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Effects of State Paid Family Leave Policies on Preventing Household Adverse Childhood Experiences (ACEs) in Early Childhood in the United States, 2011–2019

Sara P. Perrins¹, Ganna Sheremenko¹, Justice King¹, Lucas Godoy-Garraza¹, Kristen Cincotta¹, Stephanie Miedema², Laura Cremer², Ashley S. D’Inverno², Christopher R. Harper²

¹ICF, Reston, VA, USA

²Division of Violence Prevention, Centers for Disease Control and Prevention, Atlanta, GA, USA

Abstract

Adverse childhood experiences (ACEs) are preventable, potentially traumatic events that can predict a wide range of short- and long-term negative health outcomes. More research is needed on policies that may reduce ACEs. Paid Family Leave (PFL) is a state-level policy that provides economic support for employees to care for a newborn or a recently adopted child. This study evaluated effects of PFL on reduction in household challenge ACEs. To investigate whether PFL implementation reduced the occurrence of household challenge ACEs among young children in Rhode Island and New York relative to other states without PFL implementation. This study used 2011–2019 population-based National Survey of Children’s Health (NSCH) data to compare the proportion of household challenge ACEs experienced in intervention versus control states. Bayesian Additive Regression Tree (BART) and two-way fixed effects (TWFE) methods estimated post-intervention average treatment effects. United States (U.S.) Census covariates controlled for variation between states. Placebo checks bolstered the robustness of inference. Rhode Island and New York (intervention states) implemented PFL in 2014 and 2018, respectively. Control states included states that did not implement PFL as of 2019. The NSCH surveys included a 9-item ACEs questionnaire in which caregivers reported on whether their children ages 0–2 experienced various forms of abuse, and potentially traumatic household challenges (i.e., caregiver divorce, domestic violence, caregiver incarceration, caregiver mental health problems, caregiver substance use). This study focused on five household challenge ACEs and the occurrence of any household challenge ACE as primary outcomes. A treatment indicator identified intervention and control states. State-level covariates were median household income, unemployment rate, and percent

^{corresponding} Sara P. Perrins, Sara.Perrins@ICF.com.

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uninsured. Results suggest that PFL implementation was associated with significant 4% reduction in caregiver separation and 2% reduction in caregiver incarceration ACEs in the intervention states post-PFL adoption and a significant 4% reduction in the proportion of young children experiencing any household challenge ACE relative to no PFL implementation in control states. This study adds rigorous scientific support for the public health benefits of PFL for young children and their families. Existing evidence indicates caregiver incarceration and separation may affect children's short- and long-term mental health, substance use, and school related outcomes. Support through PFL may help reduce the occurrence of household challenge ACEs and promote children's well-being.

Keywords

Adverse Childhood Experiences (ACEs); Policy; Paid Family Leave

Introduction

Adverse childhood experiences (ACEs) are potentially traumatic childhood events associated with significant negative health outcomes throughout the lifespan (Anda et al., 2006; Felitti et al., 1998; National Center for Injury Prevention and Control, 2019, 2020). ACEs include abuse and neglect, and household challenges. Household challenge ACEs focusing on household challenges include living with someone who has substance use or mental health issues, witnessing domestic violence, and experiencing parental/caregiver¹ separation or incarceration. Children who experience household challenges or other ACEs are at greater risk for emotional, cognitive, and behavioral problems. They are more likely to have poorer educational outcomes, psychiatric diagnoses, and criminal involvement (Haj-Yahia et al., 2019; Mueller & Tronick, 2019; Peleg-Oren & Teichman, 2006; Rasic et al., 2014; Wakefield & Wildeman, 2013; Weaver & Schofield, 2015; Yamamoto & Keogh, 2018). The prevention of ACEs is a public health priority with potentially far-reaching implications for children's short- and long-term health outcomes. Policies that support reductions in the occurrence of any household challenge ACEs may play an important role in improving public health.

Paid Family Leave (PFL) is a state-level policy intended to aid health and economic outcomes in families with children (State of California, n.d.); State of Washington, n.d.). Presently, 20 states have enacted and implemented PFL and an additional four states (Minnesota, Maine, Delaware, and Maryland) will implement PFL by 2026 (Bipartisan Policy Center, n.d.). Existing PFL policies allow employees to take 4 to 12 weeks of partially paid leave to address personal health problems, care for an ailing family member, or, more commonly, care for a newborn or newly adopted child. In 2025, Rhode Island's Temporary Caregiver Insurance provides up to six weeks of partial wage replacement (i.e., 60% of an eligible employee's wage up to a maximum of \$1070 per week) and job protection during this time off, while New York State Paid Family Leave offers up to 12 weeks of job-projected time off at 67% of an eligible employee's average weekly wage up

¹Some ACEs use the term caregiver, while others use parental. The term caregiver will be used throughout the manuscript.

to a maximum of \$1,177.32 per week.² Each state's implementation of PFL varies and may change from year to year.

The ability to take leave following childbirth is particularly important. It allows new parents time to recover from childbirth, address health concerns for themselves and their children, and have time to bond with their children (Bullinger, 2019; D'Inverno et al., 2018). In turn, this increases protective factors such as positive parenting practices and reduces risk factors of violence such as poor mental and behavioral health and negative parenting practices. Additional pathways through which PFL may prevent or reduce intimate partner violence, teen dating violence, and child maltreatment include maintaining household income thereby reducing financial stress which could prompt violence, as well as increased egalitarian parenting and domestic practices that support a mother's return to work and her career and income advancement (D'Inverno et al., 2018). This ultimately promotes equality, which has been associated with reductions in intimate partner violence and sexual violence (Kearns et al., 2020; Willie & Kershaw, 2019). Additionally, these positive outcomes may strengthen the relationship between parents, reducing the incidence of caregiver separation. By preventing a child from becoming a victim of violence or witnessing violence, PFL helps to break the intergenerational transmission of violence and to reduce the number of ACEs a child experiences.

Studies have found links between PFL and a range of improved caregiver and child health outcomes. Findings suggest PFL is associated with improved overall child health (Bullinger, 2019). This includes decreases in low birthweight and preterm birth rates, particularly among African American and unmarried mothers (Chen, 2021; Ruhm, 2000; Stearns, 2015; Tanaka, 2005). Furthermore, the introduction of PFL was associated with decreases in infant mortality and hospitalizations (Klevens et al., 2016; Montoya-Williams et al., 2020; Pihl & Basso, 2019) and increases in on-time infant vaccinations (Choudhury & Polachek, 2021), as well as time mothers spent breastfeeding (Baker & Milligan, 2010; Hamad et al., 2019; Huang & Yang, 2015; Pac et al., 2019) and engaging in childcare activities (Trajkovski, 2019). Since birth and neonatal outcomes are strongly correlated with longer-term child well-being (Ip et al., 2007; Moster et al., 2008; Oreopoulos et al., 2008; Stein et al., 2006), policies such as PFL may have long-lasting benefits for children including educational attainment levels, income, and mortality and medical disability rates (Litchman-Sadot & Bell, 2017).

PFL is also associated with benefits for caregivers, including reduced alcohol use in fathers, and decreased psychological distress, particularly for single and younger mothers (Doran et al., 2020; Irish et al., 2021; B. C. Lee et al., 2020). These early findings on caregiver well-being are important, given the evidence that high caregiver stress can predict hostile, less responsive parenting, and poorer child well-being (Lee et al., 2018; Rominov et al., 2016; Ward & Lee, 2020). In addition, caregiver well-being has been linked to children's experiences of ACEs and maltreatment (O'Donnell et al., 2015; Reupert & Maybery, 2016).

²Information regarding the most recent paid family leave benefits for Rhode Island and New York were obtained from each state's website (i.e., <http://ripaidleave.net/> and <https://paidfamilyleave.ny.gov/2024>, respectively).

Therefore, policies that support caregivers may contribute to preventing a wide range of negative health outcomes associated with early childhood adversity.

More research is needed to establish the role of PFL in improving caregiver outcomes and preventing ACEs in early childhood. In addition to being proximal to the time in which caregivers would utilize PFL, early childhood is also an important developmental period in which adverse, traumatic experiences can alter brain development and subsequent long-term health (Merrick et al., 2019; Teicher et al., 2016). This underscores the critical need to prevent early childhood ACEs. The bulk of existing evidence for PFL and health effects used data from California, which was the first state to enact the policy (Huang & Yang, 2015; Pihl & Basso, 2019; Stein et al., 2006; Trajkovski, 2019). Studies that investigate the impacts of PFL in other states can strengthen the evidence for the policy's impact on health and improve the generalizability of inferences. This study adds to the existing literature by examining the effects of PFL on household challenge ACEs in New York and Rhode Island, two states that have implemented PFL. We employed causal inference methods to estimate PFL effectiveness in reducing household challenge ACEs for families with children. It is proposed that paid family leave can decrease family and caregiver stress and increase economic stability, ultimately decreasing risk for household challenge ACEs that focus on household challenges.

Methods

Sample

This study used publicly available data from the 2011 through 2019 administrations of the National Survey of Children's Health (NSCH), which can be obtained from the United States Census Bureau website (United States Census Bureau, 2025). NSCH collects a nationally representative sample of children's health data from caregivers with at least one child in the household. To reach population-based estimates, NSCH applied weights to respondent data to align with population controls for various demographics obtained from American Community Survey data (United States Census Bureau, n.d.). Detailed data collection and respondent characteristics are described elsewhere (National Center for Health Statistics, 2012; U.S. Census Bureau, 2017, 2019a). We analyzed data from caregivers under the age of 65 years, with children ages 0–2 years in the household, and developed an aggregate state-year dataset with $N_{total\ observations} = 245$ observations for 49 states, each with data for years 2011, 2016, 2017, 2018 and 2019, resulting in 5 years of data for each of the 49 states. Analyses were limited to caregivers with children ≤ 2 as PFL is expected to mainly affect outcomes of young children. This secondary analysis of deidentified, publicly available data was deemed exempt from ICF human subjects institutional review.

Measures

NSCH administered a modified 9-item version of the 10-item ACE questionnaire originally developed by Felitti et al. (1998). Survey items describing household challenge ACEs were included in the analyses including: caregiver divorce or separation; caregiver served time in jail (caregiver incarceration); child saw or heard caregivers or adults slap, hit, kick, punch one another in the home (domestic violence); child lived with anyone who was mentally

ill, suicidal, or severely depressed (caregiver mental health); and child lived with anyone who had a problem with alcohol or drugs (caregiver substance use). Each response was dichotomously coded as 1 (yes) or 0 (no), and then aggregated to create state-level averages for each year. We also created a dichotomous “Any Household challenge ACE” outcome to indicate the existence of at least one of the household challenge ACEs listed above.

The two intervention states with data available for this analysis were Rhode Island and New York, with PFL implementation in 2014 and 2018, respectively. Because NSCH surveys did not include ACEs assessment before 2011, data from states that implemented PFL prior to 2011 (i.e., California and New Jersey) were not included. The other 46 states and Washington DC that did not implement PFL as of 2019 were treated as controls ($N_{\text{control states}} = 47$).

Prior to obtaining state-year level estimates of the outcome measures among caregivers with children ≤ 2 , we reweighted the sample to adjust for differences in NSCH respondent-level covariates (i.e., child age, sex, race, and poverty level) across states and over time using an entropy balancing weights procedure (Hainmueller, 2011). Similar reweighting procedures are routinely used in survey sampling to adjust sample weights so that some sample characteristics match population characteristics known from auxiliary data. For the present study, the sample characteristics used as reference are from the population residing in the two intervention states in 2019.

In addition, state-level covariates included seasonally adjusted unemployment rate, median household income, and percent without health insurance coverage obtained from the U.S. Census Bureau’s Small Area Health Insurance Estimates, and Small Area Income and Poverty Estimates data, which provide single-year estimates for all U.S. states and counties (U.S. Census Bureau, 2019b, 2019c).

Statistical Analyses

We conducted analyses using SAS 9.4 (SAS Institute, 2016) and R 4.1.2–3 (R Core Team, 2022) statistical software. R packages used include *bartMachine* (Kapelner & Bleich, 2016), *lmtree* (Zeileis & Hothorn, 2002), and *multiwayvcov* (Graham et al., 2016). We used two difference-in-differences (DID)-based causal inference estimation methods to compare the proportion of household challenge ACEs among respondents in the intervention versus control states. These approaches impute counterfactuals for the intervention states using information from the control states and the pre-intervention periods. The two procedures differed in the specific way we performed this imputation, including statistical models and assumptions. In using distinct but complementary DID methods for policy evaluation, this study mutes biases that may be particular to any one statistical approach (Abadie, 2021; Lavy & Lehman-Wilzig, 2005). This is to ensure a more comprehensive, balanced inference of PFL treatment effects.

We used Bayesian Additive Regression Tree (BART) (Chipman et al., 2010), a flexible, data-adaptive regression method that combines multiple regression trees. Unlike traditional linear or generalized linear models, which assume a linear relationship between predictors and the response variable, BART can capture interactions and non-linearities learned directly

from the data without requiring explicit specification of these relationships in advance. This flexibility arises from building an ensemble of simpler models. The building blocks of this ensemble are regression trees, which partition the data based on a few covariates to create subsets with relatively homogeneous outcomes. To prevent excessive flexibility, the Bayesian framework discourages the use of deep trees and incorporates techniques to shrink predictions. BART therefore combines the flexibility of machine learning algorithms with inference to become a powerful predictive modeling tool that has grown in popularity for causal inference (J. Hill et al., 2020a, 2020b). We also used Two-Way Fixed Effects (TWFE) method, which is a more traditional, common method for estimating causal effects in policy evaluation. TWFE is particularly popular for its ability to eliminate time-invariant unmeasured confounding in panel data (Firebaugh et al., 2013; Imai & Kim, 2021). In both methods, we estimated base and adjusted (i.e., with state-level covariates) models. For inference (e.g., to construct confidence intervals), we used procedures recommended for each of these approaches. In the case of TWFE, inference relies on robust variance estimates clustered at the state level. BART is a fully Bayesian procedure. To improve confidence in the validity of study findings, placebo effect analyses were conducted in which a treatment effect was estimated for randomly selected non-intervention states for any statistically significant findings from the TWFE and BART analyses. The p -value used for significance was $p < 0.05$.

Results

Table 1 provides a descriptive summary of measures used in the analysis, including outcome summaries from a pre- and a post-intervention year for the two intervention states and 46 control states and Washington, DC ($N_{\text{control states}} = 47$). The average proportions of children who experienced household challenge ACEs in intervention states were similar in magnitude to the average proportions of children experiencing household challenge ACEs in the control states before PFL was enacted (2011). About 12% of children experienced at least one household challenge ACE in both intervention and control states in 2011. In 2019 post-PFL, 5.5% of children experienced at least one household challenge ACE in the intervention states compared to 9.1% of children in the control states.

Figure 1 shows the effects of PFL on Any Household challenge ACE outcome in the BART adjusted model. The Y axis represents the difference between the observed outcome in NY and RI and the expected outcome in those states in absence of the intervention (based on the control states and the statistical model). The X axis is the time in years relative to the start of the intervention (with year 0 as the intervention start year). Note that the difference between the observed outcome and the outcome expected in absence of the intervention should be zero before the intervention starts and represents the estimated effect of the intervention afterwards. The figure suggests adequate model fit (i.e., near zero average total treatment effects (ATT) estimates that are not statistically significant in the six years' pre-intervention period) and negatively trending ATT estimates post-intervention. Other outcomes and base model estimations followed similar trends in model fit and direction of the treatment effect (data not shown). One notable exception was the BART estimation of mental health, where the model fit was compromised by the significant ATT estimates in the pre-intervention period (data not shown).

Table 2 provides the ATT of PFL on household challenge ACEs across intervention states estimated using replication from BART and TWFE methods. Base models do not include state-level covariates. Results showed several significant effects. PFL implementation in intervention states, relative to controls, was associated with significant reductions in the proportion of young children experiencing any household challenge ACE (adjusted ATT = -0.04 , 95%CI = -0.06 ; -0.01), caregiver incarceration (adjusted ATT = -0.02 , 95%CI = -0.04 , -0.01), and caregiver separation (adjusted ATT = -0.04 , 95%CI = -0.06 , -0.02). PFL impact on caregiver substance use was only statistically significant in the adjusted model (adjusted ATT = -0.01 , 95%CI = -0.03 ; -0.00^3). Caregiver mental health outcome results were suppressed as unreliable due to poor model fit.

Base TWFE models showed a significant negative effect of PFL on household caregiver substance use (ATT = -0.01 , 95%CI = -0.02 ; -0.003), domestic violence (ATT = -0.01 , 95%CI = -0.01 ; -0.003), caregiver separation (ATT = -0.03 , 95%CI = -0.05 ; -0.02), and caregiver incarceration (ATT = -0.02 , 95%CI = -0.02 ; -0.02). However, after the inclusion of state-level covariates, only household caregiver separation (adjusted ATT = -0.04 , 95%CI = -0.06 ; -0.01) and caregiver incarceration (adjusted ATT = -0.02 , 95%CI = -0.03 ; -0.02) ACEs estimates remained statistically significant.

As a robustness check, we conducted placebo analyses for adjusted models where we identified significant effects of PFL in which the two intervention states were replaced by two randomly selected control states. Placebo analyses showed no significant effects of PFL on household challenge ACEs (see Table 3), further validating the significant findings above.

Discussion

Our study found that PFL implementation in the two intervention states of Rhode Island and New York was associated with the reduction in the proportion of young children who experienced certain household challenge ACEs. Statistically significant reductions in caregiver separation and caregiver incarceration were consistent across BART and TWFE methods, suggesting particularly robust treatment effects for these outcomes.

Our findings indicate that PFL policy implementation prevented on average 4 out of every 100 children from experiencing caregiver separation, and 2 out of 100 children from experiencing caregiver incarceration in the states each year post-intervention. In addition, BART estimations suggested a significant negative effect of PFL on the proportion of young children experiencing at least one household challenge ACE. Each year following PFL policy implementation, approximately 4 out of every 100 children were prevented from experiencing any household challenge ACE in the two states, a reduction of over 40% compared with the average rate that would have been observed had the policy not been implemented (i.e., in control states). These reductions would have large population implications with respect to preventing ACEs in early childhood if PFL was implemented in all states.

³Estimates have been rounded to the nearest hundredths. Reported coefficients of -0.00 and 0.00 are rounded from values that are < 0 and > 0 , respectively.

These findings carry potential implications for children's health. Caregiver separation is linked to short- and long-term issues with anxiety, depression, self-esteem, school problems, suicide attempts, alcohol and drug use, and smoking (Auersperg et al., 2019; Cherlin et al., 1998; Størksen et al., 2005). Researchers found that the risk factors of separation, such as intercaregiver conflict and decline in socioeconomic level, drive some of these effects (Nunes-Costa et al., 2009). Similarly, caregiver incarceration is tied to a wide range of negative child health outcomes, including increased risk for other ACEs (Turney, 2018; Wildeman et al., 2018). The U.S. Department of Justice reported 22% of state inmates and 16% of federal inmates have children ages four years and younger (Glaze & Maruschak, 2010). Separated caregivers may face parenting and childrearing challenges if the other caregiver is incarcerated. The negative impact may be especially pronounced in children experiencing these two ACEs. More than 40% of jailed mothers of minor children are single caregivers (Glaze & Maruschak, 2010), leaving the childrearing responsibilities to other family members, adults, or social services. Policies like PFL that support caregivers with young children can be especially relevant for improving child and caregiver health outcomes.

There are important data limitations to consider. NSCH did not include ACEs assessment prior to 2011, hindering our ability to add California and New Jersey (that had implemented PFL in 2004 and 2009, respectively) as intervention states in the analysis. NSCH does not contain data on place or type of employment (i.e., full-time vs. part-time vs. hourly) and whether a caregiver was employed or eligible for PFL. While individual-level PFL eligibility may confound associations, this study's adjusted models included state-level unemployment rates as covariates to partially account for the effects of employment status. Additionally, the number or percentage of people in each state that are eligible or have used PFL, as well as jobs that offer PFL is unknown. As of 2023, only 27% of private sector workers in the U.S. had access to PFL, and among the lowest wage workers, 95% had no access to PFL (U.S. Department of Labor, 2024). In some states like Rhode Island, federal, state and some municipal employees are not eligible to receive PFL benefits. This lack of knowledge prohibits understanding of the full scope of the issue and generalizations to other states. There are also methodological limitations worth noting. The study design cannot account for omitted variable bias for unmeasured characteristics that vary over time. As the current study utilized data from 2011–2019, it is possible that exposure change may be confounded by time-varying characteristics. Additionally, inferences from TWFE are vulnerable to biases when the number of time periods is limited or when the stringent parallel assumptions are violated. (T. D. Hill et al., 2020a, 2020b; Strumpf et al., 2017) Finally, BART computes inference using posterior credible intervals, as opposed to frequentist confidence intervals used by TWFE methods. (J. Hill et al., 2020a, 2020b) This study employed additional placebo checks to complement and increase the credibility of findings.

As more data on household challenge ACEs from additional intervention states become available, future studies can incorporate richer data to better estimate PFL impacts on ACEs. Additionally, examining variations in PFL implementation by length of time and benefits can contribute to a better understanding of the impacts of these policies on families.

Conclusions

ACEs may have tremendous negative effects on children's health. Policies such as PFL that support families shortly after childbirth may be particularly relevant in preventing or reducing children's experiences of household challenges. The results showed that implementation of state-PFL was consistently associated with reductions in two specific household challenge ACEs, caregiver separation and incarceration, as well as experience of any household challenge ACE. Given robust literature linking child health outcomes to household challenges, PFL may be an important policy for promoting caregiver well-being in the months surrounding childbirth, preventing ACEs, and improving children's health outcomes. Existing research on the effects of PFL largely used data from California (Lee et al., 2018). This study expanded the literature by investigating PFL effects in two more states that implemented PFL. As PFL continues to be enacted and implemented in more states and at the federal-level, researchers can build on existing evidence to estimate PFL effects on young children's health and well-being.

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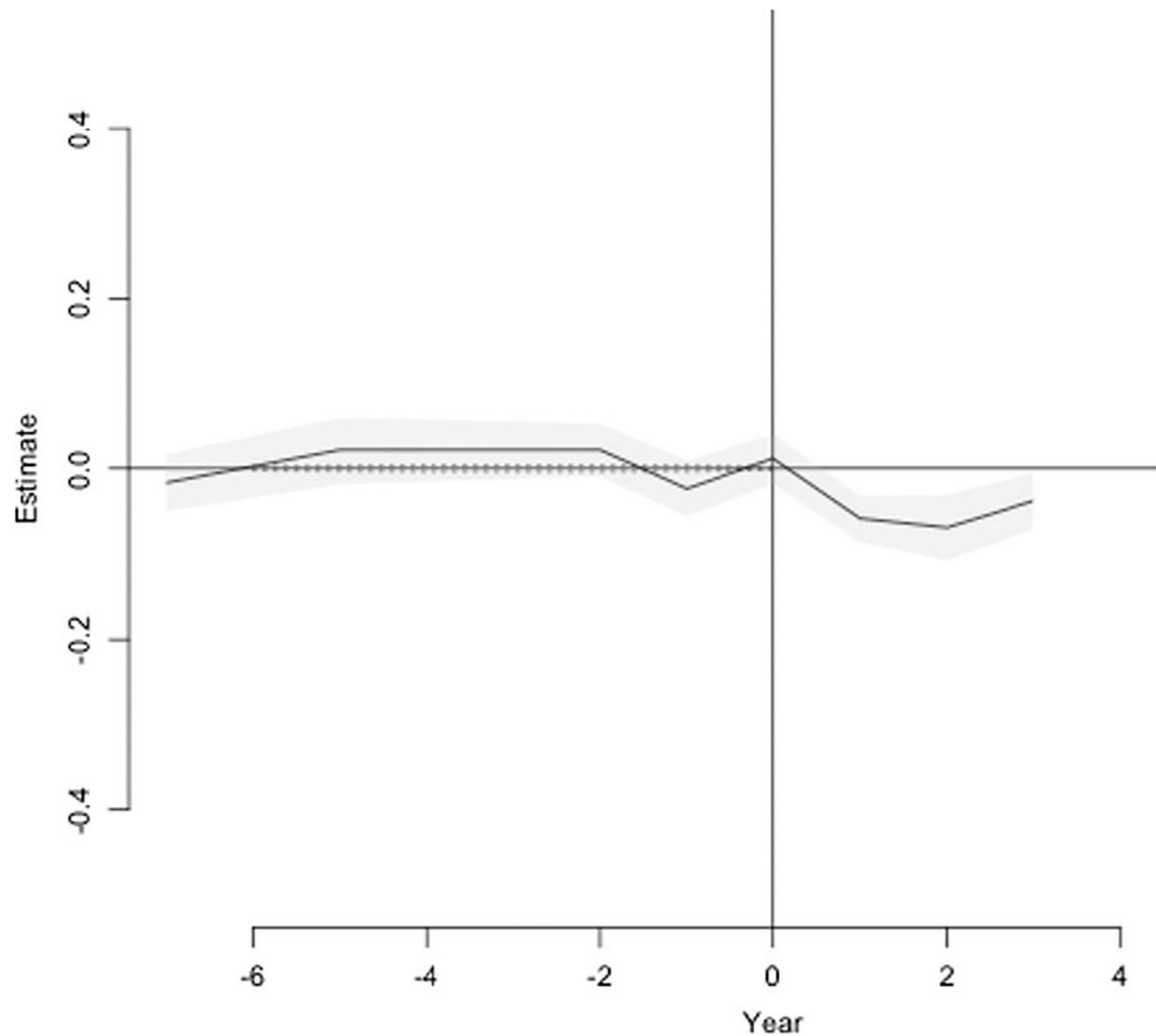


Fig. 1.

Visualization of estimated treatment effect of state paid family leave (PFL) implementation on caregiver-report of any household adverse childhood experience (ACE) from National Survey of Children's Health, 2011–2019 in NY and RI. The Y axis is the difference between the observed outcome in NY and RI and the expected outcome in those same states in absence of the intervention (based on the control states and the statistical model). The X axis is the time in years relative to the start of the intervention (with year 0 as the intervention start year), frequently termed “event time”. Note that the difference between the observed outcome and the outcome expected in absence of the intervention should be zero before the intervention starts and represents the estimated effect of the intervention afterwards. As expected, the figure shows near zero average total treatment effects estimates in the 6 years pre-intervention, suggesting adequate model fit. Figure shows decline in caregiver-report of any household challenge ACE estimate post-PFL implementation. Figure 1 shows the effects of PFL on Any Household challenge ACE outcome in the BART adjusted model. The figure suggests adequate model fit (i.e., near zero average total treatment effects (ATT) estimates that are not statistically significant in the pre-intervention period) and negatively trending ATT estimates post-intervention. Other outcomes and base model estimations followed

similar trends in model fit and direction of the treatment effect (data not shown). One notable exception was the BART estimation of mental health, where the model fit was compromised by the significant ATT estimates in the pre-intervention period (data not shown)

Table 1

Means and Standard Deviations for the Household Challenge ACEs Outcomes Included in BART and TWFE Analyses of State PFL by Intervention and Comparison States from the NSCH, 2011–2019

Outcome	Intervention States (<i>N</i> = 2)		Comparison States (<i>N</i> = 47)	
	Mean	SD	Mean	SD
<i>(Pre-Intervention—2011)</i>				
Any Household Challenge ACE	0.118	0.031	0.117	0.033
Caregiver Substance Use	0.030	0.008	0.041	0.020
Caregiver Mental Health	0.048	0.039	0.039	0.018
Domestic Violence	0.016	0.002	0.023	0.014
Caregiver Separation	0.052	0.017	0.053	0.022
Caregiver Incarceration	0.028	0.001	0.027	0.015
<i>(Post-Intervention—2019)</i>				
Any Household Challenge ACE	0.055	0.001	0.091	0.055
Caregiver Substance Use	0.007	0.010	0.029	0.032
Caregiver Mental Health	0.041	0.021	0.033	0.029
Domestic Violence	0.000	0.000	0.013	0.020
Separation from Caregiver	0.014	0.020	0.038	0.033
Caregiver Incarceration	0.000	0.000	0.018	0.023

Note: Mean value represents the average proportion of children experiencing any household challenge ACE among all children ages 0–2 years in a state for a group of states. Comparison states include 46 states and Washington, DC that had not implemented PFL before 2019. State-level covariates descriptive statistics: Unemployment rate (Mean = 4.82; SD = 2.02), median household income (Mean = 58,770, SD = 10,778), and percent uninsured (Mean = 11.03, SD = 4.79). 2019 Census data for percent uninsured population were not available at the time of analyses

Table 2

Average Treatment Effect (ATT) and Associated 95% Confidence Intervals (CI) from BART and TWFE Estimation of the Effect of State-PFL Policies on Household ACEs from the NSCH, 2011–2019

Outcome	BART		TWFE			
	Base		Adjusted		Adjusted	
	ATT	95% CI	ATT	95% CI	ATT	95% CI
Any Household ACE	-0.04[*]	-0.07 -0.01	-0.04[*]	-0.06 -0.01	-0.03	-0.07 0.01
Parental Substance Use	-0.01	-0.02 0.00 ^a	-0.01[*]	-0.03 -0.00 ^a	-0.01[*]	-0.02 -0.00 ^a
Parental Mental Health	-	- -	-	- -	-0.01	-0.04 0.02
Domestic Violence	-0.00^{*,a}	-0.02 0.01	-0.01	-0.02 0.00 ^a	-0.01[*]	-0.01 -0.00 ^a
Separation from Parent	-0.04[*]	-0.07 -0.02	-0.04[*]	-0.06 -0.02	-0.03[*]	-0.05 -0.02
Parental Incarceration	-0.02[*]	-0.04 -0.00 ^a	-0.02[*]	-0.04 -0.01	-0.02[*]	-0.02 -0.03

Note: ATT – average treatment effect. CI – confidence interval. BART – Bayesian additive regression trees. TWFE – Two-way fixed effects. Unemployment rate, percent uninsured, and median household income covariates were used as auxiliary covariates in the adjusted models. BART estimation results for caregiver Mental Health ACE are suppressed as unreliable. Statistically significant findings at $p < 0.05$ are in bold and indicated by *

^a Coefficients have been rounded to the nearest hundredth. -0.00 and 0.00 table values therefore are < 0 and > 0 , respectively. Data from N = 2 intervention states and N = 47 comparison states

Table 3

Results from Placebo Analyses of Statistically Significant Effects of State-PFL Policies on Household Challenge ACEs from the NSCH, 2011–2019

Outcome	BART		TWFE			
	Adjusted ATT	95% CI	Adjusted ATT	95% CI	Adjusted ATT	95% CI
Any Household Challenge ACE	0.01	–0.02	0.03	–	–	–
Caregiver Substance Use	0.00	–0.02	0.01	–	–	–
Separation from Caregiver	–0.01	–0.02	0.01	0.01	–0.05	0.07
Caregiver Incarceration	–0.01	–0.02	0.01	–0.02	–0.06	0.02

Note: ATT – average treatment effect. CI – confidence interval. Unemployment rate, percent uninsured, and median household income covariates were used as auxiliary covariates in the models. BART—Bayesian additive regression trees. TWFE—Two-way fixed effects. Statistically non-significant results suggest that significant effects of state-PFL are not due to preintervention characteristics