Issuance and Incidence: SNAP Benefit Cycles and Grocery Prices*

Jacob Goldin, Tatiana Homonoff, and Katherine Meckel

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Abstract

Many safety-net programs issue benefits as lump-sum payments at regular intervals. We examine how the timing of benefit distribution can shape the incidence of the transfer. We use retail scanner data from a large and nationally representative sample of grocery stores along with state and time variation in the Supplemental Nutrition Assistance Program (SNAP). We document large, SNAP-induced intra-month cycles in food expenditures and customer composition. However, we find that retailers do not adjust prices based on these predictable patterns of customer demand. Our results illustrate how decisions about program administration can shape the incidence of in-kind transfers.

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1 Introduction

The Supplemental Nutrition Assistance Program (SNAP, formerly "Food Stamps") is one of the most important safety net programs in the United States, lifting an estimated 4.7 million people out of poverty in 2014 (Hoynes and Schanzenbach 2015). Participating households receive a monthly lump sum that can be spent on most food products in participating grocery stores. SNAP constitutes a large share of the retail grocery market – in 2010, for example, SNAP purchases accounted for 14% of grocery sales in the United States (Wilde 2012) – but evidence regarding its effect on grocery markets nationwide is limited.

In this paper, we provide the first, nationally representative estimates of intra-month fluctuations in grocery food sales and prices that arise due to SNAP benefit issuance. To do so, we use a panel of transaction-level data that covers over 10,000 retail grocery stores in the U.S. from 2006-2014. Using this data, we apply a novel identification strategy in which we leverage differences across and within states in the share of SNAP participants that receive benefits in a given week. Crucially, our design allows us to control for unrelated events that occur in certain weeks of the month that may influence food purchases (e.g., wage payments and utility bills at the start of the month).

Previous research finds that food consumption and expenditures by SNAP recipients tracks monthly benefit cycles (Wilde and Ranney 2000; Shapiro 2005; Hastings and Washington 2010). Because SNAP benefits are redeemed in-kind through a larger market involving private firms and both beneficiaries and non-beneficiaries, the temporal variation in demand that benefit issuance induces can shape the incidence of the benefit. In particular, in states with compressed benefit schedules[1], grocery stores may face predictable, intra-month fluctuations in the nature and volume of customer demand. In response, retailers may strategically adjust food prices in low-income neighborhoods over the course of the month to take advantage of SNAP-induced cycles of demand. Such pricing behavior shapes the incidence of

[1]For example, in Nevada all SNAP participants receive their benefits on the first of the month. In contrast, in Missouri, the day on which SNAP participants receive their benefits varies by person – a Missourian's issuance day may fall anywhere between the first and the 22nd of the month.

the transfer, with the ultimate effect depending on whether retailers are induced to raise or lower their prices during the parts of the month associated with peak SNAP demand. The magnitude and even direction of these pricing responses are theoretically ambiguous, making it difficult to predict in advance how they shape the welfare effects of in-kind transfer programs like SNAP.

We first establish that SNAP issuance generates predictable intra-month fluctuations in shopper demand. We find that food sales increase 5.5% for the average grocer in a week in which all SNAP benefits are issued, compared to a week in which no benefits are issued. This effect is more pronounced in low-income areas: food sales rise 14.4% in ZIP codes in which more than 20% of households are eligible for SNAP. Next, we study shopper composition using a representative panel of household expenditure patterns that can be matched to the grocery stores in our data. We find that, in weeks in which a greater share of SNAP benefits are issued, the average shopper is more likely to be SNAP-eligible.

Given these intra-monthly fluctuations in sales and shopper composition, it may be profit-maximizing for stores to adjust prices over the course of the month, inter-temporally price discriminating between SNAP and non-SNAP customers. Adapting the instrumental variable strategy proposed by DellaVigna and Gentzkow (2019), and incorporating our weekly variation in SNAP benefit issuance, we estimate the change in customer demand elasticity that occurs because of SNAP benefit issuance. We find that average demand elasticity in high-SNAP neighborhoods declines by approximately 1% in weeks in which all benefits are issued, suggesting that customers shopping with SNAP benefits are slightly more price sensitive than other customers. Using a simple model of grocer profits, we predict that these elasticity changes should cause stores to modestly lower their prices (by about 0.5%) in the week of SNAP issuance.

We then investigate the existence of such price responses. We find that retailers do not lower prices in response to the SNAP-induced intra-monthly demand cycles – as our earlier findings suggest they should. Rather, we estimate that retailers *increase* prices during weeks in which SNAP benefits are issued, but by a very small amount – our estimated 95% confidence intervals for the change in prices between a week in which all benefits are issued compared to a week of no issuance exclude price changes outside 0.0% to 0.2%. We find similarly small and positive price responses across various subsets of stores in which we might expect larger responses, such as retailers located in areas with high SNAP prevalence, high market concentration, or stores that operate in states with similar SNAP issuance schedules. The results suggest that staggered issuance does not affect the prices that SNAP customers face by a significant margin.

Our paper contributes to a large literature on the incidence of redistributive transfers (e.g., Duggan and Scott Morton 2006; Rothstein 2010; Meckel 2019; Leung and Seo 2017). Our setting highlights a novel mechanism through which institutional design can shape the incidence of a redistributive program when the benefit is provided in-kind through a private market, and in which the timing of issuance generates regular and predictable variation in the nature of demand.[2] Specifically in the SNAP context, prior research suggests the timing of SNAP issuance may affect the grocery prices faced by beneficiaries; using data from three grocery stores from one chain located in a single state, Hastings and Washington (2010) find that prices were approximately three percent higher in the first week of the month (when the state issued its SNAP benefits) than at the end of the month (when SNAP expenditures were relatively low).[3] This finding suggests that concentrated issuance schedules reduce the share of SNAP benefits going towards customers and could motivate policies like staggering issuance schedules more evenly over the course of the month. We build on this analysis in two ways. First, by dramatically expanding the number of stores and retail chains considered, we increase the likelihood that our results will reflect the national grocery store market, rather

[2] For example, Social Security or TANF issuance policies are likely to affect the timing of the benefit use; however, since these benefits are cash instead of in-kind, we may not expect to see a price response by a specific retail industry. In contrast, changes to Medicare Part D may induce price responses by prescription drug providers, but the irregular timing of these benefits is unlikely to affect the use of these benefits.

[3] An earlier working paper version of that paper includes an additional four stores from the same retailer located in states that stagger benefit issuance across the first 10 days of the month and finds that prices decline beginning in the third week of the month, consistent with the issuance schedule driving the change in behavior (Hastings and Washington 2008).

than the pricing decisions of a single retailer. Second, by exploiting heterogeneity in states' SNAP issuance schedules, our identification strategy allows us to isolate pricing responses that are due to SNAP, rather than to other shocks that happen to occur at the beginning of the month. Following this approach, we find retailer price responses that are an order of magnitude lower than what the prior literature suggests. Hence, our results suggest that concerns over benefit incidence should not play a large role in states' decisions over whether to stagger their benefit issuance schedule.

Our paper also contributes to a large literature on grocery retailer pricing strategies. For example, DellaVigna and Gentzkow (2019) find that managerial decisions costs cause grocery chains to pursue a strategy of uniform pricing across outlets, despite wide variation in customer demographics and the level of competition. By contrast, other recent work finds that retail grocers employ flexible pricing schemes in response to local demand conditions (Stroebel and Vavra 2019; Jaravel 2018). We study a novel source of variation in pricing incentives: predictable within-month patterns in demand elasticity induced by SNAP issuance, for which constraints on firm price-setting may operate differently. Our finding that retailers largely do not adjust prices in response to SNAP issuance is similar to that of DellaVigna and Gentzkow (2019), although we analyze price variation within stores across weeks, whereas their focus is on price differences across stores. We do not find evidence that managerial decision costs play a role in our setting. Our analysis is also related to the literature that studies grocer responses to predictable demand fluctuations by season (e.g., turkeys on Thanksgiving). For example, Chevalier, Kashyap, and Rossi (2003) finds that grocers compete to capture seasonal demand shocks by offering a high-demand product (e.g., the turkey) below cost in order to get customers "in the door." We do not find evidence for this type of pricing scheme; if anything, our results suggest retailers *raise* prices in weeks of high SNAP-induced demand.

The paper is structured as follows. Section 2 describes the institutional background. Section 3 describes our data sources and the construction of our analysis samples. Section 4 presents our results the effect of issuance policy on shopping behavior and Section 5 presents results on retailer response. Section 6 concludes.

2 Institutional Background

SNAP is among the largest anti-poverty programs in the U.S., serving roughly 1 in 7 Americans with a budget of $78.4 billion in fiscal year 2012 (Hoynes and Schanzenbach 2015). SNAP purchases comprise a sizable share of the retail grocery market. Wilde (2012) estimates that 10-15% of food sales in recent years were purchased through SNAP and Wal-Mart estimates 4% of its total sales revenue comes from the SNAP program (add cite). The vast majority of grocers and other stores selling food participate in SNAP.

Eligibility for SNAP varies by state but federal law requires participating households to have gross monthly income below 130% of the Federal Poverty Line ($2,665 per month for a family of four in 2012). Many states also limit eligibility based on the value of a household's assets.[4]

SNAP benefits are issued via debit-like Electronic Benefit Transfer (EBT) cards that can be used to purchase most food products at participating grocery stores. Omitted foods include "ready to eat" prepared foods, alcohol and tobacco products, and vitamins.[5] Once per month, SNAP benefits are issued to participating households in a lump-sum payment. When a household's benefits are issued, their EBT card is automatically reloaded and any remaining balance is carried over from prior months. SNAP customers proceed through the standard checkout line and tender their purchases with their EBT card, as well as other payment methods if expenditures exceed their card balance.

In some states, each participating household receives their benefits on the same day as every other participating household. States that issue all SNAP benefits on a single day mostly do so on the first of the month. In contrast, other states stagger benefit issuance over multiple days for example, some households may receive their monthly benefits on the

[4]For details, refer to Center on Budget and Policy Priorities (2018).

[5]For more detail, see U.S. Department of Agriculture (2013).

first, some on the third, and some on the fifth day of the month. Among states that stagger benefit issuance, there exists considerable variation in the number of days on which benefits are issued. For example, Wyoming staggers its benefit issuance across the first four days of the month, whereas Missouri issues benefits between the first and 22nd days of the month.

Table 1 groups states by issuance policy: those that issue benefits on the first day only (5 states), on multiple days in the 1st week only (9 states); the second week only (2 states); weeks 1 and 2 (30 states); and across three or more weeks (13 states).[6] Appendix Table A.1 provides additional detail on issuance policies for each state, including changes that occur during our sample period and the method by which SNAP participants in each state are assigned an issuance day.

In recent years, a growing number of states have begun to stagger benefit issuance across multiple calendar days. In 2014, 13 of the 48 states in our study staggered issuance across three or more weeks of the month, compared to only 4 that did so in 2004.

There are multiple reasons why states may choose to stagger the issuance of their SNAP benefits. The most commonly cited rationale is to reduce congestion in grocery stores on the dates of issuance.[7] A different motivation may be a desire by the state to reduce grocery store price discrimination against SNAP customers. That is, if the benefit issuance schedule affects the timing of SNAP customer purchases, dispersing benefits throughout the month makes inter-temporal price discrimination more difficult.

3 Data

Our primary data source is the Kilts-Nielsen Retail Scanner data set, a large panel of weekly retail transaction records. The data contain point-of-sale records at the store and product level from the 48 contiguous states between 2006 and 2014. We focus our analysis on data from the 11,508 grocery stores in the sample (as opposed to, say, drug stores). The stores

[6]States that change their issuance policy during our sample period are listed in multiple categories.

[7]For example, a 2012 letter from the USDA to state SNAP authorities recommended staggering benefit issuance because "issuing SNAP benefits on a single day or over a limited number of days ... puts an unnecessary strain on SNAP clients and on participating retailers by causing surges in customer traffic at SNAP authorized stores."

included in our sample account for approximately 53% of all grocery store sales volume in the geographic markets covered by Nielsen.

Each observation includes sales volume and volume-weighted average price for each store, week, and Universal Product Code (UPC, or Product). The weekly product price is averaged across all units sold in a store, and incorporates any retailer coupons or discounts applied at the point of sale, though manufacturer (brand-level) discounts are not taken into account.

The majority of the weekly data that stores report to Nielsen corresponds to the week that begins on a Sunday and ends the following Saturday.[8] We transform the raw Nielsen data to represent the first four calendar weeks of each month. To do so, we expand the data to the daily level using the week-ending Saturday date and then re-collapse around the calendar weeks.[9] We discard any data associated with calendar days 29 to 31.

We impose two additional product-level restrictions to our data. First, Nielsen does not report a price for weeks in which a given product was not sold in a given store. To limit potential bias from changes in the composition of products for which we observe price data, we restrict our price analysis to store-month-products for which we observe all four weeks of price data. Second, because our focus is on SNAP-induced changes in demand, we exclude products sold by grocery stores for which SNAP benefits cannot be used (e.g., non-food items or prepared foods).

We supplement the Retail Scanner Data using a second Kilts-Nielsen data set, the Consumer Panel. This data set consists of daily, product-level expenditure data for a panel of 40,000 to 60,000 households each year from 2004 to 2016.[10] After a shopping trip, panelists

[8] Although all stores report price and volume data for a seven-day period, this period need not end on a Saturday; for example, stores may submit data that aligns with their promotion week instead. Rather than including the exact dates used by each retailer, Nielsen assigns the data to the "best fit Saturday," that is, the Saturday that most closely matches the promotion week. Because no information is provided on the actual date range for the weekly data by retailer, we use the given week-ending data.

[9] To illustrate, consider a month in which the 2nd day of the month is a Saturday. For the week that includes the 1st of the month, Nielsen reports a price of $1, and for the following week (the 2nd through the 8th), Nielsen reports a price of $2. We would calculate the price of this product in the first calendar week of the month as $\$1.00\,\frac{1}{7} + \$2.00\frac{6}{7} \approx \$1.86$.

[10] Participants are recruited through the mail and internet and the sample is designed to be representative of households nationwide and within individual markets throughout the U.S.

use in-home optical scanners to create a record for each product purchased, entering units purchased, price per unit, and any coupons or discounts.[11]

We incorporate data from the Consumer Panel in several ways. First, a number of our analyses rely on data about store location. Although the Retail Scanner Data include state and county identifiers for each store, they do not include location information at a finer level of geography. We address this issue by imputing store ZIP code using the Consumer Panel, which contains the ZIP code of residence for the households in the panel as well de-identified codes for the stores in which those households shop. For each store code included in both the Retail Scanner Data and the Consumer Panel, we assign the store a ZIP code equal to the most frequent ZIP code of residence of its shoppers. We restrict our analysis to the 95% of stores in the Retail Scanner Data for which this method yields a ZIP code. We use the store's ZIP code to merge in data from the American Communities Survey on the average share of households per ZIP code that participated in SNAP during 2008-2012.

Second, we use the Consumer Panel to obtain data on the share of SNAP-eligible shoppers by store and week. We impute SNAP eligibility from household income and family size by applying the federal gross income test.[12] Household income is reported with a two-year lag in the Consumer Panel (i.e., households are asked about their income two years before the panel year). Therefore, we reassign households to their income reported two years in the future. Doing so excludes households that do not participate for two consecutive years after the year in which their shopping is reported. We weight SNAP eligibility across shoppers by total spent per shopping trip, though unweighted estimates produce similar results.

Third, we construct an index to reflect the average price faced by SNAP customers in a given store and week. To do so, we create expenditure shares by product for SNAP-eligible households from the Consumer Panel by summing expenditures for a given SNAP-eligible product across households and dates, and then scaling the sum by the total food

[11]For stores that appear in the Nielsen Retail Scanner data, Nielsen automatically enters prices from the Retail Scanner Data.

[12]We cannot apply the SNAP asset test because the Consumer Panel does not report data on household assets.

expenditure for all SNAP-eligible products over this period.[13] We denote the expenditure share for product k as ω_k. We normalize the expenditure shares to sum to one in a given store-month, and denote the normalized expenditure shares by $\widetilde{\omega}_{ksmy}$ for store s, calendar month m, and year y.

Following Hastings and Washington (2010), we construct an expenditure-weighted index of log prices for each store-week using the following equation:

$$log(P_{swmy}) = \sum_k \widetilde{\omega}_{ksmy} \log(p_{kswmy}) \tag{1}$$

where p_{kswmy} denotes the unit price for product k sold in store s in calendar week w, calendar month m, and year y. Finally, we construct a corresponding measure of expenditures for purchases of SNAP-eligible products in a given store and week. The measure is defined as the log of weighted expenditures in the store-week, where the weights are identical to those used to construct the price index, described above; as a result, the index attaches higher weight to products that are more likely to be purchased by SNAP-eligible households.[14]

4 SNAP Issuance and Shopping Behavior

Our goal in this section is to isolate the causal effect of SNAP issuance on intra-month patterns in consumer behavior. The main empirical challenge we face is that differences in behavior over the course of the month could also be driven by factors unrelated to SNAP, such as the timing of paychecks, utility bills, or the issuance of other benefits. Our empirical strategy addresses this concern by exploiting cross-sectional variation in issuance timing across states as well as changes in state policy over time.

We first investigate the effect of SNAP issuance policy on the timing of expenditures

[13] By construction, the expenditure weights are constant over time to avoid conflating changes in product prices with compositional changes in the basket of products.

[14] Without weighting, fluctuations in sales driven by low-SNAP expenditure products (for which we would not predict a change in our SNAP-expenditure price index) are indistinguishable from fluctuations in high-SNAP expenditure products (for which we might expect a change in prices). However, if all customers are SNAP participants, then we may be overstating increases in sales (by "double weighting" high SNAP expenditure share products). As a robustness check, we also look at changes in sales at the product-level among the top 10 products by SNAP share.

within the month. Second, we investigate how SNAP issuance affects the composition of customers within stores over the course of the month. Third, we explore the relationship between SNAP issuance and intra-month variation in the price elasticity of demand.

4.1 Expenditures

We begin by examining weekly sales in state-years that differ in their benefit issuance schedule. To do so, we use the following econometric model, which we estimate separately for states with five different SNAP issuance policies: (1) all benefits issued on the first day of the month, (2) all benefits issued in the first week of the month, (3) all benefits issued in the second week of the month, (4) benefit issuance staggered across the first two weeks of the month, and (5) benefit issuance staggered across the first three or more weeks of the month. The model takes the following form:

$$\log Y_{swmy} = \alpha + \sum_{w=2}^{4} \beta_w \, week_w + \delta_{smy} + \varepsilon_{swmy} \tag{2}$$

where $\log Y_{swmy}$ is our weighted measure of log expenditures in a store-week, $week_w$ indicates the week of the month for $w \in \{2, 3, 4\}$, and δ_{smy} are store-by-month-by-year fixed effects. In this regression, β_w measures the change in food expenditure within a store between the first week of the calendar month (the omitted category) and the wth week of the calendar month. In this and in subsequent regressions, we cluster standard errors at the state level. All regressions are volume-weighted at the store level based on average annual food sales.

Table 2 presents results from these analyses. Column 1 displays results for stores in states that issue all benefits in the first day of the month. We find that total food expenditures are between 6 and 8 percent higher in the first week of the calendar month relative to other weeks in the month. These results are similar for stores in states that issue all benefits within the first week of the month (Column 2). While these results are consistent with SNAP issuance causing an increase in food expenditure in the week of SNAP issuance, it is possible that the cyclicality in expenditures is instead attributable to calendar month patterns in income receipt of expenditure that are unrelated to the SNAP program, such as timing of rent payments or other bills, paycheck receipt (Stephens Jr. 2006), or receipt of other monthly benefit programs such as TANF or Social Security (Stephens Jr. 2003; Mastrobuoni and Weinberg 2009).

To determine if this intra-month cyclicality in food demand is a result of SNAP issuance, we compare our results from stores in states that issue all benefits in the first week of the month to states with different issuance staggering policies. For example, food sales in stores in the two states that issue all benefits in the second week of the month (Column 3) are between three and four percent higher in weeks 2 and 3 the first two weeks of benefit receipt than in weeks 1 and 4, though these differences are not statistically significant. Column 4, which includes states that stagger issuance over the first two weeks of the month, shows that while food sales are still highest in week 1, the decline in sales from week 1 to week 2 is less than half as large as in states that issue all benefits in the first week.[15] In states that stagger issuance across the first three to four weeks of the month (column 5), food sales are only 2 to 3 percent higher in the first week of the month and these differences are not statistically significant. Taken together, these results suggest that at least part of the intra-month cyclicality in food expenditure is driven by the SNAP program.

To capture the variation in issuance policy within a single regression, we also consider the following specification:

$$\log Y_{swmy} = \alpha + \sum_{w=2}^{4} \beta_w \, week_w + \gamma \, Issue_{swmy} + \delta_{smy} + \varepsilon_{swmy} \tag{3}$$

where $Issue_{swmy}$ is the share of SNAP benefits issued in calendar week w in the state in which store s is located.[16] In this regression, γ represents the percent increase in expenditures

[15] The decrease in week 2 may also be due to the fact that many of the states that fall into this category issue benefits from the 1st through 10th of the month, so issuance is more concentrated in the 1st week than the 2nd.

[16] To illustrate, if store s is located in a state that distributes all benefits on the 1st of the month, $Issue_{s1my} = 1$ and $Issue_{swmy} = 0$ for $w \in \{2,3,4\}$. Alternatively, if the state distributes its benefits evenly from the 1st through the 15th of the month, $Issue_{swmy} = \frac{7}{15}$ for $w \in \{1,2\}$, $Issue_{swmy} = \frac{1}{15}$ for $w = 3$, and $Issue_{swmy} = 0$ for $w = 4$.

for weeks in which 100 percent of SNAP benefits are issued relative to weeks in which no benefits are issued. The β_w coefficients represent intra-month cyclicality that is unrelated to SNAP issuance.[17] The results from this regression are reported in Column 6 of Table 2, and suggest that if 100 percent of a state's SNAP benefits are issued in a given week, expenditure is 5.5 percent higher than in weeks in which no SNAP benefits are issued.[18]

If the expenditure cyclicality we observe is driven by SNAP, we would expect it to be more extreme in stores that serve a larger SNAP population. Figure 1 assesses this prediction by estimating Equation (3) separately for sub-samples of stores based on the share of households participating in SNAP in the store's ZIP code. In ZIP codes in which fewer than 5% of households participate in SNAP, there is a small amount of cyclicality: expenditures are 1.7 percent higher in weeks with 100 percent of SNAP benefits are issued relative to weeks with no issuance. By comparison, this estimate grows monotonically with local SNAP prevalence, increasing to 29 percent for stores located in ZIP codes in which over 35 percent of households receive SNAP.

In our main specification, identification of the effect of the SNAP issuance schedule comes from variation across states in issuance policy as well as within-state issuance policy changes over time. One potential source of bias is if changes in policy over time are correlated with secular changes in cyclicality over our sample period. Separately, cross-sectional policy variation between stores may be correlated with other factors that shape a store's cyclicality, unrelated to SNAP issuance. To address these possibilities we consider a robustness check on our identification strategy which incorporates month-by-year-by-week and store-by-week fixed effects. Including these fixed effects implements a difference-in-difference analysis, in which identification comes from policy changes within a state over time. A benefit of this approach is that it avoids the identification threats described above; a downside is that with

[17] To the extent that the timing of SNAP issuance affects purchases in weeks other than the week of issuance, these effects may be reflected in the β_w terms.

[18] In principle, this increase in sales could reflect a supply-side shock that causes a change in the prices that customers face, rather than a shift in customers' demand curve. We investigate (and present evidence against) this explanation in Section 5.

only 12 policy changes during our sample period (largely concentrated during the final three years), the effect it identifies is not nationally representative.

Appendix Table A.2 presents the results from the difference-in-differences specification. For the full sample, the point estimate falls from 0.05 in our main specification in Table 1, Column 6, to 0.04 in the difference-in-differences analysis (Column 1). This difference may stem from avoiding some spurious cross-sectional correlation, or could result from the fact that identification is coming from a different sample of states than in the main specification (only the states that change their policy during our sample period). Columns 2 and 3 estimate the difference-in-difference specification separately by low- and high-SNAP stores.[19] Notably, the results suggest that the observed expenditure cyclicality is driven exclusively by high-SNAP stores.

4.2 Shopper Composition

We next study how the composition of customers shopping in a given store changes over the course of the month as a function of SNAP issuance timing. We use data from the Consumer Panel to estimate how SNAP affects intra-month cyclicality in the share of SNAP-eligible customers shopping at a store during a given week of the month. Doing so allows us to investigate whether the expenditure cyclicality observed in the previous section appears to be driven by SNAP customers as opposed to other shoppers.

To study variation in customer composition over the course of the month, we estimate the regression model in Equation (3) where the outcome is an expenditure-weighted average of a customer's SNAP eligibility averaged across shopping trips in a given store-week.[20] Table 3 presents the results for the full sample of stores as well as for high- and low-SNAP stores. In weeks in which 100% of SNAP benefits are issued, the proportion of SNAP-eligible customers increases by 0.5 percentage points in our full sample, or 11% of the sample mean (Column

[19] We define low-SNAP stores as stores located in ZIP codes with a SNAP participation rate less than 5%; high-SNAP stores are those located in ZIP codes with SNAP participation of 20% or higher.

[20] Since we are aggregating over trips rather than shoppers, customers are counted twice if they shop at the same store twice in the same week.

1) and 1.7 percentage points among high-SNAP stores, or 23% of the sample mean (Column 3). We observe a change in the share of SNAP-eligible customers in low-SNAP stores that is near zero and not statistically significant (Column 2), consistent with the demographic characteristics of their neighborhoods.

The characteristics that determine SNAP eligibility – income and family structure – may correlate with a household's price elasticity of demand (DellaVigna and Gentzkow 2019). Therefore, if the SNAP benefit issuance schedule causes changes in the composition of SNAP-eligible customers, it may be profit-maximizing for stores to charge different prices in different weeks. We investigate this possibility more directly in the following sub-section.

4.3 Shopper Demand Elasticities

Thus far we have documented that SNAP issuance is associated with large increases in the level of demand as well as changes in the composition of shoppers in the weeks of issuance. To assess how these changes in behavior affect how stores adjust their prices, this sub-section investigates how SNAP issuance affects the price-elasticity of demand that retailers face. For example, the type of customers who shop following SNAP issuance may have higher or lower elasticities than other customers who shop during the rest of the month. In addition, households spending their SNAP benefits may exhibit a different price sensitivity compared to other weeks in the month when they shop using cash.[21]

To estimate how SNAP issuance affects the price-elasticity of demand faced by grocery stores over the course of the month, we begin by estimating

$$\begin{aligned} log(q_{kswmy}) = \beta_0 + \beta_1\, Issue_{swmy} * log(P_{kswmy}) + \beta_2 Issue_{swmy} + \beta_3 log(P_{kswmy}) \\ + \sum_{w=2}^{4}\{\gamma_w\, week_w + \eta_w\, week_w * log(P_{kswmy})\} + \delta_{ksmy} + \varepsilon_{kswmy} \end{aligned} \tag{4}$$

[21]There are a number of reasons that SNAP households may exhibit different price sensitivity when shopping with SNAP benefits. For example, they may put SNAP benefits in a distinct mental category than cash (Hastings and Shapiro 2018). Alternatively, if there are fixed costs of traveling to a particular store, households may prioritize cheaper stores on their bigger trips. Finally, the intensity of financial sources of stress may vary along with the SNAP benefit cycle, which could affect decision-making and purchasing behavior (Mullainathan and Shafir 2013).

in which $log(q_{kswmy})$ is the log of units of product k purchased in store s in week w of month m and year y, and the log per-unit price is denoted by $log(p_{kswmy})$. Because the outcome is quantity, we conduct this analysis at the individual product-level.[22] For computational feasibility, we restrict the analysis to 10 products frequently purchased by SNAP households. To choose these products, we first select the top 10 product groups by SNAP household expenditure share and then select the top UPC by SNAP expenditure share from each group.[23] Collectively, these products account for approximately 1% of total SNAP household food expenditures.

The main parameter of interest is β_1, which measures the change in demand elasticity between a week in which 100% of SNAP benefits are issued and one in which no benefits are issued. Equation (4) also includes product-store-month-year fixed effects, δ_{usmy}, which capture store-specific fluctuations in product demand over time, as well as calendar-week fixed effects, γ_w, which capture monthly demand cyclicality unrelated to SNAP issuance. Importantly, the η_w terms capture within-month variation in price elasticity that is due to factors other than SNAP issuance. Of course, a regression of quantity on price may fail to recover the true elasticity estimates if there are issues of reverse causality – i.e., within-month demand shocks could induce stores to adjust prices. To address this possibility, we follow DellaVigna and Gentzkow (2019) and instrument for the price of a product in a store using the price of the product at stores within the same chain but located in other regions (technically, "Designated Market Areas"). Under the assumption that local demand shocks for a store do not affect chain-level pricing decisions (conditional on the other controls included in Equation (4)), this analysis identifies the causal effect of a product's price on the quantity that consumers demand. As in DellaVigna and Gentzkow (2019), we estimate the

[22]It is necessary to estimate the equation above at the product level, rather than summing quantity across products, because size units vary across products (e.g., grams vs. fluid ounces).

[23]The 10 product groups we consider are: Soda, Bread and Baked Goods, Packaged Meat, Cheese, Snacks, Frozen Foods, Juice, Cereal, Milk and Fresh Produce. Because milk and fresh produce are largely distributed under generic labels, meaning that they are sold by a limited number of retailers, we exclude these product groups from the UPC-level analysis. We instead select the top UPC from two other product groups, Yogurt and Orange Juice, which are also perishable but are more commonly distributed by national brands.

first-stage effect of the instrument on prices to be close to 1 (see Appendix Table A.3).

Columns 1 and 3 of Table 4 present the OLS results from Equation (4), for all stores and for high-SNAP stores, respectively. Our estimates indicate that in 100% issuance weeks, demand elasticity declines by 0.026 (all stores) and 0.044 (high-SNAP stores). These results imply that average shopper price sensitivity is higher in weeks in which a greater share of SNAP benefits are issued. Columns 2 and 4 present the IV results. The estimated change in elasticity for the full sample is somewhat smaller (a decrease of 0.019), but still statistically significant and larger in magnitude when considering only high-SNAP stores (a decrease of 0.029).

To benchmark the price response one might expect from the SNAP-induced fluctuations in the price-elasticity of demand, we draw on a simple model of grocer pricing. Following Ellickson, Houghton, and Timmins (2013) and Ellickson (2006), the model assumes grocery stores act as monopolists over local consumers. We describe the model in Appendix A, and show that it implies that the price of a product evolves over the course of the month in response to changes in its aggregate price elasticity of demand. Imposing the elasticity estimates in Column 1 of Table 4, the model implies that, across all stores, prices should be approximately 0.6% lower in weeks in which all SNAP benefits are issued as compared to weeks in which no benefits are issued. For high-SNAP stores, we estimate that this reduction should be slightly larger – approximately 0.9%. When the elasticity estimates from the IV specification are used instead, the implied price change is a reduction of 0.4% in the full sample and 0.5% in high-SNAP stores.

Thus, our results suggest that SNAP issuance schedules should lead to modest price reductions by groceries in the weeks in which benefits are issued. The next section evaluates this prediction empirically.

5 SNAP Issuance and Retail Prices

The previous section provides evidence that SNAP issuance schedules cause retailers to face predictable monthly fluctuations in customer shopping behavior, especially in states with compressed benefit issuance schedules and in locations where SNAP participants comprise a large portion of customers. As a result, retailers may strategically vary prices over the course of the month to maximize profits. This section empirically estimates retailer response to these SNAP-induced demand fluctuations.

5.1 Results

Using the price index described in Equation (1), we estimate a similar specification as described in Equation (3) to identify the effect of SNAP issuance on retail prices. Column 1 of Table 5 presents these results for the full sample. Though prices appear to be slightly lower in the first week of the month than in subsequent weeks, that pattern appears unrelated to SNAP issuance; the estimated coefficient on $Issue$ implies that if 100 percent of a state's SNAP benefits were issued in one week, prices in that week would be 0.08% higher than if no SNAP benefits were issued in that week. In contrast to the predictions emerging from the elasticity analysis that stores should *lower* prices in the weeks following SNAP issuance, the 95% confidence interval rules out price changes outside 0.0% to 0.2% – i.e., any price reduction.

Columns 2 and 3 of Table 5 present the results of this analysis separately for low- and high-SNAP stores. We find that the effect of issuance policy on prices is very similar to that for the full sample. Even for stores with local SNAP participation of at least 20 percent – the group for which we observed the largest effect of SNAP issuance on customer behavior – the estimated coefficient is only 0.0015, with a 95% confidence interval of 0.0% to 0.3%. Figure 2, which replicates Figure 1 but for prices rather than expenditures, shows that the estimated coefficient on $Issue$ grows somewhat monotonically as local SNAP participation increases, but in all cases its magnitude remains close to zero. Overall, our results suggest that stores do not change their prices in response to the SNAP issuance schedule to an economically significant degree, even in markets in which SNAP issuance dramatically shapes customer shopping behavior.

We next consider several additional specifications to check the robustness of our main pricing results. First, we replicate the difference-in-differences specification in Section 4.1 with prices as the outcome to ensure that our estimated effect of SNAP on prices is not conflated with non-SNAP intra-month pricing variation across stores. Doing so yields slightly larger but qualitatively similar results as our main specification (see Appendix Table A.4).

A second concern is that our price index which creates one weekly price per store weighted by purchases of SNAP-eligible households may mask differences in price response by product. For example, retailers may only strategically price products that are in high demand among SNAP recipients or products that see the highest SNAP-induced intra-month cyclicality in demand. To shed light on this possibility, we replicate our results for the top 10 product groups by SNAP expenditure share (e.g., "cheese", "bread"), separately, in Appendix Table A.5.[24] We normalize the expenditure shares within the product group so that each product group price index represents the average price a SNAP recipient faces, conditional on shopping within that product group.

Whereas we observe that SNAP-induced cyclicality in sales varies greatly across product groups, there is relatively little effect on prices; the largest effect we observe has a 95% confidence interval of 0.1% to 0.5%. In addition, we do not find that the products with the highest cyclicality in demand consistently show the largest magnitude price responses. Appendix Table A.6 replicates this analysis at the individual product (UPC) level using the same 10 products as in Table 4, and obtains similar results.

Finally, retailers may differ from one another in the extent to which they adjust their prices in response to SNAP-induced cyclicality. For example, some retailers may increase

[24]These ten groups are Prepared Foods - Frozen, Carbonated Beverages, Milk, Bread and Baked Goods, Packaged Meat - Deli, Cheese, Ice Cream, Novelties - Frozen Food, Fresh Produce, Juice, Drinks - Canned, Bottled, and Snacks. Together, these products cover 26% of SNAP household food spending.

prices in periods of high SNAP-induced demand, such as observed in Hastings and Washington (2010), while others may adopt a loss-leader model (Chevalier, Kashyap, and Rossi 2003). To assess this possibility, we estimate Equation (3) separately for each of the 60 parent companies in our data. Figure 3 presents a histogram of the estimated retailer-specific treatment effects. We find that across retailers, most effects are clustered around zero.

5.2 Mechanisms

The elasticity results reported in Section 4.3 suggest profit-maximizing retailers would reduce prices in the weeks following SNAP issuance. Instead, we find very small but precisely-estimated *positive* effects of SNAP issuance on prices. This sub-section considers several mechanisms that might play a role in explaining these results.

First, recent research suggests it may be costly for retail chains to set different prices across outlets because of advertising or managerial decision-making costs (DellaVigna and Gentzkow 2017; Bloom and Van Reenen 2007). Such costs might deter stores from setting prices in response to predictable variation in SNAP-induced demand if pricing decisions are made at a level that spans multiple SNAP-issuance policies. To the extent this mechanism is what prevents stores from varying their prices in response to SNAP issuance, we would expect to see larger price effects for stores whose entire chain is located within a state or set of states that share a SNAP issuance schedule. We investigate this possibility in Table 6. Column 1 restricts our sample to chains in which all stores are in the same state while Column 2 expands the sample to include chains for which all stores are in states that share the same SNAP schedule. With this restriction, the 95% confidence interval is still positive and small in magnitude, ranging from 0.0% to 0.6%. Column 3 estimates an alternative specification in which we use the full sample and assign to chains the policy in the state in which the greatest share of their outlets are located; the estimated coefficients are qualitatively similar to those in the full sample.

Second, there are multiple potential explanations for our finding that stores do not substantially adjust prices in response to intra-month fluctuations in the elasticity of demand.

This (non-)response may be due to stores failing to optimize their pricing due to neoclassical transaction costs or behavioral frictions. Alternatively, it may simply reflect the fact the magnitude of the implied optimal price variation is relatively small; recall that the back-of-the-envelope calculation described above implies that the optimal price change is only about 0.5%. To distinguish these possibilities, Figure 4 plots the estimated SNAP-induced monthly optimal price change (derived from the estimated elasticity cyclicality) against estimated SNAP-induced price cyclicality for the ten products included in Table 4. Although some products are associated with relatively large within-month fluctuations in demand elasticity – for which the profit gains from price adjustments would be largest – the pricing effects for those products do not appear larger than for products associated with smaller demand elasticity cyclicality. This analysis thus provides suggestive evidence in favor of the explanation involving a failure to optimize.

Finally, one might expect the intra-monthly pricing incentives faced by firms to be most pronounced for stores located in competitive markets, where the presence of competitors could translate into larger-magnitude elasticities. To study this possibility, we estimate the intra-month elasticity and pricing cyclically separately for stores located in areas with relatively high versus low degrees of market concentration. To measure market concentration, we construct an indicator for whether there is at least one other Nielsen grocery store in a given ZIP code and year. Because grocery store prevalence (and hence, market concentration) may be correlated with local SNAP participation (Powell et al. 2007), we report our results separately for high- and low-SNAP stores. Table 7 presents the results. The results are quite similar for stores located in high and low concentration areas. However, even for stores in high-SNAP and high market concentration areas, the estimated coefficient on $Issue$ is quite small in magnitude, with a 95% confidence interval of 0.0% to 0.3%.

6 Conclusion

In this paper we study intra-month patterns in customer demand and retail pricing driven by SNAP issuance. We find that SNAP issuance causes large increases in food sales, as well as more moderate changes in the share of SNAP-eligible shoppers and the price-elasticity of demand that retailers face. Drawing on a simple model of retailer behavior, we use the estimated elasticities to calculate that profit-maximizing retailers should modestly reduce prices in weeks of SNAP issuance. However, when we investigate this question empirically, we find that the SNAP-induced changes in demand are associated with very small but statistically significant positive effects on prices.

Although the SNAP-induced price increases we observe are quite small, our results suggest two potential paths for policymakers concerned about shifting the incidence of SNAP benefits to stay with the intended beneficiaries. First, staggering benefits issuance evenly throughout the month should entirely eliminate the intra-month changes in aggregate demand faced by retailers, and therefore presumably the pricing cyclicality we observe.[25] Second, if retailers' failure to adjust prices throughout the month in response to SNAP-induced variation in demand represents a mistake, then policies that de-bias retailers so that they begin accounting for those changes in demand represent an opportunity to shape the incidence of the benefit. In particular, the intra-month cycles in elasticity we estimate suggest that retailers should lower prices in SNAP weeks to reflect the higher price-elasticity of demand that customers in those weeks exhibit. If policymakers could induce retailers to behave in this way, it would not only raise retailer profits, but would also make SNAP participants better off by increasing the purchasing power of their benefits during the weeks in which they are most likely to be spent.

[25] An added benefit of staggering issuance is that the policy would smooth demand throughout the month which would reduce complications associated with the surges in customer traffic we estimate, such as long lines or difficulty stocking shelves or staffing stores.

Appendix: Optimal Pricing Model

To assess the implications of the monthly variation in demand behavior we estimate for optimal pricing, we use a simple model of retailer and consumer behavior similar to the one described in DellaVigna and Gentzkow 2019. Specifically, we assume retailers are monopolistically competitive. Consumer demand for product j in week w is described by $Q_{jw} = k_j \, (P_{jw})^{\eta_{jw}}$, where Q_{jw} is the units of product j that are sold in week w, k_j is a product-specific scale term, and η_{jw} is the retailer's price elasticity for product j in week w, $\eta_{jw} = \frac{\partial Q_{jw}}{\partial P_{jw}} \frac{P_{jw}}{Q_{jw}}$. Stores face product-specific marginal costs c_j and fixed costs C_j, which do not vary by week. The retailer chooses prices to maximize:

$$\max_{\{P_{jw}\}} \Sigma_j (P_{jw} - c_j) \, Q_{jw}(P_{jw}) - \Sigma_j C_j \tag{5}$$

The first order conditions to this maximization problem imply $P_{jw} = c_j \frac{\eta_{jw}}{1 - \eta jw}$, or, taking logs, $\log P_{jw} = \log c_j + \log(\frac{\eta_{jw}}{1+\eta_{jw}})$. Hence, the percent change in the optimal price for product j between week w and week w' is approximately given by

$$\log P_{jw'} - \log P_{jw} = \log(\frac{\eta_{jw'}}{1 + \eta_{jw'}}) - \log(\frac{\eta_{jw}}{1 + \eta_{jw}}) \tag{6}$$

Substituting the estimated coefficients from Table 4 into Equation 6 yields our predicted optimal price change between weeks in which all SNAP benefits are issued and weeks in which no benefits are issued. For example, using the IV specification for high-SNAP stores (Column 4), we estimate an average price elasticity of -3.07 for weeks in which no benefits are issued and an average price elasticity of -3.10 for weeks in which all benefits are issued. Substituting these estimates into Equation 6 yields an implied optimal price change between weeks of approximately -0.5%.

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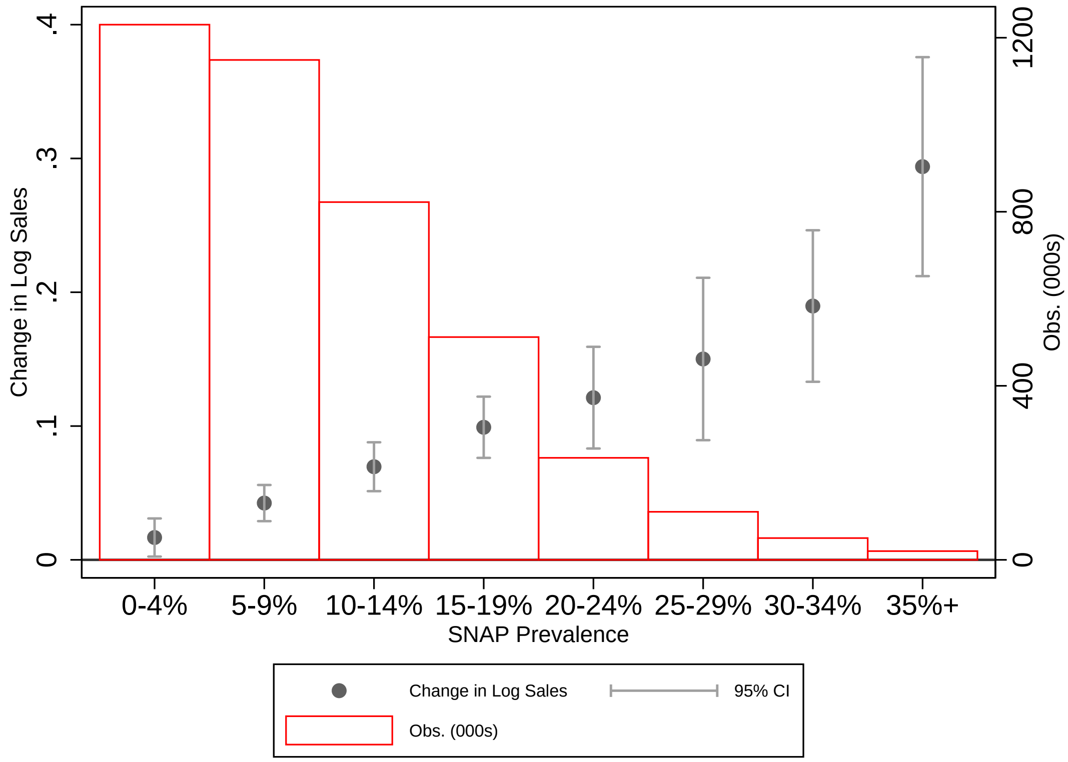
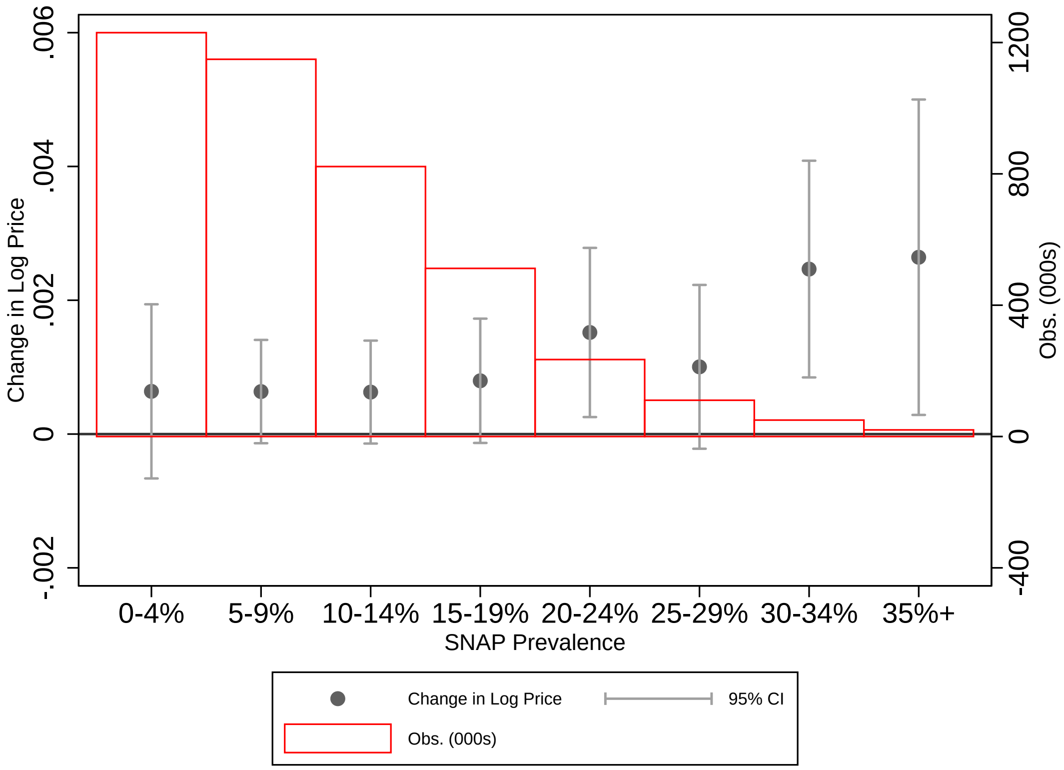
Figure 1: Issuance and Food Sales by Local SNAP Prevalence



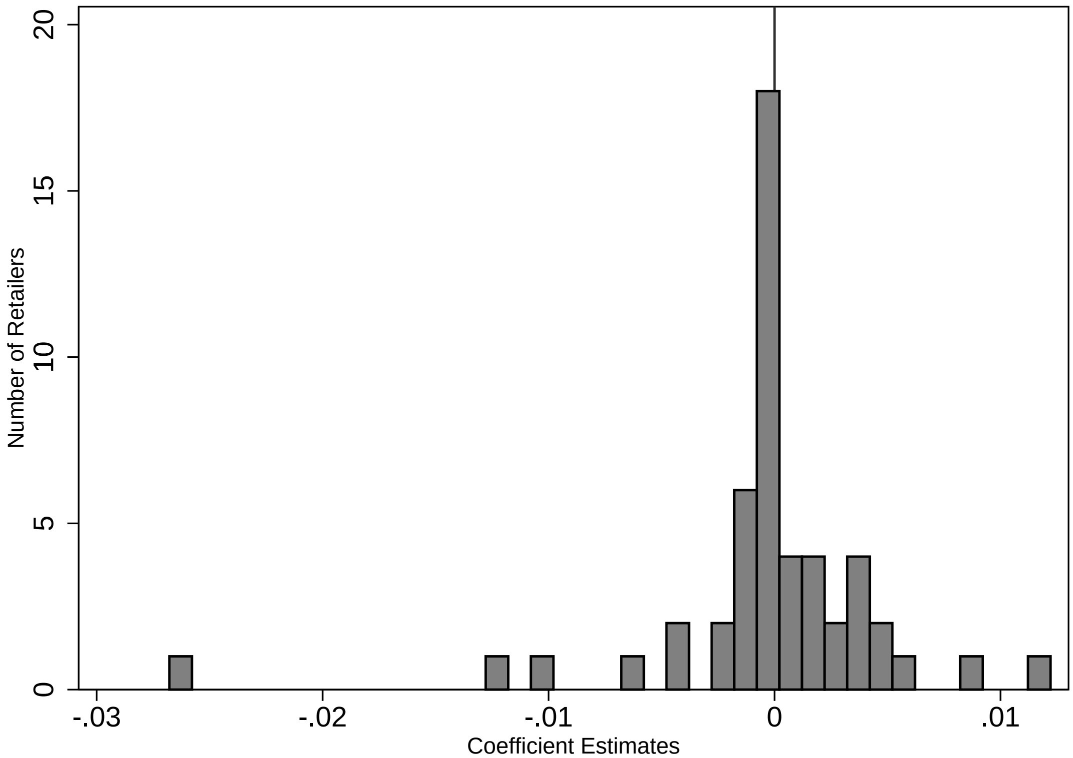
Notes: The data include information on all SNAP-eligible products purchased at grocery stores from the Nielsen Retail Scanner Dataset, 2006-2014. On the left axis, "Change in log sales" corresponds to the estimated coefficient on "Issue Share" from Equation (3), where the outcome is log sales. Bars represent the 95% confidence interval. Estimates of this regression are provided separately for the set of stores located in ZIP codes with SNAP prevalence of 0-4, 5-9, 10-14, 15-19, 20-24, 25-29, 30-34, and more than 35 percent, respectively. The right axis presents sample counts for each of these regressions.

Figure 2: Issuance and Food Prices, by Local SNAP Participation



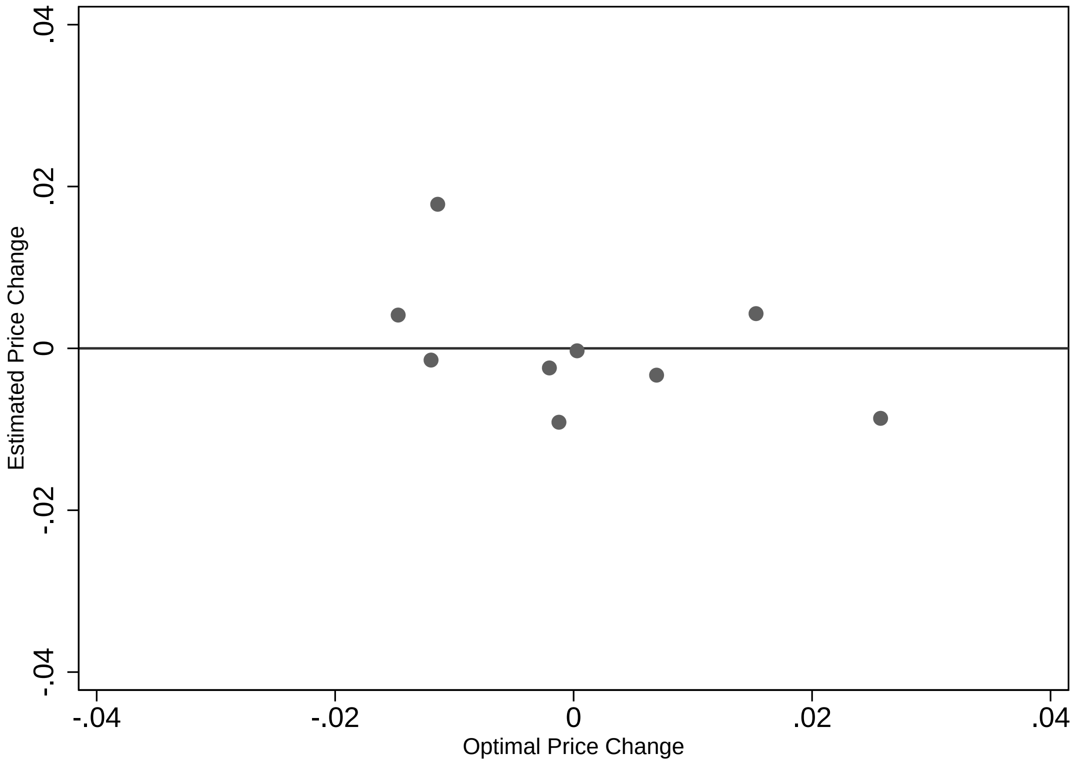
Notes: The data include information on all SNAP-eligible products purchased at grocery stores from the Nielsen Retail Scanner Dataset, 2006-2014. On the left axis, "Change in log price" corresponds to the estimated coefficient on "Issue Share" from Equation (3), where the outcome is log prices. Bars represent the 95% confidence interval. Estimates of this regression are provided separately for the set of stores located in ZIP codes with SNAP prevalence of 0-4, 5-9, 10-14, 15-19, 20-24, 25-29, 30-34, and more than 35 percent, respectively. The right axis presents sample counts for each of these regressions.

Figure 3: Issuance and Food Price Effects by Parent Company



Notes: The data include information on all SNAP-eligible products purchased at grocery stores from the Nielsen Retail Scanner Dataset, 2006-2014. The figure presents a histogram of the estimates of the coefficient on "Issue Share" from Equation (3), where the outcome is log prices. The equation is estimated separately for each parent company.

Figure 4: Estimated and Optimal Price Change by Product



Notes: The data include sales and prices at grocery stores from the Nielsen Retail Scanner Dataset, 2006-2014. Each point corresponds to a single product, as described in Section 3. The y-axis represents the coefficient on "Issue Share" from Equation (3), where the outcome is log prices. The x-axis presents the optimal price change for each product derived from the corresponding elasticity estimate, using the instrumental variable strategy described in Section 4.3.

Table 1: Issuance Policies by State

Issuance Policy	States
1st Day	ND, NV, **OK**, RI, VT
1st Week	CT, **ID**, **IL**, MT, NE, NH, NJ, **VA**, WY
2nd Week	ME, SD
Weeks 1 and 2	AR, AZ, CA, CO, **DE**, FL, **GA**, IA, **IN**, KS, KY, LA, MA, MD, **MI**, MN, **NC**, NY, **OH** ,**OK**, OR, PA, **SC**, **TN**, TX, UT, **VA**, WA, WI, WV
Weeks 1-3+ (spread)	**AL**, **DE**, **GA**, **IL**, **IN**, **MI**, MO, MS, **NC**, NM, **OH**, **SC**, **TN**

Source: USDA Food and Nutrition Services and Food Marketing Institute. Bolded states change their issuance schedule during 2006-2014, and may appear twice as a result. Hawaii and Alaska are excluded, as they are not covered in the Nielsen Retail Scanner Data. Please see Appendix Table A.1 for full detail on these issuance schedules.

Table 2: Food Sale Cyclicality by Issuance Policy

	(1)	(2)	(3)	(4)	(5)	(6)
Issuance Policy	1st Day	1st Week	2nd Week	Weeks 1-2	Weeks 1-3+	All States
Issue Share						0.0545***
						(0.0093)
Week 2	-0.0706***	-0.0630***	0.0342	-0.0297***	-0.0299	-0.0182***
	(0.0100)	(0.0066)	(0.0178)	(0.0062)	(0.0175)	(0.0056)
Week 3	-0.0805***	-0.0668***	0.0395	-0.0420***	-0.0223	-0.0111
	(0.0031)	(0.0081)	(0.0137)	(0.0081)	(0.0241)	(0.0090)
Week 4	-0.0602***	-0.0439***	0.0044	-0.0411***	-0.0138	-0.0049
	(0.0070)	(0.0115)	(0.0039)	(0.0067)	(0.0126)	(0.0071)
N	338,522	554,756	40,258	3,123,158	427,463	4,145,635

Notes: The data include information on all SNAP-eligible products purchased at grocery stores from the Nielsen Retail Scanner Dataset, 2006-2014. Each observation corresponds to a store-week. The outcome is log sales, aggregated across products using the index described in Section 3. Columns 1-5 present results from Equation (2) separately for stores in states that issue all benefits on the first day of the month, within the first week, within the second week, within the first two weeks, and across three or more weeks, respectively. Column 6 presents results from Equation (3). $Week2-4$ are indicators for sales observed in calendar weeks 2-4, respectively. "Issue Share" refers to the share of SNAP benefits issued in a given week in the state in which the store is located. Regressions are weighted at the store level by average annual food sales. Standard errors are clustered at the state level. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$.

Table 3: Issuance and the Share of SNAP-Eligible Customers

	(1)	(2)	(3)
Issue Share	0.4508***	-0.0033	1.7192***
	(0.1223)	(0.0807)	(0.4823)
Week 2	0.1274**	-0.0080	0.4328**
	(0.0564)	(0.0537)	(0.1972)
Week 3	-0.0239	-0.1385**	0.3401
	(0.0759)	(0.0642)	(0.2911)
Week 4	-0.2507***	-0.2019***	-0.2387
	(0.0768)	(0.0593)	(0.2901)
N	4,546,692	1,229,128	453,976
Mean, Dep. Var.	4.1756	2.4851	7.5224
ZIP Codes	All	Low SNAP	High SNAP

Notes: The data include shopping trips at grocery stores in the Nielsen Consumer Panel Dataset, 2004-2014. The outcome represents the average share of SNAP-eligible shoppers (estimated based on family structure and household income) weighted by total expenditures per trip. Units are percentage points (0-100). Each observation corresponds to a store-week. Each column represents a separate regression estimating Equation (3) for a different subsample: all stores (Column 1), "Low SNAP" stores located in ZIP codes in which $< 5\%$ of households participate in SNAP (Column 2), and "High SNAP" stores located in ZIP codes in which $\geq 20\%$ of households participate in SNAP (Column 3). "Issue Share" refers to the share of SNAP benefits issued in a given week in the state in which the store is located. $Week2-4$ are indicators for sales observed in calendar weeks 2-4, respectively. Regressions are weighted by total expenditures per cell. Standard errors are clustered at the state level. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$.

Table 4: Issuance and Customer Demand Elasticity

	(1)	(2)	(3)	(4)
Log(Price) x Issue Share	-0.0262***	-0.0190**	-0.0441**	-0.0291***
	(0.0071)	(0.0080)	(0.0164)	(0.0107)
Log(Price)	-2.6477***	-2.8737***	-2.7367***	-3.0742***
	(0.0649)	(0.0705)	(0.0936)	(0.0626)
Issue Share	0.0870***	0.0858***	0.1887***	0.1789***
	(0.0083)	(0.0081)	(0.0312)	(0.0269)
N	32,384,012	29,961,172	3,112,244	2,998,049
ZIP Codes	All	All	High SNAP	High SNAP
Specification	OLS	IV	OLS	IV

Notes: The data include sales and prices at grocery stores from the Nielsen Retail Scanner Dataset, 2006-2014 for the 10 products described in Section 3. Each observation corresponds to a store-week. Each column corresponds to a separate regression estimating Equation 4 (Columns (1) and (3)) or the corresponding IV strategy outlined in Section 4.3 (Columns (2) and (4)). The outcome is log units sold per product. "Log(Price)" is the log of price per unit. "Issue Share" refers to the share of SNAP benefits issued in a given week in the state in which the store is located. "High SNAP" stores are located in ZIP codes in which $\geq$ 20% of households participate in SNAP. Regressions are weighted at the store level by average annual food sales. Standard errors are clustered at the state level. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$.

Table 5: Issuance and Food Prices

	(1)	(2)	(3)
Issue Share	0.0008^{+}	0.0006	0.0015^{**}
	(0.0004)	(0.0007)	(0.0006)
Week 2	0.0031^{***}	0.0030^{***}	0.0033^{***}
	(0.0003)	(0.0004)	(0.0004)
Week 3	0.0034^{***}	0.0029^{***}	0.0042^{***}
	(0.0005)	(0.0007)	(0.0007)
Week 4	0.0011^{***}	0.0008	0.0017^{**}
	(0.0004)	(0.0006)	(0.0007)
N	4,145,635	1,230,078	414,979
ZIP Codes	All	Low SNAP	High SNAP

Notes: The data include information on all SNAP-eligible products purchased at grocery stores from the Nielsen Retail Scanner Dataset, 2006-2014. Each observation corresponds to a store-week. The outcome is the expenditure-weighted index of log prices in Equation 1. Each column represents a separate regression estimating Equation (3) for a different subsample: all stores (Column 1), "Low SNAP" stores located in ZIP codes in which $< 5\%$ of households participate in SNAP (Column 2), and "High SNAP" stores located in ZIP codes in which $\geq 20\%$ of households participate in SNAP (Column 3). "Issue Share" refers to the share of SNAP benefits issued in a given week in the state in which the store is located. $Week2-4$ are indicators for sales observed in calendar weeks 2-4, respectively. Regressions are weighted at the store level by average annual food sales. Standard errors are clustered at the state level. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$.

Table 6: Issuance and Food Prices by Chain Type

	(1) One-State Chains	(2) One-Policy Chains	(3) Plurality Policy
Issue Share	0.0030**	0.0032+	
	(0.0014)	(0.0018)	
Issue Share, Modal Policy			0.0004
			(0.0004)
Week 2	0.0038***	0.0040***	0.0030***
	(0.0009)	(0.0009)	(0.0003)
Week 3	0.0043***	0.0046**	0.0032***
	(0.0015)	(0.0017)	(0.0005)
Week 4	0.0020	0.0022	0.0009**
	(0.0013)	(0.0015)	(0.0004)
N	544,514	582,340	4,145,635

Notes: The data include information on all SNAP-eligible products purchased at grocery stores from the Nielsen Retail Scanner Dataset, 2006-2014. Each observation corresponds to a store-week. The outcome is the expenditure-weighted index of log prices in Equation 1. Each column corresponds to a separate regression estimating Equation 3. Column 1 limits the sample to chains whose stores are all located within one state. Column 2 limits the sample to chains whose stores all face the same SNAP issuance policy. Column 3 redefines "Issue Share" in Equation 3 to be the share of SNAP benefits issued in a given week in the state in which the greatest share of the chains outlets are located. Regressions are weighted at the store level by average annual food sales. Standard errors are clustered at the state level. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$.

Table 7: Issuance and Food Prices by Market Concentration

	(1)	(2)	(3)	(4)
Issue Share	0.0007^{+}	0.0017^{**}	0.0008^{+}	0.0013^{**}
	(0.0004)	(0.0008)	(0.0005)	(0.0006)
Week 2	0.0031^{***}	0.0034^{***}	0.0032^{***}	0.0034^{***}
	(0.0003)	(0.0004)	(0.0003)	(0.0004)
Week 3	0.0033^{***}	0.0044^{***}	0.0034^{***}	0.0041^{***}
	(0.0005)	(0.0007)	(0.0005)	(0.0008)
Week 4	0.0011^{***}	0.0019^{**}	0.0012^{**}	0.0016^{**}
	(0.0004)	(0.0007)	(0.0005)	(0.0008)
N	2,478,813	200,253	1,666,822	232,111
ZIP Codes	All	High SNAP	All	High SNAP
Market Concentration	High	High	Low	Low

Notes: The data include information on all SNAP-eligible products purchased at grocery stores from the Nielsen Retail Scanner Dataset, 2006-2014. Each observation corresponds to a store-week. The outcome is the expenditure-weighted index of log prices in Equation 1. Each column corresponds to a separate regression estimating Equation 3 for a different subsample of the data based on market concentration and SNAP prevalence. The "Low Market Concentration" sample includes stores located in ZIP codes with no other grocery stores in the Nielsen data in the given year; "High Market Concentration" stores are located in ZIP codes with at least one other Nielsen grocery store. "High SNAP" stores are located in ZIP codes in which $\geq 20\%$ of households participate in SNAP. Regressions are weighted at the store level by average annual food sales. Standard errors are clustered at the state level. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$.

Table A.1: SNAP Benefit Issuance Schedule, 2004-2014

State	Change Date	Determinant	Schedule	Revised Schedule
AL	9/1/13	SSN	4 to 18	4 to 23
AZ		Last Name	1 to 13	
AR		SSN	4,5,8,9,10,11,12,13	
CA,NY,PA,WA		Case Number	1 to 10	
CO, KY		SSN	1 to 10	
CT		Last Name	1 to 3	
DE	3/1/13	Last Name	5 to 11	2 to 17
DC, IA, KS		Last Name	1 to 10	
FL,TX		Case Number	1 to 15	
GA	9/1/12	Case Number	5 to 14	5 to 23
ID	9/1/09	one day	1 to 5	1
IL	3/1/10	Case Number	1	1 to 23
IN	2/1/14	Last Name	1 to 10	5 to 23
LA		SSN	5 to 14	
ME		birthday	10 to 14	
MD		Last Name	6 to 15	
MA		SSN	1 to 14	
MI	1/1/11	Case Number/SSN	1 to 9	3 to 21
MN		Case Number	4 to 13	
MS		Case Number	5 to 19	
MO		Last Name	1 to 22	
MT		Case Number	2 to 6	
NC		7/1/11	SSN 3 to 12	3 to 21
ND,NV,RI,VT		one day	1	
NE		SSN	1 to 5	
NH		one day	5	
NJ		Case Number	1 to 5	
NM		SSN	1 to 20	
OH	2/28/14	Case Number	1 to 10	2 to 20
OK	4/1/11	Case Number	1	1,5,10
OR		SSN	1 to 9	
SC	9/1/12	Case Number	1 to 10	1 to 19
SD		one day	10	
TN	10/1/12	SSN	1 to 10	1 to 20
UT		Last Name	5,11,15	
VA	10/1/12	Case Number	1	1,4,7,9
WV		Last Name	1 to 9	
WI		SSN	2 to 15	
WY		Last Name	1 to 4	

Source: USDA Food and Nutrition Services and Food Marketing Institute.

Table A.2: Issuance and Food Sales, Difference-in-Differences Specification

	(1)	(2)	(3)
Issue Share	0.0403^{+}	-0.0006	0.1301^{***}
	(0.0215)	(0.0152)	(0.0322)
N	4,144,928	1,229,848	414,924
ZIP Codes	All	Low SNAP	High SNAP

Notes: The data include information on all SNAP-eligible products purchased at grocery stores from the Nielsen Retail Scanner Dataset, 2006-2014. Each observation corresponds to a store-week. The outcome is log sales, aggregated across products using the index described in Section 3. Each column implements a difference-in-difference analysis by estimating Equation (3) adding month-by-year-by-week and store-by-week fixed effects. Each column estimates this regression for a different subsample: all stores (Column 1), "Low SNAP" stores located in ZIP codes in which $< 5\%$ of households participate in SNAP (Column 2), and "High SNAP" stores located in ZIP codes in which $\geq 20\%$ of households participate in SNAP (Column 3). "Issue Share" refers to the share of SNAP benefits issued in a given week in the state in which the store is located. Regressions are weighted at the store level by average annual food sales. Standard errors are clustered at the state level. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$.

Table A.3: First Stage Results for Customer Demand Elasticity Instrument

	(1) Log(Price)	(2) Log(Price)
Predicted Log(Price)	0.9736***	0.9668***
	(0.0108)	(0.0111)
N	29,961,172	2,998,049
ZIP Codes	All	High SNAP

Notes: The data include sales and prices at grocery stores from the Nielsen Retail Scanner Dataset, 2006-2014 for the 10 products described in Section 3. Each observation corresponds to a store-week. This table reports coefficients from the first stage of the IV regressions reported in Columns (2) and (4) of Table 4. "Log(Price)" is the log of price per unit in the given store, while "Predicted Log(Price)" is the same outcome measured at stores within the same chain, but located in other Designated Market Areas. "High SNAP" stores are located in ZIP codes in which $\geq 20\%$ of households participate in SNAP. Regressions are weighted at the store level by average annual food sales. Standard errors are clustered at the state level. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$.

Table A.4: Issuance and Food Prices, Difference-in-Differences Specification

	(1)	(2)	(3)
Issue Share	0.0020***	0.0016**	0.0028***
	(0.0006)	(0.0008)	(0.0009)
N	4,144,928	1,229,848	414,924
ZIP Codes	All	Low SNAP	High SNAP

Notes: The data include information on all SNAP-eligible products purchased at grocery stores from the Nielsen Retail Scanner Dataset, 2006-2014. Each observation corresponds to a store-week. The outcome is the expenditure-weighted index of log prices in Equation 1. Each column implements a difference-in-difference analysis by estimating Equation (3) adding month-by-year-by-week and store-by-week fixed effects. Each column estimates this regression for a different subsample: all stores (Column 1), "Low SNAP" stores located in ZIP codes in which $< 5\%$ of households participate in SNAP (Column 2), and "High SNAP" stores located in ZIP codes in which $\geq 20\%$ of households participate in SNAP (Column 3). "Issue Share" refers to the share of SNAP benefits issued in a given week in the state in which the store is located. Regressions are weighted at the store level by average annual food sales. Standard errors are clustered at the state level. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$.

Table A.5: Sales and Price Effect by Product Group

	Panel A: Food Sales									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Soda	Bread/Bakery	Milk	Meat	Frzn Meals	Snacks	Cheese	Juice	Produce	Cereal
Issue Share	0.0540***	0.0400***	0.0191***	0.0686***	0.0914***	0.0664***	0.0596***	0.0467***	0.0390***	0.0632***
	(0.0129)	(0.0060)	(0.0034)	(0.0097)	(0.0115)	(0.0099)	(0.0125)	(0.0064)	(0.0063)	(0.0100)
	Panel B: Food Prices									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Soda	Bread/Bakery	Milk	Meat	Frzn Meals	Snacks	Cheese	Juice	Produce	Cereal
Issue Share	0.0012	0.0022**	0.0004	-0.0010	0.0024+	-0.0001	0.0028***	0.0012***	0.0011	-0.0002
	(0.0019)	(0.0009)	(0.0003)	(0.0015)	(0.0013)	(0.0008)	(0.0009)	(0.0004)	(0.0010)	(0.0011)
N	4,145,308	4,144,905	4,144,553	4,144,679	4,144,679	4,145,388	4,144,593	4,145,270	4,143,798	4,144,695

Notes: The data include information on all SNAP-eligible products purchased at grocery stores from the Nielsen Retail Scanner Dataset, 2006-2014. Each observation corresponds to a store-week. The outcomes are log sales, aggregated across products using the index described in Section 3 (Panel A) and expenditure-weighted index of log prices in Equation 1 (Panel B). Each column represents a separate regression estimating Equation (3) for each product group from the top ten product groups purchased among SNAP-eligible households. "Issue Share" refers to the share of SNAP benefits issued in a given week in the state in which the store is located. Regressions are weighted at the store level by average annual food sales. Standard errors are clustered at the state level. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$.

Table A.6: Sales and Price Effect by Product

Panel A: Food Sales

	(1) OJ	(2) Sunny D	(3) Chips	(4) Raisin Bran	(5) Coke	(6) Frzn Chicken	(7) Hot Dogs	(8) Cheese	(9) Yogurt	(10) Muffins
Issue Share	0.0419***	0.0755***	0.0090	0.0518***	0.0568**	0.1028***	0.1151***	0.0753***	0.0363***	0.0328***
	(0.0104)	(0.0108)	(0.0207)	(0.0086)	(0.0225)	(0.0111)	(0.0109)	(0.0199)	(0.0062)	(0.0120)

Panel B: Food Prices

	(1) OJ	(2) Sunny D	(3) Chips	(4) Raisin Bran	(5) Coke	(6) Frzn Chicken	(7) Hot Dogs	(8) Cheese	(9) Yogurt	(10) Muffins
Issue Share	-0.0004	-0.0040	0.0166	0.0006	-0.0004	0.0021	-0.0032	-0.0014	0.0013	-0.0040
	(0.0019)	(0.0034)	(0.0112)	(0.0039)	(0.0045)	(0.0031)	(0.0039)	(0.0050)	(0.0029)	(0.0077)
N	3,177,360	3,898,488	1,091,236	2,907,648	4,101,184	3,551,344	2,735,288	3,228,924	3911108	3,781,432

Notes: The data include information on all SNAP-eligible products purchased at grocery stores from the Nielsen Retail Scanner Dataset, 2006-2014. Each observation corresponds to a store-week. The outcomes are log sales, aggregated across products using the index described in Section 3 (Panel A) and expenditure-weighted index of log prices in Equation 1 (Panel B). Each column represents a separate regression estimating Equation (3) for the 10 products described in Section 3. These products are: Simply Orange Orange Juice, 59 fl. oz. (Column 1), Sunny D Tangy Orange Citrus Drink, 64 fl. oz. (Column 2), Lay's Wavy Original Potato Chips, 11 oz, pack of 3 (Column 3), Kellogg's Raisin Bran Cereal, 20 oz. box (Column 4), Coca-Cola, Classic Cola, 12 oz., 12 Pack (Column 5), Hungry Man Frozen Fried Chicken Dinner, 16.5 oz. (Column 6), Bar S Classic Jumbo Franks, 16 oz. (Column 7), Kraft Singles Cheese Slices, 12 oz. (Column 8), Dannon Activia Low-Fat Strawberry Yogurt, 4 Pack (Column 9). Thomas' English Muffins, Original, 6 ct. (Column 10). "Issue Share" refers to the share of SNAP benefits issued in a given week in the state in which the store is located. Regressions are weighted at the store level by average annual food sales. Standard errors are clustered at the state level. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$.

Table A.7: Issuance and Customer Demand Elasticity by Market Concentration

	(1)	(2)	(3)	(4)
Log(Price) x Issue Share	-0.0254***	-0.0444***	-0.0276***	-0.0406**
	(0.0081)	(0.0138)	(0.0068)	(0.0195)
Log(Price)	-2.6401***	-2.7389***	-2.6589***	-2.6911***
	(0.0619)	(0.0977)	(0.0847)	(0.0966)
Issue Share	0.0822***	0.1665***	0.0941***	0.1961***
	(0.0081)	(0.0297)	(0.0111)	(0.0280)
N	19,646,896	1,703,480	12,737,092	1,732,584
ZIP Codes	All	High SNAP	All	High SNAP
Local Market Concentration	High	High	Low	Low

Notes: The data include sales and prices at grocery stores from the Nielsen Retail Scanner Dataset, 2006-2014 for the top product by SNAP-household expenditure from each of the top 10 product groups. Each observation corresponds to a store-week. Each column corresponds to a separate regression estimating Equation 4 (Columns (1) and (3)) or the corresponding IV strategy outlined in Section 4.3 (Columns (2) and (4)). The outcome is log units sold per product. "Log(Price)" is the log of price per unit. "Issue Share" refers to the share of SNAP benefits issued in a given week in the state in which the store is located. "Low Market Concentration" sample includes stores located in ZIP codes with no other grocery stores in the Nielsen data in the given year; "High Market Concentration" stores are located in ZIP codes with at least one other Nielsen grocery store. "High SNAP" stores are located in ZIP codes in which $\geq 20\%$ of households participate in SNAP. Regressions are weighted at the store level by average annual food sales. Standard errors are clustered at the state level. + indicates $p < 0.10$; ** indicates $p < 0.05$; *** indicates $p < 0.01$.