The Impact of Electronic Benefit Transfer on WIC Participation: Evidence from Natality Data

Charlotte Ambrozek
UMN

Timothy K.M. Beatty
UC Davis

Wenjie Zhan
UC Davis

September 25, 2024

Please click here for the latest version.

Abstract

Policymakers have an interest in ensuring participation in the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) – WIC has been shown to increase birthweight for participating mothers and improve long-run outcomes for children who participate in the first years of life. Between 2002 and 2022, WIC transitioned from paper vouchers to electronic benefit transfer (EBT) cards. This payment reform was expected to encourage WIC participation by reducing transaction costs and welfare stigma. Empirical studies of the effects of WIC EBT on participation have found mixed results, with studies often limited to one or a few states. Without detailed WIC participation data on a large scale, results are not generalizable. In this paper, we evaluate the impact of WIC EBT implementation on WIC participation nationwide by linking the WIC EBT roll-out schedule to Vital Statistics Natality Data across virtually all counties in the U.S. We document a significant increase in WIC participation among the likely eligible by 2.39-2.5 percentage points after EBT implementation. We also find WIC EBT reduces probability of low birth weights births by 0.47-0.62 percentage points and preterm births by 0.54-0.82 percentage points among the likely-eligible. Our findings suggest that facilitating the delivery of public benefits can improve program uptake and well-being of beneficiaries.

Charlotte Ambrozek is an assistant professor at Department of Applied Economics, University of Minnesota. Timothy K.M. Beatty is a professor and Wenjie Zhan is Ph.D. candidate, both at Department of Agricultural and Resource Economics, University of California, Davis. We thank Marianne Bitler and Richard Sexton for their helpful comments. This work is funded by the Gifford Center for Population Studies.

1 Introduction

The Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) provides nutritious foods and nutrition counseling for low-income pregnant or postpartum women, infants, and children under the age of five. WIC participation has been linked to improved birth outcomes and long-run education and health gains for individuals that participated in early childhood (Hoynes, Page and Stevens, 2011; Kreider, Pepper and Roy, 2016; Chorniy, Currie and Sonchak, 2020). However, the share of U.S. born infants enrolled in WIC has declined from 50% in 2009 to 30% in 2021 (Figure 1). Total WIC participation decreased by 3 million individuals in the past decade. Policymakers are interested in program changes that can stem these declines.

Between 2002 and 2022, WIC transitioned from paper vouchers to electronic benefit transfer (EBT) cards. This payment reform was expected to encourage WIC participation among eligible individuals by reducing the stigma that participants experienced when redeeming WIC benefits (Moffitt, 1983). Also, participants may perceive benefits as more valuable after WIC EBT implementation when they can redeem a food instrument across multiple transactions (Hanks et al., 2019; Li et al., 2021; Ambrozek, 2022) On the other hand, WIC EBT was also billed as a fraud reducing policy transition. Prior work examining the change in authorized WIC retailers post EBT finds that small stores in particular are less likely to be authorized post EBT, potentially affecting participant access (Meckel, 2020) It is not, therefore, obvious in which direction participation will change after WIC EBT. It is important to understand the effect that this policy change – the largest change to WIC in the past few decades – had on participation.

Empirical evidence to date that tests the effects of WIC EBT on participation shows mixed findings. For example, Hanks et al. (2019) find that WIC EBT increases WIC redemptions in Ohio. Li, Saitone and Sexton (2022) find no significant impact of WIC EBT on the share of WIC enrollment in Oklahoma. Finally, Meckel (2020) finds WIC EBT decreases the number of WIC births in Texas. A common feature of previous work is a focus on an individual state and a shorter-run time period. We contribute estimates of WIC EBT on WIC participation using data from counties implementing WIC before 2022. We estimate nationwide effects of WIC EBT on WIC participation, finding that EBT increased participation and reduced adverse birth outcomes, especially among populations that are likely WIC eligible. We link the WIC EBT roll-out schedule across virtually all counties in the U.S. to Vital Statistics Natality Data, which began reporting WIC status of live births in 2009. Using the natality data avoids misreporting of WIC participation status from survey data (Meyer, Mok and Sullivan, 2015; Meyer and Mittag, 2019). We estimate our models using a staggered-adoption difference-in-diffences (DiD) approach, following the procedure from Sun and Abraham (2021). This approach allow us to disaggregate our treatment effect esti-

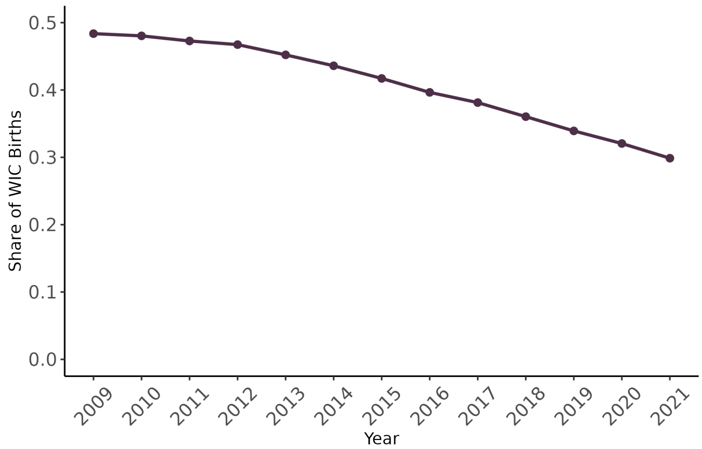


FIGURE 1: SHARE OF BIRTHS PARTICIPATING IN WIC

Notes: The share of WIC births is calculated by diving the number of WIC births by all live births from Vital Statistics Natality Data.

mates to subgroups and time periods, to show how treatment effects vary across the country, given heterogeneous policy environments in different states, and across time, to evaluate both short-run and long-run outcomes. Overall, our results inform our understanding of take-up and benefits among participants in safety net programs.

This paper contributes to three strands of literature. First, it adds to the body of research on the effects of Electronic Benefit Transfer (EBT) implementation. Existing studies have examined the impacts of EBT on participation rates (Meckel, 2020; Li, Saitone and Sexton, 2022), redemption patterns (Hanks et al., 2019), the retail environment(Meckel, 2020; Ambrozek, 2022), and crime rates (Wright et al., 2017) within the contexts of WIC, SNAP, or TANF. This paper extends this literature by providing national-scale evidence on EBT's effects on WIC participation and birth outcomes.

Second, this paper contributes to the literature on the impacts of food assistance programs on infant health. Previous research has explored how the introduction of SNAP (Almond, Hoynes and Schanzenbach, 2011) and WIC (Bitler and Currie, 2005; Figlio, Hamersma and Roth, 2009; Hoynes, Page and Stevens, 2011; Chorniy, Currie and Sonchak, 2020; Bitler et al., 2023) affects birth outcomes, generally finding that food assistance programs improve these outcomes. This study builds on this literature by examining the effects of WIC's transition to EBT on birth outcomes.

Finally, this paper relates to the broader literature on the determinants of food assistance participation in the U.S. For example, Swann (2010) finds that economic conditions, Medicaid expansion, and migration are associated with changes in WIC eligibility and participation. For WIC, factors such as the type of vendors (McLaughlin, Saitone and Sexton, 2019) and vendor accessibility (Rossin-Slater, 2013) also influence participation rates. Additionally, policy design elements, such as work requirements (Gray et al., 2023) and tax exemptions (Zhao, Kaiser and Zheng, 2022), play a role in participation decisions. This study contributes to this scholarship by providing empirical evidence on the effects of payment reform, specifically EBT implementation, on program participation.

The rest of the paper is organized as follows: Section 2 provides the policy background; Section 3 describes the data; Section 4 outlines the research design; Section 5 presents the empirical results; Section 6 includes falsification tests and robustness checks; Section 7 discusses sample composition changes; Section 8 explores potential mechanisms; Section 9 analyzes effect heterogeneity; Section 10 discusses the magnitude of the estimates; and Section 11 addresses study limitations and concludes.

2 Background

2.1 WIC

WIC is a federal assistance program of the United States Department of Agriculture (USDA) designed to safeguard the health of low-income pregnant women, breastfeeding women, non-breastfeeding postpartum women, infants, and children under the age of five who are at nutritional risk. One of the core components of WIC is its provision of nutritious foods tailored to the specific needs of women and young children. The food packages offered through WIC include essential items such as fruits and vegetables, whole grains, dairy products, and protein sources like beans and peanut butter, which are designed to address common nutrient deficiencies and support overall health. In addition to food assistance, WIC provides participants with access to valuable health and nutrition education. This education component is critical in helping families make informed choices about their diets and health behaviors. The program offers individualized counseling, group education sessions, and resources on topics such as breastfeeding, infant feeding practices, and healthy meal planning.

The impact of WIC has been widely studied, with numerous research studies documenting its effectiveness in improving birth outcomes, reducing the prevalence of anemia, promoting breastfeeding, and enhancing children's cognitive development. The program has been shown to significantly reduce the incidence of low birth weight and preterm births among participants, outcomes that are critical for reducing infant mortality and long-term health risks. Additionally, WIC's emphasis on breastfeeding support has contributed to increased breastfeeding rates among low-income women, further promoting optimal infant nutrition and health.

Despite its successes, WIC faces ongoing challenges, including barriers to participation, disparities in access, and the need to continually adapt to changing demographic and nutritional needs. Efforts to modernize the program, such as incorporating digital tools for benefits distribution and expanding outreach to underserved communities, are ongoing to ensure that WIC continues to meet the needs of vulnerable populations effectively.

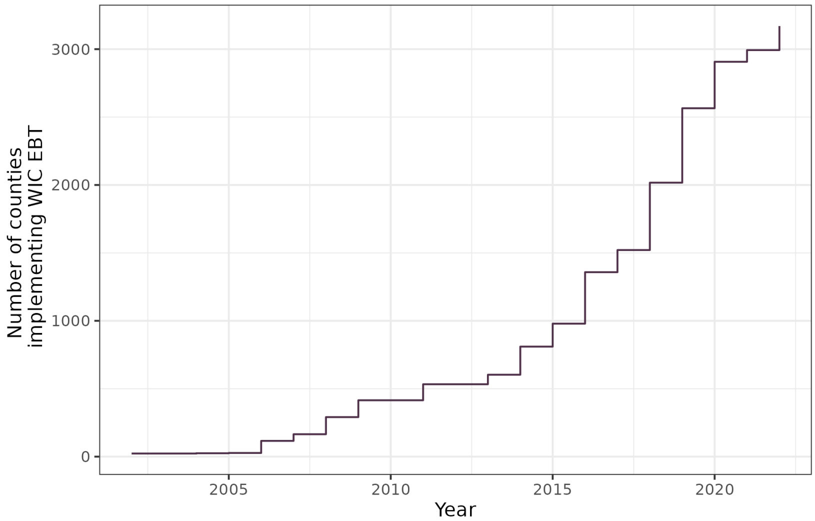
2.2 EBT Rollout form 2002 to 2022

The rollout of WIC EBT, which occurred over two decades from 2002 to 2022, aimed to enhance the efficiency, security, and accessibility of WIC benefits for participants while streamlining the administrative processes for state agencies and retailers. The adoption of EBT technology was driven by the need to address challenges associated with the paper-based system and to align WIC with broader trends in public assistance programs, such as the Supplemental Nutrition Assistance Program (SNAP), which had already transitioned to EBT. The concept of EBT for WIC was first introduced in the early 2000s, following the successful implementation of EBT systems in other federal nutrition programs. The USDA Food and Nutrition Service (FNS) began exploring the feasibility of transitioning WIC from paper vouchers to an electronic system that would allow participants to access their benefits using a card similar to a debit card.

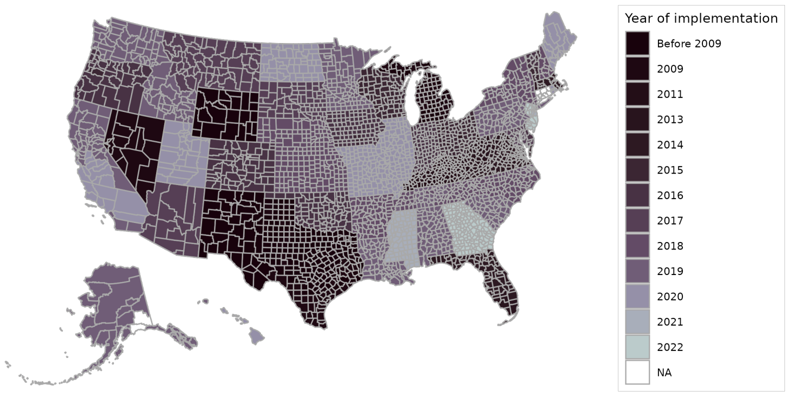
The initial phase of the WIC EBT rollout involved pilot programs in several states. These pilots were designed to test the technology, identify potential challenges, and gather data on the impact of EBT on participant satisfaction, retailer operations, and program integrity. States like Kentucky, Michigan, and Nevada were among the first to implement WIC EBT pilots, which provided valuable insights into the technical and operational aspects of the system. The early results from these pilot programs were promising, demonstrating that WIC EBT could reduce the stigma associated with using paper vouchers, improve the shopping experience for participants, and decrease the administrative burden on state agencies. However, the pilots also revealed challenges, such as the need for extensive training for participants and retailers, as well as the importance of ensuring that all WIC-authorized stores were equipped with the necessary EBT technology.

Building on the success of the pilot programs, the Healthy, Hunger-Free Kids Act of 2010 included a mandate that all state WIC agencies transition to EBT by October 1, 2020. This legislation provided a clear timeline for the nationwide implementation of WIC EBT and allocated funding to support states in the development and deployment of their EBT systems. During this period, the USDA provided technical assistance, guidance, and funding to states to support the transition. States were required to develop detailed implementation plans, which included timelines, budgets, and strategies for training participants and retailers. The expansion of WIC EBT during this phase was gradual, with states rolling out their systems in stages to ensure a smooth transition and to address any technical or operational issues that arose.

By 2016, a significant number of states had implemented WIC EBT, and the benefits of the new system were becoming increasingly apparent. Participants appreciated the convenience and privacy of using an EBT card, which allowed them to purchase WIC-approved items without the need to separate them from other groceries. Retailers also benefited from the streamlined checkout process, which reduced the time and effort required to process WIC transactions. As the 2020 deadline approached, the pace of WIC EBT implementation accelerated. By 2022, all 50 states, as well as U.S. territories and tribal organizations, had successfully transitioned to EBT systems, marking a significant milestone in the modernization of the WIC program. We collected WIC EBT rollout schedule across nearly all U.S. counties as in Figure 2b.



(A) Number of counties implementing WIC EBT over time



(B) Geographic variation in timing of WIC EBT implementation

FIGURE 2: WIC EBT ROLL-OUT SCHEDULE SINCE 2009

3 Data

3.1 Vital Statistics Natality Data

Natality data, coded from birth certificates, provide detailed birth and parental information, including the county of maternal residence, year of birth, maternal age, educational attainment, marital status, and WIC participation, among other variables. The 2003 revision of the birth certificate required the inclusion of the mother's WIC participation, though this information did not become available until 2009. We collapse the birth-level natality data to county-of-maternal-residence-by-year-of-birth cells to make the sample size more manageable. Our sample period spans 2009-2021.

We validate the WIC participation information from natality data by showing that it plausibly reflects changes in total WIC participation. First, as depicted in Figure 3, the ratio of WIC births to total WIC participants consistently remains at 20% throughout the study period. Second, we find no significant differences in observable characteristics between mothers in the natality data, women aged 15-49 years in the Current Population Survey's (March) Annual Social and Economic Supplements (CPS ASEC), and mothers of infants (postpartum women) in the Survey of Income and Program Participation (SIPP). Table 1 shows that the differences in the proportions of Black and Hispanic mothers, educational backgrounds, and regional residence between the natality data and CPS ASEC, as well as between the natality data and SIPP, are within 5%.

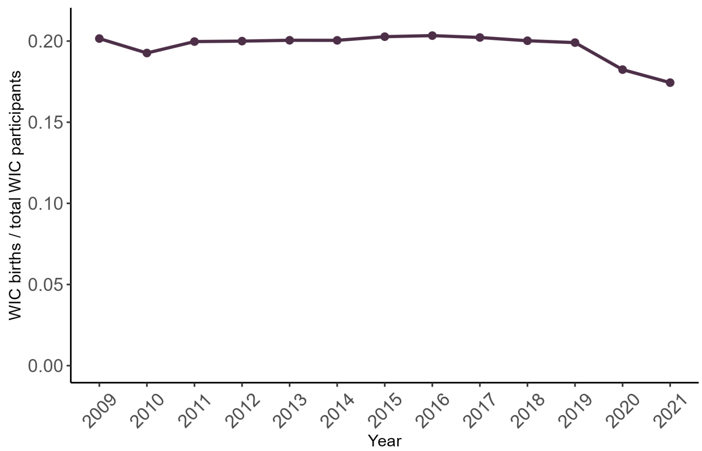


FIGURE 3: SHARE OF WIC PARTICIPANTS THAT SHOW UP IN OUR SAMPLE

Notes: Share of WIC participants that show up in our sample is calculated by dividing total number of WIC births in our sample by total WIC participants. Data on total WIC participants is from USDA FNS website: https://www.fns.usda.gov/pd/wic-program. The website only include most recent data. We use way-back machine to extract historical data.

We further validate our data by cross-referencing the natality data from Vital Statistics

TABLE 1: COMPARING NATALITY DATA WITH OTHER SURVEY DATA

	Natality data (1)	CPS ASEC (2)	Mean difference (1) - (2) (3)	SIPP (4)	Mean difference (1) - (4) (5)
Share of black	16.07%	15.85%	0.22%	15.37%	0.70%
Share of Hispanics	24.18%	21.54%	2.64%	20.04%	4.14%
Education $\leq$ high school	40.42%	42.91%	-2.49%	37.17%	3.25%
Education $\geq$ college	31.06%	27.79%	3.27%	32.94%	-1.88%
Northeast	14.77%	17.02%	-2.25%	17.47%	-2.70%
Midwest	21.65%	20.60%	1.05%	20.82%	0.83%
West	24.81%	24.07%	0.74%	23.08%	1.73%
Share of WIC participants	40.46%	6.41%		5.65%	
Full sample size	45,910,299	432,575		80,535	

Notes: Numbers in this table, unless otherwise noted, are shares of group with characteristics listed in first column. All three data sets span 2009-2021. Observations with null value are dropped. Means from natality data are unweighted since it covers population of live births; means from CPS AESC are weighted average characteristics of women at 15-49 years old; means from SIPP are the average of weighted average characteristics of mothers of infants across SIPP panels. For SIPP means, we first take weighted average of SIPP panel and then average across panels because personal weights are not comparable across panels.

with birth data from the Texas Department of State Health Services (Texas DSHS) as used in Meckel (2020). Meckel (2020) uses Texas DSHS natality data covering births in counties that implemented WIC EBT before April 2009 (239 counties) from January 2005 to December 2009. Our natality data covers births in all Texas counties (254 counties) but only extends back to January 2009. The overlapping subset of these two datasets includes births in counties that implemented WIC EBT before April 2009, from January to December 2009. A comparison of these overlapping subsets reveals that the data are nearly identical (Figure 4).

3.2 WIC EBT roll-out

We compiled the WIC EBT rollout schedule across nearly all U.S. counties using public records from state WIC agencies. For counties reporting a range of implementation dates, we used the earliest date in the range. Our data capture both cross-state and within-state variation in the timing of WIC EBT implementation, with cross-state variation being more pronounced. After excluding counties that did not report WIC participation, our final sample includes 2,549 counties, covering 81.24% of the U.S. population and accounting for 79.10% of births.

We then examined the correlations between the WIC EBT rollout schedule and baseline county characteristics. We collected baseline data for the years 2006-2008 from various sources. Data on the share of Black and Hispanic populations and income per capita were

Indian Tribal Organizations with separate WIC EBT implementation plans are excluded.

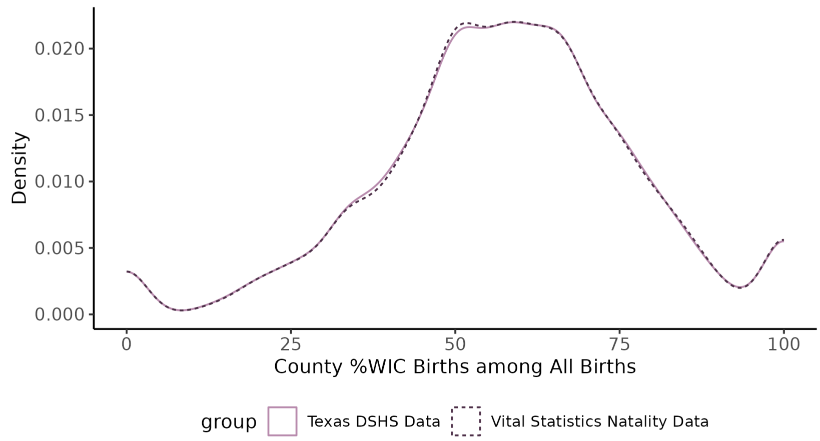


FIGURE 4: DISTRIBUTION OF COUNTY-LEVEL SHARE OF WIC BIRTH

Notes: The dashed line represents the distribution of county shares of WIC births from the overlapped subset of Meckel (2020)'s data set. The solid line represents the distribution of county share of WIC births from the overlapped subset of our data set. The overlapped subsets cover 239 counties in Texas from January 2005 to December 2009.

sourced from the American Community Survey (ACS) Public Use Microdata Sample. We constructed county-level ACS data by matching individual records with Public Use Microdata Areas (PUMA) identifiers, aggregated to the county level and weighted by ACS personal weights. Observations from PUMAs with populations under 100,000 were excluded due to suppressed geographic identifiers. While we could not find county-level data on all welfare programs that automatically qualify participants for WIC, except for SNAP, we gathered data on transfers from the Bureau of Economic Analysis's Regional Economic Information System (REIS), which include these welfare programs. Public assistance medical benefits encompass Medicaid and other medical vendor payments, while income maintenance benefits include TANF, WIC expenditures, and other general assistance such as tax credits, refugee assistance, foster care, adoption assistance, and energy aid. Additionally, we included county-level data on poverty rates and the under-five population from the Small Area Income and Poverty Estimates (SAIPE) Program, the share of low birthweight from restricted-use Vital Statistics Natality Data, and the net increase in WIC vendors from the WIC Integrity Profiles (TIP). All variables represent three-year averages for 2006-2008, except for the net increase in WIC vendors, which is a three-year total.

Columns 1-3 of Table 2 present the baseline characteristics of our sample counties compared to those excluded. In general, included counties are not significantly better off than excluded ones. Although included counties have a smaller share of disadvantaged populations, a lower share of infants with low birthweight, and receive more income maintenance benefits per capita, they receive less SNAP benefits and have lower income per capita. We found no significant differences between included and excluded counties in terms of population size, per capita public assistance medical benefits, or net increase in WIC vendors. Columns 4 and 5 of Table 2 show that while some county baseline characteristics are strongly correlated with the timing of WIC EBT implementation, these characteristics as a whole explain only a small portion of the variation in implementation timing. Most of the variation in WIC EBT rollout timing is explained by state-level unobservables, as the R^2 value approaches 1 when state fixed effects are added. Thus, after controlling for county baseline characteristics, the timing of the WIC EBT rollout can be considered plausibly exogenous.

TABLE 2: TIMING OF WIC EBT IMPLEMENTATION AND COUNTY BASELINE CHARACTERISTICS

	Included counties	Excluded counties	Mean difference (1) - (2)	Regressions of year of WIC EBT implementation on county baseline characteristics	
	(1)	(2)	(3)	(4)	(5)
Demographics, 2006-2008					
% Black	8.84	12.06	-3.22	0.0427***	-0.0014
	⟨0.26⟩	⟨0.54⟩		(0.0108)	(0.0021)
% Hispanic	5.43	19.46	-14.03	0.0480***	0.0148***
	⟨0.14⟩	⟨0.85⟩		(0.0129)	(0.0031)
% Poor × under age 5	1.64	1.95	-0.31	-0.2715	-0.1133***
	⟨0.02⟩	⟨0.03⟩		(0.3121)	(0.0421)
% Low birth weight	8.03	8.74	-0.71	-0.4072***	-0.0157
	⟨0.05⟩	⟨0.10⟩		(0.0770)	(0.0113)
Population	96,379	93,937	2,442		
	⟨6,282⟩	⟨11,143⟩			
Log population				-0.0291	-0.0188
				(0.1109)	(0.0161)
Transfers and i, 2006-2008					
Public asst. medical benefits p.p.	1.11	1.15	-0.03	0.6513***	-0.0256
(incl., Medicaid, $1,000)	⟨0.01⟩	⟨0.02⟩		(0.2417)	(0.0469)
Income maintenance benefits p.p.	0.18	0.17	0.01	-5.453***	0.4460
(incl., TANF and WIC, $1,000)	⟨0.002⟩	⟨0.003⟩		(1.656)	(0.3891)
SNAP benefits p.p. ($1,000)	0.12	0.13	-0.01	7.038**	1.233**
	⟨0.002⟩	⟨0.003⟩		(3.363)	(0.5087)
Income p.p.($1,000)	6.95	6.66	0.29	0.0166	-0.0090
	⟨0.03⟩	⟨0.06⟩		(0.0635)	(0.0133)
WIC vendors, 2006-2008					
Net increase in WIC vendors	0.04	0.03	0.004	0.4176	0.1275**
(1,000)	⟨0.002⟩	⟨0.004⟩		(0.3079)	(0.0537)
Fraction of population	81.27	18.73			
Fraction of births	79.10	20.08			
State fixed effects					✓
Observations				2,489	2,489
R-squared				0.1569	0.9892

Notes: This table shows cases means and, in angle brackets, standard errors, of the group with characteristics listed in first column. Data on share of black, share of Hispanic, and income per person is from American Community Survey (ACS) Public Use Microdata Sample; data on transfers is from Bureau of Economic Analysis, Regional Economic Information System (REIS); data on share of poor and under age 5 is from the Small Area Income and Poverty Estimates (SAIPE) Program; data on share of low birth weight is from restricted-use Vital Statistics Natality Data; data on net increase in WIC vendors is from the WIC Integrity Profiles (TIP). In the third column are differences in means of included and excluded counties. ***, **, and * indicate that mean difference are significant at the 1%, 5%, and 10% levels with Student's T-test. Units of transfer are dollars unless otherwise specified. Fractions of the population and births do not sum up to 1 because we take into account observations without geographical identifiers. Low birth weight is when birth weight is no more than 2,500 grams. In Columns 4 and 5 are results from regressions of year of WIC EBT implementation on county baseline characteristics. Each regression is weighted by the mean population during 2006-2008. Standard errors in Columns 4 and 5 are heteroscedasticity-robust.

4 Methods

To estimate effects of WIC EBT implementation, we compare counties that implemented WIC EBT with counties that have not yet implemented WIC EBT. Our baseline regression model is:

$$Y_{ct} = \alpha + \mu EBT_{ct} + \lambda_t + \eta_c + \theta_{ct} + Z_c t + X_{ct} + \varepsilon_{ct},$$

where Y_{ct} is outcome variable measured for county c in year t, η_c and λ_t are county and year fixed effects to control for national economic shocks and county time-invariant unobserved heterogeneity, θ_{ct} is census-region-by-year fixed effect to account for differential trends of outcomes across geograhical areas, $Z_c t$ is county baseline characteristics interacted with linear time trend to control for differential trends across regions with different baseline characteristics, X_{ct} is county-by-year employment rate to control for county-by-year-level local economic conditions, and ε_{ct} is an error term.

As documented in Goodman-Bacon (2021) as well as de Chaisemartin and D'Haultfœuille (2020), Imai and Kim (2021), and Sun and Abraham (2021), a standard two-way fixed effects (TWFE) OLS estimator with staggered treatment timing and heterogeneous treatment effects will implicitly make comparisons to all other units, aggregating these comparisons up with weights that may be negative. We use the interaction weighted (IW) estimator proposed by Sun and Abraham (2021) in our baseline results to avoid this issue. Sun and Abraham (2021) show that the IW estimator is consistent under assumptions of parallel trends and no anticipation. In appendix, we discuss results using other popular staggered difference-in-difference estimators as well as traditional TWFE estimators. We find that our results are not driven by the choice of estimation method.

In our baseline results, we report standard errors clustered at both the county and state levels, recognizing that the unit of treatment assignment could be the county or a group of counties, while also accounting for potential synergies among counties within the same state (Abadie et al., 2023). Regressions and dependent variable means are weighted using the number of births in each cell.

5 Results

We start our analysis identifying subgroups more likely to be WIC eligible by linking maternal characteristics and WIC eligibility using data from the Survey of Income and Program

---

We control for census-region-by-year instead of state-by-year fixed effects to avoid singular matrix in estimation as there is nontrivial synergy of implemeting WIC EBT within state.

For convenience, we report both standard errors for main results and falsification/robustness tests except for event study plots; for the other analysis, we only report standard errors clustered on county.

Participation (SIPP). Our main results are effects of WIC EBT implementation on WIC participation. EBT was expected to nudge WIC participation by reducing welfare stigma and transaction cost. We also analyze its effects on three key birth outcomes: birth weight, the probability of low birth weight (birth weight $<$ 2500 grams), and the probability of preterm birth (gestation $<$ 37 weeks). The expectation was that EBT would enhance birth outcomes by increasing both WIC participation and redemption rates, thereby improving maternal nutrition and, consequently, infant health. The raw estimates from our regressions represent the intent-to-treat (ITT) effects of EBT. To obtain treatment effects on the treated (TOT), we divide the ITT by the share of WIC-eligible individuals in each group.

5.1 The likely-eligible

Ideally, our analysis would be limited to WIC-eligible mothers. However, birth certificates do not provide data on WIC eligibility or maternal income. As an alternative, we restrict our sample to subgroups more likely to be eligible for WIC, defined by specific maternal characteristics. This method is a standard approach for studying policy impacts when data do not directly identify the policy's target population (Meckel, 2020; Alsan and Yang, 2022; East et al., 2023).

We focus on maternal age, education, marital status, race, and Hispanic origin, as these are the most commonly reported demographic characteristics. To validate these characteristics as proxies for WIC eligibility, we utilize data from SIPP. WIC eligibility requires household income below 185% of the federal poverty line or participation in Supplemental Nutrition Assistance Program (SNAP), Temporary Assistance for Needy Families (TANF) or Aid to Families with Dependent Children (AFDC), or Medicaid. The SIPP provides valuable insight into the demographic characteristics of WIC-eligible individuals, as it includes information on household income and program participation. We identify WIC-eligible mothers based on household income below 185% of the federal poverty line or participation in SNAP, TANF/AFDC, or Medicaid. From 2009 to 2021, the average proportion of WIC-eligible mothers of infants was 48.23%, slightly lower than the 54.10% estimated for WIC-eligible pregnant and postpartum women in 1998 by Bitler, Currie and Scholz (2003). Given that we do not observe pregnant women directly, we focus on mothers of infants (children aged 0). We then use the correlation between WIC eligibility and maternal characteristics to guide the selection of subgroups.

We focus on mothers with a high school education or less and mothers who are unmarried householders as both subpopulations more likely to be WIC-eligible as both of them comprise approximately 40% of the full sample and are about 17% more likely to be WIC-

Bitler, Currie and Scholz (2003) highlights a significant undercount of WIC participants in SIPP data, though this undercount appears to be random with respect to observable characteristics.

eligible than mothers overall (Table 3). When we discuss effects on WIC participation and birth outcomes, in addition to the full sample, we present results for these two groups. Since natality data does not indicate whether a mother is a householder, we report results for births where the father is not listed, as a proxy for unmarried householder mothers.

TABLE 3: REGRESSIONS OF WIC ELIGIBILITY ON MATERNAL CHARACTERISTICS, SIPP

Maternal characteristics	Individual regressions: coefficients (std.err)	Share of individuals with characteristic k	Share of WIC-eligible individuals (S_k)	$S_k - S_{all}$
	(1)	(2)	(3)	(4)
Age $\leq$ 22	0.1264*** (0.0069)	19.41%	58.11%	9.88%
Education $\leq$ high school	0.2281*** (0.0084)	37.17%	65.29%	17.06%
Unmarried	0.1558*** (0.0088)	56.00%	56.41%	8.18%
Unmarried female householder	0.1742*** (0.0103)	40.71%	64.81%	16.58%
Black	0.1809*** (0.0196)	15.37%	64.00%	15.77%
Hispanic	0.2220*** (0.0127)	20.04%	62.35%	14.12%

Notes: Dependent variables of Columns (1) are a dummy for WIC eligibility estimated with income and program participation. Data is Survey of Income and Program Participation (SIPP) panels 2008, 2014, and 2018-2021. These panels cover households interviewed from 2008-2021 (those interviewed in 2008 are excluded). In Column (1) are estimates from regressions of WIC eligibility on single maternal characteristics. We control for state and panel fixed effects. Standard errors are clustered at state level. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels. All regressions controls for state and panel fixed effects. S_{all} denotes overall share of WIC-eligible mothers. $S_{all} = 48.23\%$.

5.2 WIC participation

Table 4 shows that ITTs of EBT on WIC participation are 1.26, 1.56, and 1.62 percentage points for all births, mothers with high school education or less, and infants without documented fathers, respectively. The corresponding shares of WIC-eligible individuals are 48.23%, 65.29%, and 64.81%, yielding TOT estimates of 2.6, 2.39, and 2.5 percentage points.

Figure 5 indicates that pre-implementation trends are relatively flat, suggesting minimal differential trends before EBT implementation. We further test the sensitivity to potential violation of parallel trend assumption in Section 6. In Table A1, we aggregate estimates by cohort and observe that earlier-adopting states experienced more negative changes in WIC participation post-implementation. We discuss possible reasons at the end of the article.

TABLE 4: EFFECTS OF WIC EBT ON WIC PARTICIPATION

	All births			Education ≤ high school			No father		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Born after EBT	0.0149	0.0168	0.0126	0.0268	0.0291	0.0156	0.0275	0.0336	0.0162
	(0.0058)**	(0.0051)***	(0.0056)**	(0.0081)***	(0.0080)***	(0.0073)**	(0.0079)***	(0.0074)***	(0.0065)**
	⟨0.0156⟩	⟨0.0097⟩*	⟨0.0120⟩	⟨0.0120⟩**	⟨0.0107⟩***	⟨0.0092⟩*	⟨0.0086⟩***	⟨0.0059⟩***	⟨0.0053⟩***
County fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Census region×year		✓	✓		✓	✓		✓	✓
Baseline char.×year		✓	✓		✓	✓		✓	✓
Employment rate$_{ct}$			✓			✓			✓
Observations	34,566	33,873	28,023	33,964	33,329	27,485	32,496	31,890	26,227
R^2	0.9578	0.9635	0.9637	0.9193	0.9237	0.9290	0.8463	0.8520	0.8520
Dep. var. mean	0.3972	0.3987	0.4118	0.6395	0.6412	0.6514	0.6627	0.6641	0.6747

Notes: We report interaction weighted estimators proposed by Sun and Abraham (2021). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. We control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2009 interacted with linear time trend, and county-by-year employment rate. Regressions and dependent variable mean are weighted by the number of births in each cell. We report standard errors clustered on county in parentheses and standard errors clustered on state in angle brackets. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

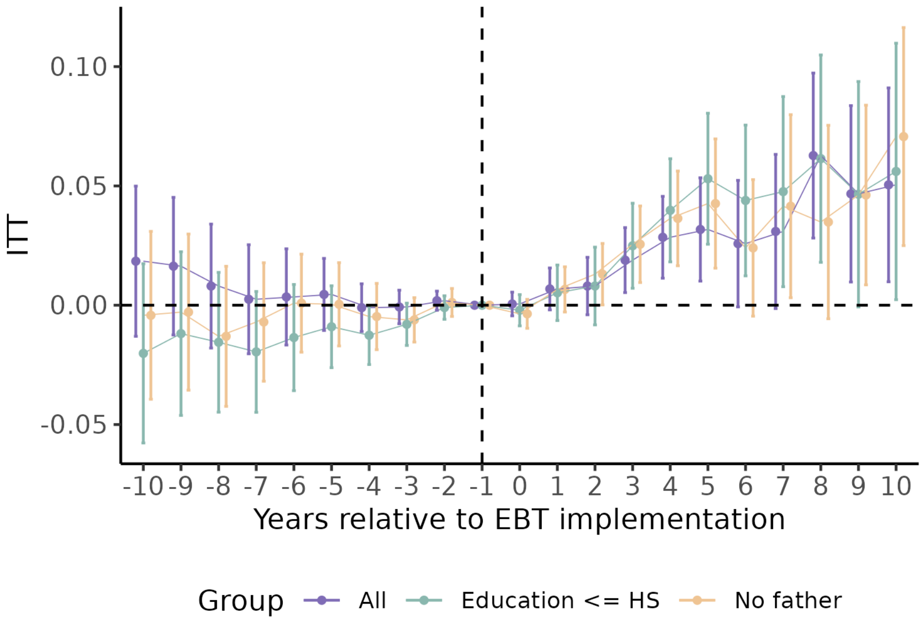


FIGURE 5: DYNAMIC EFFECTS OF WIC EBT ON WIC PARTICIPATION

Notes: We estimate dynamic effects using interaction weighted estimators proposed by Sun and Abraham (2021). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. We control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2009 interacted with linear time trend, and county-by-year employment rate. Regressions and dependent variable mean are weighted by the number of births in each cell. Standard errors are clustered at county level.

6 Composition, Sensitivity, and Robustness

6.1 Composition change

We address the possibility that the observed effects of EBT on specific subgroups could be driven by welfare migration or changes in maternal characteristics. However, Table 5 shows that this is not the case, as the EBT implementation does not significantly alter the composition of the subpopulations of interest except there were slightly fewer white infants after EBT. Thus, our estimates can be interpreted as reflecting the outcome changes among existing WIC-eligible mothers.

TABLE 5: COMPOSITION CHANGE

	Maternal characteristics used to define subgroups			Other maternal characteristics						
	Edu ≤ HS	No father	Adv. mothers	Age ≤ 22	College graduates	Unmarried	White	Black	Asian	Hispanic
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Born after EBT	-0.0003	8×10^{-6}	-0.0015	-0.0023	0.0042	0.0002	-0.0156	0.0143	0.0035	0.0033
	(0.0031)	(0.0027)	(0.0032)	(0.0019)	(0.0029)	(0.0042)	(0.0087)*	(0.0081)*	(0.0067)	(0.0029)
	⟨0.0037⟩	⟨0.0054⟩	⟨0.0034⟩	⟨0.0039⟩	⟨0.0059⟩	⟨0.0046⟩	⟨0.0056⟩***	⟨0.0115⟩	⟨0.0081⟩	⟨0.0103⟩
Observations	28,014	28,023	28,019	28,023	28,014	28,022	28,023	28,023	28,023	28,023
R^2	0.9632	0.8992	0.9642	0.9590	0.9798	0.9245	0.9767	0.9217	0.8846	0.9926
Dep. var. mean	0.4028	0.1114	0.5611	0.1812	0.3119	0.4027	0.6482	0.1366	0.0613	0.2086

Notes: Advantaged mothers (adv. mothers) have more than high school education and father of infant on birth certificate. We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. We control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2009 interacted with linear time trend, and county-by-year employment rate. Regressions and dependent variable mean are weighted by the number of births in each cell. We report standard errors clustered on county in parentheses and standard errors clustered on state in angle brackets. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

6.2 Placebo test: advantaged mothers

We begin by demonstrating that advantaged mothers—those with more than a high school education and whose infants have a father listed on the birth certificate—should not be affected by the arrival of WIC EBT, given the noisy reaction observed in the full sample. Table 6 confirms that there are no significant effects on these advantaged mothers.

6.3 Placebo test: placebo treatment timing

We conduct another placebo test by estimating results based on hypothetical treatment timings. Specifically, we re-estimate the effects assuming the treatment occurred four years earlier than it actually did. The pseudo-treatment effects are statistically insignificant, small in magnitude, and occasionally have the opposite sign (Table A2).

TABLE 6: EFFECTS OF WIC EBT ON ADVANTAGED MOTHERS

	WIC participation (1)	Birth weight (2)	Low birth weight (3)	Preterm (4)
Born after EBT	0.0086	-2.192	0.0005	0.0003
	(0.0035)**	(2.432)	(0.0010)	(0.0013)
	⟨0.0060⟩	⟨5.685⟩	⟨0.0021⟩	⟨0.0029⟩
Observations	27,712	27,710	27,710	27,712
R^2	0.9474	0.8041	0.4698	0.5230
Dependent variable mean	0.2279	3,315	0.0705	0.1014

Notes: Advantaged mothers have more than high school education and father of infant on birth certificate. We report interaction weighted estimators proposed by Sun and Abraham (2021). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. We control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2009 interacted with linear time trend, and county-by-year employment rate. Regressions and dependent variable mean are weighted by the number of births in each cell. We report standard errors clustered on county in parentheses and standard errors clustered on state in angle brackets. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

6.4 Randomization test

To assess the robustness of our results against random noise, we compute Intent-to-Treat (ITT) effects using randomized pseudo-treatment timings. We randomly assign the year of WIC EBT implementation 1,000 times while maintaining the original distribution of rollout years. This randomization test is conducted for effects on WIC participation, the likelihood of low birth weight, and preterm birth for mothers with high school education or less and for mothers without documented fathers of infants. The estimated effects in our main analysis consistently fall well into the tails of the distribution of the simulated effects, suggesting that our findings are not likely the results of random noise (Figure A2).

6.5 Event-time balanced panel

Due to the widespread distribution of EBT implementation across states, constructing a balanced panel would result in a significant reduction in sample size. Table A3 presents results for an event-time balanced panel spanning from period -4 to period 4. These findings generally align with our main results. The effects on WIC participation are larger and more precise in this balanced panel. However, the effects on the likelihood of low birth weight become smaller and less precise. For preterm births, the effects increase in magnitude for the full sample and for mothers with a high school education or less, but they are less precise for mothers without documented fathers of infants. The dynamic effects are shown in Figure A3.

6.6 Sensitivity to parallel trend violation

Some of our estimates of dynamic effects might be influenced by pre-existing differential trends, potentially compromising identification. We assess the sensitivity of our results to violations of the parallel trends assumption using the procedure proposed by Rambachan and Roth (2023). Our focus is on the dynamic effects on outcomes for two groups more likely to be WIC-eligible. Figure A4 presents the maximum deviation from the parallel trends assumption that we can tolerate while still claiming significant effects at a 10% significance level. For mothers with a high school education or less (and mothers without documented fathers of infants), the breakdown values are 0.14 (0.12) for WIC participation, greater than 0.2 (0.1) for the probability of having low-birth-weight infants, and 0.16 (0.12) for the probability of preterm births. This implies that our results remain robust at the 10% significance level unless we allow for the linear extrapolation across consecutive periods to deviate by more than these breakdown values.

6.7 Robustness to estimation methods

We also present results using alternative staggered difference-in-difference methods, including traditional two-way fixed effects estimators (Figure A5), estimators from Callaway and Sant'Anna (2021) using never-treated or not-yet-treated groups as the control group (Figures A6 and A7), and imputation estimators by Borusyak, Jaravel and Spiess (2024) (Figure A8). While these estimators are not directly comparable due to differences in comparison groups, periods, and methods of accounting for covariates (Roth et al., 2023), we find that these alternative estimators are broadly consistent with our baseline results using the Sun and Abraham (2021) approach.

6.8 Robustness to timing of exposure

Finally, we examine the robustness of our results to the timing of exposure. In our baseline results, infants are considered treated if they are born after the EBT implementation. However, this may attenuate our estimates since mothers of infants born shortly after EBT implementation might not have had enough time to obtain EBT approval if they did not anticipate its arrival. This concern is valid, as 50% of pregnant participants certify in the first trimester, 40% in the second, and only 10% in the third (Thorn et al., 2016). In Table A4, we present estimates defining exposure at the beginning of the first, second, or third trimester instead of at the time of birth. As expected, our estimates generally become larger and more precise.

7 Potential Mechanisms

7.1 Urban-rural dichotomy

Table 7 indicates that the effects on WIC participation are primarily driven by rural areas, aligning with the notion that welfare stigma is more pronounced among rural residents, where individuals are more likely to recognize fellow shoppers. The larger effects observed in rural areas might be attributed to a stronger response from poorer individuals; however, this does not explain why the effects are smaller among two particularly disadvantaged groups compared to the full sample. Another potential explanation for the larger effects in rural areas could be differences in the retail environment between urban and rural areas. However, if this were the only factor, we would expect smaller effects in rural areas, given that WIC vendors there are predominantly small, independent stores. According to Meckel (2020), these stores have a higher tendency to drop out of WIC after EBT implementation, which could hinder WIC participation or redemption.

TABLE 7: EFFECTS OF WIC EBT ON WIC PARTIPATION IN URBAN AND RURAL AREAS

	Urban areas			Rural areas		
	All births	Edu≤HS	No father	All births	Edu≤HS	No father
	(1)	(2)	(3)	(4)	(5)	(6)
Born after EBT	0.0103*	0.0127	0.0148*	0.0305***	0.0295***	0.0223**
	(0.0059)	(0.0089)	(0.0080)	(0.0059)	(0.0071)	(0.0089)
Observations	8,904	8,742	8,549	19,118	18,742	17,677
R^2	0.9729	0.9472	0.9044	0.9316	0.8877	0.6649
Dependent variable mean	0.3976	0.6515	0.6600	0.4768	0.6512	0.7287

Notes: Urban and rural areas are defined by NCHS 2006 Urban-Rural Classification Scheme for Counties. We report interaction weighted estimators proposed by Sun and Abraham (2021). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. We control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2009 interacted with linear time trend, and county-by-year employment rate. Regressions and dependent variable mean are weighted by the number of births in each cell. We report standard errors clustered on county in parentheses. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

7.2 Change in WIC eligibility

Building on the full model, we further control for county-by-year per capita income and transfers from Medicaid, SNAP, and TANF, as these variables reflect changes in average WIC eligibility. The results remain consistent with our baseline findings (Table A5). While controlling for variables related to WIC eligibility modestly attenuates the effects of EBT on WIC participation, it does not alter the effects observed on birth outcomes.

7.3 WIC vendor access

The positive effects on WIC participation may also be influenced by changes in the retail environment. Specifically, if the implementation of WIC EBT expanded access to WIC vendors, it could have led to increased participation. To explore this possibility, we linked WIC EBT rollout data to WIC Integrity Profiles from 2009-2016 to assess the impact of WIC EBT on the number of net authorized WIC vendors each year. Table 8 indicates that WIC EBT actually decreases the number of newly authorized WIC vendors, which aligns with the results reported by Meckel (2020). Even in rural areas, where the increase in WIC participation is more pronounced after the implementation of EBT, we still observe a decline in net WIC vendor authorizations. Thus, it is unlikely that the observed effects on WIC participation are driven by increased access to WIC vendors.

TABLE 8: EFFECTS OF WIC EBT ON NET NEWLY-AUTHORIZED WIC VENDORS

	All areas		Rural areas	
	Net WIC vendor authorization	Net WIC vendor authorization per person	Net WIC vendor authorization	Net WIC vendor authorization per person
	(1)	(2)	(3)	(4)
WIC EBT implementation	-0.9149	-0.0110**	-0.4736***	-0.0030**
	(0.9113)	(0.0053)	(0.1078)	(0.0012)
Observations	17,012	17,012	11,349	11,349
R^2	0.9913	0.6057	0.9457	0.9093
Dependent variable mean	58.75	0.0702	5.0105	0.0344

Notes: We report interaction weighted estimators proposed by Sun and Abraham (2021). We control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2009 interacted with linear time trend, and county-by-year employment rate. Regressions and dependent variable mean are weighted by county-by-year population. We report standard errors clustered on county in parentheses. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

8 Heterogeneity

We first explore the heterogeneity of EBT effects by race and ethnicity, with the results presented in Table A6. Our findings indicate that the observed effects are primarily driven by the white population.

Next, we analyze EBT effects across different maternal age groups. While the effects on WIC participation tend to be larger for younger mothers, the effects on birth outcomes are relatively noisy across age groups. This suggests that maternal age does not effectively capture the populations most reactive to WIC EBT (Table A7).

Finally, we examine EBT effects by population-weighted income quantiles, calculated as the average income quantiles from 2004 to 2008. Notably, 1,945 counties fall within the first income quantile, while 1,133 counties fall within the remaining income quantiles, indicating that counties in the lower income quantile tend to be less populous. As expected, EBT effects are larger and more pronounced in counties within the first population-weighted income quantile, while they are not significant in counties within higher income quantiles (Table A8).

9 Magnitudes

We compare our estimates on WIC participation with those of Meckel (2020). Meckel (2020) finds a decline in the average number of mothers participating in WIC after the introduction of EBT, based on Texas birth certificate data. However, as shown in Figures B1a-B1d, their estimates on WIC participation are compromised by violations of the parallel trends assumption. Moreover, their estimates are more susceptible to parallel trend violations, as indicated in Figures B2a-B2b. In contrast, our nationwide estimates are slightly smaller than those reported by Li, Saitone and Sexton (2022), who find an 8.54 percentage point increase in WIC participation based on WIC enrollment data from Oklahoma.

To the best of our knowledge, no other study has examined the effects of WIC EBT on birth outcomes. Therefore, we compare our results on birth outcomes with those of Hoynes, Page and Stevens (2011). Hoynes, Page and Stevens (2011) find that when WIC was made available by the third trimester, the average birth weight in the county increased by 2 grams, and by 7 grams among infants born to mothers with less than a high school education. In comparison, our estimates (Panel C, Table A4) indicate that WIC EBT implementation by the third trimester has no significant effect on average birth weight in the county, but increases the average birth weight by 5.51 grams among infants born to mothers with a high school education or less. Additionally, Hoynes, Page and Stevens (2011) find that the introduction of WIC did not reduce the share of infants with low birth weight, whereas we find a 0.4-0.6 percentage point decline in the share of low-birth-weight infants among likely-eligible individuals following EBT implementation.

From the perspective of birth outcomes, we consider WIC EBT implementation to be an effective policy. Compared to the initial introduction of WIC, WIC EBT has comparable effects on birth weight and a positive impact on reducing adverse birth outcomes.

10 EBT, WIC Participation, and Infant Health

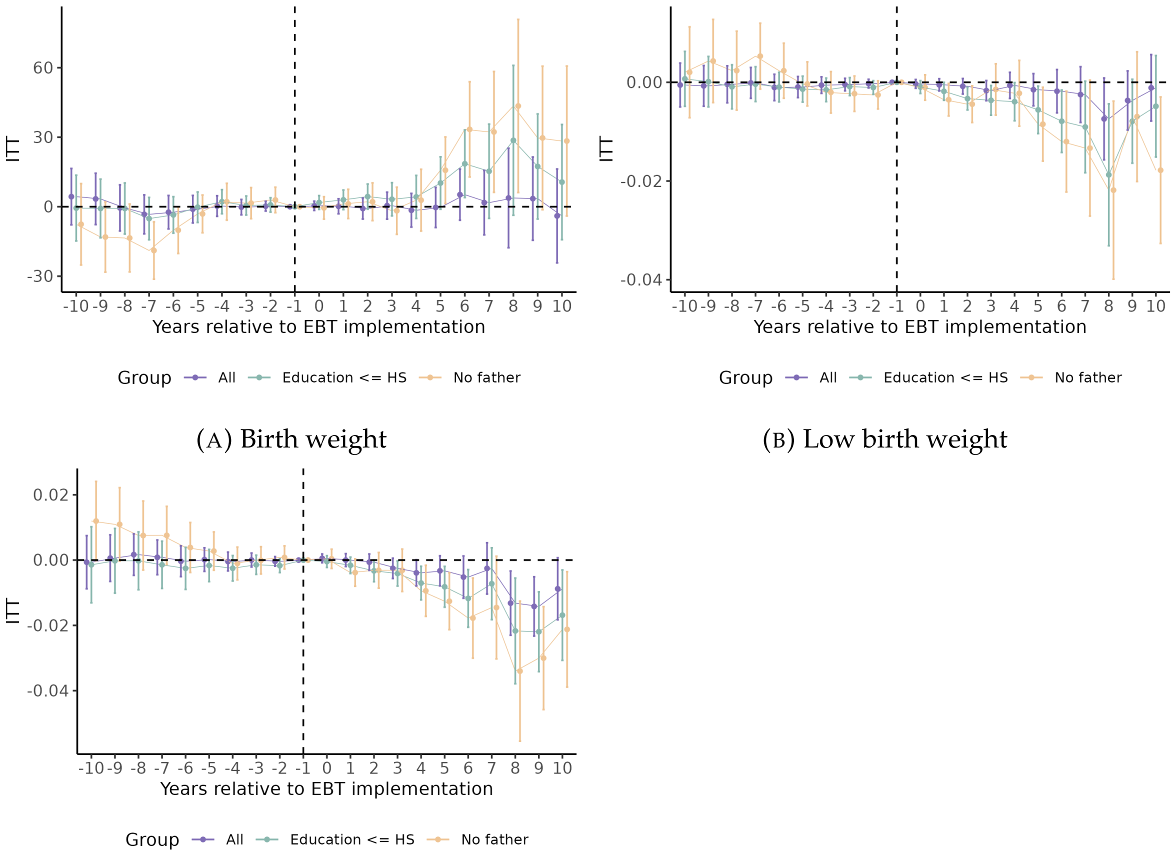
Table 9 shows that while the effects of WIC EBT on birth outcomes are noisy for the full sample, they are statically significant for subgroups more likely to be WIC-eligible. Specifically, the ITT effects of EBT on the likelihood of low birth weight are -0.31 (TOT = -0.47) and -0.4 (TOT = -0.62) percentage points for mothers with a high school education or less and mothers without documented fathers, respectively. Similarly, the ITT effects on the likelihood of preterm births are -0.35 (TOT = -0.54) and -0.53 (TOT = -0.82) percentage points for the same groups.

TABLE 9: EFFECTS OF WIC EBT ON BIRTH OUTCOMES

	Birth weight (grams)			Low birth weight (birth weight < 2500 grams)			Preterm (gestation < 37 weeks)		
	All births (1)	Edu≤HS (2)	No father (3)	All births (4)	Edu≤HS (5)	No father (6)	All births (7)	Edu≤HS (8)	No father (9)
Born after EBT	-0.1545	4.532	4.812	-0.0009	-0.0031	-0.0040	-0.0012	-0.0035	-0.0053
	(2.269)	(2.812)	(3.894)	(0.0008)	(0.0012)***	(0.0019)**	(0.0011)	(0.0015)**	(0.0024)**
	⟨4.955⟩	⟨3.600⟩	⟨4.441⟩	⟨0.0016⟩	⟨0.0010⟩***	⟨0.0015⟩**	⟨0.0020⟩	⟨0.0013⟩***	⟨0.0019⟩***
Observations	28,021	27,482	26,224	28,021	27,482	26,224	28,023	27,485	26,227
R^2	0.8865	0.8324	0.6471	0.7092	0.6458	0.4203	0.6996	0.6335	0.4292
Dep. var. mean	3,269	3,217	3,121	0.0808	0.0913	0.1224	0.1153	0.1308	0.1629

Notes: We report interaction weighted estimators proposed by Sun and Abraham (2021). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. We control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2009 interacted with linear time trend, and county-by-year employment rate. Regressions and dependent variable mean are weighted by the number of births in each cell. We report standard errors clustered on county in parentheses and standard errors clustered on state in angle brackets. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

Figures 6a–6c suggest that pre-implementation trends are flat for the full sample and for mothers with a high school education or less, while the effects observed for mothers without documented fathers may be influenced by pre-existing trends. We also assess the sensitivity of these results to violations of the parallel trends assumption in Section 6.



(A) Birth weight

(B) Low birth weight

(C) Preterm

FIGURE 6: DYNAMIC EFFECTS OF WIC EBT ON BIRTH OUTCOMES

Notes: We estimate dynamic effects using interaction weighted estimators proposed by Sun and Abraham (2021). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. We control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2009 interacted with linear time trend, and county-by-year employment rate. Regressions and dependent variable mean are weighted by the number of births in each cell. Standard errors are clustered at county level.

11 Discussion and Conclusion

11.1 Limitations

Our approach has some key limitations. The first is that the natality data will not measure WIC participation among those who enter WIC after the birth certificate is filed. This may include some older siblings who enroll at the time that the pregnant individual or newly born infant joins the program. Accordingly, we are more accurately capturing changes in participation for pregnant and postpartum individuals and newly born infants, rather than children who were on the program when WIC EBT was implemented. Rates of participation have been falling fast for children and children are the largest total participating group in WIC at any time, so that understanding children's participation is still important. On the other hand, our results are directly comparable to previous work that has used natality data to measure WIC participation. Also, nutritionists and public health experts often attempt to target pregnant people and infants given the importance of nutrition in the "first 1000 days" for later life outcomes. Ensuring participation among eligible pregnant individuals and infants covers a substantial portion of the first thousand days window.

Another limitation is that we measure EBT timing at the year level with a binary treatment variable indicating whether or not the county had any EBT implementation during the year. This binary measure aggregated up over time induces some non-classical measurement error into our treatment variable, which may bias our results. We note that in our case we have only false positives – indicating that a county has EBT when EBT has not occurred yet – so that our ATT estimates in a classical DiD set up will be attenuated (Nguimkeu, Denteh and Tchernis, 2019). The Sun and Abraham (2021) approach constructs a series of classical DiD estimates and aggregates, so we suppose that this attenuation effect holds.

A final limitation of the data is that not all counties report natality data. As mentioned in Section 3, the observable characteristics of our sample of births in the natality data are close in magnitude to a comparison population in the CPS ASEC and SIPP. However, our sample may not represent the full population in unobservable factors.

11.2 Summary

In this paper, we combine Vital Statistics Natality data from 2009-2021 with county-level data on the rollout of WIC EBT across all states. We construct the first national estimates of the effect of WIC EBT on WIC participation. This substantially advances our understanding of the effects of a major policy change in WIC on WIC participants. Where prior work using data for one state and a shorter time span find negative effects of EBT on participation, we find increases in WIC participation and decline in adverse birth outcomes on average after EBT implementation.

As noted above, our data and approach allow us to capture the effects of WIC EBT on participation across the whole country and for a longer period of time. We consider our average treatment effect estimates to be representative of the net effect of EBT. We are also able to measure WIC participation accurately with natality data (relative to survey data). Across our main results and the sensitivity and robustness checks we find significant and positive effects of WIC EBT on WIC participation and birth outcomes among likely eligible individuals.

The results are characterized by heterogeneity across space and time of WIC EBT implementation. We find that earlier-adopting states had more negative participation changes after EBT. These results are consistent with a mental model in which states learn from other states about how to implement EBT in ways that make the transition smoother for participants. It is also possible that early adopting states have other unobserved factors that mediated the effect of EBT on participation. For instance, states that were eager to implement fraud reduction technology may impose other administrative burdens to WIC participation. However, on average, WIC EBT was effective at increasing WIC participation among eligible individuals. This indicates that the net effect of reducing stigma and enabling partial redemptions outweighed any deterrence effect from fraud reduction.

References

Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey M Wooldridge. 2023. "When should you adjust standard errors for clustering?" *The Quarterly Journal of Economics*, 138(1): 1–35.

Almond, Douglas, Hilary W Hoynes, and Diane Whitmore Schanzenbach. 2011. "Inside the war on poverty: The impact of food stamps on birth outcomes." *Review of Economics and Statistics*, 93(2): 387–403.

Alsan, Marcella, and Crystal S Yang. 2022. "Fear and the safety net: Evidence from secure communities." *Review of Economics and Statistics*, 1–45.

Ambrozek, Charlotte. 2022. "WIC Participant Responses to Vendor Disqualification."

Bitler, Marianne, Janet Currie, Hilary Hoynes, Krista Ruffini, Lisa Schulkind, and Barton Willage. 2023. "Mothers as insurance: Family spillovers in WIC." *Journal of Health Economics*, 91: 102784.

Bitler, Marianne P, and Janet Currie. 2005. "Does WIC work? The effects of WIC on pregnancy and birth outcomes." *Journal of Policy Analysis and Management: The Journal of the Association for Public Policy Analysis and Management*, 24(1): 73–91.

Bitler, Marianne P, Janet Currie, and John Karl Scholz. 2003. "WIC eligibility and participation." *Journal of Human Resources*, 1139–1179.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess. 2024. "Revisiting event-study designs: robust and efficient estimation." *Review of Economic Studies*.

Callaway, Brantly, and Pedro HC Sant'Anna. 2021. "Difference-in-differences with multiple time periods." *Journal of Econometrics*, 225(2): 200–230.

Chorniy, Anna, Janet Currie, and Lyudmyla Sonchak. 2020. "Does prenatal WIC participation improve child outcomes?" *American Journal of Health Economics*, 6(2): 169–198.

de Chaisemartin, Clément, and Xavier D'Haultfœuille. 2020. "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects." *American Economic Review*, 110(9): 2964–2996.

East, Chloe N, Annie L Hines, Philip Luck, Hani Mansour, and Andrea Velasquez. 2023. "The labor market effects of immigration enforcement." *Journal of Labor Economics*, 41(4): 957–996.

Figlio, David, Sarah Hamersma, and Jeffrey Roth. 2009. "Does prenatal WIC participation improve birth outcomes? New evidence from Florida." *Journal of Public Economics*, 93(1-2): 235–245.

Goodman-Bacon, Andrew. 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics*, 225(2): 254–277.

Gray, Colin, Adam Leive, Elena Prager, Kelsey Pukelis, and Mary Zaki. 2023. "Employed in a SNAP? The impact of work requirements on program participation and labor supply." *American Economic Journal: Economic Policy*, 15(1): 306–341.

Hanks, Andrew S, Carolyn Gunther, Dean Lillard, and Robert L Scharff. 2019. "From paper to plastic: understanding the impact of eWIC on WIC recipient behavior." *Food Policy*, 83: 83–91.

Hoynes, Hilary, Marianne Page, and Ann Huff Stevens. 2011. "Can targeted transfers improve birth outcomes?: Evidence from the introduction of the WIC program." *Journal of Public Economics*, 95(7-8): 813–827.

Imai, Kosuke, and In Song Kim. 2021. "On the Use of Two-Way Fixed Effects Regression Models for Causal Inference with Panel Data." *Political Analysis*, 29(3): 405–415.

Kreider, Brent, John V Pepper, and Manan Roy. 2016. "Identifying the effects of WIC on food insecurity among infants and children." *Southern Economic Journal*, 82(4): 1106–1122.

Li, Xuemei, Patrick W. McLaughlin, Tina L. Saitone, and Richard J. Sexton. 2021. "The Magnitude and Determinants of Partial Redemptions of Food Benefits in the Special Supplemental Nutrition Program for Women, Infants and Children (WIC)." *American Journal of Health Promotion*, 35(6): 775–783.

Li, Xuemei, Tina L Saitone, and Richard J Sexton. 2022. "Impacts of Electronic Benefit Transfer on the Women, Infants and Children Program: Evidence from Oklahoma." *Journal of Agricultural and Resource Economics*, 47(2): 373–389.

McLaughlin, Patrick W, Tina L Saitone, and Richard J Sexton. 2019. "The economics of food vendors specialized to serving the women, infants, and children program." *American Journal of Agricultural Economics*, 101(1): 20–38.

Meckel, Katherine. 2020. "Is the cure worse than the disease? unintended effects of payment reform in a quantity-based transfer program." *American Economic Review*, 110(6): 1821–1865.

Meyer, Bruce D., and Nikolas Mittag. 2019. "Misreporting of Government Transfers: How Important Are Survey Design and Geography?" *Southern Economic Journal*, 86(1): 230–253.

Meyer, Bruce D., Wallace K. C. Mok, and James X. Sullivan. 2015. "Household Surveys in Crisis." *Journal of Economic Perspectives*, 29(4): 199–226.

Moffitt, Robert. 1983. "An Economic Model of Welfare Stigma." *The American Economic Review*, 73(5): 1023–1035.

Nguimkeu, Pierre, Augustine Denteh, and Rusty Tchernis. 2019. "On the estimation of treatment effects with endogenous misreporting." *Journal of Econometrics*, 208(2): 487–506.

Rambachan, Ashesh, and Jonathan Roth. 2023. "A more credible approach to parallel trends." *Review of Economic Studies*, 90(5): 2555–2591.

Rossin-Slater, Maya. 2013. "WIC in your neighborhood: New evidence on the impacts of geographic access to clinics." *Journal of Public Economics*, 102: 51–69.

Roth, Jonathan, Pedro HC Sant'Anna, Alyssa Bilinski, and John Poe. 2023. "What's trending in difference-in-differences? A synthesis of the recent econometrics literature." *Journal of Econometrics*, 235(2): 2218–2244.

Sun, Liyang, and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." *Journal of Econometrics*, 225(2): 175–199.

Swann, Christopher A. 2010. "WIC eligibility and participation: The roles of changing policies, economic conditions, and demographics." *The BE Journal of Economic Analysis & Policy*, 10(1).

Thorn, Betsy, Chrystine Tadler, Nicole Huret, E Ayo, and C Trippe. 2016. "WIC participant and program characteristics final report. 2015."

Wright, Richard, Erdal Tekin, Volkan Topalli, Chandler McClellan, Timothy Dickinson, and Richard Rosenfeld. 2017. "Less cash, less crime: Evidence from the electronic benefit transfer program." *The Journal of Law and Economics*, 60(2): 361–383.

Zhao, Jianqiang J, Harry M Kaiser, and Yuqing Zheng. 2022. "Do grocery food taxes incentivize participation in SNAP?" *Regional Science and Urban Economics*, 95: 103736.

Appendix

A Figures and tables

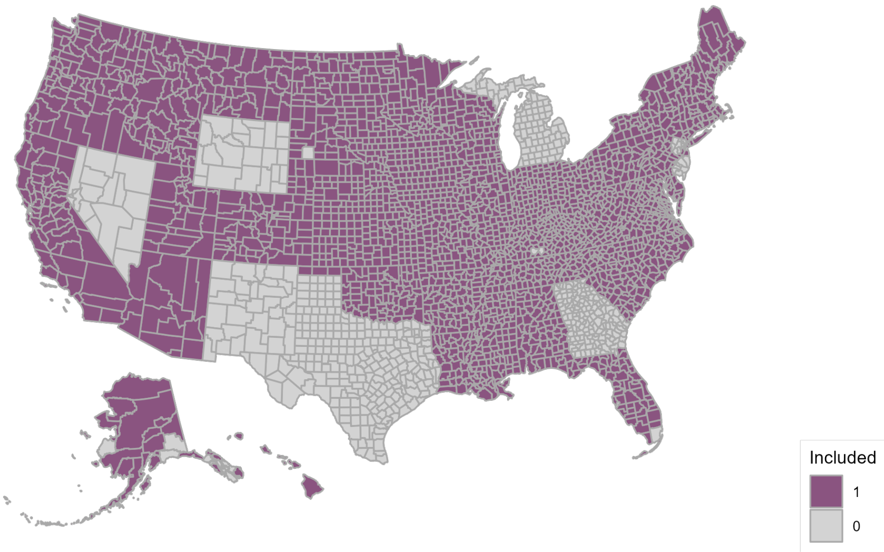


FIGURE A1: COUNTIES IN OUR SAMPLE

TABLE A1: COHORT-SPECIFIC EFFECTS OF EBT ON WIC PARTICIPATION

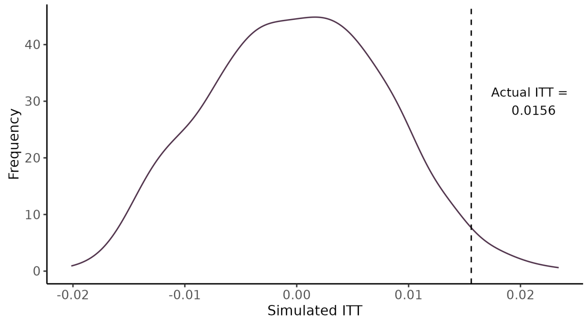
	WIC participation		
	All births	Edu≤HS	No father
	(1)	(2)	(3)
Cohort = 2011	0.0131	0.0093	0.0097
	(0.0123)	(0.0163)	(0.0132)
Cohort = 2013	0.1731***	0.1471***	0.0968*
	(0.0335)	(0.0383)	(0.0522)
Cohort = 2014	-0.0008	0.0073	-0.0007
	(0.0136)	(0.0167)	(0.0163)
Cohort = 2015	-0.0029	0.0195*	-0.0030
	(0.0110)	(0.0117)	(0.0126)
Cohort = 2016	0.0272***	0.0404***	0.0428***
	(0.0079)	(0.0105)	(0.0164)
Cohort = 2017	0.0193**	0.0207*	0.0271***
	(0.0076)	(0.0110)	(0.0101)
Cohort = 2018	0.0087	0.0085	0.0218***
	(0.0059)	(0.0092)	(0.0079)
Cohort = 2019	-0.0045	-0.0131	-0.0067
	(0.0085)	(0.0120)	(0.0089)
Cohort = 2020	0.0138**	0.0086	0.0149
	(0.0069)	(0.0088)	(0.0104)
Cohort = 2021	-0.0140	-0.0099	-0.0277*
Observations	28,023	27,485	26,227
R^2	0.9637	0.9290	0.8520
Dep. var. mean	0.4118	0.6514	0.6747

Notes: We report interaction weighted estimators proposed by Sun and Abraham (2021). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. We control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2009 interacted with linear time trend, and county-by-year employment rate. Regressions and dependent variable mean are weighted by the number of births in each cell. We report standard errors clustered on county in parentheses and standard errors clustered on state in angle brackets. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

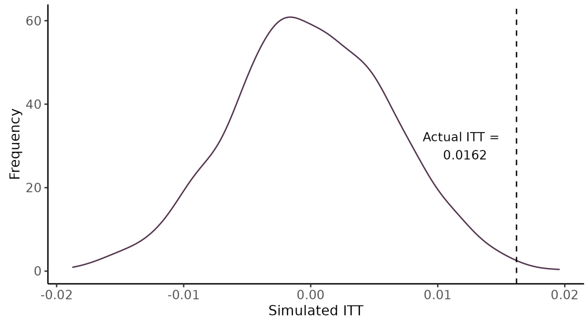
TABLE A2: PLACEBO TREATMENT TIMING

	WIC participation			Birth weight (grams)			Low birth weight			Preterm		
				(birth weight < 2500 grams)			(gestation < 37 weeks)					
	All births	Edu≤HS	No father	All births	Edu≤HS	No father	All births	Edu≤HS	No father	All births	Edu≤HS	No father
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Born after EBT	-0.0065	0.0040	-0.0016	0.9127	0.8320	2.184	0.0006	0.0005	-0.0015	0.0011	0.0023	0.0010
	(0.0052)	(0.0060)	(0.0054)	(2.174)	(2.527)	(3.134)	(0.0008)	(0.0009)	(0.0015)	(0.0015)	(0.0022)	(0.0025)
	⟨0.0111⟩	⟨0.0088⟩	⟨0.0068⟩	⟨3.911⟩	⟨4.178⟩	⟨4.130⟩	⟨0.0018⟩	⟨0.0015⟩	⟨0.0017⟩	⟨0.0026⟩	⟨0.0033⟩	⟨0.0034⟩
Observations	28,021	27,483	26,225	28,019	27,480	26,222	28,019	27,480	26,222	28,021	27,483	26,225
R^2	0.9638	0.9284	0.8510	0.8862	0.8321	0.6466	0.7087	0.6451	0.4192	0.6994	0.6330	0.4281
Dependent variable mean	0.4118	0.6515	0.6747	3,269	3,217	3,121	0.0808	0.0913	0.1224	0.1153	0.1308	0.1629

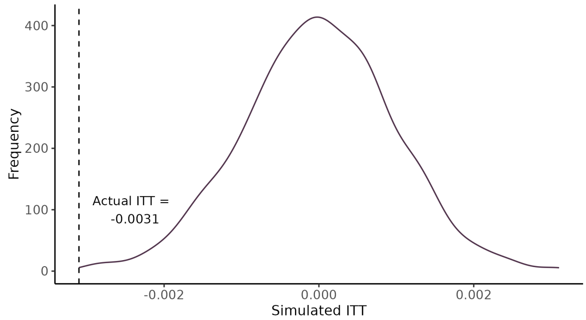
Notes: We report interaction weighted estimators proposed by Sun and Abraham (2021). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. We control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2009 interacted with linear time trend, and county-by-year employment rate. Regressions and dependent variable mean are weighted by the number of births in each cell. We report standard errors clustered on county in parentheses and standard errors clustered on state in angle brackets. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.



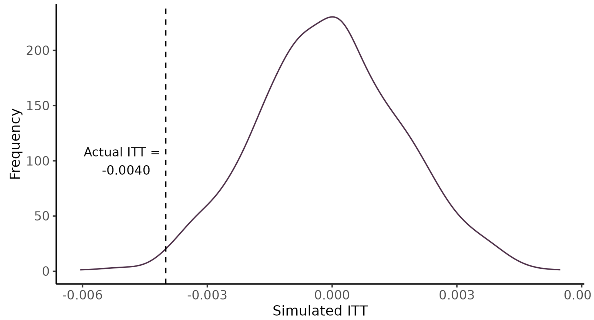
(A) WIC participation, education ≤ HS



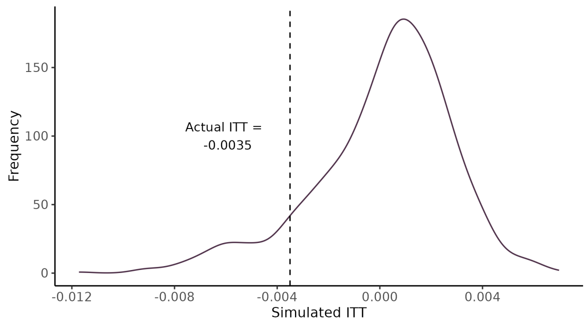
(B) WIC participation, no father



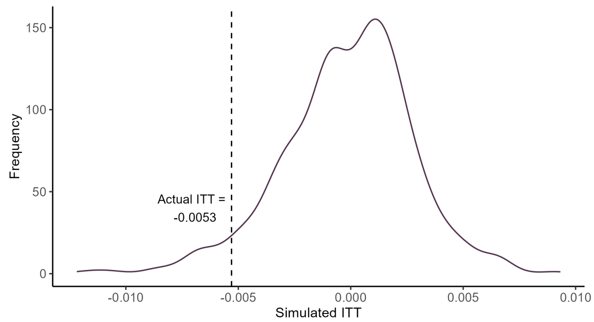
(C) Low birth weight, education ≤ HS



(D) Low birth weight, no father



(E) Preterm, education ≤ HS



(F) Preterm, no father

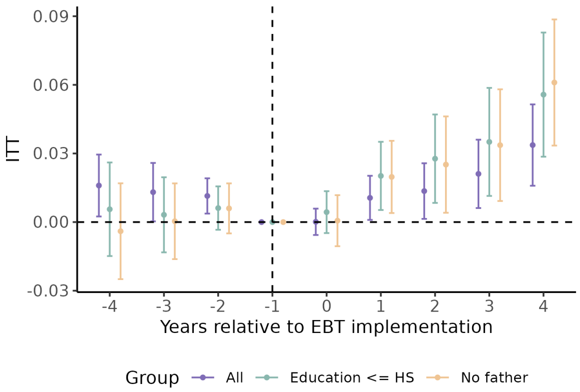
FIGURE A2: RANDOMIZATION TEST

Notes: These event study plots report results using estimators by Sun and Abraham (2021). We randomize year of EBT implementation 1,000 times while keep the distribution. We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. Regressions and dependent variable mean are weighted by the number of births in each cell. Standard errors are clustered at county level. We enforce balanced panel. We do not allow covariates because we do not know the set of covariates that can correctly specify either the outcome evolution for the comparison group or the propensity score model.

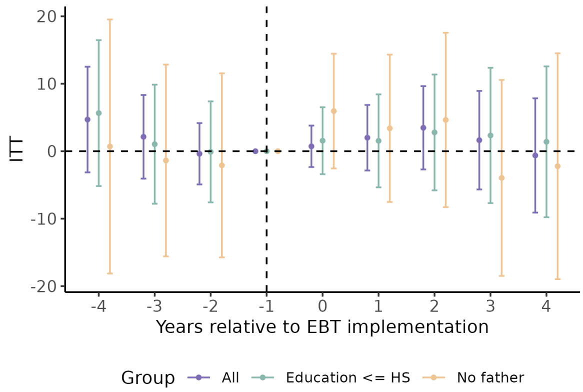
TABLE A3: EVENT-TIME BALANCED PANEL

	WIC participation			Birth weight (grams)			Low birth weight			Preterm		
			(birth weight < 2500 grams)			(gestation < 37 weeks)						
	All births (1)	Edu≤HS (2)	No father (3)	All births (4)	Edu≤HS (5)	No father (6)	All births (7)	Edu≤HS (8)	No father (9)	All births (10)	Edu≤HS (11)	No father (12)
Born after EBT	0.0157	0.0284	0.0279	1.454	1.925	1.568	-0.0004	-0.0018	-0.0010	-0.0046	-0.0075	-0.0045
	(0.0057)***	(0.0091)***	(0.0096)***	(2.774)	(3.824)	(5.604)	(0.0010)	(0.0016)	(0.0030)	(0.0017)***	(0.0024)***	(0.0038)
	⟨0.0048⟩***	⟨0.0049⟩***	⟨0.0053⟩***	⟨1.533⟩	⟨2.470⟩	⟨3.714⟩	⟨0.0005⟩	⟨0.0007⟩**	⟨0.0018⟩	⟨0.0022⟩**	⟨0.0017⟩***	⟨0.0029⟩
Observations	7,103	6,905	6,603	7,103	6,905	6,602	7,103	6,905	6,602	7,103	6,905	6,603
R^2	0.95951	0.91695	0.84913	0.88420	0.80328	0.58312	0.66103	0.55354	0.32959	0.65358	0.55156	0.32173
Dependent variable mean	0.37964	0.60518	0.65629	3,266.2	3,208.4	3,121.7	0.08209	0.09424	0.12187	0.11691	0.13278	0.16140

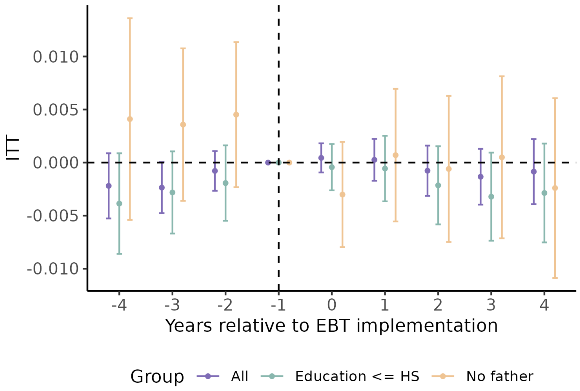
Notes: We report interaction weighted estimators proposed by Sun and Abraham (2021). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. We control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2009 interacted with linear time trend, and county-by-year employment rate. Regressions and dependent variable mean are weighted by the number of births in each cell. We report standard errors clustered on county in parentheses and standard errors clustered on state in angle brackets. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.



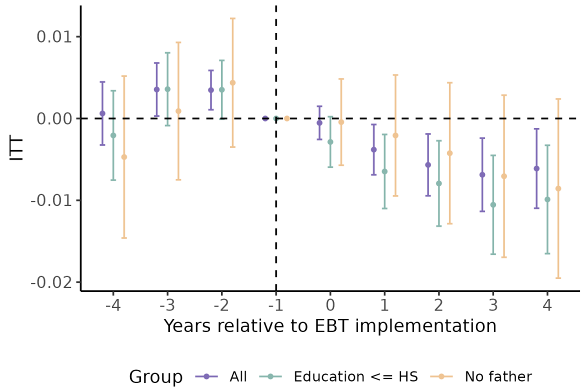
(A) WIC participation



(B) Birth weight



(C) Low birth weight



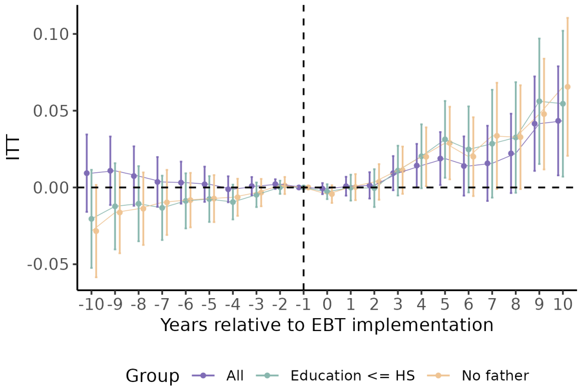
(D) Preterm

FIGURE A3: DYNAMIC EFFECTS OF WIC EBT, EVENT-TIME BALANCED PANEL

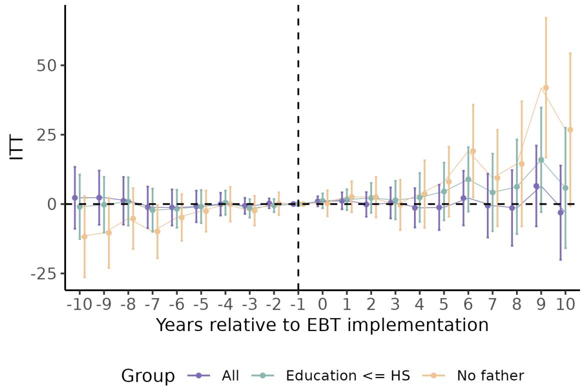
Notes: These event study plots report results using estimators by Sun and Abraham (2021). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. Regressions and dependent variable mean are weighted by the number of births in each cell. Standard errors are clustered at county level. Since this estimator use all the whole pre-treatment period as comparison, we use shorter pre-treatment period (6 years before the treatment) to ensure the relevance.

FIGURE A4: TESTING SENSITIVITY TO PARALLEL TREND VIOLATION

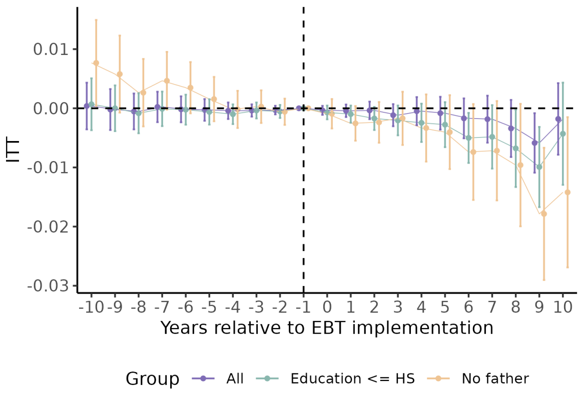
Notes: By Rambachan and Roth (2023).



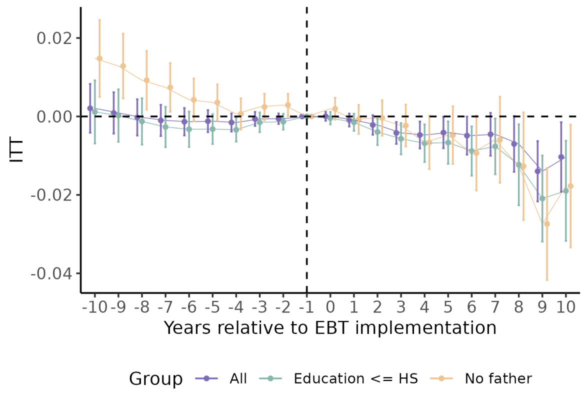
(A) WIC participation



(B) Birth weight



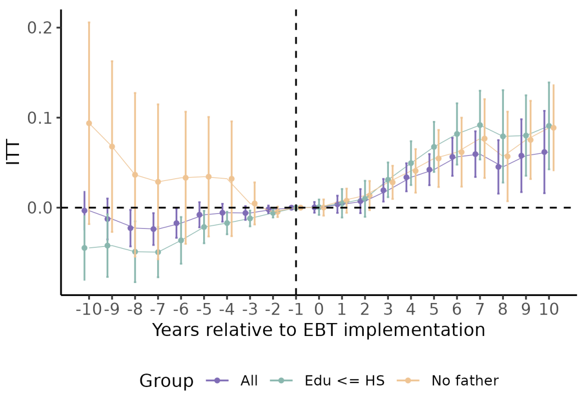
(C) Low birth weight



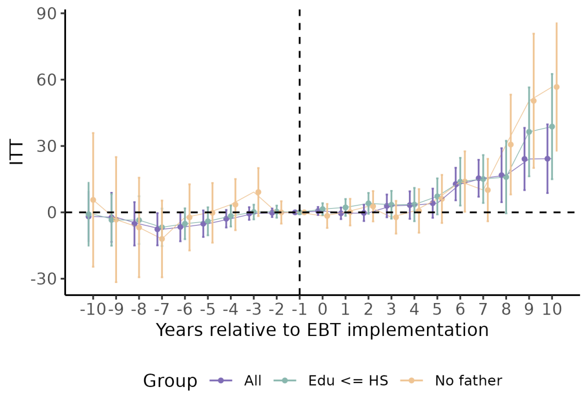
(D) Preterm

FIGURE A5: DYNAMIC EFFECTS OF WIC EBT, TWFE ESTIMATORS

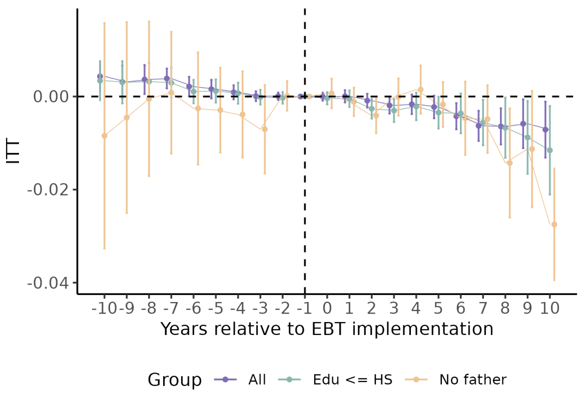
Notes: These event study plots report results using traditional two-way-fixed-effects estimators. We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. We control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2009 interacted with linear time trend, and county-by-year employment rate. Regressions and dependent variable mean are weighted by the number of births in each cell. Standard errors are clustered at county level.



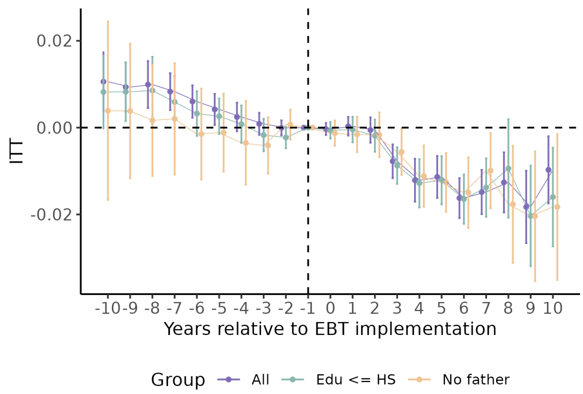
(A) WIC participation



(B) Birth weight



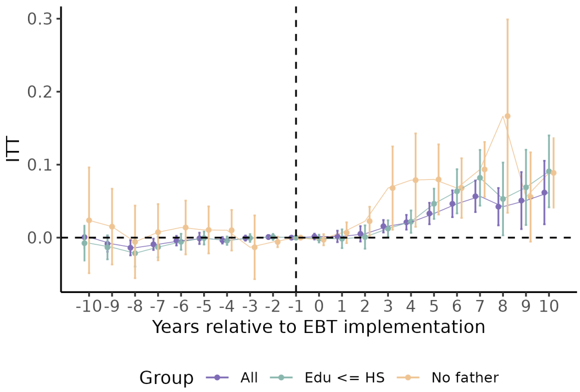
(C) Low birth weight



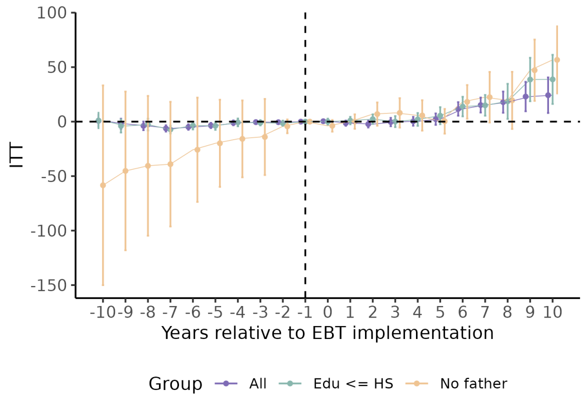
(D) Preterm

FIGURE A6: DYNAMIC EFFECTS OF WIC EBT, CALLAWAY AND SANT'ANNA (2021) Estimators, the Never-treated as Control Group

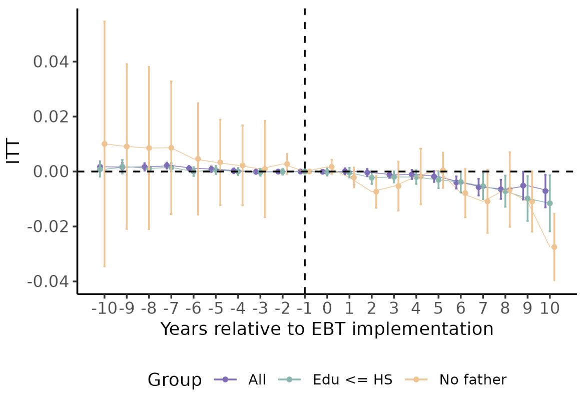
Notes: These event study plots report results using estimators by Callaway and Sant'Anna (2021). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. Regressions and dependent variable mean are weighted by the number of births in each cell. Standard errors are clustered at county level. We enforce balanced panel. We do not allow covariates because we do not know the set of covariates that can correctly specify either the outcome evolution for the comparison group or the propensity score model.



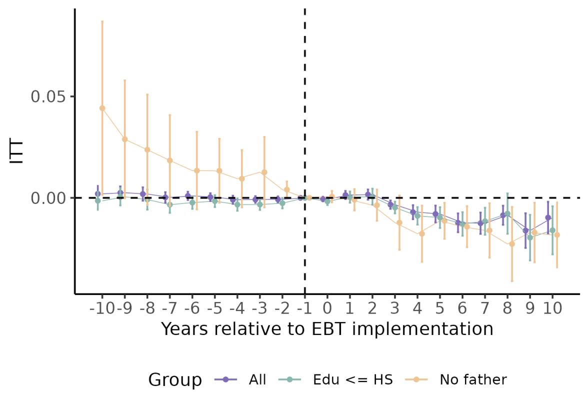
(A) WIC participation



(B) Birth weight



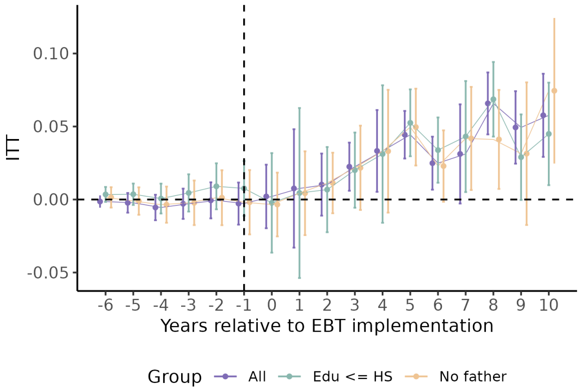
(C) Low birth weight



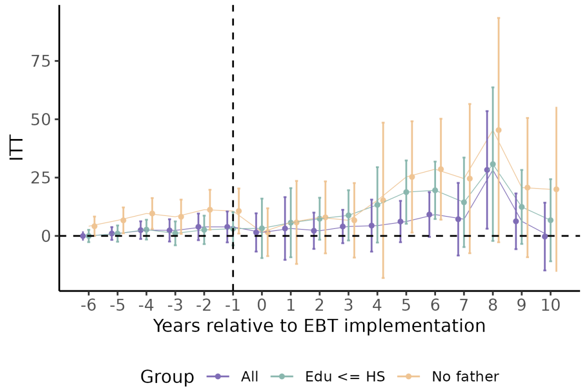
(D) Preterm

FIGURE A7: DYNAMIC EFFECTS OF WIC EBT, CALLAWAY AND SANT'ANNA (2021) Estimators, the Not-yet-treated as Control Group

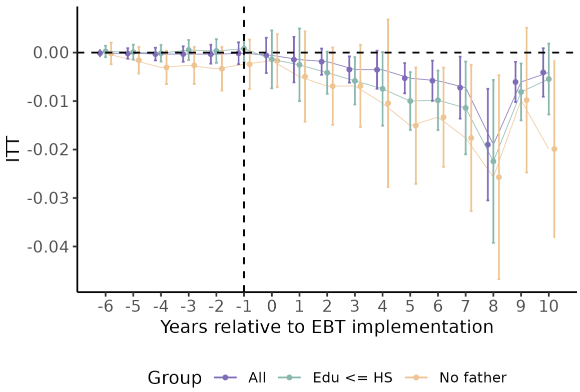
Notes: These event study plots report results using estimators by Callaway and Sant'Anna (2021). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. Regressions and dependent variable mean are weighted by the number of births in each cell. Standard errors are clustered at county level. We enforce balanced panel. We do not allow covariates because we do not know the set of covariates that can correctly specify either the outcome evolution for the comparison group or the propensity score model.



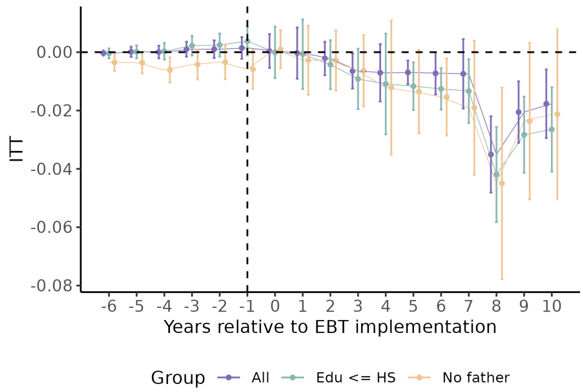
(A) WIC participation



(B) Birth weight



(C) Low birth weight



(D) Preterm

FIGURE A8: DYNAMIC EFFECTS OF WIC EBT, BORUSYAK, JARAVEL AND SPIESS (2024) Estimators

Notes: These event study plots report results using estimators by Borusyak, Jaravel and Spiess (2024). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. Regressions and dependent variable mean are weighted by the number of births in each cell. Standard errors are clustered at county level. Since this estimator use all the whole pre-treatment period as comparison, we use shorter pre-treatment period (6 years before the treatment) to ensure the relevance.

TABLE A4: ROBUSTNESS TO TIMING OF EXPOSURE

	WIC participation			Birth weight (grams) (birth weight < 2500 grams)			Low birth weight (gestation < 37 weeks)			Preterm		
	All births (1)	Edu≤HS (2)	No father (3)	All births (4)	Edu≤HS (5)	No father (6)	All births (7)	Edu≤HS (8)	No father (9)	All births (10)	Edu≤HS (11)	No father (12)
Panel A: first trimester												
Born after EBT	0.0161	0.0213	0.0241	-0.0025	3.970	5.858	-0.0013	-0.0030	-0.0042	-0.0027	-0.0039	-0.0072
	(0.0047)***	(0.0067)***	(0.0059)***	(2.093)	(2.576)	(4.026)	(0.0008)*	(0.0012)**	(0.0020)**	(0.0011)**	(0.0015)**	(0.0025)***
	⟨0.0089⟩*	⟨0.0097⟩**	⟨0.0067⟩***	⟨3.790⟩	⟨2.800⟩	⟨4.076⟩	⟨0.0012⟩	⟨0.0008⟩***	⟨0.0015⟩***	⟨0.0013⟩*	⟨0.0012⟩***	⟨0.0022⟩***
Observations	28,340	27,904	26,713	28,339	27,902	26,712	28,339	27,902	26,712	28,340	27,904	26,713
R^2	0.9660	0.9305	0.8507	0.8871	0.8298	0.6411	0.7192	0.6442	0.4271	0.7187	0.6487	0.4513
Dep. var. mean	0.4089	0.6488	0.6731	3,269	3,216	3,120	0.0811	0.0920	0.1231	0.1156	0.1316	0.1637
Panel B: second trimester												
Born after EBT	0.0143	0.0189	0.0212	0.4871	5.863	6.089	-0.0013	-0.0035	-0.0038	-0.0022	-0.0038	-0.0050
	(0.0049)***	(0.0070)***	(0.0060)***	(2.141)	(2.645)**	(3.953)	(0.0008)	(0.0011)***	(0.0020)*	(0.0011)**	(0.0016)**	(0.0025)**
	⟨0.0089⟩	⟨0.0095⟩*	⟨0.0058⟩***	⟨4.137⟩	⟨2.799⟩**	⟨4.154⟩	⟨0.0013⟩	⟨0.0008⟩***	⟨0.0015⟩**	⟨0.0014⟩	⟨0.0012⟩***	⟨0.0021⟩**
Observations	28,320	27,905	26,789	28,318	27,903	26,788	28,318	27,903	26,788	28,320	27,905	26,789
R^2	0.9655	0.9294	0.8505	0.8873	0.8296	0.6420	0.7145	0.6459	0.4234	0.7074	0.6394	0.4409
Dep. var. mean	0.4100	0.6499	0.6740	3,269	3,216	3,120	0.0810	0.0919	0.1229	0.1157	0.1316	0.1637
Panel C: third trimester												
Born after EBT	0.0135	0.0186	0.0211	0.9055	5.513	6.304	-0.0013	-0.0035	-0.0038	-0.0021	-0.0041	-0.0047
	(0.0051)***	(0.0073)**	(0.0063)***	(2.154)	(2.667)**	(3.796)*	(0.0008)*	(0.0011)***	(0.0019)**	(0.0011)*	(0.0015)***	(0.0024)**
	⟨0.0091⟩	⟨0.0092⟩**	⟨0.0055⟩***	⟨3.991⟩	⟨2.774⟩*	⟨4.101⟩	⟨0.0013⟩	⟨0.0008⟩***	⟨0.0015⟩**	⟨0.0015⟩	⟨0.0011⟩***	⟨0.0019⟩**
Observations	28,291	27,892	26,738	28,288	27,890	26,737	28,288	27,890	26,737	28,291	27,892	26,738
R^2	0.9651	0.9290	0.8501	0.8860	0.8308	0.6448	0.7109	0.6465	0.4221	0.6994	0.6355	0.4355
Dep. var. mean	0.4109	0.6508	0.6747	3,269	3,216	3,120	0.0810	0.0918	0.1228	0.1157	0.1316	0.1637

Notes: We report interaction weighted estimators proposed by Sun and Abraham (2021). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. We control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2009 interacted with linear time trend, and county-by-year employment rate. Regressions and dependent variable mean are weighted by the number of births in each cell. We report standard errors clustered on county in parentheses and standard errors clustered on state in angle brackets. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

TABLE A5: CONTROLLING FOR VARIABLES RELATED TO WIC ELIGIBILITY

	WIC participation			Birth weight (grams)			Low birth weight			Preterm		
				(birth weight $<$ 2500 grams)			(gestation $<$ 37 weeks)					
	All births	Edu$\leq$HS	No father	All births	Edu$\leq$HS	No father	All births	Edu$\leq$HS	No father	All births	Edu$\leq$HS	No father
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Born after EBT	0.0104	0.0133	0.0142	0.1654	4.648	5.042	-0.0009	-0.0030	-0.0041	-0.0011	-0.0034	-0.0053
	(0.0052)**	(0.0073)*	(0.0064)**	(2.240)	(2.803)*	(3.918)	(0.0008)	(0.0011)***	(0.0019)**	(0.0011)	(0.0015)**	(0.0024)**
	⟨0.0090⟩	⟨0.0088⟩	⟨0.0050⟩***	⟨4.873⟩	⟨3.508⟩	⟨4.485⟩	⟨0.0016⟩	⟨0.0010⟩***	⟨0.0016⟩**	⟨0.0021⟩	⟨0.0013⟩**	⟨0.0018⟩***
Observations	28,009	27,471	26,213	28,007	27,468	26,210	28,007	27,468	26,210	28,009	27,471	26,213
R^2	0.9646	0.9297	0.8530	0.8864	0.8325	0.6475	0.7095	0.6460	0.4208	0.7006	0.6344	0.4296
Dep. var. mean	0.41209	0.65162	0.67495	3,269.1	3,217.4	3,121.3	0.08075	0.09133	0.12237	0.11530	0.13081	0.16294

Notes: We report interaction weighted estimators proposed by Sun and Abraham (2021). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. We control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2009 interacted with linear time trend, and county-by-year employment rate. Regressions and dependent variable mean are weighted by the number of births in each cell. We report standard errors clustered on county in parentheses and standard errors clustered on state in angle brackets. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

Table A6: Heterogeneity by Race and Ethnicity

	WIC participation (1)	Birth weight (2)	Low birth weight (3)	Preterm (4)
	Panel A: white			
Born after EBT	0.0102***	1.146	-0.0012*	-0.0036***
	(0.0031)	(1.748)	(0.0006)	(0.0010)
Observations	23,758	23,755	23,755	23,758
R^2	0.9706	0.7953	0.4507	0.5496
Dep. var. mean	0.3936	3,316	0.0698	0.1051
	Panel B: Black			
Born after EBT	-0.0010	-1.527	0.0011	-0.0015
	(0.0044)	(2.898)	(0.0014)	(0.0016)
Observations	17,880	17,875	17,875	17,880
R^2	0.9157	0.7096	0.4539	0.5139
Dep. var. mean	0.6358	3,091	0.1299	0.1634
	Panel C: Asian			
Born after EBT	-0.0012	-0.5786	-0.0023	0.0025
	(0.0047)	(3.298)	(0.0016)	(0.0019)
Observations	16,205	16,199	16,199	16,202
R^2	0.9211	0.3474	0.2436	0.3463
Dep. var. mean	0.2992	3,187	0.0816	0.1003
	Panel D: Hispanic			
Born after EBT	0.0106	-0.5211	-0.0012	0.0031
	(0.0114)	(2.718)	(0.0011)	(0.0021)
Observations	24,378	24,374	24,374	24,373
R^2	0.9261	0.5483	0.2909	0.3772
Dep. var. mean	0.6388	3,276	0.0706	0.1120

Notes: We report interaction weighted estimators proposed by Sun and Abraham (2021). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. We control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2009 interacted with linear time trend, and county-by-year employment rate. Regressions and dependent variable mean are weighted by the number of births in each cell. We report standard errors clustered on county in parentheses. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

TABLE A7: HETEROGENEITY BY MATERNAL AGE

	WIC participation (1)	Birth weight (2)	Low birth weight (3)	Preterm (4)
	Panel A: maternal age ≤ 22			
Born after EBT	0.0185***	2.109	-0.0013	-0.0025
	(0.0065)	(3.263)	(0.0015)	(0.0018)
Observations	27,097	27,095	27,095	27,096
R^2	0.8816	0.7169	0.4658	0.4803
Dep. var. mean	0.7091	3,190	0.0899	0.1230
	Panel B: $22 < $ maternal age < 29			
Born after EBT	0.0168***	0.8979	-0.0012	-0.0015
	(0.0057)	(2.691)	(0.0009)	(0.0012)
Observations	27,592	27,592	27,592	27,592
R^2	0.9412	0.7923	0.5570	0.5901
Dep. var. mean	0.4374	3,276	0.0758	0.1077
	Panel C: maternal age ≥ 30			
Born after EBT	0.0095**	-2.444	-0.0003	-0.0006
	(0.0046)	(2.577)	(0.0010)	(0.0013)
Observations	27,507	27,504	27,504	27,506
R^2	0.9516	0.7648	0.5017	0.5938
Dep. var. mean	0.2659	3,296	0.0813	0.1187

Notes: We report interaction weighted estimators proposed by Sun and Abraham (2021). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. We control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2009 interacted with linear time trend, and county-by-year employment rate. Regressions and dependent variable mean are weighted by the number of births in each cell. We report standard errors clustered on county in parentheses. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

TABLE A8: HETEROGENEITY BY INCOME QUANTILE

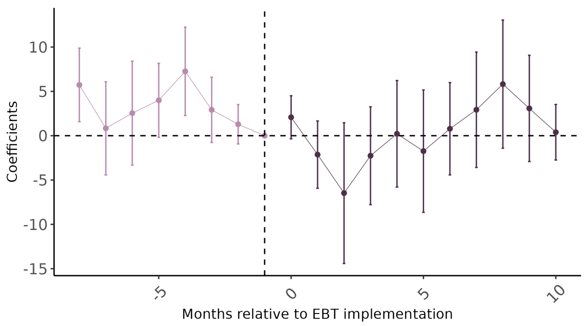
	WIC participation (1)	Birth weight (2)	Low birth weight (3)	Preterm (4)
	Panel A: 1st income quantile (1,945 counties)			
Born after EBT	0.0283***	3.857	-0.0038**	-0.0071***
	(0.0056)	(3.622)	(0.0016)	(0.0021)
Observations	18,195	18,193	18,193	18,195
R^2	0.93174	0.83196	0.62985	0.61092
Dep. var. mean	0.51059	3,246.8	0.08801	0.12856
	Panel B: 2nd-4th income quantiles (1,133 counties)			
Born after EBT	0.0033	-0.2742	-3.91×10^{-5}	8.55×10^{-7}
	(0.0070)	(3.087)	(0.0011)	(0.0015)
Observations	9,827	9,827	9,827	9,827
R^2	0.96998	0.92209	0.77673	0.77358
Dep. var. mean	0.37805	3,276.7	0.07828	0.11075

Notes: We report interaction weighted estimators proposed by Sun and Abraham (2021). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. We control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2009 interacted with linear time trend, and county-by-year employment rate. Regressions and dependent variable mean are weighted by the number of births in each cell. We report standard errors clustered on county in parentheses. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

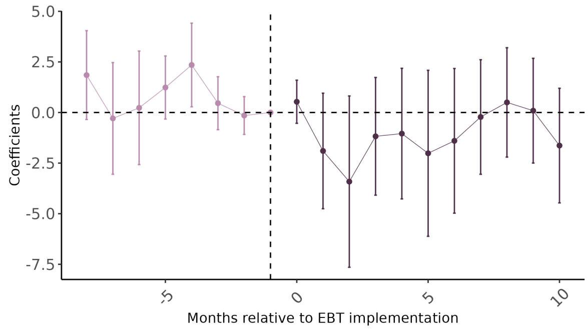
B Comparison to Meckel (2020)

In this appendix we discuss how our findings compare to those in Meckel (2020). We are able to extend both the time and geographic scope of estimates of the effect of WIC EBT on birthweight. In this section, we will make apples-to-apples comparisons across the Texas natality data we have with the results of Meckel (2020) with the same time period and with a longer time period, to understand the importance of the time dimension for results.

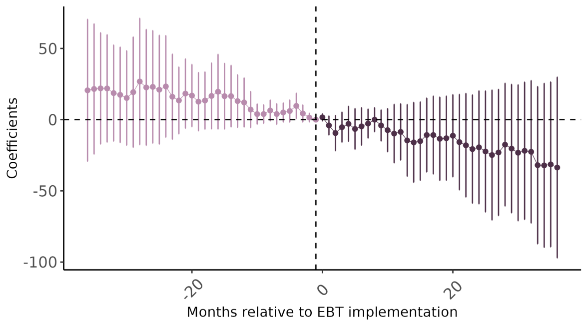
We note that with a longer time series over which to estimate treatment effects, we can capture additional trends in the data. The short run pre-trends – within 6 months prior to WIC EBT implementation – appear relatively stable around zero. However, longer run pre-trends show a path that indicates WIC EBT timing may coincide with declining birth rates, picking up a spurious relationship.



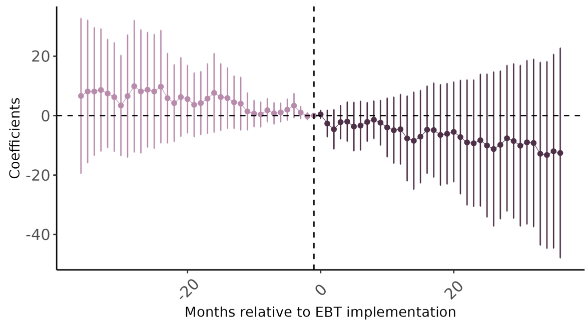
(A) EBT and WIC births per bounty (Figure 8 in Meckel (2020))



(B) EBT and high poverty WIC births per bounty (Figure 8 in Meckel (2020))

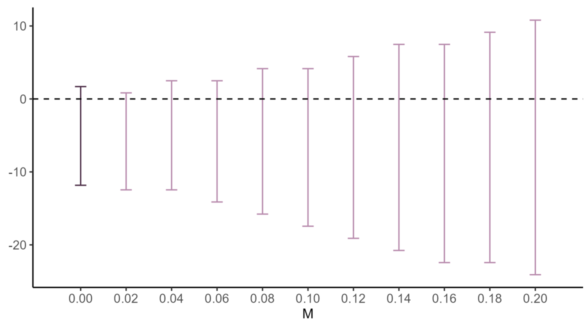


(C) EBT and WIC births per county, with larger window

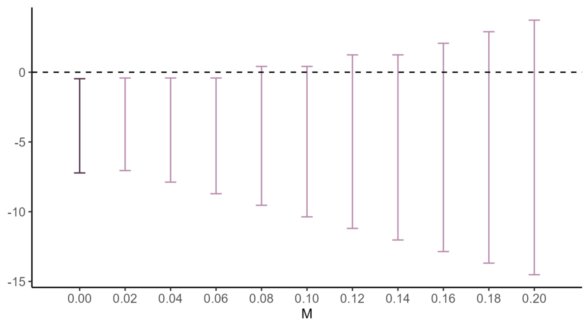


(D) EBT and high poverty WIC births per bounty, with A larger window

FIGURE B1: EXTENDING EVENT STUDY PLOTS IN MECKEL (2020) TO LARGER WINDOW



(A) WIC Births



(B) High Poverty Share of WIC Births

FIGURE B2: TESTING SENSITIVITY TO PARALLEL TREND VIOLATION FOR MECKEL (2020)'S ESTIMATORS

Notes: With similar standard, Meckel (2020)'s estimates are more susceptible to parallel trend violation.