI)	ATT (95% CI)	ATT (95% CI)
2004	-3.36 (-14.11 to 7.38)	1.42 (-6.09 to 8.94)	1.83 (-8.79 to 12.44)	-3.11 (-10.70 to 4.47)
2009	2.49 (-10.65 to 15.63)	0.22 (-8.30 to 8.74)	3.58 (-7.79 to 15.44)	7.08 (-1.00 to 15.17)
2018	-7.77 (-27.36 to 11.82)	7.61 (-7.98 to 23.19)	14.59 (-8.80 to 37.99)	1.87 (-12.96 to 16.70)
Number of observations	7,837	7,633	7,631	7,636

Notes: ATT = Average treatment effect on the treated; SE = standard error; 95% CI = 95% confidence interval. Covariates include age, gender, race, ethnicity, education, marital status, labor force status, number of paid sick days, paid vacation in weeks, income, wealth, number of household children, number of chronic conditions, parents living within 10 miles, whether parents can be left alone for at least 1 hour, provides support with personal care, household chores, or financial help, job stress, government health insurance, private health insurance.

Source: Health and Retirement Study waves 4-15 (1998-2020)

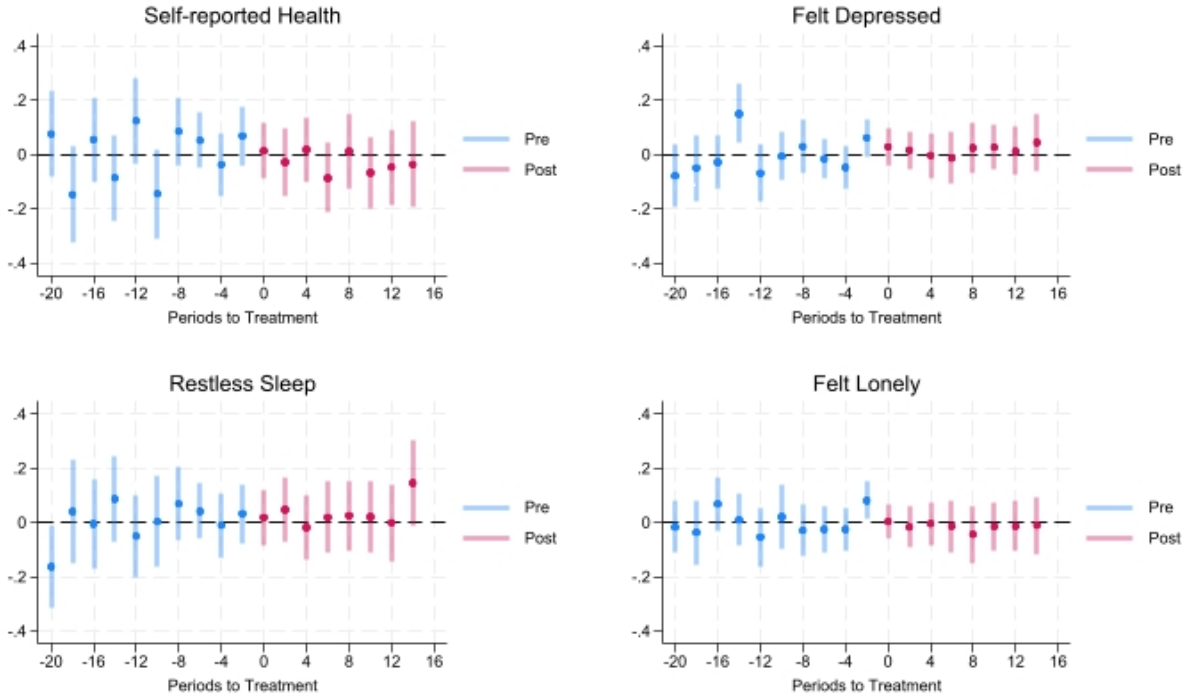


Figure 1. Event-study plot based on the staggered difference-in-differences model on four measures of caregiver health and wellbeing among parents of workers living in a state with paid family leave (PFL) compared to states without PFL before and after policy implementation. The x-axis is standardized to 0 and reflect periods (i.e. 2-year increments) leading up to and PFL implementation. The estimated treatment effect on the y-axis represents the average treatment effect on the treated. The estimated treatment reflects percentage point differences in the post-PFL period to pre-PFL period for the treatment group compared to the control group. The error bars around the point estimates represent 95% confidence intervals. Robust standard errors were clustered at the state level.
Source: Health and Retirement Study waves 4-15 (1998-2020)

Supplementary

Supplementary File 1. Staggered difference-in-differences estimates without covariates.

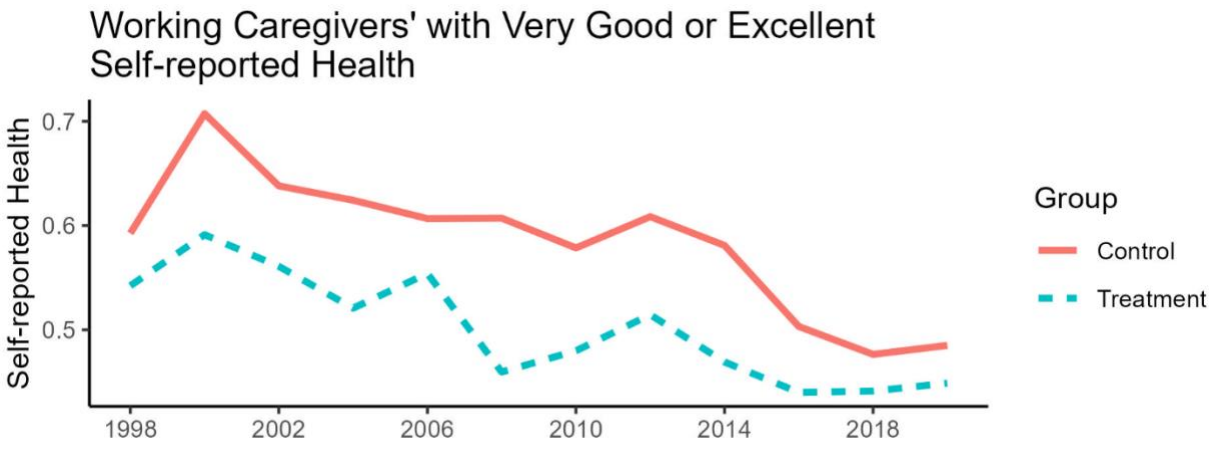
Outcome	Average Treatment Effect of PFL (95% CI)	Parallel Trends P-value	Pre-treatment Mean (%)	Relative Change (%)	N
Self-reported Health	-1.29 (-8.44 to 5.87)	0.4690	53.50	-2.41	9,328
Felt Depressed	-1.17 (-5.26 to 2.92)	0.4765	11.92	-9.82	9,321
Restless Sleep	0.18 (-6.54 to 6.90)	0.7534	28.08	0.64	8814
Felt Lonely	-0.73 (-5.22 to 3.76)	0.2314	10.90	-6.70	8821

Notes: 95% CI = 95% confidence interval; PFL = paid family leave; Average Treatment Effect of PFL reports the percentage point change in outcome after policy implementation compared to before, for respondents in the treatment group compared to the control group. Pre-treatment Mean reports the mean outcome among respondents who live in the treated states in the pre-policy period.
Source: Health and Retirement Study waves 4-15 (1998-2020)

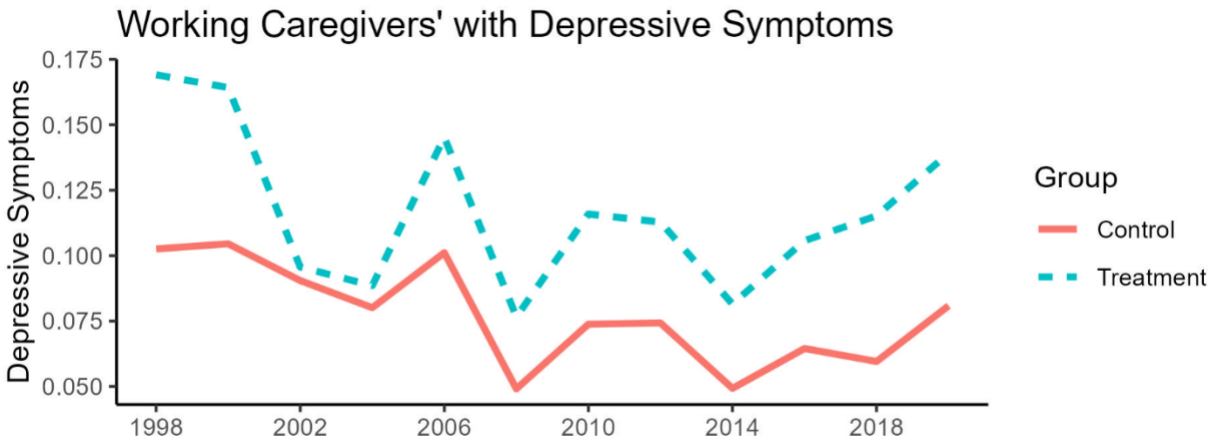
Supplementary File 2. Robustness test using all states in the treatment and control groups.

	Model 1: Self-reported Health	Model 2: Felt Depressed	Model 3: Restless Sleep	Model 4: Felt Lonely
	ATT (95% CI)	ATT (95% CI)	ATT (95% CI)	ATT (95% CI)
Overall	0.02 (-6.90 to 6.93)	1.20 (-3.60 to 5.99)	1.71 (-4.79 to 8.20)	-0.95 (-5.86 to 3.96)
By state implementation year				
2004	-0.25 (-8.37 to 7.86)	1.40 (-4.27 to 7.07)	1.31 (-6.37 to 8.98)	-2.20 (-8.04 to 3.63)
2009	3.24 (-8.90 to 15.47)	-1.66 (-9.48 to 6.17)	1.91 (-8.55 to 12.38)	4.74 (-2.60 to 12.08)
2018	-8.50 (-25.11 to 8.10)	9.71 (-3.94 to 23.36)	10.90 (-9.93 to 31.73)	3.48 (-10.72 to 17.67)
N	19,627	19,003	19,000	19,005

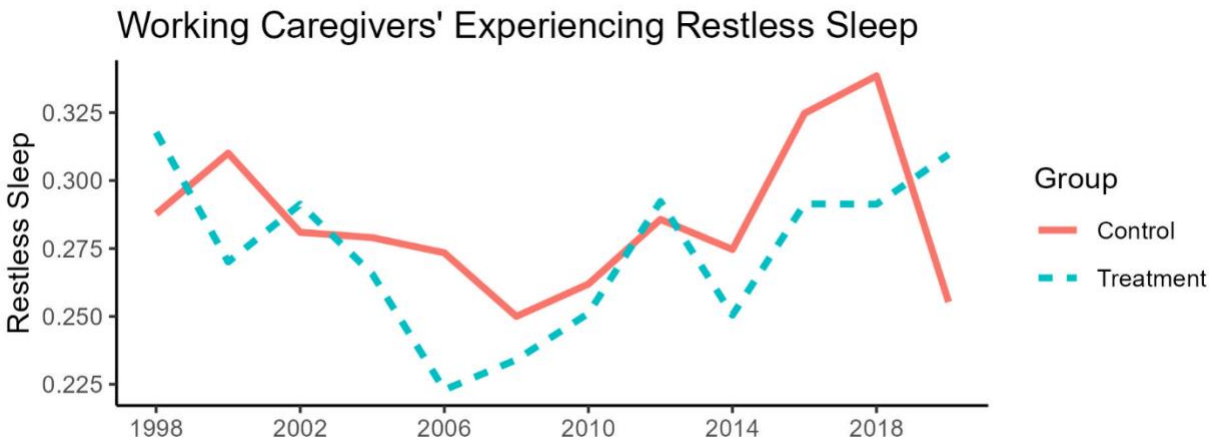
Notes: ATT = Average treatment effect on the treated; SE = standard error; 95% CI = 95% confidence interval. Covariates include age, gender, race, ethnicity, education, marital status, labor force status, number of paid sick days, paid vacation in weeks, income, wealth, number of household children, number of chronic conditions, parents living within 10 miles, whether parents can be left alone for at least 1 hour, provides support with personal care, household chores, or financial help, job stress, government health insurance, private health insurance.
Source: Health and Retirement Study waves 4-15 (1998-2020)



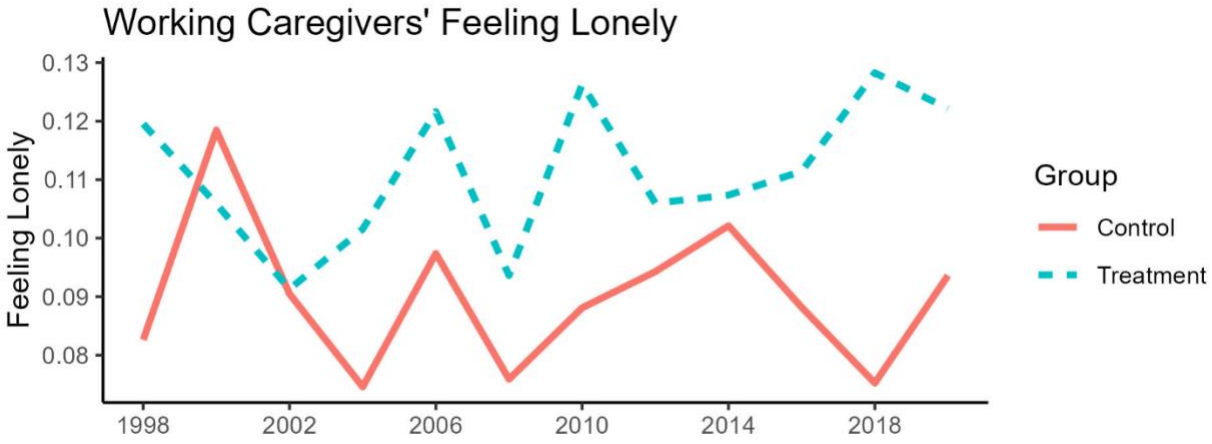
Supplementary 1. Unadjusted trends of working caregivers' self-reported health by group.



Supplementary Figure 2. Unadjusted trends of working caregivers' with depressive symptoms by group.



Supplementary Figure 3. Unadjusted trends of working caregivers' who experienced restless sleep by group.



Supplementary Figure 4. Unadjusted trends of working caregivers' reported feeling lonely by group.

Chapter 5: Conclusion

In this dissertation, I described trends in PFL utilization and characteristics associated with application approval, examined the impact of implementing PFL policies on place of residence for older adults, and identified the effect of PFL policies on the health and wellbeing of working caregivers. Key findings from the dissertation are that large difference exist between low-earning and high-earning workers on receiving benefits after taking leave, and that living in states with PFL policies did not lead to significant differences on place of residence for older adults or the health and wellbeing of working caregivers, compared to workers who live in states without PFL policies. The dissertation chapters discuss ways in which benefit designs including administrative burden create inequities in workers being able to access benefits. Importantly, experimenting with benefit designs are needed to effectively support working caregivers as the aging population continues.

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