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Issuance and Incidence: SNAP Benefit Cycles and Grocery Prices[†]

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Many safety net programs issue benefits as monthly lump-sum payments. We investigate how the timing of Supplemental Nutrition Assistance Program (SNAP) benefit issuance affects food purchases and the incidence of the transfer. Using scanner data from a large sample of grocery stores and state and time variation in SNAP issuance schedules, we document large, SNAP-induced intramonth cycles in food expenditures. However, we find that retailers do not adjust prices based on these predictable patterns of demand. Our results therefore suggest that reforming issuance schedules may reduce costs from SNAP-induced demand surges but are unlikely to affect the incidence of SNAP benefits. (*JEL* D12, H75, I18, I38, L81)

The Supplemental Nutrition Assistance Program (SNAP) is one of the largest antipoverty programs in the United States, serving roughly one in eight Americans in fiscal year 2018 (US Department of Agriculture Food and Nutrition Service (USDA-FNS) 2019). Participating households receive a monthly lump-sum benefit 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 percent of grocery sales in the United States (Wilde 2012). As such, decisions about how the program is implemented have the potential to affect a substantial share of consumers and grocery markets nationwide.

In this paper, we investigate the effects of state decisions about the timing of SNAP issuance. Previous research finds that food consumption and expenditures by SNAP recipients track monthly benefit cycles (Wilde and Ranney

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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 nonbeneficiaries, SNAP-induced variation in aggregate customer demand can affect the purchasing power of the benefit. In particular, in states with compressed issuance schedules,[1] grocery stores face predictable intramonth fluctuations in the nature and volume of customer demand. In response, retailers may strategically adjust food prices over the course of the month in stores where SNAP beneficiaries shop. Such pricing behavior shapes the incidence of 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.

To investigate this question, we use a panel of transaction-level data that cover over 10,000 retail grocery stores in the United States from 2006 to 2014. With these data, we explore the effect of SNAP issuance on food expenditures and prices by leveraging differences in the share of SNAP participants that receive benefits in a given week. Specifically, we employ two main identification strategies. The first uses cross-sectional variation in SNAP issuance schedules within and across states. The second identification strategy estimates the effect of SNAP issuance exclusively from within-state changes to the issuance schedule over time. Unlike much of the prior research on the effect of SNAP issuance timing, both of these approaches allow us to control for secular week-of-the-month effects, thus distinguishing the effect of SNAP from other regularly occurring monthly events that may influence food purchases, such as receiving a paycheck, utility bills, or the issuance of other benefits.

We first establish that SNAP issuance generates predictable intramonth fluctuations in shopper demand. Focusing initially on variation across states, we find that food sales increase 5.6 percent 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 19.2 percent in zip codes in which more than 20 percent of households participate in SNAP. In addition, 12 states changed SNAP issuance schedules during our sample period. We find that limiting our analysis to this source of variation yields similar results: in our full sample, food sales are 6.3 percent higher in weeks in which all benefits are issued compared to a week in which no benefits are issued and 16.9 percent higher in high-SNAP stores. In contrast, we find much smaller and largely statistically insignificant effects of SNAP issuance on sales of SNAP-ineligible grocery purchases.

We next investigate the relationship between the timing of SNAP issuance and within-month cyclicality in grocery store food prices. Notwithstanding the predictable variation in consumer demand that SNAP issuance generates, we find evidence against retailers adjusting food prices in response by an economically meaningful

[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 twenty-second of the month.

degree. Across specifications and samples, our point estimates are near zero and not statistically significant. Our preferred specification yields a 95 percent confidence interval that excludes average price changes larger than 0.1 percent in magnitude in all stores and 0.2 percent in high-SNAP stores. This finding is striking because it allows us to rule out SNAP-induced intramonth pricing responses an order of magnitude smaller than what has been found in prior research (Hastings and Washington 2010).

Finally, we conduct a range of exploratory analyses to better understand the lack of pricing response to SNAP issuance. In particular, to shed light on how the observed fluctuations in customer demand affect grocery pricing incentives, we investigate how SNAP issuance affects within-month patterns in the aggregate price elasticity of demand faced by retailers. Instrumenting product prices with prices of the same product from same-chain stores in other markets (Hausman 1996; Nevo 2001; DellaVigna and Gentzkow 2019), we estimate the effect of SNAP issuance on within-month changes in customer demand elasticity. We find that average demand elasticity declines by approximately 1 percent in weeks in which all benefits are issued, suggesting that on average, customers shopping in such weeks are slightly more price sensitive than customers shopping in other weeks of the month.

Using a simple model of grocery store behavior, we predict that these small changes in elasticity should induce only modest reductions in grocery store prices, approximately 0.1 percent to 0.8 percent. Thus, perhaps surprisingly in light of the large changes in consumer behavior that we observe, we do not find evidence of large incentives for retailers to adjust prices over the course of the month. In addition, although we document heterogeneity in the size of the within-month elasticity changes across individual products and chains, we observe no systematic relationship between the magnitude of these changes and the price response to SNAP issuance. We interpret these results to suggest that the effect of SNAP issuance on food prices may also be limited due to frictions that would increase the costs to grocers of making such adjustments (e.g., managerial inertia of the form explored in DellaVigna and Gentzkow 2019).

Our paper contributes to a large literature on the incidence of redistributive transfers (Duggan and Scott Morton 2006; Rothstein 2010; Meckel 2020; Handbury and Moshary 2021). Our setting highlights a potentially important but underexplored mechanism through which institutional design can shape the incidence of a redistributive program: namely, when the benefit is provided in kind through a private market and the timing of issuance generates regular and predictable variation in the nature of demand.[2] Prior research in the SNAP context suggests that the timing of issuance may affect the purchasing power of the benefits; using data from three grocery stores from one chain located in a single state, Hastings and Washington (2010) find that food prices were approximately 3 percent higher in the first week

[2] For example, social security or Temporary Assistance for Needy Families (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.

of the month (when the state issued its SNAP benefits) than at the end of the month (when SNAP expenditures were relatively low). We build on this analysis by using a dataset with broad national coverage to dramatically expand the number of stores and retail chains considered. In so doing, we increase the likelihood that our results reflect the national grocery store market rather than the pricing decisions of a single retailer.

Our second contribution is primarily methodological. A number of influential papers study the effects of SNAP issuance on the timing of food purchases (Wilde and Ranney 2000; Shapiro 2005; Hastings and Washington 2010; Castner and Henke 2011; Todd 2015) and other related outcomes (Seligman et al. 2014; Gennetian et al. 2016; Gregory and Smith 2019). Because the vast majority of such studies identify the effect of SNAP issuance from intramonth patterns in behavior, they risk conflating the effects of SNAP issuance with other regularly occurring monthly events that also affect behavior, such as timing of rent payments or other bills, paycheck receipt (Stephens 2006), or receipt of other monthly benefit programs such as TANF or social security (Stephens 2003; Mastrobuoni and Weinberg 2009).[3] In contrast, by exploiting variation in issuance schedules within and across states, our identification strategy allows us to control for monthly patterns in individuals' behavior that are unrelated to SNAP issuance.[4] Similarly, this innovation allows us to more confidently attribute retailer pricing responses to SNAP issuance rather than other "first of the month" effects that have been the focus of prior work (Hastings and Washington 2010).[5]

More generally, our paper also contributes to a growing literature on grocery pricing strategies. For example, DellaVigna and Gentzkow (2019) document uniform pricing of products across grocery stores belonging to the same chain despite wide variation in customer demographics and degree of market competition. By contrast, other recent work finds that retailer pricing responds to local demand conditions (Stroebel and Vavra 2019). Rather than focusing on differences in price setting across stores, our focus is on variation within a single store over time, for which the constraints on price setting may operate differently. Our finding that retailers do not adjust prices in response to predictable variation in demand caused SNAP issuance is similar to that of DellaVigna and Gentzkow (2019); however, an important difference is that such price responses appear less likely to be optimal in our

[3] Some prior research investigating the cyclicality of SNAP benefit use, including Todd (2015); Smith et al. (2016); Hamrick and Andrews (2016); and Castellari et al. (2017), partially addresses this concern by including in their samples multiple states that vary in their SNAP issuance schedules. Bias may persist in such designs, however, because in all states, SNAP issuance dates tend to be concentrated in the earlier part of the calendar month (online Appendix Table A.1). An important exception is Shapiro (2005), which uses states that vary in their issuance dates while also controlling for calendar day fixed effects. Finally, Beatty et al. (2019) directly study interactions between SNAP issuance and two of the possible confounding factors, paycheck receipt and the issuance of other social insurance benefits, by comparing SNAP cyclicality across individuals likely to be affected in different ways by these non-SNAP monthly income cycles.

[4] Apart from the difference in outcomes that we focus on (retailer-level sales and prices versus caloric intake and individual expenditures), this aspect of our identification strategy builds on Shapiro (2005) by avoiding potential biases from correlations between state issuance schedules and within-month purchasing patterns.

[5] Notably, an earlier working paper version of Hastings and Washington (2010) includes an additional four stores from the same retailer located in states that stagger benefit issuance across the first ten 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).

setting—even absent managerial decision costs or other frictions. Our analysis is also related to the literature that studies grocer responses to seasonal demand fluctuations. For example, Chevalier, Kashyap, and Rossi (2003) find that grocers compete to capture seasonal demand shocks by offering a high-demand product (e.g., turkey on Thanksgiving) below cost. Although this finding might suggest that retailers would lower food prices following SNAP issuance to get SNAP beneficiaries "in the door," we find no evidence supporting this hypothesis.

Finally, we contribute to broader literature that studies the effects of SNAP policy on prices. This literature investigates how the size and generosity of the SNAP program affects food prices as well as the effects of other state and federal policy changes in program enrollment rules (Jaravel 2018; Makioka 2018; Leung and Seo 2018). Whereas these papers study the effect of SNAP on average food prices during some interval of time, our focus is on how SNAP shapes short-term price fluctuations around that average over the course of a month. Because both of these channels shape the food prices faced by SNAP recipients and, hence, the real purchasing power of the SNAP benefits, both are relevant for understanding the incidence of the program.

The paper is structured as follows. Section I describes the institutional background. Section II describes our data and the construction of the variables used in the analysis. Section III presents our results related to food sales. Section IV presents our results related to food prices. Section V explores potential explanations for the observed retailer pricing response. Section VI concludes.

I. Institutional Background

SNAP served roughly 40 million individuals in an average month of fiscal year 2018, with a federal budget for that year of $65 billion (USDA-FNS 2019). SNAP purchases comprise a sizable share of the retail grocery market. Wilde (2012) estimates that 10–15 percent of food sales were purchased through SNAP, and Walmart estimates that 4 percent of its total sales revenue comes from the SNAP program (Clark 2014).

Eligibility for SNAP varies by state, but federal law requires participating households to have gross monthly income below 130 percent of the Federal Poverty Line ($2,183 per month for a family of 4 in 2020). A number of states also limit eligibility based on the value of a household's assets (for details, see Center on Budget and Policy Priorities 2018).

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 (US Department of Agriculture (USDA) 2013). 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 with other payment methods if expenditures exceed their card balance or if purchasing ineligible products.

In some states, each participating household receives its 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 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 twenty-second days of the month.

Online Appendix Table A.1 details issuance policies by state. At the start of our sample period (in 2006), 14 states issued benefits during the first calendar week only, 2 states issued benefits during the second calendar week only, 24 states issued benefits on days spanning the first 2 calendar weeks, and 9 issued benefits on days spanning 3 or more calendar weeks.[6] During the course of the years we study, 12 states expanded the number of days during the month on which they issue benefits. In 2014, 17 states in our sample staggered issuance across 3 or more calendar weeks.

II. Data

Our primary data source is the Kilts-Nielsen Retail Scanner dataset (Kilts Center for Marketing 2004–2016), 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 and the District of Columbia between 2006 and 2014. We focus our analysis on data from the 11,508 grocery stores in the sample. The stores included in our sample account for approximately 53 percent of all grocery store sales volume in the geographic markets covered by Nielsen.[7]

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. The price we observe incorporates retailer discounts and specials, such as coupons or loyalty card price reductions, but does not reflect discounts from manufacturer coupons (e.g., a manufacturer rebate).

The majority of the weekly data that stores report to Nielsen correspond 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, for each calendar week, we compute the average price of each product across the (one or two) Sunday-to-Saturday weeks in which the observed store-week falls, weighting by the number of dates in the calendar week that fall in each respective

[6] We use "calendar week" to refer to the specified week number in a given month. For example, the first calendar week refers to days 1–7 of the month.

[7] In restricting our analysis to grocery stores, we exclude drug stores as well as "superstores" that retail a more general line of goods, such as Target.

[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 align 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 date provided.

Sunday-to-Saturday week.[9] We discard any data associated with calendar days 29 to 31.

We impose two additional product-level restrictions on our data. First, Nielsen does not report a product price for store-weeks in which a product was not sold in a given store. To limit the influence on our results of changes in the composition of products for which we observe price, we restrict our analysis to store-month products for which we observe price in all four weeks.[10] Second, because our focus is on SNAP-induced changes in demand, in our main analyses, we exclude products sold by grocery stores for which SNAP benefits cannot be used (e.g., nonfood items or prepared foods).[11]

We supplement the Retail Scanner Data using a second Kilts-Nielsen dataset, the Consumer Panel (Kilts Center for Marketing 2004–2016). This dataset consists of daily, product-level expenditure data for a panel of 40,000 to 60,000 households per year from 2004 to 2014. Participants use in-home optical scanners to record their purchases. We incorporate data from the Consumer Panel in two main ways. First, a number of our analyses rely on data about SNAP prevalence in the neighborhood in which the store is located. 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. To estimate local SNAP prevalence, we use the following method, similar to DellaVigna and Gentzkow (2019). For a given store, we calculate total expenditures per zip code for each zip code of residence of its shoppers in the Consumer Panel. We then assign the store the average SNAP prevalence of its shoppers' zip codes, weighting by the number of shopping trips to the store by customers in a given zip code. We restrict our analysis to the 97 percent of stores in the Retail Scanner Data for which this method yields a zip code. We use the store's zip code to link our data with zip-code-level demographic data from the five-year American Community Survey spanning 2008–2012 (Census Bureau 2009–2019). In particular, we use the share of households that participate in SNAP from these data.

Second, we construct an index to reflect the average price faced by SNAP customers in a given store and week. To do so, we first create expenditure shares by product for SNAP-eligible households from the Consumer Panel.[12] We construct these expenditure shares for each SNAP-eligible product by summing expenditures for the product across households and dates during our sample period and then scaling that sum by total expenditures on all SNAP-eligible products over the same time period. By construction, these expenditure shares are constant over time. We denote the expenditure share for product k as ω_k. We normalize the expenditure

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

[10] Thus, the composition of products for a given store may vary across months but not within a single month.

[11] We consider the effect of SNAP issuance on purchases and prices for SNAP-ineligible products in Section III.

[12] We impute SNAP eligibility from household income and family size by applying the federal gross income test. 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 cannot apply the SNAP asset test, because the Consumer Panel does not report data on household assets.

shares to sum to one in a given store-month and denote the normalized expenditure shares by $\tilde{\omega}_{ksmy}$ for store s, calendar month m, and year y.

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

$$\log\left(P_{swmy}\right) = \sum_{k} \tilde{\omega}_{ksmy} \log\left(p_{kswmy}\right) \tag{1}$$

where p_{kswmy} denotes the unit price for product k sold in store s in calendar week w, calendar month m, and year y.

We similarly construct an index of expenditures on SNAP-eligible products in a given store and week. The expenditure index is defined as the log of weighted expenditures in the store-week, where the weights (i.e., the expenditure shares) are the same as those used to construct the price index:

$$\log\left(Y_{swmy}\right) = \sum_{k} \tilde{\omega}_{ksmy} \log\left(y_{kswmy}\right) \tag{2}$$

where y_{kswmy} denotes expenditures on product k in store s in calendar week w, calendar month m, and year y. As with the price index, the expenditure index attaches higher weight to products that are more likely to be purchased by SNAP-eligible households and in which we would therefore be more likely to observe SNAP-induced changes in demand or prices.[13]

In many of our analyses, the main explanatory variable of interest is the share of SNAP benefits a state issues in a given calendar week, $Issuance_{swmy}$.[14] To illustrate, if store s is located in a state that distributes all benefits on the first of the month, $Issuance_{s1my} = 1$ and $Issuance_{swmy} = 0$ for $w \in \{2,3,4\}$. Alternatively, if the state distributes its benefits evenly from the first through the fifteenth of the month, $Issuance_{swmy} = 7/15$ for $w \in \{1,2\}$, $Issuance_{swmy} = 1/15$ for $w = 3$, and $Issuance_{swmy} = 0$ for $w = 4$.[15]

[13] As robustness checks, we consider unweighted analyses and analyses that focus on an alternative subset of products.

[14] We allow issuance policy to vary at the county level when applicable and subject to data availability. Specifically, Pennsylvania and Ohio allow issuance policy to vary at the county level, and New York City follows a different issuance schedule than the rest of New York; however, in the case of Ohio, we do not have data on the 15 percent of counties that do not stagger, so we assume that all counties in the state follow the same schedule.

[15] Twelve states in our sample assign a case's issuance date based on the first letter of their last name, which may result in an uneven distribution across benefit issuance days, biasing our measure $Issuance_{swmy}$. We do not have data on the distribution of last names by state; however, in robustness checks below, we test the sensitivity of our results to exclusion of states with this issuance assignment method as well as a reweighting of $Issuance_{swmy}$ by nationwide name distributions. Relatedly, Illinois's policy assigns issuance date based on a combination of the case name and the type of case. We obtain administrative data from Illinois on the number of cases issued benefits by day and adjust our measure of $Issuance_{swmy}$ to match this distribution (IL SNAP Program 2008-2014).

Table 1—The Effect of SNAP Issuance on Food Expenditure Cyclicality

	(1)	(2)	(3)	(4)	(5)
Panel A. All stores					
Issuance share	0.0509	0.0560	0.0557	0.0636	0.0630
	(0.0078)	(0.0084)	(0.0086)	(0.0170)	(0.0125)
Observations	4,157,698	4,157,698	4,157,698	4,157,698	4,157,698
Panel B. High-SNAP stores					
Issuance share	0.2074	0.1922	0.1921	0.1749	0.1692
	(0.0253)	(0.0314)	(0.0307)	(0.0448)	(0.0329)
Observations	281,739	281,739	281,739	281,739	281,739
Controls					
Store-year-month	X	X	X	X	X
Year-month-calendar week		X	X	X	X
Calendar week × controls			X		X
Calendar week × store				X	X

Notes: The table shows the effect of SNAP issuance on food expenditures at a given store in a given week of the month. log food expenditures are aggregated across products using weights derived from purchases by SNAP-eligible shoppers. Issuance share reflects the share of SNAP benefits issued during a calendar week in the jurisdiction in which a store is located. Panel A contains all stores in the sample; panel B is limited to stores for which we estimate that the share of SNAP recipients in the zip code is at least 20 percent. All columns include store-by-year-by-month fixed effects. Columns 2–5 include year-by-month-by-week fixed effects. Columns 3 and 5 include interactions of calendar week with state-year measures of log population, log GDP per capita, and unemployment rate. Columns 4 and 5 include calendar-week-by-store fixed effects. All specifications are weighted by average annual store volume. Standard errors, reported in parentheses, are clustered by state.

III. SNAP Issuance and Food Expenditure Cyclicality

Our goal in this section is to isolate the causal effect of SNAP issuance on intramonth patterns in grocery expenditures. Columns 1–3 of Table 1 estimate variants of the following model:

$$\log Y_{swmy} = \beta Issuance_{swmy} + \alpha_{smy} + \delta_{wmy} + \gamma X_{sy}\zeta_w + \varepsilon_{swmy} \tag{3}$$

where α_{smy} denotes store-month-year fixed effects, δ_{wmy} denotes year-month-week fixed effects, ζ_w denotes calendar week fixed effects, and X_{swmy} is a vector of time-varying characteristics of the state in which store s is located. As described above, $Issuance_{swmy}$, denotes the share of SNAP benefits issued in calendar week w of month m of year y in the state in which store s is located. Hence, β represents the percent increase in expenditures for weeks in which 100 percent of SNAP benefits are issued relative to weeks in which no benefits are issued. Each observation is weighted at the store level by average annual food sales.

As a benchmark, column 1 of Table 1 reports the estimated effect of SNAP issuance from a regression that controls only for store-month-year fixed effects. The effect of SNAP issuance is identified from comparing expenditures across weeks in a given store based on differences in the share of SNAP benefits issued in the specified weeks. Note that because this specification includes state-month-year fixed effects, it isolates within-month variation in food expenditures from state changes to SNAP

policy that affect benefit generosity or other features of program administration of the type studied in Ganong and Liebman (2018) and Jaravel (2018). The results imply that expenditures are 5.1 percent higher in weeks in which all benefits are issued compared to weeks in which no benefits are issued.

As with much of the prior literature, the effect reported in column 1 risks conflating the effect of SNAP issuance with other sources of intramonth cyclicality in consumption, such as the timing of paychecks or utility bills or the issuance of other benefits. To address this concern, column 2 replicates column 1 but additionally controls for year-month-week fixed effects. In doing so, it absorbs within-month cyclicality that is unrelated to SNAP issuance. Figure 1, panel A graphically presents the variation underlying this specification; after partialling out the store-month-year and year-month-week fixed effects, the relationship between SNAP issuance and log expenditures appears fairly linear and remains upward sloping. Indeed, the estimated effect reported in column 2 is quite similar to that in column 1 (expenditures are 5.6 percent higher in weeks in which all benefits are issued relative to weeks in which no benefits are issued), suggesting that non-SNAP sources of within-month cyclicality are unlikely to have driven the findings of prior analyses of SNAP-induced consumption that failed to account for such factors.

The specification in column 2 identifies the effect of SNAP issuance from cross-sectional variation across states in issuance policies and, to a lesser extent, from changes in a state's issuance policy over time. However, it is possible that either of these sources of variation could be correlated with other factors that affect expenditure cyclicality. For example, larger states might tend to exhibit more within-month cyclicality (for reasons unrelated to SNAP) and stagger benefit issuance over a larger number of days. To address some of these possibilities, column 3 (our preferred specification, matching equation (3)) controls for the calendar week interacted with state population, gross domestic product, and unemployment rate (Bureau of Economic Analysis 2006–2014; Bureau of Labor Statistics 2006–2014). Again, the results are virtually unchanged by these additions.

Because our expenditure data are at the retailer level, they reflect the shopping behavior of both SNAP recipients and other shoppers. Hence, to the extent that our results are driven by SNAP-induced cyclicality, we would expect them to be more pronounced in stores that are located in neighborhoods with high SNAP prevalence. Figure 2 explores this possibility by displaying the estimated effect of SNAP issuance by local SNAP prevalence, using the specification reported in column 3 of Table 1. In zip codes in which fewer than 5 percent of households participate in SNAP, there is a small amount of cyclicality: expenditures are 1.8 percent higher in weeks in which 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 49 percent for stores located in zip codes in which over 35 percent of households receive SNAP.[16]

Along similar lines, panel B of Table 1 restricts the analysis to stores in zip codes in which we estimate that greater than 20 percent of the population receives

[16] Online Appendix Figure A.1 shows a similar relationship between SNAP-induced cyclicality and SNAP prevalence at the level of the grocery chain.

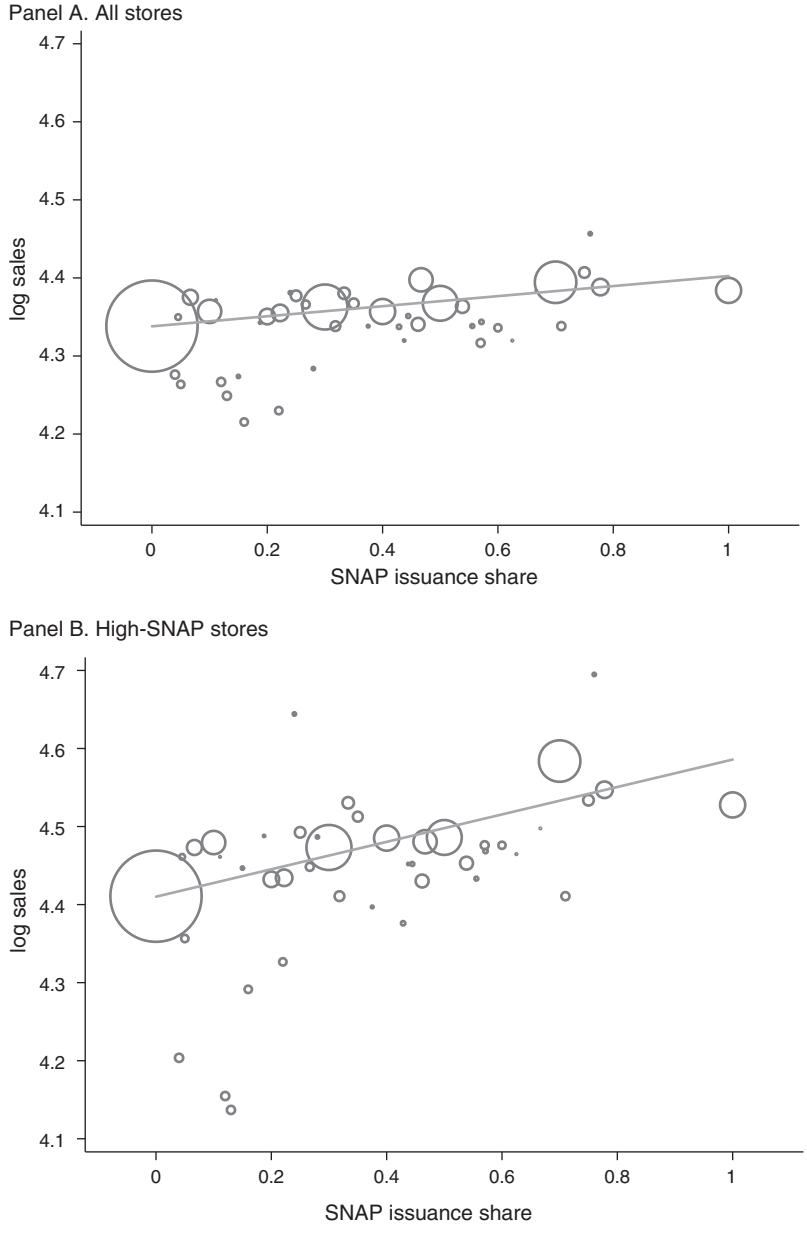


FIGURE 1. FOOD EXPENDITURES BY WEEKLY SNAP ISSUANCE

Notes: The figure displays average log food expenditures by the share of SNAP benefits issued in a given week of the month. log food expenditures are aggregated across products using weights derived from purchases by SNAP-eligible shoppers. SNAP issuance share reflects the share of SNAP benefits issued during a calendar week in the jurisdiction in which a store is located. Points in the figure are proportionate to the number of store-weeks with the specified issuance share and reflect residuals after controlling for store-year-month and year-month-week fixed effects. Panel A contains all stores in the sample; panel B is limited to stores for which we estimate that the share of SNAP recipients in the zip code is at least 20 percent. The estimated slope of the best linear fit (weighted by the number of store-weeks with the specified issuance share) is 0.06 in panel A and 0.18 in panel B.

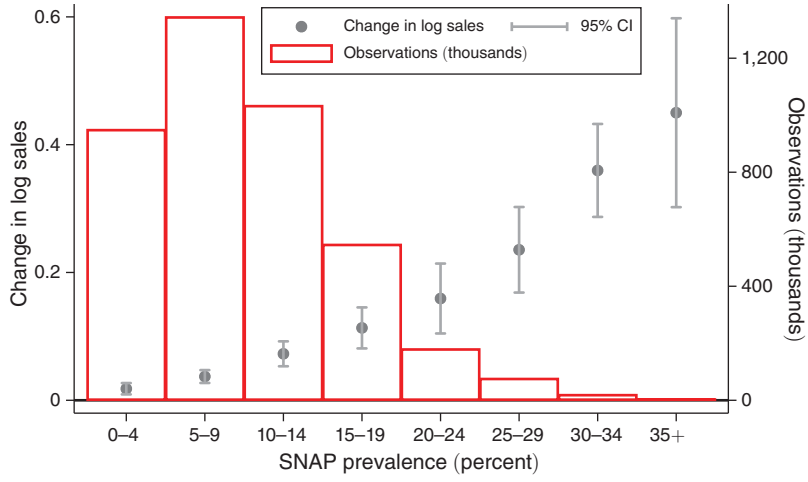


FIGURE 2. FOOD EXPENDITURE CYCLICALITY BY LOCAL SNAP PREVALENCE

Notes: The figure displays the estimated effect of SNAP issuance on log food expenditures by local SNAP prevalence. Local SNAP prevalence refers to the estimated share of the population that are SNAP recipients in the zip code in which the grocery store is located. log food expenditures are aggregated across products using weights derived from purchases by SNAP-eligible shoppers. Change in log sales refers to the estimated coefficient on SNAP issuance share, which is defined as the share of SNAP benefits issued during a given week of the month in the jurisdiction in which a store is located. The effect of SNAP issuance on log food expenditures is estimated from a specification that controls for store-year-month and year-month-week fixed effects as well as the interaction of calendar week with log state population, log gross domestic product, and unemployment rate (corresponding to column 3 in Table 1). The error bars on the estimated effects reflect the 95 percent confidence interval from standard errors clustered by state. The hollow bars reflect the number of observations in our sample (i.e., the number of store-weeks) from stores located in zip codes with the specified population share of SNAP recipients.

SNAP.[17] As suggested by Figure 2, the estimated effects of SNAP issuance for such high-SNAP stores are substantially higher than those of the overall sample. In our preferred specification, expenditures in high-SNAP stores are 19.3 percent higher in weeks in which all benefits are issued relative to weeks in which no benefits are issued.

In columns 2 and 3, 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. However, cross-sectional policy variation between stores may be correlated with other factors that shape a store's cyclicality unrelated to SNAP issuance. To address this possibility, we next turn from specifications that rely on cross-sectional variation across states in issuance policies to specifications that exclusively exploit within-state changes in policy over time. In particular, columns 4 and 5 of Table 1 estimate variants of the following model:

$$(4) \qquad \log Y_{swmy} = \beta Issuance_{swmy} + \alpha_{smy} + \delta_{wmy} + \gamma X_{sy}\zeta_w + \phi_{sw} + \varepsilon_{swmy}$$

[17] In principle, SNAP participation at a given store may differ from the general population in a neighborhood. However, using the Consumer Panel, we estimate that the share of customers in the stores in this "high-SNAP" sample of neighborhoods that are SNAP eligible is also approximately 20 percent.

where ϕ_{sw} denotes store-by-calendar-week fixed effects. Including these fixed effects implements a difference-in-differences analysis in which identification comes from within-state policy changes over time. A benefit of this approach is that it avoids the identification threats described above; a downside is that with only 12 policy changes during our sample period (largely concentrated during the final three years), the effect it identifies is not nationally representative and will be less precisely estimated.

The difference-in-differences analysis requires that absent the policy changes, intramonth cyclicality would have evolved similarly in states that did and did not modify their benefit issuance schedules. This assumption may be violated, for example, if state-level trends in expenditure cyclicality prompt lawmakers to adjust the issuance schedules to relieve congestion at grocery stores.[18] To assess the plausibility of this parallel trends assumption, Figure 3 presents an event study analysis of the effect of the policy changes on the cyclicality of within-month consumption, which we measure as the share of monthly purchases made in the first two weeks.[19] The figure suggests that the reforms reduced intramonth cyclicality in expenditures, especially within the high-SNAP stores most affected by the reforms. In contrast, the figure provides no evidence of differential trends in cyclicality in the period leading up to the reforms, consistent with the parallel trends assumption underlying the difference-in-differences analysis.

Column 4 of Table 1 presents results from a difference-in-differences analysis, adding store-by-calendar-week fixed effects to the specification reported in column 2. The point estimate increases slightly (to 6.4 percent) relative to the specifications identified from cross-sectional variation in state policy, and the standard error of the estimate doubles in size.[20] Finally, to address the possibility that the effects of the policy changes may be confounded by other state-level trends that would affect within-month expenditure cyclicality, column 5 adds controls for the time-varying state characteristics that were included in column 3. The results are similar to those in column 4. Columns 4 and 5 in panel B again show much larger effects when the analysis is restricted to the subsample of high-SNAP stores.

We next consider a range of robustness checks on the main cross-sectional and difference-in-difference results (columns 3 and 5 of Table 1). Columns 1 and 2 of online Appendix Table A.3 present versions of these analyses that are not weighted by store volume. Similarly, Columns 3 and 4 present results for total food expenditures rather than our main outcome measure, which aggregates expenditures using

[18] For example, both the USDA and grocery store lobbying groups have recommended that states stagger SNAP issuance for this reason (Cloud 2012).

[19] Ten out of the 12 policy changes in our data expand the share of benefits issued in weeks 3 and 4 relative to weeks 1 and 2. The two exceptions are Oklahoma and Virginia, which we exclude from this analysis.

[20] A potential concern with this analysis is that because states reform their SNAP issuance schedules at different times, the parallel trends assumption may be violated when the effects of the SNAP issuance reforms vary over time (Goodman-Bacon 2021). To investigate the robustness of our analysis to this issue, online Appendix Table A.2 separately estimates the effect of SNAP issuance for each state policy reform, using as controls only those states that did not revise their issuance schedule during our sample period. Although there is substantial variation in the magnitude of the individual estimates for each state, the overall story is consistent with the results of our main specification; the average of the state-specific estimates (weighted by the volume of sales in the stores in each state) is 4.4 percent for all stores and 12.8 percent for high-SNAP stores.

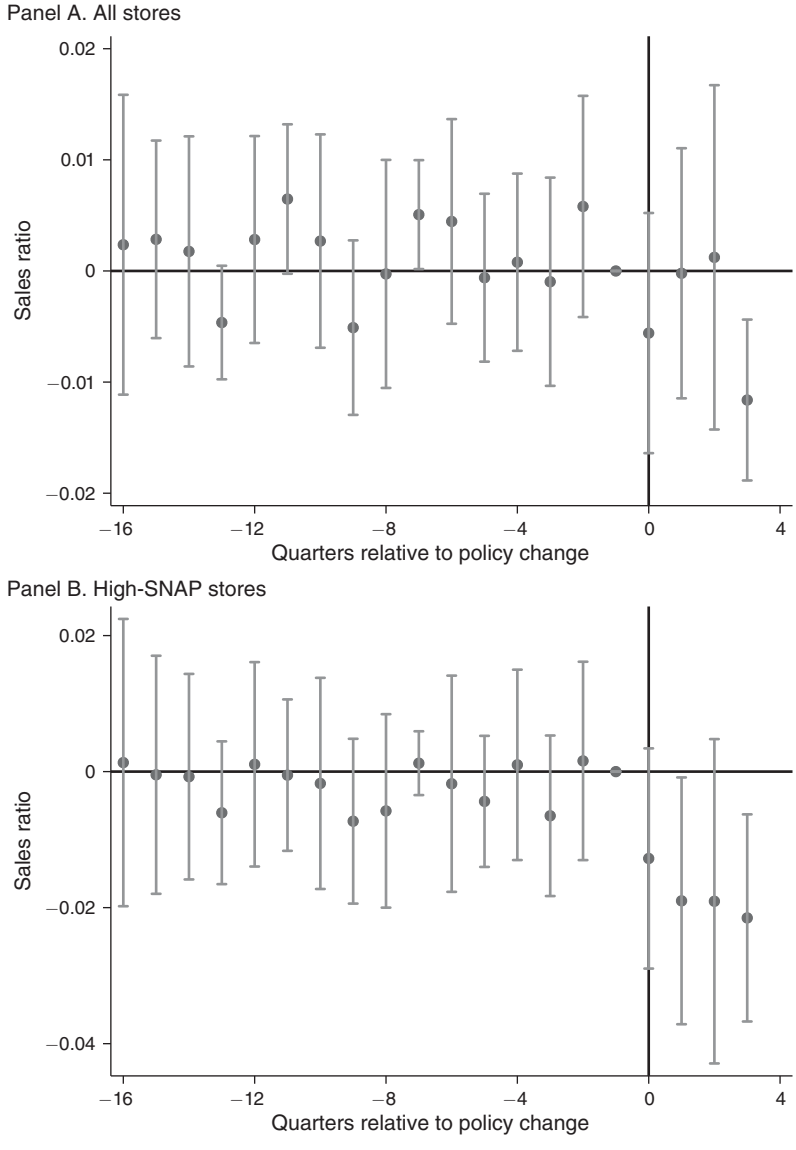


Figure 3. Event Study Analysis of SNAP Issuance Reforms on Food Expenditure Cyclicality

Notes: The figure displays the event study analysis of the effect of policy reforms that staggered SNAP issuance on the timing of food expenditures. The outcome is the ratio of monthly log food expenditures occurring in the first two calendar weeks relative to monthly log food expenditures occurring during the full month. log food expenditures are aggregated across products using weights derived from purchases by SNAP-eligible shoppers. The estimates reflect the effect of policy reforms in the ten states that expanded the share of benefits issued during the third and fourth calendar weeks of the month during our sample period (see online Appendix Table A.1). The analysis excludes the two states (Oklahoma and Virginia) that altered the share of SNAP benefits issued across calendar weeks during our sample period but did not expand the share of benefits issued during the third and fourth calendar weeks of the month. The analysis also excludes Idaho, which reformed its issuance schedule during our sample period but did not alter the share of benefits issued across calendar weeks. The estimated effects are derived from a specification that controls for store-year-month and year-month-week fixed effects and omits a coefficient for the effect of the intervention in the quarter prior to implementation (the reference period). Panel A contains all stores in the sample; panel B is limited to stores for which we estimate that the share of SNAP recipients in the zip code is at least 20 percent. The brackets surrounding the estimated effects reflect the 95 percent confidence interval from standard errors clustered by state.

weights based on the purchases of SNAP-eligible shoppers. These alternative specifications yield qualitatively similar results to our main analysis.

We estimate two robustness checks motivated by potential measurement error in our main explanatory variable reflecting the timing of SNAP issuance. Although most states issue benefits uniformly across issuance days (e.g., based on the last digit of the recipient's Social Security number or case number), ten states allocate benefit issuance across days based on first letter of the recipient's last name. To account for nonuniform issuance of benefits across recipients in such states, columns 5 and 6 of online Appendix Table A.3 construct the issuance share variable by combining the issuance schedule for such states with the national distribution of last names from the 2010 census (Census 2010).[21] As an alternative check, columns 7 and 8 exclude these states along with three others that issue benefits nonuniformly across issuance days.[22] In both cases, the results are similar to those we obtain when using our full sample or main measure of SNAP issuance share.

Thus far, we have parameterized variation in issuance policy through the share of benefits issued in a given calendar week. Online Appendix Table A.4 explores within-month cyclicality within broader categories of state issuance policy. We estimate separate regressions for states with four different SNAP issuance policies: (i) all benefits issued during the first week of the month, (ii) all benefits issued during the second week of the month, (iii) all benefits issued during the first and second weeks of the month, and (iv) benefits issued during the first three or more weeks of the month. Each of these regressions take the form

$$\log Y_{swmy} = \alpha + \sum_{w=2}^{4} \zeta_w + \delta_{smy} + \varepsilon_{swmy}. \tag{5}$$

The estimated ζ_w term 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.[23] The results suggest that within-month expenditure patterns closely track SNAP issuance schedules; for example, in high-SNAP stores located in states that issue all benefits in week 1, food expenditures in that week are between 15 and 21 percent higher than in other weeks of the month. In contrast, we observe little evidence of cyclicality in states that spread issuance across three or four weeks.

Finally, we have so far focused on the effect of SNAP issuance on the timing of SNAP-eligible purchases. It is also possible that SNAP issuance affects expenditures on food or nonfood products that cannot be paid for with SNAP benefits. For example, if benefit issuance induces more SNAP-enrolled customers to shop in a given week, those customers may also purchase more SNAP-ineligible products while at the grocery store during those weeks. To explore this possibility, online Appendix Table A.5 investigates the effect of SNAP issuance on nonfood grocery items and alcohol purchases. We observe no evidence that SNAP issuance affects the timing of

[21] This reweighting is not possible for two states, Maryland and Missouri, which employ more elaborate distribution schedules.

[22] The additional excluded states are Louisiana, Ohio, and South Carolina.

[23] 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 ζ_w terms.

alcohol purchases and some evidence for a small effect on nonfood grocery items in high-SNAP stores, although the latter is not consistent across specifications.

IV. SNAP Issuance and Retail Prices

The previous section provides evidence that SNAP issuance causes retailers to face predictable monthly fluctuations in customer shopping behavior, especially in states with compressed benefit issuance schedules and in locations where SNAP participation is high. In response to these fluctuations in demand, retailers may strategically vary prices over the course of the month to maximize profits. Alternatively, to the extent that retailer prices do exhibit SNAP-induced pricing cyclicality, it could be that this cyclicality is what induces the observed fluctuations in consumer demand. This section empirically investigates these possibilities by studying the effect of SNAP issuance on retailer prices.

Using the price index described in equation (1), we estimate a similar set of specifications as those reported in Table 1 to estimate the effect of SNAP issuance on retail prices. Column 1 of Table 2 estimates the relationship between SNAP issuance and log prices, controlling for store-month-year fixed effects. The result implies that prices are approximately 0.13 percent lower in weeks in which all benefits are issued compared to weeks in which no benefits are issued. However, adding year-month-week fixed effects (column 2) to this analysis causes the point estimate to switch signs and decline in magnitude to 0.04 percent, suggesting that the difference in prices may have been due to within-month fluctuations unrelated to SNAP issuance. We present visual evidence for this result in Figure 4.[24] Adding controls for state characteristics (column 3, our preferred specification) yields similar evidence against within-month price fluctuations. The estimated 95 percent confidence interval for the effect of SNAP issuance excludes price changes greater in magnitude than 0.1 percent. Finally, the difference-in-differences analyses, reported in column 4 and 5, yield slightly larger, but still near zero and statistically insignificant, estimates of the effect of SNAP issuance on retailer prices.[25] By comparison, Hastings and Washington (2010) estimate that prices increase by between 2.5 percent and 3.1 percent in the first week of the month, depending on their specification; these effects are approximately 20 times larger than our largest estimated effect across specifications.[26]

[24] The figure shows a higher average price level among all stores than among high-SNAP stores, which may reflect lower prices for the same products in high-SNAP stores and/or differences between stores in the composition of products purchased over the full sample period.

[25] Online Appendix Figure A.2 replicates the event study analysis in Figure 3 for the effect of the SNAP issuance policy changes on prices and provides no evidence of differential pretrends based on whether a state changed policies. In addition, online Appendix Table A.6 replicates the state-specific analyses contained in online Appendix Table A.2 for prices instead of expenditures; the average of the state specific estimates (weighted by the volume of sales in the stores in each state) is −0.18 percent for all stores and 0.02 percent for high-SNAP stores.

[26] Notably, Hastings and Washington (2010) restricted their focus to stores with particularly high shares of SNAP shoppers (14 to 45 percent of sales), meaning that our overall results are not directly comparable to theirs. As shown in Figure 5 and in panel B of Table 2, however, we find no evidence for price cyclicality even in stores for which we estimate a high share of SNAP shoppers. A potential limitation of our analysis relative to Hastings and Washington (2010) is that we do not directly observe individual-level SNAP participation, so it is possible that these neighborhood-based estimates overstate the true SNAP share in a store's customer base. That being said, the magnitude of SNAP-induced sales cyclicality that we estimate is comparable to that observed in Hastings

Table 2—The Effect of SNAP Issuance on Food Price Cyclicality

	(1)	(2)	(3)	(4)	(5)
Panel A. All stores					
Issuance share	−0.0013	0.0004	0.0002	0.0010	0.0010
	(0.0004)	(0.0004)	(0.0004)	(0.0008)	(0.0009)
Observations	4,157,698	4,157,698	4,157,698	4,157,698	4,157,698
Panel B. High-SNAP stores					
Issuance share	−0.0014	0.0011	0.0011	0.0014	0.0014
	(0.0008)	(0.0008)	(0.0007)	(0.0012)	(0.0014)
Observations	281,739	281,739	281,739	281,739	281,739
Controls					
Store-year-month	X	X	X	X	X
Year-month-calendar week		X	X	X	X
Calendar week × controls			X		X
Calendar week × store				X	X

Notes: The table shows the effect of SNAP issuance on log food prices at a given store in a given week of the month. Prices in a store-week correspond to an index of product-level log prices; the index is derived from purchases by SNAP-eligible shoppers. Issuance share reflects the share of SNAP benefits issued during a calendar week in the jurisdiction in which a store is located. Panel A contains all stores in the sample; panel B is limited to stores for which we estimate that the share of SNAP recipients in the zip code is at least 20 percent. All columns include store-by-year-by-month fixed effects. Columns 2–5 include year-by-month-by-week fixed effects. Columns 3 and 5 include interactions of calendar week with state-year measures of log population, log GDP per capita, and unemployment rate. Columns 4 and 5 include calendar-week-by-store fixed effects. All specifications are weighted by average annual store volume. Standard errors, reported in parentheses, are clustered by state.

We next investigate whether the observed null effects on prices mask SNAP-induced price fluctuations in stores located in high-SNAP neighborhoods. Panel B of Table 2 replicates the prior analysis for stores located in zip codes in which at least 20 percent of residents participate in SNAP. The analyses yield estimated effects of SNAP issuance on prices that are slightly larger than those reported in Panel A but still near zero and not statistically significant. The 95 percent confidence interval excludes price effects greater in magnitude than 0.2 percent. Figure 5 further investigates the relationship between SNAP-induced price fluctuations and neighborhood SNAP prevalence. As with Table 2, the figure reveals a slightly larger price response in higher-SNAP stores, although even in such stores, the magnitude of the observed effects are small and statistically indistinguishable from zero.[27]

A different 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 intramonth cyclicality in demand. To shed light on this

and Washington (2010), suggesting that measurement error in SNAP participation is not driving the difference between the two sets of results. In addition, as described above, we estimate that approximately 20 percent of customers in the stores located in our high-SNAP neighborhoods are SNAP participants, which, assuming a roughly 80 percent household take-up rate during the years of our sample period (Leftin, Eslami, and Strayer 2011; Gray and Cunnyngham 2017), suggests that these stores tend to face SNAP customer bases within the range of stores studied by Hastings and Washington (2010).

[27] In contrast, online Appendix Figure A.3 shows a negative relationship between SNAP-induced price cyclicality and SNAP prevalence at the the grocery chain level, although here too the result is not statistically significant.

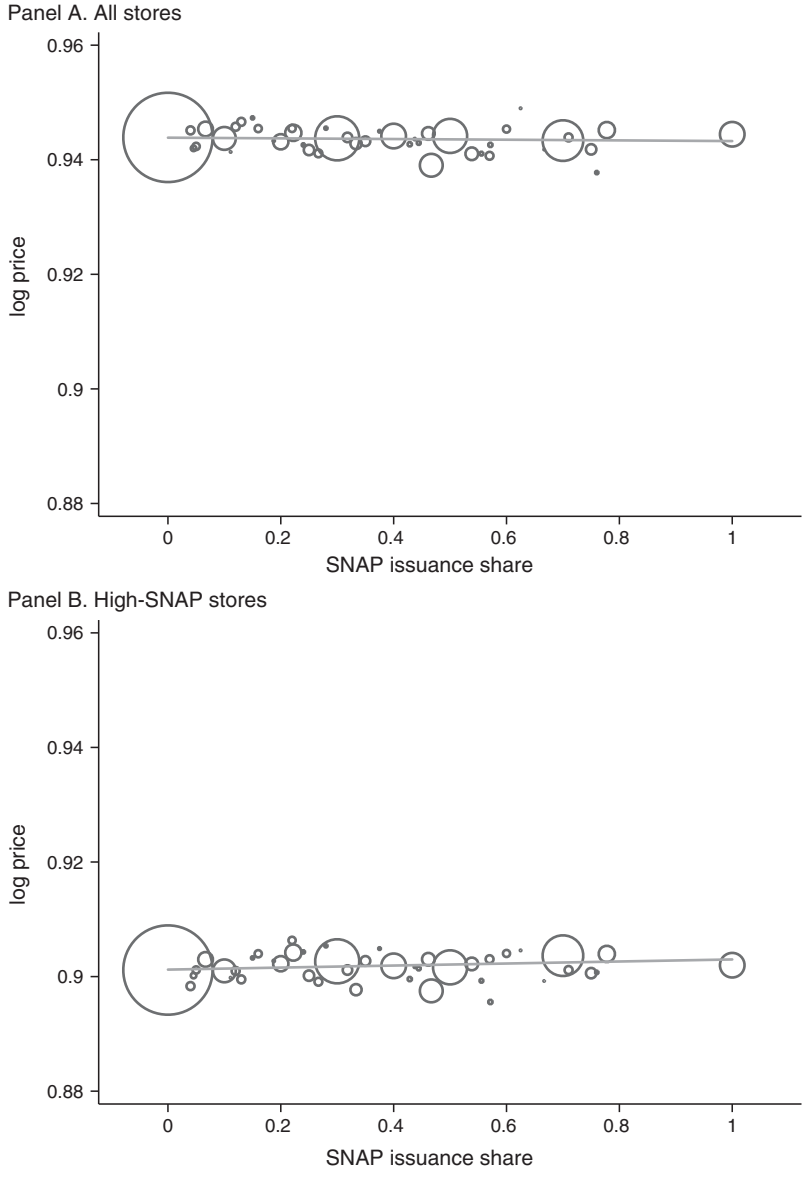


FIGURE 4. FOOD PRICES BY WEEKLY SNAP ISSUANCE

Notes: The figure displays average log food prices by the share of SNAP benefits issued in a given week of the month. Prices in a store-week correspond to an index of product-level log prices; the index is derived from purchases by SNAP-eligible shoppers. SNAP issuance share reflects the share of SNAP benefits issued during a calendar week in the jurisdiction in which a store is located. Points in the figure are proportionate to the number of store-weeks with the specified issuance share and reflect residuals after controlling for store-year-month and year-month-week fixed effects. Panel A contains all stores in the sample; panel B is limited to stores for which we estimate that the share of SNAP recipients in the zip code is at least 20 percent. The estimated slope of the best linear fit (weighted by the number of store-weeks with the specified issuance share) is −0.001 in panel A and 0.002 in panel B.

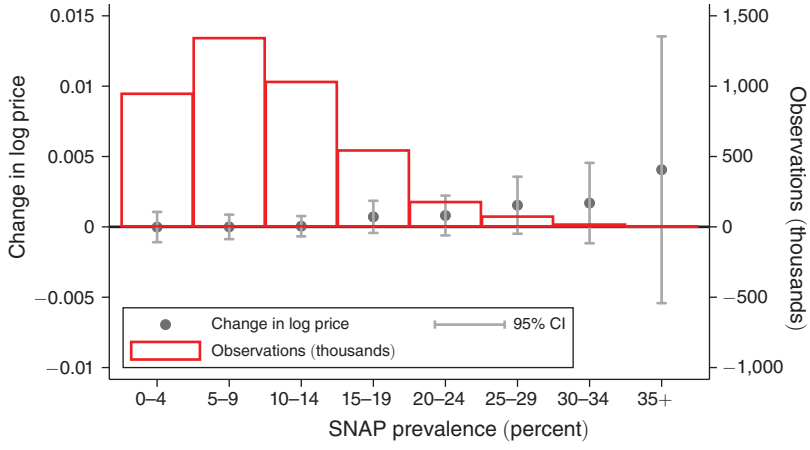


FIGURE 5. FOOD PRICE CYCLICALITY BY LOCAL SNAP PREVALENCE

Notes: The figure displays the estimated effect of SNAP issuance on log food prices by local SNAP prevalence. Local SNAP prevalence refers to the estimated share of the population that are SNAP recipients in the zip code in which the grocery store is located. Prices in a store-week correspond to an index of product-level log prices; the index is derived from purchases by SNAP-eligible shoppers. Change in log prices refers to the estimated coefficient on SNAP issuance share, which reflects the share of SNAP benefits issued during a given week of the month in the jurisdiction in which a store is located. The effect of SNAP issuance on log food prices is estimated from a specification that controls for store-year-month and year-month-week fixed effects as well as the interaction of calendar week with log state population, log gross domestic product, and unemployment rate (corresponding to column 3 in Table 2). The error bars on the estimated effects reflect the 95 percent confidence interval from standard errors clustered by state. The hollow bars reflect the number of observations in our sample (i.e., the number of store-weeks) from stores located in zip codes with the specified population share of SNAP recipients.

possibility, we replicate our results separately for the top ten product groups (e.g., "cheese," "bread") by expenditure share among SNAP-eligible customers during our sample period.[28] Whereas we observe that SNAP-induced cyclicality in sales varies greatly across product groups (online Appendix Table A.7), the estimated price effects are close to zero and, for the most part, not statistically significant (online Appendix Table A.8). Alternatively, retailers might limit their price responses to products that are the most disproportionately purchased by SNAP recipients compared to nonrecipients. To investigate this possibility, online Appendix Table A.9 restricts our analysis to the ten product modules with the highest estimated ratio of expenditures by SNAP-eligible customers relative to noneligible customers. Here too, the results are similar as with our overall product sample.

We next consider a range of robustness checks similar to those presented in the prior section. In particular, online Appendix Table A.10 shows that the results are not sensitive to unweighted analyses (columns 1 and 2), constructing the SNAP issuance variable to account for state issuance schedules based on last names (columns 3 and 4), or excluding states that issue benefits nonuniformly across issuance dates (columns 5 and 6).

[28] Together, these product groups cover 47 percent of SNAP-eligible-household food spending.

In addition, online Appendix Table A.11 investigates the possibility that the lack of pricing results are driven by the absence of price data for products not purchased during a store-week.[29] To assess the importance of this feature of our data, we replicate our expenditure and price analyses for the subset of stores for which at least 80 percent (columns 1–4) and at least 90 percent (columns 5–8) of expenditures are preserved, respectively. Although restricting the sample in this way yields slightly larger expenditure cyclicality, we observe no consistent evidence that this restriction is attenuating our price results.

Along similar lines, we next examine the role that coupon usage could play in driving our pricing results. Recall that the prices we observe in our retailer data are net of certain coupons and loyalty discounts. Hence, if SNAP customers are more likely to shop in weeks that SNAP benefits are issued and also more likely to apply such coupons or discounts to their purchases, the prices we observe may vary based on SNAP issuance even when retailers do not change them. Or, conversely, this phenomenon could cause us to observe no change in prices following benefit issuance even if stores tend to increase prices in such weeks. To investigate these possibilities, online Appendix Table A.12 explores the effect of SNAP issuance on the use of coupons (columns 1 and 2) and the purchase of discounted items (columns 3 and 4) using the Consumer Panel dataset. We find no evidence that the use of coupons or receipt of product discounts vary with the SNAP issuance schedule.

Finally, online Appendix Table A.13 considers the effect of SNAP issuance on the prices of the two categories of non-SNAP eligible grocery store products considered in the prior section: nonfood grocery items and alcohol. We observe small but statistically significant effects of issuance on nonfood grocery items, although the effects disappear for stores located in high-SNAP neighborhoods. We observe no consistent evidence of SNAP issuance affecting alcohol prices.

V. Understanding the Lack of Price Response to SNAP Issuance

The results thus far provide evidence that consumers substantially increase food expenditures in weeks that SNAP benefits are issued but retailers do not adjust food prices in those weeks by more than a very modest degree (if at all). In this section, we conduct several exploratory analyses to better understand these patterns.

As an initial step, we focus on one input into retailers' price setting decisions—within-month variation in the aggregate price elasticity of demand that retailers face. SNAP issuance may affect these elasticities through several channels. For example, the type of customers who shop following SNAP issuance may have higher or lower elasticities than customers who shop during other weeks in the month. In addition, households may exhibit different price sensitivities when spending SNAP benefits than they do when using cash because of either mental accounting (Hastings and Shapiro 2018) or a fixed cost of traveling to a store.

[29] Recall that we exclude products in store-months for which the product was not purchased in one or more weeks (approximately 17 percent of total food expenditures during our sample period). This sample restriction might distort our results if stores increase prices of certain products during SNAP issuance weeks and those higher prices prevent customers from purchasing those products—rendering the price increases unobservable to us.

To estimate how SNAP issuance affects demand price elasticities, we estimate the following product-level econometric model:

$$\log q_{kswmy} = \eta Issuance_{swmy} \log P_{kswmy} + \beta Issuance_{swmy} + \mu \log P_{kswmy} + \alpha_{ksmy} + \delta_{kwmy} + \gamma X_{sy} \zeta_{kw} + \varepsilon_{kswmy} \quad (6)$$

where $\log q_{kswmy}$ denotes the log quantity of product k purchased in store s in week w in month m of year y, $\log P_{kswmy}$ denotes the log price of that product in the corresponding store-week, α_{ksmy} denotes product-store-month fixed effects, δ_{kwmy} denotes product-week fixed effects, X_{sy} denotes year-level characteristics of the state in which the store is located, and ζ_{kw} denotes product-by-calendar-week fixed effects. We restrict this product-level analysis to the top 100 food products by expenditure share among SNAP-eligible shoppers.[30] The main parameter of interest in this model is η, which measures the change in price elasticity for a good between a week in which 100 percent of SNAP benefits are issued and a week in which no benefits are issued. As in the prior sections, the δ_{kwmy} term captures within-month variation in a product's elasticity that is due to factors other than SNAP issuance. We also consider variants of equation (6) that implement a difference-in-differences specification by including product-by-store-by-calendar-week fixed effects, ϕ_{ksw}.

An important concern with the analysis described in the prior paragraph is that 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 Hausman (1996) as adapted in 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," or DMAs). Under the assumption that local demand shocks for a store do not affect chain-level pricing decisions (conditional on our other controls), 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 first-stage effect of the instrument on prices to be close to 1 (see online Appendix Table A.16).

Columns 1 and 2 of Table 3 present the estimated effect of SNAP issuance on price elasticity (η), as well as the estimated effects of prices (μ) and SNAP issuance (β) on the quantity of a product purchased, from the OLS regression described in equation (6). Our results suggest that customers are slightly more price elastic in weeks that SNAP benefits are issued, especially in high-SNAP stores. For example, in stores

[30] More specifically, these products are those estimated from the Consumer Panel to have the highest expenditure share among SNAP-eligible customers among all food products that were purchased in at least 80 percent of the store-weeks in our data. The 80 percent threshold corresponds to the availability restriction imposed by DellaVigna and Gentzkow (2019) to select the products included in their analysis. Online Appendix Table A.14 shows the estimated effects of SNAP issuance on quantity purchased, and prices are similar for this subset of products and our main sample. In addition, to ensure that missing price data are not driving our findings for this sample, online Appendix Table A.15 imputes prices for products that are missing in a given store-week with the average observed price of the product among stores belonging to the same chain within the same state in the specified week; the results are qualitatively similar to our main specification, which excludes products that are missing in at least one week in a given store-month.

Table 3—Elasticity Estimates, 100 UPCs

	OLS		IV	
	(1)	(2)	(3)	(4)
Panel A. All stores				
Price × issuance share	−0.0216	−0.0145	−0.0207	−0.0056
	(0.0045)	(0.0082)	(0.0043)	(0.0095)
Price	−2.1025	−2.0857	−2.5917	−2.5764
	(0.1236)	(0.1250)	(0.1265)	(0.1253)
Issuance share	0.0825	0.1024	0.0818	0.0962
	(0.0107)	(0.0169)	(0.0108)	(0.0186)
Observations	379,212,892	379,212,892	379,212,892	379,212,892
Optimal price change (percent)	−0.9	−0.6	−0.5	−0.1
Panel B. High-SNAP stores				
Price × issuance share	−0.0385	−0.0323	−0.0350	−0.0161
	(0.0092)	(0.0164)	(0.0080)	(0.0181)
Price	−2.0657	−2.0202	−2.6396	−2.5747
	(0.1601)	(0.1562)	(0.2168)	(0.2064)
Issuance share	0.2335	0.2425	0.2309	0.2329
	(0.0357)	(0.0330)	(0.0362)	(0.0354)
Observations	24,576,132	24,576,132	24,576,132	24,576,132
Implied price change (percent)	−1.7	−1.5	−0.8	−0.4
Calendar week × store	No	Yes	No	Yes

Notes: The table shows the effect of SNAP issuance and price on quantity sold at a given store in a given week of the month. The analysis is conducted on the top 100 food products by expenditure share among SNAP-eligible shoppers, subject to the limitation that the product was purchased in at least 80 percent of store-weeks. The unit of observation is a product-store-week. The outcome is the log quantity of food products purchased in a given store-week. Issuance share reflects the share of SNAP benefits issued during a calendar week in the jurisdiction in which a store is located. Price refers to the log of a product's price in a given store-week. Implied price change refers to the difference in optimal prices between a week in which all SNAP benefits are issued and a week in which no SNAP benefits are issued, based on the estimated elasticity and the monopoly pricing model described in the online Appendix. In columns 1 and 2, the coefficients are obtained by estimating equation (6) in the text. In columns 3 and 4, the coefficients are obtained from a two-stage least-squares estimate in which a product's price in a given store-week is instrumented for with the price of the product in stores of the same chain but located in other DMAs. All columns include product-by-store-by-year-by-month fixed effects, product-by-year-by-month-by-week fixed effects, and interactions of product-by-calendar-week with state-year measures of log population, log GDP per capita, and unemployment rate. Columns 2 and 4 additionally include product-by-calendar-week-by-store fixed effects. Panel A contains all stores in the sample; panel B is limited to stores for which we estimate that the share of SNAP recipients in the zip code is at least 20 percent. All specifications are weighted by average annual store volume. Standard errors, reported in parentheses, are clustered by state.

located in high-SNAP neighborhoods, our difference-in-differences specification yields an estimated coefficient of −0.03 for the price-by-issuance-share interaction, suggesting that aggregate consumer demand becomes approximately 1.6 percent more elastic in weeks in which all SNAP benefits are issued compared to weeks in which no benefits are issued. The IV specification (columns 3 and 4) yield similar but slightly smaller point estimates—especially for the difference-in-difference specification, for which the estimated elasticity change is only 0.6 percent for the high-SNAP stores and is not statistically significant.

The small observed change in aggregate demand elasticities associated with SNAP issuance suggests that large price changes in response to SNAP issuance may not be profit maximizing. To link these estimated elasticities to pricing responses, online Appendix A draws on a simple model of grocer pricing in which grocery

stores have local market power due to the fact that customers are constrained by travel costs and perishable foods (as in Ellickson, Houghton, and Timmins 2013 and Ellickson 2006). Using this model, we derive the optimal price response of grocery stores as a function of changes in consumer price elasticities over the course of the month. Table 3 includes these predicted price responses under the elasticity estimates for the corresponding specification and sample. The results suggest that stores should slightly reduce food prices in weeks that SNAP benefits are issued. Focusing on the IV specification, our estimates suggest that stores should reduce prices between 0.1 and 0.8 percent in weeks in which all benefits are issued relative to weeks in which no benefits are issued.

The elasticity results, in conjunction with this simple model, suggest that retailers should modestly reduce food prices in response to SNAP issuance. However, even these modest reductions are outside our 95 percent confidence interval for the effect of SNAP issuance on prices—an estimated effect that is near zero and very slightly positive.[31]

One factor missing from our analysis that could potentially explain this discrepancy is the possibility that SNAP issuance affects grocery stores' marginal costs. For example, stores may increase staffing in weeks that SNAP benefits are issued in order to handle the increased flow of customer traffic (e.g., Cloud 2012). To the extent that SNAP issuance raises stores' marginal costs in this way, it may offset the incentive to lower prices from SNAP-induced changes in consumer elasticities.[32]

As noted above, a potential reason why stores do not adjust prices in response to SNAP issuance is that the benefits of doing so may be quite small given the small predicted price changes implied by our elasticity estimates. A complementary explanation for the lack of pricing response could be the adjustment or managerial decision costs that a store would incur by varying its prices in response to SNAP issuance cycles (Hanna, Mullainathan, and Schwartzstein 2014; Bloom et al. 2013). For example, DellaVigna and Gentzkow (2019) find that such costs contribute to uniform pricing decisions across grocery stores belonging to the same chain. The SNAP-induced elasticity changes over the course of a month are smaller than the elasticity differences across stores documented by DellaVigna and Gentzkow (2019); as such, it would not be surprising that similar factors limit grocery store price adjustments based on SNAP issuance cycles.

To assess the contribution of factors other than small elasticity changes (such as managerial inertia) in explaining stores' lack of price responses, online Appendix Figure A.4 disaggregates our results to explore the relationship between SNAP-induced variation in elasticities and prices. In particular, there may be larger changes in customer demand elasticity within subsets of the data—e.g., certain products—along with correspondingly larger fluctuations in price. To investigate

[31] Taking the prescriptions of this stylized model as optimal would suggest that by failing to reduce prices in response to SNAP issuance, retailers are forgoing profits, SNAP recipients are facing higher food prices during their shopping trips, and nonrecipients who disproportionately shop in weeks that benefits are not issued are benefiting from the (relatively) lower food prices.

[32] In principle, SNAP-induced variation in marginal costs could create a net incentive for firms to raise prices in response to SNAP issuance, notwithstanding the observed effects on customer elasticities. Our near-zero price effects thus provide some evidence against this possibility as well.

this possibility, online Appendix Figure A.4 plots the estimated effects of SNAP issuance by product on prices and elasticities. If small changes in elasticities were the only factor responsible for the lack of observed price effects, we would expect to observe larger price changes for those products experiencing larger changes in elasticities. However, the slope of the best linear fit is near zero, providing no evidence for such a pattern. Thus, while small elasticities and associated small incentives to vary prices could certainly contribute to lack of observed price, this analysis provides suggestive evidence that other factors may be at play as well.

Finally, pricing strategies that require managers to set weekly prices differently across stores may be costlier to implement than pricing strategies that vary prices by week but are uniform within a week across stores within a given chain. To explore the role played by this specific type of managerial cost in limiting store pricing responses, we focus on a subset of stores in which adjusting to SNAP issuance would not require different pricing policies across stores within a chain. In particular, online Appendix Figure A.5 replicates online Appendix Figure A.5, limiting the analysis to chains for which all stores are located entirely within a single state or a set of states that have uniform SNAP issuance schedules. Among stores located in high-SNAP neighborhoods, the figure suggests a small but positive relationship between SNAP-induced elasticity and pricing changes, closer to the predictions of the simple model. The results therefore provide suggestive evidence that managerial inertia may help explain why stores do not set prices based on intramonth cycles in SNAP issuance.

VI. Conclusion

In this paper, we study intramonth patterns in customer demand and retail pricing driven by SNAP issuance. We find that SNAP issuance causes large increases in food expenditures but little to no change in retail food prices. We investigate several potential explanations for the lack of price response. For example, notwithstanding the large effects on demand induced by SNAP issuance, we observe small effects of issuance on the price elasticity of demand facing retailers, which may limit their incentives to adjust prices in response to the SNAP issuance schedule. Although we do not provide direct evidence for them, our results are also consistent with factors such as changing marginal labor supply costs or managerial inertia contributing to the lack of observed price response.

Our results have implications for the likely effect of policy reforms that alter the SNAP issuance schedule. For example, as we have discussed, a number of states have staggered their SNAP issuance schedules to spread out the dates on which different individuals receive their monthly allotment of benefits. Similarly, some have proposed splitting the issuance of SNAP benefits to a given individual into multiple payment dates within a single month (e.g., Wilde and Ranney 2000; Hastings and Washington 2010; Dorfman et al. 2019).

First, our findings related to food expenditure cyclicality shed light on how such reforms are likely to affect customers' shopping behavior. In particular, because we find that food expenditure cyclicality is due to SNAP issuance—rather than some other monthly pattern—our results suggest that state reforms to either split or

stagger issuance would have the effect of reducing fluctuations in the aggregate food demand faced by retailers. Consequently, by smoothing food demand across the month, our findings support the notion that reforms to SNAP issuance schedules can reduce grocery costs associated with surges in customer traffic, such as long lines or difficulty stocking shelves or staffing stores.

In addition, because we find that these reforms would shape the food demand cyclicality faced by retailers, our results suggest that they may also shape the incidence of SNAP benefits. That is, to the extent that retailers face predictable fluctuations in the nature of consumer food demand, it may, in principle, be profit maximizing for them to adjust food prices over the course of the month. If retailers were to adjust food prices during the weeks that SNAP recipients purchase food, such behavior may increase or decrease the purchasing power of the benefits. Hence, assessing the welfare effect of reforms to SNAP issuance schedules requires understanding the link between issuance and retailer pricing decisions. Because we find evidence that retailers do not adjust food prices in this way, our results suggest that concerns relating to the incidence of benefits should not play a large role in state decisions about whether to adjust their issuance schedules.

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