Safety Net Payment Digitization and Participant Outcomes: Evidence from the WIC EBT Transition*

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Abstract

We evaluate the nationwide impact of electronic benefit transfer (EBT) implementation in the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) on participants' outcomes by linking the EBT roll-out schedule to Vital Statistics Natality Data. We find that WIC participation increased, and birth outcomes improved, after EBT implementation, especially among groups that are likely to be WIC eligible. We find suggestive evidence that EBT increased participation by increasing interest in WIC and by reducing stigma at retailers. Policymakers can use our results as they evaluate future program changes that affect stigma and accessibility, including WIC online shopping. (JEL H51, H53, I38)

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1 Introduction

The Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) provides food 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 (Hoynes, Page and Stevens, 2011; Chorniy, Currie and Sonchak, 2020). However, participation is declining. The share of infants enrolled in WIC has fallen from 50% in 2009 to 30% in 2021. Can policy changes mitigate enrollment declines? We use evidence from a nationwide digitization of WIC payments to show that a policy which reduces stigma and makes benefits easier to use increases participation and improves birth outcomes.

Between 2002 and 2022, WIC transitioned from paper vouchers to electronic benefit transfer (EBT) cards. WIC's EBT transition is part of a broader take-up of digital technologies in the administration of public policies. Digital technologies improve the efficiency of public administration by increasing welfare coverage (Gray, 2019), lowing redemption costs (Aker et al., 2013), facilitating monitoring and targeting (Aiken et al., 2021), and reducing errors (Muralidharan, Niehaus and Sukhtankar, 2014). Overall, digitization can improve participant outcomes in public programs (Shiferaw, 2020; Kuhn, 2021; Wang, 2021).

WIC's switch to EBT had three policy objectives. The first was to encourage WIC participation among eligible individuals by reducing the stigma that participants experience when redeeming WIC vouchers (Moffitt, 1983). The second was to increase redemptions. Unlike with paper vouchers, EBT allows participants to redeem WIC benefits across multiple transactions, making perishable food benefits like milk and fruits and vegetables more valuable (Hanks et al., 2019; Li et al., 2021). The final objective was to reduce fraud at stores. Evidence from Texas finds that EBT reduces fraud at the cost of lowering access to authorized stores (Meckel, 2020). Authorization of independent stores declined nationwide post-EBT (Ambrozek et al., 2024). In essence, EBT shifts administrative burden from participants to retailers. Therefore, the net effect of EBT on WIC participation – and health outcomes that follow from WIC participation – is ambiguous. Understanding the effect that this policy change, the largest change to WIC in the past few decades, had on participation and health outcomes is important.

We present the first nationwide evaluation of WIC EBT's impact on participation and birthweight. The existing empirical evidence on WIC EBT's impact relies on data from individual states. Effects of the EBT transition varied across states: Ohio experienced an increase in redemptions (Hanks et al., 2019), Oklahoma showed no significant change in participation rates

(Li, Saitone and Sexton, 2022), while Texas saw a decline in WIC-associated births Meckel (2020). Qualitative work done in several states finds that participants' subjective experience improves post-EBT (Phillips et al., 2014).

We quantify the effect of the nationwide roll-out of WIC EBT on participation and birthweight using Vital Statistics Natality Data. Using a staggered-adoption difference-in-differences (DiD) approach (Sun and Abraham, 2021), we compare counties implementing WIC EBT to counties that have not yet implemented. We find that WIC participation increases among all mothers of newborns post-EBT and that birth outcomes improve among likely WIC eligible groups. We observe a 3.71% increase in WIC participation at the sample mean among both mothers with no more than a high school education and a 3.58% increase in WIC participation at the sample mean among mothers without an infant's father listed on the birth certificate. WIC EBT implementation reduces the likelihood of low birth weight or preterm births by around 5% at the sample mean among likely WIC eligible groups. Based on these results, our back-of-the-envelope calculation suggests that WIC EBT lifts thousands of births out of low birth weight and preterm status, saving millions of dollars in hospital and Medicaid costs annually.

We provide evidence that WIC EBT implementation increases interest in WIC participation. Linking the rollout schedule of WIC EBT implementation to Google Trends data, we first find that WIC EBT implementation increases the relative popularity of search terms related to applying for WIC, such as "apply for WIC," "WIC application," "qualify for WIC," "WIC benefits," and "WIC foods," suggesting that EBT implementation increases intent to participate in WIC. This increased interest in WIC may result from lower stigma post-EBT. Comparing counties with characteristics that make welfare stigma salient to counties without those characteristics, we find that the EBT transition's effect on WIC participation is largest in places where stigma is likely particularly salient (see Section 6). Taken as a whole, these findings suggest that reducing stigma is a key mechanism by which EBT drives increased WIC participation.

This paper contributes to three strands of literature. First, this work relates to the broad literature on the role of stigma as a determinant of food assistance participation in the U.S. We find that a program change reducing the visibility of WIC participants at checkout–thereby lessening welfare stigma–increases participation, with effects most pronounced in communities where such stigma is particularly salient. Our results confirm qualitative findings that participants experienced faster and more discrete checkout processes after the implementation of WIC EBT (Chauvenet et al., 2019; Zimmer, Beaird and Steeves, 2021). In the marketing literature, previous research using 2015 Virginia data shows that simplifying EBT produce transactions increases the likelihood that WIC participants would use their fruit and vegetable benefits (Zhang et al., 2022). Negative experiences at checkout constitute "redemption costs" that vary with the third-party agent redeeming the benefits (Barnes, 2021). We provide national-level evidence showing that WIC participation increases in response to a program change that reduces redemption costs, including stigma-related barriers. These finding are informative for policymakers considering future innovations that can reduce redemptions stigma such as online WIC redemption.

Second, this paper contributes to the large literature assessing the impact of food assistance programs on birth outcomes. 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) affected 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.

More narrowly, we add to the body of research on the effects of EBT implementation. Prior work has considered the impacts of WIC EBT on WIC participation rates (Meckel, 2020; Li, Saitone and Sexton, 2022; Vasan et al., 2021), WIC redemption patterns (Hanks et al., 2019), and the retail environment for WIC vendors (Meckel, 2020; Ambrozek et al., 2024). Beyond WIC, Shiferaw (2020) shows that EBT implementation in SNAP increases average birth weight in California, while Wright et al. (2017) finds that the switch to EBT in the Temporary Assistance for Needy Families (TANF) program reduces crime rates in Missouri. This paper extends this literature by providing national-scale evidence on WIC EBT's effects on WIC participation and birth outcomes among mothers of newborns.

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 and provides the results of robustness checks; Section 6 discusses potential mechanisms; and Section 7 concludes.

2 Background

2.1 WIC

WIC was established to safeguard the health of low-income women, infants, and children up to the age of five who are at nutritional risk. The program provides a fixed quantity of nutrition-targeted foods to low-income women and young children[1] (USDA Food and Nutrition Service, 2022). WIC also provides nutrition education and referrals to health and other social services and supports overall health. Over time, WIC has become one of the most widely used food assistance programs; more than 30% of infants born in the US in FY 2021 received WIC benefits. In fiscal year 2023, the federal government spent $6.6 billion on WIC, making it the third-largest food assistance program by total spending (USDA Food and Nutrition Service, 2020).

WIC has been extensively studied. WIC has been linked to lower food insecurity (Kreider, Pepper and Roy, 2016) and improved diet quality (Smith and Valizadeh, 2024) among children. WIC participation has shown positive effects on birth outcomes (Hoynes, Page and Stevens, 2011; Rossin-Slater, 2013) and has contributed to long-term educational and health gains for those who participated during early childhood (Chorniy, Currie and Sonchak, 2020). When parents lose WIC benefits, they often compromise their own nutrition intake to preserve their children's (Bitler et al., 2023). Despite evidence on the health and social benefits of WIC, the program faces challenges such as declining participation and difficulties in reaching some of the most vulnerable groups (Neuberger, Hall and Sallack, 2024).

2.2 EBT Transition

Prior to EBT, WIC participants received paper vouchers from WIC clinics redeemable for food benefits at authorized retailers. Most vouchers were redeemable for multiple items and each voucher was valid for one month. At checkout WIC items had to be separated from non-WIC items, and cashiers were responsible for ensuring that each item met the voucher's requirements, including brand, size, and quantity. If recipients mistakenly selected non-WIC-eligible items, they had to either return the items, pay for them out of pocket, or go back to the shelves to find the correct items and rejoin the checkout line.[2] Once all items were verified, the cashier would ask the recipient to sign the voucher, collect it, and complete the transaction. If participants chose to redeem only some of the items listed on a voucher, unredeemed items were forfeited. After EBT, WIC and non-WIC items do not have to be separated, checkout is simpler, and items only expire at the end of the month.

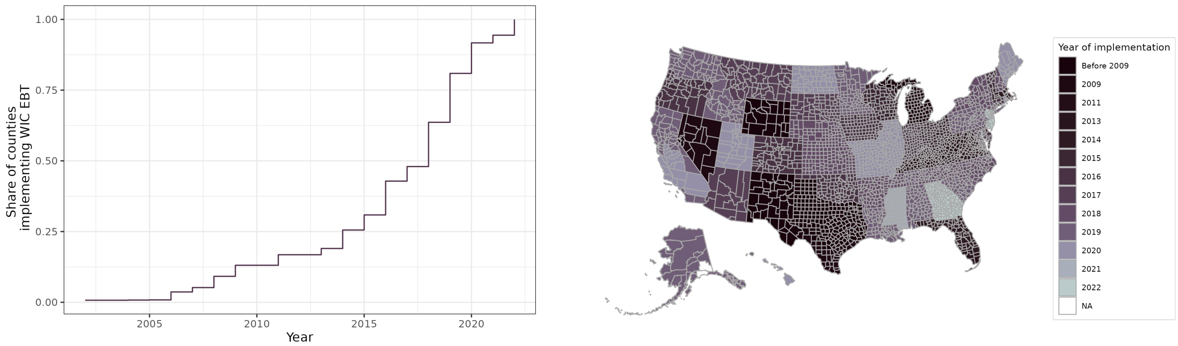
The transition to WIC EBT was a USDA Food and Nutrition Service (FNS) initiative aimed at modernizing WIC benefit delivery. Primary goals included streamlining business practices, simplifying transactions to reduce stigma, and improving program monitoring for WIC state

[1] WIC eligibility requires a household income below 185% of the federal poverty line or participation in SNAP, TANF, Aid to Families with Dependent Children (AFDC), or Medicaid.

[2] Two states did not use authorized retailers to deliver WIC food benefits prior to EBT. Mississippi had participants travel to a distribution center to pick up their foods, while Vermont had home delivery of food benefits. We include these states in our estimation to obtain average treatment effects on the treated.

agencies. Although some early WIC EBT projects began as early as 1995, the national WIC EBT transition plan was introduced in 2003, following the successful implementation of EBT in Food Stamps/SNAP.

In 2010, the Healthy, Hunger-Free Kids Act (HHFKA 2010) imposed a national mandate to complete the transition to EBT by October 1, 2020. This deadline was eventually extended due to the COVID-19 pandemic. The HHFKA 2010 directed the USDA to develop WIC EBT technical standards and operating rules for all stakeholders and to establish a national database of universal product codes for the EBT systems across all states (S.3307 — 111th Congress, 2010). The USDA shared the costs of EBT implementation with state agencies, with each state submitting a plan for how costs would be split. This plan allowed states to access grants for the transition, covering a range of participating stakeholders. (USDA Food and Nutrition Service, 2016).



(A) Share of counties implementing WIC EBT over time

(B) Geographic variation in timing of WIC EBT implementation

FIGURE 1: WIC EBT ROLL-OUT SCHEDULE SINCE 2009

To track WIC EBT rollout timelines across U.S. counties, we collect data from multiple sources including (archived) state websites, policy documents, and research papers. Most of the transition took place after 2010 (see Figure 1a). Figure 1b shows the geographic spread of EBT adoption. By 2022, all 50 states, U.S. territories, and tribal organizations had made the switch to EBT.

3 Data

3.1 WIC EBT roll-out schedule

We compile 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 use 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 do not report WIC participation in the natality data (discussed below), our final sample includes 2,489 counties, covering 81.24% of the U.S. population and accounting for 79.10% of births. Indian Tribal Organizations with separate WIC EBT implementation plans are excluded.

We then examine the correlation between the WIC EBT rollout schedule and baseline county characteristics. We collect baseline data for the years 2006-2008 from various sources. Data on the share of Black and Hispanic populations and income per capita are from the American Community Survey (ACS) Public Use Microdata Sample (US Census Bureau, 2006-2008*a*). We construct county-level ACS data by matching individual records with Public Use Microdata Areas (PUMA) identifiers, aggregated to the county level and weighted by ACS person weights.[3] Observations from PUMAs with populations under 100,000 are excluded as geographic identifiers are suppressed for these PUMAs. To measure some of the welfare programs that automatically convey WIC eligibility, we collect data on transfers from the Bureau of Economic Analysis's Regional Economic Information System (REIS), which includes these programs (Bureau of Economic Analysis, 2006-2008).[4] Finally, we include county-level data on poverty rates and the under-five population from the Small Area Income and Poverty Estimates (SAIPE) Program (US Census Bureau, 2006-2008*b*), the share of low birthweight births from the restricted-use Vital Statistics Natality Data (National Center for Health Statistics, 2009-2021), and the net increase in WIC vendors from the WIC Integrity Profiles (TIP) (USDA Food and Nutrition Service, 2006-2008). 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 1 compare the baseline characteristics of our sample counties to those excluded because of missing WIC EBT rollout or Vital Statistics Natality Data. 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 birth weight, and receive more income maintenance benefits per capita, they receive fewer 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 1 show that while

[3]We use the 2000 crosswalk between counties and PUMAs provided by the Missouri Census Data Center. See `https://mcdc.missouri.edu/applications/geocorr.html` Note that county-to-PUMA is a many-to-many relationship. The crosswalk includes an allocation factor to help align PUMAs with counties. We use the same approach to construct the county-by-year employment rate from 2009-2021 (US Census Bureau, 2009-2021*a*).

[4]In the REIS data set, public assistance medical benefits include 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. SNAP benefits are reported separately.

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 seems plausibly exogenous.

3.2 Vital Statistics Natality Data

To measure WIC participation, we use Vital Statistics Natality Data. These 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 mothers' WIC status, among other variables. Using natality data avoids the well-documented misreporting of WIC participation status in survey data (Meyer, Mok and Sullivan, 2015; Meyer and Mittag, 2019). The 2003 revision of the birth certificate required the inclusion of the mother's WIC status, 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 tractable. Our sample period spans 2009-2021 (National Center for Health Statistics, 2009-2021).

We validate our measure of WIC participation information from birth records by showing that it captures changes in total WIC participation. First, we show that the ratio of WIC births to total WIC participants consistently remains at 20% throughout the study period, with the exception of a slight decline during the pandemic (see Figure A1). Second, we find that observable characteristics, such as the proportions of Black and Hispanic mothers, educational backgrounds, and regions of residence, are comparable across the three samples: mothers in the natality data, women aged 19-45 years in the Current Population Survey's (March) Annual Social and Economic Supplements (CPS ASEC) (US Census Bureau, 2009-2021*b*) and postpartum women in the Survey of Income and Program Participation (SIPP) (US Census Bureau, 2009-2021*c*) (see Table A1). Even with this, we acknowledge that mothers in the natality data may still differ from all WIC participants in important ways. However, mothers in the natality data represent an important share of WIC participants. Natality data has also been used in other studies, such as Rossin-Slater (2013) and Meckel (2020), to examine WIC participation.

TABLE 1: 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					
% Non-white	0.1533	0.2185	-0.0652	5.5459***	-0.2260
	[0.0028]	[0.0052]		(1.9341)	(0.2354)
% Hispanic	0.0544	0.1948	-0.1404	2.0842	1.5490*
	[0.0014]	[0.0085]		(2.6679)	(0.8240)
% Poor $\times$ under age 5	1.6397	1.9541	-0.3144	-0.2538	-0.1206**
	[0.0154]	[0.0348]		(0.5438)	(0.0584)
% Low birth weight	8.0318	8.7421	-0.7103	-0.4256*	-0.0132
	[0.0486]	[0.1003]		(0.2163)	(0.0122)
Population	96,379	93,937	2,442		
	[6,282]	[11,143]			
Log population				-0.0840	-0.0149
				(0.2400)	(0.0101)
Transfers and income, 2006-2008					
Public asst. medical benefits p.p. (incl., Medicaid, $1,000)	1.1142	1.1455	-0.0313	0.6523	-0.0210
	[0.0111]	[0.0208]		(0.6237)	(0.0994)
Income maintenance benefits p.p. (incl., TANF and WIC, $1,000)	0.1833	0.1697	0.0136	-6.4838	0.3645
	[0.0016]	[0.0026]		(3.9949)	(0.5908)
SNAP benefits p.p. ($1,000)	0.1165	0.1280	-0.0116	5.6884	1.4093*
	[0.0016]	[0.0027]		(9.4534)	(0.8147)
Income p.p.(million)	27.7800	26.6126	1.1675	-0.0088	-0.0021
	[0.1128]	[0.2376]		(0.0312)	(0.0038)
WIC vendors, 2006-2008					
Number of WIC vendors	41.8748	36.6757	5.1991	0.0003	0.0001***
	[2.8241]	[4.0162]		(0.0004)	(2.98×10^{-5})
Fraction of population	81.27	18.73			
Fraction of births	79.17	19.83			
State fixed effects					✓
Observations				2,489	2,489
R-squared				0.1971	0.9893

Notes: This table shows the means and standard errors of the group with characteristics listed in the first column. Data on share of non-white, share of Hispanics, 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; 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 the number of 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 clustered on state.

3.3 USDA administrative data on state monthly WIC participation

To further validate our approach, we re-apply our research design using state agency-level data on monthly WIC participation from USDA Food and Nutrition Service (2009-2021), which includes all participant categories (see Section 5.3). The USDA FNS publishes administrative data on monthly WIC participation and program costs at the state level. The state-level monthly participation data is available for all participant types, including pregnant women, fully or partially breastfeeding women, postpartum women, fully or partially breastfed infants, and children aged 1–4. Monthly participation figures represent the number of existing participants in a given month rather than new enrollments. The USDA FNS website typically provides data for the past five years. We use the Wayback Machine to collect data from 2009 to 2021. The state-by-month administrative data provide a robustness check on results from the natality data, which only includes pregnant people. The disadvantage is that the USDA data are aggregated to the state level while the natality data is observed at the county level.

The total participant count differs from the total number of WIC decision units. For example, a breastfeeding mother with a child between the ages of 1 and 4 would be counted as three participants, the mother, the infant, and the child, while the decision unit would be considered one. Focusing solely on total participation assigns greater weight to families with multiple WIC participants, even though it is typically the mother who decides whether to enroll in WIC. As a result, we report results separately for women participants, children, and total participants when we analyze the administrative data.

3.4 Google Trends data

We use Google Trends data to explore whether EBT implementation increases awareness of and interest in WIC. Google Trends is a publicly available database that tracks the relative popularity of search terms at the city, designated market area (DMA), state, and national levels. The data portal returns an index that normalizes the share of searches relative to the maximum search share within the chosen time frame and region. We use DMA-by-year data, which provides the normalized share of searches across 210 DMAs starting from 2004. The raw data downloaded from Google Trends data portal represent the relative popularity of a search term within a DMA-year (Burchardi, Chaney and Hassan, 2019). One alternative would be to use city-by-year data, but Google Trends only reports search data above certain thresholds (Stephens-Davidowitz and Varian, 2014) and many search terms of interest are suppressed at the more disaggregated city-by-year level.

We collect search data on the general term "WIC" to measure overall awareness of WIC and terms such as "apply for WIC," "WIC application," "qualify for WIC," "WIC benefits," and "WIC foods" to capture intent to participate in WIC.[5] Due to Google Trends' reporting

[5]These five terms were selected because Google Trends only allows the comparison of five terms at a time, and they are more frequently searched than other WIC-related terms such as "WIC qualification" or "WIC clinic."

threshold, only the term "WIC" has sufficient search volume to generate a complete DMA-level panel between 2004 and 2021. To address this issue, we follow Burchardi, Chaney and Hassan (2019) and Alsan and Yang (2022) in aggregating the search data by taking a simple average of these terms.

4 Methods

4.1 Empirical strategy

To identify the effects of WIC EBT implementation, we compare cohorts born before and after WIC EBT implementation in counties that implemented EBT with counties that have not yet implemented WIC EBT. Our baseline regression model is:

$$Y_{ct} = \alpha + \mu EBT_{ct} + \eta_c + \lambda_t + \theta_{ct} + Z_c t + X_{ct} + \varepsilon_{ct}, \tag{1}$$

where Y_{ct} is an 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 a census-region-by-year fixed effect[6] to account for differential trends of outcomes across geographical areas, $Z_c t$ are county baseline characteristics listed in Table 1 interacted with a linear time trend to control for differential trends across regions with different baseline characteristics, X_{ct} is the 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 de Chaisemartin and D'Haultfœuille (2020) as well as Goodman-Bacon (2021), 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 with weights that may be negative. As a result, the TWFE estimator is not consistent for the estimand of interest – the average treatment effect on the treated (ATT). We use the interaction weighted (IW) estimator proposed by Sun and Abraham (2021) in our baseline results to avoid this issue. The IW estimator uses the last-treated counties as the control group. We first estimate the cohort-specific ITT effects for each event time (excluding period -1) using a saturated regression model that interacts event time dummies with cohort dummies, including all fixed effects and control variables. We then aggregate the coefficients on the interaction terms of event time and cohort dummies by sample shares to construct the IW estimators. Sun and

[6] We control for census-region-by-year instead of state-by-year fixed effects as many states implement WIC EBT in a single year.

Abraham (2021) and Lin and Zhang (2022) show that the IW estimator is consistent under assumptions of parallel trends conditional on covariates, no anticipation, and the outcomes of the comparison group (last-treated counties) in a given period are only linearly correlated with the contemporary covariates. In Section B5, we discuss results using other popular staggered difference-in-difference estimators as well as traditional TWFE estimators. Our results are not driven by 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 correlation of errors among counties within the same state (Abadie et al., 2023). We report both standard errors whenever possible; when inconvenient to do so, we report standard errors clustered by state. Regressions and dependent variable means are weighted using the number of births in each cell. We present results for all births, as well as for high-impact groups defined as in Section 4.2. The raw estimates from our regressions represent the 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, as determined from the SIPP.

4.2 High-impact groups

To estimate an ATT, our analysis would be ideally 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 likely to be eligible for WIC, defined by specific maternal characteristics that appear in both the natality data and the SIPP -— specifically: maternal age, education, marital status, race, and Hispanic origin. WIC eligibility can be inferred in the SIPP because it includes information on household income, demographics, and program participation.[7] We identify WIC-eligible mothers as mothers of infants (children aged 0) with 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). For characteristics observable in the natality data, we estimate the correlation between WIC eligibility in the SIPP and these characteristics to find the best groups for us to focus on.

We identify mothers with a high school education or less and mothers who are unmar-

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

ried householders as subpopulations more likely to be WIC-eligible as both of them comprise approximately 40% of the full sample and are about 14% more likely to be WIC-eligible than mothers overall (Table 2). Column 4 of Table 2 presents the results of regressing estimated WIC eligibility on individual maternal characteristics, controlling for state and panel fixed effects. These regression results align with the sample means reported in the other columns, suggesting that variations in WIC-eligible shares across maternal characteristic groups may not be driven by unobserved state or panel factors. When we discuss EBT's effects on WIC participation and birth outcomes, we present results for these two groups in addition to those for the full sample. 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 2: REGRESSIONS OF WIC ELIGIBILITY ON MATERNAL CHARACTERISTICS, SIPP

Maternal characteristics	Share of individuals with characteristic k (1)	Share of WIC-eligible individuals (S_k) (2)	$S_k - S_{all}$ (3)	Individual regressions: coefficients (std.err), x 10^{-3} (4)
Age $\leq$ 22	20.02%	62.98%	7.93%	0.0343***
				(0.0020)
Education $\leq$ high school	37.32%	69.6%	14.54%	0.0870***
				(0.0033)
Unmarried	56.48%	61.68%	6.62%	0.0861***
				(0.0040)
Unmarried female householder	41.21%	69.77%	14.71%	0.0875***
				(0.0034)
Non-white	26.78%	62.14%	7.09%	0.0384***
				(0.0077)
Hispanic	20.13%	66.23%	11.17%	0.0720***
				(0.0049)

Notes: 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). Dependent variables of Columns (4) are a dummy for WIC eligibility estimated with income and program participation and the estimates are 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. $S_{all} = 55.06\%$. In Column (4), we need to multiply all values by 10^{-3} to obtain correct estimates.

5 Results

In this section we present our findings on the effect of WIC EBT implementation on WIC participation and birth outcomes. In the first subsection we show results on WIC participation for mothers of all newborns as well as mothers of newborns from our target groups along with heterogeneity by age, race, ethnicity (Hispanic or non-Hispanic), birth order, and county income quantiles. Second, using the natality data, we examine the effects of WIC EBT on birth outcomes. Third, we show that we can replicate our findings on WIC EBT's effect on

WIC participation in state-by-month participation data including all participants. Lastly, we summarize the robustness and sensitivity analyses we implement to test the soundness of our results.

5.1 WIC EBT increases WIC participation among mothers of newborns, particularly among high-impact groups

Table 3 shows that the ITTs of EBT on WIC participation are 1.25, 1.68, and 1.68 percentage points (p.p.) for all mothers, mothers with no more than a high school education, and mothers without an infant's father listed on the birth certificate, respectively. These estimates are statistically significant for the high-impact groups when standard errors are clustered at the county or state level. Among all mothers, mothers with no more than a high school education, and those without an infant's father listed on the birth certificate, the shares of WIC-eligible individuals are 55.06%, 69.6%, and 69.77%, respectively. Adjusting for the share of WIC-eligible individuals within our group of interest, the TOT effect of WIC EBT on WIC participation is 2.27 p.p. among all mothers, 2.41 p.p. among mothers with no more than a high school education, and 2.41 p.p. among mothers without an infant's father listed on the birth certificate. Relative to the mean of the dependent variable in these subsamples, the TOT effects represent a 5.54% increase in the share of WIC participants in the county for all mothers, a 3.71% increase for mothers with no more than a high school education, and a 3.58% increase for mothers with no father appearing on the birth certificate.

TABLE 3: EFFECTS OF WIC EBT ON WIC PARTICIPATION AMONG MOTHERS OF NEWBORNS

	All mothers			Education $\leq$ high school			No father		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Born after EBT	0.0149	0.0172	0.0125	0.0268	0.0308	0.0168	0.0275	0.0342	0.0168
	(0.0058)**	(0.0050)***	(0.0050)**	(0.0081)***	(0.0074)***	(0.0073)**	(0.0079)***	(0.0073)***	(0.0065)***
	[0.0156]	[0.0094]*	[0.0092]	[0.0120]**	[0.0071]***	[0.0097]*	[0.0086]***	[0.0058]***	[0.0052]***
Observations	34,566	33,873	27,913	33,964	33,329	27,375	32,496	31,890	26,117
R^2	0.9578	0.9635	0.9643	0.9193	0.9232	0.9284	0.8463	0.8521	0.8507
Dep. var. mean	0.3972	0.3987	0.4095	0.6395	0.6412	0.6500	0.6627	0.6641	0.6741
County fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Census region×year		✓	✓		✓	✓		✓	✓
Baseline char.×year		✓	✓		✓	✓		✓	✓
Employment rate$_{ct}$			✓			✓			✓

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 2006-2008 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 square brackets. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

Figure 2 shows that pre-EBT trends are relatively flat, providing some evidence of minimal differential trends before EBT implementation. We provide additional evidence on the sensitivity to potential violations of the parallel trend assumption in Section B7. Although the WIC-eligible may have anticipated EBT implementation, Figure 2 shows that any such anticipation did not affect their participation decisions, as the relative increase in WIC participation only occurs after EBT implementation. Finally, we test the assumption that WIC participation in the last-treated counties is linearly related to these covariates (Sun and Abraham, 2021; Lin and Zhang, 2022). We compare a model with no higher-order terms to one with both quadratic and cubic terms added. The results are shown in Figure A3a. We do not observe any substantial changes in results, indicating that higher order terms do not affect the model fit or the conclusions we draw from our results.

For our main results, we define the dependent variable as the share of mothers participating in WIC. As shown in Table A5 and Figure A4, running similar regressions on the log number of mothers participating in WIC yields similar results. These are not entirely apples-to-apples comparisons, since even when computing a percent change in the share of WIC participation, results for shares depend on both the number of WIC participants as well as the number of non-WIC participating mothers. The log results reflect only the percent change in the number of WIC participating mothers in the birth records.

In Table A3, we aggregate estimates by cohort and find that the positive effects are primarily driven by counties that adopted EBT in 2013, 2016, and 2017. These cohorts include counties in states such as Arizona, Colorado, Connecticut, Delaware, Florida, Indiana, Iowa, Kansas, Maryland, Oklahoma, Oregon, South Dakota, Virginia, and West Virginia. The heterogeneity, geographic and otherwise, of these states suggests that estimates are unlikely to reflect regional trends. We explore this hypothesis in detail below.

How do our estimates on WIC participation compare to those of other papers that estimate the effect of WIC EBT on participation? Meckel (2020) finds a decline in the average number of mothers participating in WIC after the introduction of EBT in Texas, where EBT transition occurred between June 2005 and March 2009. 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, where the EBT transition occurred between February and August 2016. Our results are bounded between existing estimates of the effect of WIC EBT on WIC participation from individual states, which is reasonable given that we estimate an average nationwide effect rather than

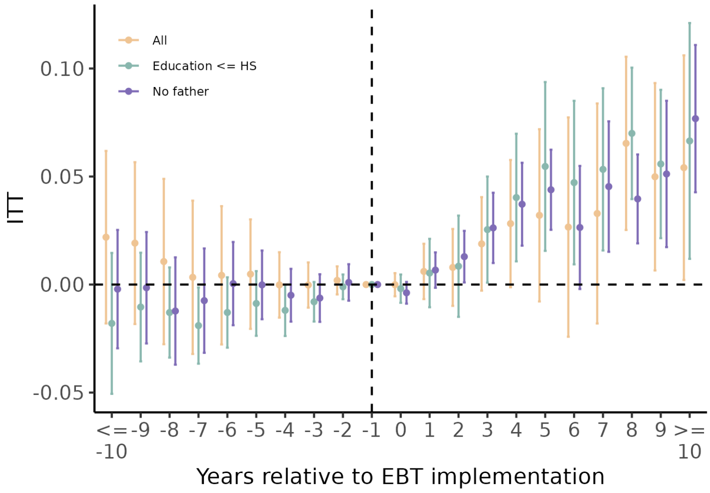


FIGURE 2: DYNAMIC EFFECTS OF WIC EBT ON WIC PARTICIPATION AMONG MOTHERS OF NEWBORNS

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 2006-2008 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 state level.

state-specific effects. The cohort-specific estimates in Table A3 also suggest heterogeneity in the effects of EBT across states that adopted the program at different times. However, unlike Texas, we do not observe a significant decline in WIC participation in any other state following the implementation of EBT.

5.2 WIC EBT reduces adverse birth outcomes among high-impact groups

We find that WIC EBT increases the share of WIC participants in counties that implement WIC EBT. We next investigate whether increasing participation results in improved three key birth outcomes: birth weight, the likelihood of low birth weight (defined as birth weight $<$ 2500 grams), and the likelihood of preterm birth (gestation $<$ 37 weeks). We find that EBT implementation significantly reduces adverse birth outcomes for high-impact groups.

Table 4 shows that while the effects of WIC EBT on birth outcomes are not precisely estimated for the full sample, they are statically significant for groups more likely to be WIC-eligible, mirroring earlier findings on WIC participation. Specifically, the ITT effects of EBT on the likelihood of low birth weight are -0.32 and -0.41 percentage points for mothers with no more than a high school education and mothers without an infant's father listed on the birth certificate, respectively. Similarly, the ITT effects on the likelihood of preterm births are -0.4 and -0.56 p.p. for the same groups. In terms of TOT, the introduction of WIC EBT reduces the likelihood of low birth weight by 0.46 p.p. and preterm births by 0.59 p.p. among mothers with no more than a high school education. For mothers without an infant's father listed on the birth certificate, the likelihood of low birth weight decreases by 0.57 p.p., and preterm births decline by 0.8 p.p. The TOT effects represent between 4.49% and 5.01% reductions in both low birth weight and preterm birth. By multiplying the average number of births per year by the TOT effect of EBT, we estimate that WIC EBT lifts 6,492 (2,258) births by mothers with no more than a high school education (mothers without an infant's father listed on the birth certificate) out of low birth weight each year, and 8,044 (3,169) births out of preterm status annually.

How much does the reduction in adverse birth outcomes translate into hospital cost savings? Using estimates from Almond, Chay and Lee (2005), we provide a back-of-the-envelope estimate of hospital cost savings associated with WIC EBT, focused solely on low birth weight. Almond, Chay and Lee (2005)'s estimates account for the omitted variable bias in the cross-sectional estimates reported by most of the scientific literature. They do not provide similar estimates for preterm births. Table A4 shows that for mothers with no more than a high school education (mothers without an infant's father listed on the birth certificate), the annual hospital cost savings are estimated at $4.82 million ($2.67 million). When compared to public expenditure, the hospital cost savings from reduced low birth weight alone amount to 25.63% (13.23%) of the USDA's annual EBT investment.[8]

TABLE 4: EFFECTS OF WIC EBT ON BIRTH OUTCOMES

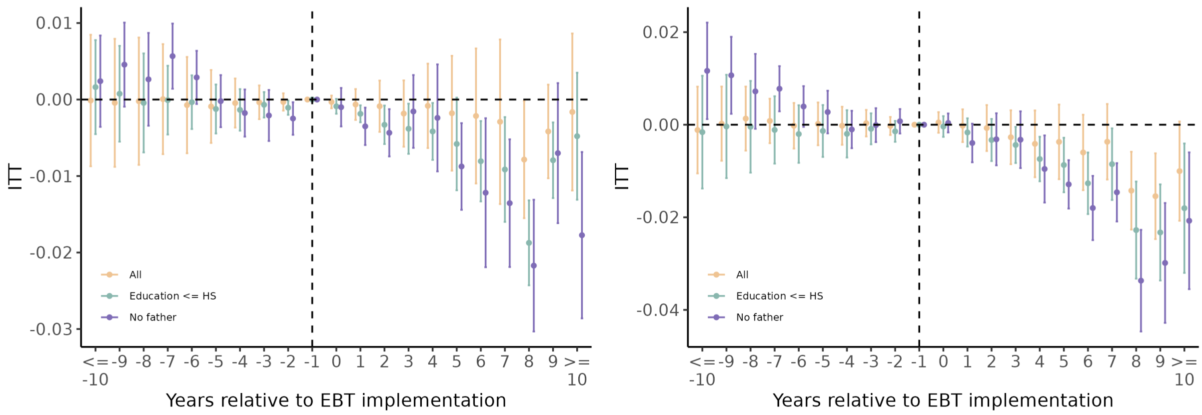
	Birth weight (grams)			Low birth weight (birth weight < 2500 grams)			Preterm (gestation < 37 weeks)		
	All births (1)	Edu≤HS (2)	No father (3)	All births (4)	Edu≤HS (5)	No father (6)	All births (7)	Edu≤HS (8)	No father (9)
Born after EBT	0.4235	5.063	5.118	-0.0010	-0.0032	-0.0041	-0.0016	-0.0040	-0.0056
	(2.247)	(2.815)*	(3.874)	(0.0008)	(0.0012)***	(0.0019)**	(0.0011)	(0.0015)**	(0.0025)**
	[4.985]	[3.576]	[4.529]	[0.0017]	[0.0010]***	[0.0016]**	[0.0022]	[0.0016]**	[0.0021]**
Observations	27,911	27,372	26,114	27,911	27,372	26,114	27,913	27,375	26,117
R^2	0.8859	0.8309	0.6461	0.7084	0.6430	0.4190	0.6983	0.6299	0.4274
Dep. var. mean	3,269	3,216	3,120	0.0809	0.0918	0.1226	0.1157	0.1315	0.1633

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 2006-2008 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 square brackets. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

Figures 3a and 3b indicate that pre-implementation trends are flat for the full sample and for mothers with no more than a high school education, suggesting no systematic changes in

[8] The USDA's investment in the EBT transition was $30.5 million during the 2013 fiscal year (USDA Food and Nutrition Service, 2017) We convert $30.5 million to 2000 dollars by dividing it by 1.35. The calculation for 25.63% is: $\frac{5.79\times1.35}{30.5}$. Given that improved birth outcomes have been linked to various long-run outcomes, such as higher educational attainment (Behrman and Rosenzweig, 2004) and adult income (Bharadwaj, Lundborg and Rooth, 2018), WIC EBT is likely to generate a positive net benefit in the long run.

outcomes prior to EBT implementation. The effects observed for mothers without an infant's father listed on the birth certificate may be potentially influenced by pre-existing trends. However, these trends occur well before the EBT implementation and do not fully account for the observed impacts. We conduct a test of sensitivity to violations of the parallel trend assumption in Section B7 and confirm that the birth outcomes results are robust to substantial linear potential violations of parallel trends. Finally, we do not observe substantial changes in the results when adding quadratic and cubic terms of covariates, as shown in Figures A3b-A3c, supporting the assumption that outcomes of comparison groups (last-treated counties) are linearly related to covariates.



(A) Low birth weight (B) Preterm

FIGURE 3: DYNAMIC EFFECTS OF WIC EBT ON ADVERSE 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 2006-2008 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 state level.

5.3 Evidence from state monthly WIC participation

While the natality data that underpin our main results have a number of advantages, they only include mothers of infants. To verify that our findings generalize to other groups of WIC participants, we re-implement our research design using a different source of WIC participation data – state agency level WIC participation by month.

We define the timing of a state's EBT implementation based on the earliest EBT implementation year among all counties within the state and then match this rollout schedule to USDA data on state-level monthly WIC participation. We divide the number of women participants by the total number of women aged 19-45, the number of child participants by the total number of children aged 1-4, and the total number of participants by the combined population of women aged 19-45, infants, and children. Table 5 presents results from regressions similar to

Equation 1, except that all regressors are measured at the state level, and year-of-birth fixed effects are replaced with month-and-year fixed effects. Our findings indicate that EBT implementation increases WIC participation by 0.22 percentage points among women aged 19-45, 1.4 percentage points among children aged 1-4, and 0.48 percentage points among the combined group of women, children, and infants. Figures 4a-4c present event study results corresponding to Table 5. We find that pre-EBT trends are relatively flat for the share of women aged 19-45 participating in WIC and the share of total participants among the combined group of women, children, and infants. As in Table A2 and Figure A2, switching our outcome variable to the log number of participants yields similar results.

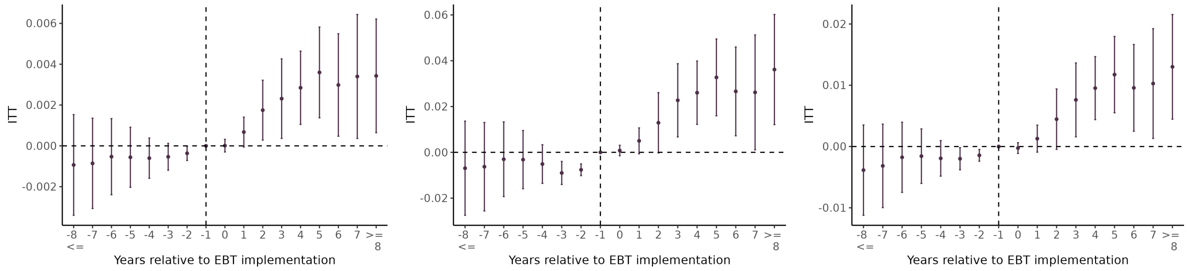
TABLE 5: EFFECTS OF WIC EBT ON STATE AVERAGE MONTHLY WIC PARTICIPANTS

	Share of women participants among women aged 19-45			Share of children participants among children aged 1-4			Share of total participants among women aged 19-45, infants, and children aged 1-4		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
WIC EBT implementation	0.0022***	0.0017***	0.0016**	0.0186***	0.0145***	0.0140***	0.0069***	0.0050***	0.0048**
	(0.0002)	(0.0005)	(0.0006)	(0.0024)	(0.0043)	(0.0048)	(0.0007)	(0.0016)	(0.0018)
Observations	7,020	6,864	6,864	7,020	6,864	6,864	7,020	6,864	6,864
R^2	0.9562	0.9823	0.9824	0.9561	0.9690	0.9690	0.9586	0.9784	0.9784
Dep. var. mean	0.0301	0.0301	0.0301	0.1965	0.1965	0.1965	0.0913	0.0913	0.0913
State fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Month-and-year fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Census region×year		✓	✓		✓	✓		✓	✓
Baseline char.×year		✓	✓		✓	✓		✓	✓
Employment rate$_{ct}$			✓			✓			✓

Notes: We report interaction weighted estimators proposed by Sun and Abraham (2021). In the full model, we control for state and month-and-year fixed effects, census-region-specific linear time trend, state baseline characteristics from 2006-2008 interacted with linear time trend, and state-by-year employment rate. Regressions and dependent variable mean are weighted by the number of women aged 19-45 for results on women participants and by the number of children aged 1-4 for results on child participants, respectively. We report standard errors clustered on state in parentheses. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

5.4 Robustness

In this section we summarize the results of a large number of robustness and sensitivity checks. The details of these procedures, including a description of the methods, and tables and figures appear in Online Appendix B. First, we check that mothers that are less likely to be WIC eligible show smaller and less precise effects on WIC participation than mothers in our target groups. Second, we assign placebo EBT timing five years prior to actual EBT implementation and show that these pseudo-treatment effects are insignificant and small. Third, in a similar vein, we randomly assign EBT timing to counties while maintaining the original timing distribution. Across 1,000 simulations, we show that the distribution of our estimates is centered at zero and that our original estimates fall well into the tail of this simulated null distribution. Fourth,



(A) Share of women participants among all women of 19 to 45 y.o.

(B) Share of children participants among all children aged 1-4

(C) Share of total participants among women of 19 to 45 y.o., infants, and children aged 1-4 combined

FIGURE 4: DYNAMIC EFFECTS OF WIC EBT ON STATE MONTHLY WIC PARTICIPANTS

Notes: We report interaction weighted estimators proposed by Sun and Abraham (2021). We control for state and month-and-year fixed effects, census-region-specific linear time trend, state baseline characteristics from 2006-2008 interacted with linear time trend, and state-by-year employment rate. Regressions and dependent variable mean are weighted by the number of women aged 19-45 for results on women participants, by the number of children aged 1–4 for results on child participants, and by the number of women aged 19–45, infants, and children aged 1-4 combined for results on total participants, respectively. Standard errors are clustered on state.

we show that our results are not sensitive to the choice to use an unbalanced panel in event time. Fifth, we present results using alternative estimation procedures including Callaway and Sant'Anna (2021), Borusyak, Jaravel and Spiess (2024), and TWFE. Sixth, we assess how potential violations of the parallel trends assumption would affect our estimates following the procedures outlined in Roth (2022) and Rambachan and Roth (2023). Seventh, we show that the earlier in the pregnancy a mother is exposed to WIC EBT, the larger the magnitude of the effects on participation and birth outcomes. Lastly, we show that changes in underlying demographic variables do not move simultaneously with WIC EBT implementation, making it less plausible that spurious demographic changes drive our results.

6 Potential Mechanisms

In this section, we explore mechanisms through which WIC EBT might affect WIC participation. We focus on mechanisms that shift WIC participation as the extant evidence on the positive link between WIC participation and birth outcomes is large. First, we show using Google Trends data that interest in WIC participation increases after WIC EBT. Second, we show that the effects of EBT on participation are largest in areas where prior work has suggested that stigma may be more salient, with the implication being that reducing stigma leads to increased participation.

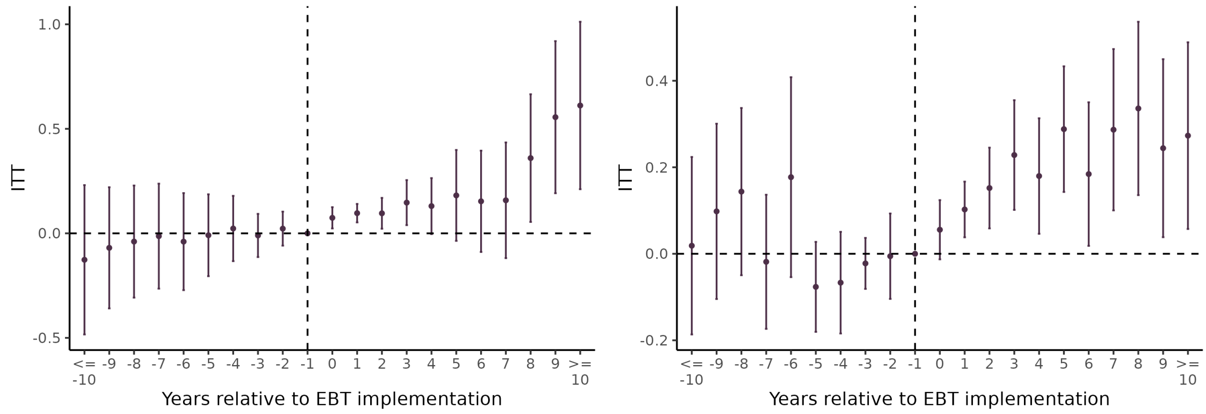
6.1 EBT increases interest in WIC participation: Evidence from Google trends

WIC EBT can increase WIC participation among mothers of newborns through both the extensive margin (encouraging more WIC-eligible individuals to participate) and the intensive margin (existing participants redeem a greater share of their WIC benefits), potentially contributing to improved birth outcomes. However, we do not observe the intensive margin of WIC participation in the Vital Statistics Natality Data. Prior work finds that the rollout of WIC EBT does not significantly affect zip-code-level WIC redemptions (Ambrozek et al., 2024). Taken with results above, this suggests that observed changes in birth outcomes are less likely to be attributable to an increase in the share of WIC benefits redeemed and more likely to be driven by an increase in participation. To explore this question further, we ask whether EBT implementation increases awareness of and interest in WIC. To this end, we match the earliest EBT implementation date among all counties within a DMA to Google Trends data on the relative popularity of WIC-related search terms. Column (1) of Table 6 shows that the relative popularity of searches for "WIC" increases by 0.19 standard deviations, suggesting a rise in awareness of the WIC program following EBT implementation. In Columns (2), we find that EBT implementation increases searches for WIC application-related terms by 0.18 standard deviations. This suggests that EBT implementation increases intent to participate in WIC. Figures 5a and 5b show that the increase in relative popularity of searches for WIC-related terms is not driven by pre-existing trends between DMAs that have implemented EBT and those that have not yet done so.

TABLE 6: EFFECTS OF WIC EBT ON WIC-RELATED GOOGLE SEARCHES

	Google search terms	
	"WIC"	"apply for WIC", "WIC application", "qualify for WIC", "WIC benefits", and "WIC foods"
	(1)	(2)
WIC EBT implementation	0.19***	0.18***
	(0.07)	(0.05)
Observations	3,154	3,757
R^2	0.8770	0.5530
Dep. var. mean	-0.40	-0.04

Notes: We report interaction weighted estimators proposed by Sun and Abraham (2021). In Column (2), the dependent variable is the simple average of the relative popularity indexes of five WIC-application-related terms including "apply for WIC", "WIC application", "qualify for WIC", "WIC benefits", and "WIC foods". We control for designated-market-area (DMA) and year fixed-effects. We report standard errors clustered on DMA in parentheses. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.



(A) Search "WIC" (B) Search WIC-application-related terms

FIGURE 5: DYNAMIC EFFECTS OF WIC EBT ON WIC-RELATED GOOGLE SEARCHES

Notes: WIC-application-related terms include "apply for WIC", "WIC application", "qualify for WIC", "WIC benefits", and "WIC foods". We estimate dynamic effects using interaction-weighted estimators proposed by Sun and Abraham (2021). We control for designated-market-area (DMA) and year fixed effects. Standard errors are clustered at DMA level.

6.2 EBT's effect on WIC participation is larger in counties where participants may experience greater welfare stigma before EBT

Welfare stigma refers to the feelings of shame or degradation associated with receiving welfare benefits (Horan and Austin, 1974). Welfare stigma can deter participation in welfare programs (Moffitt, 1983). EBT can reduce welfare stigma by making WIC redemption less visible (Pukelis, Heath and Holcomb, 2024), as the EBT card closely resembles a regular credit or debit card. EBT also shortens checkout times (Hanks et al., 2019), which lessens the stigma participants experience from feeling like they are holding up the checkout line (Chauvenet et al., 2019; Isaacs, Shriver and Haldeman, 2020). EBT cards can also be used with self-checkout machines. Anecdotal evidence also suggests that EBT reduces stigma for WIC participants (Phillips et al., 2014).[9]

Examining the effect of EBT on welfare stigma is challenging due to the lack of systematic data on both self-reported and objective measures of stigma. Instead, we identify three county groups where welfare stigma may be particularly salient for participants: (1) rural counties, (2) counties with lower peer engagement in WIC redemption, and (3) counties with a higher share of Republican voters.

Theory from economists, sociologists, and other disciplines suggests that welfare stigma

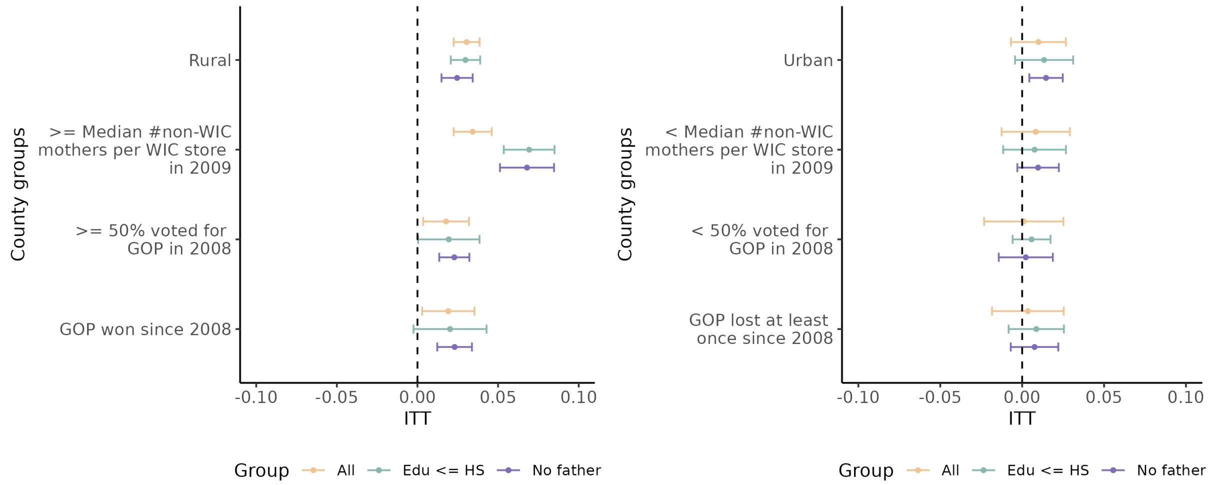
[9] Phillips et al. (2014) documents that, for example, a Michigan WIC participant shared: "Even now [with self-checkout] you can check out on your own [with] no hassle, so you don't have to worry about people or the cashier having a fit about [your WIC].", and a Nevada WIC participant said: "[When] the cashiers see you coming with WIC, they're not like, 'Oh no.' Before, when they had to do everything ... it was kind of complicated for them, but now ... it's a lot easier for them to check us out [and] a lot faster too."

may be particularly salient in specific communities. First, sociologists have found that welfare stigma tends to be larger in rural communities (Findeis et al., 2001; Meij, Haartsen and Meijering, 2020). For example, Findeis et al. (2001) find that smaller, more integrated networks can amplify the stigma attached to needing help, which may reduce willingness to participate in welfare programs. They note that rural families worry that accepting welfare could harm their family reputation, which is important for securing work opportunities in rural communities. Anecdotal evidence documents that, in rural areas, WIC participants reported being identified as "one of them" by other shoppers or being publicly criticized by store clerks for "wasting the government's money" (Isaacs, Shriver and Haldeman, 2020). Second, Celhay, Meyer and Mittag (2022) find that welfare stigma is most salient when fewer peers engage in the stigmatized behavior. To get at this, we construct a measure that captures whether WIC participants are likely to shop in stores with other WIC shoppers. Lastly, Republicans are more likely to view participation in welfare programs negatively (Levy, 2021; Goenka and Thomas, 2022). A Pew Research Center report by Doherty, Kiley and Asheer (2019) finds that Republicans and Republican-leaning individuals are less likely to support expanding government assistance for people in need and are more inclined to believe statements such as "poor people have it easy because they can get government benefits without doing anything in return" and "most people can get ahead if they are willing to work hard."

If stigma reduction is a mechanism driving increased WIC participation post-EBT, increases in WIC participation should be larger in regions with higher levels of existing stigma. Alsan and Yang (2022) use a similar strategy to provide evidence that fear of a family member or close contact being deported may be an explanatory mechanism for the reduced welfare program participation observed among Hispanic citizens following immigration enforcement. In Figure 6, we divide the sample by county groups and present the IW estimators for EBT's effect on WIC participation within each group. We find that the effect of EBT implementation is generally larger in these counties, suggesting that reducing welfare stigma leads to increased WIC participation.

The first set of estimates from top to bottom in Figures 6a and 6b indicate that, for high-impact groups, EBT's effect on WIC participation (ITT) is 2.98 p.p. for mothers with no more than a high school education and 2.46 p.p. for mothers without an infant's father listed on the birth certificate in rural counties, compared to 1.34 p.p. and 1.46 p.p., respectively, in urban counties.

We calculate the number of non-WIC mothers per WIC vendor as a proxy for peer engage-



(A) High stigma

(B) Low stigma

FIGURE 6: EFFECTS OF WIC EBT ON WIC PARTICIPATION BY COUNTY CHARACTERISTICS RELATED TO WELFARE STIGMA

Notes: Urban and rural areas are defined by the NCHS 2006 Urban-Rural Classification Scheme for Counties. The number of non-WIC mothers per WIC store is calculated using data on non-WIC mothers from the Vital Statistics Natality Data 2009 and number of WIC vendors from the WIC Integrity Profiles 2009. The share of voters who supported the Republican candidate in the 2008 presidential election is collected by Morris (2016). Data on the last time the Republican Party won in the presidential elections is collected by Leip (2025). Medians are weighted by population. We divide the sample by county groups and present the interaction weighted estimators proposed by Sun and Abraham (2021) for EBT's effect on WIC participation within each group. 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 2006-2008 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 state.

ment in WIC redemption. A higher number of non-WIC mothers per WIC vendor indicates a greater likelihood of shopping in an environment where fewer peers are redeeming benefits. The second set of estimates from top to bottom in Figures 6a and 6b shows that, among high-impact groups in counties with a high number of non-WIC mothers per WIC vendor, EBT's effect on WIC participation (ITT) is 6.93 p.p. for mothers with no more than a high school education and 6.79 p.p. for mothers without an infant's father listed on the birth certificate in counties with at least the median number of non-WIC mothers per WIC store, compared to 0.76 p.p. and 0.97 p.p., respectively, in counties with fewer than the median number of non-WIC mothers per WIC store.

To capture higher welfare stigma caused by the negative attitudes of Republicans towards welfare, we calculate the share of voters who supported the Republican candidate in the 2008 presidential election using data collected by Morris (2016) and collect data on the last time the Republican Party won in the presidential elections from Leip (2025). The last two sets of estimates from top to bottom in Figures 6a and 6b suggest that EBT's effect on WIC participation is both larger and more precise in counties with at least 50% voters voted for GOP in the 2008 presidential election, and in counties where the Republican Party has consistently won presidential elections since 2008, compared to other counties. EBT's effect on WIC participation (ITT) is 1.94 p.p. for mothers with no more than a high school education and 2.28 p.p. for mothers without an infant's father listed on the birth certificate in counties with at least 50% voters voted for GOP in the 2008 presidential election, compared to 0.57 p.p. and 0.22 p.p., respectively, in counties with fewer than 50% voters voted for GOP in the 2008 presidential election. EBT's effect on WIC participation (ITT) is 2.02 p.p. for mothers with no more than a high school education and 2.3 p.p. for mothers without an infant's father listed on the birth certificate in counties where the Republican Party has consistently won presidential elections since 2008, compared to 0.86 p.p. and 0.75 p.p., respectively, in counties where the Republican Party has lost at least one presidential election since 2008.

In sum, we find that EBT's impact on WIC participation is greater in rural counties, counties with lower peer engagement in WIC, and counties with a higher share of Republican voters, all places where theory suggests welfare participants may experience larger welfare stigma. These findings suggest that reducing welfare stigma may be an important driver of EBT's positive effect on WIC participation. The heterogeneity results for birth outcomes in high- and low-stigma areas are broadly consistent with the participation results (see Figure A5).

7 Discussion and Conclusion

We provide the first national evidence on the effect of WIC payment digitization, known as WIC EBT transition, on participants' outcomes. Using hand-collected data on WIC EBT rollout at the county level linked to Vital Statistics Natality Data, we find that WIC EBT increases the share of likely eligible individuals participating in WIC by 2.41 percentage points, representing 3.58%-3.71% of the sample mean. These increases in participation translate to improved birth outcomes for likely WIC-eligible mothers with the incidence of low birth weight and preterm birth falling by 0.46-0.8 percentage points (around 5% of the sample mean), after EBT implementation in treatment versus control counties. Our approach leverages the rollout of EBT over two decades using the staggered adoption difference-in-difference estimator of Sun and Abraham (2021). We also offer novel insights to the mechanisms by which EBT leads to increased participation. From Google Trends data, we provide evidence that WIC EBT increases interest in WIC, which may in turn lead to increased participation. Increased interest may be due to less stigma at retailers after EBT implementation. We identify counties where stigma is more likely to be salient – rural counties, counties with lower peer engagement in WIC, and heavily Republican counties – and show that the effect of EBT on participation is largest where

WIC is likely most stigmatized.

Our main results are robust to a wide range of empirical choices. Specifically, the inclusion of controls and fixed effects, use of a balanced versus unbalanced panel, changes in the estimation approach, potential timing of the treatment, or potential linear violation of parallel trend assumption. Estimating the effect of WIC EBT on state-agency level data which includes all participants, not just individuals giving birth, shows positive effects on participation, so our results are not driven by novel use of natality data.

One limitation of our empirical approach 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 TOT 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 speculate that this attenuation effect may still hold.

Our work contributes to a broader literature on adopting digital technologies in public programs. Like prior papers in the literature, we show that program changes to incorporate digital technologies that make benefit redemption more accessible – in our setting both directly and through reduced stigma – improve participation and participant outcomes. Declining WIC enrollment among eligible groups has been a focus for leaders of WIC state and federal agencies in the past ten years. In a policy environment where stigma from program participation is on the rise and the health of women, infants, and children is more important than ever, it is important that policymakers understand the factors that can make food assistance programs more efficient. Funding and facilitating use of technology to improve the participant experience is one such policy.

Online shopping is the next big step in the digitization of WIC. Allowing participants to select items and check out online eliminates key sources of program stigma, such as trying to purchase ineligible items and long checkout processes. Online WIC shopping is currently being piloted at select retailers in Iowa, Massachusetts, Minnesota, Nebraska, South Dakota (Rosebud Sioux), and Washington (Center for Nutrition & Health Impact, 2024). 62% of WIC participants indicate that they would use online WIC shopping were it available and the most common reason for not redeeming benefits fully was a lack of access to online shopping –

(Ritchie et al., 2021). While online WIC shopping requires substantial updates to program rules and existing technology, our results on stigma and participation suggest that this change in WIC is likely to boost WIC participation and improve birth outcomes.

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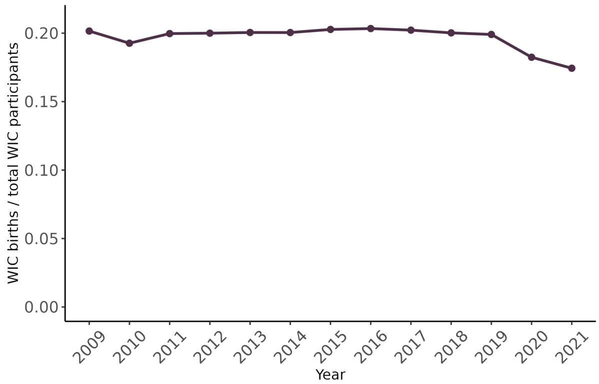
Appendix

A Figures and tables

FIGURE A1: RATIO OF WIC BIRTHS TO TOTAL WIC PARTICIPANTS



Notes: Ratio of WIC births to total WIC participants is calculated by dividing total number of WIC births (from natality data) by total WIC participants (from USDA FNS). 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 the Way-Back Machine to extract historical data.

TABLE A1: COMPARING NATALITY DATA WITH SURVEY DATA

	Natality data (1)	CPS ASEC (2)	Mean difference (1) - (2) (3)	SIPP (4)	Mean difference (1) - (4) (5)
Share non-white	24.07%	24.85%	-0.78%	26.78%	-2.71%
Share Hispanic	24.11%	22.98%	1.13%	20.13%	3.99%
Education $\leq$ high school	40.42%	37.03%	3.39%	37.32%	3.11%
Education $\geq$ college	31.06%	30.21%	0.85%	32.74%	-1.68%
Northeast	14.77%	15.89%	-1.12%	17.35%	-2.58%
Midwest	21.65%	19.8%	1.85%	20.85%	0.8%
West	24.81%	28.39%	-3.57%	23.07%	1.74%
Share of WIC participants	40.46%	7.87%		19.93%	
Full sample size	45,910,299	363,734		78,054	

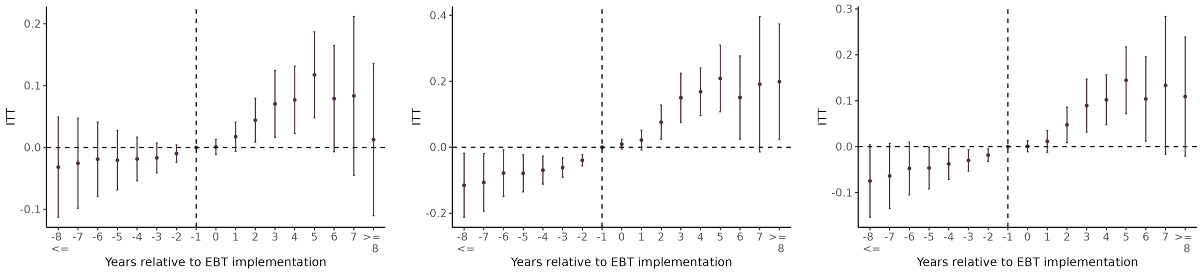
Notes: Numbers in this table, unless otherwise noted, are shares of the group with characteristics listed in the first column. All three data sets span 2009-2021. Observations with null values are dropped. Means from natality data are unweighted since it covers population of live births; means from CPS AESC are weighted average characteristics of women at 19-45 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 the weighted average of SIPP panel and then average across panels because personal weights are not comparable across panels.

TABLE A2: EFFECTS OF WIC EBT ON LOG NUMBERS OF STATE AVERAGE MONTHLY WIC PARTICIPANTS

	Log number of women participants (1)	Log number of children participants (2)	Log number of total participants (3)
WIC EBT implementation	0.0434**	0.0873***	0.0537***
	(0.0189)	(0.0255)	(0.0192)
Observations	6,864	6,864	6,864
R^2	0.9985	0.9967	0.9982
Average number of state monthly participants	32,501	73,274	139,218

Notes: We report interaction weighted estimators proposed by Sun and Abraham (2021). We control for state and month-and-year fixed effects, census-region-specific linear time trend, state baseline characteristics from 2006-2008 interacted with linear time trend, and state-by-year employment rate. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

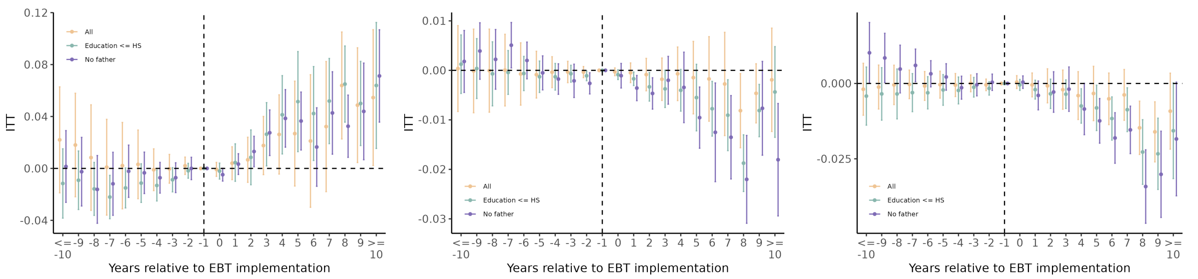
FIGURE A2: DYNAMIC EFFECTS OF WIC EBT ON LOG NUMBERS OF STATE AVERAGE MONTHLY WIC PARTICIPANTS



(A) Log number of women participants (B) Log number of children participants (C) Log number of total participants

Notes: We report interaction weighted estimators proposed by Sun and Abraham (2021). We control for state and year fixed effects, census-region-specific linear time trend, state baseline characteristics from 2006-2008 interacted with linear time trend, and state-by-year employment rate. Standard errors are clustered on state.

FIGURE A3: DYNAMIC EFFECTS OF WIC EBT, ADDING QUADRATIC AND CUBIC TERMS OF COVARIATES



(A) WIC participation (B) Low birth weight (C) Preterm

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, and all covariates and their quadratic and cubic terms. Regressions and dependent variable mean are weighted by the number of births in each cell. Standard errors are clustered at state level.

TABLE A3: COHORT-SPECIFIC EFFECTS OF EBT ON WIC PARTICIPATION

	WIC participation		
	All mothers (1)	Edu≤HS (2)	No father (3)
Cohort = 2011	0.0150	0.0149*	0.0126*
	[0.0097]	[0.0076]	[0.0065]
Cohort = 2013	0.1740***	0.1519***	0.0995***
	[0.0167]	[0.0082]	[0.0109]
Cohort = 2014	-0.0001	0.0092	0.0013
	[0.0186]	[0.0134]	[0.0096]
Cohort = 2015	-0.0036	0.0195	-0.0030
	[0.0235]	[0.0154]	[0.0166]
Cohort = 2016	0.0271**	0.0405***	0.0430***
	[0.0105]	[0.0125]	[0.0129]
Cohort = 2017	0.0185***	0.0196*	0.0273**
	[0.0055]	[0.0109]	[0.0109]
Cohort = 2018	0.0088	0.0089	0.0220**
	[0.0059]	[0.0100]	[0.0098]
Cohort = 2019	-0.0049	-0.0131	-0.0078
	[0.0070]	[0.0131]	[0.0067]
Cohort = 2020	0.0110	0.0083	0.0146
	[0.0082]	[0.0122]	[0.0119]
Cohort = 2021	-0.0141	-0.0099	-0.0273
	[0.0155]	[0.0240]	[0.0166]

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 2006-2008 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. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels. Standard errors are clustered at state level.

TABLE A4: HOSPITAL COST SAVING OF WIC EBT ASSOCIATED WITH LOW BIRTH WEIGHT

Birth weight segment	Excess hospital costs per mother (in 2000 dollars)	Percentage of births in each birth weight segment (%)	
		Edu≤HS	No father
(1)	(2)	(3)	(4)
< 600 g	61213	0.26	0.46
600-800 g	$67,816	0.24	0.36
800-1000 g	$36,846	0.26	0.37
1000-1500 g	$22,309	0.83	1.16
1500-2000 g	$6,806	1.78	2.42
2000-2500 g	604	0.26	0.37
Aggregated cost saved per mother		$891.93	$1326.16
Hospital cost saved per year		$5.79 million	$2.99 million

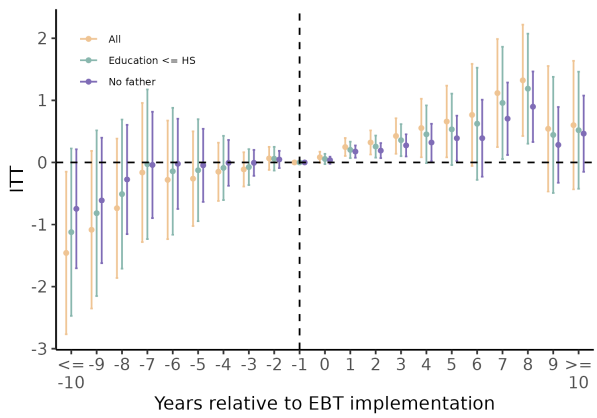
Notes: Total hospital cost saved = aggregated cost saved per mother × average number of mothers per year × reduced likelihood of low birth weight due to WIC EBT (TOT). Thus, total hospital cost saved per year for mothers with no more than a high school education is: aggregated cost saved per mother ($891.93) × average births to mothers with no more than a high school education (1,411,305) × TOT on the incidence of low birth weight for mothers with no more than a high school education (0.46%) = $5.79 million; the number for mothers without an infant's father listed on the birth certificate is: $1326.16 × 396,125 × 0.0057 = $2.99 million.

Table A5: Effects of WIC EBT on log number of WIC mothers

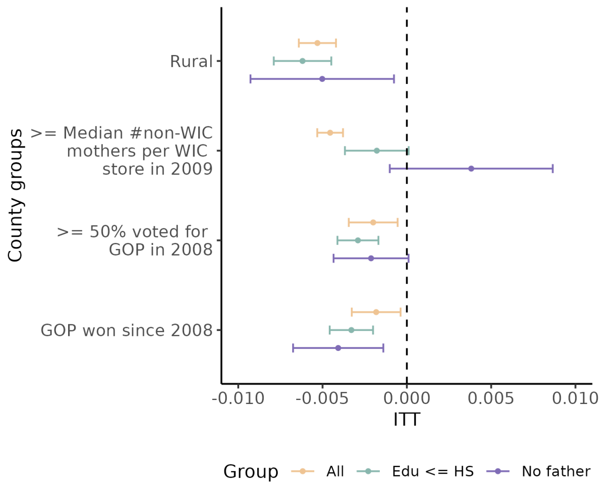
	Log(Number of WIC mothers)		
	All mothers (1)	Edu≤HS (2)	No father (3)
Born after EBT	0.3756	0.3080	0.2326
	(0.0396)***	(0.0394)***	(0.0348)***
	[0.1323]***	[0.1295]**	[0.0828]***
Observations	27,231	26,826	25,302
R^2	0.8328	0.8482	0.8480
Mean number of WIC mothers	439	280	85

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 2006-2008 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 square brackets. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

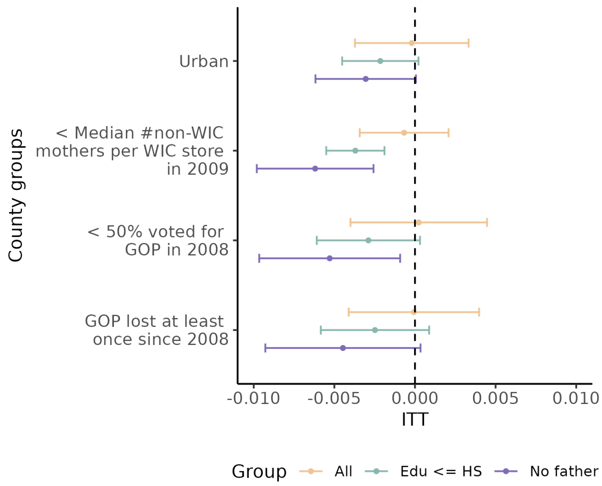
Figure A4: Dynamic effects of WIC EBT on log number of WIC mothers



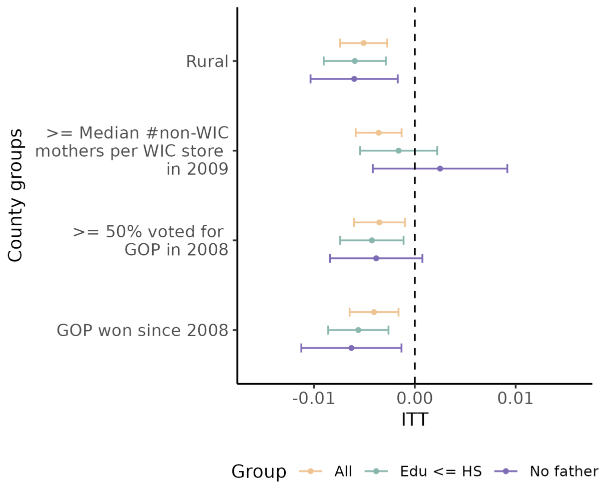
Notes: We estimate dynamic effects using interaction weighted estimators proposed by Sun and Abraham (2021). We collapse birth data to county-of-maternal-residence-by-year-of-birth cells. We control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2008 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 state level.



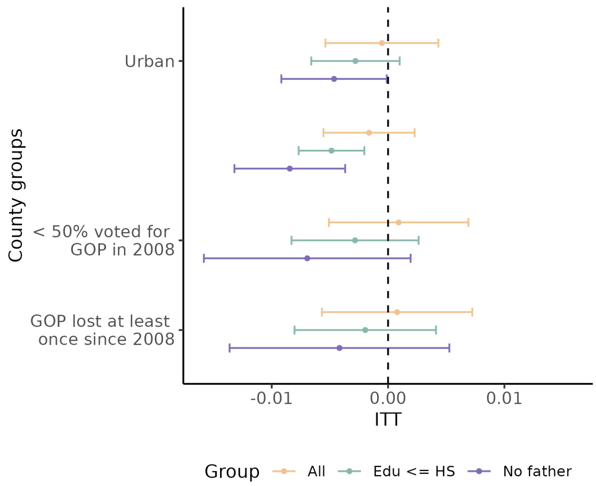
(A) Low birth weight, high stigma



(B) Low birth weight, low stigma



(C) Preterm, high stigma



(D) Preterm, low stigma

FIGURE A5: EFFECTS OF WIC EBT ON BIRTH OUTCOMES BY COUNTY CHARACTERISTICS RELATED TO WELFARE STIGMA

Notes: Urban and rural areas are defined by the NCHS 2006 Urban-Rural Classification Scheme for Counties. Population data is collected from the Intercensal Population Estimates. Data on non-WIC mothers is from the Vital Statistics Natality Data. Data on WIC vendors is from the WIC Integrity Profiles for 2009-2016. Population and non-WIC mothers per vendor are calculated as the county-level average from 2009 to 2016. The share of voters who supported the Republican candidate in the 2008 presidential election is collected by Morris (2016). Data on the last time the Republican Party won in the presidential elections is collected by Leip (2025). Medians are weighted by population. We divide the sample by county groups and present the interaction weighted estimators proposed by Sun and Abraham (2021) for EBT's effect on WIC participation within each group. 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 2006-2008 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 state.

Online Appendix

B Robustness and Sensitivity Checks

This section describes in more detail, and provides results of, the robustness and sensitivity checks that we summarized in 5.4.

B1 Results for non-target groups

In the main results, we focus on effects in the full sample of mothers as well as likely WIC eligible mothers, those with no more than a high school education and those without a father on the birth certificate. The WIC EBT transition should not affect individuals who are not WIC eligible. To test that our results are not caused by spurious trends in underlying WIC participation that coincide with WIC EBT timing, we estimate the effect of WIC EBT on WIC participation for groups that are less likely to be WIC eligible: individuals with more than a high school education and with a father on the birth certificate. There will still be WIC-eligible individuals in these non-target groups, so we expect to find smaller and less precise estimates rather than null effects. Results appear in Table B1.

TABLE B1: EFFECTS OF WIC EBT ON NON-TARGET MOTHERS

	(1)	(2)	(3)
Born after EBT	0.0074	0.0087	0.0076
	(0.0038)*	(0.0032)***	(0.0033)**
	[0.0114]	[0.0065]	[0.0061]
Observations	34,238	33,562	27,602
R^2	0.9402	0.9483	0.9482
Dep. var. mean	0.2181	0.2193	0.2255
County fixed effects	✓	✓	✓
Year fixed effects	✓	✓	✓
Census region×year		✓	✓
Baseline char.×year		✓	✓
Employment rate$_{ct}$			✓

Notes: Non-target 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 2006-2008 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 square brackets. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

We show that, for mothers not likely to participate in WIC, the estimates are statistically significantly different from zero with standard errors clustered at the county level but are not statistically significant when clustered at the state level. Effect sizes for this group are also markedly smaller than those observed in high-impact groups. We interpret these results as providing evidence that observed effects of the WIC EBT transition on WIC participation are driven by WIC eligible individuals.

B2 Placebo treatment timing

To ensure that the observed effect on WIC participation is not due to unrelated trends in the treated counties, we conduct a placebo test by estimating results based on hypothetical treatment timings rather than actual ones. Specifically, we re-estimate the effects as if the treatment had occurred five years earlier than it did.[10] If our results do not capture any spurious trends in the treated counties, we should observe no significant effects based on these hypothetical timings. Results in Table B2 line up with this hypothesis: the pseudo-treatment effects are not statistically significant, small in magnitude, and occasionally have the opposite sign, suggesting that our results are unlikely to be driven by unobserved differences between treatment and control units that coincide with EBT timing.

TABLE B2: PLACEBO TREATMENT TIMING

	WIC participation		
	All mothers (1)	Edu≤HS (2)	No father (3)
Born after EBT	-0.0037	0.0030	-0.0005
	(0.0047)	(0.0055)	(0.0056)
	[0.0080]	[0.0072]	[0.0060]
Observations	27,910	27,372	26,114
R^2	0.9637	0.9276	0.8493
Dep. var. mean	0.4095	0.6500	0.6741

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 2006-2008 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 square brackets. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

B3 Randomization test

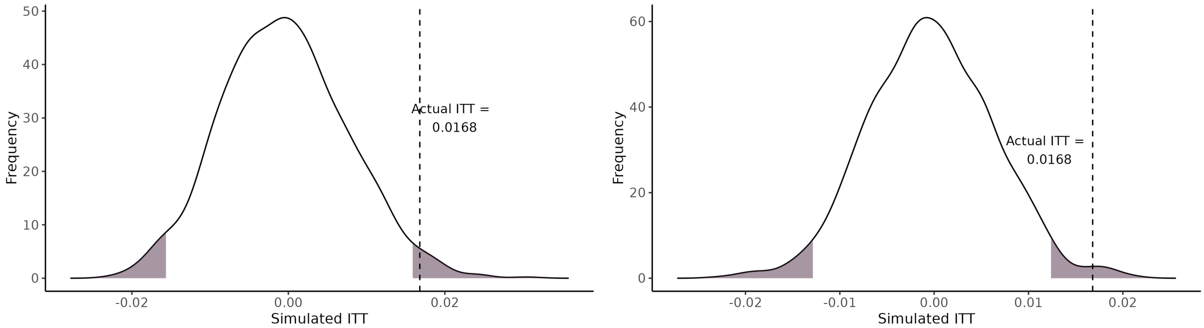
To assess the robustness of our results against random noise, we compute Intent-to-Treat (ITT) effects using randomized pseudo-treatment timings. We randomly assign the year of WIC EBT implementation 1,000 times while maintaining the original distribution of rollout years.[11] This

[10]There is no strict rule for determining how many years before the actual treatment year should be used as a placebo treatment year. Economists sometimes randomly select a year that is sufficiently distant from the actual treatment year, while other times they choose the middle year of the pre-treatment period. Here, we follow the latter approach. An example of this kind of test can be found in Kose, O'Keefe and Rosales-Rueda (2024). Note that if the placebo test passes (i.e., no effect is found), it adds to the confidence in the validity of the original findings; if the placebo test fails (i.e., an effect is found), it raises concerns about the reliability of the original results. However, passing a placebo test does not directly validate the original findings.

[11]The randomization test, which traces its origins to Fisher (1936), is widely used as a placebo test in applied research such as Adukia, Asher and Novosad (2020) and Kose, O'Keefe and Rosales-Rueda (2024).

randomization test is conducted for effects on WIC participation for mothers with high school education or less and for mothers without an infant's father listed on the birth certificate. 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 unlikely to be spurious (Figure B1).

FIGURE B1: RANDOMIZATION TEST



(A) WIC participation, education $\leq$ HS (B) WIC participation, no father

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 state level. We enforce a 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. The shaded areas represent $\leq$ 2.5th and $\geq$ 97.5th percentiles of our simulated null distribution.

B4 Event-time balanced panel

Another concern with our main results is the use of an unbalanced panel of treated counties over event time, which could mean that our results are driven by changes in the composition of counties across event time. However, estimates from a balanced panel also have limitations. Given the widespread implementation of EBT across states and data availability starting in 2009, constructing a balanced panel requires choosing between the number of pre- and post-periods and the number of counties included in the estimation. Maximizing the former would significantly reduce the sample size, while maximizing the latter would limit our ability to observe extended pre-trends and longer-term dynamic effects (see the distribution of event time of counties treated between 2010 and 2021 in Figure B2). Despite these trade-offs, Table B3 presents results for a balanced panel from period -4 to period 4, which align with our main results. In this balanced panel, the effects on WIC participation are larger and more precise. The dynamic effects based on this balanced panel are shown in Figure B3, which are also consistent with our previous findings. However, this balanced panel includes only 844 counties, far fewer than the 2,489 counties used in our main specification. While we prefer to use all available data in our main specification, the balanced panel results provide evidence that our findings are not driven by changes in the composition of counties over event time.

FIGURE B2: DISTRIBUTION OF EVENT TIME OF COUNTIES TREATED BETWEEN 2010 AND 2021

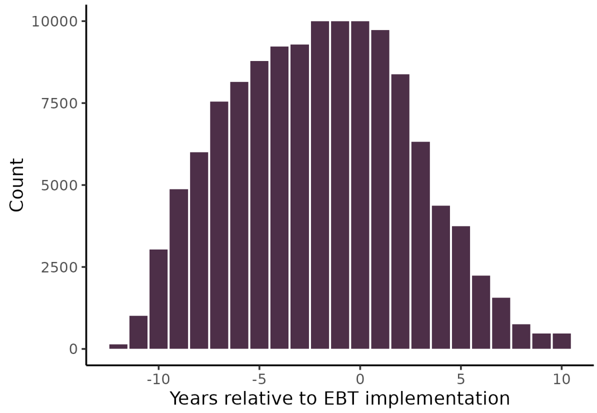
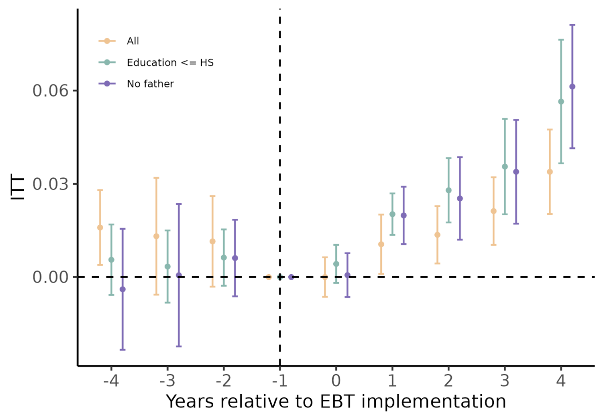


TABLE B3: EFFECTS OF WIC EBT ON WIC PARTICIPATION, EVENT-TIME BALANCED PANEL

	WIC participation		
	All mothers (1)	Edu≤HS (2)	No father (3)
Born after EBT	0.0157	0.0286	0.0280
	(0.0053)***	(0.0082)***	(0.0096)***
	[0.0042]***	[0.0050]***	[0.0056]***
Observations	8,063	7,896	7,149
R^2	0.9665	0.9306	0.8728
Dep. var. mean	0.3769	0.6063	0.6459

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 square brackets. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

FIGURE B3: DYNAMIC EFFECTS OF WIC EBT ON WIC PARTICIPATION, EVENT-TIME BALANCED PANEL



Notes: This 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. 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 state level.

B5 Robustness to estimation approach

We also present results using alternative staggered difference-in-difference methods, including traditional two-way fixed effects estimators (Figure B4a), estimators from Callaway and Sant'Anna (2021) using never-treated or not-yet-treated groups as the control group (Figures B4b and B4c), and imputation estimators by Borusyak, Jaravel and Spiess (2024) (Figure B4d). 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.

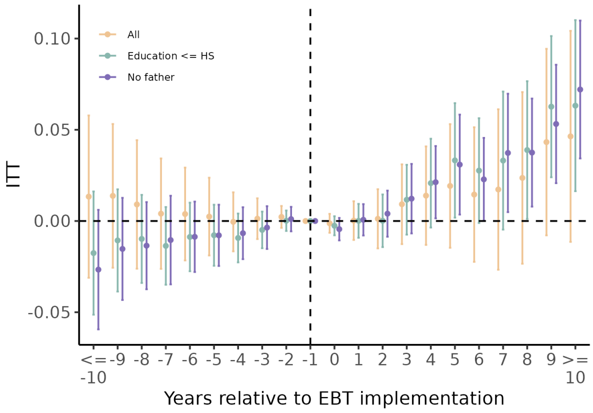
B6 Sensitivity to timing of exposure

We examine how our results change when we consider that birth outcomes may not be affected by the WIC EBT transition if the transition happens later in the pregnancy. In our baseline results, infants are considered treated if they are born after 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 WIC authorization if they did not anticipate its arrival. This concern seems plausible, 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 B4, we present estimates defining exposure at the beginning of the first, second, or third trimester instead of at the time of birth. The earlier exposure to WIC EBT is in the pregnancy, the more time the mother has to change her priors about WIC participation and enroll in the program to obtain the benefits that will lead to better birth outcomes. Consistent with this reasoning, our estimates generally become larger and more precise as we shift exposure timing back in to earlier trimesters.

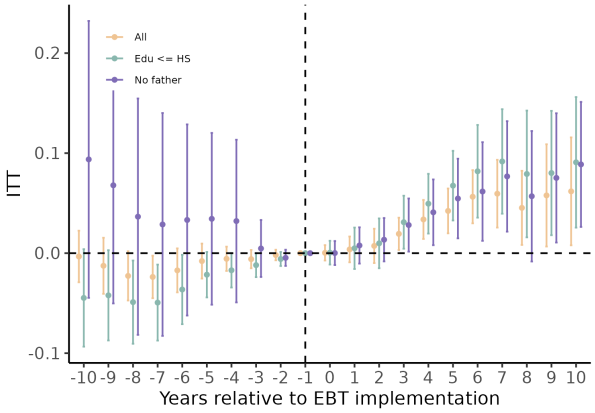
B7 Pretrend test and sensitivity to potential violations of parallel trends

In this section, we assess the sensitivity of our results to potential violations of parallel trends. Following the procedure outlined in Roth (2022), we first estimate the slope of a linear pretrend in WIC participation, the incidence of low birth weight, or the incidence of preterm birth among mothers with no more than a high school education (and mothers without an infant's father listed on the birth certificate) with 50 or 80 percent power. We then estimate the bias caused by the pre-trend, which equals the average effect across all post-treatment periods if our results were entirely driven by differential trends between the treatment and control groups. Finally, we compare our overall ITT estimates to the estimated bias. Table B5 presents

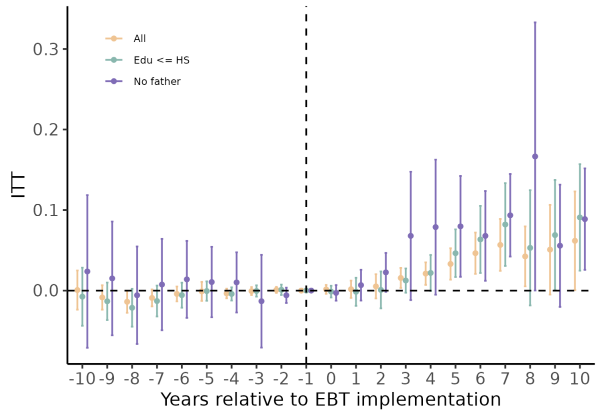
FIGURE B4: DYNAMIC EFFECTS OF WIC EBT BY ESTIMATION METHODS



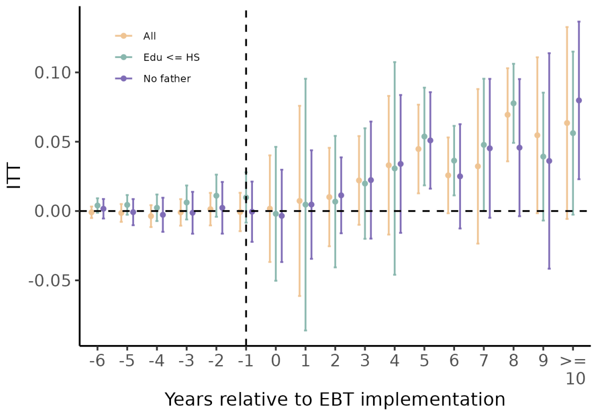
(A) Traditional TWFE estimators



(B) Callaway and Sant'Anna (2021) estimators, the never-treated as control group



(C) Callaway and Sant'Anna (2021) estimators, the not-yet-treated as control group



(D) Borusyak, Jaravel and Spiess (2024) estimators

Notes: For all regressions, 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. For traditional TWFE estimators, we control for county and year fixed effects, census-region-specific linear time trend, county baseline characteristics from 2006-2008 interacted with linear time trend, and county-by-year employment rate. Standard errors are clustered at state level. For Callaway and Sant'Anna (2021) estimators, we enforce a 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. By default, standard errors are bootstrapped and clustered at the county level, as their validity depends on having a large number of clusters. If standard errors are forced to be clustered at the state level, they will be much larger in magnitude than the coefficients. For Borusyak, Jaravel and Spiess (2024) estimators, we use a shorter pre-treatment period (6 years before the treatment) to ensure relevance since this estimator uses the whole pre-treatment period as a comparison. Standard errors are clustered at state level.

TABLE B4: ROBUSTNESS TO TIMING OF EXPOSURE

	WIC participation								
	First trimester			Second trimester			Third trimester		
	All mothers (1)	Edu≤HS (2)	No father (3)	All mothers (4)	Edu≤HS (5)	No father (6)	All mothers (7)	Edu≤HS (8)	No father (9)
EBT exposure	0.0160	0.0223	0.0256	0.0142	0.0198	0.0224	0.0134	0.0195	0.0221
	(0.0047)***	(0.0068)***	(0.0058)***	(0.0048)***	(0.0070)***	(0.0059)***	(0.0050)***	(0.0072)***	(0.0062)***
	[0.0089]*	[0.0097]**	[0.0066]***	[0.0088]	[0.0096]**	[0.0058]***	[0.0089]	[0.0095]**	[0.0054]***
Observations	28,223	27,786	26,582	28,204	27,789	26,661	28,174	27,776	26,614
R^2	0.9660	0.9302	0.8497	0.9654	0.9288	0.8491	0.9649	0.9283	0.8486
Dep. var. mean	0.4084	0.6472	0.6725	0.4094	0.6482	0.6734	0.4103	0.6491	0.6740

Notes: We report interaction weighted estimators proposed by Sun and Abraham (2021). The dependent variable is WIC participation rate for all regressions. 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 2006-2008 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 square brackets. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.

the results of Roth (2022) pre-trend tests. We find that, in general, our overall ITT estimates are 2–3 times larger than the hypothetical bias in absolute value, suggesting that differential underlying trends between the treatment and control groups are unlikely to drive our results.

TABLE B5: PRETREND TEST RESULTS FOLLOWING THE PROCEDURE OUTLINED IN ROTH (2022)

Variable	Group	Power	Slope	Bias	ITT	ITT/Bias
WIC participation	Edu <= HS	0.8	0.0047	0.0083	0.0164	1.9759
WIC participation	Edu <= HS	0.5	0.0030	0.0053	0.0164	3.0943
WIC participation	No father	0.8	0.0048	0.0095	0.0165	1.7368
WIC participation	No father	0.5	0.0031	0.0061	0.0165	2.7049
Low birth weight	Edu <= HS	0.8	-0.0007	-0.0012	-0.0023	1.9167
Low birth weight	Edu <= HS	0.5	-0.0004	-0.0007	-0.0023	3.2857
Low birth weight	No father	0.8	-0.0012	-0.0024	-0.0041	1.7083
Low birth weight	No father	0.5	-0.0007	-0.0014	-0.0041	2.9286
Preterm	Edu <= HS	0.8	-0.0014	-0.0024	-0.0033	1.3750
Preterm	Edu <= HS	0.5	-0.0009	-0.0015	-0.0033	2.2000
Preterm	No father	0.8	-0.0016	-0.0031	-0.0069	2.2258
Preterm	No father	0.5	-0.0010	-0.0019	-0.0069	3.6316

Notes: This table presents the results of pretrend test proposed by Roth (2022). We calculate these values using the formula presented in Roth (2022), which accounts for the additional bias introduced by passing a pretest.

We also use the methods outlined in Rambachan and Roth (2023) to examine the sensitivity of our estimates to the maximum violation observed in the five years right before EBT implementation. For year 5 following EBT implementation, we estimate that the breakdown value at which we can no longer reject the null hypothesis at the 90% confidence level is 0.9 for WIC participation among mothers with no more than a high school education and 0.6 for mothers without an infant's father listed on the birth certificate. For birth outcomes, the breakdown values are 0.3 (0.2) for the likelihood of having low-birth-weight infants and 0.3 (0.3) for the likelihood of preterm births for mothers with a high school education or less (and mothers without documented fathers of infants). While we cannot entirely rule out this possibility, it appears unlikely given the observed changes in the pre-period event times, especially for the WIC participation results. This suggests that our results are reasonably robust to unrelated deviations between the already-treated and last-treated counties based on pre-EBT data.

B8 Demographic change is unlikely to drive our results

We might observe a spurious positive effect on WIC participation if demographic change in the county coincides with the WIC EBT transition. Individuals with certain demographic characteristics are more likely to participate in WIC. If these groups are growing as a share of the population at the same time that EBT is being implemented, it could confound our effects. Table B6 shows that EBT implementation does not significantly alter the composition of maternal characteristics in the county-year. This suggests that we are comparing mothers with similar characteristics across periods, allowing us to interpret our estimates as reflecting changes in outcomes among a consistent group of WIC-eligible mothers.

TABLE B6: EFFECTS OF WIC EBT ON MATERNAL CHARACTERISTICS

	Maternal characteristics used to define subgroups			Other maternal characteristics						
	Edu $\leq$ HS	No father	Adv. mothers	Age $\leq$ 22	College graduates	Unmarried	White	Black	Asian	Hispanic
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Born after EBT	-4.35×10^{-5}	0.0007	-0.0018	-0.0016	0.0039	0.0007	-0.0087	0.0164	-0.0015	0.0039
	(0.0029)	(0.0020)	(0.0030)	(0.0016)	(0.0028)	(0.0039)	(0.0081)	(0.0088)*	(0.0071)	(0.0019)**
	[0.0035]	[0.0033]	[0.0031]	[0.0021]	[0.0058]	[0.0052]	[0.0079]	[0.0176]	[0.0095]	[0.0038]
Observations	27,904	27,913	27,909	27,913	27,904	27,912	27,913	27,913	27,913	27,913
R^2	0.9629	0.9137	0.9640	0.9598	0.9795	0.9282	0.9785	0.9263	0.8932	0.9939
Dep. var. mean	0.4016	0.1130	0.5619	0.1815	0.3138	0.4006	0.6485	0.1382	0.0607	0.2027

Notes: Non-target 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 2006-2008 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 square brackets. ***, **, and * indicate that t-test are significant at the 1%, 5%, and 10% levels.