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Supplementary Appendix

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1. Background

Maternal diet is a well-studied risk factor for a wide range of perinatal complications.[1-5] For example, overconsumption of carbohydrates have been shown to increase the risk of gestational diabetes mellitus (GDM),[6, 7] while excess sugar consumption increases the risk of gestational weight gain (GWG), doubles the odds of having an infant born small-for-gestational age, and increases the risk of preeclampsia, gestational hypertension, and preterm birth by nearly one quarter.[8-11]

More specifically, a growing knowledge base highlights the adverse health effects sugar-sweetened-beverages (SSBs) consumption not only in the general population,[12] but also among pregnant individuals and their offspring. In a prospective cohort study of nearly 14,000 women, investigators found that mothers who consumed ≥5 servings per week of soft drinks had 22% greater GDM risk, while other cohort studies have also identified SSBs as an independent risk factor of GDM.[13] A second study conducted among Norwegian women found that each 100 ml intake of SSB was associated with a 7.8 g decrease in birthweight. [14] Additionally, SSB consumption has been shown to be associated with increased risk of preterm delivery, preeclampsia, and gestational hypertension in several recently published studies.[8, 15, 16] Approximately 20% of pregnant individuals consume SSBs at least once per day, yet to our knowledge, little evidence exists of the health effects of dietary interventions aimed at reducing

SSB consumption, including population-level interventions like SSB taxes. Pregnancy is a time-limited period during which nutrition policies can have observable health effects, as well as implications for later-life outcomes, [17] and therefore, this study aims to address these knowledge gaps.

2. Sample Selection

As of December 31, 2019, excise taxes on SSBs had been levied in seven US cities: Berkeley, Oakland, Albany, San Francisco, Seattle, Philadelphia, and Boulder. In the National Center for Health Statistics (NCHS) national birth certificate database, relatively complete data were available for five cities with an SSB tax (San Francisco, Oakland, Berkeley, Philadelphia, Seattle). The birth data files include city of residence only for pregnant individuals residing in large cities (≥100,000 population). Therefore, we could not identify pregnant individuals residing in the smaller tax-exposed cities of Boulder or Albany, and these cities were consequently excluded from the analysis. Cook County implemented an SSB tax for 2 months in 2017, and so, individuals in Cook County were also excluded from the study sample. Additionally, prior to 2013, several key variables, including gestational diabetes mellitus (GDM) and gestational hypertension, had a high degree of missingness (>10%). For this reason, we restricted our sample to births between January 1, 2013, and December 31, 2019. To ensure that infants were born with a plausible birthweight for gestational age, we excluded infants with birth-weight-for-gestational-age more than 3 standard deviations from the mean (Appendix Figure 1).[18] Lastly, to ensure our panel was balanced, birthing individuals residing in Berkeley 12 to 19 quarters after SSB tax implementation (Q1 2013), and birthing individuals from comparator cities that were not represented across all quarters, were excluded from analysis. Overall, 5.0% of pregnant individuals in our sample lived in an intervention city, and 95.0% in a comparator city.

3. Exposure Classification

Month and year of birth are reported in the NCHS national birth certificate database; however, day of birth is excluded to protect confidentiality. We were nevertheless able to accurately define the child's quarter of birth and pregnant individual's quarter of delivery, and we therefore used this measure along with the quarter and year of tax implementation in each of the five cities with an SSB tax to define before- and after-SSB tax periods, as well as exposure to an SSB tax. Pregnant individuals were categorized as before-SSB tax if their delivery date fell before the year-quarter of SSB tax implementation in the individual's city of residence, and after-SSB tax thereafter. Among pregnant individuals residing in SSB taxed cities, exposure to an SSB tax was set to 1 if the pregnant individual's quarter and year of delivery fell on or after the quarter and year of SSB tax implementation in their city of residence.

4. Differences-in-Differences Analysis

Growing economics literature suggests that standard difference-in-differences (DiD) models may suffer from bias in the presence of variation in treatment timing, such as staggered adoption of interventions.[19-24] Goodman-Bacon showed that standard DiD estimates can be decomposed into a weighted average of all possible 2×2 DiD estimates comparing each combination of groups (e.g., never-adopters vs. early adopters, early adopters vs. late adopters). This weighted average includes the "forbidden" comparison of already-treated groups as a comparator, potentially biasing estimates in the presence of heterogeneous treatment effects r.[19] Other studies have noted

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that the implicit assumption of homogeneous treatment effects in two-way fixed effects DiD models and associated event studies may lead to estimates putting negative weight on long-run lags under differential treatment timing.[20, 21] The DiD approach developed by Callaway and Sant'Anna (CS), one of the leading recently developed methods to address the potential biases that occur with standard DiD in the presence of treatment timing variation.[25] The CS DiD approach has also been shown to require weaker assumptions than certain alternatives, including the imputation-based difference-in-differences approach by Borusyak, Jaravel, and Spiess.[26] Further, the CS DiD approach is able to incorporate a "doubly robust" approach that can help meet the so-called parallel trends assumption of DiD analysis. We, therefore, have used the doubly robust version of the CS DiD estimator as our primary estimation strategy.

We estimate the models as linear regressions because of their ability to handle large numbers of fixed effects and interaction terms.[27] Logistic models with fixed effects suffer from the "incidental parameters problem," in which the number of dummy variables increases directly with the sample size, violating one of the conditions that underlie asymptotic theory of maximum likelihood estimation.[28, 29] We express DiD estimates as risk differences as well as average percent changes before- and after-tax, calculated as the DiD estimate divided by the average pre-tax outcome of individuals in the tax-exposed group.[30-32]

As with standard DiD models, the CS DiD estimator assumes parallel outcome trends between treated and untreated units and no anticipation effects (i.e., no differential changes in outcomes for treated units prior to the intervention going into effect). We conducted event-study difference-in-difference models, described below in Section 5, to test parallel pre-trends as suggestive evidence of this assumption. The results are noted in Figure 1 and Appendix Figure 2 in the main text.

A second assumption in DiD analysis is that no unobserved factors differentially influenced outcome trends between intervention and control groups. It is not possible to directly test this counterfactual scenario. To gather indirect support for this assumption, we conducted placebo tests of whether placebo outcomes changed contemporaneously with SSB tax implementation (see Section 8 below). We also examined whether there were differences in key covariates between pre- and post-SSB tax implementation among tax-exposed versus tax-unexposed pregnant individuals. We did not find large differences between groups (Table 1). Further, we adjusted for the observed characteristics in our regression models to reduce the chance of confounding.

5. Event Studies

We generated balanced event-study plots from the CS DiD estimators for perinatal outcomes by quarter to assess for parallel trends in perinatal outcomes of interest pre-SSB tax adoption using all available units. The event-study plots are shown in Figure 1 and Appendix Figure 2 and described in the main text.

Although we did not find a statistically significant association between SSB taxes and hypertensive disorders of pregnancy, event-study results revealed a decreasing risk of hypertensive disorders of pregnancy in later quarters (Appendix Figure 2). We did not find any significant post-tax trends for outcomes above, below and within recommended IOM gestational

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weight gain (GWG) recommendations, or other neonatal outcomes. Additionally, pre-trends appear to show some statistically significant control-intervention city differences for outcomes LGA, preterm birth, birthweight, and gestational age, potentially violating the parallel trends assumption. Estimates for these outcomes should, therefore, be interpreted cautiously, although none are significant in the main analyses.

6. Subgroup analyses

Using stratified analyses, we applied the same CS DiD methods outlined above to produce an estimate for changes in maternal and neonatal outcomes of interest pre- and post-SSB tax adoption among each sociodemographic subgroups of interest, omitting the stratifying variable from the covariate set in each regression. We also conducted event studies for each subgroup and outcome to assess parallel trends prior to tax implementation.

Results can be found in Figure 2 in the main text, Appendix Figure 3, and Appendix Figure 8. We found modest subgroup differences in the estimated associations between SSB taxes and some secondary outcomes; however event studies for some subgroups indicated imbalance between intervention and control cities prior to tax implementation, and therefore, those results should be interpreted cautiously. Future studies using larger subgroup sample sizes should be conducted to produce more reliable subgroup estimates.

7. Sensitivity analyses

Cohort-Specific Effects

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We did not find heterogenous effects across tax implementation date cohorts for secondary outcomes, except for SGA and hypertensive disorders of pregnancy. For SGA, Philadelphia and Seattle/San Francisco experienced significantly larger effects (Appendix Table 3, Appendix Figure 5), and Philadelphia had a significantly larger decrease in risk of hypertensive disorders of pregnancy compared to other cohorts. Cohort-specific effects for primary and secondary outcomes are shown in Appendix Table 3, Appendix Figure 4, and Appendix Figure 5.

Statistical Methods

To test the robustness of our results to alternate estimation strategies, we compared the main results from the CS difference-in-differences analyses to two other approaches. The first, a generalized difference-in-differences approach with two-way fixed-effects (TWFE) for unit and time, applied the multivariable linear regression model of outcome Y for pregnant person *i* living in city *c* in state *s* who gives birth in year-quarter *t*. We let $Policy_i$ equal 1 for pregnant individuals and infants exposed to a city-level SSB tax on and 0 otherwise, corresponding to the $Treat \times Post$ interaction term. We adjusted models for the vector of individual-level covariates outlined in the main text (X_i), including fixed effects for city (η_c), year-quarter (ρ_t), and state-by-year (π_{st}) to address fundamental sources of confounding, and clustered standard errors at the city level. The equation for our TWFE models is as follows:

$$Y_{icst} = \alpha + Policy_i + X_i + \eta_c + \rho_t + \pi_{st} + \varepsilon_{icst}$$

The second method was a difference-in-differences imputation approach designed for staggered policy adoption developed by Borusyak, Jaravel, and Spiess, (BJS).[21, 33] Like the CS difference-in-differences approach, the BJS approach avoids biases that occurs for TWFE DiD estimates in the presence of staggered adoption. The BJS estimator proceeds in three steps: 1) estimating expected potential outcomes using OLS using control units only, 2) imputing missing counterfactuals and calculating treatment effects using the coefficients in Step 1, and 3) estimating the DiD target parameter as a weighted sum of these imputation-based treatment effects. The BJS estimator is efficient among all linear unbiased estimators. Results from our DiD analyses are found in Appendix Table 1.

Overall, as shown in Appendix Figure 6 and Appendix Figure 7, all estimation approaches performed well in the pre-tax period, providing support for parallel pre-trends of the primary and secondary outcomes. In the post-implementation period, outcome trends varied somewhat across estimation approaches. The BJS models consistently produced implausibly narrow confidence intervals and very different point estimates. Because of this, we consider the BJS estimates to be unreliable. The CS and TWFE estimates were more similar, with TWFE frequently biased toward the null. This is the expected direction of the known bias in TWFE with variation in treatment timing, given the heterogeneous treatment effects over time. In general, the findings from the CS models are more consistent with the expected mechanistic pathways linking diet and sugar consumption to perinatal health outcomes (Appendix Figure 6, Appendix Figure 7).[11, 13, 34, 35 36, 37]

Census Division

We conducted another sensitivity analysis including only birthing individuals and live births from cities located in the Census Divisions where tax-exposed cities were located testing robustness of choice comparator cities. This included cities in six states - Washington, Oregon,

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California, New York, New Jersey, and Pennsylvania. Consistent with our primary analysis, we found an 18.5% decrease in GWG z-score (-0.35 standard deviations [SD]; 95%CI -0.62, -0.09). However, there were some findings that differed from those of our primary analysis including improvements in GWG below IOM recommendations, low birth weight, and infants born large for gestational age. Additionally, we found no significant improvements for GDM nor infants born SGA as in our primary analysis. Results for all outcomes can be found in Appendix Table 1. Despite these findings, cohort-specific results outlined in the main text and above provide evidence of heterogeneous effects across cohorts, with Philadelphia having the strongest treatment effects. For this reason, our findings from restricting our sample to Census Divisions where tax-exposed cities were located are not surprising. Lastly, qualitative assessment of parallel trends showed significant differences in outcome trends pre-SSB tax implementation for primary and secondary outcomes, potentially violating the parallel trends assumption of DiD. For this reason, results from this sensitivity analysis should be interpreted cautiously.

Date of conception

We conducted another sensitivity analysis for primary and secondary outcomes of interest defining pregnant individuals and infants as exposed if their date of conception was on or after the date of SSB tax implementation in their reported city of residence. This classification ensured that individuals in the exposed cohort were exposed to an SSB tax for their pregnancy's entirety only, and individuals who were partially exposed to an SSB tax during their pregnancy were excluded from the study sample. Date of conception was imputed by subtracting days of gestation from the reported birth date. Because only birth month and birth year are reported in birth data files to protect confidentiality, we assigned all birth dates to the first day of the month

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and year of birth, then subtracted the days of gestation from this date. Due to the inability to use CS models with date of conception as our exposure variable because it induces an unbalanced panel, we conducted this sensitivity analysis using TWFE estimation instead. Data excluded pregnant individuals who were exposed to an SSB tax for only part of their pregnancy, and for which exposure to an SSB tax was defined as residence in an SSB-taxes city on or after imputed quarter of conception (N=5,236,472).

Results from this TWFE model using date of conception were very similar to the overall TWFE model. For example, in both TWFE models, we found decreased risk of SGA and no significant findings for other outcomes of interest, with the exception of gestational age which was significant in the main TWFE model (Appendix Table 1).

Exclusion of San Francisco

Lastly, we conducted a sensitivity analysis excluding individuals in San Francisco from our study sample. A major hospital in San Francisco modified its GDM testing procedures from a one-step to a two-step diagnostic test in May 2016 and subsequently reverted to the one-step test in February 2018, altering the number of GDM cases detected.[38] Excluding pregnant people in San Francisco from GDM analyses, we found no association between SSB taxes and prevalence of GDM (-1.50 pp; 95% CI, -3.17 to 0.17), although the point estimate is of a similar magnitude as the primary analysis (Appendix Table 1).

8. Placebo test

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We conducted two “placebo” tests by examining the effect of the SSB tax on pre-pregnancy smoking status and marital status, both outcomes which are unlikely to be associated with SSB taxes. Pre-pregnancy smoking was included as a binary variable equal to 1 if an observation reported to have ever smoked cigarettes pre-pregnancy. Marital status was included in a separate model as a binary variable equal to 1 if an observation was married, and 0 otherwise. For these placebo tests, we would expect to find no effect of the SSB tax on outcomes in each model. Results support our hypotheses of no significant effects (Appendix Table 2), suggesting our findings are less likely to be attributable to time-varying confounding.

9. Main results (continued)

In the overall sample, we report an increase in GDM prevalence in tax-exposed cities following tax implementation in Table 2 of the main text; however, the national prevalence of GDM has increased by ≥4% over the last two decades, with a marked rise among non-White, overweight, and low-income groups.[77] Our interpretation of the crude means reported in Table 2 therefore, would be that the tax moderated the increase in GDM prevalence experienced in comparator cities (and nationally). It is also noteworthy that the crude (unadjusted) estimates in the first four columns in Table 2 do not adjust for observed confounders and fixed effects, as is reflected in the adjusted difference-in-differences estimates. It is, thus, possible that the crude estimates are subject to confounding bias.

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Appendix Table 1. Sensitivity analyses difference-in-differences estimates

	Full sample	Full sample	Full sample	Census Region	Quarter of conception	Omit San Francisco
	CS	TWFE	BJS	CS	TWFE	CS
Outcomes	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Primary outcomes						
Gestational diabetes, %	-2.22* (-4.22 to -0.22)	-0.90 (-2.23 to 0.43)	-0.62*** (-0.84 to -0.39)	0.61 (-1.80 to 3.02)	-1.18 (-2.37 to 0.07)	-1.50 (-3.17 to 0.17)
Weight-gain-for-gestational-age *z*-score	-0.15* (-0.28 to -0.01)	0.04 (-0.18 to 0.26)	0.55*** (0.49 to 0.61)	-0.35** (-0.58 to -0.13)	-0.08 (-0.26 to 0.10)	
Panel B. Secondary outcomes						
Hypertensive disorders of pregnancy, %	-1.63 (-3.30 to 0.05)	1.05 (-0.77 to 2.88)	0.60 (-0.14 to 1.35)	4.10** (0.98 to 7.22)	0.61 (-1.15 to 2.36)	
GWG 2009 IOM recommendations, %						
Below recommendations	-2.21 (-5.07 to 0.66)	-0.31 (-1.22 to 0.61)	-2.32*** (-2.65 to -1.98)	1.98 (-2.37 to 6.33)	0.02 (-0.99 to 1.03)	
Above recommendations	-0.39 (-4.13 to 3.36)	0.24 (-1.89 to 2.38)	5.11*** (4.46 to 5.75)	-8.15** (-13.37 to -2.94)	-1.09 (-3.25 to 1.07)	
Within recommendations	2.59 (-0.78 to 5.97)	0.06 (-1.30 to 1.42)	-2.79*** (-3.16 to -2.42)	6.17* (0.98 to 11.37)	1.07 (-0.28 to 2.42)	
Birthweight, grams	17.17 (-26.06 to 60.40)	4.15 (-9.79 to 18.09)	35.07*** (31.60 to 38.55)	-6.10 (-48.20 to 36.01)	5.85 (-2.35 to 14.06)	
Low birth weight, %	0.61 (-1.46 to 2.68)	-0.28 (-0.76 to 0.21)	-1.05*** (-1.20 to -0.89)	-2.09** (-3.54 to -0.65)	-0.15 (-0.60 to 0.30)	
Gestational age, weeks	-0.03 (-0.20 to 0.13)	-0.03* (-0.06 to -0.01)	0.02*** (0.02 to 0.03)	-0.07 (-0.20 to 0.06)	-0.02 (-0.04 to 0.00)	
Small for gestational age, %	-4.28*** (-6.49 to -2.06)	-0.65* (-1.15 to -0.15)	-1.64*** (-1.83 to -1.45)	-0.44 (-3.37 to 2.50)	-0.67*** (-1.06 to -0.29)	
Large for gestational age, %	0.47 (-1.52 to 2.45)	0.32 (-0.16 to 0.80)	1.36*** (1.19 to 1.53)	-2.50** (-4.14 to -0.86)	0.25 (-0.14 to 0.64)	
Preterm birth, %	0.59 (-1.60 to 2.77)	-0.03 (-0.35 to 0.29)	-0.69*** (-0.76 to -0.62)	-0.66 (-2.20 to 0.88)	0.00 (-0.27 to 0.27)	

Note: Regression coefficients with 95% confidence intervals in parentheses. Estimates for binary outcomes are expressed as percentage points. Models adjusted for race (non-Hispanic Black, non-Hispanic White, non-Hispanic Asian or Native Hawaiian and Other Pacific Islanders, non-Hispanic other race), ethnicity (Hispanic), maternal age (<25, 25-29, 30-34, 35+), education (some high school, diploma/GED, some college, college degree), parity (nulliparous, primiparous, multiparous), prepregnancy smoking status, and prepregnancy BMI (underweight, normal weight, overweight, obese). Gestational weight gain outcomes

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incorporated prepregnancy BMI into the outcome measure and did not adjust for it as a separate covariate. Model 1 is the primary CS difference-in-differences model reported in main manuscript, includes fixed effects for maternal city of residence and quarter of birth (N =5,324,548). Model 2 is a TWFE difference-in-differences model that includes fixed effects for maternal city of residence, quarter of birth, and state-by-birth-year (N=6,052,153). Model 3 is a BJS difference-in-differences model that includes fixed effects for maternal city of residence, quarter of birth, and state-by-birth-year (N= 6,017,090). Model 4 is a CS difference-in-differences model restricting the sample to birthing individuals residing in the Pacific and Mid-Atlantic Census Divisions, the same Census Divisions where tax-exposed cities were located (N= 2,613,135). Model 5 is a TWFE model classifying exposure to SSB taxes by quarter of conception (N= 5,236,464). Model 6 is a CS difference-in-differences model for gestational diabetes excluding birthing individuals from San Francisco (N= 5,261,859). Robust standard errors are clustered by maternal city of residence. Statistical significance: * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Abbreviations: Body mass index (BMI); Borusyak, Jaravel, and Spiess (BJS); Callaway-Sant'Anna (CS); General Educational Development (GED); Institute of Medicine (IOM); Two-way fixed effects (TWFE).

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Appendix Table 2. Difference-in-differences estimates for "placebo" outcomes

	Adjusted Difference-in-Differences Estimate [a]		
Outcomes	Coef. (95% CI)	*p*-value	Adjusted % change [b]
Prepregnancy cigarette use, %	1.91 (-0.19, 4.01)	0.075	32.14
Married, %	2.16 (-1.63, 5.95)	0.263	3.33

Note: Sample size restricted to observations with data on cigarette use (N=5,324,548).
[a] Estimates, expressed as percentage points for binary outcomes, from models adjusted for race (NH-Black, NH-White, NH-Asian/NHOPI, NH-other race), ethnicity (Hispanic), maternal age (<25, 25-29, 30-34, 35+), education (some high school, diploma/GED, some college, college degree), parity (nulliparous, primiparous, multiparous), and prepregnancy BMI (underweight, normal weight, overweight, obese), and fixed effects for maternal city of residence and quarter of birth.
[b] Percent change and difference-in-differences estimates are based on Callaway-Sant'Anna regression analyses. The percent change was calculated by dividing the difference-in-difference estimate by the average pre-tax outcome in the intervention city. The numerator represents the change in outcomes in the post-tax period compared with the pre-tax period controlling for secular trends using all large US cities without an SSB tax as a comparator.
Abbreviations: Body Mass Index (BMI); General Educational Development (GED); Non-Hispanic (NH), Native Hawaiians and Other Pacific Islanders (NHOPI).

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Appendix Table 3. Cohort-specific difference-in-differences estimates

Outcomes	Overall	Berkeley	Philadelphia	Oakland	Seattle / San Francisco
	Coef. (95% CI)				
Panel A. Primary outcomes					
Gestational diabetes, %	-2.22* (-4.22 to -0.22)	1.25 (-4.19 to 6.70)	-1.41 (-3.51 to 0.70)	-3.23 (-6.88 to 0.42)	-3.63 (-8.82 to 1.56)
Weight-gain-for-gestational-age *z*-score	-0.15* (-0.28 to -0.01)	0.23 (-0.07 to 0.53)	-0.43*** (-0.64 to -0.22)	0.20 (-0.01 to 0.41)	0.23* (0.04 to 0.41)
Panel B. Secondary outcomes					
Hypertensive disorders of pregnancy, %	-1.63 (-3.30 to 0.05)	0.72 (-3.89 to 5.33)	-3.90*** (-5.40 to -2.40)	1.26 (-2.44 to 4.96)	1.48 (-3.35 to 6.31)
GWG 2009 IOM recommendations, %					
Below recommendations	-2.21 (-5.07 to 0.66)	-4.47 (-13.05 to 4.11)	1.34 (-3.07 to 5.75)	-1.96 (-7.03 to 3.11)	-9.02*** (-12.98 to -5.05)
Above recommendations	-0.39 (-4.13 to 3.36)	7.93 (-2.50 to 18.35)	-3.21 (-8.40 to 1.98)	-1.24 (-6.68 to 4.19)	4.86 (-2.71 to 12.42)
Within recommendations	2.59 (-0.78 to 5.97)	-3.45 (-14.27 to 7.36)	1.87 (-2.47 to 6.20)	3.20 (-2.73 to 9.14)	4.16 (-3.33 to 11.65)
Birthweight, grams	17.17 (-26.06 to 60.40)	34.14 (-74.88 to 143.15)	13.33 (-51.98 to 78.65)	-57.34 (-123.26 to 8.58)	53.02 (-16.14 to 122.18)
Low birth weight, %	0.61 (-1.46 to 2.68)	-5.13** (-8.69 to -1.57)	0.81 (-2.36 to 3.98)	5.55* (0.60 to 10.50)	-1.37 (-4.20 to 1.45)
Gestational age, weeks	-0.03 (-0.20 to 0.13)	0.01 (-0.33 to 0.36)	-0.11 (-0.35 to 0.14)	-0.19 (-0.44 to 0.05)	0.17 (-0.09 to 0.42)
Small for gestational age, %	-4.28*** (-6.49 to -2.06)	1.84 (-5.97 to 9.65)	-4.90** (-8.26 to -1.54)	-0.36 (-4.84 to 4.12)	-5.03** (-8.26 to -1.81)
Large for gestational age, %	0.47 (-1.52 to 2.45)	-3.57 (-9.51 to 2.37)	0.88 (-2.30 to 4.05)	0.21 (-2.25 to 2.68)	0.04 (-2.52 to 2.60)
Preterm birth, %	0.59 (-1.60 to 2.77)	-4.49 (-9.02 to 0.04)	0.94 (-1.79 to 3.67)	1.94 (-1.72 to 5.60)	-0.30 (-5.35 to 4.74)

Note: Estimates are expressed as percentage points for binary outcomes. Models were adjusted for covariates race (NH-Black, NH-White, NH-Asian/NHOPI, NH-other race), ethnicity (Hispanic), maternal age (<25, 25-29, 30-34, 35+), education (some high school, diploma/GED, some college, college degree), parity (nulliparous, primiparous, multiparous), prepregnancy smoking status, prepregnancy BMI (underweight, normal weight, overweight, obese), and fixed effects for quarter of birth and city of residence. Statistical significance: * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Seattle and San Francisco combined due to shared quarter of SSB tax implementation. Abbreviations: Body Mass Index (BMI); General Educational Development (GED); Non-Hispanic (NH), Native Hawaiians and Other Pacific Islanders (NHOPI).

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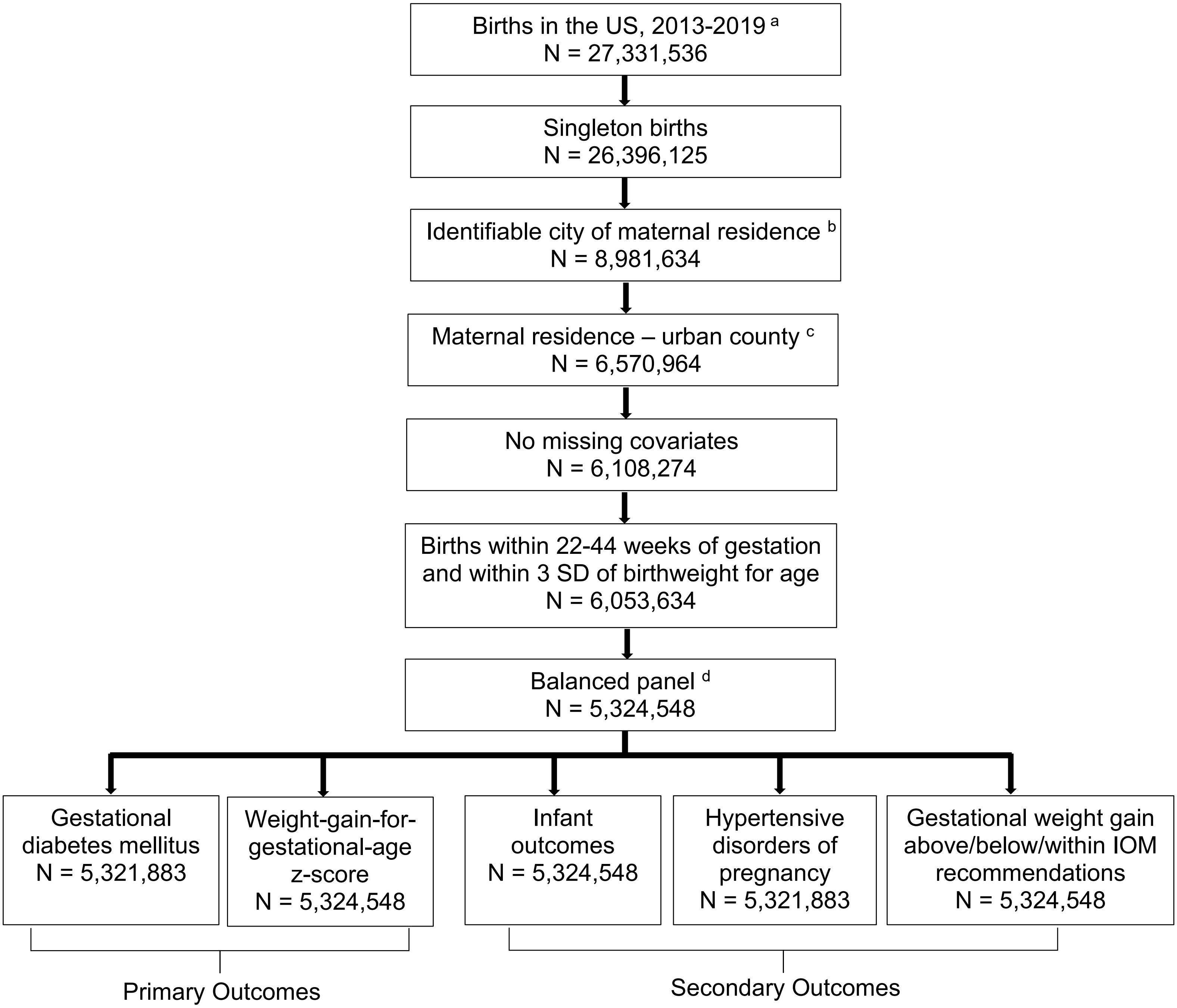
Appendix Figure 1. Sample Flowchart



Note: Data drawn from the National Center for Health Statistics national birth certificate database (2003-2019). Abbreviations: Institute of Medicine (IOM).
[a] Data available for all five SSB tax cities starting 2013.
[b] Maternal city of residence only available for cities with population >100,000.
[c] Excluding Cook County because its SSB tax was only implemented for two months in 2017.
[d] Birthing individuals residing in Berkeley 12 to 19 quarters post SSB tax implementation (Q1 2013), and birthing individuals from comparator cities which were not represented across all quarters were excluded from the final sample.

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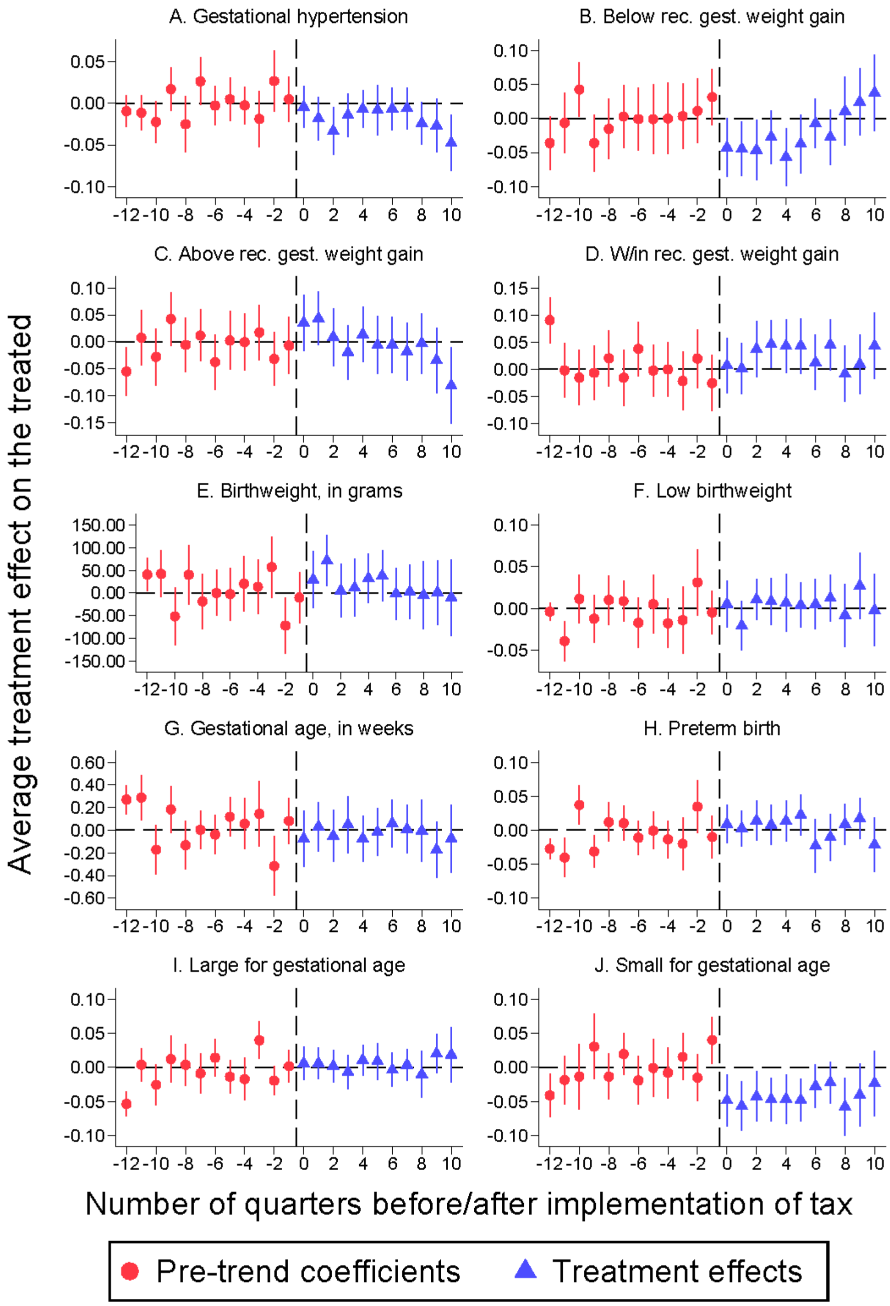
Appendix Figure 2. Time-varying association between sugar-sweetened beverage taxes and secondary health outcomes



Note: These plots of the time-varying differences in outcomes between those in SSB tax cities vs. comparator cities are estimated from Callaway-Sant'Anna event-study difference-in-differences regressions. Quarterly estimates are relative to the quarter just prior to SSB tax implementation (quarter -1, red dotted line). 95% confidence intervals calculated from robust standard errors.
Abbreviations: Recommended (rec); Within (w/in).

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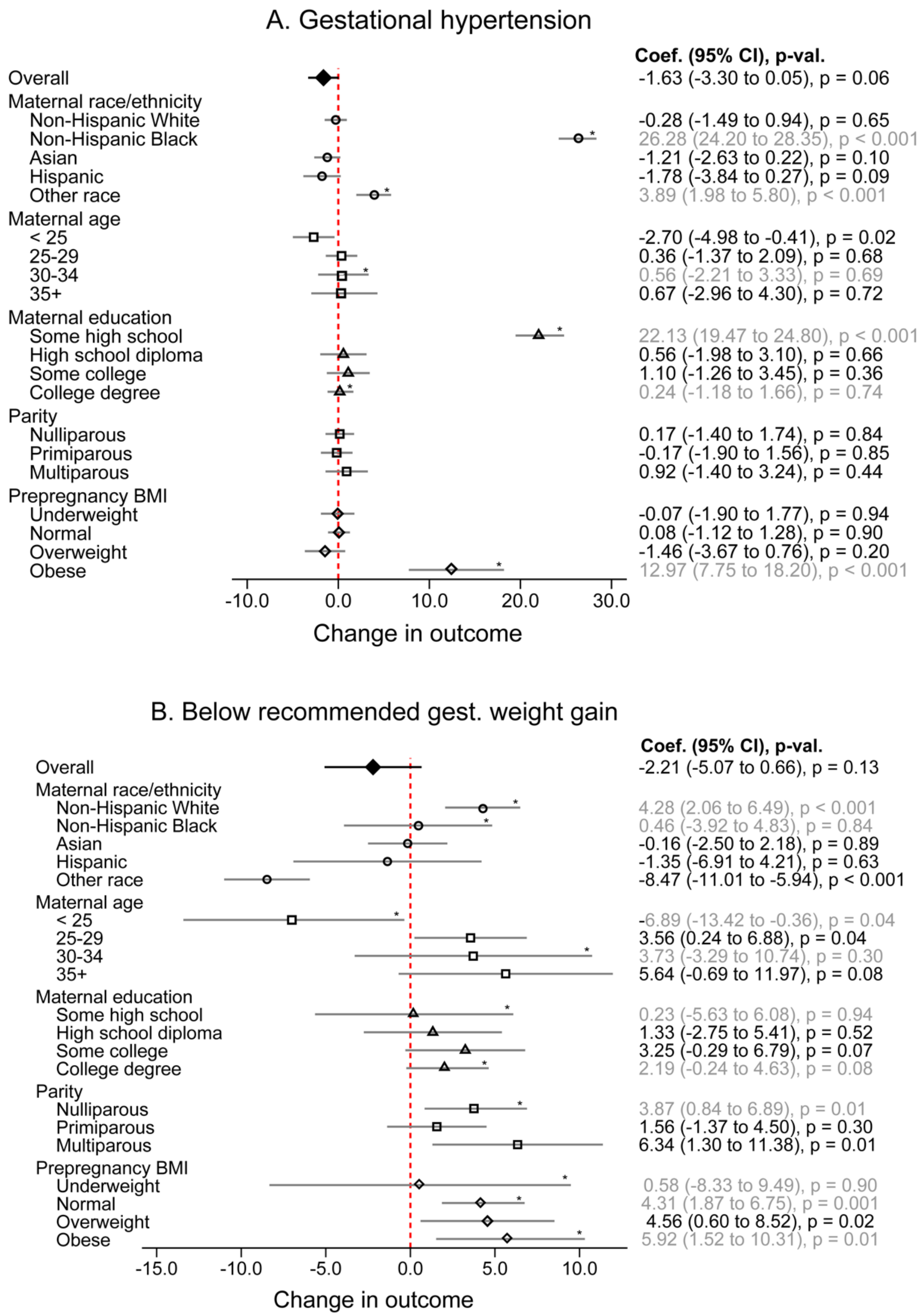
Appendix Figure 3. Associations between sugar-sweetened beverage taxes and secondary outcomes by population subgroup



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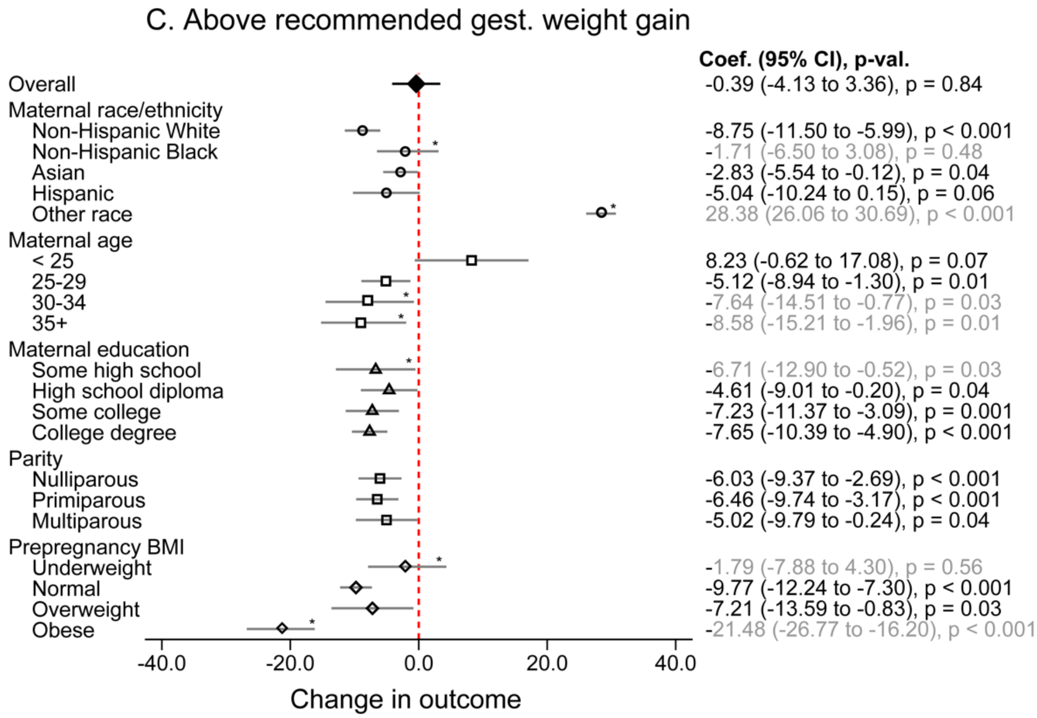

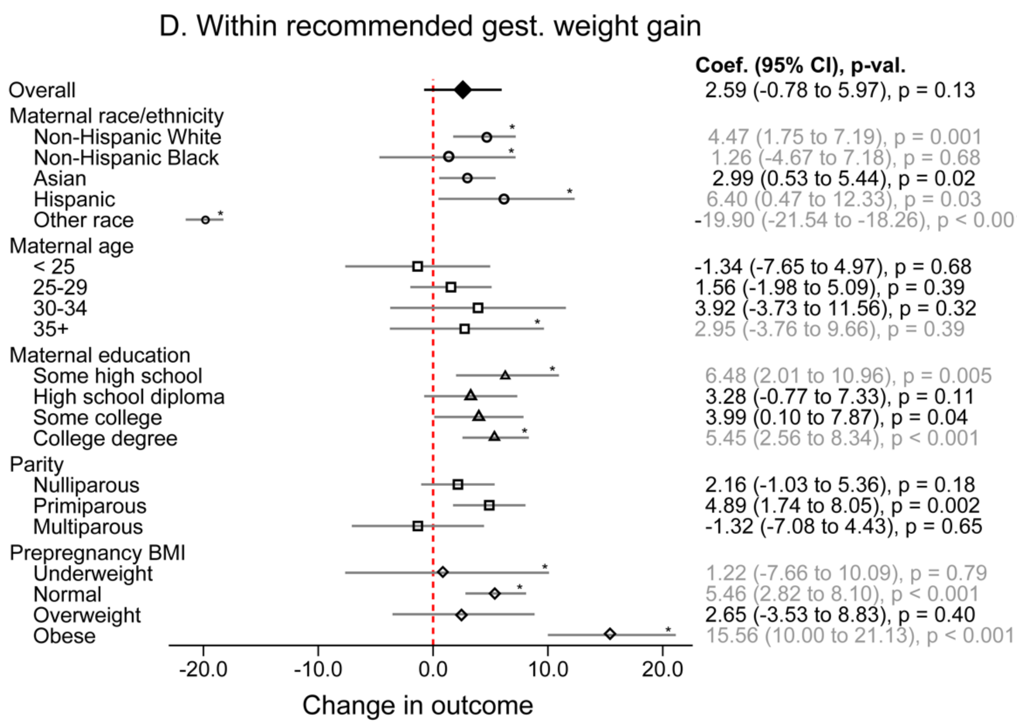

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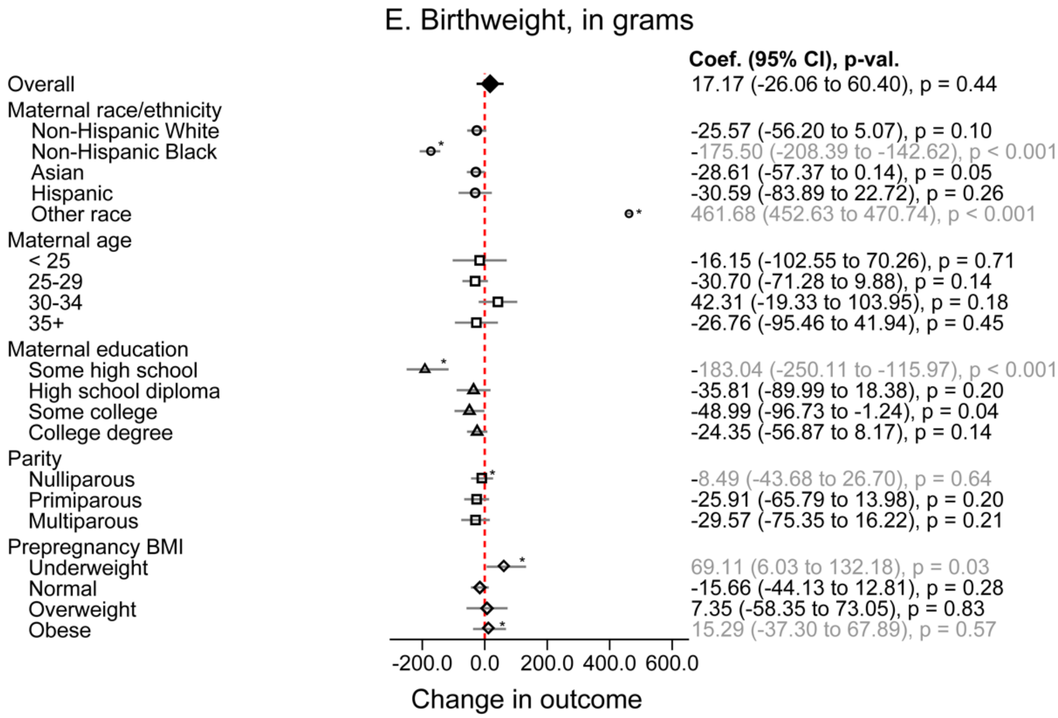

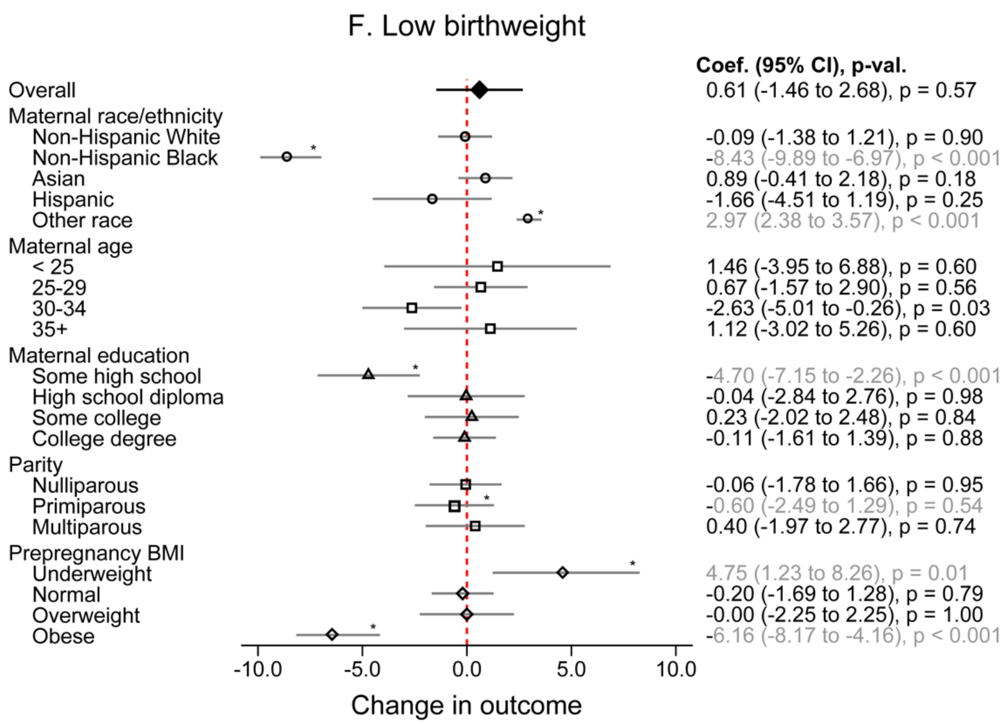

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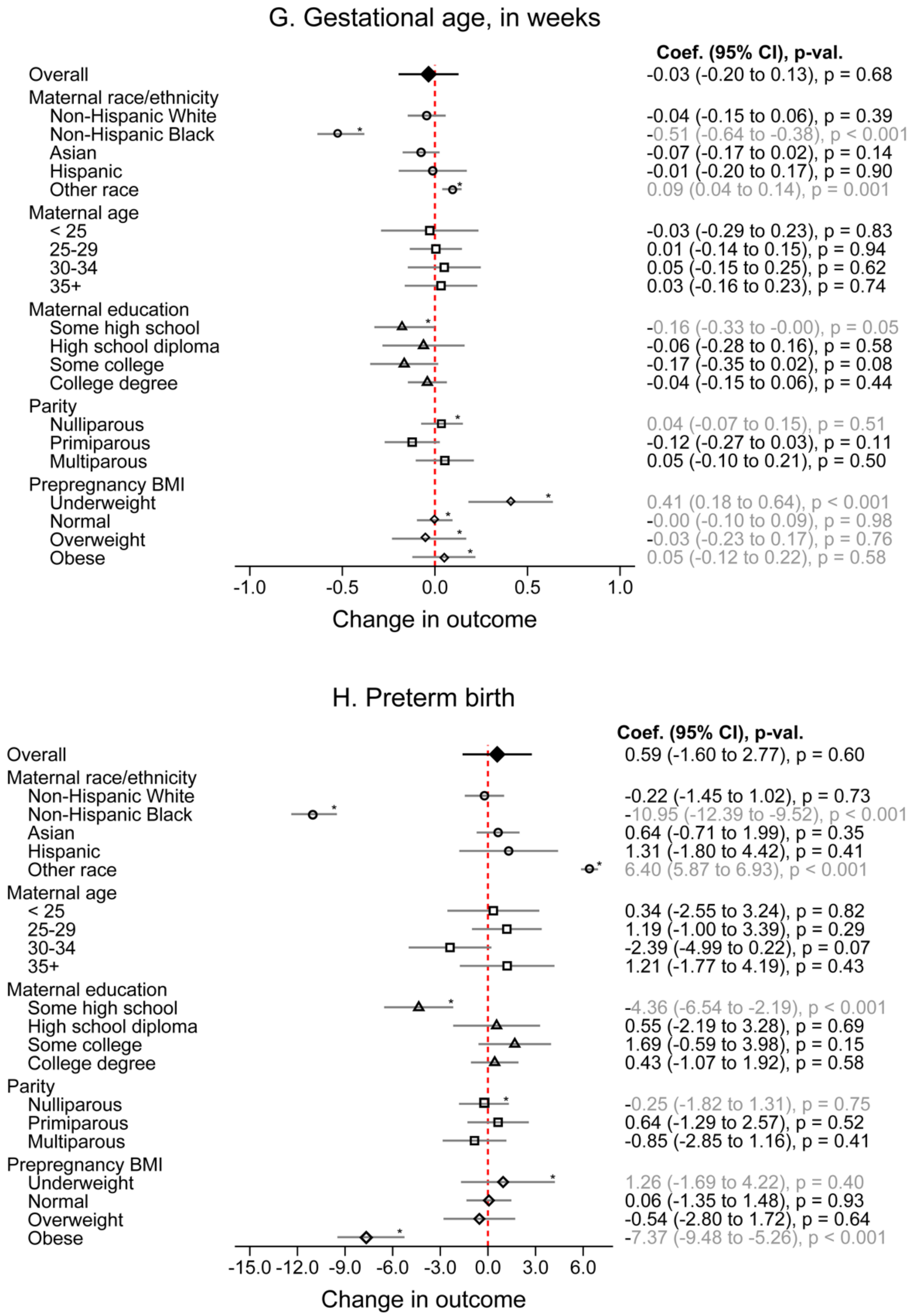

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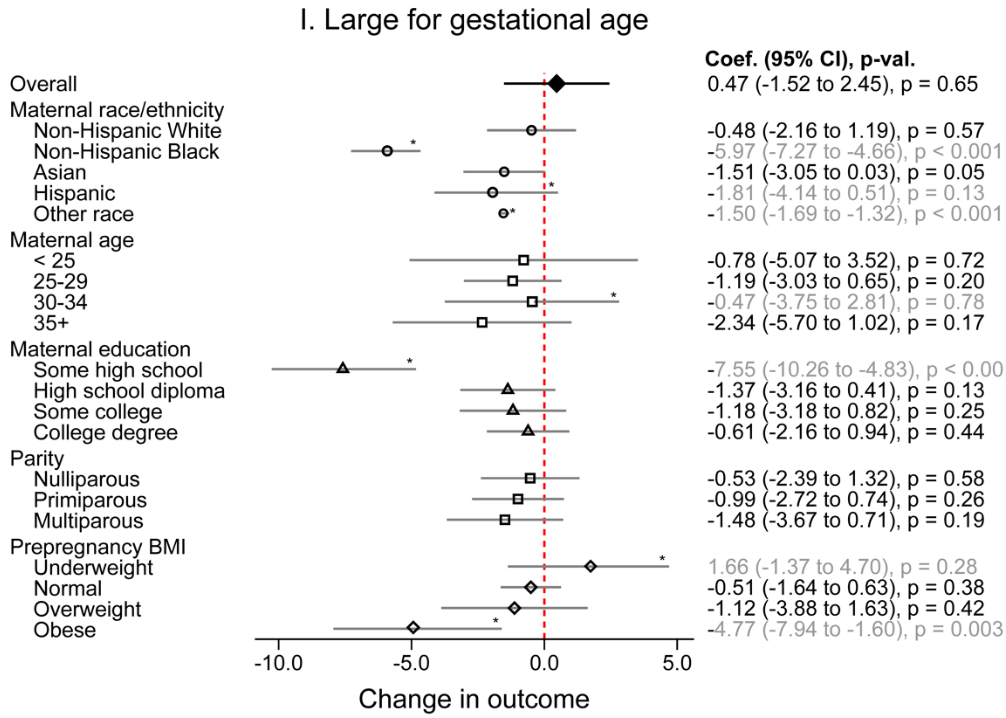

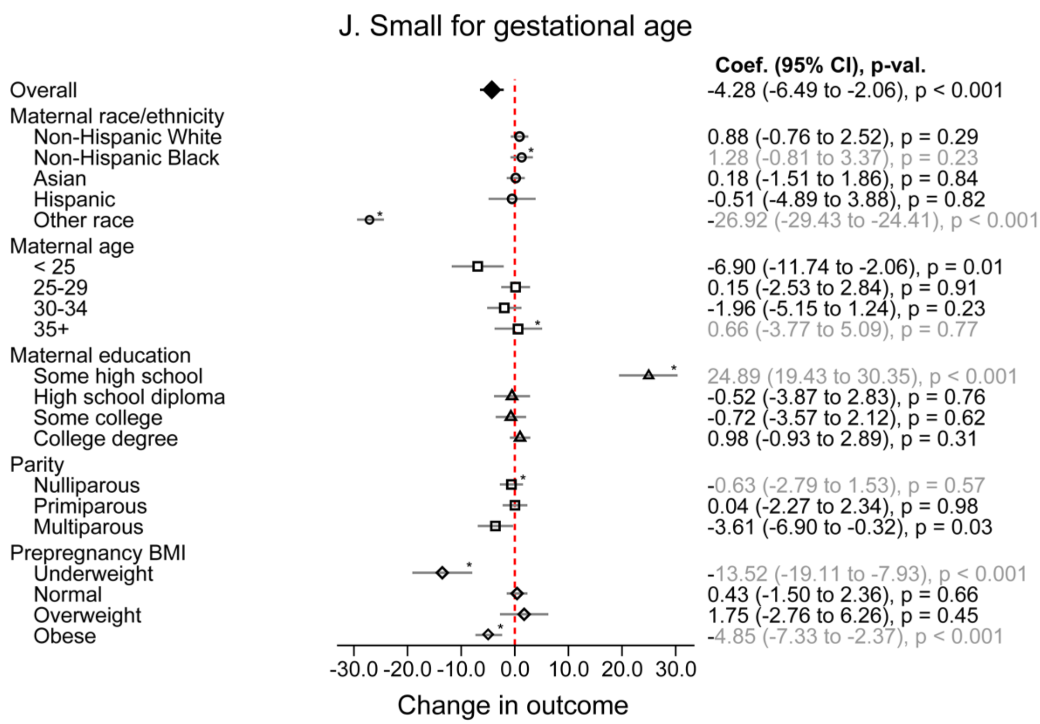

Note: Each row represents a Callaway-Sant'Anna difference-in-differences estimate from a separate regression, either using the full sample or stratifying by a population subgroup and adjusting for race and ethnicity (NH-Black, NH-White, NH-Asian/NHOPI, Hispanic, NH-other race), maternal age (<25, 25-29, 30-34, 35+), education (some high school, diploma/GED, some college, college degree), parity (nulliparous, primiparous, multiparous), prepregnancy smoking status, and prepregnancy BMI

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(underweight, normal weight, overweight, obese), and fixed effects for maternal city of residence and quarter of birth. Gestational weight gain-related outcomes excluded covariates for prepregnancy BMI. Estimated values written in light gray and with an asterisk (*) indicate imbalance during the pre-tax period (≥2 quarters with significant intervention-comparator differences at $p > 0.05$) and likely violate the "parallel trends assumption" required for valid inference.
Abbreviations: Body Mass Index (BMI); General Educational Development (GED); Non-Hispanic (NH), Native Hawaiians and Other Pacific Islanders (NHOPI).

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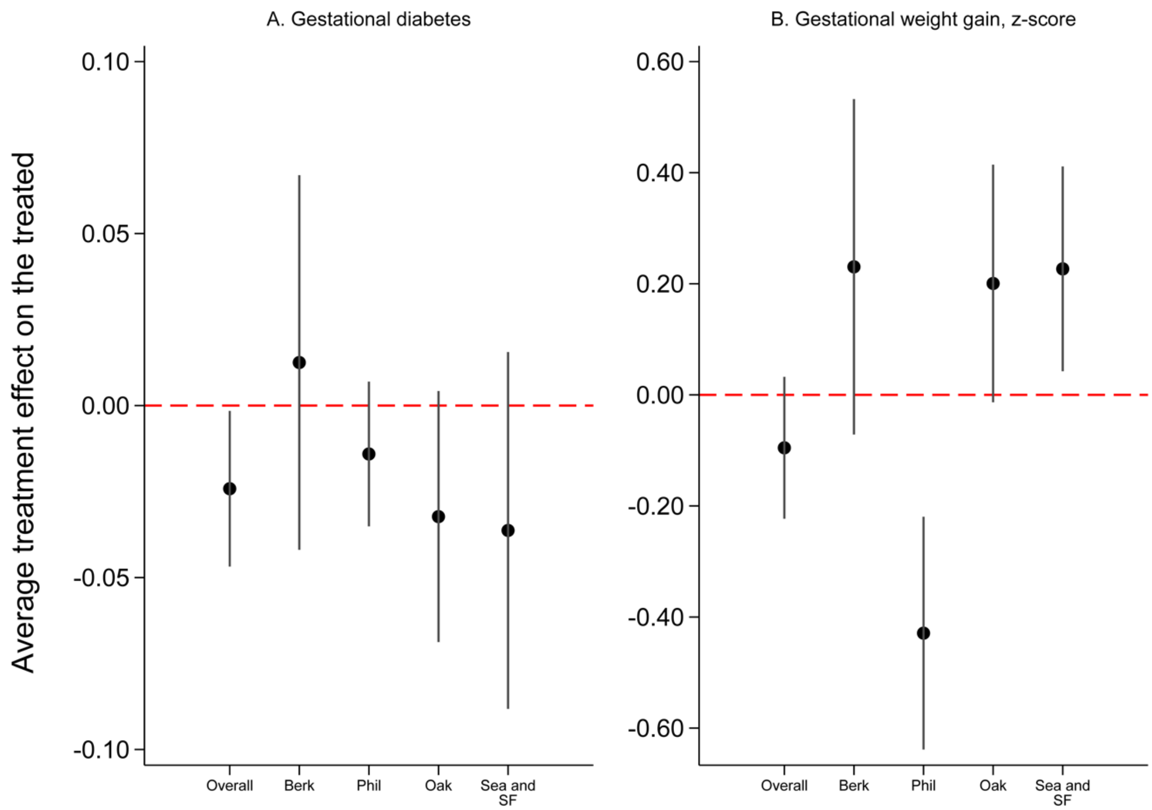
Appendix Figure 4. Cohort-specific effects of SSB taxes on primary outcomes by SSB tax implementation date



Note: Estimates from Callaway-Sant'Anna difference-in-difference models adjusted for race (NH-Black, NH-White, NH-Asian/NHOPI, NH-other race), ethnicity (Hispanic), maternal age (<25, 25-29, 30-34, 35+), education (some high school, diploma/GED, some college, college degree), parity (nulliparous, primiparous, multiparous), prepregnancy smoking status, and prepregnancy BMI (underweight, normal weight, overweight, obese), and fixed effects for maternal city of residence and quarter of birth. Gestational weight gain-related outcomes excluded covariates for prepregnancy BMI.

Abbreviations: Berkeley (Berk); Philadelphia (Phil); Oak (Oakland); Sea (Seattle); San Francisco (SF); Body Mass Index (BMI), Non-Hispanic (NH), Native Hawaiians and Other Pacific Islanders (NHOPI); General Educational Development (GED).

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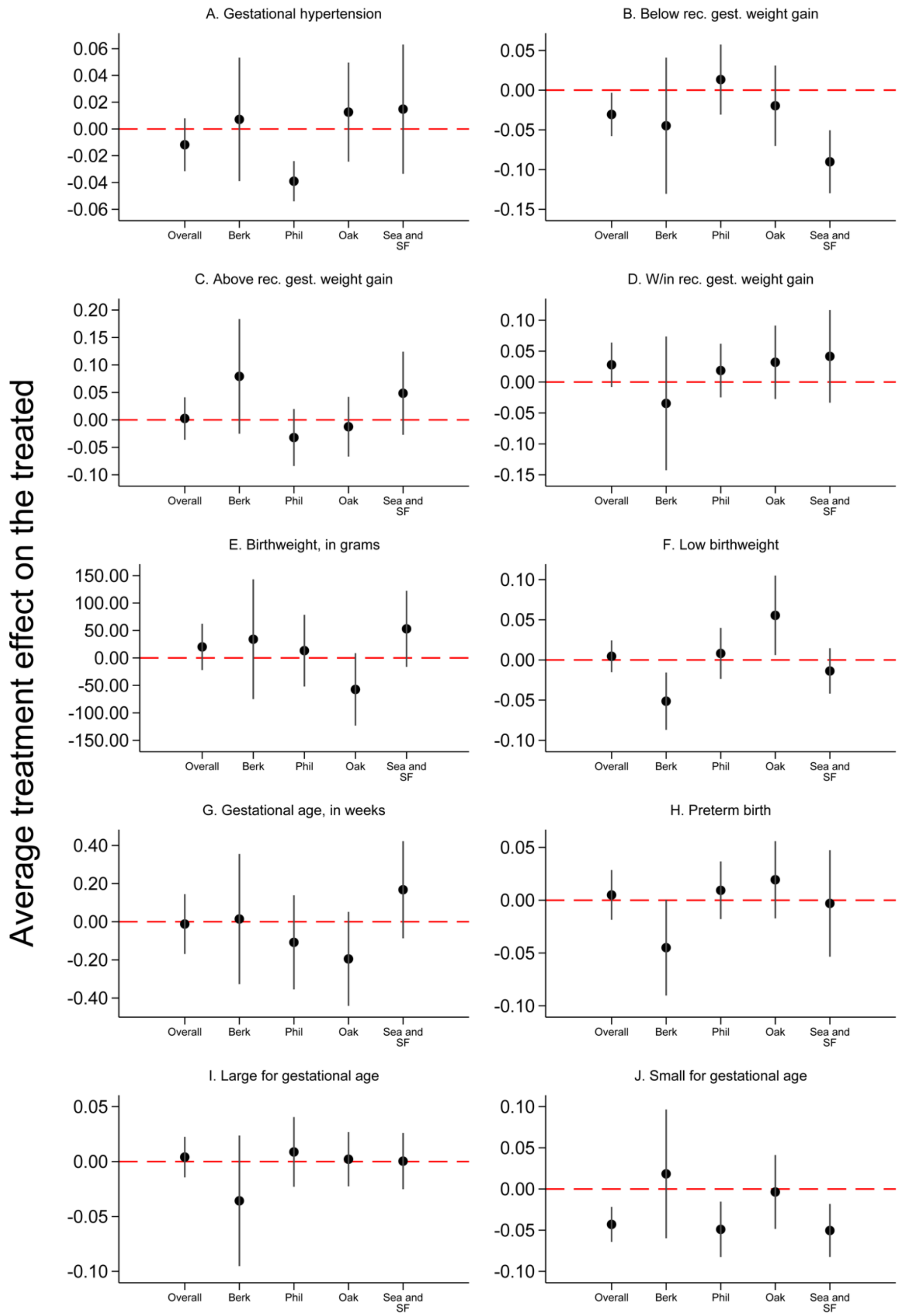
Appendix Figure 5. Cohort-specific effects of SSB taxes on secondary outcomes by SSB tax implementation date



Note: Estimates from Callaway-Sant'Anna difference-in-difference models adjusted for race (NH-Black, NH-White, NH-Asian/NHOPI, NH-other race), ethnicity (Hispanic), maternal age (<25, 25-29, 30-34, 35+), education (some high school, diploma/GED, some college, college

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degree), parity (nulliparous, primiparous, multiparous), prepregnancy smoking status, and prepregnancy BMI (underweight, normal weight, overweight, obese), and fixed effects for maternal city of residence and quarter of birth. Gestational weight gain-related outcomes excluded covariates for prepregnancy BMI.
Abbreviations: Berkeley (Berk); Philadelphia (Phil); Oak (Oakland); Sea (Seattle); San Francisco (SF); Body Mass Index (BMI), Non-Hispanic (NH), Native Hawaiians and Other Pacific Islanders (NHOPI); General Educational Development (GED).

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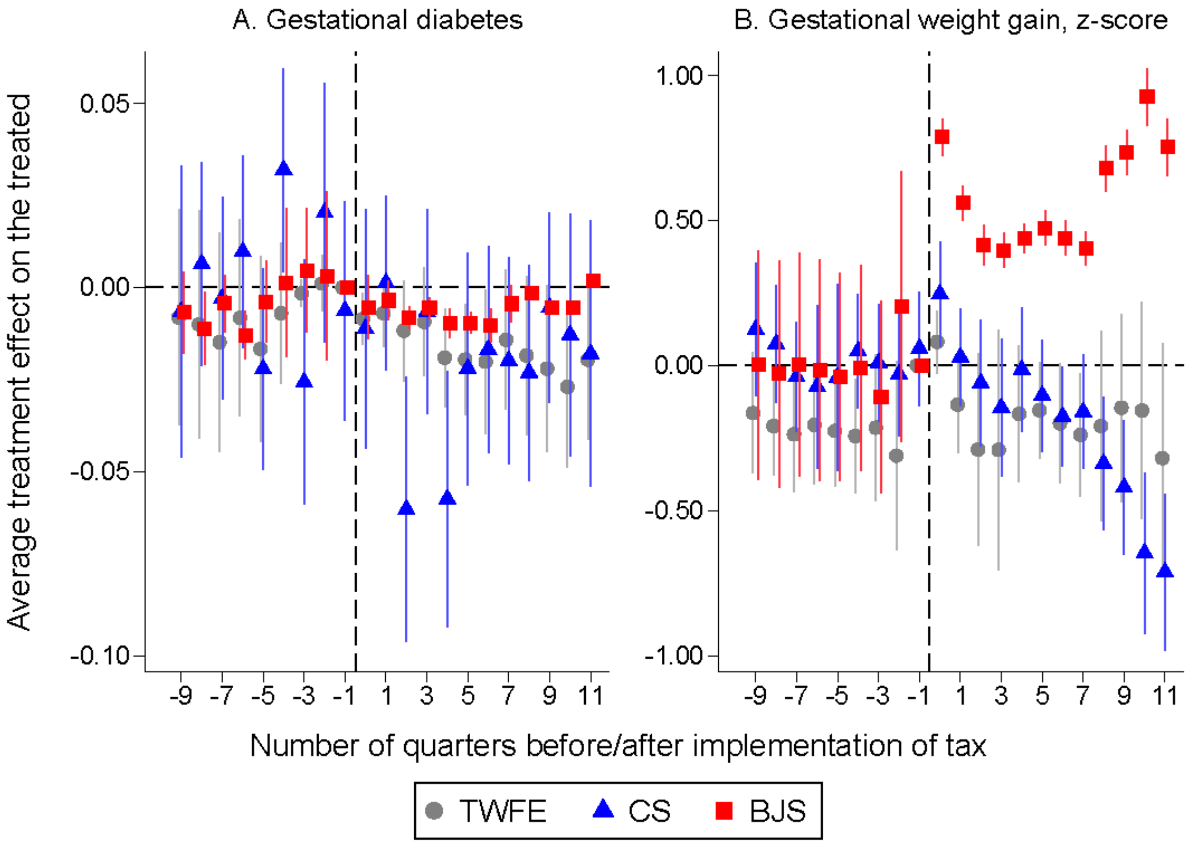
Appendix Figure 6. Sensitivity analysis comparison of statistical models for primary outcomes



Note: These plots of the time-varying differences in outcomes between those in SSB tax cities vs. comparator cities are estimated from three separate methods for event-study difference-in-differences regressions, TWFE, CS, and BJS. Quarterly estimates are relative to the quarter just prior to SSB tax implementation (quarter -1, red dotted line). 95% confidence intervals calculated from robust standard errors clustered by city of residence. All models are adjusted for race and ethnicity (NH-Black, NH-White, NH-Asian/NHOPI, Hispanic, NH-other race), maternal age (<25, 25-29, 30-34, 35+), education (some high school, diploma/GED, some college, college degree), parity (nulliparous, primiparous, multiparous), prepregnancy smoking status, and prepregnancy BMI (underweight, normal weight, overweight, obese), and fixed effects for maternal city of residence and quarter of birth. Gestational weight gain-related outcomes excluded covariates for prepregnancy BMI. TWFE and BJS models included robust standard errors clustered by maternal city of residence. TWFE and BJS also include state-by-birth-year fixed effects.

Abbreviations: Body Mass Index (BMI), Non-Hispanic (NH), Native Hawaiians and Other Pacific Islanders (NHOPI); General Educational Development (GED); Two-way fixed effects (TWFE); Callaway-Sant'Anna (CS); Borusyak, Jaravel, and Spiess (BJS).

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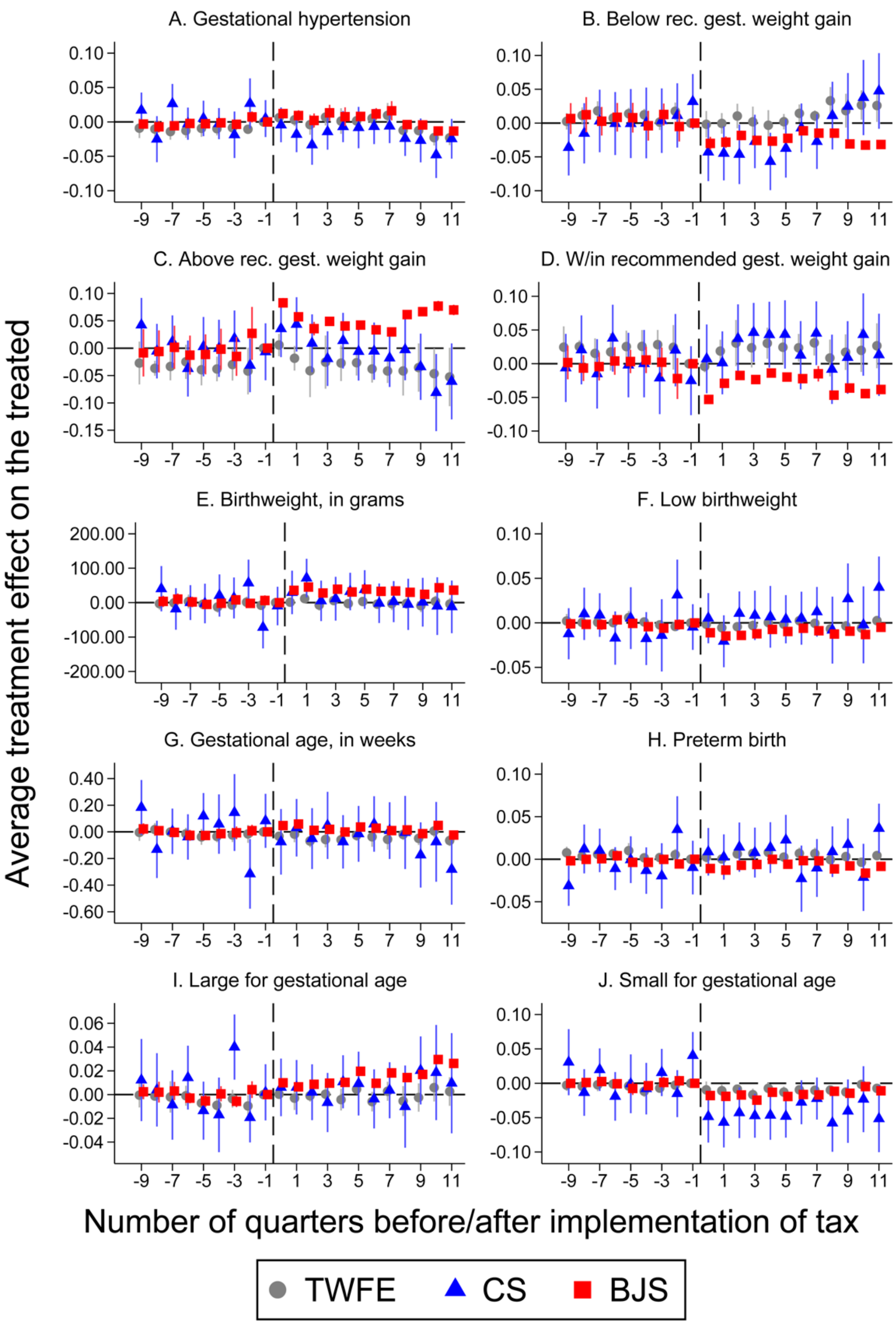
Appendix Figure 7. Sensitivity analysis comparison of statistical models for secondary outcomes



Note: These plots of the time-varying differences in outcomes between those in SSB tax cities vs. comparator cities are estimated from three separate methods for event-study difference-in-

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differences regressions, TWFE, CS, and BJS. Quarterly estimates are relative to the quarter just prior to SSB tax implementation (quarter -1, red dotted line). 95% confidence intervals calculated from robust standard errors clustered by city of residence. All models are adjusted for race and ethnicity (NH-Black, NH-White, NH-Asian/NHOPI, Hispanic, NH-other race), maternal age (<25, 25-29, 30-34, 35+), education (some high school, diploma/GED, some college, college degree), parity (nulliparous, primiparous, multiparous), prepregnancy smoking status, and prepregnancy BMI (underweight, normal weight, overweight, obese), and fixed effects for maternal city of residence and quarter of birth. Gestational weight gain-related outcomes excluded covariates for prepregnancy BMI. TWFE and BJS models included robust standard errors clustered by maternal city of residence. TWFE and BJS also include state-by-birth-year fixed effects.
Abbreviations: Body Mass Index (BMI), Non-Hispanic (NH), Native Hawaiians and Other Pacific Islanders (NHOPI); General Educational Development (GED); Two-way-fixed-effects (TWFE); Callaway-Sant'Anna (CS); Borusyak, Jaravel, and Spiess (BJS).

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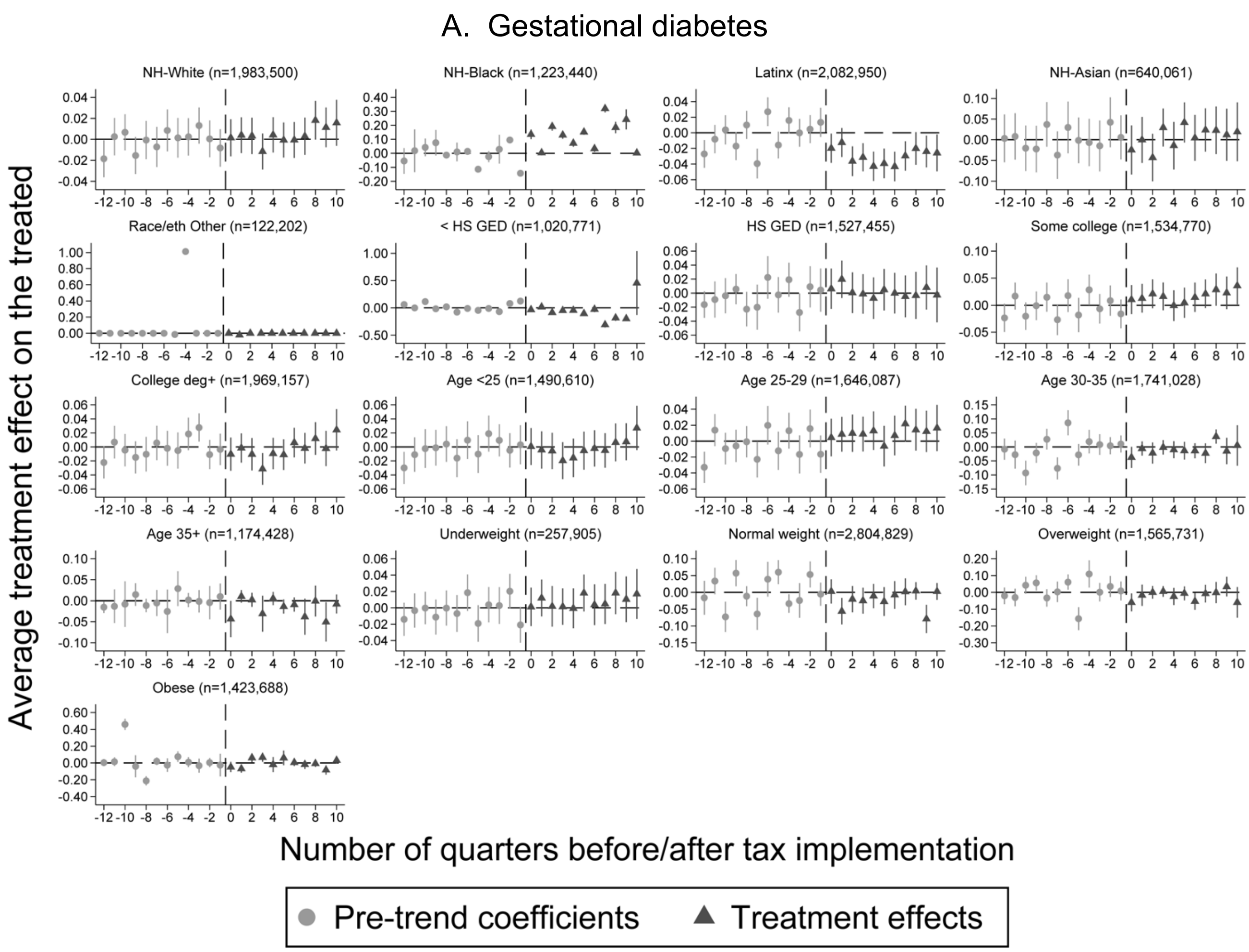
Appendix Figure 8. Time-varying association between sugar-sweetened beverage taxes and perinatal outcomes by subgroup



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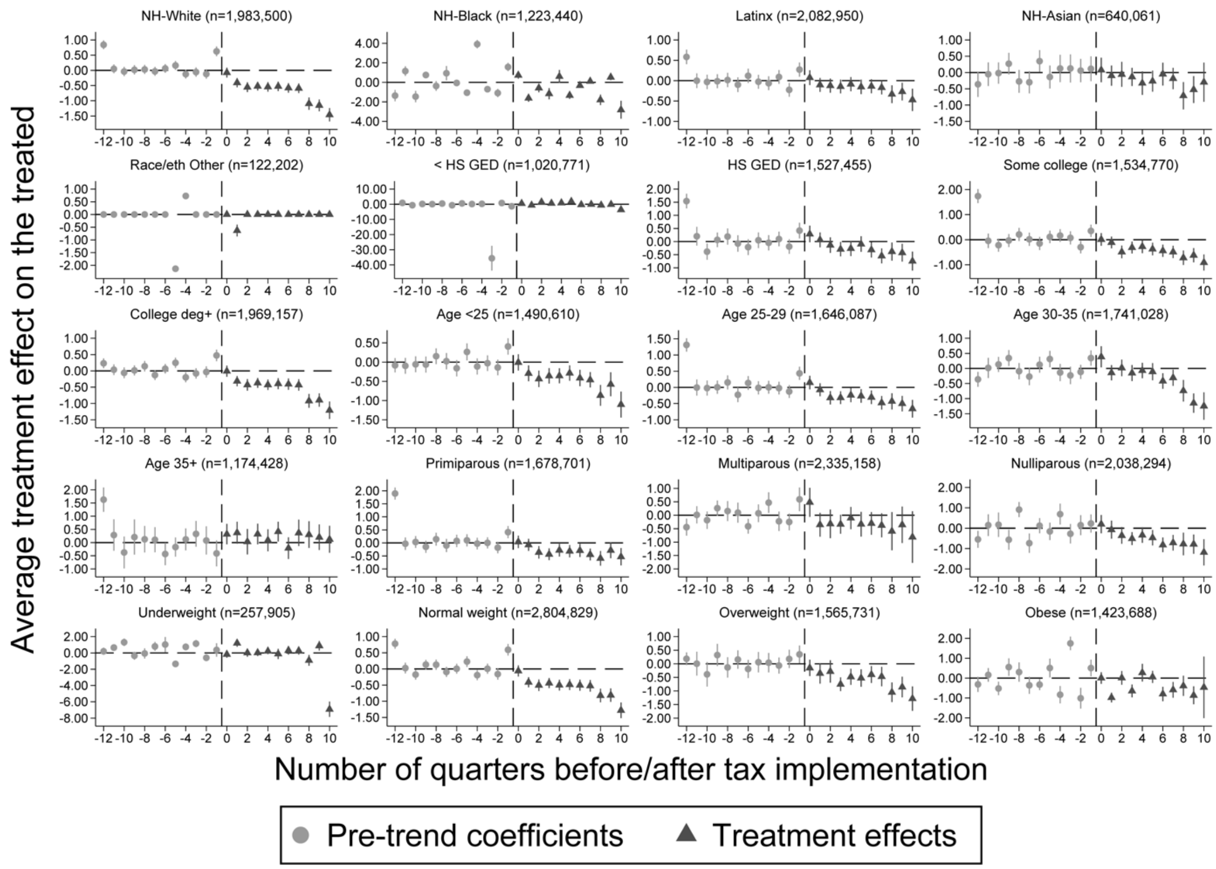
B. Weight-gain-for-gestational-age-z-score



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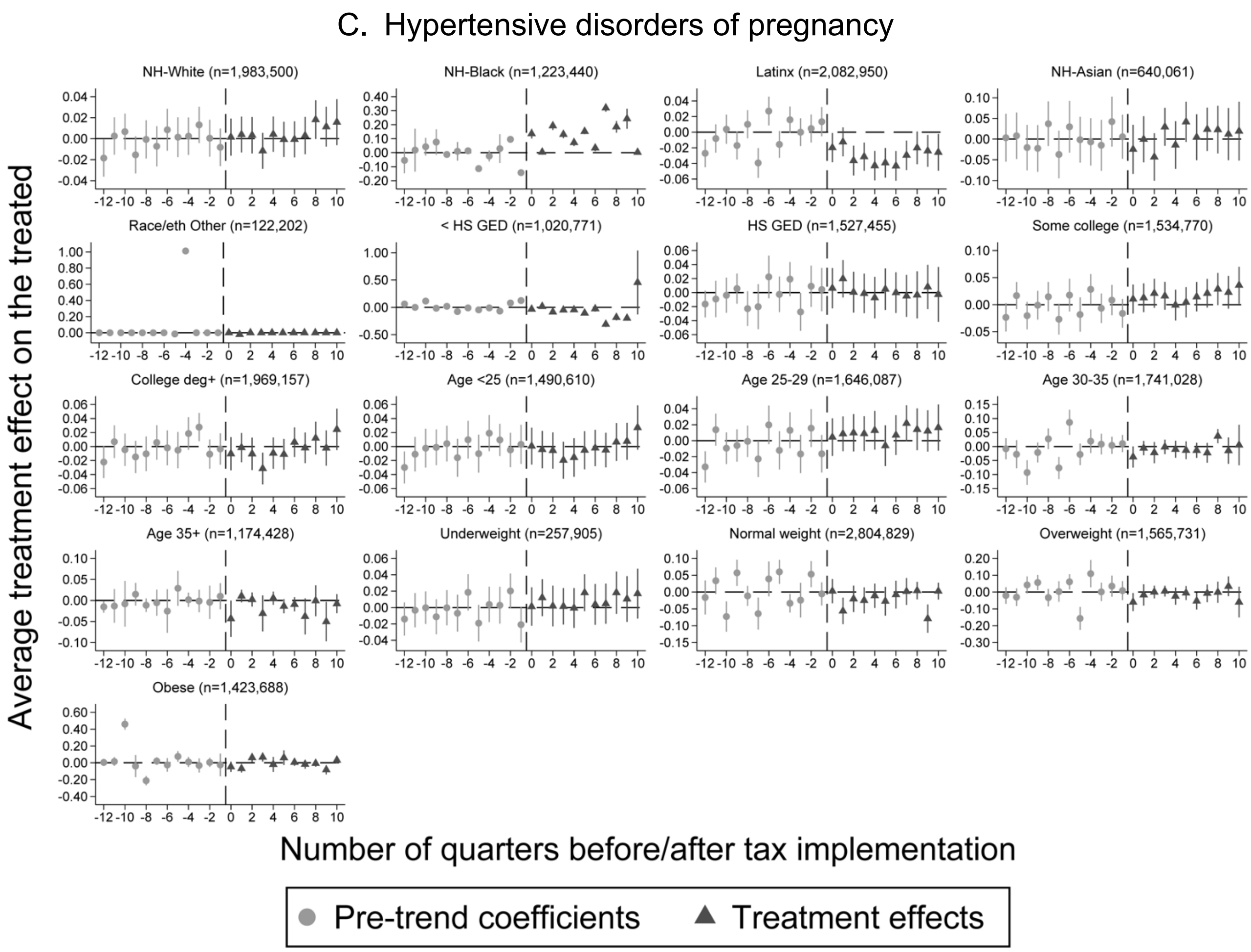

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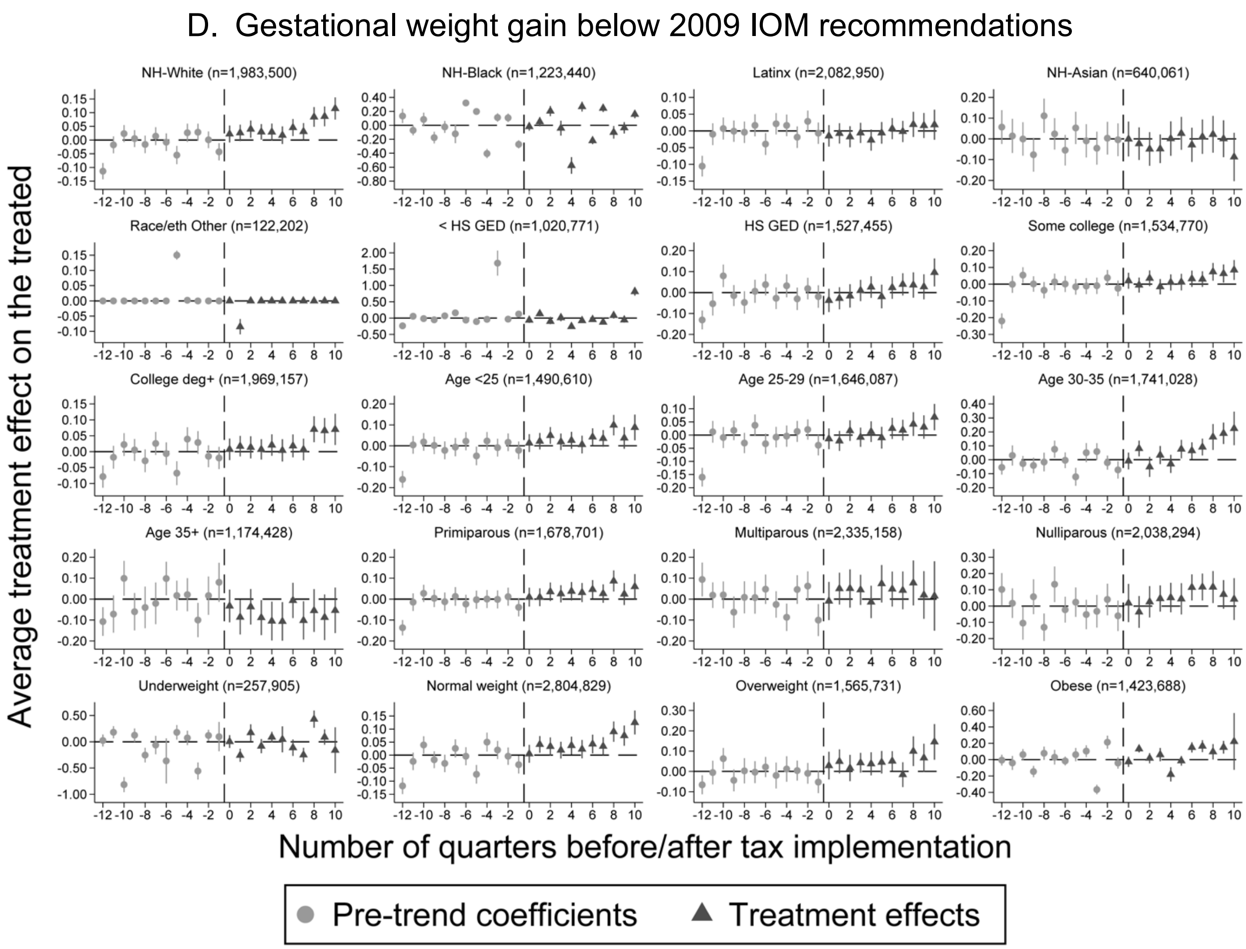

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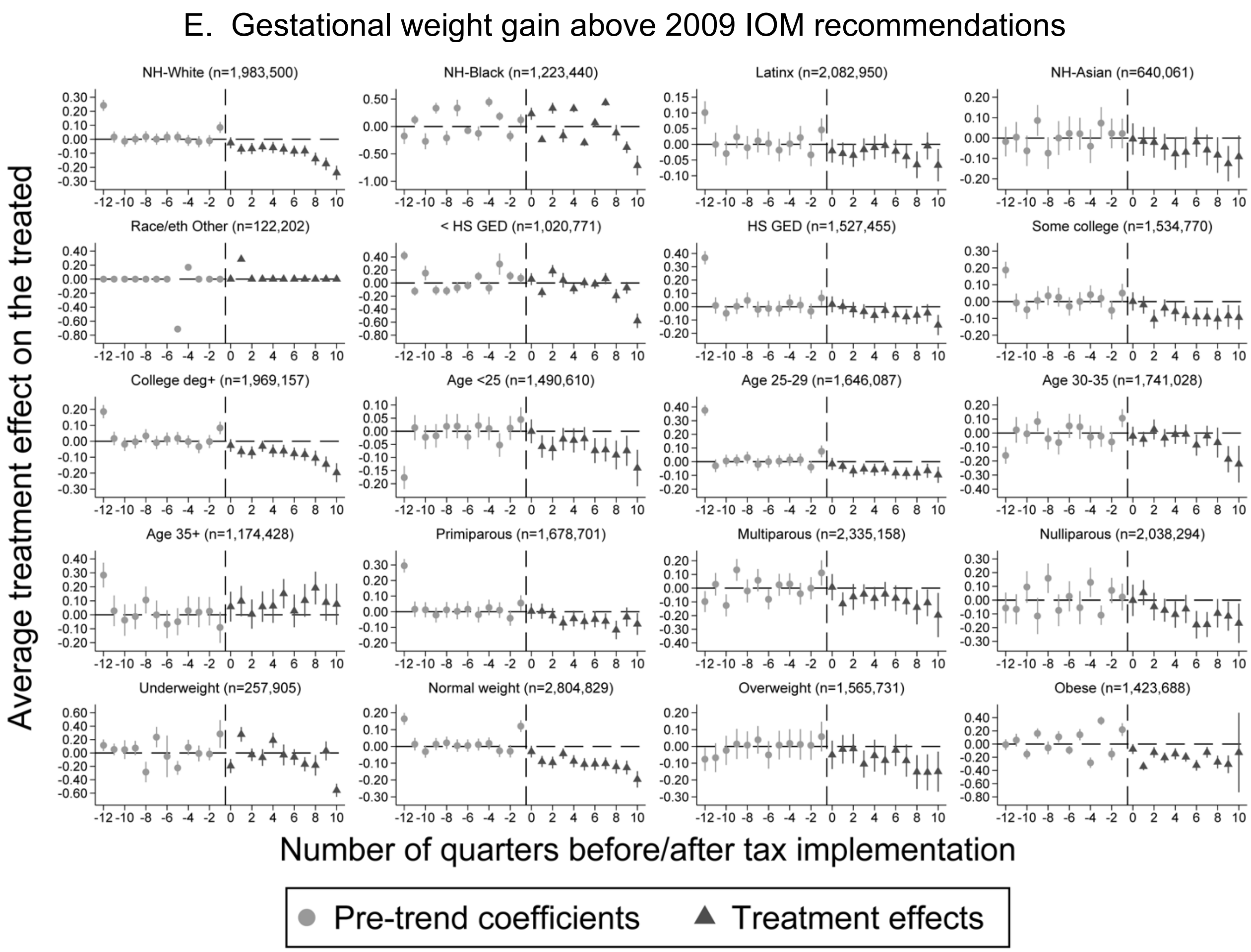

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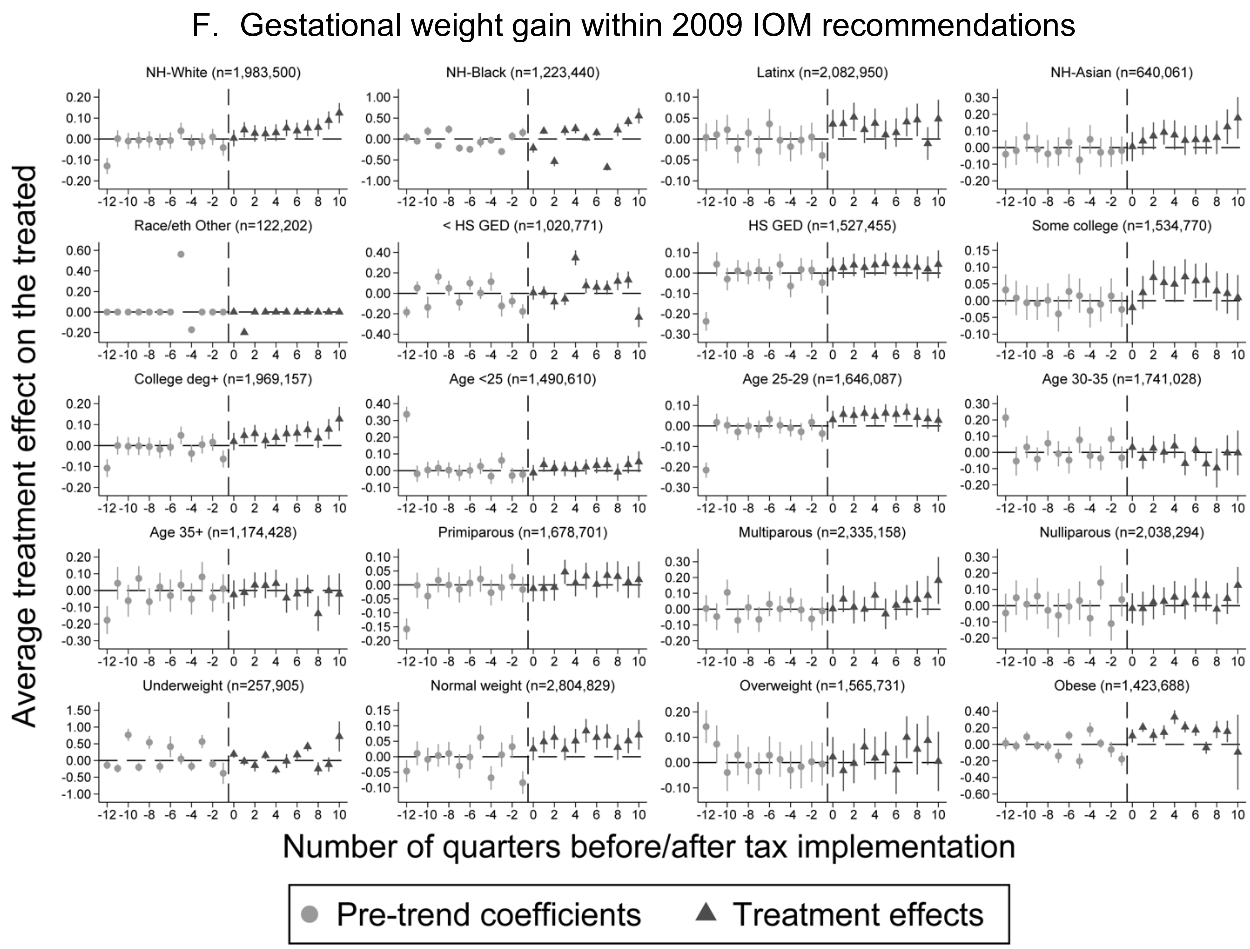

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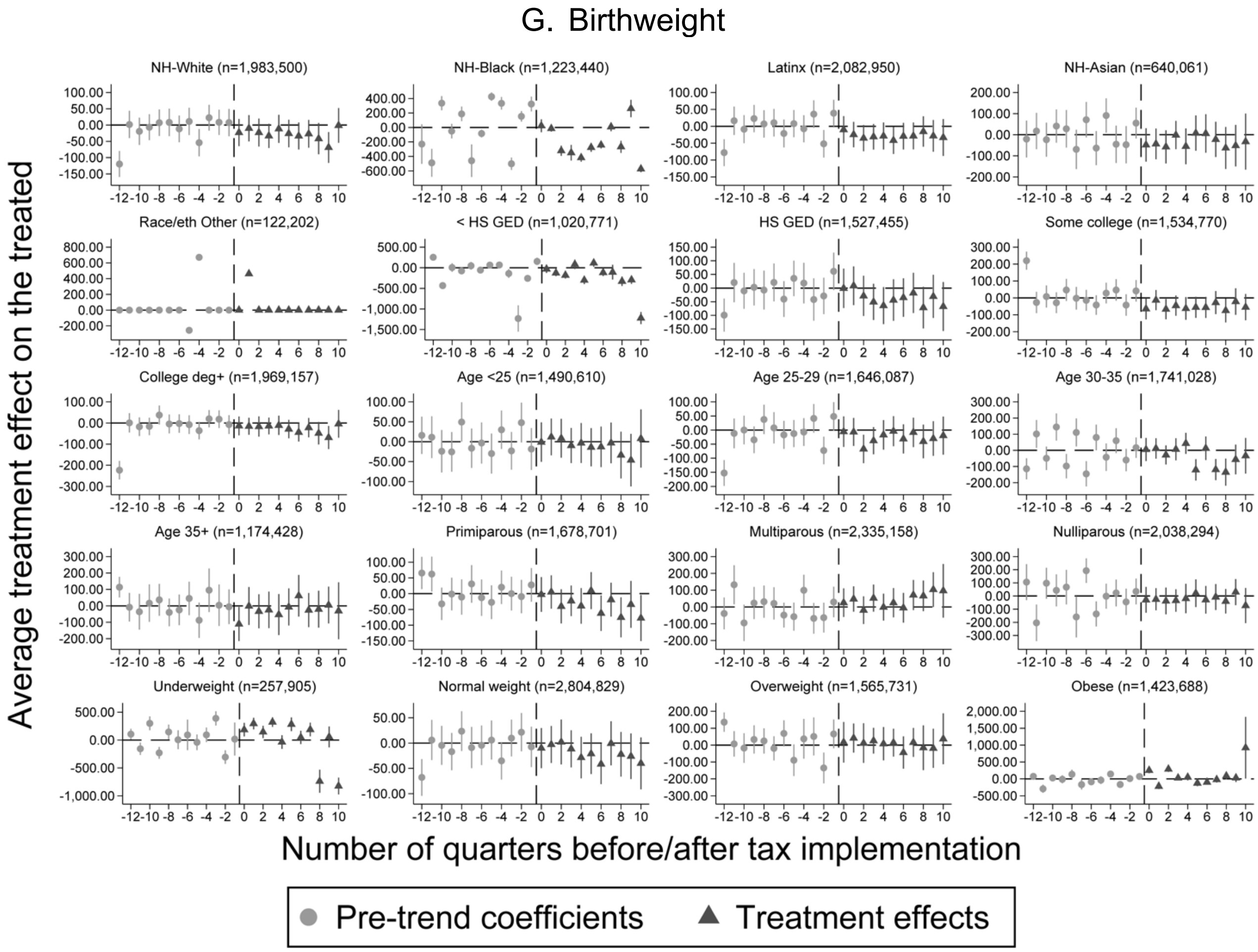

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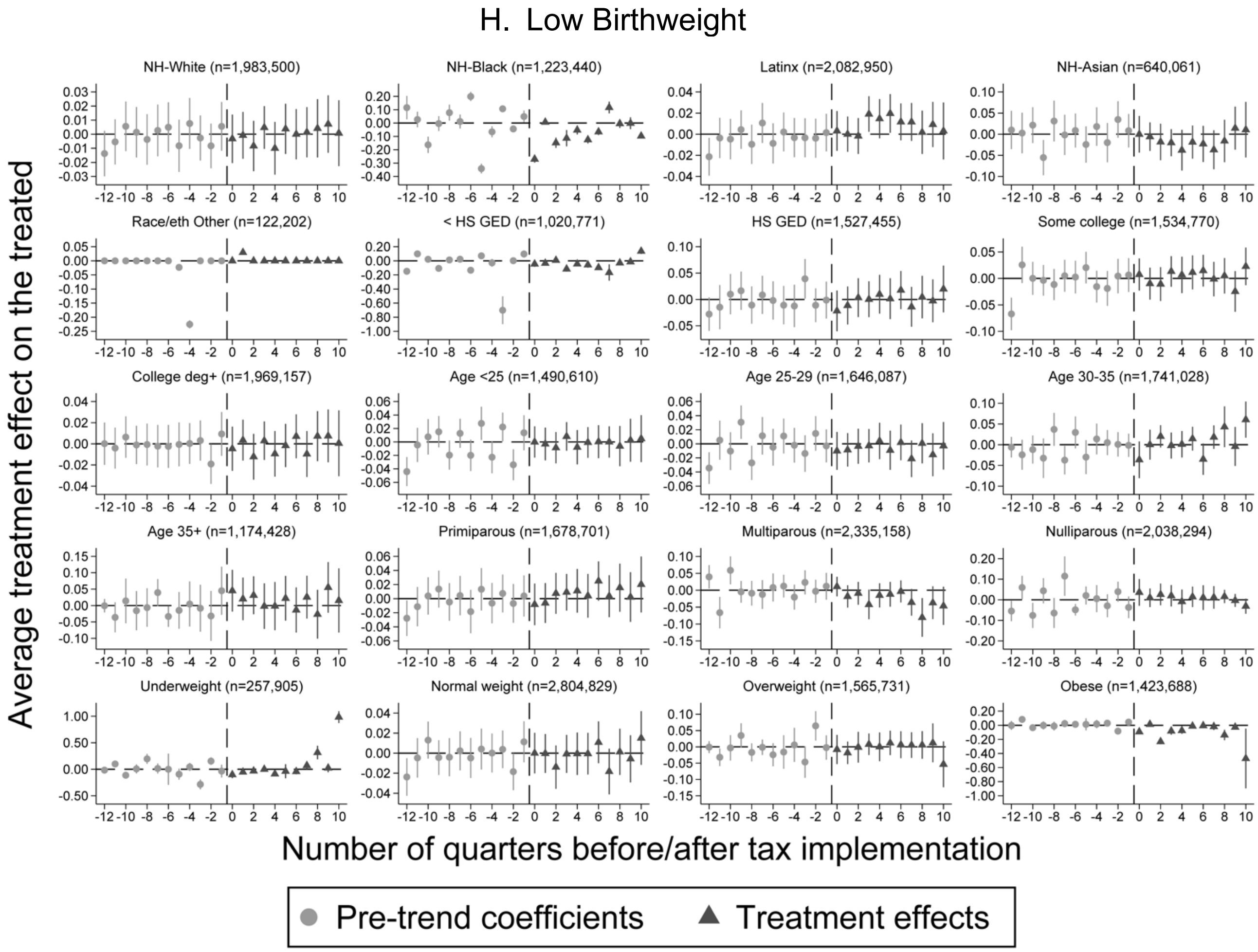

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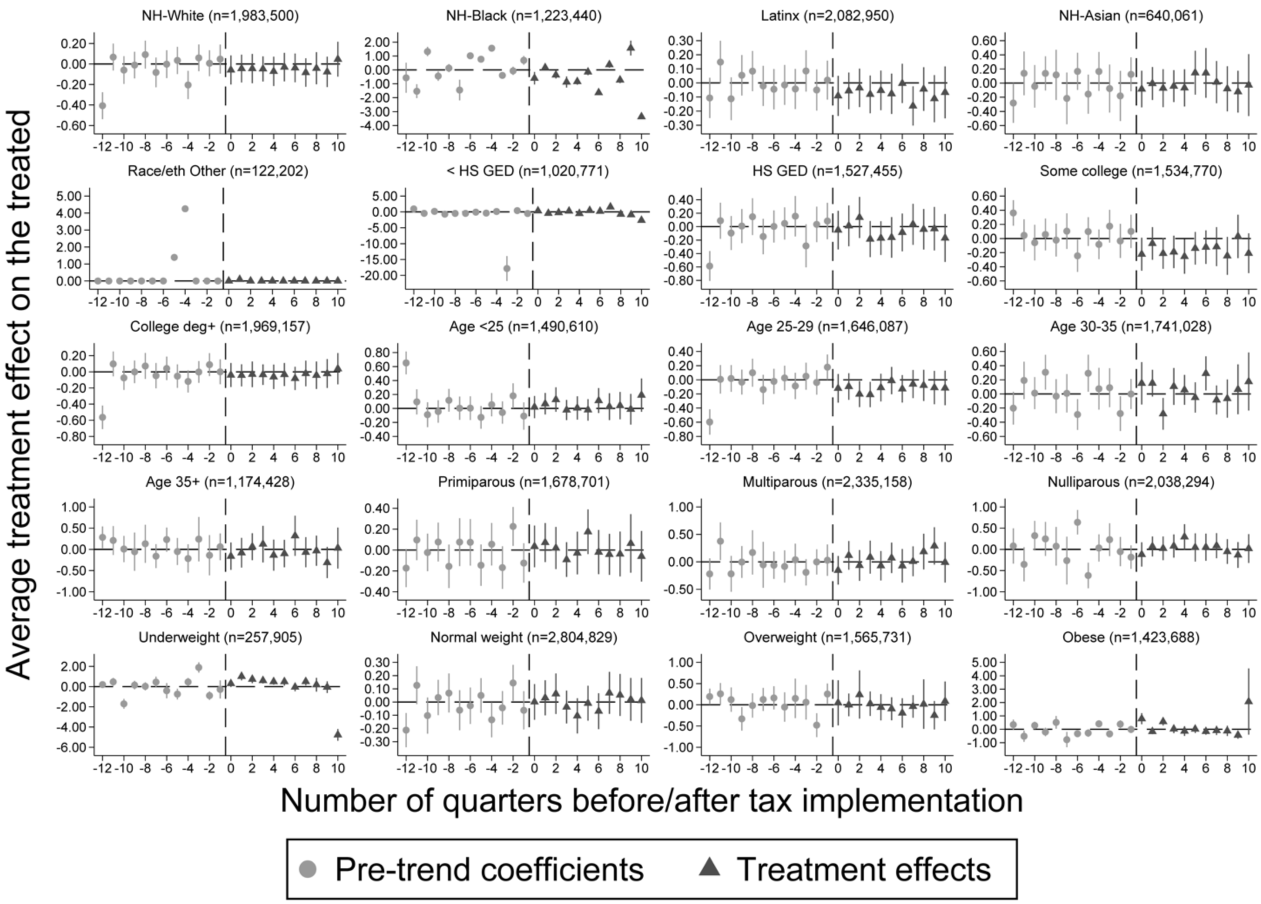
I. Gestational age



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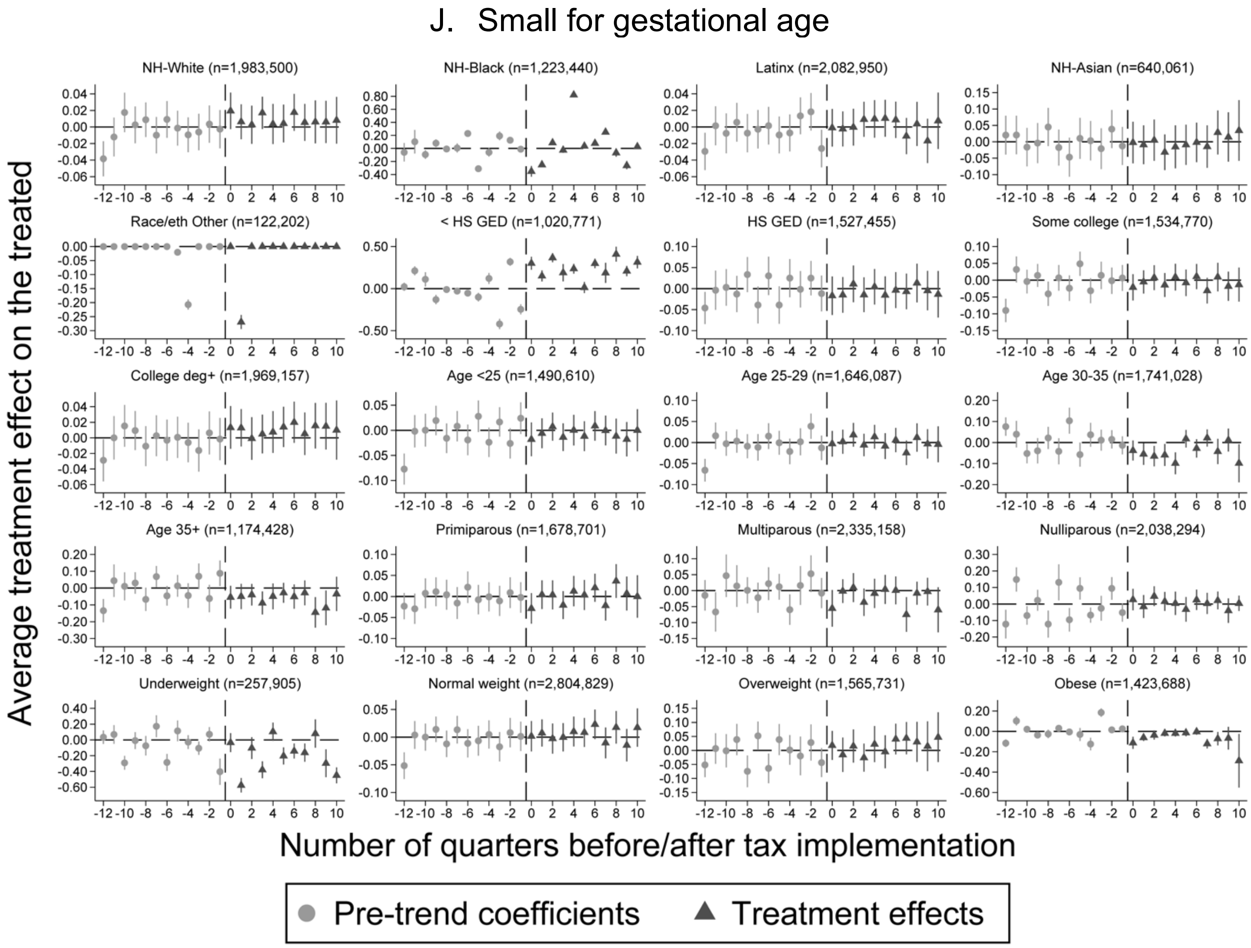

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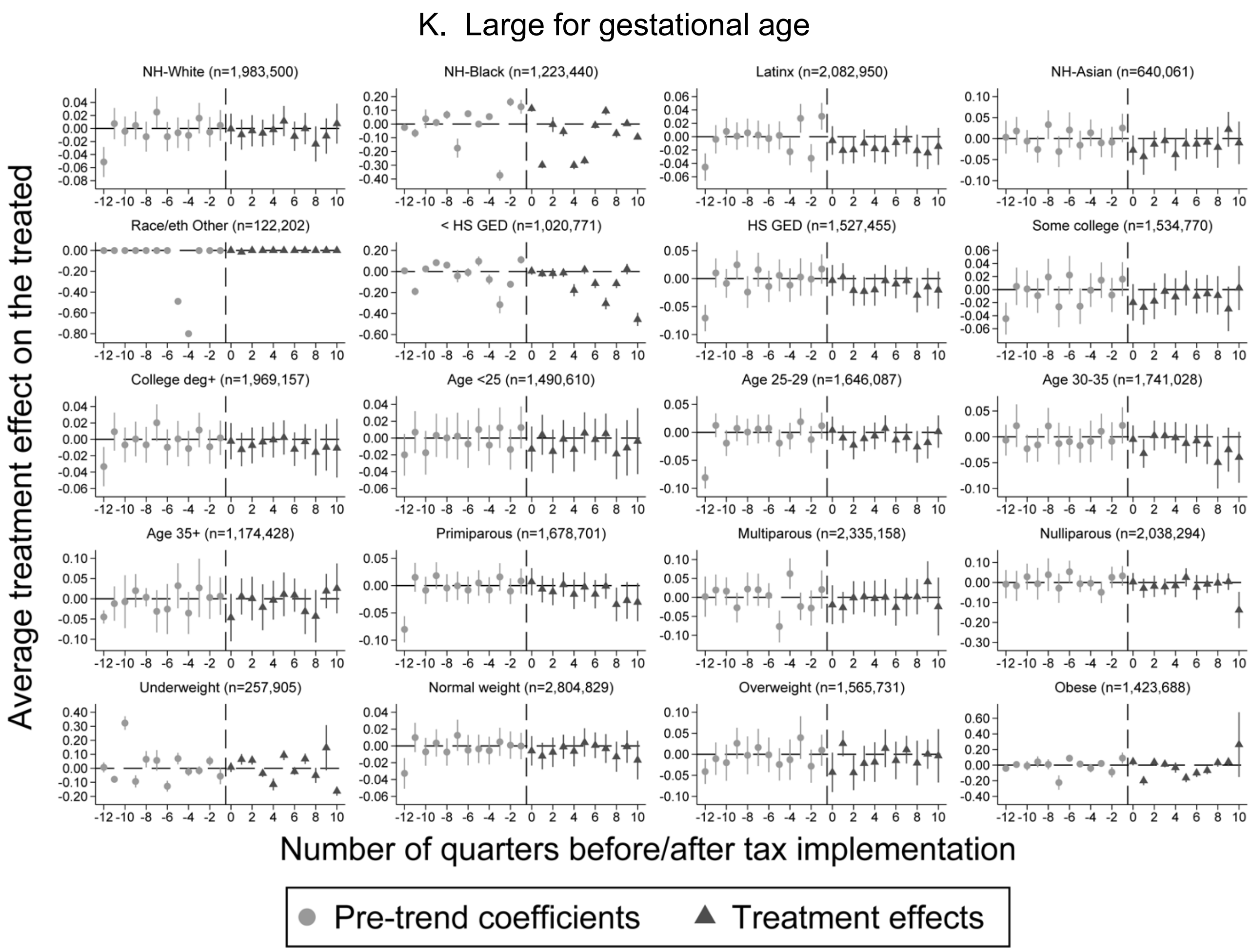

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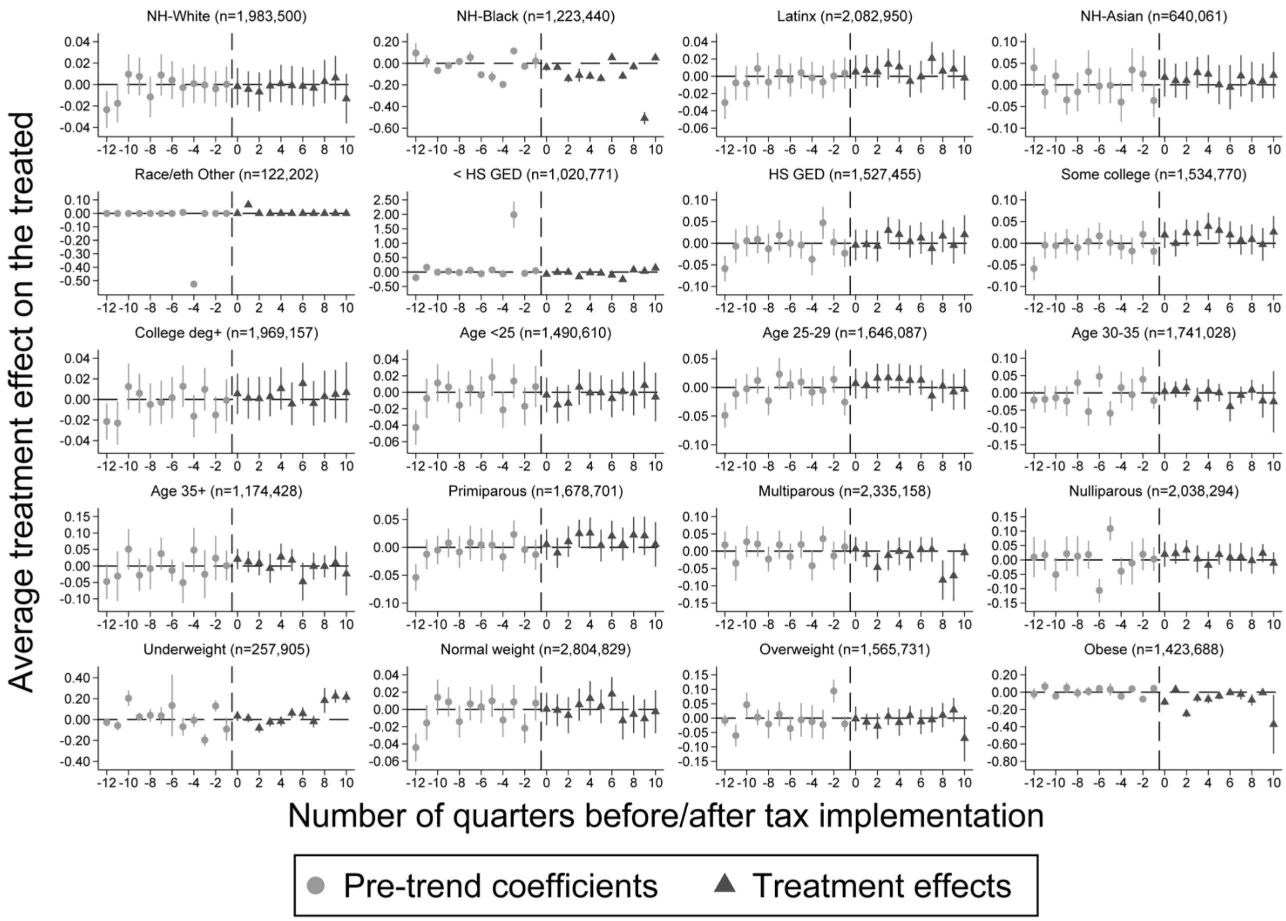
L. Preterm birth



Note: These plots of the time-varying differences in outcomes between those in SSB tax cities vs. comparator cities are estimated from Callaway-Sant'Anna event-study difference-in-differences regressions among subgroups. Quarterly estimates are relative to the quarter just prior to SSB tax implementation (quarter -1, dotted line). 95% confidence intervals calculated from robust standard errors.