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Selected presentation prepared for presentation at the 2025 AAEA & WAEA Joint Annual Meeting in Denver, CO; July 27-29, 2025
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## Payment Digitization and Retailer Fraud in Food Assistance: Evidence from Store Sanctions\*

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May 15, 2025

#### **Abstract**

We study the impact of payment digitization that transitions food assistance payments from paper vouchers to debit cards on retailer fraud. We hand-collected the rollout schedule of payment digitization for two major federal food assistance programs: Supplemental Nutrition Assistance Program (SNAP) and Special Supplemental Nutrition Program for Women, Infants, and Children (WIC). We link these schedules to administrative data on store sanctions and compare sanction patterns between counties that implemented digitized payments and those that had not yet transitioned. We find that payment digitization increases disqualifications under SNAP but decreases them under WIC. We explore potential explanations for this divergence and discuss its implications. Our findings highlight how digital technologies can have varying effects on the administration of public programs.

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#### 1 Introduction

Under the stress of surging national debt, the U.S. government has long aimed to cut federal spending. Social safety net programs, including federal food assistance, have been frequently targeted in these efforts. Meanwhile, total spending on food assistance has soared from \$92.4 billion in 2019 to \$166.4 billion in 2023 (Jones and Toossi, 2024), which places additional strain on the federal budget. A persistent challenge to these programs is fraud: individuals and businesses exploit loopholes to steal benefits, causing billions of dollars in losses to federal funds each year (Edwards, 2023). Combating fraud is essential to ensure that limited government resources are directed to households that are genuinely in need.

Over the last four decades, payment digitization has been a key policy intervention to address fraud in food assistance programs. The digitization replaced paper vouchers with Electronic Benefit Transfer (EBT) cards as the method of distributing benefits. However, evidence on its effectiveness in reducing fraud remains limited. This paper examines the impact of payment digitization on retailer fraud in two major federal food assistance programs: the Supplemental Nutrition Assistance Program (SNAP) and the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC).

We combine data on the EBT rollout schedules for both SNAP and WIC with restricted-use administrative data on store disqualifications (DQ) for both programs to examine whether the adoption of EBT reduces fraud. This paper builds on Meckle (2020), which found that EBT implementation in Texas reduces the number of independent SNAP stores, as these stores were more likely to commit fraud before EBT adoption. We extend Meckle's analysis by providing nationwide evidence on EBT's impact on disqualifications of SNAP stores and introducing new evidence on its effects on disqualifications of WIC stores.

We manually compiled EBT rollout schedules for both SNAP and WIC using historical public records from state agencies. Data on store disqualifications for SNAP and WIC were obtained from restricted-use administrative records provided by the USDA Food and Nutrition Service. The SNAP store data include the start and end dates of store authorization, addresses, and vendor types. WIC store data are derived from the WIC Integrity Profile, which provides annual information on the names and addresses of authorized and unauthorized WIC stores. We matched the EBT rollout schedules to store disqualifications and compared disqualification rates before and after EBT implementation and in counties that had already implemented EBT and those that had not.

We estimate our models using a staggered-adoption difference-in-differences (DiD) approach, following the procedure from Sun and Abraham (2021). This approach allows us to disaggregate our treatment effect estimates to subgroups and time periods, to show how treatment effects vary across the country, given heterogeneous policy environments in different counties, and across time.

Our preliminary results reveal an interesting divergence in EBT's effects on store disqualifications for SNAP and WIC. Specifically, we find that EBT increases the incidence of store disqualifications under SNAP but decreases it under WIC. These results are robust across functional forms and whether the sample is balanced.

#### 2 Background

Fraud in the coupon-based food stamp program can occur in several primary ways. First, eligibility fraud happens when applicants misrepresent their income or other information to qualify for benefits. Second, counterfeiting can occur when individuals produce fake food stamp vouchers. Third, food stamp mail theft arises when vouchers delivered through the mail are stolen and used by unauthorized individuals. Fourth, benefit trafficking involves recipients selling or trading their food stamp vouchers for cash or other goods. Finally, some recipients may misuse their benefits by purchasing items that are not eligible under the program (United States General Accounting Office, 1994). We focus on retailer fraud in this paper.

The transition to Electronic Benefit Transfer (EBT) can help reduce counterfeiting, mail theft, and benefit trafficking, but it does not address eligibility fraud (United States General Accounting Office, 1994).

FNS may disqualify a SNAP-authorized retail store based on evidence from on-site investigations, inconsistent redemption data, EBT transaction reports, or reciprocal disqualification from the WIC program. FNS will send a charge letter to firms being considered for disqualification, allowing them to submit information, explanations, or evidence before a final administrative determination is made. Sanctions imposed by FNS include permanent disqualification, term disqualification, and civil money penalties. A store may face permanent disqualification for violations such as trafficking SNAP benefits, selling ineligible items more than twice, or submitting false applications. Term disqualifications, ranging from six months to five years, are applied for less severe violations. Civil money penalties may be issued instead of disqualification if the penalty would cause hardship for SNAP households or in cases involving a

<sup>&</sup>lt;sup>1</sup>However, counterfeiting is relatively rare, as it is both technically demanding and costly, and the value of food stamp benefits is generally too low to provide sufficient incentive for such efforts.

#### 3 Data

We hand-collected county-level SNAP EBT rollout schedules using information from EBT Project Status Reports, archived state agency websites, and USDA FNS administrative data. The EBT Project Status Reports provide details on the timing of both pilot programs and statewide implementation. We first identified the year of EBT implementation for states that completed the rollout within a single year, including AL, AK, CT, DE, DC, HI, IA, KY, LA, ME, MA, MS, MT, NE, RI, VT, and WA. Next, we used the Wayback Machine to gather data on EBT rollout schedules from archived state agency websites. Finally, we drew on the USDA FNS Bi-Annual (January and July) County-Level Participation and Issuance Data to determine the start of EBT issuance. One advantage of this bi-annual administrative data is that the initiation of EBT issuance may reflect the actual timing of take-up. However, a limitation is that some states might not report EBT and paper voucher issuance separately after EBT implementation.

We manually compiled county-level SNAP EBT rollout schedules using archived state agency websites, policy reports, existing literature, and personal contacts at state WIC agencies. We documented the implementation timing for every state and the District of Columbia.

We request the USDA administrative data on store disqualifications from 1997-2021 via the Freedom of Information Act. This dataset includes records on store address, store name, store type, sanction type, and sanction date. Sanction type includes disqualification for terms or permanent disqualification. Store type includes convenience stores (CS), combination stores or other (CO), direct marketing farmers (DF), delivery route (DR), farmers' market (FM), grocery stores with different sizes (large: LG, medium: MG, and small: SG), military commissary (MC), non-profit food-buying cooperatives (BC), specialty food stores (bakery/bread: BB, fruits/vegetables: FV, meat/poultry: ME, and seafood: SE), supermarket (SM), super stores or chain stores (SS), and wholesalers (SH). Our sample covers a total of 38,436 disqualification incidents.

Our data on WIC store unauthorizations comes from the WIC Integrity Profile (TIP), which provides information on store name, address, and store type (including retail vendor, pharmacy, home food delivery contractor, and commissary) for authorized and unauthorized stores during fiscal years 2005–2016. Since the dataset does not include county identifiers, we assign counties to stores by matching addresses using city-to-county and ZIP-code-to-county crosswalks, supplemented with fuzzy matching and verification via Google Maps. Our sample

includes a total of 44,833 unauthorization cases.

Our data on time-varying covariates come from the Intercensal Population Estimates provided by the U.S. Census Bureau and the Local Area Unemployment Statistics (LAUS) from the Bureau of Labor Statistics. The Intercensal Population Estimates offer county-by-year estimates of total population and demographic characteristics, including age groups, gender, race, and ethnicity, based on decennial census results. The LAUS dataset provides county-by-month estimates of unemployment rates.

#### 4 Methods

To study the effects of payment digitization, we compare store outcomes in counties that have adopted EBT with those in counties that have not yet implemented it. A standard estimation approach is to use the two-way fixed effects (TWFE) model:

$$Y_{ct} = \alpha + \mu EBT_{ct} + \eta_c + \lambda_t + \varepsilon_{ct}$$

where  $Y_{ct}$  is the outcome for county c in year t,  $EBT_{ct}$  is an indicator for whether the county had implemented EBT by that year,  $\eta_c$  and  $\lambda_t$  are county and year fixed effects that control for time-invariant differences across counties and national shocks over time, and  $\varepsilon_{ct}$  is the error term.

However, recent research has shown that the TWFE model can give misleading results when the treatment is introduced at different times across counties and the effects of the treatment are not the same for all counties or over time. In these cases, the TWFE estimate combines many different comparisons of treated and untreated units, including cases where already-treated units are incorrectly used as controls. This can lead to biased estimates, and in some situations, the average treatment effect may even have the wrong sign, even when all individual treatment effects are positive (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021).

To address this problem, we use the method proposed by Sun and Abraham (2021). This approach begins by estimating a dynamic TWFE model that includes interactions between event time and cohort:

$$Y_{ct} = \eta_c + \lambda_t + \sum_{g \in \mathcal{G}} \sum_{k \neq -1} \delta_{gk} \cdot \mathbb{1}[G_c = g] \cdot \mathbb{1}[t - G_c = k] + \varepsilon_{ct},$$

where  $G_c$  is the year in which county c first received the treatment, k indexes event time (i.e.,

years since treatment), and  $\delta_{gk}$  captures the effect for cohort g in relative year k. The year before treatment (k=-1) is excluded as the reference period. Unlike the conventional TWFE model, this specification allows treatment effects to vary flexibly by both cohort and time since treatment. The estimator then uses the estimated  $\delta_{gk}$  to recover cohort-specific treatment effects over event time. To aggregate these into an overall treatment effect, we compute the sample share of each cohort in each event-time period, Cohort Share $_{gk}$ , and use these as weights. The dynamic and overall effects are then given by:

$$\delta^{ ext{Dynamic}} = \sum_{g} ext{Cohort Share}_{gk} \cdot \widehat{\delta}_{gk},$$
 and  $\delta^{ ext{Overall}} = \sum_{g} \sum_{k} ext{Cohort Share}_{gk} \cdot \widehat{\delta}_{gk}.$ 

In our baseline results, we report standard errors clustered at the county level, weight observations equally, and do not include covariates. In Section ??, we present results under alternative specifications. We also discuss results using other popular staggered difference-in-difference estimators as well as traditional TWFE estimators. We find that our results are robust and not sensitive to the choice of specification or estimation method.

#### 5 Results

We find that SNAP EBT increases SNAP disqualifications, while WIC EBT decreases WIC disqualifications. These effects are transitory. Effects are larger among independent stores compared to chain stores. For reciprocal disqualifications, we find a decline in SNAP disqualifications following the implementation of WIC EBT; however, we cannot rule out the influence of pre-existing downward trends. Figures and tables are available upon request.

#### 6 Discussion

Given the observed divergence in EBT's effects on SNAP and WIC store disqualifications, we would like to explore potential explanations with other economists in this field. One possibility is that the two datasets on store disqualifications may capture different aspects of compliance or misconduct. Another explanation could lie in the fundamental differences between SNAP and WIC programs themselves, such as their store requirements, participant demographics, or operational structures. Discussing these findings at the AAEA annual meeting is important for refining our analyses of these results, identifying plausible explanations, and advancing the understanding of the impacts of EBT transition in both programs.

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