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The effect of California's paid family leave policy on parent health: A quasi-experimental study

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Abstract

The U.S. is the only high-income country without a national paid family leave (PFL) policy. While a handful of U.S. states have implemented PFL policies in recent years, there are few studies that examine the effects of these policies on health. In this study, we tested the hypothesis that California's PFL policy—implemented in 2004—improved parent health outcomes. Data were drawn from the 1993–2017 waves of the Panel Study of Income Dynamics, a large diverse national cohort study of U.S. families (N = 6,690). We used detailed longitudinal sociodemographic information about study participants and a quasi-experimental difference-in-differences analytic technique to examine the effects of California's PFL policy on families who were likely eligible for the paid leave, while accounting for underlying trends in these outcomes among states that did not implement PFL policies in this period. Outcomes included self-rated health, psychological distress, overweight and obesity, and alcohol use. We found improvements in self-rated health and psychological distress, as well as decreased likelihood of being overweight and reduced alcohol consumption. Improvements in health status and psychological distress were greater for mothers, and reductions in alcohol use were greater for fathers. Results were robust to alternative specifications. These findings suggest that California's PFL policy had positive impacts on several health outcomes, providing timely evidence to inform ongoing policy discussions at the federal and state levels. Future studies should examine the effects of more recently implemented state and

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local PFL policies to determine whether variation in policy implementation and generosity affects outcomes.

Keywords

paid family leave; natural experiment; policy evaluation; health behaviors; obesity; mental health

INTRODUCTION

The U.S. is the only high-income country without a national paid family leave (PFL) policy (1). The federal Family and Medical Leave Act (FMLA) of 1993 provides 12 weeks of unpaid leave, but nearly half of workers are ineligible, and many eligible workers cannot afford to take leave without pay (2). In 2004, California became the first U.S. state to implement a mandated PFL policy, followed by other states in more recent years (3). Given the increased discussion of implementing and expanding PFL policies among U.S. federal, state, and local governments, evidence is needed to inform policymakers and the general public about the effects of these policies on health outcomes.

Only a handful of studies have examined the health effects of state PFL policies and related policies on temporary disability insurance for new mothers. These have found increased breastfeeding after implementation of PFL policies (4,5), improved mental health among parents (6,7), and health improvements among infants and young children (8–10). Most existing studies use data sources with limited information on parental income and employment, which means that they are unable to precisely identify families who are likely to be eligible. While there is a larger literature examining the effects of PFL policies in other high-income countries (11–13), these may not generalize to the U.S. due to differences in the generosity of policies in other countries (which tend to offer full wage replacement and longer leaves), as well as the more robust social welfare systems and childcare options available.

PFL policies may influence health through several mechanisms (2). Because it provides salary support, paid leave increases family income relative to unpaid leave (11). The protected time allows more opportunities for bonding and a focus on the needs of the new family, which may reduce stress and improve mental health for parents. With reduced stress, parents may be less likely to engage in unhealthy behaviors like physical inactivity, unhealthy eating, and alcohol use, which are often considered coping mechanisms related to elevated psychological distress (14–16). Few of these outcomes have been examined in prior studies of U.S. PFL policies.

In this study, we used a large national dataset and a quasi-experimental difference-in-differences approach to examine the effects of California's PFL policy on parent health. We focus on California, where take-up of PFL has increased rapidly for parents of both genders. For example, in 2014, there were over 200,000 PFL claims requesting bonding leave in California, with roughly a third of these representing fathers (17). Using a longitudinal cohort of U.S. families, we are better able to identify likely eligible families compared with many prior studies that have limited or no information on parental employment during the prenatal period, and we also assess a more comprehensive set of parent health outcomes for both mothers and fathers. These findings provide timely evidence to inform ongoing policy discussions at the federal and state levels.

METHODS

Dataset

We analyzed data from the 1993–2017 waves of the Panel Study of Income Dynamics (PSID) (see sample flowchart, Figure 1). PSID is a longitudinal nationwide cohort study that has followed participants and their descendants since 1968. We used data starting in 1993, when a consistent variable for employment became available (N = 72,727). Data were collected yearly from 1993 to 1997 and biennially from 1999 to 2017. Even after 1999, survey questions were structured to collect annual data on income and employment. We restricted the sample to parents of children with a recorded state of birth, and we further restricted the sample to parents with children under two, as they would be most likely to experience the health effects of PFL policy. New Jersey and Rhode Island implemented PFL policies in 2009 and 2014, respectively. We excluded parents of children born in these states because the small number of observations led to unstable estimates. Other states have passed PFL policies more recently, but these occurred after the final year of our study period, so these states were included in the control group (Supplemental Figure 1).

We next excluded households in which neither parent was employed one year before the child's birth, as they were likely ineligible to benefit from the PFL policy (remaining N = 7,797). We also restricted the sample to individuals for whom at least one outcome of interest was available; in PSID, only the household heads and spouses are asked questions about their health. To reduce potential misclassification, we excluded parents if the child was born in California during the month that the PFL policy was enacted. We also excluded parents of multiple children under age two if one child was born under PFL policy and another was not.

The final sample was 6,690 parents.

Variables

Exposure—The primary exposure variable was whether the parent's child was born in California after July 2004, when the state implemented its PFL policy. California provides qualifying workers with up to 6 weeks of partially paid leave (55% of weekly earnings, up to a maximum of $1,173 weekly in 2017) (18). Coverage is near-universal among private sector workers. Self-employed and state and local workers need to opt in to receive coverage. California's PFL policy does not provide job protection, although many employees are covered by FMLA. The number of PFL claims paid each year has been increasing since the policy was first implemented even while birth rates have fallen (Supplemental Figure 2).

Outcomes—We examined several aspects of parent health. First, parents' self-rated health was dichotomized as very good or excellent versus good, fair, or poor (19). Self-rated health is a validated predictor of morbidity, mortality, and health behaviors (20–23). This question was asked of both the head of the household and the spouse. Parental mental health was assessed using the Kessler-6 (K6, range 0–24), a screening instrument for nonspecific psychological distress with higher scores indicating greater risk of mental illness (24). PSID ascertained the K6 score for either the head of household or the spouse (preferentially the head of household). We calculated parental body mass index (BMI) from self-reported height and weight. We analyzed BMI as binary variables for overweight (>25kg/m^2) and obese (>30kg/m^2) (see Supplemental Methods). We also examined whether participants drank any alcohol (binary) and whether they consumed three or more drinks daily (binary, zero for non-drinkers). PSID does not consistently capture a continuous measure of daily number of drinks.

Covariates—Covariates included parental gender, age, and educational attainment, household size, inflation-adjusted household income in the year before the child's birth, and the head of household's race. (PSID does not ask about race for all household members.) We also included fixed effects (i.e., indicator variables) for state of birth to account for unobserved time-invariant characteristics of states, and indicator variables for child's birth year to control for secular trends.

We also adjusted for a range of time-varying state-level covariates, including gross domestic product, unemployment rates, the percent of the adult population with less than a high school education, Aid to Families with Dependent Children / Temporary Assistant for Needy Families benefit size, Supplemental Nutritional Assistant Program benefit size, poverty rate, whether the governor was a Democrat, the state EITC rate, and the minimum wage. We selected these because they may confound the relationship between PFL policy and the outcomes of interest, and because they were available for all years of the study period. State-level variables were drawn from online government databases (25–27) and the University of Kentucky Center for Poverty Research (28).

Primary Analysis

We tallied sample characteristics separately for California and non-PFL states. We then used difference-in differences (DiD) analysis to assess the impact of the PFL policy on health outcomes. DiD is a quasi-experimental method that is ideally suited to estimating the effect of a policy while accounting for secular trends. To do so, DiD compares the average change in outcome before and after policy implementation in the "treated" group (i.e., California) while "differencing out" pre-post changes in the "control" group (i.e., non-PFL states) (29).

We modeled the effect of California's PFL policy using the following equation:

$$Y_{ijt} = \beta_0 + \beta_1\left(Policy_j \times Post_t\right) = \beta_2 Policy_j + \beta_3 Post_t + \beta_4 Cover_{ijt} + \beta_5 Year_t + \beta_6 State_j + \varepsilon_{ijt}$$

The analysis was conducted at the individual level, for individual i in state j and year t. Y_{ijt} represents an outcome of interest, $Policy_j$ indicates whether the child was born in California, and $Post_t$ indicates whether the child was born after California implemented its PFL policy in July 2004. $Covar_{ijt}$ represents the individual- and state-level time-varying (e.g., household size) and non-varying (e.g., gender) covariates described above. $Year_t$ represents indicator variables for birth year, and $State_j$ represents fixed effects for state of birth. ε_{ijt} is the random error term, clustered at the state level to account for correlated observations within families and within states (see Supplement for additional sensitivity analysis to account for the presence of only a single treated cluster). We did not include individual-level fixed effects, since fewer than 1,000 parents were observed more than once in our analytic sample, with very little "within person" variation among those with more than child (i.e., exposed to PFL policy for one child and not exposed for another child). The coefficient of interest, β_1, represents the change in the outcome attributable to California's enactment of the PFL policy.

We used linear regression models for both continuous and binary outcomes. Linear models are preferred in DiD analyses due to differences in the interpretation of interaction terms in nonlinear models (30,31). For binary outcomes, which are estimated as a linear probability model, the DiD effect is therefore interpreted as the percentage-point change in risk. We did not include survey weights since the appropriateness of weights is diminished when adjusting for variables related to the sampling strategy and when the goal of modeling is causal inference rather than descriptive population characteristics (32).

Gender-Stratified Analysis

Since prior work and theory suggest that mothers and fathers may benefit differently from PFL policies, we stratified the DiD analysis by parent's gender. We also ran interaction models to assess whether there was a statistically significant difference between the estimates from these stratified models.

DiD Assumptions

A key assumption of DiD analyses is parallel trends in the outcomes between the treated and control groups in the period prior to policy implementation. To test this assumption, we restricted the sample to the pre-policy period and modeled the primary predictors as a continuous variable for year, an indicator for California versus non-PFL states, and the interaction term between them (33). We then regressed each outcome on these three terms in addition to the covariates from our primary analyses. A statistically significant interaction term would indicate differential trends in the outcomes during the pre-policy period. We also graphed trends in outcomes to examine any potential differences qualitatively.

Another assumption of DiD analyses is that no time-varying omitted variables, such as events co-occurring with the policy, confound the relationship between the exposure and outcome. While this assumption is not empirically testable, we examined whether there were differential compositional changes over time in the treatment and control groups by carrying out our primary analysis with the inclusion of each covariate (e.g., parent age) as the dependent variable (34). We also conducted placebo analyses in which we arbitrarily set the date of California policy passage to 2001 and 2007 (three years before and after the actual policy passage). We would expect the results of these analyses to be null, unless there were other secular changes happening around the time of PFL policy implementation.

Finally, we tested whether our results were sensitive to group-specific (i.e., California versus non-PFL states) and state-specific linear time trends by including an interaction term between $Policy_j$ and $Year_t$ and between $State_j$ and $Year_t$, respectively (33). These specifications allow outcomes to change differentially over time by group or by state, representing a relaxation of the parallel trends assumption.

Missing Values

The percent of missing values ranged from <1% for gender and age to 25% for employment. As a secondary analysis, we therefore performed multiple imputation using chained equations to impute missing values of covariates, which can reduce bias and increase precision (35–37). For each person-year observation, we used covariates and outcomes from that year, as well as the previous three years of household income and employment, to predict missing values. This form of imputation does not require normality assumptions, thereby allowing us to specify a model for a variety of variable types. It assumes that data were missing “at random” (as opposed to missing “completely at random”) (38). We included all variables including outcome variables in imputation models to improve the prediction. However, we did not impute missing outcomes, as this may introduce noise to resulting estimates (40). We conducted 25 iterations of multiple imputation, which is sufficient to reduce sampling variability from the imputation process (41).

RESULTS

Sample sociodemographic characteristics were generally similar across California and non-PFL states (Table 1), although California had fewer white and black individuals and more Hispanic individuals and individuals of other races compared with non-PFL states, as well as higher mean household income. Importantly, DiD requires that outcome trends (not levels) are similar between treatment and control groups during the pre-policy period.

Primary Analyses

We next examined the effect of California’s PFL policy on parents’ health (Table 2). We found increased likelihood of being in very good or excellent self-rated health (11.0 percentage points, 95%CI: 5.2, 17.0), reductions in psychological distress (−0.79, 95%CI: −1.26, −0.32), and decreased overweight (−8.2 percentage points, 95%CI: −15.0, −1.6), any alcohol consumption (−12.0 percentage points, 95%CI: −1.6, −7.1), and daily consumption of three or more drinks (−5.7 percentage points, 95%CI: −9.5, −1.9). We did not find changes in obesity risk.

Gender-Stratified Analyses

We examined whether the effects of PFL implementation differed for mothers versus fathers (Table 2). PFL implementation improved health status more for mothers than fathers ($p = 0.04$ from interaction test for difference by gender). It also reduced maternal psychological distress with no statistically significant change in paternal psychological distress ($p < 0.01$ from interaction test). Fathers had greater reductions in the probability of being obese ($p = 0.04$) and any alcohol consumption ($p < 0.01$) compared with mothers. Effects on being overweight were similar for men and women.

Testing DiD Assumptions

Trends in outcomes between the treatment and control groups were similar during the pre-policy period (Supplemental Table 2, Supplemental Figure 3). When testing whether there were differences in the composition of the sample in California versus other states before and after policy implementation, we found no substantial differential changes in composition for 11 of the 13 demographic characteristics (Supplemental Table 2). The exceptions were age and other race.

We next conducted placebo tests in which we arbitrarily set the date of California policy passage to 2001 and 2007 (Supplemental Table 3). For 2001, the results of each analysis were null, except for psychological distress, which demonstrated a reduction similar to that of the main analysis. For 2007, the results of each analysis were null, except for increased psychological distress (opposite to our primary findings) and increased daily consumption of three or more drinks (also opposite to our primary findings).

We then conducted analyses that included group- and state-specific linear time trends (Table 3). Point estimates and confidence intervals were similar to our main analysis for health status, psychological distress, and daily consumption of three or more drinks, while confidence intervals for overweight, obese, and any alcohol consumption now included the null.

Multiple Imputation

Results from the analysis using multiple imputation to account for missingness demonstrated similar results to the main analysis (Supplemental Table 4), with reduced likelihood of overweight and reduced alcohol consumption. While the direction of point estimates in the imputed analysis suggested improved overall health and reduced psychological distress, as in the main analysis, confidence intervals now included the null, perhaps due to the imprecision introduced by the imputation process.

DISCUSSION

This study used a quasi-experimental approach to examine the effects of California's PFL policy on a robust set of parent health outcomes. We found clinically relevant and policy-relevant improvements in several outcomes, including self-rated health, psychological distress, overweight, and alcohol consumption. Most of these results were robust to several alternative specifications.

Our study is consistent with prior work that longer leave is associated with improved maternal health (42–46), as well as two prior quasi-experimental studies of state PFL policies (6,7). Improved parental mental health may result from decreased stress, increased income, and more time to bond with the new child (2). Maternal mental health was also found to improve after a Swedish policy increased new fathers' access to paid leave (47), suggesting that PFL policies may also support healthier family dynamics. Mental health disorders are common among parents after a birth and are associated with decreased quality of parenting practices and poor physical and mental health outcomes in children (48–55), and future studies could examine additional downstream effects of PFL policies on these outcomes.

In stratified analyses, we found that reductions in psychological distress were greater for mothers. It may be that fathers' mental health is less likely to benefit from paid leave because women are more likely to take the leave or due to gender differences in expectations for men at work and at home (56,57). Of note, PSID preferentially elicits K6 scores from household heads, and the survey also preferentially designates men as household heads. Therefore, the sample of women who reported a K6 score was smaller than the sample of men and may over-represent female single-headed households. This means that results of this analysis may not generalize to households where the mother is not the head, although our finding is consistent with other studies using representative samples that have found improved maternal mental health after implementation of PFL policies (6,7). Also, although this outcome did meet the assumption of parallel trends during the pre-policy period, the results from placebo tests for psychological distress were contradictory, suggesting both underlying improvements in secular trends in California during the pre-period and worsening during the post-period (which includes the Great Recession); thus, results for this outcome should be interpreted with caution.

By reducing stress, paid leave may improve health behaviors among new parents. Our study is among the first to examine the effects of California's PFL policy on alcohol use, finding reduced alcohol consumption. In stratified analyses there was no effect of PFL on women's alcohol consumption, but a large effect for fathers. This is perhaps because mothers during the prenatal and postpartum periods are already unlikely to consume alcohol, making this a rare outcome for women (58). Moreover, PFL increases family resources relative to unpaid leave, which would positively affect all household members. Prior research also suggests that women are more likely to manifest stress through internalizing symptoms such as depression (59), which are likely captured in self-reported health and psychologic distress. Meanwhile men are more likely to express distress through externalizing symptoms such as heavy drinking. Correlational studies using Swedish data also found that parental leave was associated with reduced alcohol-related deaths among fathers of infants (60). Parental substance use may harm child health through its association with poorer family functioning, less intellectual stimulation, and increased interpersonal violence, as well as poor motor development in babies if maternal drinking happens during breastfeeding (61,62).

We also found that California's PFL policy reduced rates of overweight and obesity. PFL policies may affect parental weight by providing working parents with more time for exercise and with increased income to promote better nutrition (63). For mothers, PFL policies have been found to increase breastfeeding (4,5), which has been associated with postpartum weight loss (64). Our study is consistent with a prior study in Norway that found that paid maternal leave policy was associated with reduced BMI (12). Gestational weight gain and postpartum weight retention may predict mothers' later risk of obesity and diabetes (65–67), and maternal obesity and excessive gestational weight gain are associated with long-term health issues in children, including obesity, cardiovascular disease, and premature death (66–72). Future studies can examine whether PFL policies have effects on these downstream outcomes.

This study has several strengths. Our use of longitudinal PSID data allowed us to more precisely identify parents likely to be eligible for PFL based on employment at the time of birth, and to adjust for confounders like pre-birth income more robustly than prior studies of state PFL policies that relied on cross-sectional data from the postpartum period. For example, prior studies could not identify parents' employment status at the time of the child's birth due to a lack of information on prenatal demographic characteristics (6,7). Also, we examined a range of outcomes to more comprehensively assess the health effects of PFL policies on affected families.

This study also has several limitations. PSID does not ask whether parents took paid leave, so our analysis likely suffers from some degree of misclassification, which may bias results towards the null. In other words, while we are able to exclude those who were not employed during the prenatal period based on PSID's longitudinal structure, we do not know whether employees were eligible (e.g., based on California's eligibility criteria related to State Disability Insurance deductions (73)) or whether they actually took advantage of the leave. Our analysis thus represents the effects of PFL policy at the population level, and would therefore underestimate the policy's effects on those who actually took advantage of the leave. Also, outcomes and covariates are self-reported, which may result in bias if these are associated with PFL policy exposure. Future studies could attempt to link administrative sources of health, income, and leave-taking. In addition, our analysis only evaluated California's PFL policy. Future studies should examine more recently implemented policies in other states once data become available, in particular comparing those with different levels of generosity. Also, due to the size of our sample, we were unable to examine effect heterogeneity based on parent characteristics like income or race. Prior studies suggest that some workers are unable to take advantage of PFL because the wage replacement is too low (55% of weekly earnings in California) or they fear negative consequences at work (74), with other studies finding different benefits of PFL policies based on families' socioeconomic status (5,6,8). Future studies should continue to examine effect heterogeneity, to assess whether PFL policies should be better designed with health equity in mind. Also, DiD methods assume that there are no other changes in California occurring at the same time as the policy which might explain the observed results. While we can never fully rule out this possibility, we conducted analyses to test this assumption. For example, we include a robust set of state-level time-varying covariates that may be associated with PFL implementation and the outcomes of interest, and we also found that there were no major differential compositional changes in California versus other states for the majority of observed demographic characteristics. However, we did find compositional differences for age and other race among parents, and it may be possible that other unobserved characteristics might explain the observed results. Finally, while PSID is a cohort study following the same individuals over time, we were unable to fully leverage this survey design to conduct an individual-level fixed effects analysis. Fewer than 1,000 parents were observed more than once in our analytic sample, with very little "within person" variation among those with more than one child (i.e., exposed to PFL policy for one child and not exposed for another child). This panel design may be possible in data sets with larger samples.

CONCLUSION

In summary, this study provides some of the first estimates of the effects of California's PFL policy on parent health, using longitudinal national data and a quasi-experimental study design. We find improvements across a number of health outcomes, suggesting that PFL policies have the potential to support the health of families with newborn children. Future studies should examine the effects of more recently implemented PFL policies to determine whether variation in policy implementation and generosity affects outcomes.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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RESEARCH HIGHLIGHTS

- We test whether a U.S. paid family leave policy affected parent health.
- California's policy improved the self-rated health of parents with young children.
- The policy reduced psychological distress for mothers and alcohol use for fathers.
- Paid leave is an important intervention to support families with young children.

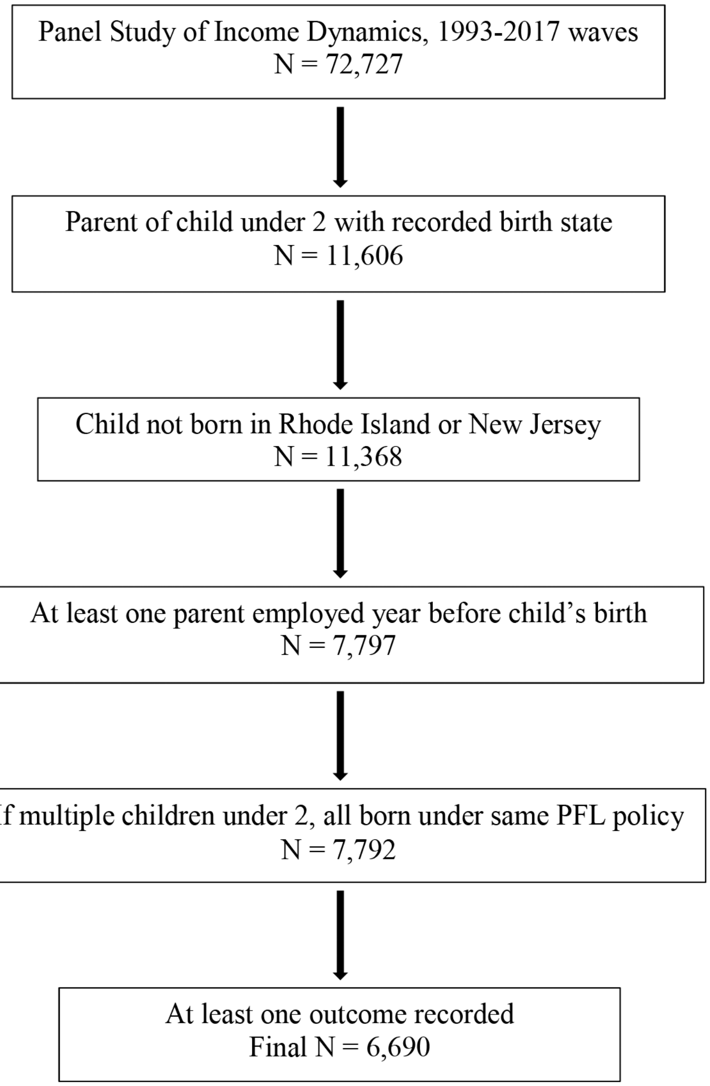

Figure 1.
Sample selection

Table 1.

Sample characteristics

Variables	California Mean (SD) or %	All other states Mean (SD) or %	Overall Mean (SD) or %
Predictors			
Female (%)	52.0	53.1	53.0
Age (years)	29.8 (7.6)	29.1 (7.4)	29.2 (7.4)
Married (%)	66.9	67.6	67.5
Education (%)			
Less than high school	19.5	10.0	10.9
High school	30.1	35.9	35.4
Some college	25.9	29.2	28.9
College graduate	24.5	24.9	24.9
Head of household race (%)			
White	33.5	60.0	57.5
Black	17.5	31.2	29.9
Hispanic	42.6	6.6	10.0
Other	6.3	2.2	2.6
Household income	73,164 (66,745)	67,341 (64,079)	67,884 (64,348)
Children in household	1.8 (1.1)	1.8 (1.1)	1.8 (1.1)
Child born in CA after policy (%)	53.9	–	5.1
Outcomes			
Excellent/very good self-rated health (%)	65.6	68.9	68.6
Psychological distress, 0–24 scale	2.5 (3)	3.6 (3.7)	3.5 (3.7)
Overweight (%)	57.4	57.7	57.7
Obese (%)	21.8	23.3	23.1
Drinks alcohol (%)	53.8	62.3	61.5
3+ alcoholic drinks per day (%)	11.0	16.7	16.1
Number of participants	631	6,059	6,690

Sample was drawn from the 1993–2017 waves of the Panel Study of Income Dynamics. Although Rhode Island and New Jersey passed paid family leave policies during the study period, parents of children born in these states were excluded due to the small number of observations and subsequent unstable estimates.

Table 2.

Effect of paid family leave policy on parent health

	β [95% CI] No. person-years		
	Overall	***Mothers***	***Fathers***
Self-rated health	0.11 **	0.14 **	0.081 *†
	[0.052, 0.17]	[0.077, 0.20]	[0.0044, 0.16]
	7,626	5,057	4,490
Psychological distress	−0.79 **	−6.23 **	0.36 †
	[−1.26, −0.32]	[−8.54, −3.92]	[−0.14, 0.87]
	3,159	512	2,673
Overweight	−0.082 *	−0.096 *	−0.044
	[−0.15, −0.016]	[−0.19, −0.0027]	[−0.10, 0.017]
	6,766	3,605	3,275
Obese	−0.026	−0.025	−0.078 †
	[−0.082, 0.030]	[−0.037, 0.087]	[−0.16, 0.00092]
	6,766	3,605	3,275
Drinks alcohol	−0.12 **	−0.017	−0.23 **†
	[−0.16, −0.071]	[−0.069, 0.035]	[−0.29, −0.17]
	6,891	3,705	3,303
3+ drinks daily	−0.057 **	0.015	−0.15 **†
	[−0.095, −0.019]	[−0.027, 0.057]	[−0.19, −0.10]
	6,787	3,627	3,271

*** $p < 0.001$,

** $p < 0.01$,

* $p < 0.05$

† Estimate for fathers was statistically significantly different from the estimate for mothers at p < 0.05 in interaction models.

Sample was drawn from the 1993–2017 waves of the Panel Study of Income Dynamics. Analyses involved multivariable linear regressions adjusting for parental gender, age, and educational attainment, household size, inflation-adjusted household income in the year before the child's birth, the head of household's race, and several time-varying state characteristics. We also included fixed effects (i.e., indicator variables) for state and year of birth. Robust standard errors were clustered by state of birth.

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Table 3.

Effect of paid family leave policy on parent health, sensitivity analyses

	β [95% CI] No. person-years	
	With group-specific trends	*With state-specific trends*
Self-rated health	0.10**	0.10**
	[0.042, 0.16]	[0.037, 0.17]
	9,547	9,547
Psychological distress	−0.59**	−0.47**
	[−1.10, −0.078]	[−1.00, −0.057]
	3,185	3,185
Overweight	−0.048	−0.049
	[−0.11, 0.015]	[−0.11, 0.013]
	6,880	6,880
Obese	−0.030	0.036
	[−0.026, 0.087]	[−0.022, 0.094]
	6,880	6,880
Drinks alcohol	−0.046	−0.043
	[−0.097, 0.0051]	[−0.097, 0.0051]
	7,008	7,008
3+ drinks daily	−0.045*	−0.042
	[−0.087, −0.0036]	[−0.089, 0.0053]
	6,898	6,898

** $p < 0.01$,

* $p < 0.05$

Sample was drawn from the 1993–2017 waves of the Panel Study of Income Dynamics. Analyses involved multivariable linear regressions adjusting for parental gender, age, and educational attainment, household size, inflation-adjusted household income in the year before the child's birth, the head of household's race, and several time-varying state characteristics. We also included fixed effects (i.e., indicator variables) for state and year of birth. Robust standard errors were clustered by state of birth.