Hamad et al., *AJPH* 2018
Supplemental Material

METHODS

Dataset

We analyzed data from the 2003-2015 waves of the National Immunization Survey (NIS), a nationally representative serial cross-sectional survey of vaccination that includes questions about breastfeeding (N=348,211). Details of the sampling design have been published previously (1). Parents were surveyed when their children were 19-35 months old, so our sample included children born during 2001-2013. The NIS asked about the child's current state of residence, but not state of birth. We thus restricted our sample to respondents who had not moved since the child's birth (N=314,966). We further restricted our sample to respondents living in the 50 states and the District of Columbia (N=311,587). Finally, we included only children for whom at least one breastfeeding outcome was available (N=310,242). The primary exposure was whether a child was born in a state and year in which a PFL policy had been implemented (i.e., July 2004 or later in California, or July 2009 or later in New Jersey). The NIS does not give children's exact birthdate, but rather a categorical variable. As the NIS conducts each survey wave during specific windows (e.g., January 2006 to February 2007 for the 2006 wave), we calculated the earliest and latest possible birthdate for each child. Children who could have been born during a range that spanned pre- and post-policy dates (N=3,976) were excluded from the analysis to avoid misclassification. The final sample size was 306,266 children.

As this study used de-identified public datasets, ethical approval was not required. All analyses were conducted using Stata 14 (College Station, Texas).

Paid Family Leave Policies

Neither the California nor New Jersey policies guarantees job protection, although most workers are covered under the Family and Medical Leave Act (FMLA). In California, workers receive 55% of usual pay up to a maximum amount ($1,173/week in 2017). In New Jersey, workers receive 67% of usual pay up to a maximum ($633/week in 2017). California's PFL policy increased average leave-taking from three to six weeks and doubled leave take-up (2), despite half of workers not being aware of the program's existence (3). In New Jersey, claims for child bonding increased from 23,900 in 2010 to 26,800 in 2015 (4). Additional information on eligibility, financing, and other policy details have been described previously (5).

Measures

Outcome variables took on a value of zero for those who never breastfed. Covariates included child's age, race, and gender; mother's age, marital status, and educational attainment; and household size and income group. We also included time-varying state-level covariates: proportion of the population with less than a high school education, unemployment rate, and gross domestic product per capita.

Difference-in-Differences Analysis

We used a difference-in-differences (DiD) analysis to assess whether PFL policy implementation changed breastfeeding practices. This method compared the pre-post change in California and New Jersey with the change in non-PFL states. In other words, it compared the average change in the outcomes over time in the "treatment" group with the change in the "control" group before and after the policy was implemented, similar to an experimental set-up (6). The independent variable of interest was the interaction term between timing of the PFL policy (pre- vs. post-implementation) and treatment status (i.e., California and New Jersey vs.

non-PFL state). The estimated coefficient on this term represents the average difference in outcomes attributable to the PFL policies. These linear regression models were adjusted for the individual- and state-level characteristics listed above and indicator variables for birth-year to control for secular trends, with robust standard errors clustered by state. All models also included state fixed effects (i.e., state-level indicator variables). This approach uses only within-state variation in treatment over time, controlling for any unobserved time-invariant confounders.

Difference-in-differences (DiD) analyses assume that the slopes (not the levels) for the treatment and control groups are similar during the pre-policy period, commonly known as the parallel trends assumption. This was assessed by first conducting a graphical analysis, fitting kernel-weighted local polynomial regressions. These figures show the trends in outcomes, taking the child's birthday relative to the date of PFL implementation (day 0). The trends overall appeared similar, although trends in the treatment states were somewhat noisier due to the smaller sample size relative to the control states. Consistent with the descriptive statistics, California (Supplemental Figure A) had higher rates of breastfeeding than other states for children born prior to PFL implementation, although the trends ran largely parallel. New Jersey (Supplemental Figure B) also had similar trends to other states.

The equation for the DiD model in this analysis is:

$$Y_{ijt} = \beta_0 + \beta_1 Year_t + \beta_2 Policy_j + \beta_3 (Post_t \; x \; Policy_j) + \beta_4 C_{ijt} + \beta_5 S_{jt} + \mu_j + \varepsilon_{ijt}$$

Here, Y_{ijt} represents one of the breastfeeding outcomes of interest for a given child. $Year_t$ is a vector of indicator variables for year of birth. This adjusts for secular trends and accounts for whether the child was born during the post-policy period in California or New Jersey. $Policy_j$ is a dummy variable indicating whether the child was born in California or New Jersey (as opposed to any other state). β_3 represents the coefficient of interest on the interaction term between

policy period and state of birth, i.e., the average treatment effect. C_{it} is a vector of individual-level control variables, while S_{jt} is a vector of state-level control variables. State fixed effects are represented by μ_j, which account for any time-invariant factors at the state level. ε_{ijt} is a random error term. The policy variables of interest only vary at the state level and breastfeeding outcomes may be correlated for individuals within the same state. Therefore we follow prior literature and use robust standard errors clustered by state to account for heteroskedasticity and serial correlation (7).

DiD analyses commonly implement placebo tests, in which investigators simulate a treatment earlier than it actually took place, in order to test whether there are general secular trends that could account for the observed effect. In our data set, we are unable to run a placebo test for California, as there were a limited number of observations during the pre-policy period. We did, however, implement such an analysis for New Jersey, in which we assigned the treatment variable in 2004 and allowed the post period to continue through 2009, when the policy was actually implemented. We found no improvements in the outcome variables with this placebo test, and in fact several coefficients were statistically significantly negative (results available upon request).

DiD models assume that there are no omitted time-varying confounders that influence both the treatment and the outcome. While this is not directly testable, we were able to test whether measured individual- and state-level covariates vary over time in relation to the treatment, by regressing each of these and examining the association with the policy as represented by the interaction term described above. In these tests, we found that state-level education and unemployment, but not the individual-level covariates, were associated with the treatment. While we adjusted for these covariates and state fixed effects in our models, we cannot rule out

that other time-varying state-level factors may confound our results, nor can we determine the direction of such bias. This is a limitation of all DiD models.

As the goal of this study is to draw causal inferences rather than to estimate statistics representative at the population level, and because we adjusted for several variables related to the sampling strategy, we followed the recommended practice not to include survey weights in the main analyses presented in the manuscript (8). We did also estimate the primary findings using survey weights, and the results were largely similar (results available upon request).

We used linear rather than logistic or Poisson models, as these are preferred in DiD analyses due to the interpretability of the interaction term (9, 10). However, in secondary analyses we conducted logistic regressions for the binary outcomes and Poisson regression for the duration outcomes. These demonstrated similar coefficient direction and statistical significance levels as our primary linear models (results available upon request).

Alternative Specifications

First, we examined the effects of the PFLs among pre-specified subgroups. To do so, we included additional interaction terms between each subgroup and the treatment variable. Using a joint *F*-test, we first assessed whether each set of interaction terms (e.g., for race) were statistically significantly different from zero; about half met this criteria. Because prior theoretical and empirical work suggests that there may be differences in the effects of PFLs among these groups, we present the results of each in Supplemental Tables C-F, although the coefficients on the individual interaction terms should be interpreted cautiously for those models in which the *F*-test was not statistically significant at $p < 0.05$. In the main manuscript, we therefore only discuss the subgroup analyses for those regressions for which the *F*-test *p*-value was less than 0.05.

Second, we separately examined the effects of the PFLs in California and New Jersey.

Third, since many women did not breastfeed at all, a single model of breastfeeding duration may not be appropriate. In particular, the large mass of observations with a duration of zero violates the ordinary least squares (OLS) assumption that the outcome variable is normally distributed. Therefore, we next estimated a two-part model that accounts for the mass of zeros by combining separate submodels of the effects of PFLs on (1) ever breastfeeding (initiation) and (2) duration. This produces estimates of the effect of PFLs on the probability of initiation and duration conditional on initiation, as well as the overall unconditional effect of PFLs accounting for the large proportion of women who did not breastfeed. This technique can only be applied to our continuous outcomes. The two-part model is appropriate for modeling observed actual outcomes with a large mass at zero (11). The two-part model is preferred over the Heckman selection model when analyzing actual outcomes (as opposed to potential latent outcomes) on theoretical grounds and due to its lower mean square error, especially in the absence of a valid exclusion restriction (12-14). In practice, both models produce nearly identical estimates of marginal effects (15). We model any breastfeeding $\Pr(Y_{ijt} > 0 \mid X_{ijt})$ as a logit and conditional duration $E[Y_{ijt}|Y_{ijt} > 0, X_{ijt}]$ as linear, where for simplicity we use X_{ijt} as a notational stand-in for all covariates and state fixed effects in the DiD equation above from our main analysis. The unconditional demand for breastfeeding $E[Y_{ijt} \mid X_{ijt}]$ can then be recovered by taking the product of the two parts:

$$E[Y_{ijt} \mid X] = \Pr(Y_{ijt} > 0 \mid X_{ijt}) \times E[Y_{ijt}|Y_{ijt} > 0, X_{ijt}].$$

Estimates are reported as average marginal effects, clustering standard errors by state.

Finally, we conducted pooled OLS analyses for each of the models above, i.e., excluding the state fixed effects. This type of model uses both within- and across-state variation, although it is less conservative than the more traditional fixed effects models used in DiD analyses.

Missing Data

Complete data were available for all covariates except household size (<0.1% missing) and income (<10% missing). We assume that these values are missing at random, as opposed to missing not at random, although this is not empirically testable. We did not impute these values, as complete case analysis is not thought to introduce substantial bias at low levels of missingness (16-19). Furthermore, we do not impute missing outcome values, as this is thought to add noise to the estimates (20). This results in slightly different sample sizes in each of our models.

ADDITIONAL RESULTS

Subgroup Analyses by State

In subgroup analyses by state, the California and New Jersey PFLs differed in their effects on breastfeeding practices, including both improvements as well negative effects on several measures of breastfeeding (Supplemental Table G).

Two-Part Model

The two-part model also found that PFLs did not statistically significantly influence the probability of ever breastfeeding (Supplemental Table H). Rather, the main effect was a marginally significant decrease in breastfeeding duration among those who ever breastfed of 3.2 days (95% CI: -6.6, 0.2), and increased duration of exclusive breastfeeding of 2.5 days (95% CI: 1.1, 4.0). The overall effect (unconditional on initiation) was not statistically significant. Similar

to our primary models, the effects were more beneficial for married, white, and higher-income women (results available upon request).

Pooled OLS Models

In pooled OLS models (Supplemental Table I), the PFL policies increased the percentage of children ever breastfed by a marginally statistically significant 6.0 percentage points (95% CI: -0.23, 12.0). There was a statistically significant increase in the percent exclusively breastfeeding at six months (5.0 percentage points, 95% CI: 3.1, 7.0), and still breastfeeding at six months (8.5 percentage points, 95% CI: 4.0, 13.0) and 12 months (5.9 percentage points, 95% CI: 2.3, 9.5). The policies increased exclusive breastfeeding duration by a marginally statistically significant 12.8 days (95%CI: -1.12, 26.8) and breastfeeding duration by 31.5 days (95% CI: 2.8, 30.5). Exclusive breastfeeding at three months was not statistically significantly different.

ADDITIONAL DISCUSSION

The PFL in New Jersey resulted in more improvements relative to the policy in California. The results of two-part models suggested increased exclusive breastfeeding duration and reductions in overall breastfeeding duration, again with more beneficial effects among women of higher SES. Finally, pooled OLS models also demonstrated improvements in breastfeeding at 12 months and breastfeeding duration, although these associations are more likely to be confounded by unobserved state characteristics.

This study contributes to the growing literature on policies that can support and prolong breastfeeding practices, a key goal highlighted by Healthy People 2020 (21). It is the first to examine health effects of PFL policies across multiple states. One other study by Huang and colleagues that examined only the California policy found that the enactment of the PFL law

increased the probability of children being breastfed at 6 months by 17 percentage points among employed women (22), while we find a 1.3-percentage-point increase among both employed and unemployed women. Prior work suggests increased unemployment among young women in response to PFLs (23), but our results suggest that the increases in breastfeeding are likely accruing among employed rather than unemployed women.

Alternatively, these differences relative to Huang and colleagues may be due to differences in California and New Jersey's PFL policies. California's policy is more generous to middle- and high-income mothers and has been in place for a longer duration with potentially higher take-up. We found differences when examining each state separately. For example, in New Jersey, we see improvements across most outcomes. In California, the results are counterintuitive, with improvements in breastfeeding at 6 months relative to early declines. Given the absence of data on employment and actual leave-taking for women in this dataset, we are unable to fully explore the potential mechanisms of these findings. For example, PFL implementation increased long-term employment in California (2, 24), but no studies have examined employment effects in New Jersey.

The key strengths of this study include the use of a quasi-experimental method and a large diverse sample drawn from a nationally representative dataset. While prior work has employed similar DiD analyses to examine the California policy (22), we specifically exploited a natural policy experiment across multiple states, which increases the generalizability of the results. We also used 12 years of data from the NIS, which allowed us to examine breastfeeding behavior over an extended period of time.

This study also has several limitations. We could not identify working and non-working mothers or leave duration, which likely leads us to understate the policies' impacts since the PFL

benefits are targeted to working mothers; yet our estimates reflect population-level effects on both working and non-working mothers, including the possible effects on unemployment as a result of PFL policies. We accounted for state characteristics in California and New Jersey by including state fixed effects and controlling for several state-level time-varying covariates, although we cannot rule out that differences are affected by other time-varying individual- and state-level factors. In particular, DiD analyses assume that there are no other contemporaneous exposures affecting the outcome in just the treatment states; this assumption is not directly testable, but our inclusion of two PFL states means that violations of this assumption in a single state would be less likely to bias the results. Also, the NIS data do not include exact income or ages of participants; therefore we are limited to using the categorical variables provided, which limits the granularity of the analyses. To avoid misclassification we excluded children born near the enactment of the policies, which reduces our sample size but is unlikely to bias the results. In fact, since the California PFL policy was shown to shift births to later in the year, particularly for disadvantaged mothers (25), our approach may have reduced selection bias by eliminating children born in this window. We were also limited to self-reported breastfeeding based on retrospective interviews, although this has been found to be valid and reliable when recall is under three years (26). Notably, the NIS was conducted after the children's birth, so covariates were not collected before the implementation of the policy; thus, there may be residual confounding if the policy influenced characteristics such as income and marital status. In addition, restricting our sample to those who had not moved since birth means that results may not be generalizable to individuals who moved.

ADDITIONAL REFERENCES

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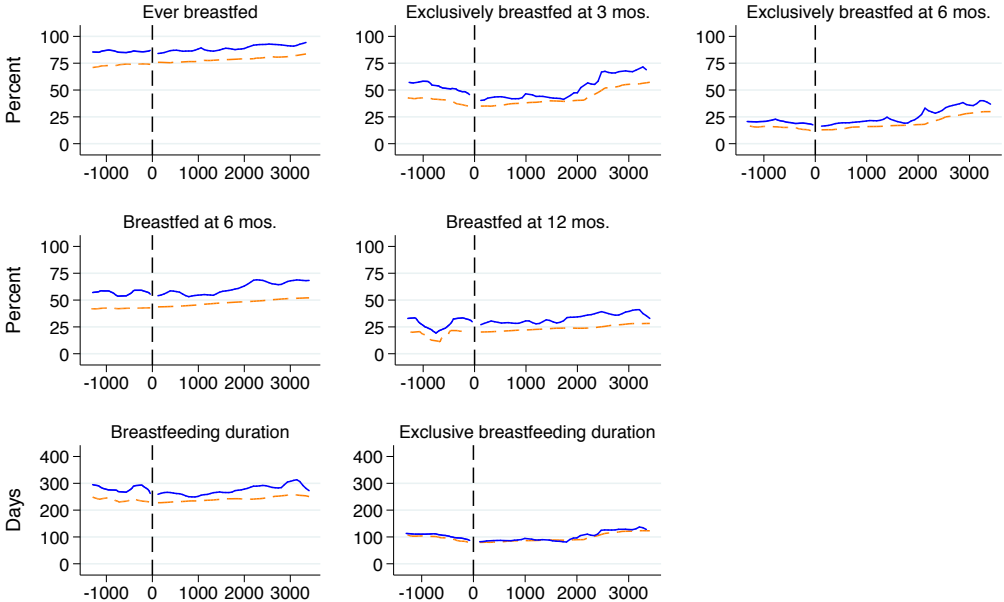
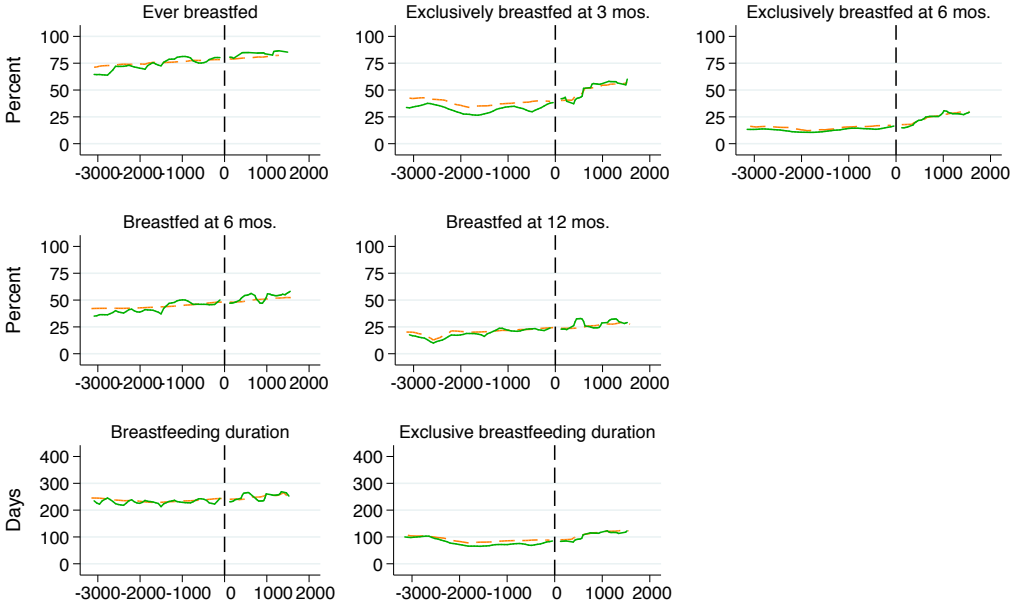
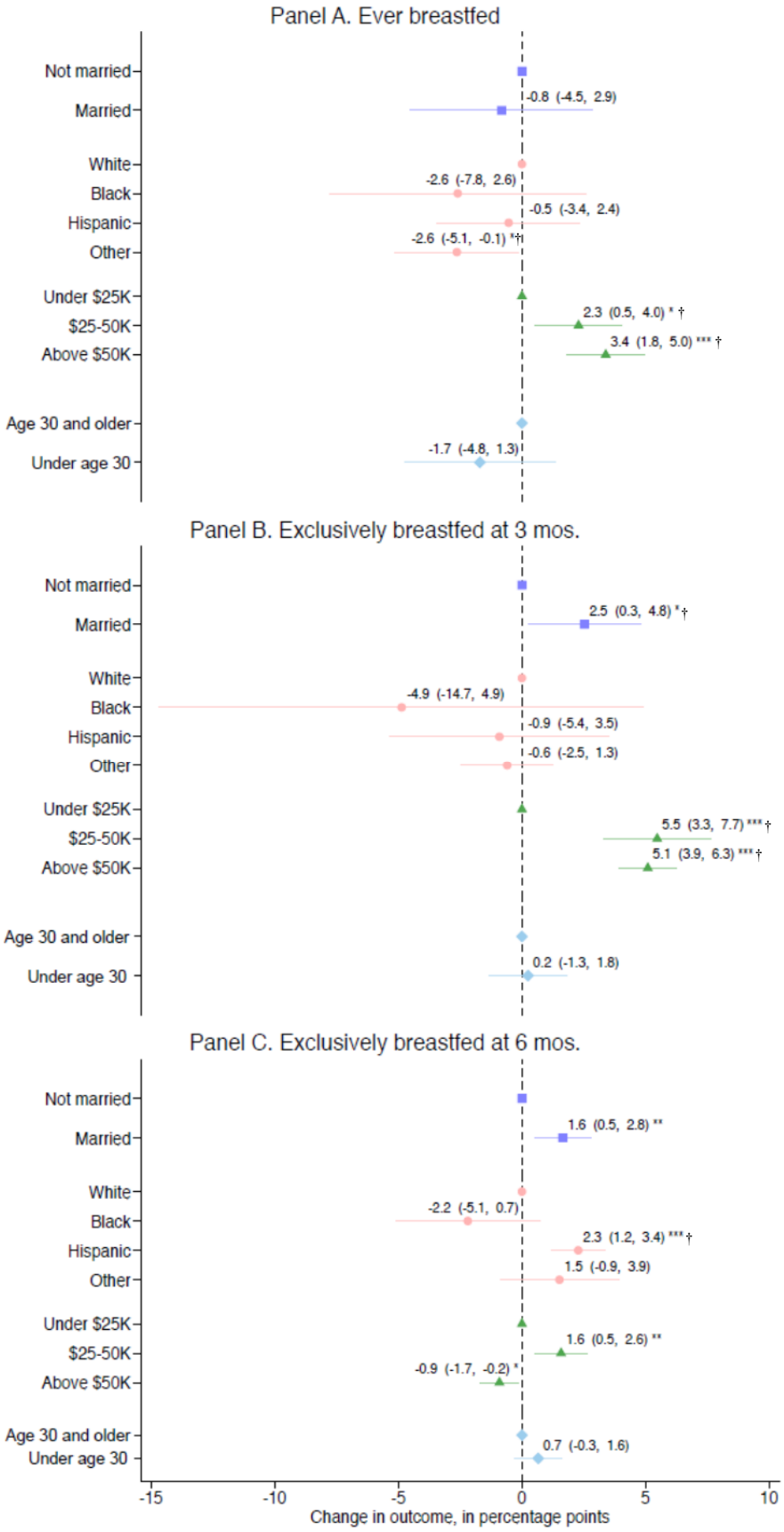


Supplemental Figure A. Trends in breastfeeding relative to PFL implementation (days)



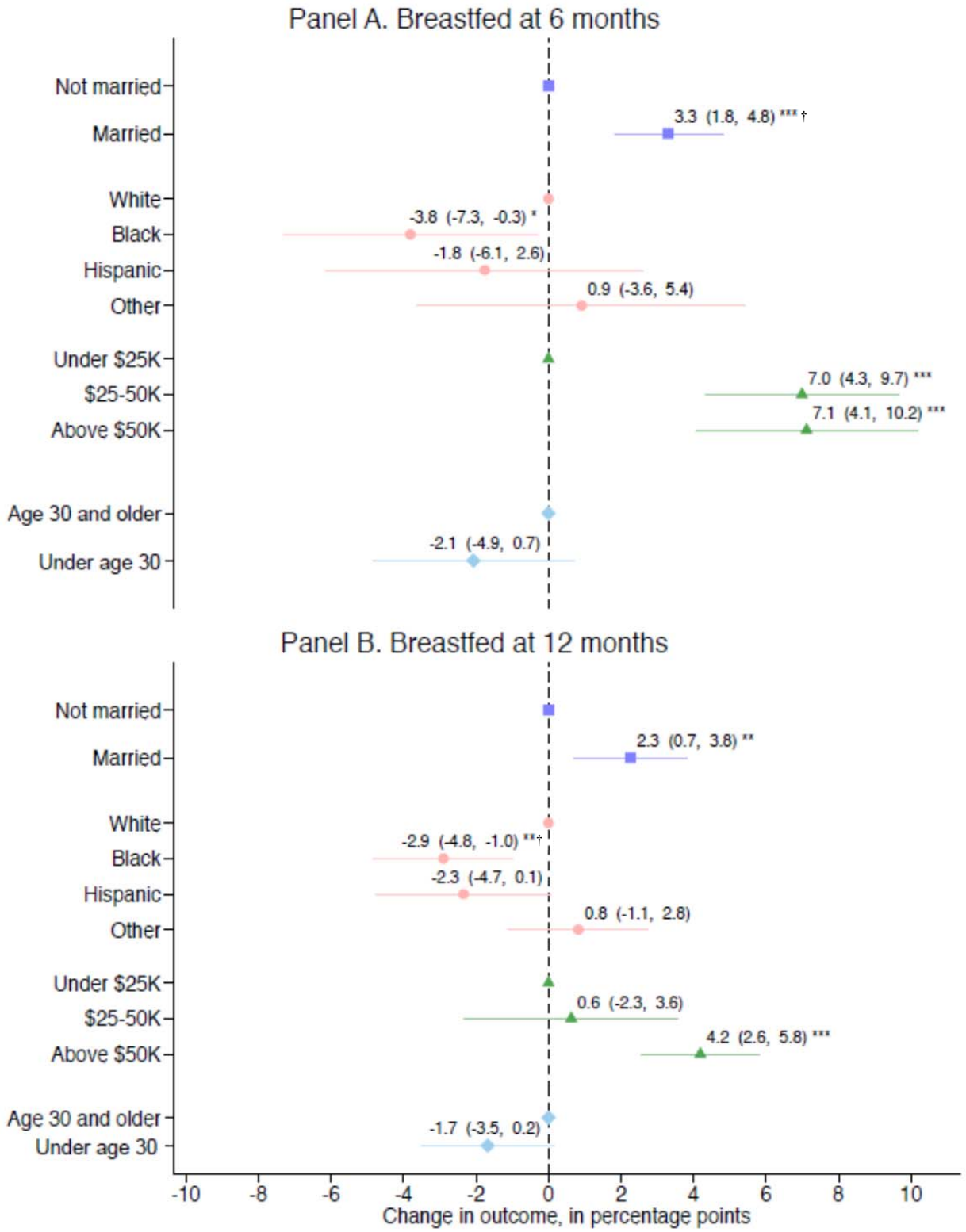
Supplemental Figure B. Trends in breastfeeding relative to PFL implementation (days)

Supplemental Figure C. Changes in ever and exclusive breastfeeding after state implementation of a paid family leave policy



* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$
† Joint F-test for addition of interaction terms, p-value < 0.05.
Note: This figure uses 2003-2015 National Immunization Survey data (N=306,266) to show the change in breastfeeding outcomes after a treatment state passed a PFL. These difference-in-differences estimates are based on multivariable regression models with state fixed effects, fully adjusted for covariates. Error bars represent 95% CI, clustered at the state level. Full results are in Supplemental Tables C, D, E, and F.

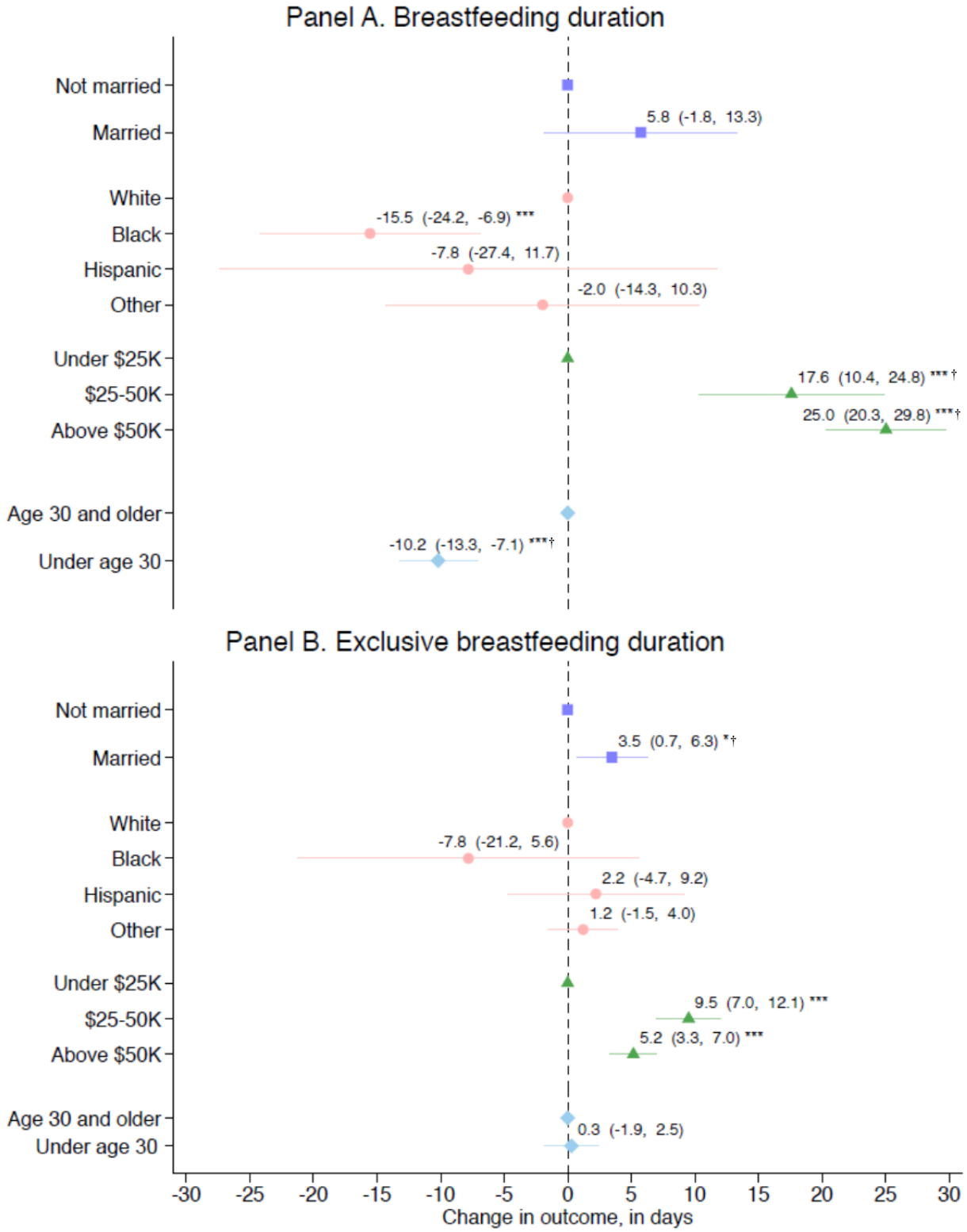
Supplemental Figure D. Changes in long-term breastfeeding practices after state implementation of a paid family leave policy



* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$
† Joint F-test for addition of interaction terms, p-value < 0.05.

Note: This figure uses 2003-2015 National Immunization Survey data (N=306,266) to show the change in breastfeeding outcomes after a treatment state passed a PFL. These difference-in-differences estimates are based on multivariable regression models with state fixed effects, fully adjusted for covariates. Error bars represent 95% CI, clustered at the state level. Full results are in Supplemental Tables C, D, E, and F.

Supplemental Figure E. Changes in breastfeeding duration after state implementation of a paid family leave policy



breastfeeding outcomes after a treatment state passed a PFL. These difference-in-differences estimates are

based on multivariable regression models with state fixed effects, fully adjusted for covariates. Error bars represent 95% CI, clustered at the state level. Full results are in Supplemental Tables C, D, E, and F.

Supplemental Table A. Sample characteristics

	California		New Jersey		All Other States	
	N = 10,030		N = 6,370		N = 289,866	
Variables	Mean/%	SD	Mean/%	SD	Mean/%	SD
Panel A. Socio-demographic characteristics						
Child female (%)	48.8%		48.3%		48.7%	
Child's age (months) (%)						
19 to 23	28.7%		29.6%		29.7%	
24 to 29	37.4%		36.4%		33.6%	
30 to 35	33.9%		34.0%		36.7%	
Mother's age under 30 (%)	34.4%		31.5%		37.4%	
Mother married (%)	74.2%		69.5%		73.2%	
Mother's education (%)						
Less than high school	18.2%		11.4%		11.2%	
High school	20.1%		22.5%		20.8%	
Some college	20.5%		18.9%		24.2%	
College graduate	41.2%		47.2%		43.8%	
Race (%)						
White	31.6%		43.0%		59.8%	
Black	4.3%		17.5%		11.8%	
Hispanic	46.4%		28.5%		18.4%	
Other	17.7%		11.0%		10.0%	
Family income (%)						
$25,000 or less	29.8%		26.5%		24.6%	
$25,001-50,000	19.7%		17.3%		22.9%	
More than $50,000	50.5%		56.2%		52.5%	
Number of people in household	4.57	1.38	4.38		4.45	1.32
Born after paid family leave policy (%)	58.8%		24.7%		-	-
Panel B. Breastfeeding outcomes						
Ever breastfed (%)	87.4%		74.9%		77.0%	
Exclusively breastfeeding at 3 mos. (%)	51.3%		37.0%		42.1%	
Exclusively breastfeeding at 6 mos. (%)	23.0%		15.8%		18.1%	
Still breastfeeding at 6 mos. (%)	58.6%		44.3%		46.2%	
Still breastfeeding at 12 mos. (%)	30.1%		20.6%		22.3%	
Duration of breastfeeding (days)	237.0	199.5	174.4	185.6	183.2	187.3
Duration of exclusive breastfeeding (days)	88.0	83.7	64.4	80.2	73.3	82.1

Note: Sample includes mothers and children from the 2003-2015 waves of the U.S. National Immunization Survey.

Supplemental Table C. Difference-in-differences analysis by marital status, with state fixed effects

	Ever breastfed	Exclusively BF at 3 mos.	Exclusively BF at 6 mos.	Breastfed at 6 mos.	Breastfed at 12 mos.	Breastfeeding duration	Exclusive BF duration
CA/NJ × postpolicy × married	-0.0082	0.025*	0.016**	0.033***	0.023**	5.75	3.48*
	[-0.045, 0.029]	[0.0027, 0.048]	[0.0051, 0.028]	[0.018, 0.048]	[0.0069, 0.038]	[-1.82, 13.3]	[0.71, 6.25]
CA/NJ × postpolicy	0.0094	-0.027	0.00067	-0.018**	-0.0094*	-4.76	-2.67
	[-0.053, 0.072]	[-0.10, 0.048]	[-0.013, 0.014]	[-0.030, -0.0063]	[-0.016, -0.0023]	[-18.3, 8.79]	[-12.1, 6.76]
CA/NJ × married	0.061**	0.067***	0.018	0.054***	0.031*	19.7***	9.34***
	[0.020, 0.10]	[0.056, 0.078]	[-0.0098, 0.045]	[0.032, 0.077]	[0.0053, 0.056]	[14.0, 25.4]	[6.12, 12.6]
Mother married	0.12***	0.11***	0.059***	0.13***	0.080***	54.3***	21.4***
	[0.087, 0.15]	[0.089, 0.14]	[0.042, 0.075]	[0.11, 0.16]	[0.064, 0.096]	[46.6, 61.9]	[17.4, 25.3]
Joint F-test (p-value)	< 0.01	< 0.01	0.07	0.02	0.11	0.01	< 0.01
Observations	277,930	268,529	268,529	264,678	264,678	264,678	268,529

*** p<0.001, ** p<0.01, * p<0.05

95% CI in brackets. Analyses were conducted using difference-in-differences linear models. Models adjusted for child age, race, and gender; maternal age and educational attainment; household size and income; and state-level education levels, unemployment rate, and gross domestic product per capita. All models also included indicator variables for year to adjust for secular trends and fixed effects for state. Robust standard errors clustered by state.

Supplemental Table D. Difference-in-differences analysis by race with state fixed effects

	Ever breastfed	Exclusively BF at 3 mos.	Exclusively BF at 6 mos.	Breastfed at 6 mos.	Breastfed at 12 mos.	Breastfeeding duration	Exclusive BF duration
CA/NJ × postpolicy × Black	-0.026	-0.049	-0.022	-0.038*	-0.029**	-15.5***	-7.80
	[-0.078, 0.026]	[-0.15, 0.049]	[-0.051, 0.0072]	[-0.073, -0.0030]	[-0.048, -0.0097]	[-24.2, -6.91]	[-21.2, 5.60]
CA/NJ × postpolicy × Hispanic	-0.0054	-0.0091	0.023***	-0.018	-0.023	-7.81	2.22
	[-0.034, 0.024]	[-0.054, 0.035]	[0.012, 0.034]	[-0.061, 0.026]	[-0.047, 0.00053]	[-27.4, 11.7]	[-4.70, 9.15]
CA/NJ × postpolicy × Other	-0.026*	-0.0059	0.015	0.0092	0.0083	-1.96	1.22
	[-0.051, -0.0013]	[-0.025, 0.013]	[-0.0086, 0.039]	[-0.036, 0.054]	[-0.011, 0.028]	[-14.3, 10.3]	[-1.51, 3.95]
CA/NJ × postpolicy	0.017	0.017	0.0070*	0.027*	0.028***	9.18	1.79
	[-0.035, 0.068]	[-0.054, 0.088]	[0.0015, 0.012]	[0.0018, 0.051]	[0.014, 0.041]	[-5.88, 24.2]	[-7.69, 11.3]
CA/NJ × Black	-0.038	0.011	0.013*	-0.0057	0.014	1.36	1.83
	[-0.11, 0.031]	[-0.050, 0.071]	[0.00054, 0.025]	[-0.11, 0.097]	[-0.016, 0.043]	[-30.2, 32.9]	[-6.05, 9.71]
CA/NJ × Hispanic	0.029	0.034*	0.014	0.026	0.036*	14.0	5.96
	[-0.0011, 0.059]	[0.0028, 0.064]	[-0.025, 0.053]	[-0.0058, 0.059]	[0.0051, 0.067]	[-0.065, 28.1]	[-0.65, 12.6]
CA/NJ × Other	-0.0038	0.035	-0.0063	0.014	0.021	8.93	3.02
	[-0.023, 0.015]	[-0.0058, 0.077]	[-0.044, 0.031]	[-0.014, 0.041]	[-0.015, 0.058]	[-3.08, 20.9]	[-4.74, 10.8]
Race (ref: White)							
Black	-0.11***	-0.081***	-0.019	-0.026	-0.022	-26.3***	-13.6***
	[-0.16, -0.065]	[-0.11, -0.047]	[-0.040, 0.00065]	[-0.061, 0.0090]	[-0.045, 0.0019]	[-40.0, -12.5]	[-18.9, -8.22]
Hispanic	0.074***	0.090***	0.0038	0.062**	0.038*	25.0***	9.06***
	[0.036, 0.11]	[0.056, 0.12]	[-0.016, 0.024]	[0.028, 0.095]	[0.0061, 0.069]	[11.1, 38.9]	[4.42, 13.7]
Other	-0.023	-0.015	0.0098	0.019	0.041	5.04	-0.98
	[-0.057, 0.0100]	[-0.051, 0.021]	[-0.020, 0.039]	[-0.018, 0.055]	[-0.00096, 0.083]	[-13.1, 23.2]	[-7.13, 5.16]
Joint F-test (p-value)	< 0.01	< 0.01	< 0.01	0.18	< 0.01	0.06	0.26
Observations	277,930	268,529	268,529	264,678	264,678	264,678	268,529

*** p<0.001, ** p<0.01, * p<0.05

95% CI in brackets. Analyses were conducted using difference-in-differences linear models. Models adjusted for child age and gender; maternal age, marital status, and educational attainment; household size and income; and state-level education levels, unemployment rate, and gross domestic product per capita. All models also included indicator variables for year to adjust for secular trends and fixed effects by state. Robust standard errors clustered by state.

Supplemental Table F. Difference-in-differences analysis by maternal age with state fixed effects

	Ever breastfed	Exclusively BF at 3 mos.	Exclusively BF at 6 mos.	Breastfed at 6 mos.	Breastfed at 12 mos.	Breastfeeding duration	Exclusive BF duration
CA/NJ × postpolicy × age < 30	-0.017	0.0025	0.0066	-0.021	-0.017	-10.2***	0.30
	[-0.048, 0.013]	[-0.013, 0.018]	[-0.0028, 0.016]	[-0.049, 0.0071]	[-0.035, 0.0015]	[-13.3, -7.11]	[-1.86, 2.45]
CA/NJ × postpolicy	0.0097	-0.0075	0.010***	0.013*	0.012	2.80	0.069
	[-0.015, 0.034]	[-0.071, 0.056]	[0.0049, 0.016]	[0.0016, 0.025]	[-0.0031, 0.027]	[-4.87, 10.5]	[-8.04, 8.18]
CA/NJ × age under 30	-0.027*	-0.027	-0.0075	-0.029**	-0.024	-11.4	-4.57
	[-0.051, -0.0021]	[-0.057, 0.0026]	[-0.040, 0.025]	[-0.048, -0.010]	[-0.060, 0.011]	[-25.6, 2.85]	[-10.3, 1.13]
Age under 30	-0.0034	-0.018	-0.023*	-0.042**	-0.041***	-24.8***	-5.71**
	[-0.027, 0.020]	[-0.040, 0.0042]	[-0.040, -0.0053]	[-0.067, -0.016]	[-0.062, -0.021]	[-35.3, -14.3]	[-9.83, -1.59]
Joint F-test (p-value)	0.15	< 0.01	0.18	0.85	0.64	< 0.01	0.98
Observations	277,930	268,529	268,529	264,678	264,678	264,678	268,529

*** p<0.001, ** p<0.01, * p<0.05

95% CI in brackets. Analyses were conducted using difference-in-differences linear models. Models adjusted for child age, race, and gender; maternal age and educational attainment; household size and income; and state-level education levels, unemployment rate, and gross domestic product per capita. All models also included indicator variables for year to adjust for secular trends and fixed effects by state. Robust standard errors clustered by state.

Supplemental Table G. Difference-in-differences analysis by state, with state fixed effects

	Ever breastfed	Exclusively BF at 3 mos.	Exclusively BF at 6 mos.	Breastfed at 6 mos.	Breastfed at 12 mos.	Breastfeeding duration	Exclusive BF duration
Panel A: California							
CA × postpolicy	-0.016***	-0.041***	0.016***	0.0066	0.0037	-4.14***	-4.17***
	[-0.022, -0.0096]	[-0.051, -0.031]	[0.011, 0.021]	[-0.0024, 0.016]	[-0.0017, 0.0090]	[-7.19, -1.08]	[-5.72, -2.61]
Observations	272,402	263,338	263,338	259,491	259,491	259,491	263,338
Panel B: New Jersey							
NJ × postpolicy	0.036***	0.049***	0.0073**	0.0074	0.016***	6.90***	7.14***
	[0.028, 0.045]	[0.041, 0.057]	[0.0024, 0.012]	[-0.0027, 0.017]	[0.0097, 0.023]	[3.15, 10.6]	[5.76, 8.52]
Observations	269,001	260,220	260,220	256,520	256,520	256,520	260,220

*** p<0.001, ** p<0.01, * p<0.05

95% CI in brackets. Analyses were conducted using difference-in-differences linear models. Models adjusted for child age, race, and gender; maternal age, marital status, and educational attainment; household size and income; and state-level education levels, unemployment rate, and gross domestic product per capita. All models also included indicator variables for year to adjust for secular trends and state fixed effects. Robust standard errors clustered by state.

Supplemental Table I. Difference-in-differences analysis, pooled ordinary least squares analysis

	Ever breastfed	Exclusively BF at 3 mos.	Exclusively BF at 6 mos.	Breastfed at 6 mos.	Breastfed at 12 mos.	Breastfeeding duration	Exclusive BF duration
CA/NJ × postpolicy	0.060	0.070	0.050***	0.085***	0.059**	31.5*	12.8
	[-0.0023, 0.12]	[-0.025, 0.17]	[0.031, 0.070]	[0.040, 0.13]	[0.023, 0.095]	[6.67, 56.4]	[-1.12, 26.8]
Observations	277,930	268,529	268,529	264,678	264,678	264,678	268,529

*** p<0.001, ** p<0.01, * p<0.05

95% CI in brackets. Analyses were conducted using difference-in-differences linear models. Models adjusted for child age, race, and gender; maternal age, marital status, and educational attainment; household size and income; and state-level education levels, unemployment rate, and gross domestic product per capita. All models also included indicator variables for year to adjust for secular trends. Robust standard errors clustered by state.