Unanticipated Effects of Electronic Benefits Transfer on WIC Stores and Redemptions: Evidence from Administrative Data on Vendors *

Charlotte E. Ambrozek†
Timothy K. M. Beatty‡
Marianne P. Bitler §
Xinzhe H. Cheng ¶
Matthew P. Rabbitt **

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Abstract

We evaluate the effect of the nationwide transition in the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) from paper vouchers to Electronic Benefit Transfer (EBT) cards on the decisions of stores to be authorized to accept WIC benefits. We combine novel administrative data from The Integrity Profile (data on stores participating in WIC and their WIC reimbursements) and the Store Tracking and Redemptions System (data on SNAP-authorized vendors) with new nationwide policy data on WIC EBT implementation. Using a staggered adoption difference-in-differences approach, we find that the transition had heterogeneous and occasionally unanticipated effects across states. The number of WIC authorized independent vendors declined following WIC EBT implementation. We find no significant effect of WIC EBT implementation on WIC redemptions and no significant evidence of spillovers on to SNAP retailer authorization or redemptions. Treatment effects on authorized WIC vendors are more negative for early adopters, which may be due to learning effects or improvements in technology. Past experience with EBT implementation by financial services providers (private firms hired by states to implement WIC EBT) reduces the magnitude of negative effects of EBT implementation on store participation in WIC.

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†University of Minnesota, Department of Applied Economics
‡University of California, Davis, Department of Agricultural and Resource Economics
§University of California, Davis, Department of Economics, National Bureau of Economic Research, and IZA
¶Congressional Budget Office
**US Department of Agriculture, Economic Research Service

1 Introduction

The Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) provides specific nutritious foods to low-income, nutritionally at-risk infants; children under 5; and pregnant, postpartum, and breastfeeding women. The WIC program touches almost half of the population, with 46% of infants obtaining WIC benefits in 2020. Benefits are exchanged (redeemed) for specific foods at WIC-authorized stores, with nearly 46,000 stores authorized to redeem benefits in 2012, according to the US Department of Agriculture (USDA). Stores that participate in WIC play a crucial rule in making it possible for WIC recipients to use their WIC benefits, which expire at the end of each month. Between 2002 and 2022, WIC underwent a transformative change, transitioning from issuing benefits in the form of paper vouchers to loading benefits onto an Electronic Benefits Transfer (EBT) card.

In this paper, we evaluate the effects of the WIC EBT transition on retailers. We ask: Does the probability of a store being WIC-authorized, and thus able to provide WIC-specific foods to recipients in exchange for benefits, change in response to the transition from paper vouchers to electronic WIC benefits? Do WIC benefit redemptions (the dollar amount of benefits used) increase or decrease after this transition? Is there heterogeneity in the effects by retailer characteristics, adoption timing, or the private firm implementing the EBT system? We answer these questions with previously-unused USDA administrative data on the number of WIC-authorized vendors and total redemptions at the ZIP code level, and use a differences in differences approach, contrasting experiences before and after redemptions in locations implementing EBT with those same changes over time in places who have not yet adopted.

WIC benefits consist of a quantity voucher (food instrument or FI) that participants can redeem for a bundle of pre-specified items (and since 2009, a set dollar amount of fruits and vegetables) at WIC-authorized retailers. This differs from SNAP, which provides a fixed dollar amount of EBT benefits that recipients can redeem for a wide range of foods, trading off price and quantity.[1] Vendors apply to their state's WIC programs, and must meet a set of federal and state-specific criteria to be approved to participate. Vendors must periodically reapply to continue in the program. States determine if retailers are eligible to participate in WIC and are also responsible for monitoring and enforcing program regulations.

A priori, the effects of WIC EBT implementation on food retailer behavior and WIC redemptions are ambiguous. Effects may vary across store types and states using different approaches to implementing the EBT program. Becoming WIC authorized can be costly for stores; vendors incur both fixed and ongoing costs. Beyond the direct costs associated with certification, stores must update Point-of-Sale (POS) technology to accept benefits and workers must be trained on the use of WIC FIs. Fixed implementation costs may lead smaller retailers to exit. WIC authorization also entails ongoing costs. Vendors must stock minimum types and quantities of WIC foods.[2] To the extent that EBT makes it harder for stores to commit fraud (e.g. by charging WIC recipients higher prices than non-recipients, or by making pricing monitoring easier for states), it may raise the marginal cost of WIC participation and reduce the incentive to become authorized. Overall, technology costs and ease of fraud enforcement may reduce profits from being WIC authorized.

On the other hand, there are also reasons to think that EBT implementation might increase the intensity

[1] Since 2009, the WIC benefit has also included a cash-value voucher/benefit for a set amount of fruits or vegetables without any added salt or sugar. These cash-value vouchers for fruits and vegetables are similar to SNAP benefits.

[2] An example of stocking requirements from California can be found at California Department of Public Health (2020).

of program use for recipients and/or make it more profitable for stores to participate. Because the bulk of the food benefit is for a specific quantity of food, WIC participants are not price sensitive when redeeming most of their benefits. This creates opportunities for firms to mark up products, potentially leading to higher profits (Saitone et al., 2015). WIC participation can expand stores' customer base and sales (Wallace et al., 2020). It may also increase the share of benefits redeemed by making it easier for participants to use their benefits more flexibly across the month (Hanks et al., 2018). WIC EBT may increase enrollment by reducing the stigma associated with participation – stigma has been posited to reduce program enrollment since Moffitt's seminal paper (Moffitt, 1983).

We also consider spillover effects onto the participation of stores and spending by individuals in the SNAP program. WIC EBT implementation aligns WIC benefit technology more closely with SNAP benefit technology. Given that in many states WIC vendors are required to be SNAP authorized, modifications in WIC vendor policy could plausibly affect SNAP outcomes, especially for recipients enrolled in both programs. Despite the central role retailers play in administering WIC, work examining the supply side of WIC is limited, and this paper seeks to address this gap.

We find that, on average, WIC EBT implementation decreased the probability that stores would be WIC authorized, with the declines driven entirely by independent stores that are not part of larger chains. In contrast, we find no significant effect of the implementation on the probability of being WIC authorized for chain stores. We also find no evidence of an effect on the average amount of WIC redemptions in a ZIP code, which we take as a proxy for WIC participation or redemption intensity. This suggests that on average, this change in vendor authorization did not hurt recipients. Finally, we find no effect on SNAP authorization or redemption, suggesting no spillovers from WIC EBT on to SNAP outcomes.

EBT adoption varied across locations and time. This allows us to leverage changes in locations that did not yet adopt WIC EBT as a counterfactual for changes in places that adopt WIC EBT before and after adoption. Of course, a recent literature (surveyed in Roth et al., 2023; de Chaisemartin and D'Haultfoeuille, 2023) suggests such models may be biased if there is heterogeneity over time of implementation and across locations in the average treatment effects. To address this, we examine each adoption separately, as advocated by a number of authors, using Callaway and Sant'Anna (2021). By decomposing the results into group-by-time adoption sets (county-by-year-of-adoption specific treatment effects), our evidence suggests that counties adopting WIC EBT earlier saw decreases in the number of authorized WIC retailers. These challenges stemmed from factors such as technological constraints, (lack of) prior experience by EBT processors or firms, or other factors discussed above that related to firms' costs and benefits from authorization—fixed costs, reduced fraud opportunities, or increased monitoring (Crespo-Bellido et al., 2024; Ayala et al., 2012; Wallace et al., 2020).

The rollout of WIC EBT spanned a long, 21-year period. Our findings point to a potential "learning-by-doing" effect for EBT processors. Our analysis suggests that as processors gained experience with setting up the back-end systems for EBT, the vendors' experience became increasingly positive. This indicates potential learning effects across states and/or within processors. Additionally, point-of-sale (POS) systems might have become more efficient, affordable, and widespread, potentially facilitating the transition to EBT.

We make several contributions to the existing literature. First, we fill an important gap in our understanding of how private actors matter for means-tested programs. These actors are not limited to food retailers - Frisvold and Price (2019) and Fletcher and Frisvold (2017) note that schools are an important component of the food environment for children. In this paper, we examine the intersection of the effects of WIC policy changes and WIC retailer and participant program entry and exit.

Second, we contribute to existing research on WIC and SNAP EBT transitions. These studies have often been limited to a single state (e.g., Meckel (2020) for WIC EBT, Shiferaw (2020) for SNAP EBT), or focus on SNAP (Oh, 2024). We expand on earlier work by focusing on county-level WIC rollout across the US. This allows us to capture a national perspective, which may be important given variation in the food retail environment over time and a wide assortment of state-specific WIC policies. For example, Texas, which serves as the backdrop for important research (Meckel 2020), distinguishes itself from other states with early EBT implementation and a set of distinctive policies, like the "least expensive brand" rules, differentiating it from most other states.

Third, we use previously untapped store-level administrative data. This novel approach combines administrative records on both WIC- and SNAP-authorized vendors and on WIC and SNAP redemptions, providing insights into local responses to changes in state WIC disbursement policy. This contrasts with previous work on WIC vendors that focused on individual states or data that uses self-reported WIC participation (e.g. Rossin-Slater (2013)).

Fourth, we integrate advancements in the econometric literature, particularly concerning difference-in-differences approaches (Roth et al., 2023). This allows us to account for treatment effect heterogeneity based on the timing and location of policy changes (Callaway and Sant'Anna, 2021).

Finally, our work offers insight for policymakers who are concerned about the potential costs and benefits of policy changes and, more broadly, of WIC. Our finding that WIC EBT adversely affects WIC authorization of independent WIC retailers suggests potential trade-offs between reducing program costs—given that WIC EBT is in part a fraud reduction program (Meckel, 2020) and larger stores tend to mark up WIC products less than smaller stores (Saitone et al., 2015)—and maintaining or increasing participants' access to WIC vendors (Meckel, 2020; Meckel et al., 2021; Ambrozek, 2022). Our work suggests that despite EBT-associated declines in the number of WIC authorized stores, there is no change in WIC redemptions. Next, we discuss the program and relevant work on WIC. Then we touch on the rollout of WIC EBT, our data, methods, and results. We then discuss takeaways from our findings and conclude.

2 Background

2.1 The WIC Program

The WIC program is important for low-income pregnant and postpartum women and children under 5. In FY2022, WIC served 6.3 million individuals, including children, infants, and both pregnant and postpartum women. To put this into perspective, about half of all US-born infants benefited from WIC that year. This involved the federal government spending $5.1 billion on WIC food, delivered through over 45,000 authorized retailers (and additional payments from rebates from private firms). WIC is the third largest domestic food assistance program when measured by total spending.[3] These benefits represent both an economically meaningful share of food-at-home spending and an important source of nutrition for low-income families with young children.

In addition to providing a package of nutritious foods to supplement diets, WIC ensures that participants receive referrals to other safety net and local programs, nutrition education, and breastfeeding support. The food benefits (food packages) from WIC enable the purchase of food such as infant formula, fruits and vegetables, whole grains, and milk. These foods are chosen because they are dense in nutrients of concern (those insufficiently consumed in the target populations), with nutrients such as iron, protein, calcium, vitamin D, and vitamin A, among others. Evidence suggests that WIC participation shifts participants' purchasing decisions towards these nutritious foods (Frisvold et al., 2020).

Participants apply for WIC at WIC clinics and, once enrolled, redeem their benefits at private vendors (stores). Vendors are a critical link in the WIC benefit delivery system as benefits issued by the government are converted to food at authorized retailers. If there are no nearby vendors it becomes costly for recipients to use their benefits. Vendors also must "check out" recipients, and their behavior can impact the recipient experience. Despite their self-evident importance, WIC vendors are understudied.

2.2 Relevant Literature

Our paper is closest in spirit to Meckel (2020), who uses Texas' WIC EBT rollout to evaluate how program take-up, birth outcomes, and prices for WIC goods paid by non-recipients respond to WIC EBT implementation. Meckel considers implementation effects with a focus on the goal of fraud reduction—one of the reasons the federal government introduced WIC EBT. Specifically, EBT technology makes fraud—in the form of price discrimination between WIC and non-WIC customers—more difficult. With paper vouchers, stores could potentially charge different, higher prices to price-inelastic WIC participants.

The switch to WIC EBT may make it less profitable for authorized vendors to participate in WIC and some may choose to leave the program after EBT implementation. In addition, vendors may find the EBT system burdensome, especially if the new equipment or training results in significant one-time fixed costs. Meckel (2020) finds relatively large negative effects on WIC authorization for independent vendors in Texas (0.11 stores lost per county, 10.7% of the sample mean). The effect is negative but small and statistically insignificant for chain stores.

Other works by Hanks et al. (2018) and Li (2020) find increases in redemptions as larger retailers, and concomitant reductions in redemptions at small and medium WIC vendors. Qualitative work documents declines in participation by smaller vendors in some states but increases in larger vendors in others (Phillips et al., 2014). Taken as a whole, prior work on a subset of states suggests that WIC EBT shifts redemptions from independent stores to chain stores, and that some independent stores become unauthorized. Thus, the net effect on WIC redemptions and access to the program among recipients is a priori ambiguous: There may be no total effect on redemptions or potentially a negative effect, or if, recipients switched to larger stores, there could even be increases.[4] We discuss this in greater detail in Section 3.2.2.

[3] WIC spending makes up 0.5% of $1.05 trillion total FY22 spending on food at home. For perspective, the largest US food assistance program (SNAP) provides benefits equal to 10.9% of US food-at-home spending.

[4] Unfortunately, given confidentiality concerns, we cannot distinguish redemptions at chain stores from redemptions at independent stores, although we do examine the number of WIC-authorized stores.

We consider potential mechanisms for treatment effect heterogeneity over time. We estimate results on processor-specific positive trends in treatment effects. A model of firm-specific learning by doing could explain the growth in output (probability of vendor authorization) and technology efficiency we observe (Parente, 1994; Pérez and Ponce, 2015). States may also be learning socially from each other about steps to improve the efficiency of adoption and reduce disruption costs (Conley and Udry, 2010; Foster and Rosenzweig, 1995).

Before the transition to EBT for WIC, which began in 2002, the SNAP program (formerly known as Food Stamps) had already largely completed a switch from paper vouchers to EBT. Research on the SNAP EBT transition has mostly focused on participants' responses and documents an increase in participation after EBT implementation (Klerman and Danielson, 2011; Lovett and Xue, 2017; Shiferaw, 2020; Kuhn, 2021). One exception is Oh (2024), who finds that SNAP EBT lead to a decline in authorization among convenience stores. While results for SNAP may help form priors on the effects of WIC EBT, important program differences mean that effects observed for the earlier SNAP rollout may not extend to WIC.

3 Data

The ideal dataset for answering our research question would include the set of all authorized WIC vendors and information on their WIC redemptions and store and recipient characteristics, as well as similar store characteristics for the set of potential WIC vendors. This would span both time and place, accompanied by data on the timing of policy variation. While our data come closer to this ideal than the data used by other related papers, there are some differences between these ideal data and ours. First, to protect confidential information about vendors, the USDA does not release vendor-level administrative redemption data to the public.[5] Second, we lack comprehensive data on the existence of all firms that could possibly participate in WIC, although we do have data on the universe of SNAP-participating stores. Nevertheless, to the best of our knowledge, we are the first to document this important link between WIC EBT and administrative program data using national data.

3.1 WIC EBT Rollout

WIC EBT was primarily rolled out at the county level within 50 states and the District of Columbia over 20 years.[6] We observe the vast majority of this rollout - starting in FY 2005 - but miss some of the final adopters in our vendor and redemption data since our sample ends in 2018 (the last states adopted in 2022). We hand collect data on this rollout and augment them with administrative data on the universe of WIC-authorized retailers collected annually by the USDA's Food and Nutrition Service (USDA FNS), which administers WIC at the federal level. This dataset includes administrative data on WIC redemptions, aggregated to the ZIP code level and redacted where necessary to preserve vendor confidentiality. As a result, we have data on about 20% of total redemptions.

[5] §246.26(e)

[6] Although state WIC agencies determined the rollout's geography and timing, we model this by using counties as the common unit of geography.

We also consider spillover effects onto SNAP. To this end, we use administrative data on SNAP authorized retailers and SNAP redemptions by county (redacted where necessary to preserve vendor confidentiality). These data represent an important improvement over prior work due to our national focus and the use of administrative rather than scanner data, which likely do not include all WIC related expenditures.

In terms of the WIC EBT rollout, we document the implementation timing for every state and the District of Columbia. For each county, we record the date on which EBT implementation occurred, as reported in publicly available documents from state WIC agencies or USDA FNS.[7] We model rollout with staggered permanent adoption so that counties begin implementation at different times and only ever move from not treated to treated. This precludes complications like multiple events within a county, which only occurred in Nevada, so that we drop Nevada from our analysis (see additional discussion below). For some counties, the state agency reports a range of implementation dates – for instance, May 2, 2018 to August 2, 2018 for Kearny County, Kansas. In this case, we use the implementation's start date in our analyses, conservatively treating a county as treated if it has any WIC EBT implementation in the fiscal year. This methodology allows us to construct a binary treatment indicator that only turns on once and stays on once turned on, satisfying the structure required for the Callaway and Sant'Anna (2021) approach we describe further in Section 4.

Figure 1 shows the first fiscal year of WIC EBT implementation by county. From this figure, we note that any state in which not all counties has implemented WIC before FY 2005, but some counties introduced WIC EBT by FY 2018, will be part of our panel of treated states at some point. We observe 1,821 counties across 28 states (with 2,006 counties total) implementing WIC EBT between FY 2005 and FY 2018. We exclude Mississippi, Nevada, and Vermont from our sample entirely. We exclude Mississippi and Vermont because their pre-EBT benefit delivery system was different from other states'.[8] We exclude Nevada because they implemented EBT early, reverted to paper vouchers for a time, then re-implemented EBT by the end of 2009. We do not have reliable timing on the initial implementation, time of the roll back to paper vouchers, or re-implementation of EBT. States that do not implement WIC EBT before FY 2019 will always be comparison units that remain untreated for each treatment group. In this always untreated group, there are 1,210 counties across 18 states plus the District of Columbia. One state - Wyoming - adopts WIC EBT entirely before our window.

[7] Indian Tribal Organizations are not explicitly included in our analysis.

[8] Mississippi used a pick up system from centralized locations; Vermont used home delivery.

Figure 1: WIC EBT Rollout by Fiscal Year

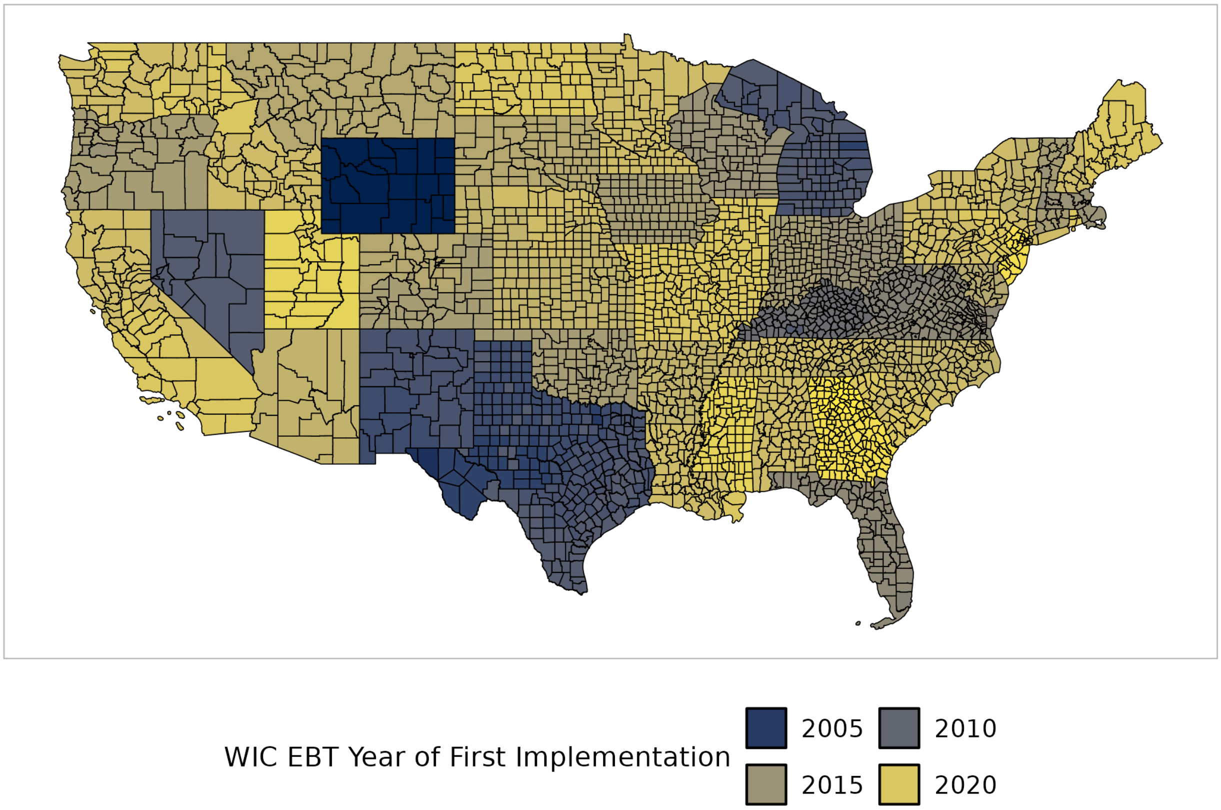


Figure shows first year of EBT implementation by county. Data collected by authors.

One concern with staggered adoption approaches where timing may be endogenous is that both observed and unobserved factors can determine treatment timing as well as the treatment's effect on outcomes of interest. This overlap can confound the estimated effect of the treatment (Hoynes and Schanzenbach, 2009). Of course, in our setting, states not counties are choosing where to rollout EBT, but nonetheless there is a concern about how they select the first and last counties in which to roll out WIC EBT. To see whether there is evidence that states systematically selected places to start or end the rollout, we examine the relationship between WIC EBT implementation timing and various observable factors related to categorical eligibility or income thresholds for WIC eligibility as well as SES in the beginning of our sample. We regress the year of WIC EBT implementation in a county on 2005 levels of county population (measured in natural logarithms), the share of the county population under age 5, the share of the population with income less than 185% of the federal poverty level, the interaction of these two population shares, the share of the Black population, the share of the Hispanic population, the share that report SNAP participation, the share that report receiving cash welfare, median income, and geographic factors including region and rural/urban classification. The income, poverty, and safety net statistics come from the American Community Survey via the Census API (Walker and Herman, 2023).[9] We use population age, race, and ethnicity statistics from the US Census Bureau's 2000–2010 County Intercensal Estimates (U.S. Census Bureau, 2023) and rural/urban classifications from the 2013 NCHS Urban-Rural Classification Scheme for Counties (National Center for

[9]Some of these controls are only publicly available for counties with a population greater than 65,000, which reduces our set of counties from more than 3,000 to fewer than 800. We thus show results both with and without these income statistics.

Health Statistics, 2013). We report the results both with and without state fixed effects. Results in the model without state fixed effects can be interpreted as the average change in WIC EBT implementation timing across all counties in all states associated with a particular factor, holding others constant. In the model without fixed effects, results represent *within state* associations with timing – answering the question: once a state is implementing WIC EBT, is the county order associated with demographics?

Table 1 shows the determinants of WIC EBT implementation timing by county within state. Columns 1 and 3 control for the demographic breakdown of counties. Additionally, column 1 factors in income, SNAP participation, and median income for large states. Columns 2 and 4 add state fixed effects. We see that in models (1) and (3)—which exclude state fixed effects and include variation *across* states—locations with a larger share of individuals under age five (the age-eligible population of infants and children) tend to implement WIC EBT later, although this relationship is noisier in the subsample of large counties than in the set of all counties. That said, states with a higher Hispanic share of the population tend to implement earlier, while states with a higher Black share implement later.

Table 1: Estimates of Location Characteristics on WIC EBT Timing

	Dependent variable: WIC EBT Year			
	Subsample:			
	Population > 65,000		All counties	
	(1)	(2)	(3)	(4)
Log population	−0.026	0.014	−0.126	0.018**
	(0.319)	(0.031)	(0.255)	(0.009)
Share < 5	70.476	−5.381	68.362***	−0.628
	(83.452)	(5.357)	(21.952)	(1.504)
Share < 185% FPL	8.564	−0.826		
	(17.895)	(1.367)		
(Share < 5) × (Share < 185% FPL)	−51.929	27.318		
	(231.231)	(18.400)		
Share Black	8.358***	0.057	8.452***	0.175
	(3.061)	(0.166)	(2.575)	(0.148)
Share Hispanic	−11.709***	0.261	−13.719***	0.177
	(4.389)	(0.448)	(2.784)	(0.169)
Share SNAP	−5.925	−1.192*		
	(10.586)	(0.621)		
Share cash aid	−2.446	−1.379		
	(22.086)	(1.254)		
Median income	0.00003	0.00000		
	(0.00003)	(0.00000)		
Northeast	3.807**		2.283*	
	(1.580)		(1.287)	
South	−0.391		−2.262	
	(1.687)		(1.576)	
West	3.550**		0.698	
	(1.702)		(1.455)	
Constant	2,008.543***	2,018.991***	2,014.333***	2,018.842***
	(6.231)	(0.803)	(2.238)	(0.100)
State FE	No	Yes	No	Yes
Adj. R^2	0.25	0.99	0.3	0.99
N	775	775	3142	3142

*p<0.1; **p<0.05; ***p<0.01

Columns 1 and 3 do not include state fixed effects, while columns 2 and 4 do. The table includes indicators for urban-rural divides: large metro, large fringe metro, medium metro, small metro, micropolitan, and non-core. All of these are insignificant at the 5% level. Heteroskedasticy-robust standard errors are clustered at the state level.

Key to our research design, the models including economic and demographic explanatory variables only explain a small portion of the variation in the year of WIC EBT implementation. We find that across all states, models that include both other demographic controls and these socio-economic variables explain less than a third of the variation in implementation timing (column 3). Most of the variation in timing is explained by state-specific time-invariant factors (adding them drives the adjusted R^2 to 0.99). We view this as a promising indication for our approach. It suggests that within a state, the timing of the implementation is not driven by observable factors that could be confounding estimates of the policy change's effect on WIC vendor authorization or WIC redemptions. Given our DD approach, our main models include county fixed effects, ensuring that any county-specific time-invariant drivers of adoptions are controlled for.[10] The results from Table 1 support the assumption we make that store outcomes and redemptions without EBT do not depend on the timing of WIC EBT adoption. We now turn to the effects of EBT adoption on other outcomes.

3.2 Outcome Variables

3.2.1 WIC-Authorized Retailers

We use restricted-access data on the universe of WIC-authorized retailers from the TIP administrative data provided by USDA's Food and Nutrition Service (FNS). For FY 2005–2018, we observe vendors' names, address information, and type, as well as an indicator that the vendor is authorized in that year. We assign vendors to treatment timing by fiscal year, based on the date when the county in which they are located began implementing the relevant policy.[11]

Figure 2 shows that in FY 2005 at the start of our sample, with the exception of Mississippi and Vermont(which use an alternative delivery system),[12] the distribution of stores approximately follows patterns of population density. This indicates that WIC stores are located where we expect them to be given the eligible population.

[10] That said, state fixed effects do explain a large share of the variation in WIC EBT implementation timing (the adjusted R^2 is 0.99). This suggests the presence of unobservable state-specific factors, such as bureaucratic effectiveness, that determine the timing of implementation. This could threaten our analysis if, in the absence of WIC EBT, the year-to-year changes in vendor authorization in early adopting states were different than changes in vendor authorization in late-adopting states. We will assume that outcomes will change in parallel between a given state and all the states that adopt WIC EBT after it. When interpreting our findings, we will be careful to consider how patterns in state-specific factors could moderate our treatment effects.

[11] We drop vendors listed as home food delivery contractors and direct distribution centers, since they generally do not transition to EBT or represent participants' differences in the retailer experience after the package change. Mississippi and Vermont, the states with entirely non-retail WIC food distribution before WIC EBT, switched to retailer-based distribution when they implemented EBT. Together, these two vendor types represent 640 out of 527,707 (0.12%) raw observations of authorized vendors.

[12] Mississippi and some parts of Chicago use direct distribution, while Vermont used home delivery up to 2016. We drop Mississippi and Vermont for our empirical analysis.

Figure 2: Location of FY 2005 WIC-Authorized Food Retailers

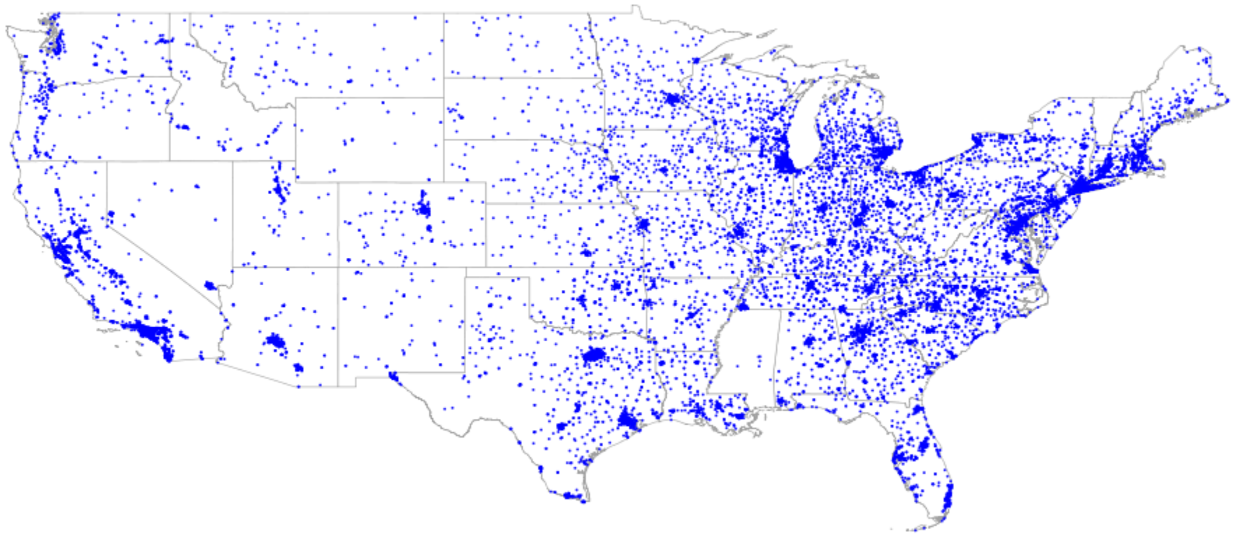


Figure shows location of WIC authorized food retailers are the start of the TIP vendor data in FY 2005. Data provided by USDA FNS. Visualization by the authors.

3.2.2 Redemption Data

We also use ZIP-code-level annual WIC redemption data from TIP for FY 2009–2018. These data come from USDA FNS and are reported for ZIP codes with at least 10 or more WIC-authorized vendors.[13] For each ZIP code in each year in our data, we observe the sum of all WIC redemptions made within that ZIP code in that year.

Table 2 shows the share of total WIC redemptions in the US (column 1) and the share of total food cost in the US observed in our redacted sample of large ZIP codes (those with at least 10 WIC vendors redeeming benefits in any year, column 2). The table also shows the number of ZIP codes in the TIP data that exist in our redacted redemption sample (column 3) and the number that do not (column 4). We can only observe the share of national food cost from FY 2009 onward given the limitation of publicly available data on rebates received in FY 2005–2008. In general, while we only observe a relatively small share of ZIP codes, they account for about 30% of all WIC redemptions over our sample period.

[13]We remind the reader that for confidentiality reasons, USDA FNS suppresses ZIP codes with fewer than 10 authorized vendors.

Table 2: Share of WIC Redemptions and Share of ZIP Codes Observed in The Data

Fiscal Year	Observed WIC redemption shares	Observed WIC redemption shares of national food cost	Redemptions available ZIPs	Redemptions suppressed ZIPs
2005	.	0.301	577	15,486
2006	.	0.274	549	15,358
2007	.	0.266	534	15,336
2008	.	0.266	530	15,246
2009	0.202	0.289	566	15,131
2010	0.204	0.280	565	15,194
2011	0.228	0.288	634	15,033
2012	0.216	0.292	616	14,870
2013	0.219	0.310	619	14,746
2014	0.208	0.295	596	14,561
2015	0.198	0.284	561	14,382
2016	0.189	0.270	527	14,135
2017	0.181	0.268	509	14,254
2018	0.167	0.253	456	14,175

Notes: The observed WIC redemption share is calculated as the ratio of WIC redemptions in our data to the sum of food cost and rebates received as recorded in FNS WIC data tables. We can only obtain rebate data for FY 2009–2018 via the Wayback Machine. In general, rebates are about one-fourth to one-half of food cost, meaning that the unobserved ratio of WIC redemptions in our sample to total redemptions is about 66%–80% of the always observed ratio of WIC redemptions in our sample to food cost. The ratio of WIC redemptions to total national food costs is thus an upper bound on the share of WIC redemptions in our sample since food cost includes rebates on infant formula, while redemptions do not. Matched ZIP codes have non-missing redemptions from our restricted-use TIP data and at least one authorized store. Unmatched ZIP codes have missing redemptions in restricted-use TIP data and at least one authorized store.

To protect the privacy and confidentiality of WIC participants and WIC vendors, the USDA does not share any information on participant characteristics at redeeeming stores or the type of food instruments (individual foods) redeemed. The data are at the most detailed geography publicly available, limiting our ability to examine heterogeneity in WIC EBT implementation on subpopulations of WIC participants. That said, our data are the most detailed (and only) national administrative data available for use by researchers.

No exact one-to-one mapping exists between ZIP codes and counties since a few ZIP codes cross county borders. To address this, we use a ZIP-code-to-county crosswalk from the Department of Housing and Urban Development by decade. When necessary, we assign ZIP codes to treatment dates based on the earliest possible implementation date for the policy in the ZIP code, using the treatment timings for all the counties contained in the ZIP code. However this issue is not substantive and is unlikely to affect our results. Potential mismeasurement of true treatment timing through this assignment procedure affects 24 ZIP codes and 144 retailers.

3.3 SNAP Store Tracking and Redemptions System Data

We also use SNAP Store Tracking and Redemptions System data, obtained from USDA FNS by request, to estimate spillover effects on SNAP-authorized vendors and redemptions from WIC EBT implementation. These administrative data come from the USDA on vendors and redemptions in the SNAP program.

SNAP Vendor Data. We observe SNAP-authorized vendors from FY 2005 to 2018. The data for each SNAP-authorized vendor include the vendor's authorization start date, authorization end date, store type, and store address (including ZIP code, state, and county). We use authorization start and end dates to infer whether SNAP vendors are actively authorized in a fiscal year, harmonizing the SNAP vendor data with the WIC vendor data, which are reported only at the fiscal year level.

SNAP Redemption Data. We observe county-level SNAP redemptions for each month from FY 2005 to 2018. To ensure consistency with the WIC data, we aggregate the SNAP redemption data annually. The county-level measurement of redemptions makes these data easily mappable to the treatment-timing data. The data are suppressed for counties with fewer than three SNAP retailers in a given month, though this likely does not have a significant impact on our analysis. The data are reported in dollars, which we divide by a million, reporting all results as effects in millions of dollars.

4 Methodology

To estimate the effect of the WIC EBT transition on authorized WIC vendors, we compare annual changes in the probability of authorization for any individual retailer in counties that have implemented WIC EBT to those in counties that have not yet implemented it. Using this difference-in-differences approach, we can estimate average effects across all counties treated in our sample period as well as treatment effects for specific groups of counties treated in the same fiscal year. This enables us to extend previous work on WIC EBT implementation, assessing national-level effects and contrasting our treatment group-specific finding with results from prior papers. Moreover, this approach aids in identifying the factors driving variations in treatment effects across states and allows us to examine how average effects spanning multiple states measure up against group-specific treatment effects.

We start with a standard two-way fixed effects (TWFE) approach to estimating average treatment effects in a difference-in-difference framework. In this case, unit fixed effects absorb firm- or geography-specific characteristics that reflect any baseline differences in the outcome of interest across units, and they do not change over time. The fiscal year fixed effect captures common patterns across units over time. After accounting for these unit- and year-specific effects, τ represents the average effect of WIC EBT implementation.

The estimating equation for the TWFE specification is

$$y_{it} = \beta_0 + \alpha_i + \gamma_t + \tau \times EBT_{it} + \epsilon_{it}, \tag{1}$$

where y is the outcome of interest—either store authorization (a binary indicator that the store is WIC or SNAP authorized in that year) or redemptions (measured in hundred thousand dollars for WIC redemptions and million dollars for SNAP redemptions). α_i is the unit fixed effect vector for the level of analysis of the outcome: store fixed effects for authorization outcomes, ZIP code fixed effects for WIC redemptions, and county fixed effects for SNAP redemptions. γ_t represents a vector of fiscal year fixed effects. τ, the coefficient on the WIC EBT indicator, represents the average effect of WIC EBT implementation per unit. EBT_{it} is an indicator that unit i experiences any WIC EBT implementation in fiscal year t.

A recent and growing literature documents potential biases resulting from the TWFE approach to estimating average treatment effects. When estimating differences-in-differences using TWFE with ordinary least squares (OLS) across multiple units and treatment times, OLS implicitly compares both newly treated units with not-yet-treated units and newly treated units with those previously treated. The former comparison aligns well from the perspective of the difference-in-differences framework, where the counterfactual comes from untreated potential outcomes. However, to provide an unbiased estimate, the latter comparison requires an assumption that all units experience the same treatment effect.

The challenges of correctly estimating a parameter of interest (the average treatment effect) in a TWFE model using OLS with treatment effect heterogeneity are described in more detail in a recent and growing literature including Goodman-Bacon (2021), de Chaisemartin and D'Haultfœuille (2020), Imai and Kim (2021), Callaway and Sant'Anna (2021), and Sun and Abraham (2021). We account for these known possible problems with difference-in-differences research designs estimated using TWFE by implementing the method of Callaway and Sant'Anna (2021).

We construct treatment-group-by-year specific estimates of the treatment effect for each of the policies following the procedure outlined in Callaway and Sant'Anna (2021).[14] These individual average treatment effects on the treated (ATTs) for treatment group g at in fiscal year t using the not-yet-treated groups as a comparison and without additional controls are

$$ATT_{g,t} = E[Y_t - Y_{g-1}|G_g = 1] - E[Y_t - Y_{g-1}|G_g = 0, D_t = 0], \tag{2}$$

where $t \in \{2006, \ldots, 2018\}$ is the fiscal year of interest to compare, g is the period of the first treatment, with $g\ leqt$, G_g is an indicator of the first treatment occurring at time g and zero otherwise, and D_t is an indicator for treatment at time t.

For WIC EBT, treatment groups are defined by the fiscal year of treatment. They can include stores or ZIP codes from multiple states if counties in those states implement WIC EBT in the same year. For instance, Crawford County in Michigan and Bowie County in Texas both had WIC EBT implementation start dates in July 2008, and so the effects of EBT on vendors from both states will contribute to ATT estimates for FY 2008. Texas' main implementation phase spanned from FY 2006 to 2009, so its counties will contribute to the treated group when computing ATT estimates for the FY 2006, 2007, 2008, and 2009 subsamples, while Michigan counties will only contribute to the treatment group for estimates for FY 2008 and 2009. To address the possibility that unobserved shocks to vendor authorization and WIC redemptions are correlated within states, we cluster our standard errors at the state level.

The estimating procedure requires several assumptions laid out in Callaway and Sant'Anna (2021). We satisfy both parts of their Assumption 1, the irreversibility of treatment assumption. The first part of the assumption is that no county is treated in the first period of the sample. Counties that are treated in all periods of the sample, such as very early adopters like Wyoming and parts of Texas, are not included in our samples and thus do not contribute to estimates of the treatment effects. The second part of the assumption is that once counties have entered the treatment (have begun WIC EBT implementation), they do not switch back to paper vouchers.[15] A second, important assumption, is random sampling, is satisfied by our panel data structure. Another assumption imposes limited anticipation effects (that is, that stores and recipients

[14]We use Stata/MP 17 for Unix to estimate the models using the `csdid` package, version 1.6, by Rios-Avila et al. (2021).

[15]To satisfy this, we omit the relatively small state of Nevada, which was a very early implementer but redesigned and reimplemented its system before statewide rollout in 2009.

did not change their behavior because of the imminent switch to WIC EBT). Thus, we assume that before WIC EBT was implemented, vendors' authorization status and county redemption levels are equivalent to those which would have occurred in a counterfactual world without WIC EBT implementation. Finally, we impose an unconditional parallel trends assumption. We assume that for any set of two years $\{t, s\}$, the expectation of the change in the outcome between $t-1$ and t is the same between any treatment group $g \leq t$ and all units that are not treated before $s > t$. This assumption is analogous to the parallel trends assumption in a static difference-in-difference estimation approach. While not directly testable, as this assumption concerns unobservable counterfactuals, one can bound estimate sensitivity to potential violations of the assumption using the approach in Rambachan and Roth (2023).[16]

The Callaway and Sant'Anna method provides estimates of the average effect of the policy in each treatment group in each fiscal year over the relevant window. We compare treated counties to not-yet-treated counties, avoiding potential negative weighting issues induced by comparing later-treated units to units treated earlier in the sample (Gibbons et al., 2019). To construct average treatment effects across treatment groups, we construct three different aggregations. The first is an aggregation across all treated groups and all time periods, which weights treatment group-by-year ATTs up by the group size and duration of treatment, as noted in equation 3.

$$ATT = \frac{\sum_{g \in \mathcal{G}} \sum_{t=2006}^{2018} \mathbf{1}\{t \geq g\} ATT_{g,t} P(G = g | G \leq 2018)}{\sum_{g \in \mathcal{G}} \sum_{t=2006}^{2018} \mathbf{1}\{t \geq g\} P(G = g | G \leq 2018)} \tag{3}$$

where G is the fiscal year in which a unit first becomes treated and $\mathcal{G}$ is the set of all treatment groups in our sample. These estimates and their respective confidence intervals – computed using the analytical standard errors from the doubly robust estimator of the varience-covariance matrix – appear as solid horizontal lines and shaded areas in figures 3 and 4.

The second aggregation is by event time, showing dynamic effects by years relative to treatment timing across treatment groups. For any event time e, this aggregation is

$$ATT_e = \sum_{g \in \mathcal{G}} \mathbf{1}\{g + e \leq 2018\} ATT_{g,g+e} P(G = g | G + e \leq 2018) \tag{4}$$

With this aggregation, we model effects over time since WIC EBT adoption. We set a four-year window on either side of implementation to examine treatment effect dynamics over time. This would represent a balanced event window for implementation that occurs between 2012 and 2014. Early implementation years will be missing from average estimates of early pre-periods, while later implementation years will be missing from average estimates of later pre-periods. We show these event time results in figures 5, 6, 9, and 10, as well as the pre- and post-EBT average effects.

The last aggregation is across fiscal years t for treatment groups g^*, to obtain an ATT_{g^*}.

$$ATT_{g^*} = \frac{\sum_{t=g^*}^{2018} ATT_{g^*,t}}{T - g^* + 1} \tag{5}$$

[16] The last assumption of the approach is that the generalized propensity score used to weight estimates when combining them into average treatment effects is almost surely bounded away from one. This implies there is some non-zero probability that each unit will not be treated, conditional on covariates. This is a form of an overlap assumption, restricting units with the same set of covariates to potentially overlap each other in the treatment space.

We show these results in figures 7 and 8. This aggregation allows us to examine heterogeneity in treatment effects of subgroups of interest such as store chain/independent status or EBT processor groups (see Section 5 for a discussion). We estimate effects for subsamples of our overall data. For instance, to estimate the effect of WIC EBT implementation on independent stores' probability of authorization, we subset the sample to include only independent stores and then estimate the Callaway and Sant'Anna (2021) model on this subset. We take a similar approach to estimate processor-specific effects, restricting the sample to specific counties. For this analysis, we select a subset that includes all counties that share a processor, combined with all counties that were treated after 2018. This method yields a version of a treatment group-specific effect that we can use to provide results by processor.

We generally consider authorization at the individual store level and ZIP-code level redemptions. The administrative records we use for vendor authorization analysis—the TIP data—do not include a USDA-assigned identifier for each vendor. We therefore use vendor names and addresses to construct a unique identifier for name/address combinations and treat this identifier as a vendor-level identifier.[17] Our vendor authorization data make assumptions about how vendors are defined (with name and address) and may be mismeasured if, for instance, a store's name changes without a disruption to authorization. Redemptions (at the ZIP code level) are likely measured more precisely than the WIC vendor authorization since we use publicly available administrative data from USDA FNS for redemptions. However, the redemption data only cover ZIP codes that FNS deems sufficiently large to avoid being able to identify redemptions from single-stores. This means that our results may not be generalizable to all locations given that they represent areas with more WIC retailers that are likely urban or peri-urban.

5 Results

5.1 Two Way Fixed Effects Results

We start with standard two way fixed effects estimates as a baseline for comparison to the existing literature. Table 3 shows that, using the standard TWFE approach to difference-in-differences estimation, WIC EBT implementation has no statistically significant average effect on the probability of WIC or SNAP authorization for either chain or independent retailers. Results within the subgroups of chain and independent retailers are also statistically insignificant, with negative signs. We note that the magnitude of the estimate for the independent subgroup is notably larger than that for the chain subgroup. A negative estimate implies that WIC EBT implementation reduced the probability that any given vendor at that time was authorized after EBT. For the SNAP authorization outcome, in contrast, all the estimates of the effect of WIC EBT implementation on SNAP retailer authorization are imprecisely estimated and statistically insignificant but positive. The estimated magnitude for independent stores is, again, larger than for chain stores. Positive point estimates here indicate that WIC EBT implementation increased the likelihood of a store being SNAP authorized, plausibly through spillovers by harmonizing the technologies used across programs.

[17] It is possible that there is measurement error in our definition of these identifier variables, which would affect our estimated changes within-vendor for authorization status. This mismeasurement would not affect our estimates on counts of authorized stores by area.

Table 3: WIC EBT Effects on WIC and SNAP Vendor Authorization: TWFE Estimates

	WIC authorization			SNAP authorization		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Chain	Indep.	All	Chain	Indep.
WIC EBT	-0.019	-0.016	-0.059	0.024	0.013	0.020
	[-0.059,0.022]	[-0.040,0.009]	[-0.126,0.009]	[-0.002,0.050]	[-0.007,0.034]	[-0.005,0.045]
FY FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1274168	842324	431844	6241396	3848250	2393146

95% confidence intervals in brackets

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

Table 4 uses the TWFE approach to estimate the effect of WIC EBT implementation on redemptions of WIC and SNAP benefits. In the table, WIC redemptions are measured in hundreds of thousands of dollars and SNAP benefits are measured in millions of dollars. The results indicate no statistically significant or economically important effects. As with the store-level results above, finding no significant effect on average could indicate that the true effect of the implementation on both WIC and SNAP redemptions is zero. This would imply that WIC EBT implementation had no negative effects on access to WIC or value of benefits obtained by participants.

One reason we may be finding null effects is that using TWFE and OLS to estimate average treatment effects of the implementation's staggered adoption results in biased estimates due to comparisons between treated and already-treated units when there is heterogeneity across time in the average treatment effect (Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; Gibbons et al., 2019). Alternately, in the case of the WIC and SNAP redemption outcomes, we cannot identify the treatment effect because of censoring in the reporting of WIC and SNAP redemptions for ZIP codes and counties that have an insufficient number of stores. While we cannot address the issue that arises from censoring, we can address the first concern of treatment effect heterogeneity. To do this, we estimate the model from Callaway and Sant'Anna (2021) to determine the treatment-group-specific average treatment effects on the treated. The results using this method are our preferred estimates.

Table 4: WIC EBT Effects on WIC and SNAP Redemptions: TWFE Estimates

	Redemptions	
	(1)	(2)
	WIC	SNAP
WIC EBT	-0.035	-0.232
	[-0.973,0.904]	[-1.708,1.244]
FY FE	Yes	Yes
N	7839	51340

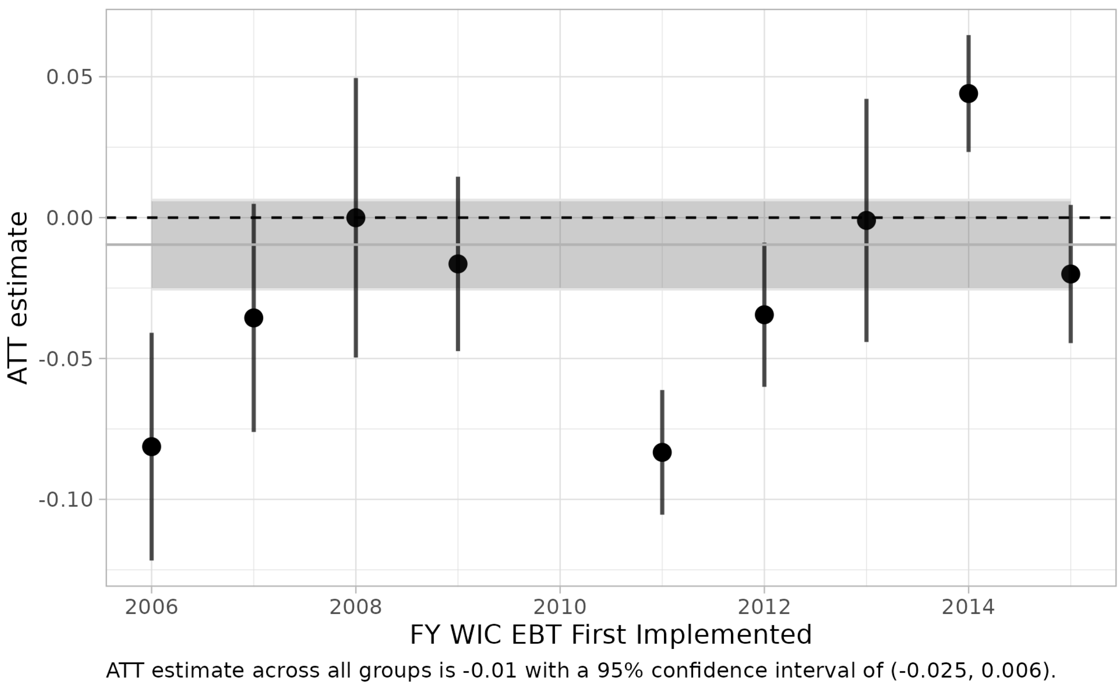
95% confidence intervals in brackets

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

5.2 Callaway and Sant'Anna Results

Next, we turn to the Callaway and Sant'Anna (2021) results. Figure 3 shows ATTs for the probability that a store is WIC authorized, based on the initial year of WIC EBT implementation for the county containing the store. The black dots show individual estimates of ATT_g, where g is the fiscal year WIC EBT was first implemented. The black bars show 95% confidence intervals resulting from the analytical standard error computation outlined in Callaway and Sant'Anna (2021) and implemented using the package `csdid` in Stata (Rios-Avila et al., 2021). The light gray horizontal line shows a weighted average ATT across all groups, while the gray shaded area shows a 95% confidence interval for the entire sample estimated using the same package. Across all stores and all years of implementation, the average effect of the implementation on authorization is approximately zero (–0.01, or –1 percentage point) and not statistically significant.

Figure 3: Effect of WIC EBT Implementation on Vendor Authorization, by Year of First EBT Implementation

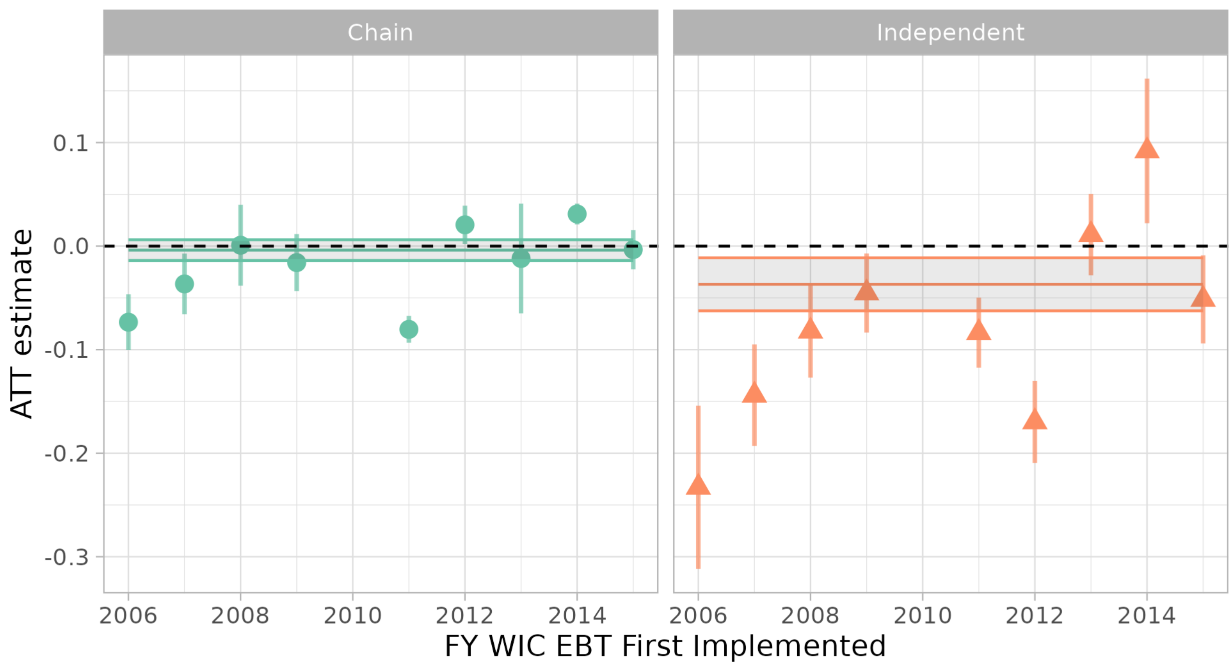


There is, however, a fairly clear difference in the ATT_g between early and late implementing states. Early-implementing states experienced much more negative effects on vendor authorization relative to later-implementing states. For example, counties in Texas that implemented WIC EBT relatively early (in FY 2006)—as well as one county in Michigan which implemented at the same time—experienced an 8 percentage point average decrease in the probability of store authorization, eight times larger than the overall sample average treatment effect on the treated (approximately –0.08 compared to –0.01).

5.2.1 Differences in Effects for Independent and Chain Stores

We also observe that the heterogeneity by time of first implementation is larger for independent stores, which have only one location, relative to chain stores, which, by definition, have multiple ones. These results are in Figure 4 just below, with the chain store results on the left and the independent store results on the right. Again, dots represent individual ATT_gs, bars represent 95% confidence intervals around ATT_gs, and solid horizontal lines represent the overall ATT and its 95% confidence interval (also shaded). For independent stores, the treatment group-specific ATT_gs show an increasing trend and have more negative estimates in the early years that are significantly different from group average treatment effects in later periods. Across all treatment groups for independent stores, there is a statistically significant 3.7% decline in the probability of WIC authorization after the implementation. Chain stores also show an increasing trend in their treatment group-specific ATTs, with more negative effects for early adopters. The magnitude of the chain store point estimates are uniformly smaller compared to those for independent stores for all subsamples except FY 2011. This means that in Kentucky – the only state to implement WIC EBT in FY 2011 – chain stores experienced a larger percentage point reduction in the probability of being WIC authorized after WIC EBT implementation relative to independent stores, perhaps due to state-specific implementation procedures or interactions with existing state policies and vendor authorization patterns. The average effect, weighted by group size and propensity to be treated, across all chain stores is statistically and economically insignificant. We find no significant effect of WIC EBT implementation on the probability of authorization for chain stores. The more negative and slightly noisy point estimate in the full sample shown in Figure 3 (which does not distinguish between chain and independent stores) is a combination of this larger magnitude effect for independent stores and a more precise zero for chain stores.

Figure 4: Effect of WIC EBT Implementation on Vendor Authorization, by Year of First EBT Implementation



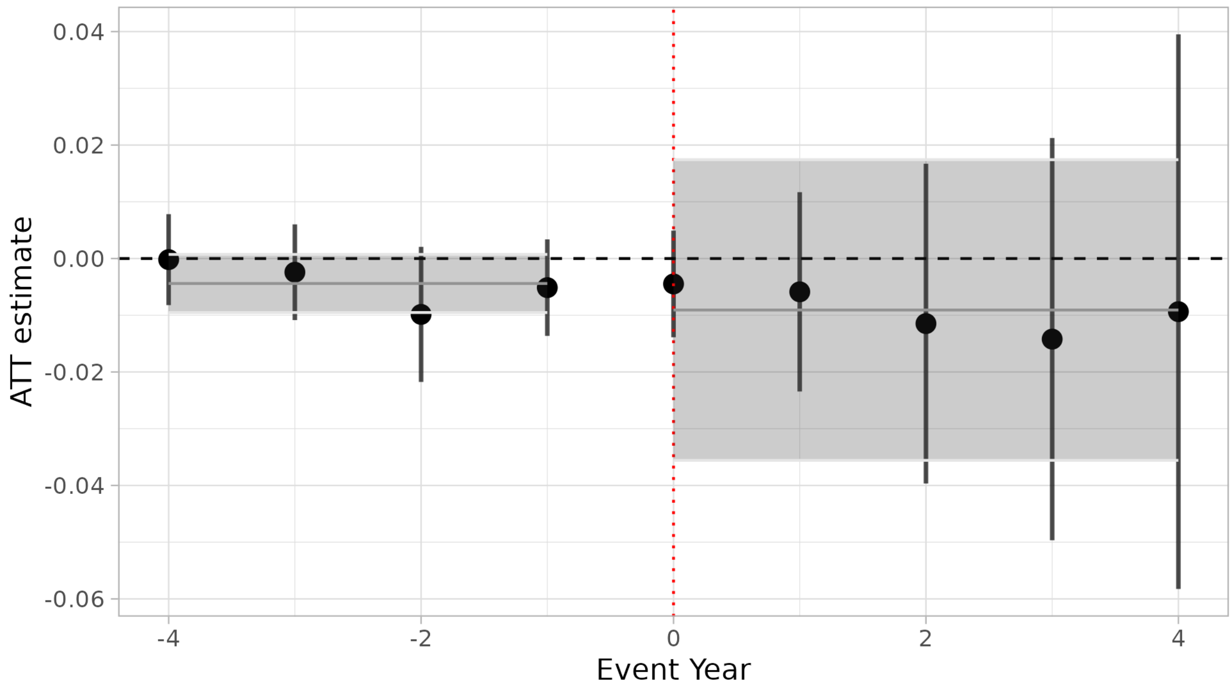
ATT estimate for the chain subsample is -0.004 with a 95% confidence interval of (-0.014, 0.006)
ATT estimate for the independent subsample is -0.037 with a 95% confidence interval of (-0.063, -0.011).

In the event-study framework, where we restrict to event years four years before and after EBT implementation,[18] we find small average effects of WIC EBT implementation on the number of WIC authorized retailers. Figure 5 shows no significant change in the probability that a vendor is WIC authorized in the four years following the implementation. Each black dot represents an event study type estimate showing the average effect of the implementation on the probability that a WIC vendor is authorized in a given year relative to

[18] We can observe up to eight years before and after WIC EBT implementation. We show a smaller event window here as the very late event years are driven by a small subset of early adopters, as shown in the treatment group-specific estimates.

the implementation. Ninety-five percent confidence intervals constructed using the Callaway and Sant'Anna (2021) procedure are shown as black bars around these point estimates. The year of the implementation is shown in red, with a zero effect indicated by the black dashed horizontal line. In the pre-periods, there is no measured effect of the implementation on authorization probability.

Figure 5: Effect of WIC EBT Implementation on Store-Level WIC Authorization



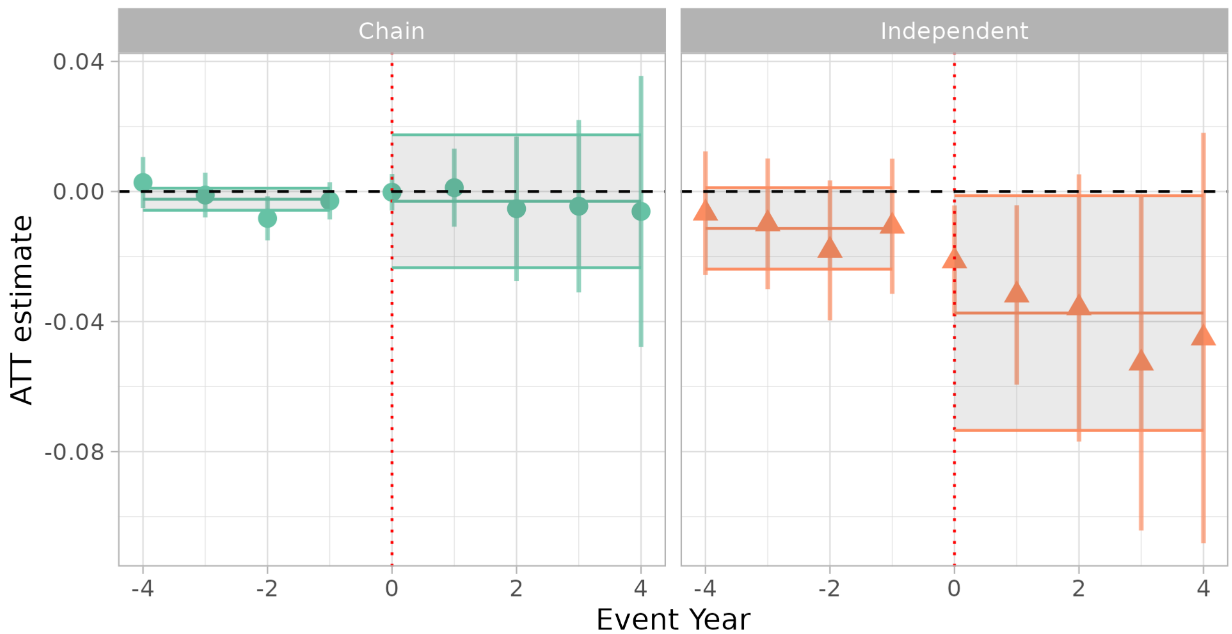
ATT estimate for the post period shown here is -0.009 with a 95% confidence interval of (-0.036, 0.017).

The figure also shows that the point estimates of the effects of the WIC EBT implementation on vendor authorization are negative in the post periods but statistically insignificant. The point estimates show no trend, remaining persistently small through the last estimated post period. The average treatment effect on the treated for all vendors, indicated by the light gray horizontal line, is –0.009, indicating that the probability of a vendor being WIC authorized decreased by 0.9 percentage points, on average, in the seven years after the implementation. These effects are relatively imprecisely estimated. We note that a symmetric positive effect—a 0.9 percentage point increase in the probability of authorization—falls within the 95% confidence interval for the effect size, covered by the gray shaded area.

While we estimate a negative ATT_{post} of WIC EBT implementation on authorization on average, these effects are not statistically significant. This is in line with estimates from the treatment group-specific model, where we find no significant effect of EBT implementation on the probability of authorization across stores. However, truncating the event years to exclude post periods more than four years after the implementation will downplay the representation of very early adopting counties with more negative treatment effects for independent vendors, as shown in Figure 6. We highlight this nuance before delving into the event study type results presented in Figure 6.

The average effect in Figure 5 masks heterogeneity between independent stores, which have a single outlet, and chain stores, which have multiple ones. Figure 6 shows event-year-specific estimates and average effects for chain stores, represented by green circles, and independent stores, represented by orange triangles. The effect of WIC EBT implementation on the probability of authorization for chain stores is more precisely estimated than the full sample ATT, with a 95% confidence interval spanning –0.023 to 0.017. This effect is not statistically different from zero. We conclude that there is no statistically or economically meaningful relationship between the implementation and the probability that a chain-affiliated WIC vendor remains authorized.

Figure 6: Effect of WIC EBT Implementation on Store-Level WIC Authorization, by Chain Status



ATT estimate for the chain subsample in the post period is -0.003 with a 95% confidence interval of (-0.023, 0.017).
ATT estimate for the independent subsample in the post period is -0.037 with a 95% confidence interval of (-0.073, -0.001).

For independent stores, the effect of WIC EBT implementation on the probability of authorization is negative. On average, in the four years following the initial implementation of WIC EBT, there is a statistically significant decrease of 3.7 percentage points in the probability that an independent store is WIC authorized, with a 95% confidence internal from -7.3 to -0.1 percentage point decrease in the probability of WIC authorization for retailers in the four years after WIC EBT implementation. This indicates that while there is no significant effect of EBT implementation on the overall average probability of vendor authorization, the overall average effect masks significant negative effects in the population of independent stores.

There are two broad patterns potentially at play here. First, WIC EBT implementation was broadly marketed by policymakers and WIC state agencies as a strategy to reduce fraud. As discussed by Meckel (2020), the transition to EBT could make detecting fraudulent WIC redemptions less costly for states and hiding fraud more costly for stores, relative to using paper FIs. As fraud becomes more costly, the returns to fraud decrease. If stores are remaining authorized to engage in fraud, the transition to EBT will decrease authorization. Generally speaking, more small and independent stores engage in fraud relative to chain stores

(Gleason et al., 2013). This pattern of fraud could explain why we find a significant decrease in authorization post-implementation among independent vendors but not chain vendors.

Another broad pattern that could explain these heterogeneous effects is non-fraud costs related to EBT implementation or higher costs for stores due to states' ability to better set maximum reimbursements. Regarding fixed costs of transitioning, anecdotally, the transition from paper FIs to EBT caused short- to medium-run technical challenges for state agencies, participants, and vendors; which likely incurred costs for vendors. After implementation, authorized vendors were also required to have a POS system that could run the EBT software and to have a staff member available at all times who was trained on the software. This type of ongoing cost is more likely to bind for an independent relative to a chain vendor. Further, chain vendors anecdotally report maintaining WIC authorization as a matter of corporate policy regardless of costs. We can provide some evidence for whether the disruption caused by the implementation contributes to the magnitude of authorization effects by looking at whether treatment effects are more negative when the firms that work with states to implement EBT have less experience. We assume the transition to EBT is smoother when firms have previous experience, meaning they should experience fewer disruptions and costs during implementation. It is also possible that access to these electronic redemption data makes it easier for states to adjust maximum reimbursements allowed.

Interestingly, we also find that in both the full sample and the subsamples by chain status, the ATT estimate shifts downward for later event years. For data covering 2004–2018, post-event years two, three, and four represent places that implemented WIC EBT at least before 2014. This indicates that some mechanism is causing earlier adopters of WIC EBT to have more negative effects on authorization, especially for independent stores. We consider two possible mechanisms: one, the evolution of point of sale systems over time; and two, learning-by-doing among WIC EBT processors.

Technology was evolving over the period in which states implemented WIC EBT. The first implementation dates we analyze occurred before the widespread adoption of smartphones,[19] at which point vendors—particularly independent ones—would have needed costly separate POS systems, and to learn how to use them, in order to implement WIC EBT. Currently in some states, WIC vendors can use a Square extension and a mobile application to accept WIC benefits, drastically reducing the barriers to entry for WIC authorization. Interviews with WIC vendor staff indicate that staff may not be aware of existing training materials and experience confusion about authorized products when checking out customers (Wallace et al., 2020). With more intuitive POS technology, barriers at check out are lower. This could account for EBT treatment effects being more negative early in the adoption period. Figure 3 shows the evolution of average treatment effects by the year of first implementation of WIC EBT in states. More negative effects on the left-hand side indicate that vendors in counties that adopted WIC EBT earlier in our sample are less likely to be WIC authorized after the implementation relative to counties that adopted EBT at a later stage (particularly after 2012).

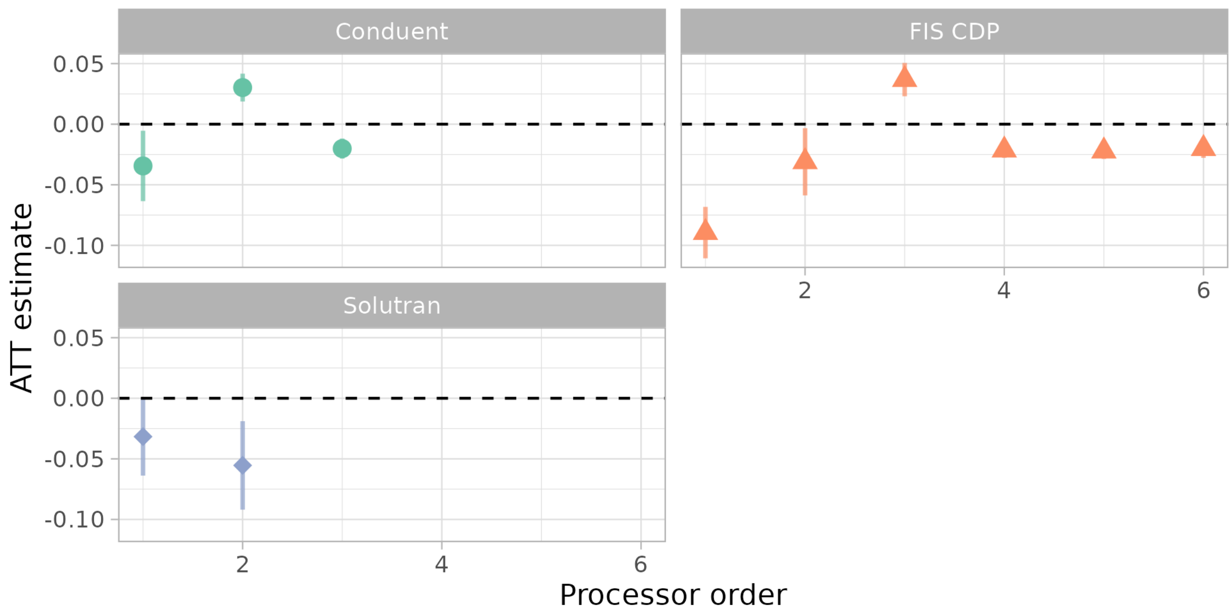
One possible mechanism is that there are learning effects for states and for the private firms that contract with states to construct the backend systems to implement WIC EBT in the POS system and interact with state data systems. Figure 7 shows the estimated average effects of the WIC EBT implementation on the probability of authorization for the three major financial services companies or processors that imple-

[19] WIC EBT implementation in FY2006 and 2007 would have been complete before the release of the iPhone, a common marker of the beginning of universal smartphone adoption.

mented WIC EBT over our sample period: Solutran, FIS/CDP, and Conduent. Each panel shows that as a processor gains experience implementing WIC EBT in states, the average effect of the implementation on vendors becomes more positive. We measure experience by the order of implementation, and we assume that the processor has gained experience with each additional state that it contracts with to implement WIC EBT.

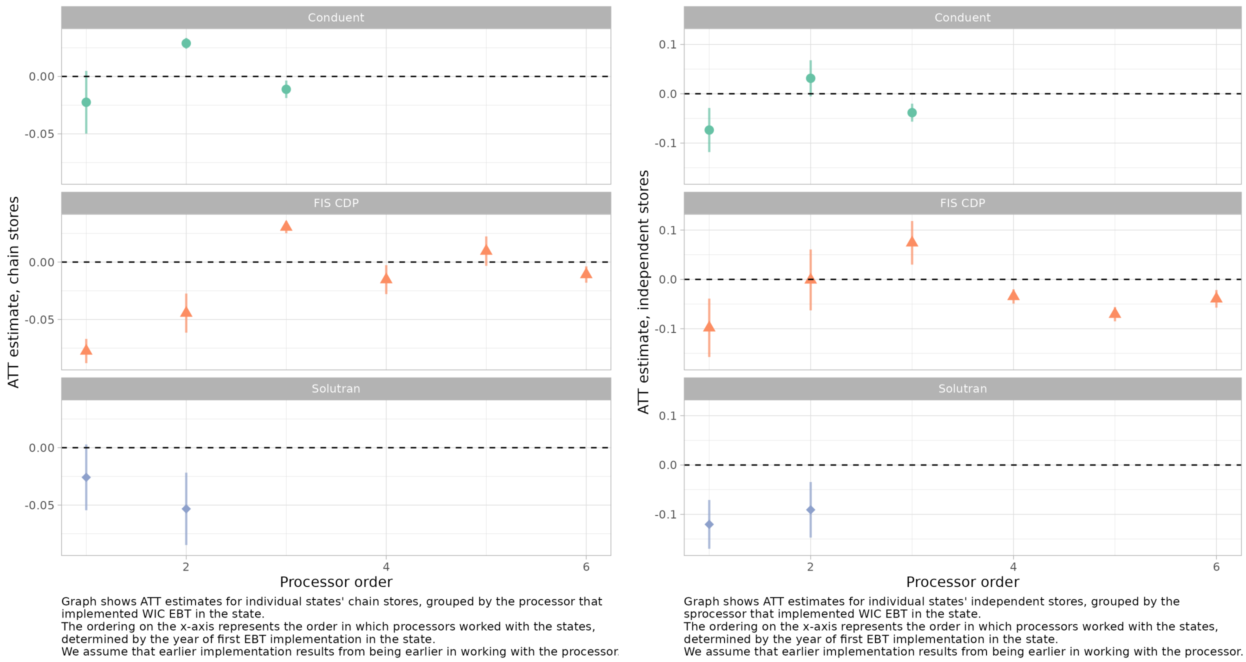
Considering heterogeneity by chain and independent status, the association between processor implementation order and the magnitude and direction of the implementation effect on authorization holds for both chain (Figure 8a) and independent (Figure 8b) vendors. The point estimates for independent stores lie uniformly below the estimates for chain stores in all cases. We caution against inferring too much from these results, but consider that they provide a possible mechanism for our findings and suggest a direction for further research.

Figure 7: Effect of WIC EBT Implementation on WIC Vendor Authorization, by Processor



Graph shows ATT estimates for individual states, grouped by the processor that implemented WIC EBT in the state.
The ordering on the x-axis represents the order in which processors worked with the states, determined by the year of first EBT implementation in the state.
We assume that earlier implementation results from being earlier in working with the processor.

Figure 8: Effect of WIC EBT Implementation on WIC Vendor Authorization, by Processor and Chain Status



(a) Chain Stores (b) Independent Stores

5.3 Did These Changes Affect WIC Participant Access?

Of course, changes in the number of stores participating in the WIC program may or may not mean changes in access for participants. Ideally, we would measure the costs and benefits of WIC EBT adoption and determine the welfare effects of this policy. Unfortunately, we lack the data to do so since deterred fraud is hard to measure. However, our unique administrative data allow us to consider whether the reduction in independent stores lead to declines in WIC spending, our best proxy for participant welfare.

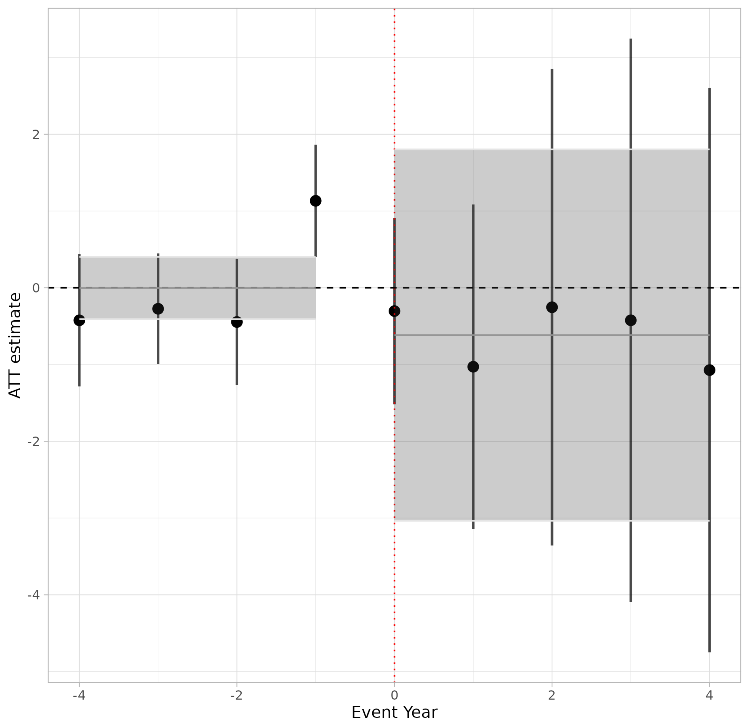
Authorization is a measure of WIC shopping accessibility for participants, but we also consider WIC redemptions from our administrative data as an outcome that measures the intensive margin of program participation. Prior work shows that reduced authorization of WIC vendors, especially small and independent ones, lead to decreases in participation in WIC (Meckel, 2020; Meckel et al., 2021),[20] Thus, we examine how WIC redemptions change in response to national WIC EBT implementation. WIC redemptions measure the combination of the intensity with which participants are using benefits and the number of participants. If decreasing probabilities of authorization for independent vendors corresponded with WIC participants leaving the program or using their benefits less intensely, we would expect to see a decrease in WIC redemptions.

As shown in Figure 9, WIC redemptions (measured in hundreds of thousands of dollars per ZIP code) do not significantly change in the years after WIC EBT implementation. While the point estimate for the average effect of EBT on redemptions is negative, at $61,600 lower redemptions per year per ZIP code, the effect is

[20]We also confirm an outcome from Meckel (2020), that independent stores in Texas were less likely to be authorized after WIC EBT implementation, and that the number of independent stores in ZIP codes in Texas decreased after WIC EBT. However, our yearly data cannot entirely replicate the month-level dynamics. We have data for a larger set of years than reported in Meckel and results become less robust if we extend the set of years used for estimation beyond FY 2007–2010.

not precisely estimated. Additionally, a symmetric positive effect of equal magnitude on redemptions falls within the 95% confidence interval. We conclude that any change in access that resulted from WIC EBT implementation is not large enough to offset the potential positive effects of it, including 1) being able to redeem foods from one food instrument on multiple occasions, 2) less difficult transactions, and 3) reduced stigma.

Figure 9: Effect of WIC EBT Implementation on WIC Redemptions, by ZIP Code



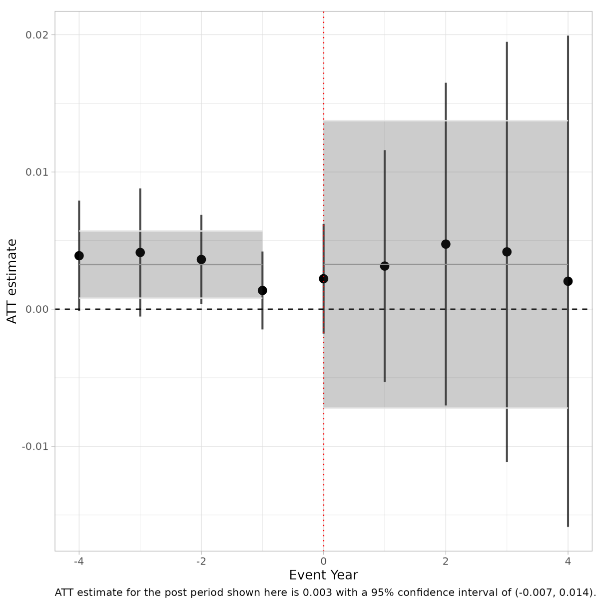
ATT estimate for the post period shown here is -0.616 with a 95% confidence interval of (-3.036, 1.804).

5.4 Effects on SNAP Authorization and Redemptions

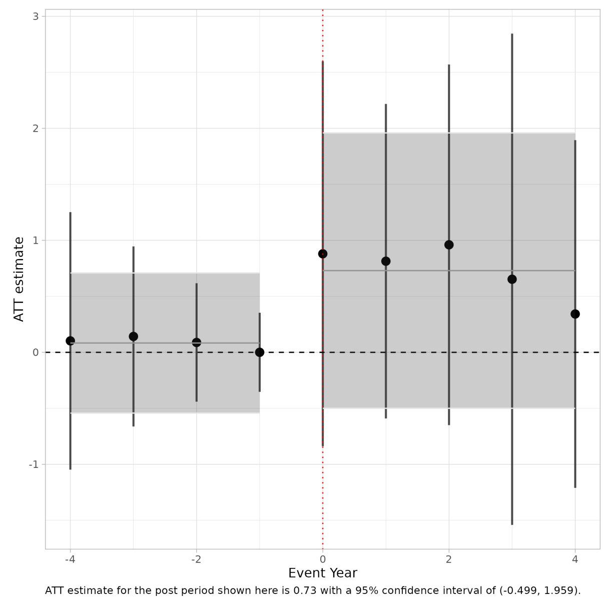
Another potential effect of WIC EBT implementation is the greater harmonization of technological requirements for both SNAP and WIC authorization after the adoption of WIC EBT. In all states, SNAP had adopted EBT technology to redeem benefits before the implementation of WIC EBT. This means that prior to WIC EBT, SNAP authorization required a POS system that could handle EBT, while WIC did not. While the backend software on POS systems to manage WIC EBT and SNAP EBT are different, the checkout procedure looks more similar between SNAP and WIC after WIC EBT. In many states, SNAP authorization is a requirement for WIC vendor authorization. For instance, Minnesota and California both require vendors to be SNAP authorized or have pending SNAP retailer applications, although their respective neighbors Wisconsin and Nevada do not have this requirement. In areas where SNAP authorization is a requirement, the transition to EBT may have been smoother given stores' previous experience with EBT (Crespo-Bellido et al., 2024; Vogel and O'Connor, 1998).

Harmonization between technologies and prior EBT experience suggest that WIC EBT implementation may lead to increases in the number of SNAP authorized retailers and value of SNAP redemptions. On the other hand, our previous results on WIC authorization show decreases in the number of WIC authorized independent stores after WIC EBT implementation. If these stores were maintaining SNAP authorization in order to have WIC authorization – due to state rules requiring SNAP authorization to be a WIC vendor as mentioned above – then losing WIC authorized retailers may lead to decreases in the number of SNAP authorized retailers. *Ex ante*, then, the effect of WIC EBT on SNAP authorization and redemptions is ambiguous. Figures 10a and 10b show these results. We find no statistically significant effects of the WIC EBT implementation on SNAP authorization or SNAP redemptions. It is possible that the two mechanisms we propose above have opposite effects, leading to a net null effect.

Figure 10: Spillover Effects of WIC EBT Implementation on SNAP Outcomes



(a) WIC EBT Effect on SNAP Authorization



(b) WIC EBT Effect on SNAP Redemptions ($ million) by County

6 Discussion and Conclusion

We have comprehensively examined the response of WIC vendors to the implementation of an important policy change in WIC—the transition from paper vouchers to EBT. Transitioning to EBT was a large policy change in WIC that stakeholders expected to improve the experience of participants by reducing stigma and increasing flexibility when obtaining supplemental foods. Policymakers also expected that it would decrease fraud among vendors. For vendors authorized to redeem WIC food benefits, WIC EBT implementation represented a substantial technological transition, requiring additional POS equipment, software, and training. If EBT increased demand for WIC while potentially increasing costs, the net effect on vendors is unclear ex ante.

We find that WIC EBT implementation led to a small, statistically significant, and economically meaningful decrease in the number of WIC-authorized independent vendors but no significant change in the number of WIC-authorized chain vendors. The results for independent vendors suggests that participant access to authorized food retailers may be declining in response to implementation of WIC EBT. Examining changes in the dollar value of benefits redeemed (standardized across ZIP codes) shows no significant change in redemptions, on average, across ZIP codes, with WIC EBT adoption. This suggests that the amount of supplemental foods obtained by participants in the ZIP codes for which we have data do not change significantly after WIC EBT implementation. Consequently, if the amount of food benefits redeemed is not changing, then participants have substituted to use alternate authorized WIC vendors when some vendors lose their authorization after the implementation or any declines in use at some stores are offset by increases at others.

We examine one potential mechanism for the decline in authorized vendors after EBT implementation: vendor's interactions with the processor implementing EBT. Three firms—Conduent, FIS/CDP, and Solutran—implemented EBT in most states that transitioned through 2015. We find evidence to support the hypothesis that each of these firms changed their implementation of WIC EBT in ways that lead to fewer vendors leaving the WIC program as they had more experience with the implementation process. The average effect of the implementation of WIC EBT on vendors became more positive as the processors accumulate more experience implementing EBT. Thus, processors may learn from previous implementations and incorporate that learning to improve subsequent implementations. Technological improvement over time may have made the WIC EBT transition smoother for all stores.

Considering the potential harmonization of redemption technologies between WIC and SNAP after WIC EBT, as well as existing regulations in some states requiring SNAP authorization for WIC vendors, we examine whether WIC EBT implementation has spillover effects on to the probability of retailers' SNAP authorization and the value of SNAP redemptions. We note that there are mechanisms working in opposite directions from WIC EBT implementation on to SNAP outcomes, so that the expected sign of the effect is uncertain *ex ante*. Linking WIC EBT implementation to SNAP administrative data on retailers and redemptions, we find no significant effects of WIC EBT implementation on either SNAP outcome. The null results suggest that positive spillovers from making WIC redemption technology closer to SNAP redemption technology are offset by negative spillovers from declining probability of authorization for independent WIC authorized retailers.

Overall, we find that WIC EBT implementation led to a decrease in the number of non-chain WIC-authorized food retailers. However, our results on WIC redemptions and SNAP-authorized retailers suggest that the estimated change in authorization does not affect WIC participants' ability to obtain supplemental foods or spill over on to SNAP access. While EBT results in fewer independent WIC authorized retailers, these changes in the set of authorized retailers on average do not change WIC or SNAP redemptions.

References

Ambrozek, C. (2022). WIC Participant Responses to Vendor Disqualification.

Ayala, G. X., Laska, M. N., Zenk, S. N., Tester, J., Rose, D., Odoms-Young, A., McCoy, T., Gittelsohn, J., Foster, G. D., and Andreyeva, T. (2012). Stocking characteristics and perceived increases in sales among small food store managers/owners associated with the introduction of new food products approved by the Special Supplemental Nutrition Program for Women, Infants, and Children. *Public Health Nutrition*, 15(9):1771–1779. Publisher: Cambridge University Press (CUP).

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230. Themed Issue: Treatment Effect 1.

Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2019). The Effect of Minimum Wages on Low-Wage Jobs. *The Quarterly Journal of Economics*, 134(3):1405–1454.

Conley, T. G. and Udry, C. R. (2010). Learning about a New Technology: Pineapple in Ghana. *American Economic Review*, 100(1):35–69.

Crespo-Bellido, M., Steeves, E. A., Hill, J. L., Kersten, S., and Nitto, A. M. (2024). Vendors' Perceptions and Experiences with Special Supplemental Nutrition Program for Women, Infants, and Children Online Shopping Implementation. *Current Developments in Nutrition*, page 102084.

de Chaisemartin, C. and D'Haultfœuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–2996.

de Chaisemartin, C. and D'Haultfoeuille, X. (2023). Two-way fixed effects and differences in differences with heterogeneous treatment effects: A survey. *The Econometrics Journal*, 26(3):C1–C30.

Fletcher, J. M. and Frisvold, D. E. (2017). The Relationship between the School Breakfast Program and Food Insecurity. *Journal of Consumer Affairs*, 51(3):481–500.

Foster, A. D. and Rosenzweig, M. R. (1995). Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture. *Journal of Political Economy*, 103(6):1176–1209.

Frisvold, D., Leslie, E., and Price, J. P. (2020). Do targeted vouchers instill habits? evidence from women, infants. and children. *Contemporary Economic Policy*, 38(1):67–80.

Frisvold, D. and Price, J. (2019). The Contribution of the School Environment to the Overall Food Environment Experienced by Children. *Southern Economic Journal*, 86(1):106–123.

Gibbons, C. E., Serrato, J. C. S., and Urbancic, M. B. (2019). Broken or fixed effects? *Journal of Econometric Methods*, 8(1):1–12.

Gleason, S., Pooler, J., Bell, L., Erickson, L., Eicheldinger, C., Porter, J., and Hedershott, A. (2013). 2013 WIC Vendor Management Study. Technical report, U.S. Department of Agriculture, Food and Nutrition Service, Office of Policy Support.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277. Themed Issue: Treatment Effect 1.

Hanks, A. S., Gunther, C., Lillard, D., and Scharff, R. L. (2018). From paper to plastic: Understanding the impact of eWIC on WIC recipient behavior. *Food Policy*.

Hoynes, H. W. and Schanzenbach, D. W. (2009). Consumption responses to in-kind transfers: Evidence from the introduction of the food stamp program. *American Economic Journal: Applied Economics*, 1(4):109–139.

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

Klerman, J. A. and Danielson, C. (2011). The transformation of the Supplemental Nutrition Assistance Program. *Journal of Policy Analysis and Management*, 30(4):863–888.

Kuhn, M. A. (2021). Electronic benefit transfer and food expenditure cycles. *Journal of Policy Analysis and Management*.

Li, X. (2020). *Impacts of Electronic Benefit Transfer on the Women, Infants and Children Program: Evidence from Oklahoma*. PhD thesis, University of California, Davis.

Lovett, N. and Xue, Y. (2017). Have electronic benefits cards improved food access for food stamp recipients? *Journal of Economic Studies*, 44(6):958–975.

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

Meckel, K., Rossin-Slater, M., and Uniat, L. (2021). Efficiency Versus Equity in the Provision of In-Kind Benefits: Evidence from Cost Containment in the California WIC Program. *Journal of Human Resources*. Publisher: University of Wisconsin Press _eprint: https://jhr.uwpress.org/content/early/2021/02/03/jhr.58.4.0120-10677R1.full.pdf.

Moffitt, R. (1983). An economic model of welfare stigma. *The American Economic Review*, 73(5):1023–1035.

National Center for Health Statistics (2013). NCHS urban-rural classification scheme for counties. Technical report, National Center for Health Statistics.

Oh, S. (2024). Ebt technology in snap and retailers' program participation. Technical report, UC Davis.

Parente, S. L. (1994). Technology Adoption, Learning-by-Doing, and Economic Growth. *Journal of Economic Theory*, 63(2):346–369.

Phillips, D., Bell, L., Morgan, R., and Pooler, J. (2014). Transition to EBT in WIC: Review of impact and examnation of participant redemption patterns. Technical report, Altarum Institute.

Pérez, C. J. and Ponce, C. J. (2015). Disruption costs, learning by doing, and technology adoption. *International Journal of Industrial Organization*, 41:64–75.

Rambachan, A. and Roth, J. (2023). A More Credible Approach to Parallel Trends. *Review of Economic Studies*.

Rios-Avila, F., Sant'Anna, P. H., and Callaway, B. (2021). CSDID: Stata module for the estimation of difference-in-difference models with multiple time periods. Statistical Software Components, Boston College Department of Economics.

Rossin-Slater, M. (2013). Wic in your neighborhood: New evidence on the impacts of geographic access to clinics. *Journal of Public Economics*.

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

Saitone, T. L., Sexton, R. J., and Volpe, R. J. (2015). A WICked problem? Cost containment in the Women, Infants and Children program. *Applied Economic Perspectives and Policy*, 37(3):378–402.

Shiferaw, L. (2020). *Understanding the Effects of Access to the U.S. Social Safety Net*. PhD thesis, University of California, Berkeley.

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199. Themed Issue: Treatment Effect 1.

U.S. Census Bureau (2023). County intercensal datasets: 2000-2010. Technical report, U.S. Census Bureau.

Vogel, R. J. and O'Connor, T. (1998). Approval of WIC EBT Systems. Final Policy Memorandum 99-2, USDA FNS.

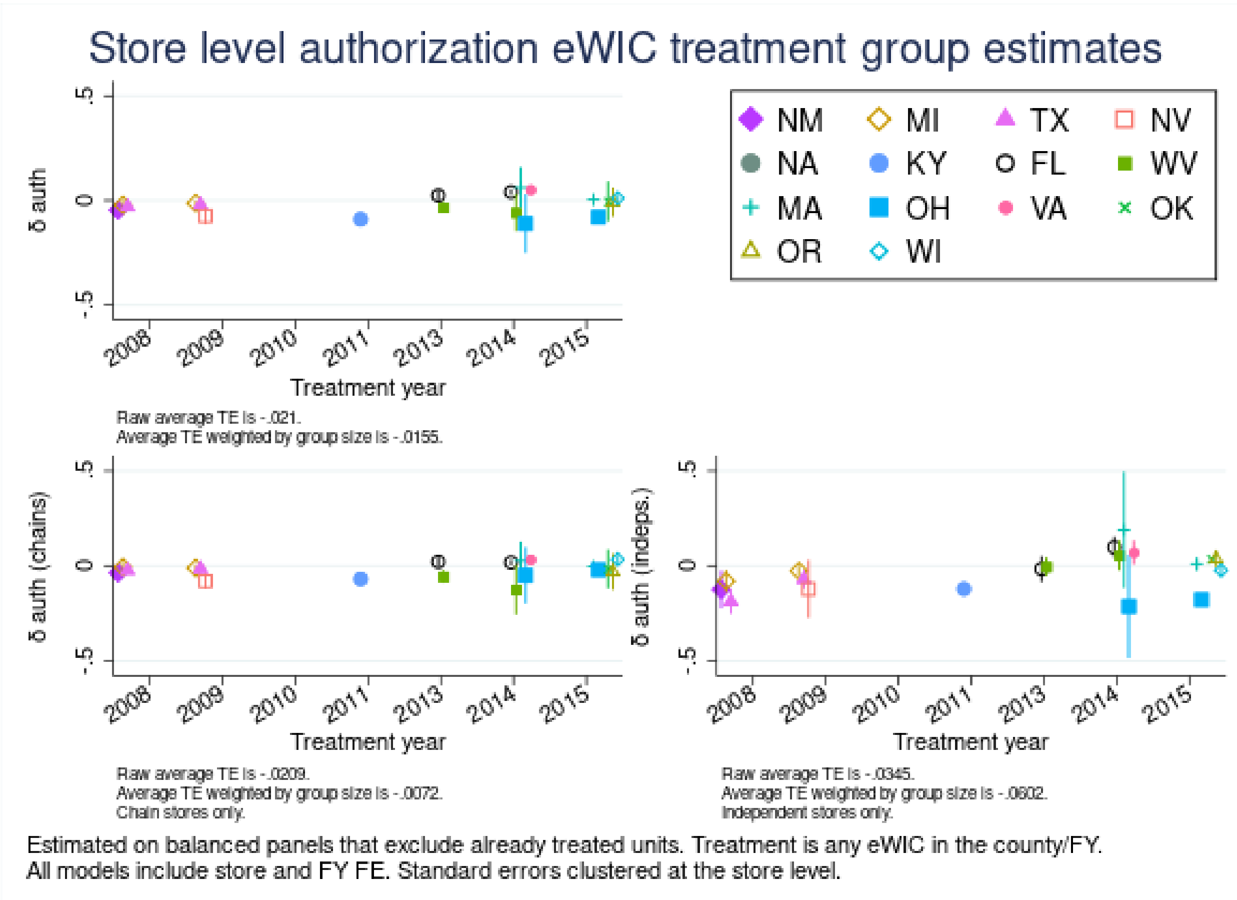
Walker, K. and Herman, M. (2023). *tidycensus: Load US Census Boundary and Attribute Data as 'tidyverse' and 'sf'-Ready Data Frames*. R package version 1.3.3.

Wallace, L. A., Morris, V. G., Hudak, K. M., and Racine, E. F. (2020). Increasing Access to WIC through Discount Variety Stores: Findings from Qualitative Research. *Journal of the Academy of Nutrition and Dietetics*, 120(10):1654–1661.e1.

A Tables and Figures

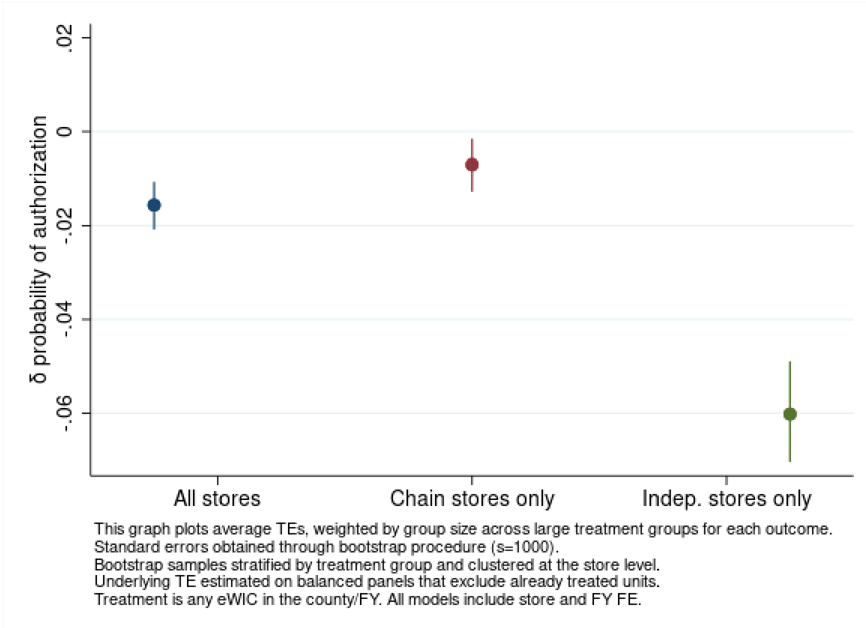
The following figures show results from the approach outlined in Cengiz et al. (2019) for a main set of outcomes.

Figure 11



Decreases in authorization are largest for independent stores, with a weighted average treatment effect of -6% for independent stores compared to -0.8% for chain stores. This pattern holds for most of the treatment groups.

Figure 12: Average store level changes in authorization as a result of WIC EBT



Aggregated up to the ZIP level, we find a decrease of 0.06 stores per ZIP overall after WIC EBT implementation. Decomposing this effect into chain and independent stores, we find that most of the decrease (0.041 out of 0.06 stores per ZIP) is attributable to decreases in independent stores. Chain stores account for the remaining decrease of 0.02 stores per ZIP.

Figure 13

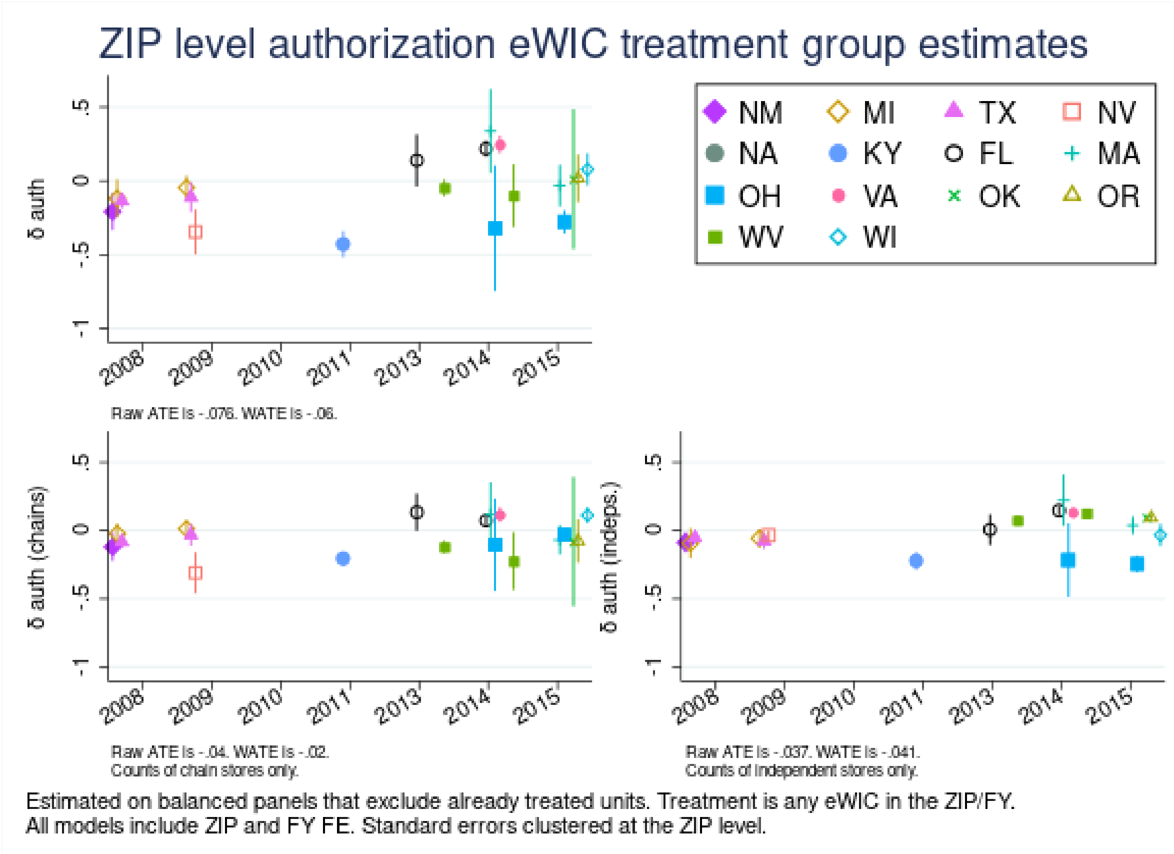


Figure 14: Average ZIP level changes in authorization after WIC EBT

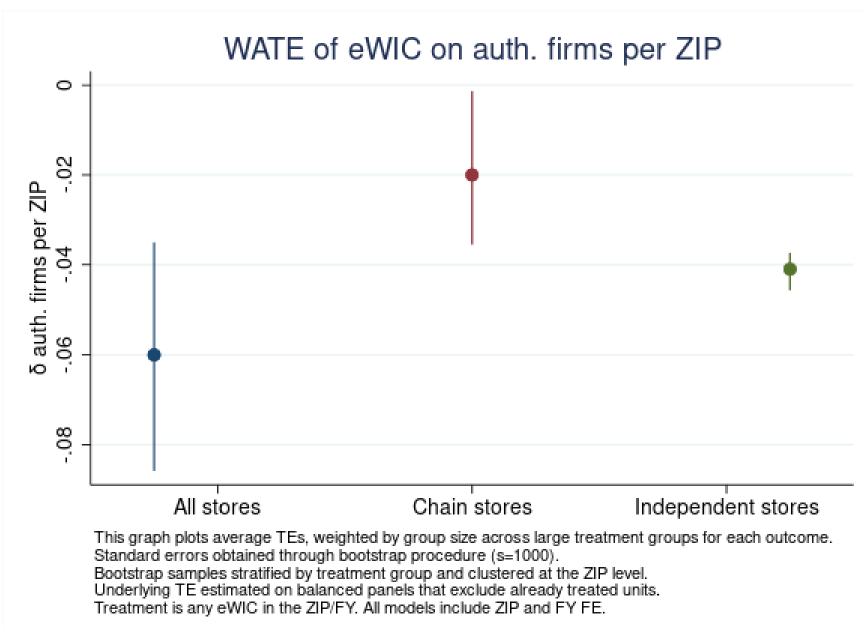


Figure 15

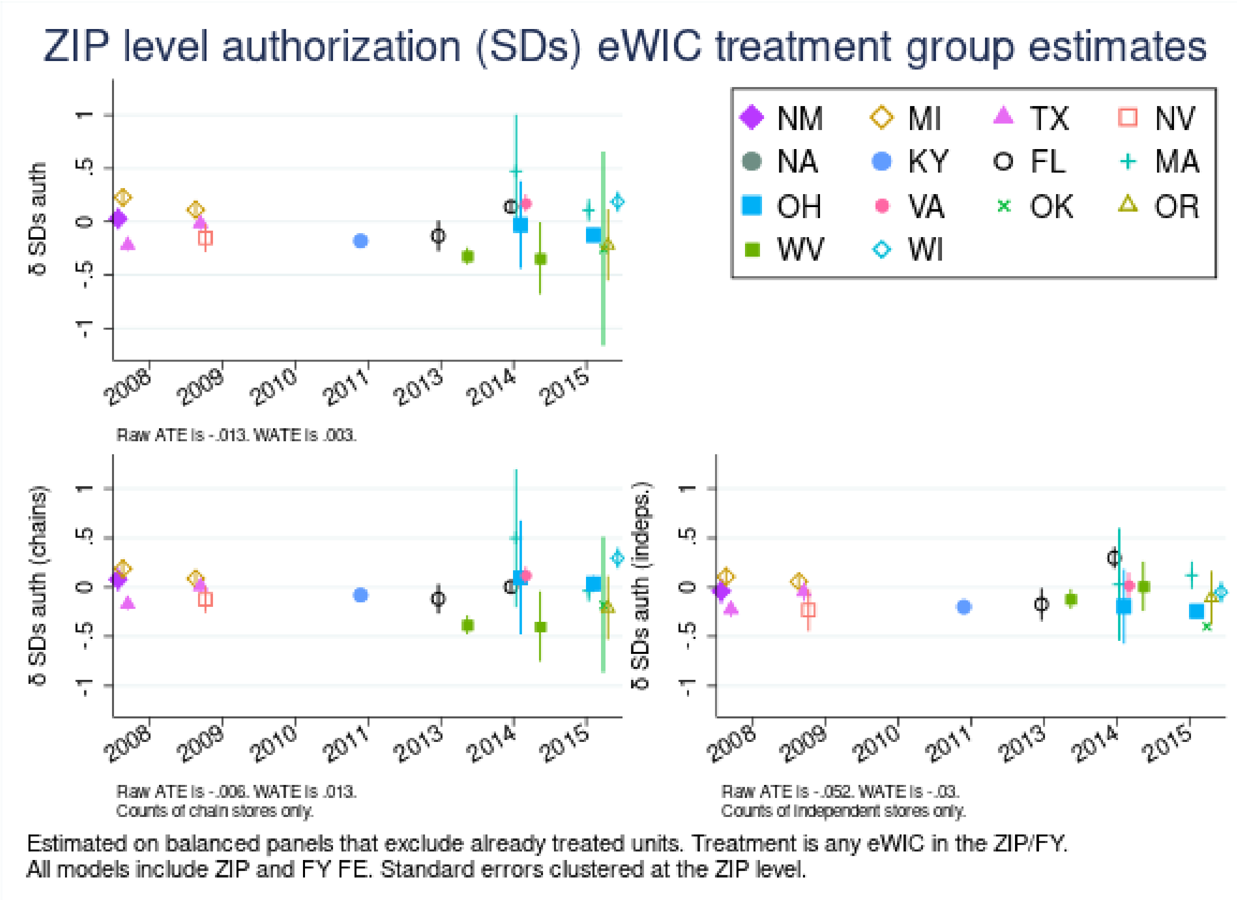


Figure 16: Average ZIP level SD changes in authorization as a result of WIC EBT

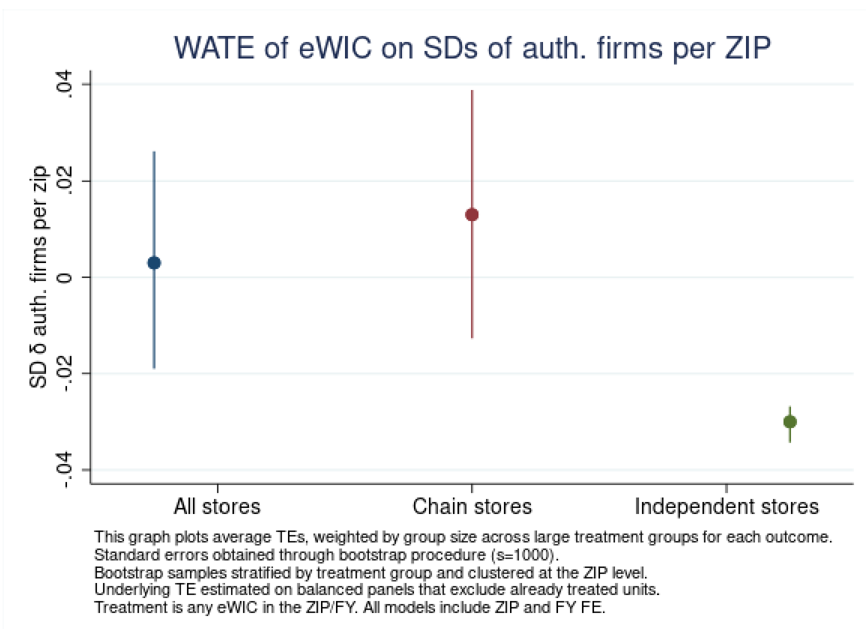
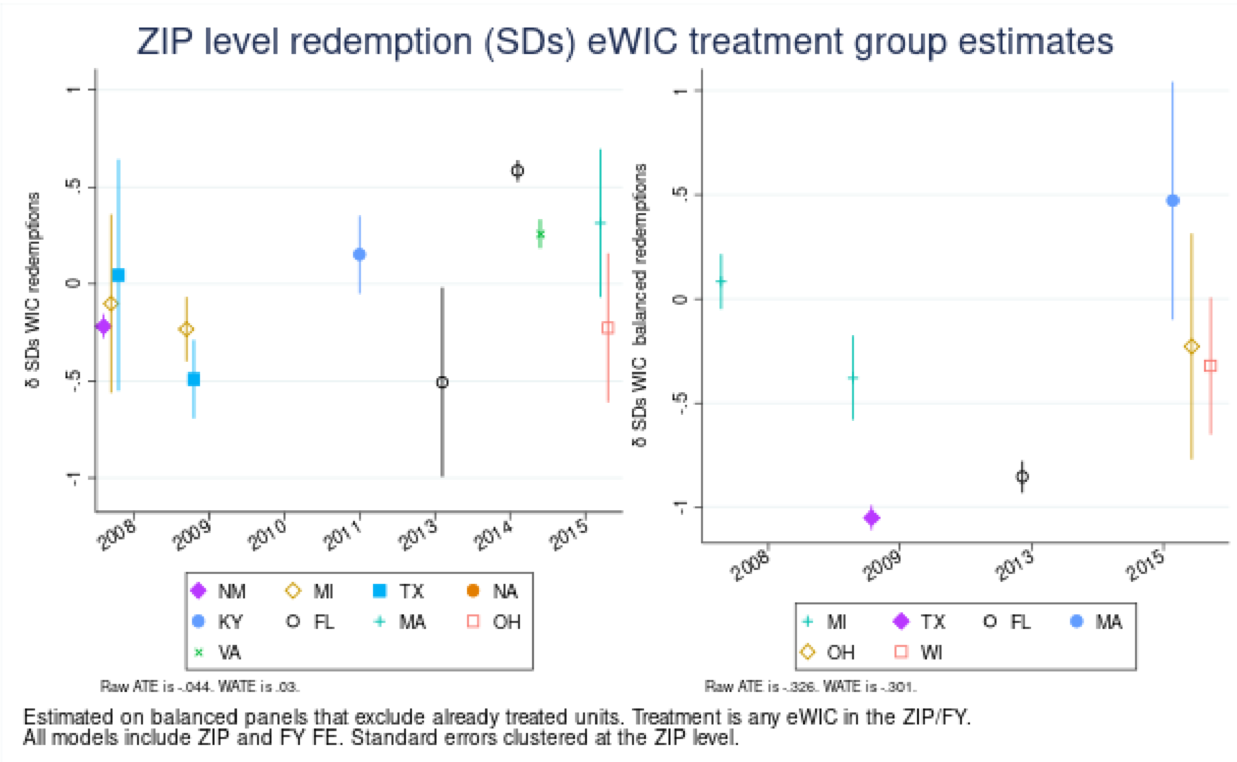


Figure 17



The following graphs estimate spillover effects from WIC EBT implementation onto SNAP retailer authorization using the Cengiz et al. (2019) approach.

Figure 18

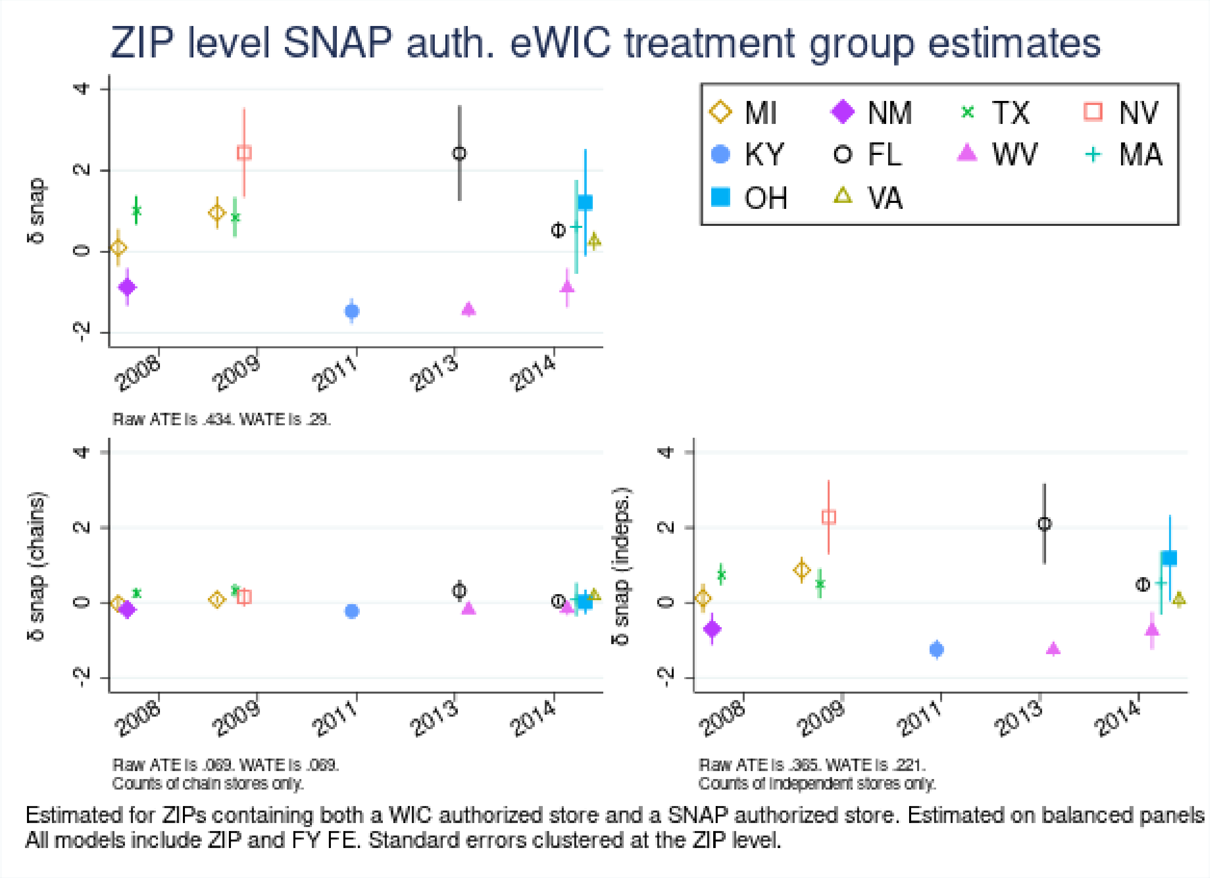

ZIP level SNAP auth. eWIC treatment group estimates
MI
NM
TX
NV
KY
FL
WV
MA
OH
VA
δ snap
δ snap (chains)
δ snap (indeps.)
4
2
0
-2
2008
2009
2011
2013
2014
Raw ATE is .434. WATE is .29.
Raw ATE is .069. WATE is .069.
Counts of chain stores only.
Raw ATE is .365. WATE is .221.
Counts of independent stores only.
Estimated for ZIPs containing both a WIC authorized store and a SNAP authorized store. Estimated on balanced panels
All models include ZIP and FY FE. Standard errors clustered at the ZIP level.

Figure 19

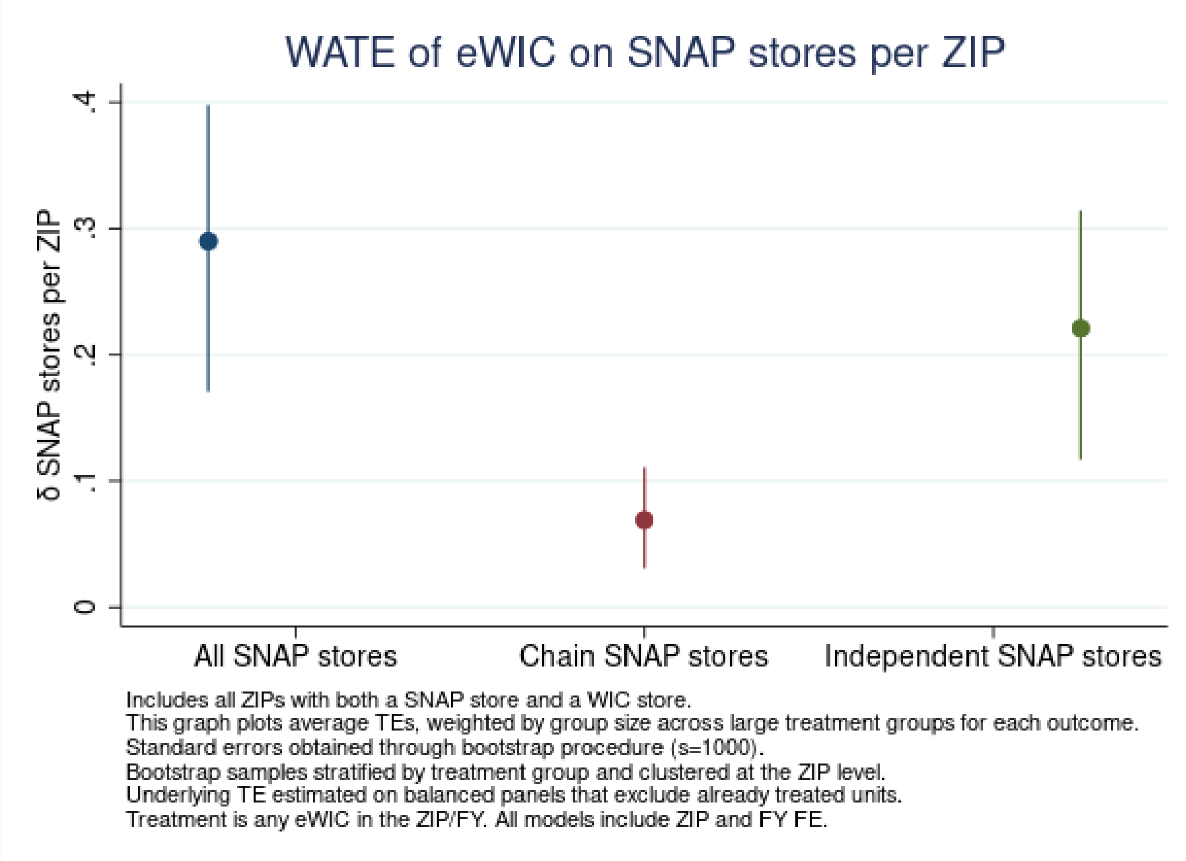

WATE of eWIC on SNAP stores per ZIP
δ SNAP stores per ZIP
0
.1
.2
.3
.4
All SNAP stores
Chain SNAP stores
Independent SNAP stores
Includes all ZIPs with both a SNAP store and a WIC store.
This graph plots average TEs, weighted by group size across large treatment groups for each outcome.
Standard errors obtained through bootstrap procedure (s=1000).
Bootstrap samples stratified by treatment group and clustered at the ZIP level.
Underlying TE estimated on balanced panels that exclude already treated units.
Treatment is any eWIC in the ZIP/FY. All models include ZIP and FY FE.

Figure 20

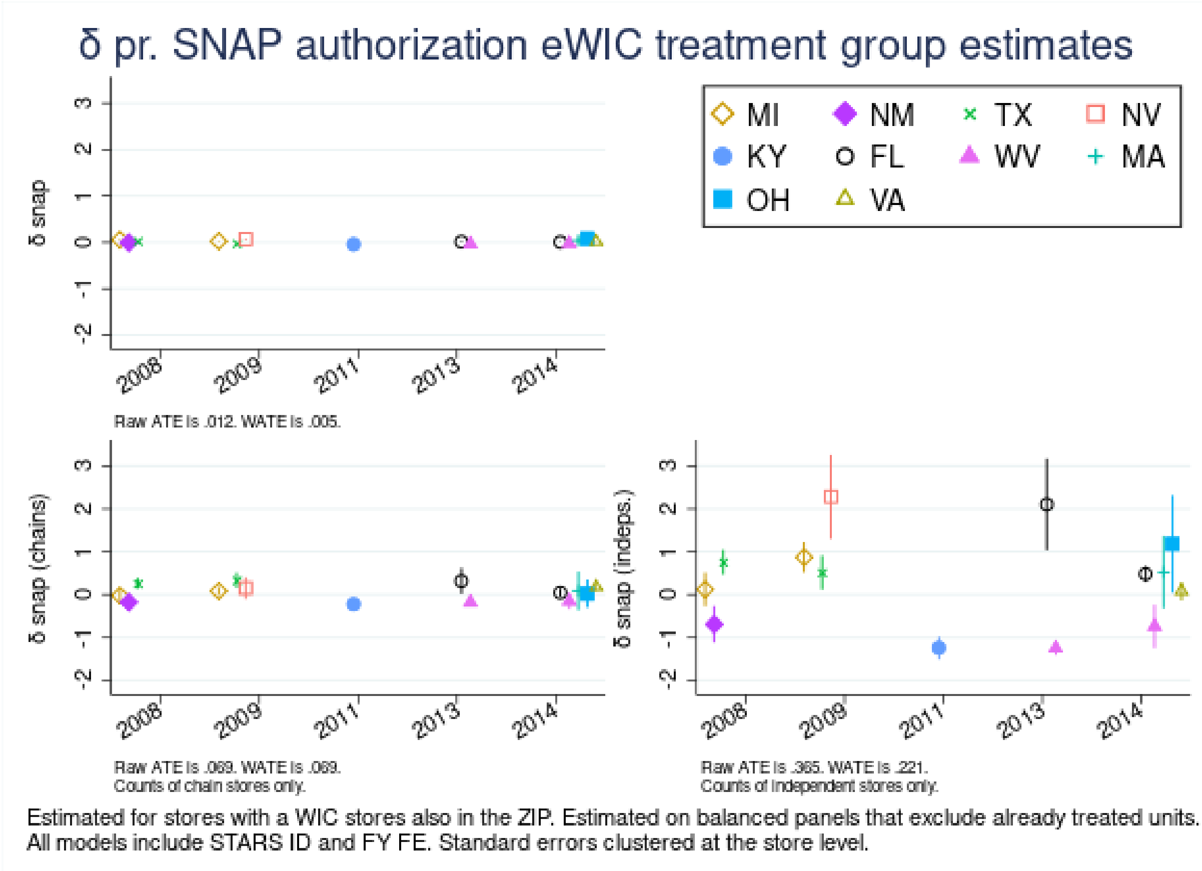
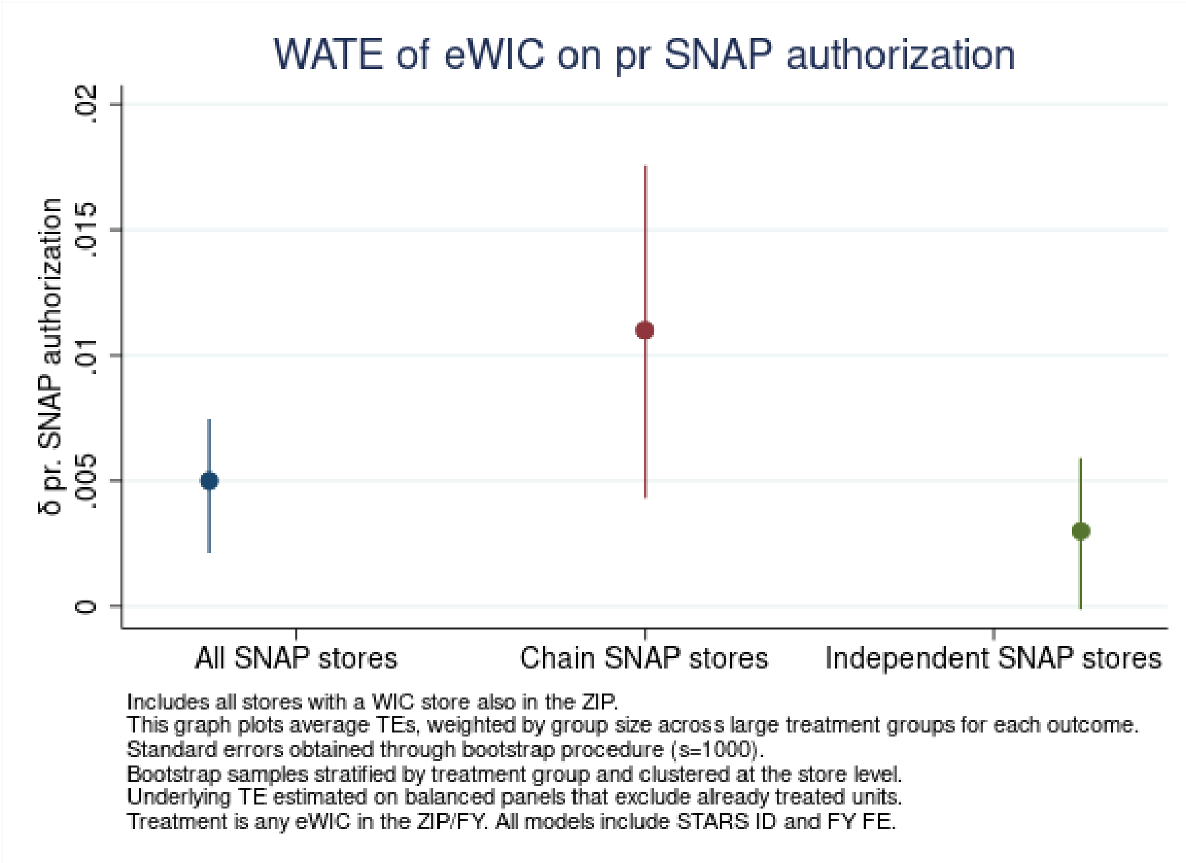

δ pr. SNAP authorization eWIC treatment group estimates
MI
NM
TX
NV
KY
FL
WV
MA
OH
VA
δ snap
δ snap (chains)
δ snap (indeps.)
3
2
1
0
-1
-2
2008
2009
2011
2013
2014
Raw ATE is .012. WATE is .005.
Raw ATE is .069. WATE is .069.
Counts of chain stores only.
Raw ATE is .365. WATE is .221.
Counts of independent stores only.
Estimated for stores with a WIC stores also in the ZIP. Estimated on balanced panels that exclude already treated units. T
All models include STARS ID and FY FE. Standard errors clustered at the store level.

Figure 21


WATE of eWIC on pr SNAP authorization
δ pr. SNAP authorization
0
.005
.01
.015
.02
All SNAP stores
Chain SNAP stores
Independent SNAP stores
Includes all stores with a WIC store also in the ZIP.
This graph plots average TEs, weighted by group size across large treatment groups for each outcome.
Standard errors obtained through bootstrap procedure (s=1000).
Bootstrap samples stratified by treatment group and clustered at the store level.
Underlying TE estimated on balanced panels that exclude already treated units.
Treatment is any eWIC in the ZIP/FY. All models include STARS ID and FY FE.