SUPPLEMENTARY MATERIAL

Effects of U.S. state paid family leave policies on perinatal and postpartum health: A quasi-experimental analysis

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Appendix S1. Supplemental Methods and Results

Study sample

PRAMS is designed to recruit a representative sample of all people with a live birth during that year, with a sample of roughly 1,000-3,000 participants per site. The sampling frame uses birth certificate records to recruit eligible participants, defined as resident individuals who gave birth in their state during the surveillance year. Most US states participate in PRAMS, though data is released only for sites that meet a minimum response rate of 50-70% each year.[1] New York City and New York state participate separately in PRAMS; we combined their observations as "New York."

Income

PRAMS captures household income the year prior to delivery in brackets as a categorical variable. We harmonized data across slightly different bracket options by state by using the maximum value in each income bracket. We then created a dichotomous variable for income greater than $50,000.

Outcomes

The two Patient Health Questionnaire questions used to capture postpartum depressive symptoms were: "Since your new baby was born, how often have you felt down, depressed or hopeless?" and "Since your new baby was born, how often have you had little interest or little pleasure in doing things?"

Maternal postpartum depressive symptoms were captured on a five-point scale; "always, often, sometimes, rarely, or never. Based on prior literature, we used a scoring system where a response of "always" or "often" to either question was classified as at-risk for postpartum depression.[2]

Postpartum check-up attendance was captured via the following question: "Since your new baby was born, have you had a postpartum checkup for yourself? A postpartum checkup is the regular checkup a woman has about 4-6 weeks after she gives birth."

Statistical analysis

Primary analysis

The Callaway-Sant'Anna (CS) difference-in-differences estimator separately estimates the treatment effect for each policy implementation date that are then aggregated into a single effect estimate. It allows doubly robust estimation with inverse probability weighting. In our main analysis, we used the default "never treated" specification (where states without PFL policies as of the study period end are used as controls) rather than the "not yet treated" specification (where PFL states prior to policy activation are included in controls). For event study specifications, we included six lead periods and used "long differences" where all coefficients are compared to the period prior to treatment as is common in conventional event-study plots.[3] In order to incorporate state fixed effects, we followed a standard approach that demeans the outcome variable by state fixed effects, and then uses the residuals from that regression as the outcome in the CS difference-in-differences estimation.[4]

Model assumptions

We graphically assessed potential violations of the parallel trends assumption using Callaway-Sant'Anna event study plots, showing the average treatment effect of the treated (ATT) in each period relative to treatment. All outcomes showed roughly parallel trends between the exposed and unexposed groups during the pre-period; the overall trends appeared flat (Figure 1, Appendix Figure S4). However, we note some deviations from zero for the postpartum check-up attendance outcome during the pre-period so caution should be used interpreting estimates from this outcome.

We tested the assumption of no differential compositional changes between people exposed and not exposed to PFL by running a regression with each covariate as the dependent variable with an indicator for being born in a PFL state after policy adoption as the exposure. Only two covariates (respondent's age 25-34 years old and marital status) showed potential differential compositional changes; however, the magnitudes of the coefficients were extremely small (Appendix Table S2). Therefore, there appear to be no concerning differential changes in the distribution of our covariates between those exposed and not exposed to PFL. We cannot rule out potential differences in unmeasured covariates but controlled for all the listed measured covariates in our analysis.

Secondary analyses

Generalized DiD

To compare estimates from the more recently developed Callaway-Sant'Anna estimator to the traditional approach, we carried out a generalized DiD approach with two-way fixed effects adjusted for the same set of covariates including fixed effects for state and year, with standard errors clustered by state. Recent research has highlighted some scenarios (i.e. staggered adoption with constant and homogenous treatment effects) where generalized DiD may show minimal bias and greater efficiency than more recent estimators;[5] it is valuable to compare both estimates when there is uncertainty regarding constant vs dynamic and/or heterogeneous treatment effects.

We modeled the effect of the policies in states with PFL policies with the following equation. Data are repeated cross-sectional, and subscripts denote individuals i clustered within state s in year t.

$$\boldsymbol{\Upsilon_{ist} = \beta_0 + \beta_1 Policy_{ist} + \beta_2 C_{ist} + \beta_3 X_{st} + \theta_t + \alpha_s + \mathcal{E}_{ist}}$$

where $Policy_{ist}$ indicates whether the child was born in a state with an active PFL policy at the time of their birth, and β_1 is the coefficient of interest, representing the average change in outcomes attributable to the PFL policies. C_{ist} represents individual-level covariates (e.g., maternal age) and X_{st} represents state-level time-varying covariates (e.g., state GDP per capita), described above. θ_t represents fixed effects (i.e. indicator variables) for child's birth year to account for secular trends and α_s represents fixed effects for state to account for time-invariant state factors. $\mathcal{E}_{ist}$ represents the random error term, clustered by state.

Results based on generalized DiD results were consistent in direction to the main analysis, although exact estimates and 95% CI varied (Appendix Figure S10).

Multiple imputation

Missingness for all covariates was less than 5%, except for household income which had 9% missingness. Imputation can be used in the presence of missing data to minimize bias and appropriately estimate precision. As a secondary analysis, we performed multiple imputation using chained equations (MICE) to impute missing covariate values using the *mi* package in Stata.[6] Because this package does not currently support the CS estimator, we performed this sensitivity analysis on the generalized DiD specification. We assumed that data were missing "at random" (conditional on observed covariates).[7] We conducted 20 iterations, and included all covariates and exclusion criteria as well as state and infant's year of birth in the imputation models. One covariate (marital status) failed to converge in the imputation model and was therefore not imputed; it had extremely low missingness (0.1%). We did not include imputed values for outcome variables, as this can introduce noise into subsequent estimates.[8] Imputation was performed only for the generalized DiD analysis given that the imputation package is not compatible with the package for the Callaway-Sant'Anna estimator.

Effect estimates using multiple imputation were very similar to the results using complete case analysis (Appendix Figure S11; all effect estimates were similar in magnitude and direction. Overall, this suggests that the use of complete case analysis

in our main analysis is unlikely to result in substantial bias compared to multiple imputation.

Additional robustness checks

We also performed analyses excluding Hawaii from our control states; while Hawaii does not provide PFL, it does provide Temporary Disability Insurance, which may impact its ability to serve as an appropriate control. Results were consistent with main analysis direction and significance (Appendix Figure S9).

As a robustness check to account for possible confounding by other state-level factors, we compared results to a model that adjusted for state-level time-varying covariates that could potentially influence both PFL policies and outcomes. These measures, drawn from the University of Kentucky Center for Poverty Research,[9] included the state's unemployment rate and combined monthly maximum benefit size for Temporary Assistance for Needy Families and Supplemental Nutrition Assistance Program for a 3-person family. These state-level time-varying covariates were excluded from main analysis given their potential to be influenced by the exposure itself. Recent developments in heterogeneity-robust DiD estimators have urged caution in controlling for time-varying post-treatment covariates that could theoretically be affected by the exposure, which would serve as both confounder and mediator.[5,10] We have also found that model convergence can be more difficult to attain when adjusting for more covariates. Results adjusting for state-level covariates were consistent with the main analysis in direction and significance (Appendix Figure S12).

We performed analyses including “not yet treated” states in our control set in addition to the “never treated” states, to evaluate robustness of results to this specification. Results were consistent with the main analysis in direction and significance (Appendix Figure S13).

We performed a robustness check including people in the lowest income category, given this category also includes individuals with non-zero income who may be eligible for PFL. Results were consistent with main analysis in direction and significance (Appendix Figure S14).

We performed a robustness check restricting to earlier adopting states (New Jersey, Rhode Island, and New York), given effect estimates are likely more substantially driven by states contributing more exposed time to the analysis. Results were consistent with the main analysis in direction except for postpartum check-up attendance which now showed a decrease. This suggests our overall results are largely, but not entirely, driven by differences in earlier adopting states (Appendix Figure S15).

To assess potential for bias due to survey non-response, we investigated whether response rates varied according to PFL policy availability using PRAMS response rates by state by year. PRAMS has published response rate data for 2012-2021.[11] We conducted an unadjusted CS DiD analysis with response rates as the outcome variable

and did not find evidence that response rates differed by PFL status (-1.3; 95% CI: -5.89 to 3.23).

We also investigated whether average time between birth and PRAMS survey varied according to PFL policy availability to assess whether this could lead to bias in the results for breastfeeding duration and postpartum check-up attendance. We conducted an unadjusted CS DiD analysis with time-to-survey as the outcome and observed a small difference in time between birth and survey by PFL status (0.12 months; 0.01 to 0.23). Therefore, as a robustness check for whether our findings on breastfeeding duration could be influenced by survey timing (since breastfeeding in particular may have continued long after the survey was administered), we generated an alternative specification of duration, defined as whether the infant was breastfed for at least 8 weeks. Given PRAMS samples people 2-6 months after giving birth, a minimum of 8 weeks will have elapsed for all participants, and therefore this measure will not be influenced by survey timing.[1] Similar to our main analysis, we found that PFL led to an increase in parents breastfeeding for at least 8 weeks (2.51pp; 0.08 to 4.94).

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Supplemental Tables and Figures

Appendix Table S1. State paid family leave policy details for states included in PRAMS with paid family leave polices active as of end 2021[12]

State	Active	Duration	Maximum Weekly Benefit
New Jersey	July 2009	6 weeks	$667[13]
Rhode Island	Jan 2014	4 weeks	$795[14]
New York	Jan 2018	12 weeks	$972[15]
Washington	Jan 2020	12 weeks	$1,206[16]
DC	July 2020	8 weeks	$1,000[17]
Massachusetts	Jan 2021	12 weeks	$850[18]

Note: Several states have updated policy details over time; data listed reflects policy details as of end of 2021. Abbreviations: Pregnancy Risk Assessment Monitoring System (PRAMS).

Appendix Table S2. Test of differential compositional changes

Variable	Coefficient	95% CI	p-value
Respondent's age (years)			
<25	0.01	(-0.00, 0.02)	0.09
25-34	-0.02	(-0.04, -0.00)	0.02
35+	0.01	(-0.00, 0.03)	0.15
Respondent's education			
Less than high school	-0.00	(-0.01, 0.01)	0.81
High school	0.01	(-0.01, 0.03)	0.42
Some college	-0.02	(-0.05, 0.01)	0.14
College +	0.01	(-0.01, 0.04)	0.17
Respondent's race/ethnicity/ethnicity			
White	0.01	(-0.02, 0.04)	0.51
Black	-0.01	(-0.02, 0.01)	0.41
Hispanic/Latina	0.00	(-0.02, 0.02)	0.99
Other	-0.01	(-0.03, 0.01)	0.60
Married (%)	0.03	(0.01, 0.05)	0.01
Prenatal household income >$50,000 (%)	-0.01	(-0.03, 0.01)	0.41
Family size			
1	0.00	(-0.00, 0.01)	0.52
2	0.01	(-0.00, 0.01)	0.08
3	-0.00	(-0.01, 0.01)	0.61
4+	-0.01	(-0.02, 0.00)	0.10
Unemployment rate	0.49	(-0.35, 1.32)	0.25
TANF/SNAP benefit size	0.04	(-25.72, 25.80)	1.00

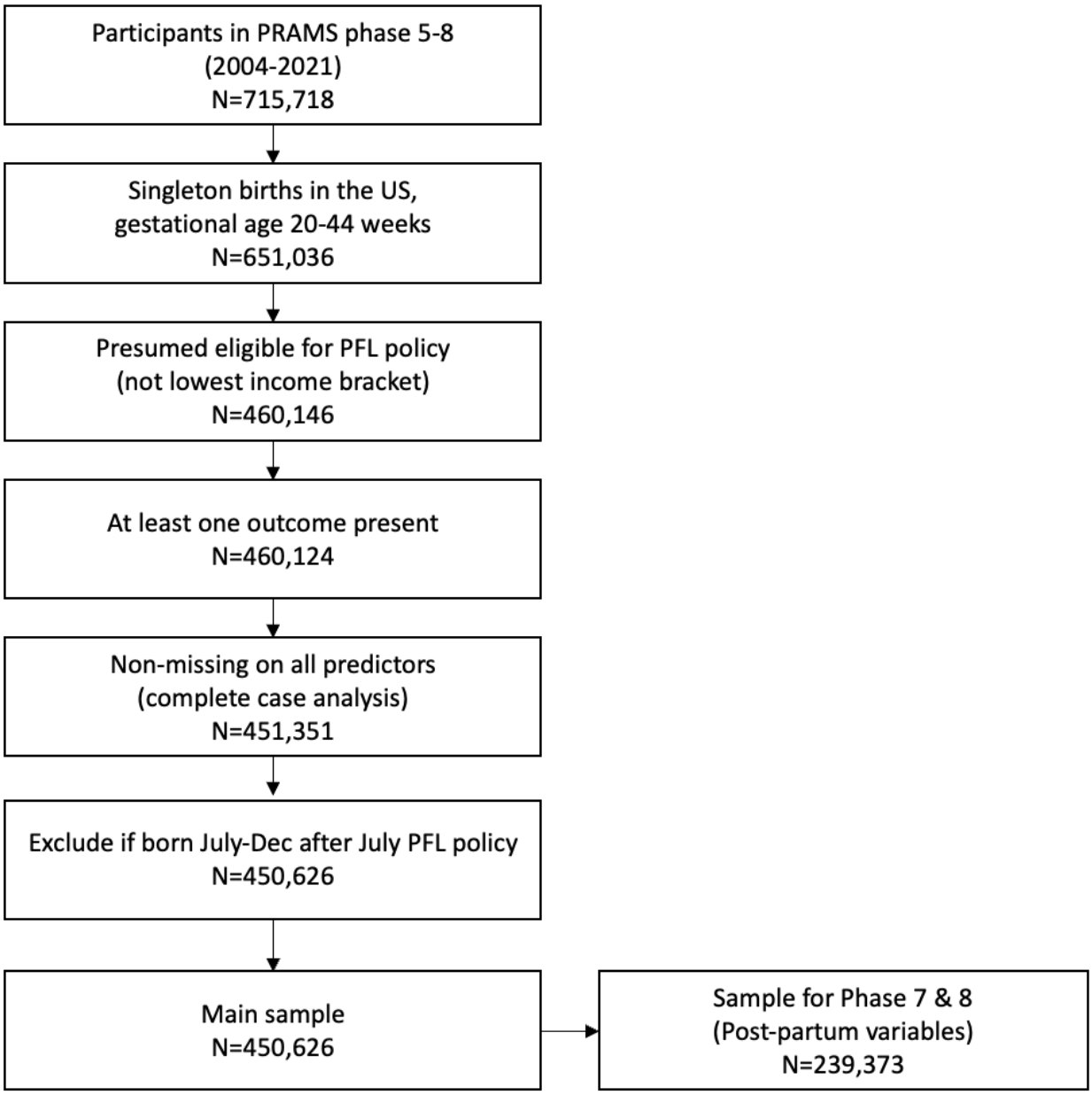
[a]During the year before delivery

Notes: Data drawn from the Pregnancy Risk Assessment Monitoring System years 2004-2021. N=450,626. All models are adjusted for fixed effects for infant's year of birth and state and include robust standard errors clustered by state. The models assess whether there are differential compositional changes in the covariates in treatment and control groups by setting each covariate as the dependent variable and regressing it on exposure to paid family leave. A coefficient with a 95% CI that crosses zero would indicate no differential compositional changes in the treatment and control groups for a given covariate.

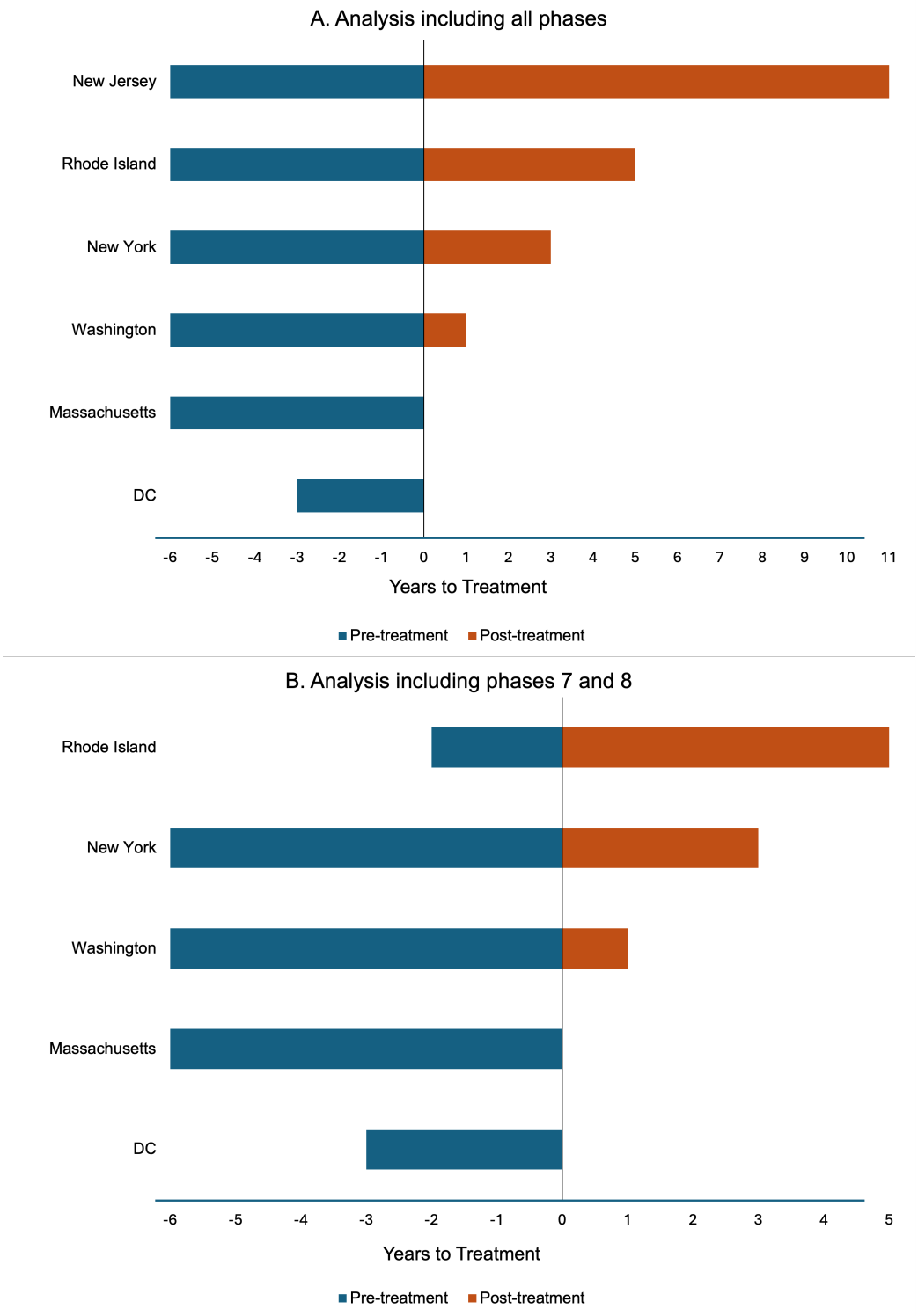
Appendix Table S3. State-specific estimates for effect of paid family leave on perinatal and postpartum health

	New Jersey	Rhode Island	New York	Washington	District of Columbia & Massachusetts
	Coefficient (95% CI)				
Main outcomes					
Weeks breastfed	0.94*** (0.68, 1.20)	0.67*** (0.40, 0.95)	0.50** (0.16, 0.83)	0.12 (-0.19, 0.43)	-1.69** (-2.67, -0.70)
Ever breastfed (pp)	5.53*** (4.54, 6.52)	0.50 (-0.34, 1.34)	-0.01 (-0.87, 0.86)	0.15 (-0.54, 0.84)	-0.21 (-1.11, 0.69)
Postpartum check-up (pp)	N/A[a]	-0.56** (-0.99, -0.14)	-0.35 (-0.90, 0.20)	1.87*** (1.4, 2.33)	0.56 (-0.15, 1.28)
Postpartum depressive symptoms (pp)	N/A[a]	0.03 (-0.61, 0.67)	-1.62*** (-2.28, -0.97)	-1.46** (-2.3, -0.62)	0.10 (-0.95, 1.15)
Secondary outcomes					
Preterm birth (pp)	1.89** (0.62, 3.16)	2.74** (0.8, 4.68)	1.21 (-0.79, 3.21)	-0.21 (-1.50, 1.09)	1.08 (-1.13, 3.29)
Low birthweight (pp)	3.87** (1.56, 6.17)	7.65*** (4.82, 10.47)	1.75 (-0.3, 3.8)	0.38 (-1.55, 2.32)	1.09 (-2.07, 4.24)
Very low birthweight (pp)	0.86 (-0.01, 1.72)	1.78*** (0.85, 2.72)	-0.72 (-1.51, 0.07)	0.23 (-0.60, 1.06)	1.17 (-0.38, 2.72)
Small for gestational age (pp)	3.16** (2.08, 4.24)	2.94*** (1.72, 4.16)	0.78 (0.00, 1.55)	0.15 (-0.75, 1.05)	0.25 (-1.92, 2.41)
Appropriate for gest. age (pp)	-3.66*** (-5.09, -2.23)	-3.27*** (-5.11, -1.43)	-0.39 (-1.61, 0.83)	-0.43 (-1.91, 1.06)	-0.94 (-3.32, 1.45)
Large for gestational age (pp)	0.50 (-0.18, 1.19)	0.33 (-1.06, 1.72)	-0.39 (-1.16, 0.39)	0.28 (-0.70, 1.25)	0.69 (-1.14, 2.52)

[a] New Jersey omitted given policy enactment was not during study period for analysis restricted to Phase 7 and 8.
Notes: Data drawn from the Pregnancy Risk Assessment Monitoring System years 2004-2021. N=450,626. Change in outcome represents percentage point change for binary outcomes. Washington and Massachusetts are combined given activation of PFL in same time period. Callaway-Sant'Anna difference-in-differences models adjusted for maternal age, education, race/ethnicity, marital status, household income, family size, and fixed effects for infant's year of birth and state. Models include robust standard errors clustered by state. States are listed left to right in order of PFL activation. Statistical significance: *p < 0.05 **p < 0.01 ***p < 0.001. Abbreviations: Percentage point change (pp).

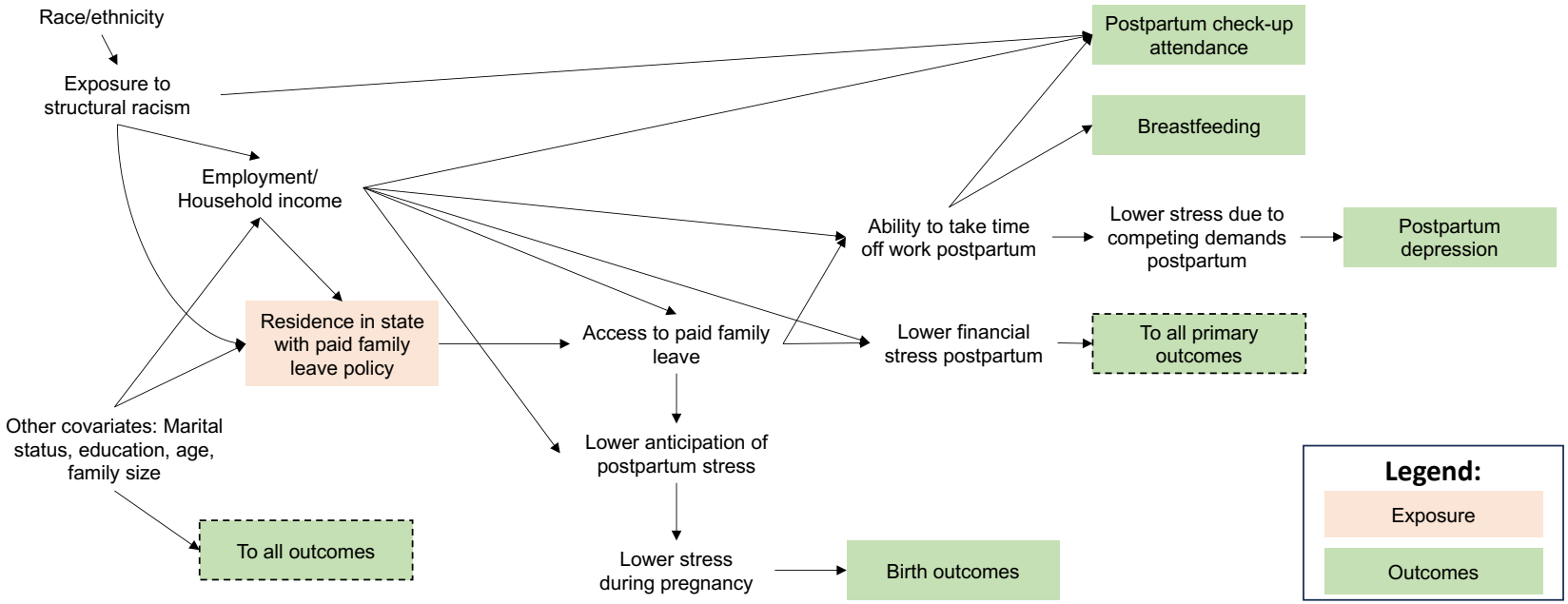


Appendix Figure S1. Sample selection
Abbreviations: Pregnancy Risk Assessment Monitoring System (PRAMS), Paid family leave (PFL)

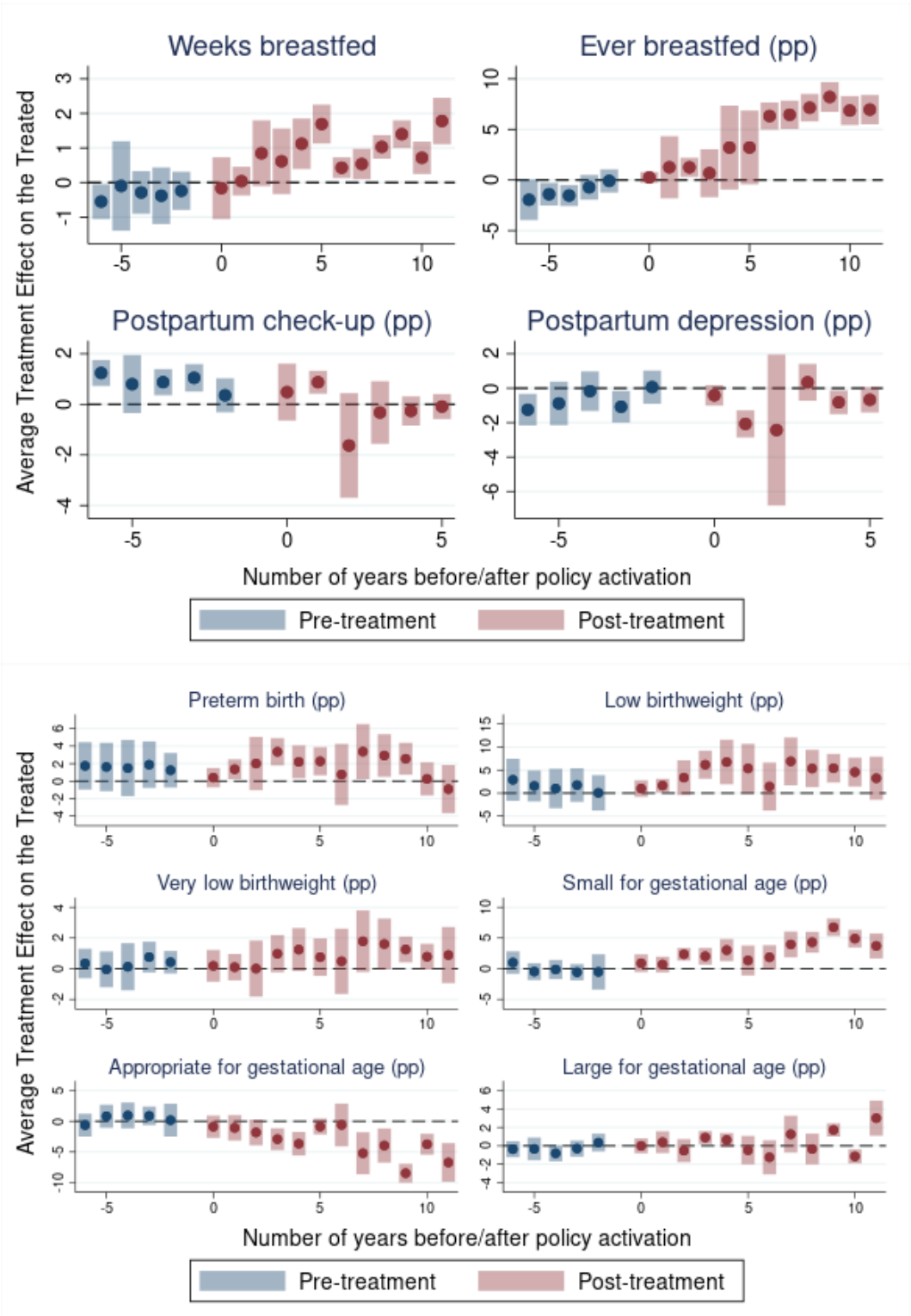


Appendix Figure S2. Presence of states with paid family leave in PRAMS, by years to treatment

Notes: Data drawn from the Pregnancy Risk Assessment Monitoring System years 2004-2021. Panel A: N=450,626. Panel B: N=239,373. Rhode Island is excluded from T=1 as data was not reported.



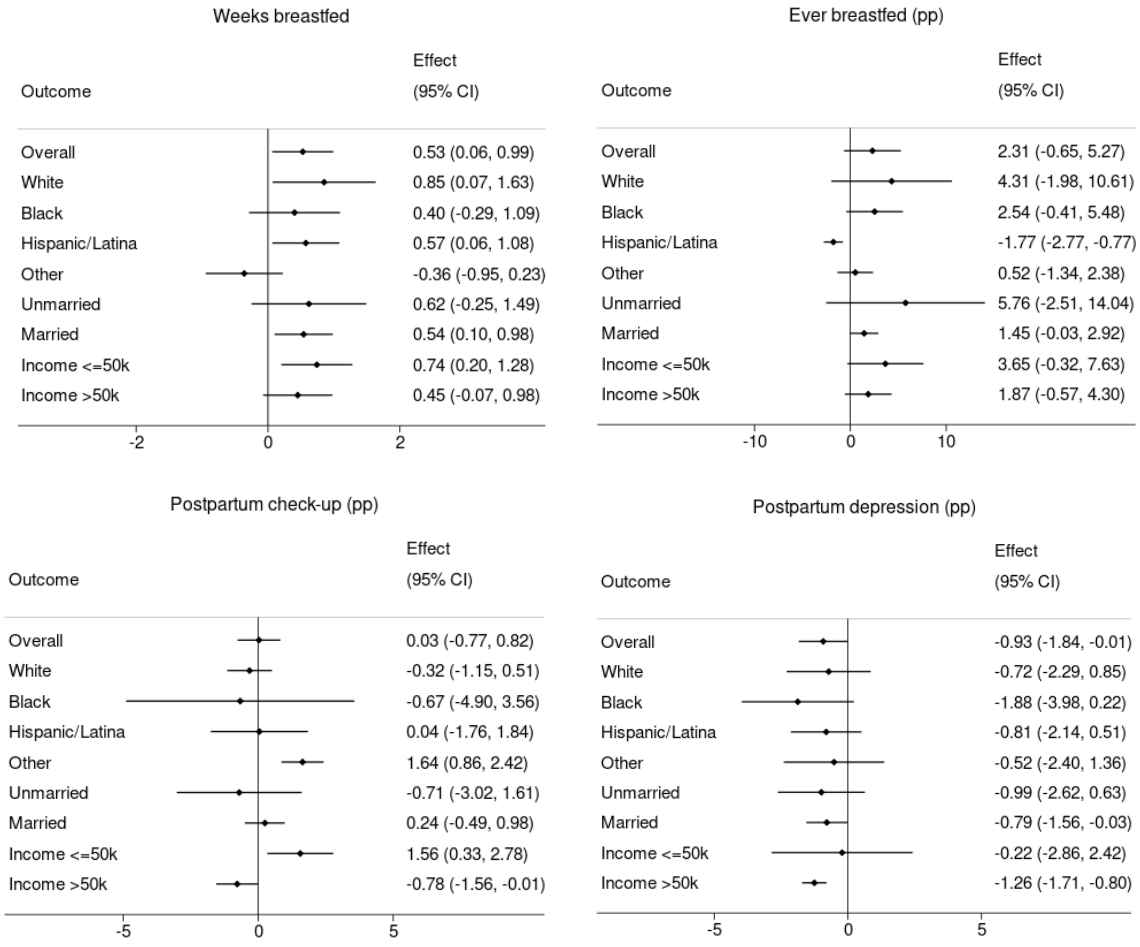
Appendix Figure S3: Conceptual diagram of hypothesized relationships between paid family leave and perinatal and postpartum health



Appendix Figure S4. Event study plot for effect of paid family leave on perinatal and postpartum health, full post-periods

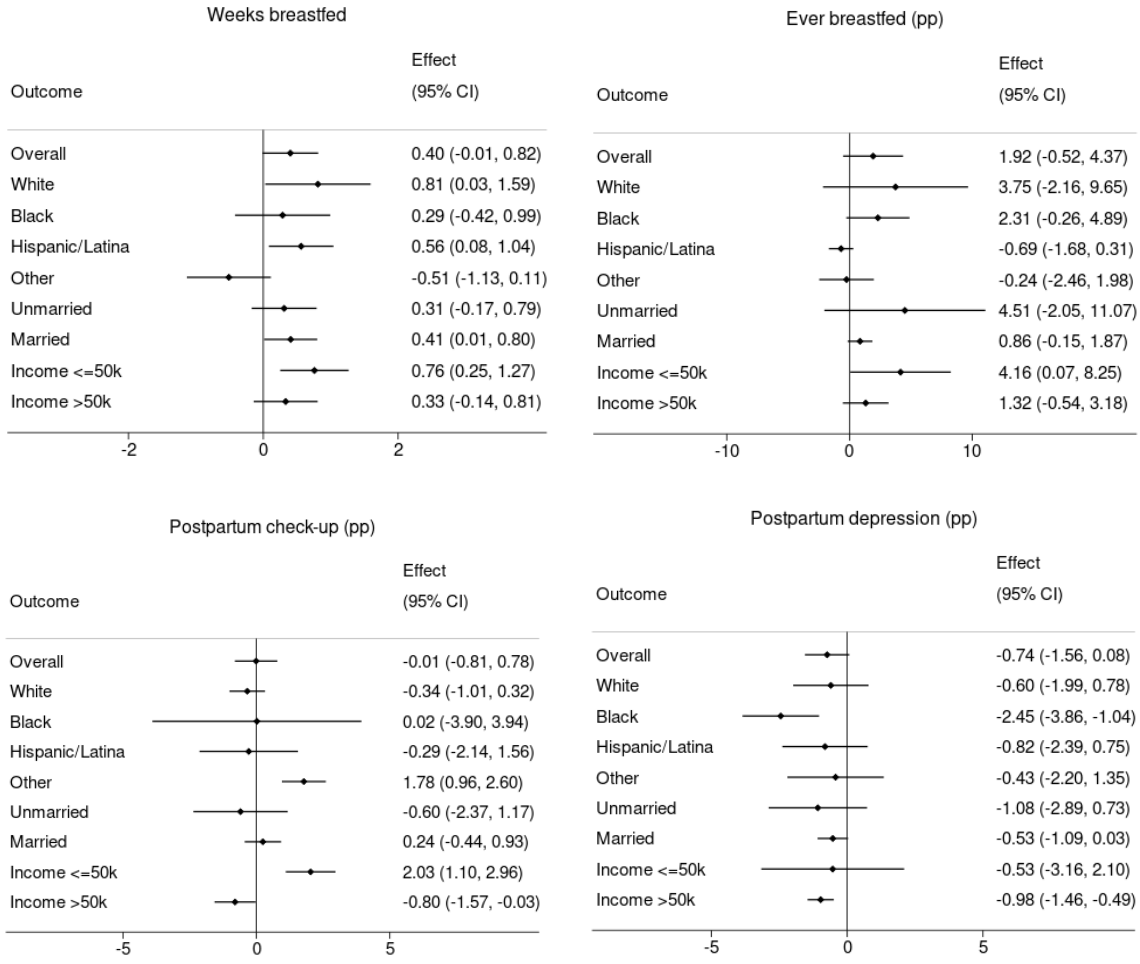
Notes: Data drawn from the Pregnancy Risk Assessment Monitoring System years. N=450,626. The reference period is T-1 (omitted from figure). Change in outcome represents percentage point change for binary outcomes. Callaway-Sant'Anna

difference-in-differences models adjusted for maternal age, education, race/ethnicity, marital status, household income, family size, and fixed effects for infant's year of birth and state. Models include robust standard errors clustered by state. Abbreviations: Percentage point change (pp). Changes in the number of treatment states present at each time point are due to differences in timing of policy implementation. These result in fluctuations in the estimates, since each estimate is the aggregation of treatment effects for treatment states present in that time period (i.e., discontinuity between T5 and T6 for breastfeeding outcomes). The presence of treatment states by years to treatment is shown in Appendix Figure S2.



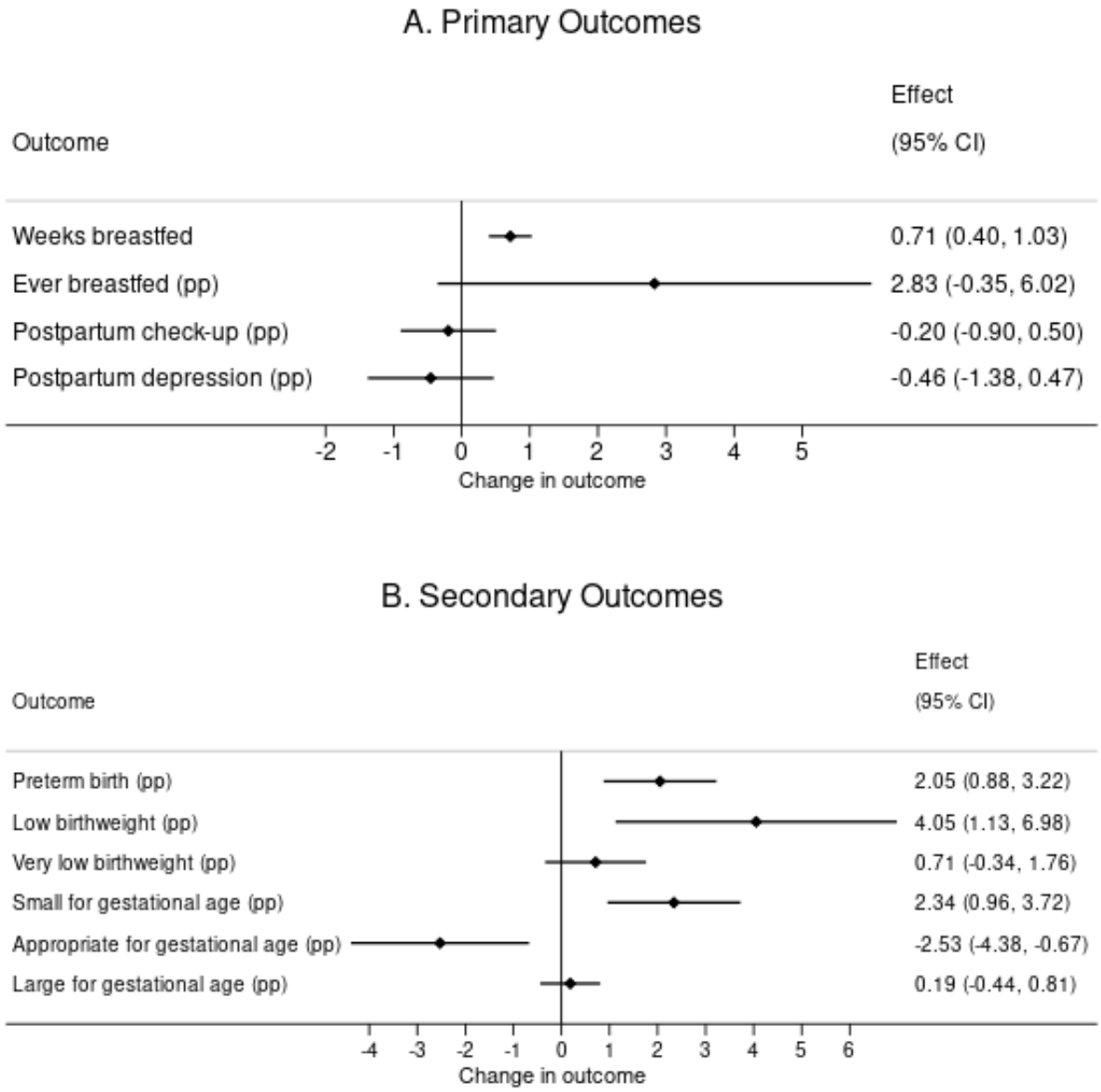
Appendix Figure S5. Effect of paid family leave on perinatal and postpartum health, by subgroup

Notes: Data drawn from the Pregnancy Risk Assessment Monitoring System years 2004-2021. N=450,626. Change in outcome represents percentage point change for binary outcomes. Callaway-Sant'Anna stratified models adjusted for all covariates (excluding the stratifying factor), including: maternal age, education, race/ethnicity, marital status, household income, family size, state unemployment rate and state average benefit size and fixed effects for infant's year of birth and state. Models include robust standard errors clustered by state. Abbreviations: Percentage point change (pp).

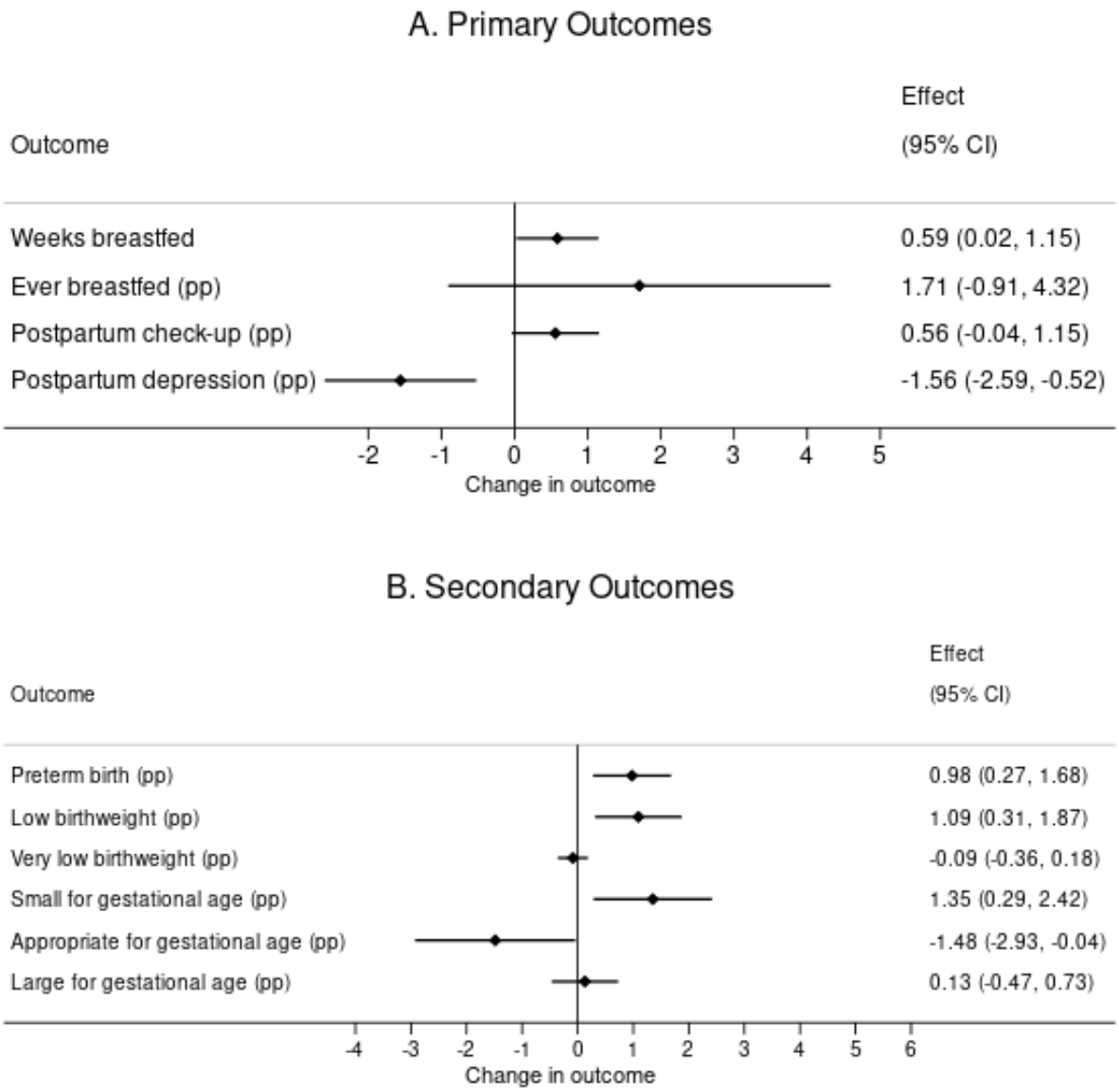


Appendix Figure S6. Effect of paid family leave on perinatal and postpartum health by subgroup, minimally adjusted

Notes: Data drawn from the Pregnancy Risk Assessment Monitoring System years 2004-2021. N=450,581. Change in outcome represents percentage point change for binary outcomes. Minimally adjusted Callaway-Sant'Anna difference-in-differences models adjusted for maternal age and fixed effects for infant's year of birth and state. Models include robust standard errors clustered by state. Abbreviations: Percentage point change (pp).

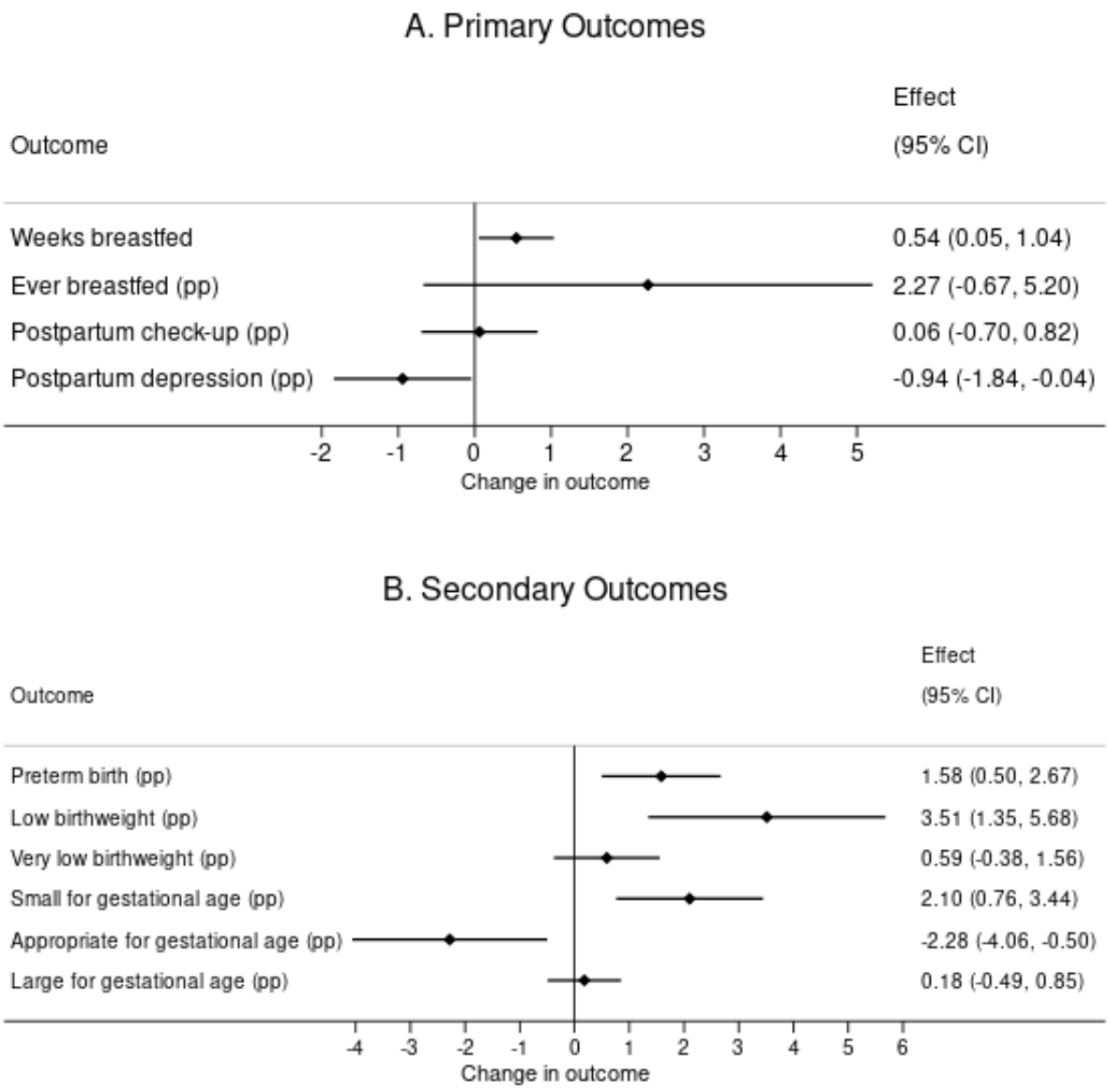


Appendix Figure S7. Effect of paid family leave on perinatal and postpartum health, excluding COVID-19 period
Notes: Data drawn from the Pregnancy Risk Assessment Monitoring System years 2004-2021. N=399,023. Change in outcome represents percentage point change for binary outcomes. Callaway-Sant'Anna models adjusted for maternal age, education, race/ethnicity, marital status, household income, family size, and fixed effects for infant's year of birth and state. Models include robust standard errors clustered by state. Abbreviations: Percentage point change (pp).



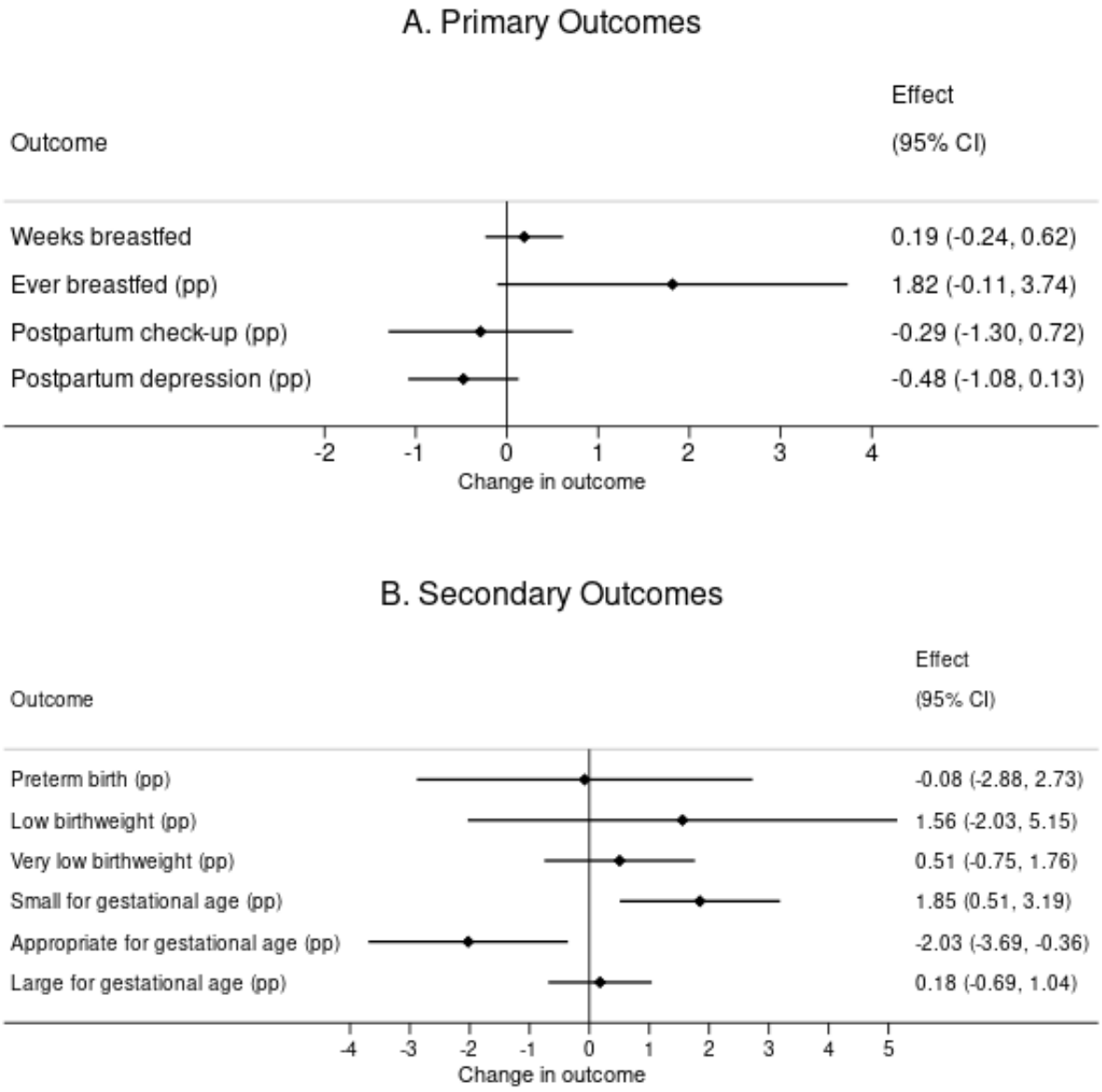
Appendix Figure S8. Effect of paid family leave on perinatal and postpartum health, weighted

Notes: Data drawn from the Pregnancy Risk Assessment Monitoring System years 2004-2021. N=450,626, weighted N=23,801,206. Change in outcome represents percentage point change for binary outcomes. Callaway-Sant'Anna difference-in-differences models adjusted for maternal age, education, race/ethnicity, marital status, household income, family size, and fixed effects for infant's year of birth and state. Models include robust standard errors clustered by state. Abbreviations: Percentage point change (pp).

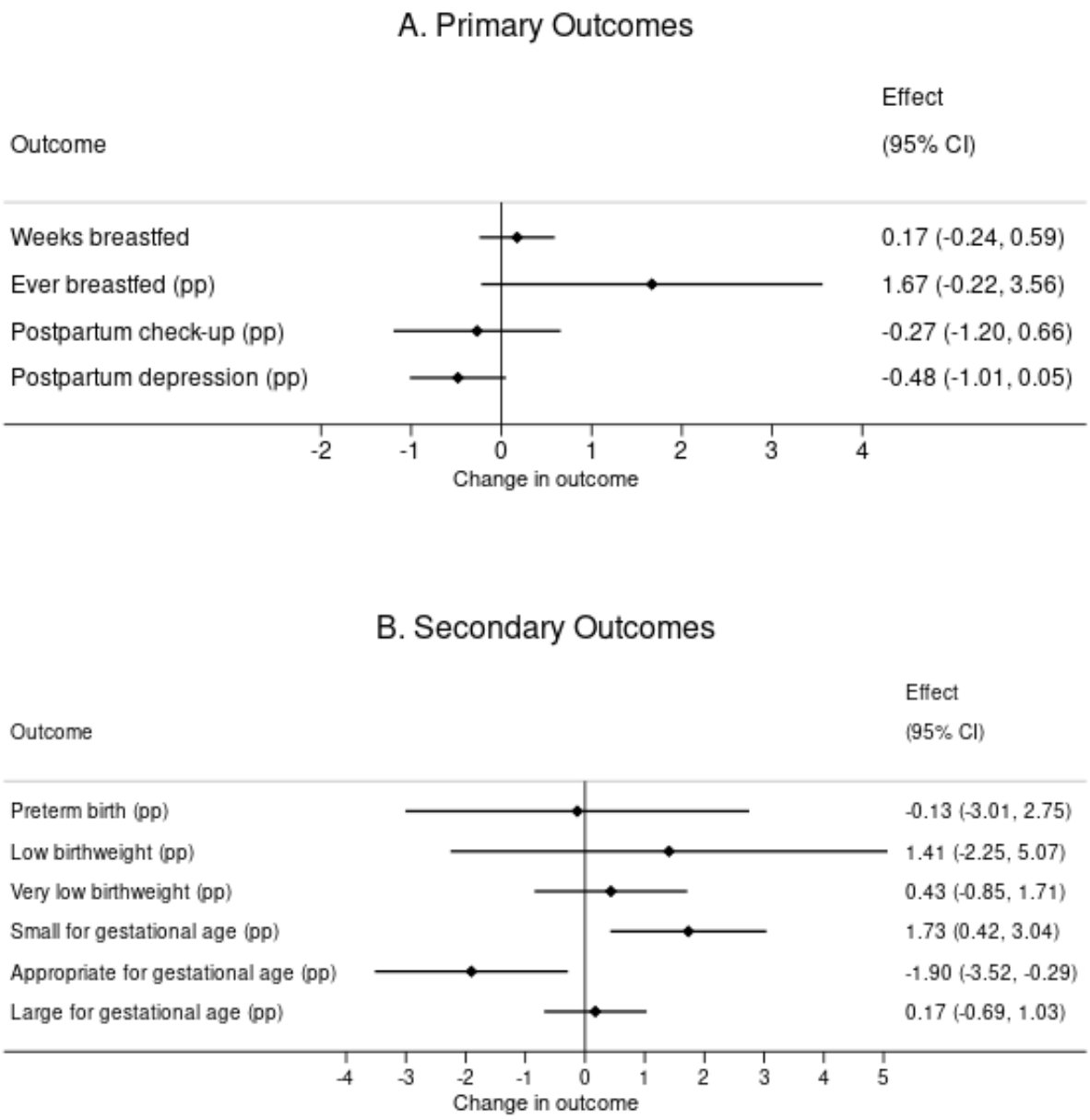


Appendix Figure S9. Effect of paid family leave on perinatal and postpartum health, excluding Hawaii

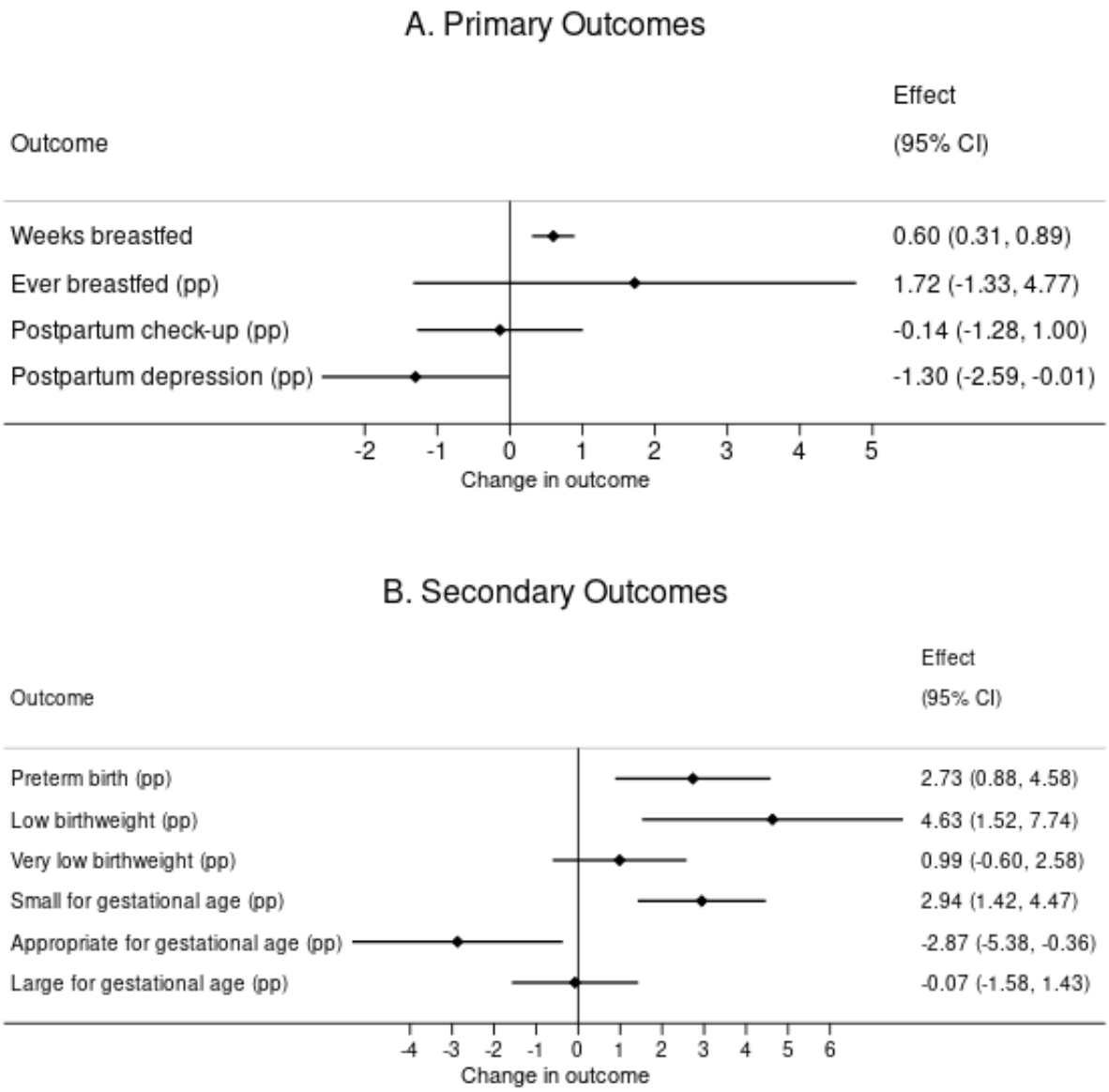
Notes: Data drawn from the Pregnancy Risk Assessment Monitoring System years 2004-2021. N=434,482. Change in outcome represents percentage point change for binary outcomes. Callaway-Sant'Anna difference-in-differences models adjusted for maternal age, education, race/ethnicity, marital status, household income, family size, and fixed effects for infant's year of birth and state. Models include robust standard errors clustered by state. Abbreviations: Percentage point change (pp).



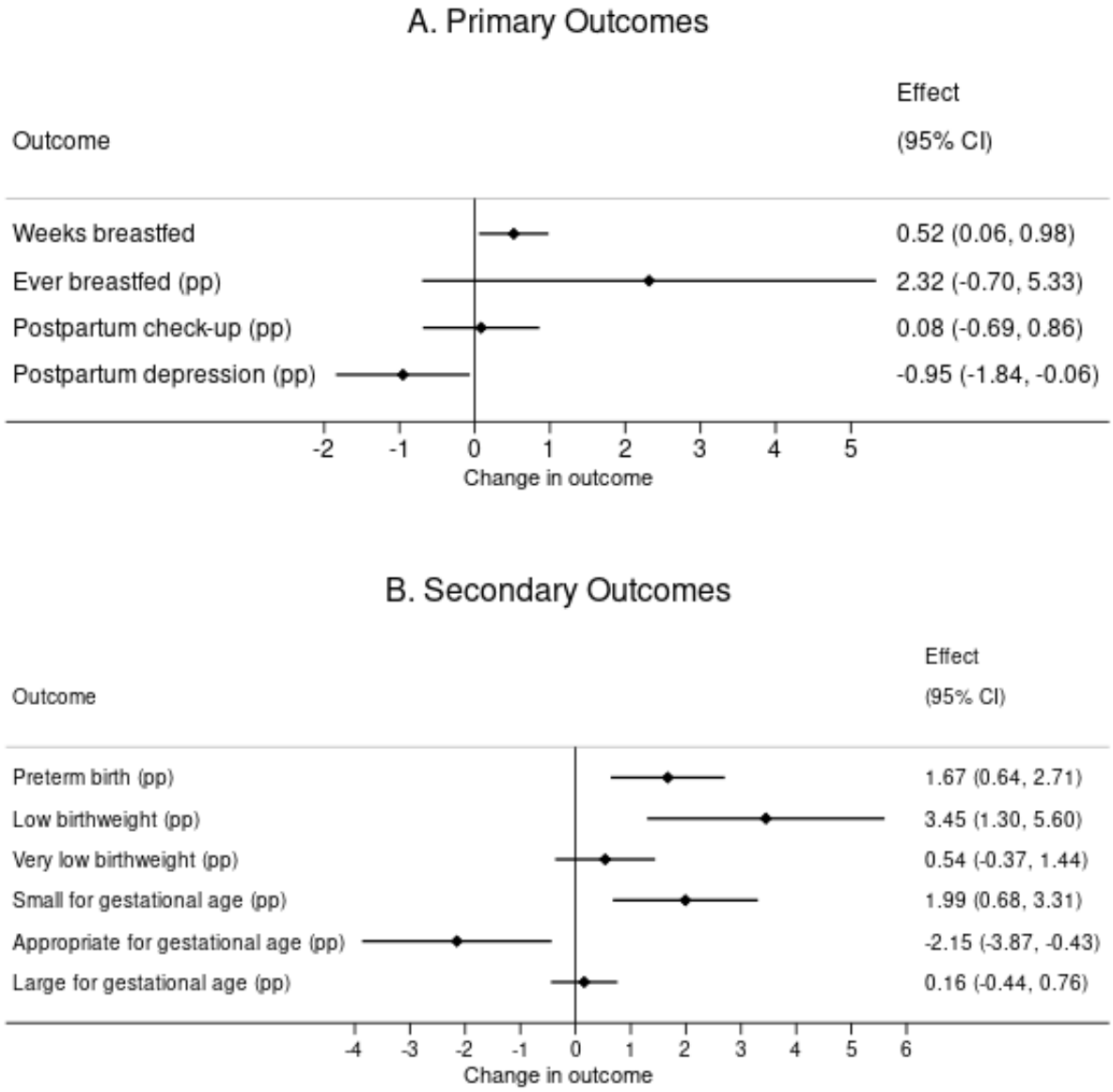
Appendix Figure S10. Effect of paid family leave on perinatal and postpartum health, using generalized difference-in-differences approach
Notes: Data drawn from the Pregnancy Risk Assessment Monitoring System years. N=450,626. Change in outcome represents percentage point change for binary outcomes. Difference-in-differences models adjusted for maternal age, education, race/ethnicity, marital status, household income, family size, and fixed effects for infant's year of birth and state. Models include robust standard errors clustered by state.
Abbreviations: Percentage point change (pp).



Appendix Figure S11. Effect of paid family leave on perinatal and postpartum health, using generalized difference-in-differences approach with multiple imputation
Notes: Data drawn from the Pregnancy Risk Assessment Monitoring System years 2004-2021. N=459,411. Change in outcome represents percentage point change for binary outcomes. Difference-in-differences models adjusted for maternal age, education, race/ethnicity, marital status, household income, family size, and fixed effects for infant's year of birth and state. Models include robust standard errors clustered by state. Abbreviations: Percentage point change (pp).

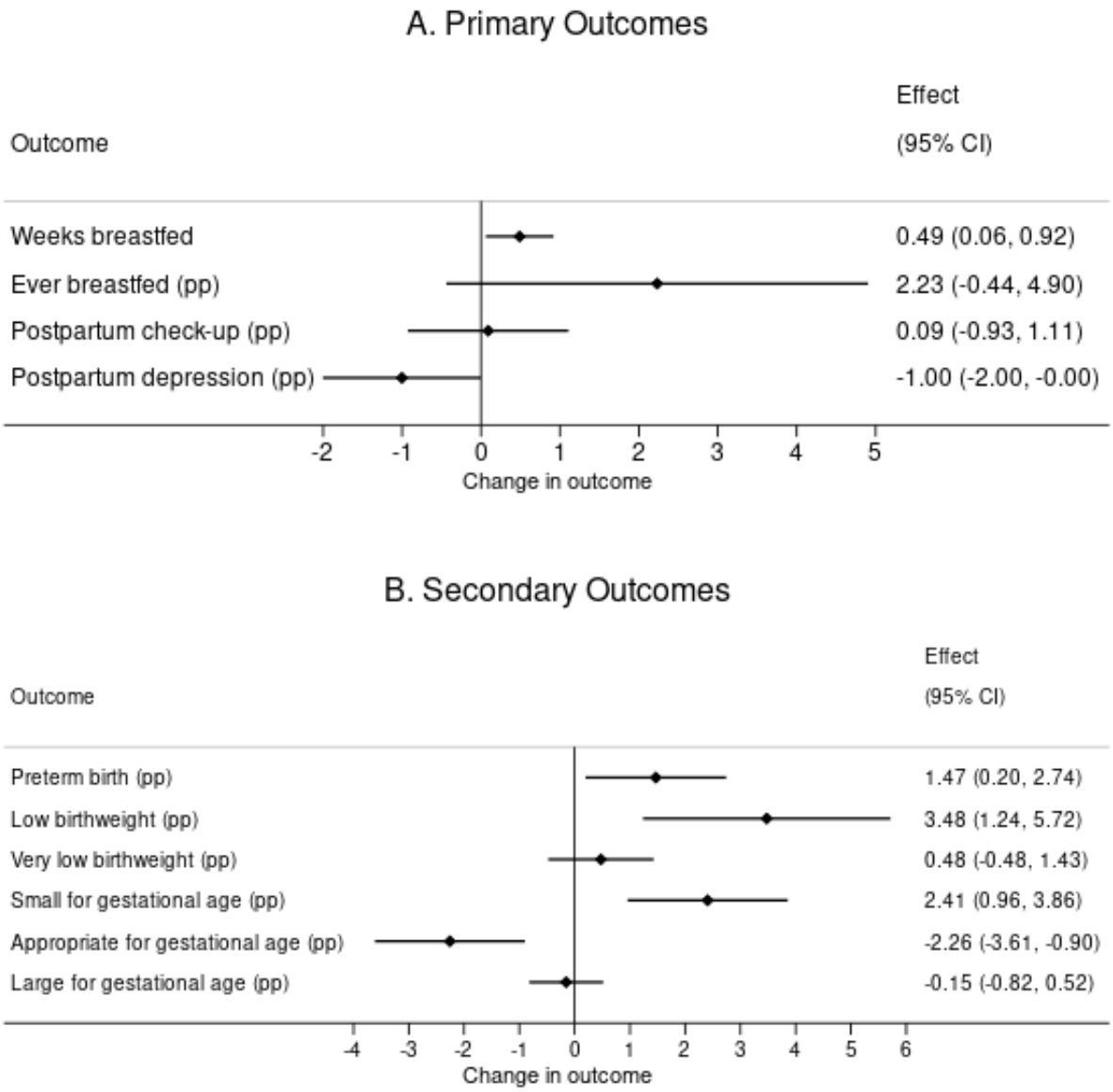


Appendix Figure S12. Effect of paid family leave on perinatal and postpartum health, additionally adjusted for state-level covariates
Notes: Data drawn from the Pregnancy Risk Assessment Monitoring System years. N=450,626. Change in outcome represents percentage point change for binary outcomes. Callaway-Sant'Anna models adjusted for maternal age, education, race/ethnicity, marital status, household income, family size, state unemployment rate and state average benefit size and fixed effects for infant's year of birth and state. Models include robust standard errors clustered by state. Abbreviations: Percentage point change (pp).

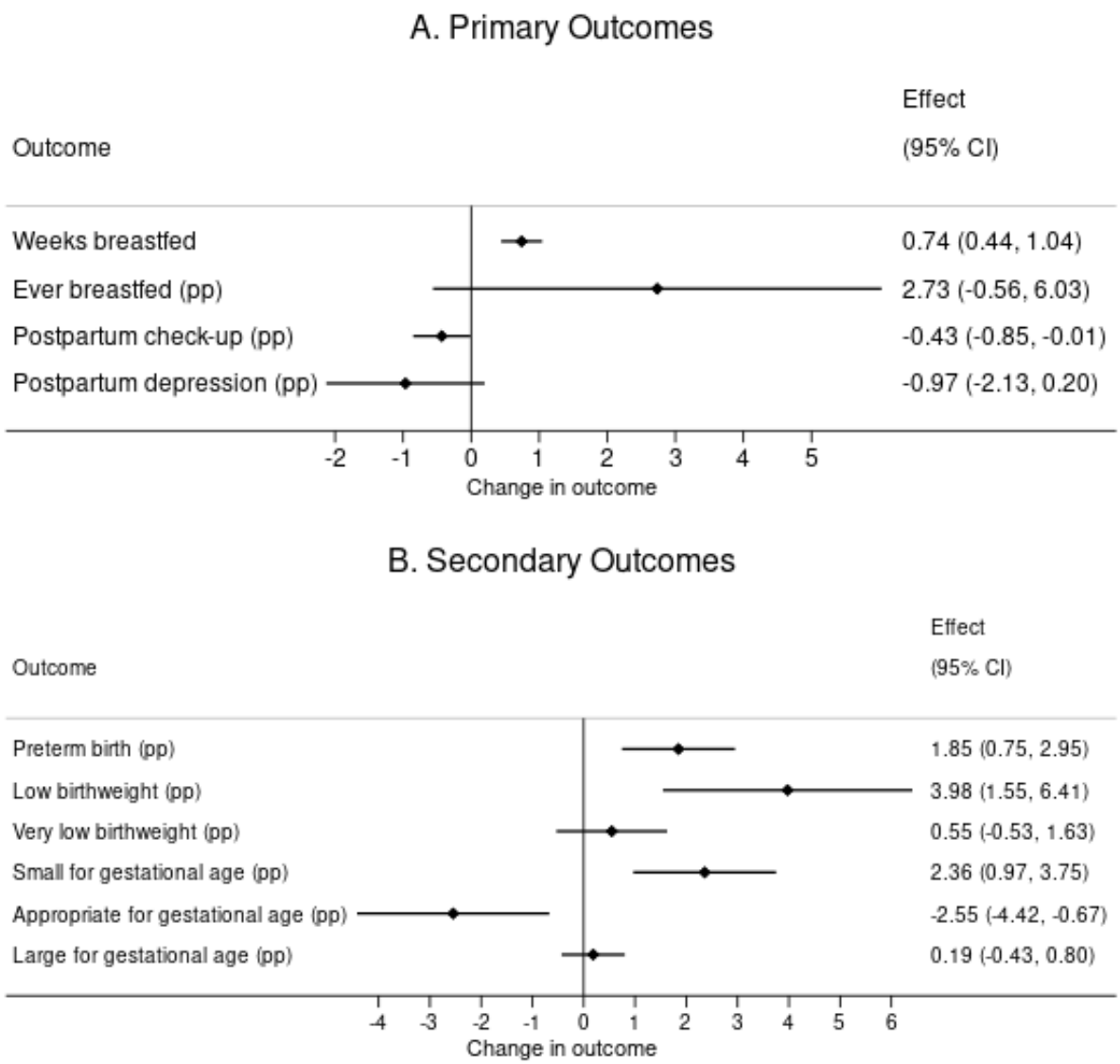


Appendix Figure S13. Effect of paid family leave on perinatal and postpartum health, including not yet treated states in control set

Notes: Data drawn from the Pregnancy Risk Assessment Monitoring System years 2004-2021. N=450,626. Change in outcome represents percentage point change for binary outcomes. Callaway-Sant'Anna difference-in-differences models adjusted for maternal age, education, race/ethnicity, marital status, household income, family size, and fixed effects for infant's year of birth and state. Models include robust standard errors clustered by state. Abbreviations: Percentage point change (pp).



Appendix Figure S14. Effect of paid family leave on perinatal and postpartum health, including those in the lowest income category
Notes: Data drawn from the Pregnancy Risk Assessment Monitoring System years 2004-2021. N=576,669. Change in outcome represents percentage point change for binary outcomes. Callaway-Sant'Anna difference-in-differences models adjusted for maternal age, education, race/ethnicity, marital status, household income, family size, and fixed effects for infant's year of birth and state. Models include robust standard errors clustered by state. Abbreviations: Percentage point change (pp).



Appendix Figure S15. Effect of paid family leave policies on breastfeeding, maternal outcomes, and birth outcomes, restricted to earlier adopting treatment states
Notes: Data drawn from the Pregnancy Risk Assessment Monitoring System years 2004-2021. N=417,611. Change in outcome represents percentage point change for binary outcomes. Callaway-Sant'Anna difference-in-differences models adjusted for maternal age, education, race/ethnicity, marital status, household income, family size, and fixed effects for infant's year of birth and state. Models include robust standard errors clustered by state. Abbreviations: Percentage point change (pp).