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How Do Government Transfer Payments Affect Retail Prices and Welfare?

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Abstract

This paper studies the effect of the Supplemental Nutrition Assistance Program (SNAP) on retail prices in the United States. State-level program adjustments motivate the identification strategy. A 1 percent increase in benefits per population raises grocery prices by a persistent 0.08 percent. A calibrated partial-equilibrium model implies a marginal benefit dollar raises a recipient's consumer surplus from groceries by $0.7, producer surplus by $0.5, and lowers each non-SNAP consumer's surplus by $0.05, because of a large marginal propensity to consume food out of SNAP, low elasticities of demand, and moderate market power. To guarantee the real intended spending power on food, benefits should be increased by 7 percent.

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How Do Government Transfer Payments Affect Retail Prices and Welfare? Evidence from SNAP*

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1 Introduction

As the second-largest means-tested aid program in the United States, the Supplemental Nutritional Assistance Program (SNAP) is a central element of the US safety net, providing about $70 billion in electronic benefits for food to more than 40 million Americans annually.[1] Although much attention has focused on the impact of SNAP on participating households, less is known about the response of retailers from the supply side.[2] Quantifying how producers respond to changes in SNAP, in particular by changing prices, is essential to understanding the welfare consequences of transfer programs. Price effects could attenuate the real spending power of government transfer payments and distort the redistributions such transfer programs intend to achieve. These effects are an empirical question.

We present new evidence on this question by estimating the impact of SNAP benefit changes on retail prices, sales, and household consumption, leveraging national retail and consumer scanner data between 2006 and 2015. To understand economic incidence, we develop and calibrate a partial-equilibrium framework. The mechanisms examined may help better understand implications of other social insurance programs such as universal basic income to the extent that electronic benefits for food are comparable, which we examine.

Two main challenges arise when estimating the causal impact of SNAP. First, endogenous local economic conditions affect program participation, as eligibility for the program is determined by household economic characteristics. Second, because SNAP is a federal program, key parameters determining eligibility and benefits per recipient have been thought to leave little room for panel variation.

In this paper, we first formally document the benefit formula by analyzing computer algorithms used by the federal government to audit state-level-benefit disbursements, en route to introducing our identification strategy.[3] We investigate the factors that impacted the scale of the program during the Great Recession and its aftermath. We find that the program expanded by 140% between 2007 and 2014 not only because of the endogenous economic downturn, but also because of changes induced by the 2008 Farm Bill and the 2009 American Recovery and Reinvestment Act (ARRA). We report rich variation that resulted both from (1) the interaction of heterogeneous recipient profiles across states with

[1]The largest means-tested aid program in the US is Medicaid. SNAP was formerly known as the Food Stamp Program. In 2013, Americans spent $425 billion buying food for consumption at home across food stores, whereas SNAP spent $76 billion, or 18% of the US total (USDA, 2016, 2017). Appendix Figure O1 shows that SNAP benefits account varied between 8% and 18% of US food-at-home sales in food stores between 2006 and 2015. Since not all food at home is sold in stores classified as food stores, the actual shares may be smaller.

[2]Over 280,000 authorized retailers sell food to SNAP recipients.

[3]We are able to do so thanks to the Food and Nutrition Service (FNS) and Mathematica Policy Research teams, the owners of the codes, who have allowed us to analyze their audit codes (see Appendix B).

idiosyncratic fluctuations in state-level standard utility allowances (SUA); and (2) from the subsequent interaction of receipt profiles with rising federal maximum benefit levels (an economic stabilizer during this time).

We document that changes in SUA explain much of the variation in the intensive margin (benefits per recipient) in the month of the Farm Bill, and that the levels set up by SUA interacted with rising federal maximum benefit levels explain much of the variation during the month of ARRA. We note that SUA parameters were being updated according to formulas specific to each state set decades prior to 2006. Since states had their hands tied in the updating of these numbers, we determine that growth rates in SUA, especially after controlling for state-level energy-price and consumption trends, are prediction errors plausibly exogenous to unobserved fundamentals affecting prices during this period.[4] New Hampshire (NH) and Wyoming (WY) present cases in point: even though both states had nearly identical temperature trends across 2007 and 2008, NH raised SUA by about 29% while WY lowered it by 23% in the month of the Farm Bill in October 2008. As a result, even though the two states had almost identical benefits per recipient before this month, their benefit amounts diverged by 11 percentage points after this month, with NH receiving $10 more per recipient than WY.

Motivated by these findings, we develop an instrumental variable (IV) in the spirit of Currie and Gruber (1996) by simulating how payments would have evolved had recipient characteristics remained fixed at pre-specified levels. The identifying assumption in our setting is that SUA shocks as well as participant types in the pre-period were exogenous to unobserved economic trends governing prices. We support this assumption with (1) parallel pre-trends; (2) lack of correlation between the IV and key economic observables; and (3) evidence from Ganong and Liebman (2018) that in the pre-recession year of 2006, changes in unemployment rates, a proxy for economic fundamentals, were not contributing to changes in local SNAP participation profiles.[5]

We then turn to national retailer scanner data available from 2006-2015 to document the impact of benefit changes on retail prices and sales. As in Leung (2021), we build on Beraja et al. (2019) to construct a wide variety of store-level price indices based on data spanning over 20,000 stores, 2.6 million barcodes, and 50% of US grocery-store sales.[6] We estimate that a 1% increase in benefits per population causes a moderate and persistent

[4]According to USDA (2019), "the degree of the variation in methodologies and therefore SUA amounts is of concern as similarly situated households living a few miles apart could have significantly different benefit amounts."

[5]This is shown in Panel A of Figure 3 in their paper: the contribution of unemployment-rate growth to participation-rate growth vanishes in 2006.

[6]See Appendix Section D for details about the choice and construction of these indices. Income-group-specific price indices are discussed in Section 5.

increase in grocery-store prices of 0.08%. The effect is stronger in counties with higher SNAP participation rates and higher grocery market concentration. Increases in sales, after controlling for price effects, are also larger in counties with higher SNAP participation rates. We estimate small and statistically insignificant effects on other store types, firm dynamics such as retailer entry and exit, and market structure. We estimate a positive price effect not only for SNAP-eligible products but also for SNAP-ineligible products, although the sales effect is much stronger in high-participation counties for SNAP-eligible goods but not SNAP-ineligible goods. We regard this as evidence consistent with multi-product pricing models such as that of Chen and Rey (2012), suggesting that retailers are able to raise markups on both eligible and ineligible products.

Next, we use consumer scanner data to estimate the effect of SNAP on household consumption. We classify consumption by eligible and ineligible households, as well as by eligible and ineligible products. We estimate a marginal propensity to consume food (MPCF) out of SNAP of about 0.44 for eligible households, in line with previous literature. We estimate that the MPCs for ineligible products and ineligible households are statistically insignificant and different from the MPCF out of SNAP for eligible households. Using cross-state variation in issuance schedules, we find that the MPCF out of SNAP is larger in weeks of benefit disbursement, complementing previous literature on impacts of issuance schedules (Goldin et al. 2022). We also investigate the effect of SNAP on shopping behavior, and report small and mixed effects.

In order to understand economic incidence, we develop and calibrate a simple partial-equilibrium model of supply and demand, extending upon the tax-incidence analyses from Weyl and Fabinger (2013) to shed light on the incidence of social-safety-net transfers. The exercise allows us both to test the consistency of empirical findings with theory and to interpret the results. The framework takes our reduced-form estimates of the price response and the MPCF out of SNAP as a set of sufficient statistics to measure the local incidence of changes in SNAP benefits. We find that for SNAP-eligible goods, SNAP recipients experience a large increase in consumer surplus as expected. We also find that retailers exercise market power by increasing prices to capture producer surplus. On the other hand, non-SNAP consumers experience a decline in consumer surplus. A marginal dollar of SNAP benefits increases SNAP consumer surplus—specific to groceries consumption—by about \$0.7, increases producer surplus by about \$0.5, and decreases non-SNAP consumer surplus by about \$0.4, or \$0.05 per non-SNAP consumer on average. We derive pass-through formulas to show that the size of the price response is consistent with the theoretically-calibrated prediction based on the MPCF out of SNAP, demand elasticity, and pass-through rate. Furthermore, the model predicts that the price responses should increase with SNAP participation rates and market power, consistent with our results on heterogeneity.

First, this paper contributes to an extensive literature that evaluates the impacts of SNAP. Recent papers regarding SNAP (Hoynes and Schanzenbach, 2009; Almond et al., 2010; Hoynes et al., 2016) exploit the county-level rollout of the program in the 1970s as a quasi-experiment to evaluate the impact of SNAP on consumption, birth weights, and long-run measures of human development. Furthermore, a growing number of studies have estimated the MPCF out of SNAP benefits. Hastings and Shapiro (2018) (hereafter HS) use transaction-level data from a large US grocery retailer's operations in five states to estimate an MPCF out of SNAP of 0.5 to 0.6 but an MPCF out of cash of 0.1. Based on these estimates and other evidence, they reject the fungibility of SNAP benefits.[7] Hoynes and Schanzenbach (2016) provide a review of the literature.

The supply-side responses of retailers have received less attention. A number of recent papers have investigated cross-state variation in within-month issuance schedules to investigate how quickly consumers exhaust their benefits upon receipt, and whether retail stores take advantage of these predictable expenditure phases (Hastings and Washington 2010; Goldin et al. 2022). Jaravel (2018) studies relationships between SNAP take-up rates, prices, and product variety using consumer scanner data.[8] We utilize a novel source of variation to study the incidence of a persistent increase in SNAP benefits.

Second, this paper contributes to a literature studying the incidence of social programs through their impacts on prices. Cunha et al. (2019) study a village-level randomized experiment in Mexico and find that in-kind transfers of food decrease prices due to increases in supply, whereas equivalently valued cash transfers have a negligible impact on prices. Filmer et al. (2018) analyze a randomized evaluation of a Philippine cash transfer program and show prices of perishable protein-rich foods rose as a result of the transfers, leading to a negative impact on the nutrition of non-beneficiary children. Banerjee et al. (2021) study an experiment in Indonesia that randomized rice vouchers versus rice deliveries across districts. They find that the former intervention led to higher transfers due to lower leakages; while they do not explicitly calculate price incidence and their household-survey-based price difference is imprecise, our back-of-the-envelope calculation based on their numbers suggest a price incidence of 0.16%, comparable in order of magnitude to our finding for the US context. A literature on the price effect of minimum wages also exists.[9] Village-level transfers directly

[7]Other work includes Beatty and Tuttle (2015), who report an MPCF of 0.484 estimated using the Consumer Expenditure Survey data and the matching-on-observables method, comparing food expenditure patterns of SNAP-recipient and non-SNAP recipient households before and after the 2009 ARRA.

[8]We lay out the main differences between our papers in Appendix Section A.

[9]Aaronson et al. (2008) provide evidence for complete labor-cost pass-through in restaurants. Leung (2021) suggests that in addition to the cost channel, changes in product demand could further increase prices under variable markups while Renkin et al. (2020) highlights the effects on the costs of both manufacturers

increase food supply, whereas minimum wages decrease product supply by increasing labor costs and exert demand-side effects by increasing the income of consumers. By contrast, as an in-kind electronic-benefit-transfers program, SNAP would mostly shift the demand curve without directly shifting the supply curve. Similar to Filmer et al. (2018), we find that transfer programs can have unintended consequences on both recipients and non-recipients through equilibrium effects.

Third, we contribute to a growing literature providing empirical evidence on how demand shocks affect prices. Recent work using retail scanner data suggests price responses to demand shocks can be significant. Stroebel and Vavra (2019) find a strong positive relationship between housing-price shocks and retail price indices at the zip-code level. They argue their results are driven by procyclical markups due to decreases in demand elasticities as a result of increases in housing wealth. Beraja et al. (2019) show a negative relationship between unemployment rates and retail prices at the state level.[10] Our paper shows that another source of demand shocks—in our context driven by government transfers—increases prices. We additionally contribute pass-through formulas that shed light on the factors that determine the size of the price response. We also show that regional pricing can be significant. DellaVigna and Gentzkow (2019) show that uniform pricing in retail chains are prevalent and suggest that the uniform pricing could dampen price response to local demand shocks. Nuancing their evidence, we find that grocery chains in particular price more flexibly or have limited geographic representations with stores spanning at most one or two states, such that prices in the sector show significant responses to locally clustered demand shocks.[11] Furthermore, our analysis provides an informative foil to results by Egger et al. (2022), who find a significant price effect but one that is an order of magnitude smaller than ours in their analysis of a general cash-transfer program provided to three subcounties (653 villages) in rural Kenya. Although some products showed price inflation as large as 1.2%, the marginal consumption propensity was generally dispersed, and individual and aggregated price responses across products (including food) were far smaller in their setting, contrasting with our setting where the MPC was concentrated on food. This comparison suggests the significant roles that in-kind designation of government electronic benefits and product-specific MPCs can play in influencing consumer demand and market outcomes.[12]

This paper is structured as follows. Section 2 discusses the data we use and the

and retailers. Meckel (2020) studies the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), another social program in the US.

[10]Earlier work such as Nakamura and Steinsson (2014) uses variation in military spending and alternative, sparser price data sources that do not derive from retail scanner data and find insignificant price effects.

[11]Butters et al. (2020) find that local prices can be more responsive to local cost shocks than to demand shocks, suggesting that retailers may set prices according to a constant markup over wholesale costs.

[12]Also at play may be heterogeneous market power across specific product markets.

institutional details of SNAP payments, and introduces the instrument. Section 3 formally lays out the empirical specifications. Section 4 reports the main results. Section 5 derives pass-through formulas to shed light on the factors that determine the size of the price response, calibrates a theoretical partial-equilibrium framework to compare with the empirical findings, and calculates the incidence of changes in SNAP benefits. Section 6 concludes.

2 Data and Institutional Details

This section gives an overview of the data used for analysis, including data on SNAP benefits, retail prices, quantities sold, household expenditures, and other information. We also explain the formula used by the government to determine SNAP benefits for a given household, which motivates the construction of the IV.

2.1 SNAP Benefits

We use publicly available state-by-month data on SNAP benefits and SNAP participation released by the Department of Agriculture (USDA) Food and Nutrition Service (FNS). We use state-by-month data for our main results; the results are robust to using county-level benefits for the set of available states.[13]

Figure 1 plots out the SNAP benefits per population over our sample period from 2006 to 2015, which we use as our variable of interest to capture the amount of SNAP spending retailers receive. We divide total SNAP benefits by population as we are interested in changes in the scale of SNAP that are not driven by changes in population or market size. Substantial variation exists across states, with benefits per population ranging from \$5 to \$30 per month. Large discrete jumps in SNAP benefits per population mainly come from two events, the 2008 Farm Bill and the 2009 ARRA, in which maximum benefits for SNAP households were raised by around 8.5% and 13.6%, respectively. Both of these events increased SNAP benefits at the federal level in October 2008 and April 2009, respectively, through the intensive margin (SNAP benefits per recipient) as shown in Figure 2a, with benefits per recipient ranging from \$80 to \$150. This led to state-level variation in the percentage change of average SNAP benefits per population, as shown in Figure 3, ranging from around 6% to 25%. SNAP participation rates—ranging from 5% to 25%—were growing over this period, contributing to the smooth rise in the time series through the extensive margin (SNAP recipients per

[13]County-level benefits are available at the bi-annual level for 33 states (the remaining states do not report them). County-level participation counts are available for all states at the annual level. Data at a higher spatial resolution is not available.

population), as shown in Figure 2b. Other major changes include cost-of-living adjustments (COLA) in 2007 as well as the expiration of the ARRA in 2013. Figure 4a plots the changes in SNAP benefits per population across these four events. The Farm Bill and the ARRA contribute large and dispersed changes across states, whereas the 2007 COLA and 2013 ARRA expiration contribute limited and negligible variation.

We also use the SNAP Quality Control (QC) Survey, which contains detailed demographic, economic, and program-eligibility information for a nationally representative sample of approximately 50,000 SNAP households. This data set is collected by the USDA FNS and generated from monthly quality-control reviews of SNAP cases that are conducted by state SNAP agencies to assess the accuracy of eligibility determinations and benefit calculations for the state's SNAP caseload. We get the formula from the FNS to impute synthetic benefit amounts. That is, we analyze the algorithms used by the FNS to audit benefit amounts and construct the QC data, and use the same algorithms to build the simulated instrument. The formula we use generates identical benefits to those in the QC data for 98% of households.[14]

2.2 The SNAP Formula and Instrumentation Strategy

The federal SNAP formula is designed to ensure a floor of spending power on what the government considers sufficient nutrition for households in poverty. Every year, the USDA prepares a monthly dietary budget called the "Thrifty Food Plan" for a typical four-person household adjusting for changes in the Consumer Price Index (CPI). In October, the USDA updates the SNAP-benefit parameters based on the size of this budget, which becomes the maximum level of benefit a four-person household can receive from SNAP. The annual formula adjusts maximum levels for households with different numbers of family members based on a sliding scale. SNAP may update these parameters in months other than October at the discretion of the Congress. For example, the 2009 ARRA included a provision to add 13.6% to the Thrifty Food Plan budget, increasing the maximum benefit level for a single-member household to $200, and for a household of seven or more members to $150 per person. We show how maximum benefits changed over time in Appendix Figure O2a and how the maximum benefits per recipient decrease as household size increases in Appendix Figure O2b.

Because the federal formula's intent is to ensure a floor of spending power on food, the benefit amount falls as a given household's estimated ability to contribute to food spending

[14]We do not code in the Supplemental Security Income Combined Application Projects (SSI-CAP) adjustments, which affect only 2% of the national sample of participants, yet are extremely complex and render the costs of coding prohibitive.

rises above the floor. The final benefit level of a household is given by the maximum benefit level minus 30% of household "net countable income," which is the household's gross income minus expenses considered indispensable. Examples of indispensable expenses include the standard utility allowance (SUA) determined by each state to cover utility expenses, rental costs, and a homeless deduction for living expenses conditional on being homeless (e.g., transportation). Some components of the formula, such as the federal maximum benefit level and the state-determined SUA, are determined by government policy, whereas others, such as household gross income and rental costs, are determined by household characteristics.

We first introduce the instrument using a few examples before laying out the details. To construct the instrument, we use the SNAP benefits formula to simulate what a fixed sample of participants would have received throughout the sample period, by allowing only policy parameters to vary over time while holding household economic variables such as household gross income and rental costs fixed, using a sample of about 50,000 SNAP participating households surveyed in the pre-period of 2006 from the SNAP QC data. We then sum over these simulated benefits for each recipient to construct our IV: simulated (used interchangeably with "synthetic") benefits per population at the state-level.

Variation in the instrument is almost entirely driven by two policy changes. First, federal maximum benefits were raised and state-specific adjustments to the SUA were made during the Farm Bill. We illustrate these changes in Figure 5 by again focusing on the comparison between New Hampshire and Wyoming, two states that had the largest difference in percentage changes of the instrument during the Farm Bill. In Figure 5a, we show that New Hampshire raised the heating and cooling SUA (HCSUA) by about 29% in October 2008 while Wyoming lowered it by about 23%. These changes led to a much larger percentage increase in synthetic benefits per recipient for New Hampshire as shown in Figure 5b. The two states had almost identical synthetic benefits per recipient until they diverged during the Farm Bill.

Second, the ARRA also raised federal maximum benefits, as illustrated in Figure 6 which juxtaposes Missouri and New York, two states that had the largest difference in percentage changes of the instrument during the ARRA. In Figure 6a, we show the two states had only small changes in the HCSUA during the Farm Bill and the ARRA, with New York raising the HCSUA in February 2009 instead. However, the ARRA led to a 20.26% increase in the instrument for Missouri but only a 15.31% increase for New York. The reason is that Missouri has a lower synthetic benefits per recipient, because it has continually had a lower HCSUA relative to New York. Because the ARRA raised federal maximum benefits by the same absolute magnitude for all states, Missouri had a higher percentage change in the instrument as it started from a lower base level, determined largely by the lower SUA.

Next, we introduce a simplified approximation of how the government specifies the SNAP-benefits formula. The approximation is meant to isolate the intuition; more details follow in Appendix Section B, where we formalize the SNAP algorithm in its full complexity.

Let $X_{it} = \{N_{it}, S_{it}, I_{it}, R_{it}\}$ represent the set of potential SNAP recipient i's household characteristics observed by the government at time t. Characteristics important to the government include N_{it}, the person's household size; S_{it}, the person's state of residence; I_{it}, the person's gross income minus earned income deduction; R_{it}, the person's rent.[15] Let $p_t(X_{it}) = \{b_t, o_t, u_t\}$ represent SNAP's formulaic parameters, which are functions of X_{it}. b_t represents the maximum-benefits formula; u_t, the utility-cost deduction formula; and o_t, the deduction formulae for various basic needs other than housing. The SNAP benefits per recipient, denoted by $\tilde{B}_{it}$, can be approximated by

$$\tilde{B}_{it} \approx b_t(N_{it}) - 0.45\, I_{it} + 0.45\, o_t(X_{it}) + 0.3R_{it} + 0.3\, u_{st}(N_{it}). \tag{1}$$

As described before, b_t decreases in N_{it}. o_t also generally decreases in N_{it}. u_{st} is determined by the state-determined SUA in which each state sets a uniform utility-deduction standard intended to reflect the average state utility cost per household; these deductions apply uniformly across the state to households with a positive reported utility cost.

The problem with using state-level SNAP benefits per population directly is that variables such as I_{it} and R_{it} are endogenously correlated with trends in unobservable economic fundamentals that vary over time. In order to address this problem, we propose a simulated instrument: the benefits' process that relies only on (1) household characteristics of the program participants that are fixed at pre-recession (2006) levels, and (2) the way that these fixed characteristics interact with changes in formulaic parameters determined by the state and federal governments.[16]

Instrumenting for the state-level benefits per population, the IV $\tilde{Z}_{st}$ is constructed by aggregating the simulated benefits per recipient, $\tilde{B}_{it}\left(X_{i0}; p_{st}(X_{i0})\right)$, up to the state-level using sampling weights in the QC data and then dividing by $n_{s,0}$, the population of state s

[15] The government uses other observed characteristics as well, but in this subsection, we do not focus on these characteristics, which include legal child-support expenses, dependent-care expenses, and medical expenses for households with elderly or disabled members; in 2008, deductions based on these expenses comprised only 2.2% of total expense deductions granted by the program.

[16] As mentioned in Ganong and Liebman (2018), the impact of state-level reforms such as electronic applications on SNAP enrollment mostly occurred before the recession in the early 2000s. During the recession, there was indeed increased state-level adoption of Broad-Based Categorical Eligibility (BBCE), which they calculate to only account for about 8% (1.57/19.1 in Table 2) of SNAP enrollment increases. They discuss that the benefit calculation rule sharply limited the scope of this eligibility expansion. Given these facts and our sample period, we focus on intensive margin changes in this paper.

in the pre-period of 2006, denoted as $t = 0$:

$$\tilde{Z}_{st} = \frac{1}{n_{s,0}} \sum_{i \in s,0} \left[\tilde{B}_{it} \left(X_{i0}; p_{st}(X_{i0}) \right) \right]. \tag{2}$$

We use the SNAP QC sample of participants in 2006 to conduct the simulation. The state-level benefits per population B_{st} are obtained from the FNS data.

Given that we use log points instead of levels in our empirical specification to translate into elasticities, the percentage changes in simulated benefits per population can be approximated as,

$$\begin{aligned}\Delta \ln \tilde{Z}_{s,t} &\approx \frac{\tilde{Z}_{s,t} - \tilde{Z}_{s,t-1}}{\tilde{Z}_{s,t-1}} \\ &= \frac{\bar{\Delta}_s\, b_t(N_{i0}) - 0.45\bar{\Delta}_s\, o_t(X_{i0}) + 0.3\bar{\Delta}_s\, u_{st}(N_{i0})}{\frac{1}{n_{s,0}} \sum_{i \in s,0} \left[b_{t-1}(N_{i0}) - 0.45\, I_{i0} + 0.45\, o_{t-1}(X_{i0}) + 0.3 R_{i0} + 0.3\, u_{s,t-1}(N_{i0}) \right]},\end{aligned}$$

where $\bar{\Delta}_s$ is the average difference operator.

The IV is similar in spirit to that of Currie and Gruber (1996) and used in a series of related approaches. The instrument maps to a generalized Bartik-style shift-share framework recently laid out by Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2018); however, our strategy depends on an additional source of variation compared to traditional shift-share instruments. Our initial measure of local shock exposure is pre-recession SNAP household characteristics while the shocks are policy changes both at the national and local level, and we also allow for local shock exposures to be updated over time by plausibly exogenous local policy changes, namely, changes in the SUA.

How are changes to the SUA determined? As documented in detail in Appendix Section C.1, the intent of the government was to have the SUA reflect state-specific energy quantities consumed and prices by fuel type, and states were given the flexibility to use their own formulas to determine how to reflect these costs. Most states ended up using two main methodologies to set the SUA: (1) 43% update the SUA annually from a base using lagged changes in fuel CPI, and (2) 57% recalculate "averages" based on recent utility data. According to state surveys on this topic, these state-specific methodologies were determined independently of each other decades prior to 2006.[17] Anticipating the discussion, we show our results do not change when estimated separately for either set of states.

How are changes in the SUA plausibly exogenous? States had their hands tied in the updating of these numbers. Therefore, changes in synthetic benefits, especially after

[17] Only two states, New York and Vermont, changed their formulas in 2011 in all the years of our analysis from 2006-2015 (Holleyman et al. 2017).

controlling for a vector of current state-level energy usage and prices as well as state- and time-fixed effects, were being driven by prediction errors of idiosyncratic methodologies—and the errors' idiosyncratic interaction with recipient profiles—that were set prior to the events and remained unchanged over the sample period. Indeed, the government's own view is that differences in SUA amounts do not fully reflect actual utility costs across state lines: according to USDA (2019), "the degree of the variation in methodologies and therefore SUA amounts is of concern as similarly situated households living a few miles apart [across state lines] could have significantly different benefit amounts."

Corroborating the discussion, we first show below that the SUA continues to drive variation in the IV even after controlling for energy usage and prices as well as observable economic variables. Second, we also show in Section 3 that our results are robust to controlling for these energy variables. Third, we show that the pre-trends are parallel in Section 3. Fourth, our results are robust to relaxing the identifying assumption by allowing the IV to be plausibly exogenous à la Conley et al. (2012), with the IV having a direct impact on outcomes even after controls. We obtain a back-of-the-envelope estimate of how large this impact would quantitatively be using pass-through formulas as in Appendix Section E.

In order to understand the composition of this variation empirically, we regress state-level percentage changes in synthetic benefits per population on the log of state-level average SNAP household characteristics such as gross income, rent, and household size, focusing on the variation during the months of the Farm Bill and the ARRA. We also include the share of participating households with elderly or disabled members and homeless members, because certain restrictions on the benefit amount, such as the shelter cap, do not bind for these households. All these measures are calculated in the pre-period of 2006 to match the sample used to construct the IV. In addition, we include the log of the amount of the SUA before each event as well as the percentage change in the SUA during the Farm Bill, because no change occurred in the SUA during the ARRA. We then decompose the variance in the percentage change in the IV into components driven by each variable.[18]

The results in Table 1 show that almost 80% of the variation in the IV is driven by variation in state-level changes in the SUA during the Farm Bill. A higher level of gross income, a lower level of rent, and a lower level of the SUA in the pre-period also lead to a larger percentage change for the same absolute change in the IV, but altogether account for a much smaller share. In contrast, over 70% of the variation in the IV in the month of ARRA is driven by variation in base levels of the SUA. These results show the extent

[18] Consider a state-level regression $Y_s = \alpha + \sum_{i=1}^{n} \beta_i X_{i,s} + \varepsilon_s$ with n covariates. Variance can then be decomposed as $var(Y_s) = \sum_{i=1}^{n} cov(Y_s, \beta_i X_{i,s}) + var(\varepsilon_s) = \sum_{i=1}^{n} var(\beta_i X_{i,s}) + \sum_{i \neq j} cov(\beta_i X_{i,s}, \beta_j X_{j,s}) + var(\varepsilon_s)$. We define the covariance share for covariate X_i as $cov(Y_s, \beta_i X_{i,s})/var(Y_s)$.

to which the variation during the Farm Bill and ARRA are closely chained. We find that results are similar using the share of R-squared explained by each variable as an alternative following Huettner and Sunder (2012).[19]

Anticipating the discussion of controls, we assess how the results change with further inclusion of housing prices, unemployment rates, average state wage bills, average state income, as well as average state income and rent of program participants as controls. We find that, among these, the housing-price control is sufficient for meaningful precision, because the program scale also varied over this period, and housing prices and retail prices were strongly positively correlated during this period. Including the housing-price control substantially improves the first stage.[20] Results are robust to the inclusion or exclusion of any other combination of controls.

We show in Appendix Table N1 that our conclusions about the sources of variation in the IV remain unchanged even after controlling for this extensive list of controls, which together explain a negligible proportion of the variation in the IV. The vector of state-level changes in energy usage and prices does explain about 10%-20% of the IV variation, but the SUA continues to drive variation in the IV, suggesting that idiosyncratic prediction errors are accounting for much of the residual variation. As mentioned, our results are robust to controlling for these energy usage and price variables.

2.3 Price Indices

2.3.1 Nielsen Retail Scanner

We use the Nielsen Retail Scanner Dataset through a partnership between the Nielsen Company and the James M. Kilts Center for Marketing at the University of Chicago Booth School of Business.[21] The data consists of weekly pricing, volume, and store merchandising conditions generated by participating retail store point-of-sale systems across the US from 2006-2015.[22] Data is included from approximately 35,000 participating stores and include store types such as drug, grocery, and mass merchandise stores, covering around 53%-55% of

[19]This measure uses Shapley and Owen values, which calculate the average marginal contribution of each regressor over all possible orderings.

[20]As discussed in Section 4.1, this occurs given that the benefits series contains a large disturbance term, muting the observable first stage; the housing-price control helps to net out this disturbance term, improving relevance.

[21]Information on access to the retail scanner data as well as the consumer panel data below is available at `http://research.chicagobooth.edu/nielsen/`.

[22]The data measures the weighted average weekly price of each good at the store-level, which includes retailer discounts such as loyalty cards and coupons. We find minimal economically meaningful changes to shopping behavior of households, suggesting that discounts and coupons do not explain our findings of price incidence (see Appendix Table N13).

national sales in food and drug stores and 32% of national sales in mass merchandise stores. The finest location of each store is given at the county level. We only use stores that appear throughout the entire sample period such that store entry and exit do not affect results. Among the stores in the sample in 2006, 84% remain throughout the entire sample period. A large number of products from all Nielsen-tracked categories are included in the data: 2.6 million universal product codes (UPCs) in total aggregated into around 1,100 product modules, which are further aggregated up to 125 product groups.

Although alternate price indices released by government agencies do exist, they have limitations that render them less suitable for our analysis, especially due to sampling error. These limitations are outlined in Beraja et al. (2019). Therefore, this paper uses price indices constructed from micro data.

The advantage of using the retail scanner data as opposed to the Nielsen Consumer Panel is that a wider range of goods is observed at higher frequencies and quantities. Scanner price indices are constructed as in Beraja et al. (2019). We briefly describe the approach they adopt in Appendix Section D and refer interested readers to their paper for details. Leung (2021) also investigates the behavior of the constructed indices and finds grocery store price indices are quite similar to the CPI city-level food-price indices, which are published for around 20 sample areas in the US. We construct a range of additional price indices using alternative methods, which give nearly identical results.

Retail stores need to apply to the FNS to accept SNAP payments. We obtain a panel of SNAP participating retail stores from the FNS and are able to match this panel with Nielsen stores. Our string-matching algorithms match over 90% of Nielsen stores to SNAP participating stores across store types, which implies that almost all stores in our data participate in SNAP.[23] However, we focus on results from grocery stores for several reasons. First, as shown in DellaVigna and Gentzkow (2019) (hereafter DVG) and Leung (2021), not only do drug and merchandise chains mostly implement chain-level pricing, but also the chains tend to locate stores across the entire US, such that local price responses to local policy changes are negligible. We show this is indeed the case in Section 4.1. On the other hand, we show in Appendix Section H that a large amount of grocery stores belong to chains that price flexibly or chains that are located only in a few states, which implies that most grocery stores engage in regional pricing.[24] Second, grocery stores derive the highest proportion of revenue from food, at around 77% based on the retail scanner data.

[23]Since the string-matching algorithm is fuzzy, this implies that the unmatched stores may still participate in SNAP. This would make the sample of non-SNAP stores even smaller, making it difficult to use it as a control group.

[24]Specifically, Leung (2021) finds that 72% of grocery stores in his sample belong to chains that have a flexibility measure above or at the median across all chains or are located in one or two states.

2.4 Quantities Sold and Expenditures

Data on expenditures are obtained in two ways. First, we use the total nominal monthly sales for each store constructed from the retail scanner data. In particular, we construct a measure for quantities using real sales, which is defined as the nominal sales divided by the store price index. Second, we use the Nielsen Consumer Panel Dataset.

2.4.1 Nielsen Consumer Panel

The Nielsen Consumer Panel Dataset represents a longitudinal panel of approximately 40,000-60,000 US households who continually provide information to Nielsen about their households and what products they buy as well as when and where they make purchases. Panelists use in-home scanners to record all their purchases, from any outlet, intended for personal, in-home use. Products include all Nielsen-tracked categories of food and non-food items, across all retail outlets in the US Nielsen samples all states and major markets. Panelists are geographically dispersed and demographically balanced. Each panelist is assigned a projection factor, which enables purchases to be projectable to the entire US.

For each period, we calculate the total expenditures of each household on SNAP-eligible and SNAP-ineligible products. We classify goods as SNAP-eligible based on guidelines published by the FNS. The average SNAP-eligible-goods-expenditure share across households is close to 60%. The advantage of using this measure as opposed to the nominal sales for each store is that demographic information for the household can be observed instead of county-level demographics for the store, such that we can use information on household income and household size to classify households as SNAP-eligible.[25] We also construct several measures of shopping intensities among households, following Stroebel and Vavra (2019). For each good purchased, the household records whether the good is purchased with coupons and if it is on sale. The barcode of the good is also scanned so the brand of the good is observed. We use three measures of shopping intensity: (1) the share of expenditures using coupons (coupon share), (2) the share of expenditures on goods that are on sale (deal share), and (3) the share of expenditures on generic store brands (store-brand share).[26]

[25] We classify households as SNAP-eligible if their household incomes are 130% of the poverty line or below during both the event periods in 2008-2009. Since household income is given in brackets with a 2-year lag, we take the mid-point of each bracket. Results are nearly identical using lagged or current incomes.

[26] To construct these variables in a way that controls for changing composition of the consumer basket, we follow HS by using the difference between actual and predicted shares for each household, predicting the shares using the average across all households consuming the same product group in the same time period.

2.5 Auxiliary Data

To construct control variables and measures of grocery industry concentration in addition to other measures of interest, we use a variety of auxiliary data sources, which we document in detail in Appendix Section F.

3 Empirical Strategy

3.1 Empirical Specifications

The discussion in Section 2 makes it clear that, despite the maximum benefit levels being set at the federal level, state-level idiosyncrasies can be introduced to the benefit series. To estimate the impact of SNAP benefits on prices, we first lay out typical panel fixed-effects approaches before combining it with our IV. Our research design exploits variation in magnitudes of benefit increases across states and events, because benefit increases mostly occur at the same time across states due to federal implementation of the Farm Bill and the ARRA. While both price indices at the state and store level can be constructed, we report store-level regressions because more information is available on store type and geographic location, although results are robust to using indices aggregated up to the state level. In addition, we report results using monthly price indices to take advantage of the sharp timing of the events. In our preferred specification, the log of outcome Y_{it} for store i in state s is regressed on state-level log benefits per population B_{st} for the store-year-month panel with store and period fixed effects to control for unobserved store characteristics and common time trends that affect prices, as shown in equation (3):

$$\ln Y_{it} = \alpha + \beta \ln B_{st} + X_{it}'\gamma + \alpha_i + \alpha_t + \varepsilon_{it}. \tag{3}$$

Y_{it} are outcomes such as the store price index or store real sales. Because the level of the price index is not interpretable, only relative changes are relevant. The log-log specification gives the interpretation of β as the elasticity of prices (or real sales) with respect to SNAP benefits per population.[27] We also include control variables X_{it} matched to the store's location, such as log state housing price, log county unemployment rate, log county average

[27]Note that since we define real sales as nominal sales divided by the price index, the sum of the coefficients on log prices and log real sales gives the coefficient on log nominal sales, which we do not focus on for brevity. Regarding the use of SNAP benefits per population as the independent variable of interest, we show in Section 5 that the price response, i.e., the benefit pass-through elasticity, can be written as a function of SNAP benefits per population. In the theory, we remain agnostic to whether the increase in the SNAP benefits per population is stemming from an (exogenous) increase SNAP benefits per recipient or an (exogenous) increase in SNAP participation.

wages and log county population. Stroebel and Vavra (2019), Beraja et al. (2019), and Handbury and Weinstein (2015) show that these variables have impacts on regional prices. Other controls include average gross income and rent of SNAP recipients in each state, state tobacco taxes, and energy prices and quantities consumed by fuel type. Standard errors are clustered by state to allow for autocorrelation in unobservables within states because the identifying variation is at the state level (Bertrand et al. 2004).

Second, we use a distributed-lag model to estimate a cumulative impulse response function starting 12 months prior to impact, which allows us to check whether the pre-trends are parallel. If the pre-trend is flat and the impulse response exhibits sharp timing, we can infer that the benefit series, after controls, is largely exogenous to unobservable trends that are determining prices around the impact. The distributed lag model provides a useful falsification test, and is shown in equation (4):

$$\ln Y_{it} = \alpha + \sum_{j=-k}^{k} \beta_j \ln B_{s,t-j} + X_{it}'\gamma + \alpha_i + \alpha_t + \varepsilon_{it}. \tag{4}$$

We can obtain the cumulative effect by adding together all the coefficients. Whereas the standard cumulative effect includes only the sum of the contemporaneous effect and all the lag coefficients, the lead coefficients are added as well because benefit changes are often announced ahead of time, and anticipatory as well as chained changes in prices could occur. The Farm Bill was passed four months before its implementation, while the ARRA was announced two months before its implementation, and the two implementations were separated by six months.

Third, we estimate a triple-difference model at the store level to examine whether the estimated interaction coefficients are consistent with hypotheses predicted by theory. In our triple-difference regression, we interact log benefits per population measured at the state level with the number of recipients per population measured at the county level in 2006. Intuitively, the interaction coefficient should be positive and statistically significant, because a higher share of recipients means that the recipient population figures more importantly in that county's composition of demand. On the contrary, if the contamination by recessionary forces was severe and if this influence was stronger in counties with higher shares of recipients, as suggested by previous literature, we would expect the negative bias contributed by recessionary forces to attenuate the interaction coefficient between benefits per population and recipient share. This specification is shown in equation (5):

$$\ln Y_{it} = \alpha + \beta_1 \ln B_{st} + \beta_2 \ln B_{st} \times \ln A_{i0} + X_{it}'\gamma + \alpha_i + \alpha_t + \varepsilon_{it}, \tag{5}$$

where, A_{i0} is the SNAP participation ratio in each county in the pre-period of 2006, which allows us to exploit county-level variation in the interaction variables.

Fourth, we implement a quadruple-difference model at the household level. In analyzing the consumer panel data, we are able to exploit the richness of the data to further relax the identifying assumptions. Specifically, we expect a rise in SNAP benefits to have the largest effect on SNAP-eligible goods consumed by SNAP-eligible households. Neoclassical theory predicts that if households are inframarginal in food spending, they will treat benefit increases as cash and non-SNAP spending could rise. Nevertheless, HS find that most households are inframarginal and have a low MPC for SNAP-ineligible goods relative to SNAP-eligible goods, and also demonstrate that mental accounting is a channel that could raise the MPCF out of SNAP.

We test these predictions by the following specification in equation (6). Each observation is a household-product group-period and classified into one of four groups based on whether a household is SNAP-eligible as well as whether the expenditures are on products categorized as SNAP-eligible or not. We regress (log) expenditures of household i in group g in period t on the (log) benefits per participant in state s that household i resides in period t, and interact this variable with four group indicators T_g. Household-month-of-the-year fixed effects are included to control for household-specific characteristics that may vary seasonally, along with group fixed effects and period fixed effects:

$$\ln Y_{igt} = \alpha + \sum_{g=1}^{4} \beta_g \times T_g \times \ln B_{st} + X'_{it}\gamma + \alpha_{im} + \alpha_g + \alpha_t + \varepsilon_{igt}. \tag{6}$$

This specification allows us to provide supporting evidence that the SNAP-benefit shocks are exogenous to unobservable recessionary shocks and other contextual factors, because unobservable shocks that affect spending are unlikely to differentially impact only SNAP-eligible households and SNAP-eligible product groups. The level-level specification, as opposed to the log-log specification, provides an estimate of the MPC of a SNAP household.

Fifth, we estimate IV regressions for each of the specifications discussed above. We construct the instrument, denoted as synthetic benefits per population, as illustrated in Section 2.2. For each of the specifications discussed above, we use the synthetic benefits per population as an IV for the actual benefits per population.

4 Main Results

We first focus on results using the retail scanner data and then discuss our findings using the consumer panel data. All results use data from 2007-2010 only to focus on the period around the Farm Bill and the ARRA where substantial variation exists in SNAP-benefit disbursement. Our results are robust to using the entire sample period of 2006-2015.

4.1 Retail Stores

We estimate the contemporaneous effect of SNAP-benefit increases on prices and real sales using equation (3). We first show the estimated price effects for grocery stores in Table 2. Without controls, the OLS estimate is statistically insignificant, because endogenous counter-cyclical variations in program scale induce a negative bias on the coefficient. The IV is also weak without controls. We argue that this is because the disturbance term in the SNAP-benefit series overwhelms the IV's idiosyncratic signal. Economic variables such as housing prices help to net out some of this disturbance term, improving relevance and sharpening the observable alignment between the benefit series and the IV. When a set of economic variables such as housing prices are included to control for recessionary shocks and disturbance terms, the effect of raising SNAP benefits is positive and significant. The effect remains positive and significant with further addition of controls such as the state-level tobacco tax, which strongly affected tobacco prices over this period. Other controls include economic characteristics of SNAP recipients, energy quantities consumed and energy prices, all of which affect benefits per recipient as shown in Section 2 and Appendix Section C.1.[28]

Regarding our IV approach, the first-stage F-test passes standard thresholds benchmarked in the literature.[29] We report the first stage and reduced form in Appendix Table N2 and N3, respectively. The first-stage coefficients are larger than 1 (although 1 is included in their confidence intervals), suggesting that idiosyncratic increases in intensive-margin program generosity encouraged more people to take up the program and raised program scale on the extensive margin.[30]

Even with the full set of controls included, the size of the IV coefficient is larger than the OLS coefficient by almost a factor of four, which is consistent with the hypothesis that local macroeconomic trends not fully controlled for in the OLS specification were driving SNAP benefits up and prices down. A 1% increase in benefits per population increases prices across goods in grocery stores by about 0.08%. Because the average change in benefits was about 15% for the two events, we can infer that prices were raised by 1.2% by each event. Given

[28] Appendix Figure O5 plots the observations (collapsed into 50 bins) used in the estimation in a binned scatter plot, which shows the data support a log-log specification with most of the observations lying close to the regression line.

[29] According to Lee et al. (2021), a first-stage F-statistic of 20.682 in column (6) requires a standard error adjustment factor of about 1.32, at which the point estimates remain statistically significant.

[30] Hence, the two-stage least squares procedure downscales the reduced-form coefficient to give the response per 1% increase in total benefits per population. We also show in Appendix Figures O6 and O7 how the changes in the synthetic-benefit series track changes in the actual series with and without controls.

that national and grocery store inflation was around 2% per year over this period, these effects are economically meaningful.

To assess the use of housing prices as a control variable and potential endogeneity concerns, we show that the results are robust to several additional specifications in Appendix Table N4. First, we show that the results are robust to dropping housing prices as a control variable when the full set of control variables is included, although the first-stage F-statistic drops by about half. Second, we show that our results are robust to restricting the sample to stores in a set of contiguous county pairs that straddle state borders and adding county-pair fixed effects. When dropping the housing-price control in such specifications, the first-stage F-statistic again decreases, although the point estimate remains nearly identical. Further restricting the sample to only contiguous counties in different states but in the same commuting zones, we obtain similar point estimates, although there is a further weakening of the instrument to levels below standard thresholds. We note that this is a demanding test since over 80% of the stores in the original sample are dropped and since benefits (the explanatory covariate of interest) in these selected counties are imprecisely aligned with state-level benefits (the covariate available). Reassuringly, the point estimate remains stable and the average SNAP participation rate is nearly identical in the smaller sample. In addition, our results are robust to relaxing the identifying assumption by allowing the IV to be plausibly exogenous à la Conley et al. (2012) with the IV having a direct impact on outcomes even after controls. We elaborate on this check in Appendix Section E.

We also estimate the potential impact of retail chains that adopt uniform pricing, adding a variable that measures the average log benefits per population for each store at the retail chain level, weighted by store revenue in the pre-period of 2006, excluding stores in the same state. We find that the estimated coefficient for state-level benefits per population is only reduced by about 20% and the sum of the two coefficients is similar to our previous estimates. This finding is consistent with our earlier discussion that a large amount of grocery stores belong to chains that price flexibly or chains that are located only in a few states, which implies that most grocery stores engage in regional pricing.

Furthermore, we conduct a series of additional robustness checks in Appendix Table N5 to show the estimated price response is robust to using log benefits with or without population controls; weighting by store revenue or county population; regressing with state-level observations; using county-level benefits; using the full sample from 2006 to 2015, which includes the recovery periods; removing SNAP disaster payments; including a set of government transfer policy controls at the state-year level; and using states with each of the two main methodologies in setting the SUA. Note that we can observe how states that use lagged CPI are setting the SUA by using CPI data, and we control for contemporaneous energy prices and quantities consumed. The fact that prices in these states and prices in states that recalculate the SUA using utility data respond in a similar manner suggests that any unobservable variation in the SUA is not posing an endogeneity concern. We also show our results are robust to using alternative price indices in Appendix Table N6. The construction methods for these indices are explained in Appendix Section D.

In order to examine pre-trends and dynamics, we estimate equation (4) and plot the cumulative effects of the increase in synthetic benefits in Figure 7. We also present an alternative graphical illustration of parallel pre-trends in Appendix Section G. We see that pre-trends are parallel over the entire pre-period of 12 months. Prices rise sharply when benefits rise, and continue to rise after the event, although a small and insignificant portion of the price rise begins slightly before the event.[31]

The impact of increased SNAP benefits on real sales for all products is smaller and statistically insignificant at 0.006% as shown in Table 3. Given that SNAP is only eligible for food items, this estimate includes both eligible and ineligible products. We also estimate the effect for eligible and ineligible products separately in Table 6. The real sales effect for eligible products is similar in magnitude with the price effect at 0.06% although somewhat noisily estimated. The magnitude of the real-sales coefficient can be understood in two parts. First, the low aggregate demand elasticity for food implies that consumers do not substantially decrease their purchases in response to the price rise. Second, while the MPCF of SNAP consumers is large, its impact on real sales is downscaled by the share of sales accounted for by SNAP consumers (around 17%). We explain in detail how these magnitudes are consistent with theory in Section 5.

We expect the effect of SNAP-benefit changes will be stronger for stores located in regions with higher SNAP participation rates. Therefore, we interact county-level SNAP participation per population, which is fixed at its pre-period value in 2006, with log benefits per population as shown in equation (5). Results are shown for both OLS and IV specifications in Table 4. The interaction coefficient is positive and significant for both prices and real sales. Increasing the SNAP participation ratio from the 10th percentile of 2.8% to the 90th percentile of 13.7% increases the price elasticity by about 0.014 and the real-sales elasticity by about 0.034. The price response to SNAP-benefit changes is also stronger in counties with higher concentration measures, a proxy for market power, as shown in Table 5. We use two different county-level measures of concentration in the pre-period:

[31] Given that the Farm Bill was announced four months before its implementation, this finding could be consistent with announcement effects found in Agarwal and Qian (2014) as explained by life-cycle theory, along with Karadi and Reiff (2019) and Renkin et al. (2020) as explained by price-setting models with adjustment frictions. It could also be reflecting how closely chained the Farm Bill and ARRA variations were, separated by six months.

the number of grocery establishments per population and the HHI in the grocery industry, using the number of employees as a measure of firm size. We provide theoretical derivations in Section 5 to show that higher market power leads to a stronger benefit pass-through for many standard parameterizations of demand.

We now further elaborate on our IV results by product eligibility in Table 6. Although at first glance the effect of SNAP-benefit increases should be strongest only for food, there might be reasons the data show otherwise.

First, as mentioned above, previous literature investigating whether consumers consider SNAP benefits fungible has estimated the MPCF out of SNAP to be as large as 0.6, but below 1. Hence, SNAP participants could be increasing their purchases of other items, depending on their MPC for SNAP-ineligible products.[32]

Second, previous literature studying the behavior of multi-product retailers argues that firms maximize profits across product categories, such that shocks to one product category may transmit to others. Table 6 illustrates that the positive effect on food prices is strongly significant, whereas the effect on food real sales is of a similar magnitude albeit imprecisely estimated. As mentioned, we explain in detail how these magnitudes are consistent with theory in Section 5.

The effect on prices in ineligible products is also positive and statistically significant, with a magnitude similar to eligible products, but the real-sales response is again imprecisely estimated. These results would be consistent with increased retail markups in other product categories caused by lower price sensitivities of SNAP consumers across products due to their increased disposable income.

To explore this mechanism further, we estimate equation (5) by product department in grocery stores. Table 6 provides further evidence that food is the main product department with a positive demand shock caused by SNAP-benefit hikes. The effects on both prices and real sales become stronger in high-SNAP-participation regions. The interaction effect for prices is also higher in other product departments, although the interaction effect for real sales is imprecisely estimated. We show analogous results across five product departments in Appendix Tables N7 and N8.

We show in Appendix Table N10 that results are statistically insignificant and smaller for both drug and merchandise stores. As mentioned above, these store types adopt national chain pricing and have negligible response to local shocks as shown in DVG and Leung (2021).[33] We repeat the approach and results in Leung (2021) in Appendix Section H.

[32]SNAP benefits can be rolled over to the next month; however, Hastings and Shapiro (2018) find that a negligible proportion of recipients roll their benefits over each month.

[33]In addition, many stores from these store types did not begin participating in SNAP until the time of the Farm Bill and ARRA.

In Appendix Section I, we present results on the effects of SNAP-benefit changes on firm dynamics and market structure in the grocery industry. The estimated effect on entry and exit is positive, but almost all of the estimates are statistically insignificant and economically small, suggesting SNAP-benefit changes had little impact on entry and exit margins and market structure.

4.2 Households

To understand how consumption and shopping behavior responds across SNAP-eligible and -ineligible households, as well as how each type of household responds in SNAP-eligible and -ineligible product groups, we estimate equation (6) and present the results in Table 7. For expenditures, these results show a statistically significant MPC only for the both-eligible group, and the point estimate is positive and large despite somewhat large standard errors. The implied MPC is 0.44, which is close to previous estimates of MPC out of food stamps of 0.5-0.6 from HS. Note that our estimate of MPC also captures price responses whereas the estimate in HS does not, because their variation comes from individuals transitioning into and out of SNAP. Netting out the price response, our estimates of MPC would be slightly smaller. The MPC estimated from the both-eligible group is statistically larger than those from other groups. This finding suggests the state variation we are using is differentially impacting SNAP-eligible goods and households consistent with our assumptions. The point estimates from the product- or household-eligible-only groups are imprecisely estimated. This finding is suggestive of both increased prices raising food expenditures of the ineligible households and increased consumption of ineligible products among eligible households.[34]

Furthermore, following Goldin et al. (2022), we estimate the response of consumption by week of the month. Whereas Goldin et al. (2022) show that the average consumption patterns follow state-specific SNAP-benefit-issuance schedules, we show the MPC is also higher in the weeks in which more SNAP benefits are issued to households, by interacting each eligibility indicator with the fraction of SNAP benefits issued in a given week by state. As shown in Appendix Table N12, the interaction coefficient for the MPC is positive and strongly significant for eligible households in both product groups, and significantly higher for eligible products. As suggested by Goldin et al. (2022) and Baker et al. (2017), consumption is complementary for both eligible and ineligible product groups due to fixed shopping-trip costs. The percentage increase in consumption during weeks with higher SNAP issuance is

[34]The noise in these point estimates could also be attributed to the fact that we are unable to identify household eligibility with complete accuracy given limited data on households selected by the Nielsen Consumer Panel. Note also that the point estimates include the price response; they would be smaller without the price response.

positive but marginally insignificant, despite the higher base levels of consumption in weeks with higher SNAP issuance. On the other hand, the MPC does not vary with SNAP-issuance schedules for ineligible households.

We also investigate the effect of increased benefits on shopping behavior, using the outcomes described in Section 2, which include coupon share, deal share, store brand share. We include the number of shopping trips taken. In Appendix Table N13, we show the results are mixed and inconclusive, and the point estimates all imply the response to a 1% increase in benefits is less than 0.001. HS find that coupon share and store-brand share decrease as SNAP benefits increases but also that the magnitudes are economically negligible.

We present results during the 2013 ARRA expiration in Appendix Tables N14 and N15. In this period, there is no first stage and hence the coefficients are small: while the average drop in benefits per population was 8% during this period, the variation across states is negligible especially in the IV, as shown in Figure 4b.

5 Model

In this section, we develop and calibrate a simple theoretical partial-equilibrium model. The purpose of this exercise is three-fold. First, the exercise allows us to check whether the magnitudes of the estimated reduced-form price and quantity elasticities fall within reasonable bounds of theory-based predictions. Second, it allows us to gain insights into the underlying economic mechanisms determining the reduced-form estimates. Third, it allows us to quantify the local incidence of changes in SNAP benefits by using the estimates of the price response and the MPCF out of SNAP as a set of sufficient statistics.

To build intuition, we proceed in a series of steps. First, we begin with simplified graphical illustrations in Section 5.1. Next, in Sections 5.2 and 5.3, we present results derived from a model of symmetric imperfect competition with constant market conduct. Note that constant market conduct represents a broad class of models such as Bertrand competition, Cournot competition, monopolistic competition, and monopoly as shown in Weyl and Fabinger (2013). Extending upon their work that examined unit-tax incidence, we examine price and quantity responses to a heterogeneous demand shock (some consumers receiving a demand shock but not others). In Section 5.4, we use our reduced-form estimates as sufficient statistics to calculate program incidence under a range of assumptions about relevant parameters. In Section 5.5, we also discuss multi-product versions of these formulas and suggest explanations for why SNAP-ineligible products also showed an increase in prices.

5.1 Graphical Illustration

We first use graphical illustrations to build intuition (see Appendix Section J). We first model a shift in demand from a set of homogeneous (representative) consumers receiving a transfer in partial equilibrium. The equilibrium price rises in a perfect-competition setting if the supply curve is upward sloping or in a monopoly setting. The price rise shifts a portion of the welfare gains afforded by the transfer from consumers to producers.

Next, we allow for SNAP and non-SNAP consumers. Under perfect competition and upward-sloping supply, we show that SNAP-consumer surplus increases from increasing SNAP benefits, and non-SNAP-consumer surplus decreases because of higher prices. Producer surplus increases because of higher prices. Deadweight loss arises as a result of SNAP consumers buying marginal units they value at less than the marginal cost for producers. Under monopoly and constant marginal cost, SNAP-consumer surplus increases, non-SNAP-consumer decreases, and producer surplus increases. Deadweight loss now results from the monopolist further restricting output to non-SNAP consumers, which may be partially or more than offset by a decrease in deadweight loss when the monopolist sells more to SNAP consumers. Hence, the change in deadweight loss is theoretically ambiguous.

5.2 Pass-through Formulas

We extend upon the unit-tax pass-through formulas derived in Weyl and Fabinger (2013). Our extensions allow for analyses of price and quantity responses to a heterogeneous demand shock (some consumers receiving a demand shock but not others). The results allow us to gain intuition over the mechanisms of the pass-through using sufficient statistics.

Let market demand for SNAP-eligible goods $Q^D(p, b)$ be a function of price p and SNAP benefits per population b. Let supply $Q^S(p)$ be a function of p. Market demand is composed of demand by SNAP recipients $Q^{D,S}(p, b)$ and non-SNAP recipients $Q^{D,NS}(p)$; the latter quantity does not directly depend on b. We first present the pass-through formula derived from the equilibrium condition in the case of perfect competition (see Appendix Section K for all steps of the derivation):

$$\varepsilon_\rho \equiv \frac{dp}{db}\frac{b}{p} = \left(1 - \frac{1}{1 + \frac{-\varepsilon_D}{\varepsilon_S}}\right) \frac{\varepsilon_{Q^{D,S},b}}{-\varepsilon_D} \frac{pQ^{D,S}}{pQ}. \tag{7}$$

This formula can be thought of as extending the unit-subsidy pass-through elasticity, $1 - \frac{1}{1+\frac{-\varepsilon_D}{\varepsilon_S}}$, which is higher when demand is relatively more elastic than supply.[35] The

[35]The unit-subsidy pass-through elasticity is given by 1 minus the cost pass-through rate, $\frac{1}{1+\frac{-\varepsilon_D}{\varepsilon_S}}$. The

benefit-pass-through elasticity, ε_ρ, depends on additional terms, which derive from the relation, $\frac{\partial p}{\partial b}\frac{b}{p} = \frac{\varepsilon_{Q^{D,S},b}}{-\varepsilon_D}\frac{pQ^{D,S}}{pQ}$.[36] This term, which we call the "shift magnitude," represents the percentage change in price that would keep aggregate quantity demanded the same despite a marginal change in b affecting SNAP consumers' demand.[37] As seen, the benefit-pass-through elasticity is higher when the MPC out of SNAP (in elasticity form) is higher; when the aggregate demand elasticity is lower; and when the proportion of sales accounted for by SNAP recipients is higher. The benefit-pass-through elasticity represents the upward price change along the supply curve as producers respond competitively to the benefit-induced shift in aggregate demand.

Next, we present the benefit pass-through formula under symmetric imperfect competition with constant market conduct, $\theta \equiv [(p-mc)/p](-\varepsilon_D)$.[38] The formula is derived in an analogous manner (see Appendix Section K).

$$\varepsilon_\rho \equiv \frac{dp}{db}\frac{b}{p} = \left(1 - \frac{1}{1 + \frac{-\varepsilon_D - \theta}{\varepsilon_S} + \frac{\theta}{\varepsilon_{ms}}}\right)\frac{\varepsilon_{Q^{D,S},b}}{-\varepsilon_D}\frac{pQ^{D,S}}{pQ} + \left(\frac{1}{1 + \frac{-\varepsilon_D - \theta}{\varepsilon_S} + \frac{\theta}{\varepsilon_{ms}}}\right)\frac{\theta}{-\varepsilon_D}\varepsilon_{|p'|,b}, \quad (8)$$

where $|p'| = \left|\frac{\partial p}{\partial Q}\right|$ represents the slope of the inverse demand; and ε_{ms} the inverse marginal-consumer-surplus elasticity, which reflects the curvature of demand.[39] The pass-through elasticity now consists of two terms. The first term, which we call the "shift effect," is a direct carryover from the perfect competition case: it represents the upward price change along the supply curve as producers respond to the benefit-induced shift in aggregate demand holding fixed the slope of aggregate demand. The second term, which we call the "slope effect," can be thought of as reflecting additional pricing power that producers exercise based on the benefit-induced change in the slope of aggregate demand.

Next, we present the quantity response formula, which derives from an application of the

latter term is frequently estimated in the pass-through literature and analyzed by Weyl and Fabinger (2013). An incomplete-cost pass-through—a rate below 1—is typically found in the literature, which in turn implies a unit-subsidy pass-through rate below 1.

[36]The derivation is given in Appendix Section K.

[37]Intuitively, it is the vertical upward shift in the aggregate demand curve caused by a marginal change in b affecting SNAP consumers' demand.

[38]Note that we assume θ reduces to a constant as is the case in a broad range of models of competition as mentioned before. We do so because our reduced-form estimates suggest that the underlying market structure itself did not get affected by the scale of benefit increases analyzed.

[39]$(ms)^{-1} \equiv (-p'q)^{-1}$ denotes the level of demand at which a marginal expansion in quantity would generate a given level of marginal consumer surplus. As shown by Weyl and Fabinger (2013), $\frac{1}{\varepsilon_{ms}} = 1 + \frac{p''Q}{p'}$.

chain rule and depends on the benefit pass-through elasticity:[40]

$$\frac{dQ}{db}\frac{b}{Q} = \varepsilon_{Q^{D,S},b}\frac{pQ^{D,S}}{pQ} - |\varepsilon_D|\,\varepsilon_\rho, \tag{9}$$

We can see that the response is a linear combination of two terms. The first is the increase in demand contributed by SNAP consumers. The second is the reduction in aggregate quantity demanded in response to the price rise.

In Section 5.4, we examine whether the magnitude estimated for the left-hand-side responses are comparable to what would be predicted by terms on the right-hand sides calibrated independently based on estimates from separate regressions reported in previous sections or from existing literature.

5.3 Incidence

We now present the changes in consumer and producer surplus of the program. The change in consumer surplus can be derived from the construction of consumer surplus as the integral of the market demand curve, $\int_{p(Q,b)}^{\infty} Q^D(x,b)dx$. To make the analysis tractable, we additionally assume that the inverse aggregate-market-demand curve $p(Q,b)$ shifts up by a constant amount in response to an increase in benefits.[41] The change can then be decomposed into that for SNAP consumers and non-SNAP consumers:

$$\frac{dCS}{db} = \left(\frac{\varepsilon_{Q^{D,S},b}}{-\varepsilon_D} - \varepsilon_\rho\right)\frac{pQ^{D,S}}{b} + \left(-\,\varepsilon_\rho\right)\frac{pQ^{D,NS}}{b}. \tag{10}$$

For the change in producer surplus, we again start with perfect competition and then proceed to symmetric imperfect competition as before. Under perfect competition,

$$\frac{dPS}{db} = \rho Q = \varepsilon_\rho \frac{pQ}{b}. \tag{11}$$

Under symmetric imperfect competition, whereas the formula for $\frac{dCS}{db}$ remains unchanged,

[40]The derivation is given in equation (27) in Appendix Section K.

[41]That is, we assume the shift magnitude $\frac{\partial p(x,b)}{\partial b}$ is constant in x, so that $\frac{dCS}{db} = -\rho Q + \int_p^\infty \frac{\partial Q^D(x,b)}{\partial b}dx = -\rho Q + \int_0^Q \frac{\partial p(x,b)}{\partial b}dx = -\rho Q + \frac{\partial p}{\partial b}Q$. See Appendix Section K for details.

the change in producer surplus can be generalized as follows:

$$\frac{dPS}{db} = \left(\varepsilon_\rho + \frac{p-c}{p}\frac{dQ}{db}\frac{b}{Q}\right)\frac{pQ}{b} \tag{12}$$

$$= \left[\varepsilon_\rho + \theta\left(\frac{\varepsilon_{Q^{D,S},b}}{-\varepsilon_D}\frac{pQ^{D,S}}{pQ} - \varepsilon_\rho\right)\right]\frac{pQ}{b}. \tag{13}$$

The change in producer surplus can be evaluated either via equation (12), using retail margins from existing literature and our estimate of real-sales response, or via equation (13).

5.4 Calibration

Given the formulas afforded by our theoretical framework, we now calibrate the right-hand-side terms using estimates independently obtained from separate regressions reported above or from existing literature. We then compare the combined calibrated pass-through elasticity with the reduced-form pass-through elasticity estimated for the left-hand side. We also calculate local incidence. These results are reported in Table 8.

As the first step, we restate two empirical estimates for $\varepsilon_{Q^{D,S},b}$, the MPCF elasticity, in equation (8). We take these estimates, discussed earlier in Section 4.2, to serve as the lower- and upper-bound anchors determining reasonable bounds of price elasticities to consider. For the lower-bound anchor, we net out the price effect from the MPCF of SNAP consumers in elasticity form as reported in Table 7, column (2), row 4: 0.411 - 0.0724 = 0.339. We take this to be the lower bound because, in our definition, $\varepsilon_{Q^{D,S},b}$ is a partial derivative assuming no price change, whereas the estimate in Table 7 is the response in equilibrium with the price change. The real-sales response should be higher without the price change.[42] For the upper-bound anchor, we take the MPCF estimated by HS—whose magnitude is higher with a very small standard error—and multiply it by 0.9, the mean of SNAP benefits to food spending in the CEX, to obtain an elasticity: 0.58 * 0.9 = 0.522. Since this MPCF was estimated using variation in the timing of program exit across individuals, price responses are not a factor in this estimate. While this estimate is not necessarily biased upward, we take this to be an upper bound to be conservative in our calibration of the price response. These numbers are shown in the first and second rows of the first column of Table 8.

The second column of Table 8 restates the benefit-pass-through elasticity estimated in Table 6, column (3), row 1: 0.0724. Our aim is to check whether this number falls in line with the theory-based calibrations.

The third column of Table 8 reports the shift magnitude, $\frac{\partial p}{\partial b}\frac{b}{p} = \frac{\varepsilon_{Q^{D,S},b}}{-\varepsilon_D}\frac{pQ^{D,S}}{pQ}$. As discussed

[42] Another possible reason making this a lower bound is imperfect designation of SNAP versus non-SNAP consumers in the consumer scanner data.

in Section 5.2, this term can be thought of as the vertical upward shift in the aggregate demand curve caused by a marginal change in benefits affecting SNAP consumers' demand. For the demand elasticity for food (ϵ_D), we obtain from the data directly an estimate of -0.709, which falls within the typical range reported in the literature as summarized by Andreyeva et al. (2010).[43] We obtain from USDA data the proportion of sales accounted for by SNAP recipients ($\frac{pQ^{D,S}}{pQ}$): 0.168. Combining these numbers together with the aforementioned estimates for $\varepsilon_{Q^{D,S},b}$, we obtain a range of [0.0802, 0.124].

In order to calibrate the benefit pass-through elasticity (ε_ρ), we consider the last two remaining terms: the unit-subsidy pass-through elasticity and the slope effect from equation (8). For the unit-subsidy pass-through elasticity, we calibrate the term at 0.5 based on Besanko et al. (2005).[44] For the slope effect, which reflects incremental pricing power that producers can exercise based on the benefit-induced change in the slope of aggregate demand, we assume this is close to zero. This assumption follows as a corollary to our previous assumption in Section 5.4 that the inverse aggregate-market-demand curve $p(Q, b)$ shifts up by a constant amount in response to a benefit increase.[45] Multiplying the shift-magnitude range by 0.5, we arrive at a range of [0.0401, 0.062]. Comparing the range [0.0401, 0.062] with our reduced-form estimate 0.0724 and its standard error 0.0269 in Table 6, we see that the range falls well within the confidence interval of our reduced-form estimate.[46]

We now present the calibration of the quantity response, which is straightforward based on the discussion above and equation (9).[47] Plugging in the estimates for the MPC elasticity, proportion of SNAP sales, demand elasticity, and the calibrated price elasticity, we obtain a range of [0.028, 0.044]. If we use our reduced-form estimate for the price elasticity, with the MPCF from HS instead of the calibrated price elasticities, we obtain 0.036. All these numbers are close to our reduced-form point estimate for the real-sales response reported in Table 6:

[43] See column (3) of Appendix Table N16 (and discussion in Appendix Section L), where we regress log real sales on log price indices with store and period fixed effects. Results are nearly identical using Hausman IVs (average of other stores in the same chain) following DVG. Both DVG and Hitsch et al. (2017) estimate product-level elasticities using panel variation and find that these estimates are similar to those obtained using IVs and other alternative methods. We follow Hitsch et al. (2017) and use 3-digit zip-code-period fixed effects; estimates are similar using period or market-period fixed effects. Note that this approach estimates the residual demand elasticity for the store as opposed to the market demand elasticity, which is the object of interest. The magnitude of the residual demand elasticity may be an upper bound for the magnitude of the market demand elasticity. Hence, the calibrated shift effect may represent a lower bound.

[44] In fact, as shown in in Appendix Section L, we also obtain a similar unit-subsidy pass-through rate of 0.49 by estimating the curvature of demand, subject to caveats.

[45] Assuming that $\frac{\partial p(x,b)}{\partial b}$ is constant in x implies $\frac{\partial^2 p}{\partial b \partial Q} = 0$, which implies $\varepsilon_{|p'|,b} \equiv \frac{\partial^2 p}{\partial b \partial Q} \frac{b}{\partial p / \partial Q} = 0$.

[46] One potential explanation for why the point estimate itself is slightly higher than the calibrated bounds—while this is stretching what we can say with statistical confidence—is a small positive slope effect. Based on the differences, the slope effect would be [0.011, 0.032] which, if θ is around 0.2 as discussed further below, would imply $\varepsilon_{|p'|,b}$ within [0.075, 0.229].

[47] We do not report this in Table 8 for brevity.

0.061. We can further examine how the magnitude 0.036 decomposes into parts explained by the demand increase of SNAP consumers, 0.522 * 0.168 = 0.088, and the quantity demanded reduction from the price increase, -0.709 * 0.0724 = -0.051. We see that while the MPCF of SNAP consumers is large, its impact on real sales is downscaled by the share of sales accounted for by SNAP consumers. We also see that the low aggregate demand elasticity for food means that consumers do not substantially decrease their purchases in response to the price rise. Both numbers, 0.088 and -0.051, are small.

Having rationalized the price and quantity responses, we also quantify the corresponding movement in aggregate demand elasticity. Given symmetric imperfect competition with constant market conduct and constant marginal cost, we take the total derivative of the market-conduct equation, $\theta = [(p-c)/p](-\varepsilon_D)$, to obtain the relation, $\frac{d|\varepsilon_D|}{db}\frac{b}{|\varepsilon_D|} = -\left(\frac{c}{p-c}\right)\frac{dp}{db}\frac{b}{p}$. That is, the aggregate demand elasticity moves in proportion with the price in response to a marginal-benefit increase. Given Hottman (2016) reports that average retail margins are around 0.3, dividing the benefit pass-through elasticity (0.0724) by this number (0.3) implies an aggregate-demand-elasticity response of 0.24; that is, a 1% rise in benefits leads to a decrease in aggregate demand elasticity of 0.24%.

For a given store, if the rise in benefits decreases the elasticity of demand of SNAP consumers, this would lead to a fall in the aggregate demand elasticity ("treatment effect"). On the other hand, if the rise in benefits also raises the share of sales accounted for by SNAP consumers who may have relatively high elasticities of demand, this would counteract the rise in aggregate demand elasticity ("composition effect").[48] Indeed, Goldin et al. (2022) compare prices during weeks of SNAP issuance versus weeks of non-issuance within the same month across states with different issuance schedules and find that retailers do not adjust prices in between these weeks; the authors suggest that this is because the composition effect counteracts the treatment effect between weeks intramonth. In contrast, we examine monthly trends in prices and SNAP benefits aggregated across weeks; therefore, any intramonth intertemporal substitutions cancel each other out in our estimates. Also, any potential menu costs which may deter price changes week to week are less of a concern for our variation which involves a one-time, large-scale rise in benefits separated by at minimum half a year apart.

The fourth column of Table 8 reports the producer surplus, evaluated using equation (13). The estimates of average retail markups by Hottman (2016) together with the low demand elasticity for food implies a market-conduct parameter of roughly 0.2.[49] Plugging in our estimated reduced-form benefit pass-through elasticity, the shift magnitudes, and the inverse of the SNAP-sales proportion along with the market-conduct parameter, we obtain the range

[48] We thank an anonymous referee for this discussion.

[49] For example, five firms in a symmetric Cournot competition have $\theta = 0.2$ (Weyl and Fabinger, 2013).

of [0.440, 0.492].[50]

The fifth, sixth, and seventh columns of Table 8 reports consumer surpluses for all consumers, SNAP consumers, and non-SNAP consumers, respectively, evaluated using equation (10) and its component terms. Using again our estimated reduced-form benefit pass-through elasticity, we obtain [0.0466, 0.305], [0.405, 0.664], and -0.358, respectively.[51]

Summarizing incidence, the increase in producer surplus takes up around 49%, whereas the increase for SNAP consumers is around 66%. These increases come at the expense of non-SNAP consumers whose loss is close to 36%, which comes out to about 5% per non-SNAP consumer.[52] Given the large standard errors on our MPC estimate, we prefer the calculations using the larger MPC estimate from HS. Overall, these results imply that as SNAP benefits increase, producers benefit because they raise prices to extract additional surplus, although SNAP benefits increase SNAP consumer surplus the most.

Several points are worth noting regarding our incidence calculations. First, because the MPCF out of SNAP is not 1, some of the benefits disbursed lead to changes in consumption in other product markets. Hence, the changes in surplus calculated above apply only to the SNAP-eligible goods market, that is, the market for food. Because SNAP is a food-consumption safety-net program, this market is of particular interest for policy. Effects on other product markets could either increase or decrease both consumer and producer surplus, but the same mechanism for incidence can apply. We show in Appendix Table N17 the incidence for the ineligible goods market in grocery stores. Because ineligible goods account for only around 25% of revenue in grocery stores, the magnitudes of consumer- and producer surplus- changes are smaller. At a calibrated market conduct parameter of 0.5, a marginal dollar of SNAP benefits increases producer surplus by about \$0.1, decreases SNAP consumer surplus by about \$0.01, and decreases non-SNAP consumer surplus by about \$0.02 per non-SNAP consumer on average, because grocery stores raise markups on ineligible goods.

Second, our results take the MPCF out of SNAP as given and is agnostic to whether fungibility is violated. If we assume the MPCF out of SNAP is equal to the MPCF out of cash of around 0.1 as found in previous literature, the calculated changes in surplus would be much smaller and changes in consumption in other product markets become more important.[53] The price response under a unit-subsidy pass-through rate of 1 would be around

[50] If we use the calibrated benefit pass-through elasticities instead, we obtain [0.287, 0.442].

[51] If we use the calibrated benefit pass-through elasticities, we obtain [0.239, 0.368], [0.437, 0.674], and [-0.199, -0.306], respectively. Note that the non-SNAP consumer-surplus term gives a single number if we use the reduced-form pass-through elasticity, because the term does not vary with the shift magnitude.

[52] In 2010, there were about 6.7 non-SNAP consumers for every SNAP consumer. If we use the calibrated benefit pass-through elasticities, the decrease in per-non-SNAP-consumer surplus comes out to 0.029-0.046%.

[53] HS use changes in gas prices to estimate a MPCF out of cash of no more than 0.1 and earlier literature

0.02, whereas the changes in producer surplus and SNAP consumer surplus are around 0.1 for each marginal dollar of SNAP.

Third, our baseline calculations assume that non-SNAP consumers face the same change in prices as SNAP consumers for simplicity. However, as shown in Section 4, price responses are stronger in stores located in regions with higher SNAP participation rates.[54] The exact incidence calculations would vary across different regions. For non-SNAP consumers shopping in stores with a smaller proportion of SNAP consumers, we would expect them to face a smaller decrease in consumer surplus and vice versa. Furthermore, SNAP consumers and non-SNAP consumers also buy different goods within the same store. Using income-group specific weights for products based on the Nielsen Consumer Panel to construct alternative store-level price indices, we find that price responses are smaller for high-income groups, but the difference in price response between the top and bottom income quartile is only about 0.01, which does not affect incidence calculations substantially.

Fourth, if we account for the distortionary cost of taxation as in Hendren (2020) by using efficient welfare weights, surplus to SNAP consumers could be weighted 1.5-2x more than surplus to non-SNAP consumers who are richer. Likewise, we may assume producer surplus is redistributed to shareholders of retailers who are richer than SNAP consumers. Implementing these weights would raise the economic efficiency of SNAP-benefit changes. On the other hand, the relative burden for non-SNAP consumers may particularly fall on those consumers whose incomes are just high enough to make them ineligible for SNAP, although the absolute burden for any single non-SNAP consumer is found to be small.

5.5 Multi-Product Pricing

To better understand the price and quantity movements seen in Table 6, we extend pass-through formulas to a multi-product setting. In the case of perfect competition, we show in Appendix Section K that we can rewrite the equilibrium condition with demand $Q_j^D(p)$ for good j as a function of a vector of prices $p = (p_1, ..., p_n)$ and obtain the pass-through formula as shown below:

has also found a range of estimates of about 0.03-0.17 (Hoynes and Schanzenbach 2009).

[54]Table 6 also shows that the quantity response is higher in regions with higher SNAP participation rates. This result provides further evidence consistent with equation (9), which shows that the quantity response is larger when the proportion of SNAP sales (proxied for by the SNAP participation rate empirically) is higher. This large heterogeneity in the quantity response across regions may contribute to the large standard error for our estimate of the real-sales response in Table 3, which aggregates across regions.

$$\varepsilon_{\rho_j} \equiv \frac{dp_j}{db}\frac{b}{p_j} = \left(1 - \frac{1}{1 + \frac{-\varepsilon_j^D}{\varepsilon_j^S}}\right)\left(\frac{\varepsilon_{Q_j^{D,S},b}}{-\varepsilon_j^D}\frac{p_j Q_j^{D,S}}{p_j Q_j} + \sum_{i \neq j} \frac{\varepsilon_{j,i}^D - \varepsilon_{j,i}^S}{-\varepsilon_j^D}\varepsilon_{\rho_i}\right). \tag{14}$$

In the multi-product extension, the pass-through formula for a particular good contains an additional term: assuming the supply elasticity is zero with respect to other goods, this term sums over all other goods the ratio of cross-price elasticities to own-price elasticity (the cross-good diversion ratio in elasticity form) multiplied by the pass-through elasticity of other goods. Intuitively, for goods that are complements, a larger increase in price for one good leads to lower demand for the other and hence a smaller price increase, and the converse for substitutes. Again, for constant marginal costs, the supply elasticity is infinite and hence the pass-through elasticity is zero. We can also solve for the pass-through of each product explicitly as shown in Appendix Section K.

In the case of symmetric imperfect competition, we show in Appendix Section K that the pass-through can be written as a function of the response of marginal revenues to quantities and benefits. Given this multi-product pass-through formula involves many additional terms for which estimates are not available, we focus on the single-product formula for calibrations.

We then illustrate in a theoretical model how an increase in demand for SNAP-eligible goods can raise prices for SNAP-ineligible goods. Chen and Rey (2012) find that loss leading and cross-category pricing can arise when firms with broader product ranges exploit their market power to discriminate between consumers with heterogeneous shopping costs. Their model is driven by asymmetric market power across product departments and firms. A large firm competes with a competitive fringe of smaller firms in one product department, but monopolizes another product department. We show in Appendix Section M that when the valuation for products in the competitive department increases, prices in the monopolized department will increase. This mechanism would explain our results if food (SNAP-eligible) were the competitive department and non-food products (SNAP-ineligible) face less competition, which is consistent with anecdotal evidence of large grocery chains competing with small discount grocers. We also use this model as an example to further illustrate the intuition behind the multi-product pass-through formula for two products in Appendix Section K.

These results could be extended to imperfect competition among multiple large retailers with market power over non-food products, as well as heterogeneous consumer valuations for food, relaxing the degree of asymmetric market power between food and non-food markets. Given that we find that prices rise but quantities fall for SNAP-ineligible products, this result would be consistent with predictions of increased markups for SNAP-ineligible products.[55]

Therefore, there are at least two possible reasons for the large pass-through elasticity for SNAP-ineligible products. First, because SNAP benefits lead to a rise in disposable income for SNAP consumers, demand for SNAP-ineligible products could increase. Second, because of the multi-product nature of all grocery stores in our data, food and non-food products can become complementary due to shopping costs.[56] Multi-product retailers with asymmetric market power over food and non-food can leverage this complementarity to raise markups on non-food products when SNAP benefits increase.

6 Conclusion

In this paper, we find evidence that large increases in government transfer payments in the form of electronic benefits for food increase retail prices in the grocery sector. Applying an instrumental-variable approach that uses state-specific program adjustments, we estimate that a 1% increase in SNAP benefits per population raises grocery store prices by about 0.08%. Using this reduced-form estimate as a sufficient statistic in a theoretical partial-equilibrium framework, we estimate that a marginal dollar of SNAP benefits increases producer surplus by about \$0.5, increases SNAP consumer surplus by about \$0.7, and decreases non-SNAP consumer surplus by about \$0.4, or about \$0.05 per non-SNAP consumer. The price response is larger in regions with higher proportions of SNAP participants and higher market concentration. Our estimates of MPCF out of SNAP are around 0.44 and consistent with those from recent literature.

These findings have several policy implications. First, if the objective of SNAP is to guarantee a floor of *real* spending power on food, federal maximum benefits should be increased by about 7% to account for the price response.[57] Alternatively, this implies that programs that provide in-kind transfers, such as The Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), would enable beneficiaries to receive the full benefit. However, this advantage must be weighed against the disadvantages of providing in-kind transfers, which could include shifting the price effect onto the government, limiting consumer choice, and leakages. Second, supply-side interventions in neighborhoods with

[55] Theoretically, Cowan (2004) shows that under imperfect competition such as monopoly and symmetric Cournot oligopoly, the quantity response can be negative for an increase in demand, depending on the curvature of demand.

[56] Thomassen et al. (2017) provide empirical evidence by applying a novel demand model to UK consumer data and find that product categories are complements due to shopping costs.

[57] Suppose an experiment raising benefits per population by 1%. This raises the price of food by 0.0724%, but since this cuts into the spending power of 100% of benefits, the real spending power of the marginal benefit gets reduced by 7.24%. The same logic applies to the case of extrapolating to inframarginal changes.

weaker competition in the grocery sector, often known as "food deserts," may improve the targeting properties of SNAP by shifting more surplus to SNAP consumers. Third, interpreting our findings using a partial-equilibrium model of incidence, we find that while the intended beneficiaries, SNAP consumers, obtain most of the consumer surplus, the increased SNAP benefits also benefit producers at the expense of non-SNAP consumers. Fourth, increased SNAP benefits could raise total welfare and reduce deadweight loss due to the expansion of output by producers with market power. Fifth, given that SNAP benefits per population rose by about 30% due to the Farm Bill and the ARRA, our findings suggest expansions in SNAP countered deflationary pressures by contributing to price hikes of 2.4% in grocery stores. Sixth, the fungibility of SNAP benefits would lower the magnitude of the effects on the market for food, and fully capturing incidence would require a study of the effect on other product markets. A recent experimental study by Egger et al. (2022) examining price effects of a cash-transfer program in rural Kenya, as referenced earlier, shows that indeed marginal consumption propensities in response to undesignated cash transfers are far more dispersed across goods and the aggregate price response far lower. Policy changes in non-recessionary periods and transfer-payment changes in sectors beyond groceries could be useful for further elucidating the significant roles that in-kind designation of electronic benefits, product-specific MPCs, and product-specific market power can play in influencing consumer demand, welfare, and market outcomes in future research.

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Tables

Table 1: Decomposing variance in percentage changes in synthetic benefits per population, Farm Bill and ARRA

	(1)			(2)		
VARIABLES	% change in IV, FB	Covariance share	R2 share	% change in IV, ARRA	Covariance share	R2 share
Log average gross income	7.321***	0.268	0.166	6.412***	-0.0915	0.167
	(0.954)			(0.785)		
Log average rent	-0.925**	-0.0459	0.043	-1.409***	0.160	0.098
	(0.456)			(0.392)		
Log average household size	4.758	-0.0812	0.058	2.666	0.0806	0.068
	(2.925)			(1.736)		
Share elderly/disabled	6.222***	0.0811	0.052	0.479	-0.00265	0.015
	(1.960)			(1.442)		
Share homeless	16.63	-0.00388	0.008	1.655	-0.00183	0.009
	(10.61)			(7.429)		
Log SUA	-1.849***	-0.0520	0.029	-2.846***	0.712	0.578
	(0.276)			(0.247)		
% change in SUA	0.179***	0.770	0.644	-0.000765	0.00323	0.065
	(0.0148)			(0.00986)		
Residual		0.0637			0.140	
Observations	48			48		
R-squared	0.936			0.860		
Prob > F	0.000			0.000		

Notes: Robust standard errors are in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1. % change in IV refers to the percentage change in synthetic benefits per population, FB refers to the Farm Bill in 2008m10, ARRA refers to the American Recovery and Reinvestment Act in 2009m4. Covariance share refers to the share of the variance in the outcome explained by each variable. R2 share refers to the share of R-squared explained by each variable following Huettner and Sunder (2012). This measure uses Shapley and Owen values, which calculate the average marginal contribution of each regressor over all possible orderings. All variables are measured in 2006 except for two variables. Log standard utility allowance (Log SUA) is measured the month before the event of interest, and the percentage change in the standard utility allowance (% change in the SUA) is measured at the Farm Bill only because the SUA did not change during the ARRA.

Table 2: Effect of SNAP-benefit changes on prices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specification	OLS	IV	IV	IV	IV	IV	OLS	IV
VARIABLES				Log price index				
Log benefits per population	0.00397	0.232	0.157***	0.148***	0.118***	0.118***	0.0211**	0.0820***
	(0.0177)	(0.165)	(0.0323)	(0.0267)	(0.0300)	(0.0295)	(0.00951)	(0.0234)
Log housing price			0.126***	0.118***	0.106***	0.107***	0.0474***	0.0752***
			(0.0214)	(0.0190)	(0.0171)	(0.0172)	(0.0115)	(0.0124)
Log unemployment rate				-0.00802	-0.00518	-0.00493	0.0000128	-0.00383
				(0.00619)	(0.00599)	(0.00573)	(0.00244)	(0.00355)
Log population				-0.146**	-0.136**	-0.134**	-0.132***	-0.144***
				(0.0648)	(0.0627)	(0.0618)	(0.0383)	(0.0391)
Log average wage				0.00755	0.00830	0.00852	0.00930*	0.00748
				(0.00559)	(0.00544)	(0.00540)	(0.00552)	(0.00555)
Log tobacco tax					0.00741***	0.00740***	0.00826***	0.00519***
					(0.00268)	(0.00265)	(0.00158)	(0.00180)
Log SNAP average gross income						0.00382	0.00133	0.00634
						(0.0139)	(0.00472)	(0.00851)
Log SNAP average rent						-0.00512	-0.00348	-0.00490*
						(0.00369)	(0.00269)	(0.00291)
Observations	382560	382560	382560	382560	382560	382560	382524	382524
R-squared	0.884	0.771	0.868	0.874	0.884	0.884	0.904	0.899
Prob > F	0.824	0.010	0.000	0.000	0.000	0.000	0.000	0.000
Number of units	7970	7970	7970	7970	7970	7970	7970	7970
Number of clusters	48	48	48	48	48	48	48	48
First stage F-stat		2.578	13.996	17.857	20.655	20.682		20.194
Energy controls							X	X

Notes: Robust standard errors are in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1. Store and period fixed effects are included. Energy controls refer to annual state-level total energy, electricity, LPG, and natural gas quantities consumed and prices for the residential sector.

Table 3: Effect of SNAP-benefit changes on real sales

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specification	OLS	IV	IV	IV	IV	IV	OLS	IV
VARIABLES	Log real sales							
Log benefits per population	-0.0702*	0.0318	-0.0338	-0.0661	-0.0448	-0.0402	0.0617*	0.00597
	(0.0404)	(0.150)	(0.0770)	(0.0866)	(0.108)	(0.106)	(0.0324)	(0.109)
Log housing price			0.110*	0.0228	0.0316	0.0357	0.0665	0.0412
			(0.0607)	(0.0518)	(0.0553)	(0.0564)	(0.0403)	(0.0566)
Log unemployment rate				-0.135***	-0.137***	-0.139***	-0.141***	-0.137***
				(0.0298)	(0.0307)	(0.0306)	(0.0288)	(0.0297)
Log population				-0.149	-0.156	-0.162	-0.153	-0.142
				(0.165)	(0.166)	(0.165)	(0.117)	(0.126)
Log average wage				0.00271	0.00219	0.00112	0.000677	0.00234
				(0.0395)	(0.0394)	(0.0394)	(0.0395)	(0.0395)
Log tobacco tax					-0.00514	-0.00541	-0.00298	-0.000174
					(0.00777)	(0.00773)	(0.00608)	(0.00747)
Log SNAP average gross income						-0.0333	-0.0193	-0.0239
						(0.0236)	(0.0172)	(0.0212)
Log SNAP average rent						0.00501	-0.000600	0.000703
						(0.00959)	(0.00920)	(0.00890)
Observations	382560	382560	382560	382560	382560	382560	382524	382524
R-squared	0.962	0.962	0.962	0.963	0.963	0.963	0.963	0.963
Prob > F	0.089	1.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of units	7970	7970	7970	7970	7970	7970	7970	7970
Number of clusters	48	48	48	48	48	48	48	48
First stage F-stat		2.578	13.996	17.857	20.655	20.682		20.194
Energy controls							X	X

Notes: Robust standard errors are in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1. Store and period fixed effects are included. Energy controls refer to annual state-level total energy, electricity, LPG, and natural gas quantities consumed and prices for the residential sector.

Table 4: SNAP participation and effect of SNAP-benefit changes on prices and real sales

	(1)	(2)	(3)	(4)
Specification	OLS	IV	OLS	IV
VARIABLES	Log price index		Log real sales	
Log benefits p.p.	0.0165	0.0738***	0.0466	-0.0108
	(0.0107)	(0.0250)	(0.0335)	(0.104)
x Participation rate	0.0774**	0.130***	0.254**	0.265**
	(0.0329)	(0.0371)	(0.115)	(0.128)
Observations	382524	382524	382524	382524
R-squared	0.904	0.899	0.963	0.963
Prob > F	0.000	0.000	0.000	0.000
Number of units	7970	7970	7970	7970
Number of clusters	48	48	48	48
First stage F-stat		10.439		10.439

Notes: Robust standard errors are in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1. Control variables as well as store and period fixed effects are included. Log benefits p.p. refers to log benefits per population. Participation rate refers to the ratio of SNAP participants to population in each county fixed to the pre-period of 2006.

Table 5: Concentration measures and effect of SNAP-benefit changes on prices

	(1)	(2)	(3)	(4)
VARIABLES	Log price index			
Log benefits p.p.	0.0726***	0.0338	0.0662***	0.0264
	(0.0232)	(0.0288)	(0.0246)	(0.0295)
x HHI	0.0399***		0.0360***	
	(0.00730)		(0.00741)	
x Log est. per pop.		-0.00407***		-0.00397***
		(0.000959)		(0.000937)
x Participation rate			0.116***	0.129***
			(0.0370)	(0.0374)
Observations	382524	381984	382524	381984
R-squared	0.900	0.900	0.901	0.901
Prob > F	0.000	0.000	0.000	0.000
Number of units	7970	7958	7970	7958
Number of clusters	48	47	48	47
First stage F-stat	10.098	10.017	6.950	6.956

Notes: Robust standard errors are in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1. Control variables as well as store and period fixed effects are included. Log benefits p.p. refers to log benefits per population. Participation rate refers to the ratio of SNAP participants to population in each county fixed to the pre-period of 2006. HHI refers to the county-level measure of HHI for the grocery industry fixed to the pre-period of 2006. Log est. per pop. refers to log of the number of grocery establishments per population in each county fixed to the pre-period of 2006.

Table 6: SNAP participation and effect of SNAP-benefit changes on prices and real sales by product eligibility

	(1)	(2)	(3)	(4)
SNAP eligibility	Ineligible		Eligible	
VARIABLES	Log price index	Log real sales	Log price index	Log real sales
Baseline				
Log benefits p.p.	0.0898***	-0.126	0.0724***	0.0605
	(0.0286)	(0.107)	(0.0269)	(0.108)
Interaction				
Log benefits p.p.	0.0750**	-0.123	0.0657**	0.0376
	(0.0303)	(0.103)	(0.0277)	(0.104)
x Participation rate	0.234***	-0.0489	0.106**	0.362***
	(0.0418)	(0.179)	(0.0401)	(0.117)
Observations	382428	382428	382140	382140
Number of units	7968	7968	7962	7962
Number of clusters	48	48	48	48

Notes: Robust standard errors are in parentheses, clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1. Control variables as well as store and period fixed effects are included. Log benefits p.p. refers to log benefits per population. Participation rate refers to the ratio of SNAP participants to population in each county fixed to the pre-period of 2006. SNAP-eligible goods account for around 75% of revenue in grocery stores.

Table 7: Effect of SNAP-benefit changes on consumption of households

	(1)	(2)	(3)	(4)
Specification	OLS, log-log	IV, log-log	OLS, level-level	IV, level-level
VARIABLES	Consumption			
Both ineligible	0.0444	0.193	0.106*	0.200
	(0.0587)	(0.180)	(0.0571)	(0.148)
Household eligible only	0.0635	0.208	0.170*	0.254
	(0.109)	(0.219)	(0.0908)	(0.172)
Product eligible only	0.0231	0.193	0.0376	0.128
	(0.0376)	(0.167)	(0.0420)	(0.140)
Both eligible	0.252***	0.411**	0.354***	0.442**
	(0.0557)	(0.164)	(0.0866)	(0.170)
Observations	2044662	2044662	2044666	2044666
R-squared	0.561	0.561	0.573	0.573
Prob > F	0.000	0.000	0.000	0.000
Number of units	23911	23911	23911	23911
Number of clusters	49	49	49	49
First stage F-stat		12.258		15.642

Notes: Robust standard errors are in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1. Each coefficient comes from a regression of (log) consumption on (log) SNAP benefits per recipient, interacted with 4 group indicators. Both ineligible refers to expenditures by SNAP-ineligible households on SNAP-ineligible products, household eligible only refers to expenditures by SNAP-eligible households on SNAP-ineligible products, product eligible only refers to expenditures by SNAP-ineligible households on SNAP-eligible products, and both eligible refers to expenditures by SNAP-eligible households on SNAP-eligible products. Control variables as well as household-month and period fixed effects are also included. Observations are weighted by sampling weights.

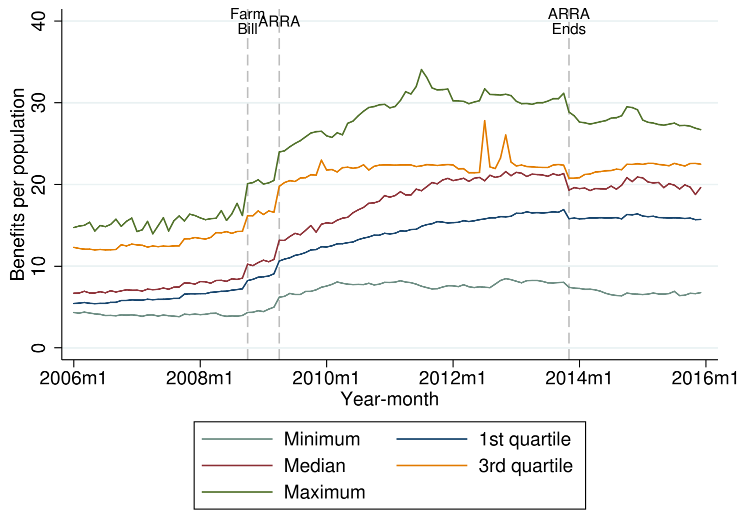
Table 8: Incidence of an additional dollar of SNAP benefits for SNAP-eligible goods

MPC elasticity	Pass-through elasticity	Shift magnitude	PS	CS	CS (SNAP)	CS (non-SNAP)
0.339	0.0724	0.0802	0.440	0.0466	0.405	-0.358
0.522	0.0724	0.124	0.492	0.3051	0.664	-0.358

Notes: MPC elasticities are obtained from Section 4.2 and from HS. A market conduct parameter of 0.2 is assumed using markups as shown in Hottman (2016). A demand elasticity of -0.709 is obtained using panel variation as described in Section 5.4 and falls within the typical range reported in the literature as surveyed by Andreyeva et al. (2010). Proportion of SNAP sales of 0.168 is obtained from USDA data. Pass-through elasticity is obtained from Section 4.1 and the shift magnitude is the predicted pass-through elasticity obtained using equation (8) assuming a unit-subsidy pass-through rate of 1. Surplus calculations are changes in surplus per marginal dollar of SNAP disbursed. PS refers to producer surplus and CS refers to consumer surplus, CS (SNAP) and CS (non-SNAP) refers to consumer surplus for SNAP consumers and consumer surplus for non-SNAP consumers, respectively. See Section 5.4 for a detailed explanation.

Figures

Figure 1: SNAP benefits per population by state, 2006-2015

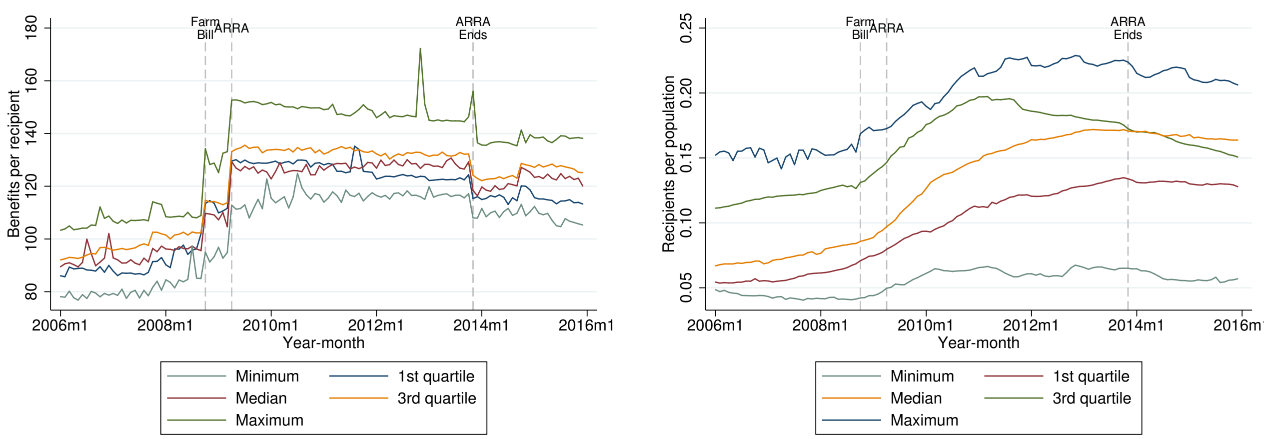


Notes: This figure plots out the SNAP benefits per population for five states from 2006 to 2015, ranking states by their average SNAP benefits per population from 2006 to 2015 and picking the states at the minimum, 1st quartile, median, 3rd quartile, and maximum.

Figure 2: SNAP benefits per recipient and recipients per population by state, 2006-2015

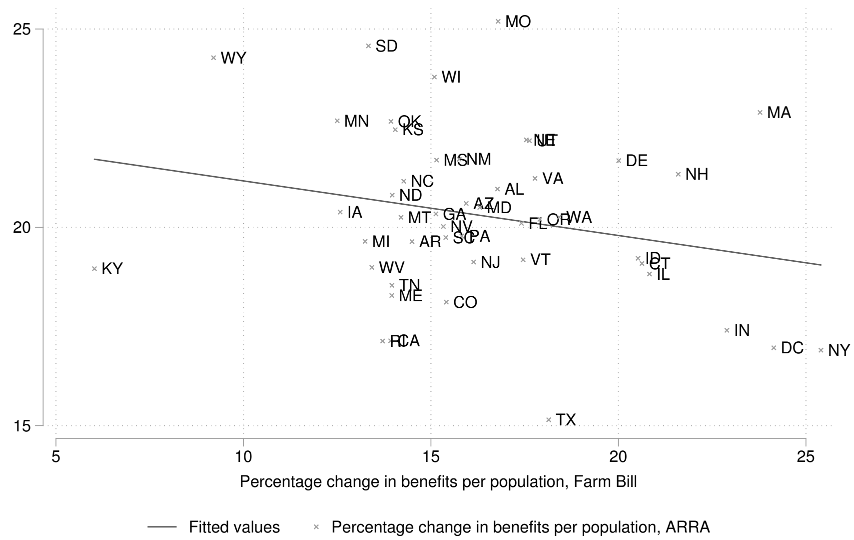
(a) Benefits per recipient

(b) Recipients per population



Notes: This figure plots out the SNAP benefits per recipient and recipients per population, each for five states from 2006 to 2015, ranking states by their average SNAP benefits per recipient or recipients per population from 2006 to 2015 and picking the states at the minimum, 1st quartile, median, 3rd quartile, and maximum.

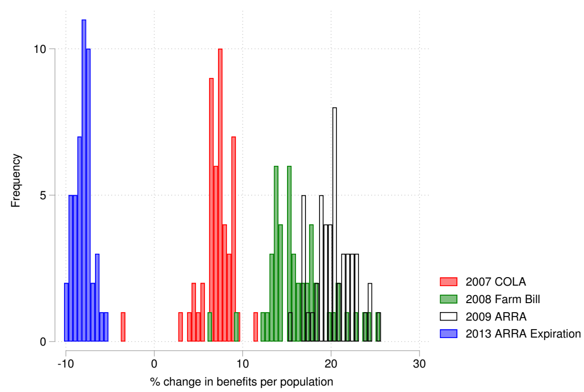
Figure 3: Percentage change in SNAP benefits per population due to the 2008 Farm Bill and the 2009 ARRA by state



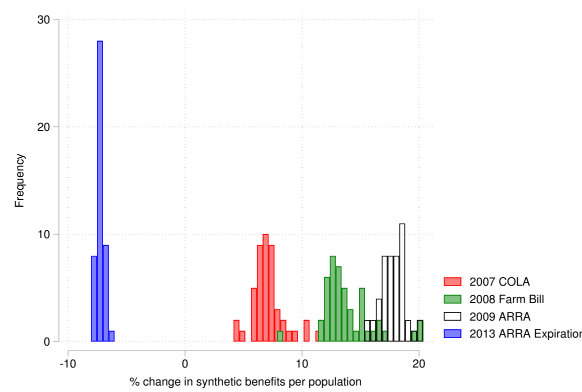
Notes: This figure plots out the percentage change in SNAP benefits per recipient for all states, excluding Ohio and Louisiana which were both outliers due to disaster relief events. The slope is negative and insignificant with a point estimate of -0.138 (0.098).

Figure 4: Variation across states during major changes in SNAP benefits per population and synthetic benefits per population, 2006-2015

(a) SNAP benefits per population



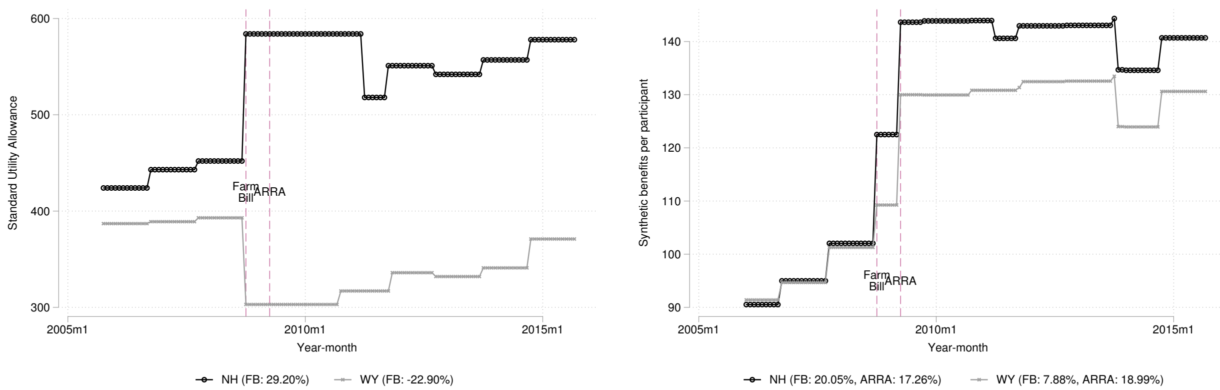
(b) Synthetic benefits per population



Notes: This figure plots out the changes in SNAP benefits per population and synthetic benefits per population from 2006 to 2015 across four major events in which SNAP benefits changed. These four events are 2007 cost-of-living adjustments, 2008 Farm Bill, 2009 ARRA, and 2013 ARRA expiration. For SNAP benefits per population, the mean (standard deviation) of these 4 events are 0.072 (0.016), 0.16 (0.037), 0.20 (0.022), and -0.080 (0.010) respectively. For synthetic benefits per population, the means (standard deviations) of these four events are 0.073 (0.021), 0.14 (0.028), 0.18 (0.010), and -0.072 (0.0033), respectively. Several outliers due to disaster-relief events are dropped.

Figure 5: HCSUA and synthetic benefits per recipient, New Hampshire and Wyoming

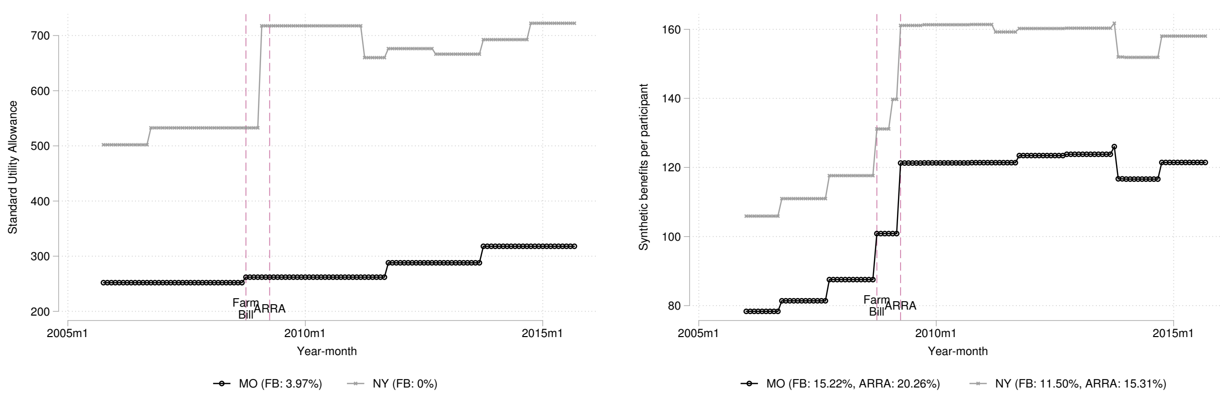
(a) HCSUA (b) Synthetic benefits per recipient



Notes: This figure plots out the heating and cooling standard utility allowance (HCSUA) and synthetic SNAP benefits per recipient from 2006-2015 for two states, New Hampshire and Wyoming, to illustrate how differential changes in the SUA lead to differential changes in synthetic benefits per recipient and synthetic benefits per population. Inside the parentheses behind each state, we show the percentage change of the HCSUA during the Farm Bill (FB) for Figure 5a, and the percentage change in synthetic benefits per population during the FB and the ARRA for Figure 5b.

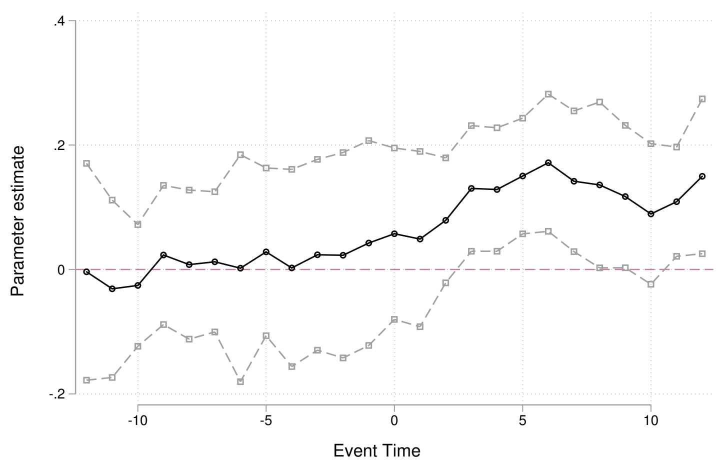
Figure 6: HCSUA and synthetic benefits per recipient, Missouri and New York

(a) HCSUA (b) Synthetic benefits per recipient



Notes: This figure plots out the HCSUA (heating and cooling standard utility allowance) and synthetic SNAP benefits per recipient from 2006 to 2015 for two states, Missouri and New York, to illustrate how differences in initial levels of synthetic benefits per recipient lead to different percentage changes in synthetic benefits per recipient and synthetic benefits per population. Inside the parentheses behind each state, we show the percentage change of the HCSUA during the Farm Bill (FB) for Figure 6a, and the percentage change in synthetic benefits per population during the FB and the ARRA for Figure 6b.

Figure 7: Cumulative effects of synthetic benefits per population on prices



Notes: This figure plots the sum of estimated coefficients for each period, along with the 95% confidence intervals, from regressions using a distributed lag model, where log price index is regressed on log synthetic benefits per population. Control variables as well as store and period fixed effects are included.

For Online Publication: Appendix

A Comparisons with Contemporaneous Work

There are at least two possible reasons why the conclusion of our paper differs from that of Jaravel (2018), a contemporaneous work which concludes that higher SNAP take-up rates among eligible households reduce inflation rates. At a high level, we differ in (1) data series and time period; (2) explanatory variation; and (3) methodology used to address endogeneity. Whereas we examine both Nielsen Retail Scanner and Nielsen Consumer Panel prices over 2006-2015, Jaravel (2018) examine Nielsen Consumer Panel prices over 2004-2008. Whereas we focus on the intensive-margin variation in SNAP benefits using an IV approach, Jaravel (2018) focuses on the SNAP take-up rates by regressing 2004-2008 prices on 2001-2007 SNAP take-up rates among eligible households using a long-difference approach.

One possible reason for the discrepancy is that both conclusions are valid and limited only by external validity: that is, mechanisms specific to each time period and/or each explanatory variation (intensive versus extensive) explain the difference.

Another possible reason may be biases due to endogeneity or measurement error in using take-up rates to proxy for benefits. Jaravel (2018) writes that take-up rate changes were mainly affected by state-level policy changes and that "these policies had a large impact on the take-up rate for food stamps and their implementation across states was not correlated with economic fundamentals such as unemployment," mentioning Ganong and Liebman (2018). However, the results of Ganong and Liebman (2018) say that not all of the take-up rate changes during this period stemmed from state policy changes, and that much of the variation could have been endogenous. Indeed, Ganong and Liebman's (2018) estimates that in some years between 2001 and 2007, 20% to 30% of the take-up variation could be attributed to changes in unemployment, suggesting that simply controlling for a long difference in unemployment rates between years 2001 and 2007 may not be sufficient to partial out unobservable economic trends spanning this period. Ganong and Liebman (2018) conclude that perhaps 25% to 50% of the variation could be explained by policy changes, with the rest of the variation left unaccounted for.

B Formalizing the Actual SNAP Formula and Instrumentation Strategy

We first formalize the SNAP formula illustrated mathematically in Section 2.2. Comprehensively, let $X_i = \{N_i, S_i, I_i, R_i, U_i, UI_i, EI_i, C_i, D_i, M_i, L_i\}$ represent the set of a potential SNAP recipient i's demographic characteristics the government sees at a given time period. Characteristics important to the government include N_i, the person's household size; S_i, the person's state of residence; I_i, the person's gross income minus earned income deduction; R_i, the person's rent; and U_i, the person's utility expenditure. Let $p = \{b, o, u, \hat{h}, \check{h}\}$ represent the set of SNAP parameters, which are functions of X_i. b represents the maximum-benefits formula. The SNAP formula is given by

$$B_i = max\Big(0.08 \times b(N_i) \times 1[N_i \leq 2],\ b(N_i) - 0.3 \times max\left(0, I_i - o_i - H_i\right)\Big). \tag{15}$$

Note that, in the real formula above, households of sizes 1 and 2 are allowed a minimum benefit (8% of the maximum benefit), should their calculated benefit fall short of the minimum benefit threshold. Note also that in the real formula above, expected ability to contribute to food spending is bounded from below at 0. Note that these bounds do not affect our heuristic analysis in the previous subsection as the average marginal relationships between the arguments and the output of the formula remain the same.

Next we define each component I_i, o_i, and H_i, which are given by:

$$I_i = UI_i + 0.8EI_i \tag{16}$$

$$o_i = d(N_i) + C_i + D_i + M_i \tag{17}$$

$$H_i = \begin{cases} R_i + u(N_i, S_i, U_i) + 0.5o_i - 0.5I_i & L_i = 1 \\ \min(R_i + u(N_i, S_i, U_i) + 0.5o_i - 0.5I_i, \hat{h}) & L_i = 2 \\ \max(R_i + u(N_i, S_i, U_i) + 0.5o_i - 0.5I_i, \check{h}) & L_i = 3 \end{cases} \tag{18}$$

Equation (16) shows I_i is the sum of unearned income UI_i and earned income EI_i minus 20% of EI_i applied as an earned income deduction.

Equation (17) shows deductions for basic needs other than shelter include standard deduction per household (set annually at the federal level) $d(N_i)$, legal child-support-expense deduction C_i, dependent-care-expense deduction D_i, and medical-expense deduction M_i.

Equation (18) describes how the excess shelter deduction H_i is determined for different types L_i of households: $L_i = 1$ identifies non-homeless households with elderly or disabled members; $L_i = 2$ identifies non-homeless households without elderly or disabled members; $L_i = 3$ identifies homeless households. The equation shows that, for households of type $L_i = 1$, H_i is the sum of rental cost R_i and utility-standard cost $u(N_i, S_i, U_i)$ in excess of half of net countable income prior to considering shelter costs $0.5I_i - 0.5o_i$.[58] For households of type $L_i = 2$, H_i is bounded by $\hat{h}$, a shelter cap set at the federal level (inflation-adjusted every year). For households of type $L_i = 3$, H_i is bounded from below by $\check{h}$, a homeless-shelter allowance set at the federal level (which, curiously, has not been updated since 2003).

Summarizing the discussion, we have,

$$B_i = max\Big(0.08 \times b(N_i) \times 1[N_i \leq 2],\ b(N_i) - 0.3 \times NI(X_i; p)\Big), \tag{19}$$

where NI stands for calculated net countable income. The actual instrument we use in the paper is given by,

$$Z_{st} = \frac{1}{n_{s,0}} \sum_{i \in s,0} max\Big(0.08 \times b(N_{i0}) \times 1[N_{i0} \leq 2],\ b(N_{i0}) - 0.3 \times NI(X_{i0}; p_t)\Big). \tag{20}$$

For most households for whom the minimum-benefit threshold does not bind, the changes

[58] The excess shelter deduction seems to be motivated by a desire of the federal government to ameliorate differences in shelter costs across regions not fully reflected in differences in wage levels across regions. The federal government seems to assume one-half of a household's net countable income before shelter costs is available to cover the household's cost of shelter.

over time in log points of the instrument can be expressed as

$$\Delta \ln Z_{st} \approx \frac{Z_{s,t} - Z_{s,t-1}}{Z_{s,t-1}} = \frac{\bar{\Delta}_s \, b(N_{i0}) - 0.3 \times \bar{\Delta}_s \, NI(X_{i0}; p_t)}{\frac{1}{n_{s,0}} \sum_{i \in s,0} \left[b(N_{i0}) - 0.3 \times NI(X_{i0}; p_{t-1}) \right]}. \tag{21}$$

The same intuitions from Section 2.2 carry over to our comprehensive formulation of the SNAP formula, although they are more difficult to see here. As in Section 2.2, changes in the numerator no longer depend on realized trends either in rents or in incomes of program participants. The simulated variable is also free from the influence of participants joining the program after 2006. Again, note that we find it necessary to include a housing-price control to net out the influence of these new participants on the actual benefits, which crucially affects the first stage. The simulated benefits depend only on the intensive-margin changes based on the levels of demographic characteristics of participants X_{i0} realized prior to the Great Recession.

C Adjustments to the SNAP Formula Made by Individual States

Although the SNAP formula is set at the federal level as described above, a number of adjustments to the formula occur at the state-level during implementation that introduce cross-state idiosyncrasies in final disbursement levels. These include, most importantly, the standard utility allowance program (SUA).

C.1 Standard Utility Allowance

First, all states participate in the SUA. States set their own utility-deduction standards, which are designed to reflect the average within-state utility costs of households. According to Holleyman et al. (2017), states' methodologies fall into two categories: (1) methodologies that rely on state-specific recent utility data and (2) methodologies that adjust a base number using an inflation measure such as the Consumer Price Index (CPI) of utility costs. Some states use a methodology that combines both approaches. The first set of states recalculate the SUA yearly while the second set of states update the SUA based on the change in fuel CPI. Considerable variation exists within these methodologies. For example, some states use only data for low-income households, whereas others gather data for all households. States incorporate a variety of fuel types, and some assign weights to the different fuel types, whereas others do not. Over time, FNS has found some variation between established SUA values and average household utility expenses in many states. Over 40 states make the usage of these standards mandatory, and the standards are generally larger than utility expenses to encourage usage and simplify application procedures. Furthermore, 15 states participate in a related program called "Heat and Eat," which allows households participating in the Low-Income Home Energy Assistance Program (LIHEAP) to receive the highest-bracket utility deduction without having to provide utility-cost verifications. The "Heat and Eat" program especially benefits households with elderly or disabled members, because LIHEAP gives priority to these households during application.

Based on some additional documents from Holleyman et al. (2017) that supported the released report, we find that for the states on which we have additional information, they use data from the previous year to set the SUA in the coming year. We do not find any states setting the SUA based on predictions of future utility expenses. We are also able to verify for nearly half of the states that update their base that they indeed use lagged regional CPI data on fuel and utilities to set the SUA.

Because shelter expenses account for a substantial amount of deductions and the SUA accounts for over 50% of shelter expenses, the SUA has a particularly strong effect on state-level variation in benefits per population. We plot the relationships between changes in synthetic SNAP benefits per population, SUA per population, energy usage per population and prices for the residential sector by different fuel types, and temperature by state during the Farm Bill in Appendix Figure O8. We focus on this period because the SUA only changes in October and not in April when the ARRA led to a rise in maximum benefits. We also focus on the heating and cooling SUA (HCSUA) because households predominantly use the HCSUA and the HCSUA has the largest value relative to other types of the SUA, such as telephone expenses. We see that changes in the SUA are highly positively correlated with changes in synthetic benefits per population and that these changes are also correlated with drops in temperature and rises in total energy usage from heating using sources such as electricity, LPG, and natural gas, and less so for changes in fuel prices. These figures also show variation in synthetic benefits per population that is not explained by the HCSUA, since maximum benefits are also changing during the Farm Bill. Therefore, we show our results are robust to controlling for a vector of energy usage and prices at the state-level in Table 2, because these variables could have an impact on retail prices directly. Residual policy variation should be driven by prediction errors by states in setting the SUA since most of them use lagged data, as well as idiosyncratic state-level differences in methodologies used to set the SUA. We show that results are nearly identical for states using either SUA methodology in Table N5. Since we can fully observe how states that use lagged CPI are setting the SUA and we control for contemporaneous energy prices and quantities consumed, the fact that states that recalculate the SUA using utility data also have similar price responses suggests that any unobservable variation in the SUA does not pose significant endogeneity concerns.

C.2 Other Adjustments to the SNAP Formula Made by Individual States

Second, states have the flexibility to relax the federal eligibility rules through a policy called Broad-Based Categorical Eligibility (BBCE).[59] For instance, in the case of the gross income limit in 2015, 11 states followed the federal 130% limit, whereas 14 states extended the limit to 200%, with other states choosing a limit in between. In the case of the asset limit, 24 states waive it altogether; 11 states waive it for most households, but if a household cares for an elderly or a disabled member and the household's gross income exceeds 200% of the federal poverty line, the states apply an asset limit of $3,250; New Hampshire waives the asset limit for households with children; New York waives it for households with dependents or households with earned income. All states except four allow for at least one vehicle per household to be excluded from countable assets. This implies that heterogeneity exists in the composition of SNAP participants across states.

[59] BBCE allows states to equate their SNAP eligibility rules with TANF eligibility rules, over which states have some jurisdiction.

Third, some state-level policies change the formula entirely, and these include MFIP and SSI-CAP. MFIP applies to recipients of Temporary Assistance for Needy Families (TANF) program, and determines SNAP payment levels in conjunction with TANF payment levels via a state-specific formula.[60] SSI-CAP is a program that allows SSI recipients to apply for SNAP benefits through the SSI application process rather than requiring them to step through a separate application process for SNAP, and participating states are given substantial leeway over the setting of eligibility rules and benefit levels. Among the 18 states that have participated in the program, some states have allowed only single-member households to participate, whereas others have allowed couples to participate; some states have allowed households with earned income to participate, whereas others have not; age restrictions and shelter-expense cutoffs vary across states. No deductions are allowed for participating households, and benefit levels are determined by a state-specific function of state-specific household rent brackets.

Another policy aimed at standardizing deductions at the state level also introduces additional variation across states: the medical-deduction demonstration program. Sixteen states participate in the former, each state stipulating a fixed amount of medical deduction for households with any elderly or disabled member, whose recorded medical expenses fall below a state-specific threshold.

An additional reason SNAP-benefit levels may vary across states is disaster-relief payments. Disaster-relief payments can be made when a presidential disaster declaration is made for a particular area. Our results are robust to cleaning out the disaster-relief payments from the benefit series.

Lastly, not all eligible recipients participate in SNAP, hence varying the participation-rate series across states. Ganong and Liebman (2018) study the variation in the participation rate between 1994 and 2011, and note the participation rate showed a negative correlation with the unemployment rate between 2001 and 2007, but then showed a positive correlation during the Great Recession. They also note that variation in the unemployment rate can explain two thirds of the the participation rate variation, whereas BBCE rules explain 18%.

D Construction of Price Indices

Beraja et al. (2019) adopt a two-stage procedure that is very similar to the one used by the BLS in constructing the CPI, and introduce some improvements enabled by scanner data. A viable alternative would have been to use an exact-price index as defined in Diewert (1976) for the CES unit-cost function by applying Sato (1976) and Vartia (1976) weights, which would be theoretically founded. These exact-price indices can also account for new product varieties within the CES framework as demonstrated in Feenstra (1994) and implemented in Broda and Weinstein (2010). However, we did not choose this alternative for two reasons. First, we wish to make the indices more comparable to the CPI for easier comparison. Second, theoretically founded indices that account for product turnover require estimation

[60] To highlight some important differences, deductions other than the earned income deduction are not considered, and the earned-income-deduction rate is set higher at around 40 % to 50%. The formula itself is also quite different, although it uses some of the same SNAP parameters. Practically, though, the average payout amounts do not differ greatly from the payout amounts of other states. Our results are robust to excluding Minnesota from the sample.

of parameters that are very computationally intensive given the size of the data set.[61]

In the first stage, the index is constructed at both the monthly and quarterly levels for each product group (125 groups) and store. Stores that do not appear throughout the entire sample period are dropped, retaining around 23,500 stores in the sample. Therefore, the results are not affected by store entry and exit. Among the stores that are in the sample in 2006, 84% remain throughout the entire sample period. Although the scanner data are weekly, they are aggregated up to the monthly or quarterly level to decrease missing values and reduce chain drift, as pointed out by Ivancic et al. (2011). Each base observation is a monthly or quarterly unit value for each store-product, that is, monthly or quarterly revenue divided by the total number of units, which is equivalent to a quantity-weighted average price. Products are defined as UPC codes. Alternatively, weekly prices can be sampled from each store-product-period. Only goods that appear consistently across an entire year are included, such that around 50% and 70% of all sales are used in constructing store-level monthly and quarterly indices, respectively.[62] Quantities are directly observed and used as weights, which is a major advantage relative to the CPI, which collects price quotes at the store level but not quantities, so that they use quantities that are lagged three to four years and are obtained from the BLS CEX. Quantity weights are updated yearly to avoid chain drift, and the weights (denoted as $q_{i,y}$) are lagged one year to ensure price changes are not a result of changing consumption patterns in response to current prices or shocks. The CPI weights are updated every two years, which is less frequent than the scanner index. Hence, the CPI is more subject to substitution bias and the basket is less relevant over time. The price index $P^L_{j,t,y}$ at time t and year y for product group j for each store is shown below in equation (22):

$$P^L_{j,t,y} = P^L_{j,t-1,y} \times \frac{\sum_{i \in j} p_{i,t} q_{i,y-1}}{\sum_{i \in j} p_{i,t-1} q_{i,y-1}}. \tag{22}$$

Each unique item is defined by its UPC code. Prices and quantities are observed for each store and UPC pair, which is denoted as product i. By construction, changes in the price index only reflect relative changes in prices for a given bundle and are unaffected by price levels. Therefore, product switching among consumers to more expensive bundles does not change the price index for given price levels.

The second stage is similar to the first stage and aggregates the product group-specific price indices for each store using expenditure shares $s_{j,y-1}$ that are lagged one year and fixed within year. To follow the CPI more closely, a Tornqvist price index can also be constructed using the average expenditure shares between two periods as weights. Although we present results using the first method, both methods give almost identical results and are shown in

[61] There are limitations with the publicly available BLS indices such that we do not to use them in this paper. First, there are only about 25 cities for the BLS indices with many cities defined across state borders, making it difficult to apply our IV which utilizes state-level variation. Second, our retail scanner indices are robust to many weighting schemes and correlates strongly with the BLS indices for the cities that are available, as shown in Leung (2021). Third, with our indices, we can segment by store types, focus on grocery stores and chains that price locally, and have finer location to implement triple differences etc.

[62] Prices of goods that did not sell within a given week are not recorded in retail scanner data. Therefore, aggregating up to the monthly or quarterly level decreases missing values. Furthermore, products that are not bought by consumers are inherently not an important part of the consumer basket.

equation (23):

$$\frac{P_t}{P_{t-1}} = \sum_{j=1}^{N} s_{j,y-1} \left(\frac{P^L_{j,t,y}}{P^L_{j,t-1,y}} \right) \tag{23a}$$

$$\frac{P_t}{P_{t-1}} = \prod_{j=1}^{N} \left(\frac{P^L_{j,t,y}}{P^L_{j,t-1,y}} \right)^{\frac{s_{j,t}+s_{j,t-1}}{2}} . \tag{23b}$$

We also construct a range of price indices at the quarterly level using alternative methods. The first index weights each product group using the expenditure shares of only products chosen to construct the price index, that is, products that satisfy the consistency criterion illustrated above, as opposed to all products in the data. The second index uses the Tornqvist index mentioned above. The third index constructs the price index in one stage instead of two stages. The fourth index uses a weighted geometric average in the first stage instead of a weighted arithmetic average. The fifth index uses weights that are fixed over time at the base period to ensure that the results are not driven by shifts in the consumption bundle over time as opposed to actual price changes. To construct such an index, only products that appeared consistently over the entire sample period can be used. The sixth index again uses fixed weights but also base observations that are sampled from the last observable posted price for each store-product-quarter.[63] The seventh index uses weights constructed from households using the Nielsen Consumer Panel instead of the Nielsen Retail Scanner, which allows us to construct weights by household income brackets. We present results focusing on SNAP-eligible households as classified above. All indices are highly correlated and results are robust to using any of the above methods. We show these indices for New York City in Appendix Figure O9, which are nearly identical across construction methods.

E Plausible Exogeneity

We relax the identifying assumption by allowing the IV to be plausibly exogenous ala Conley et al. (2012) with the IV having a direct impact on outcomes even after controls.

We obtain a back-of-the-envelope estimate of how large this impact would be quantitatively. Since SUA depends on both energy costs and idiosyncratic state policies, we allow the IV to reflect energy costs, which may have an impact on the outcomes even after energy controls if the controls are not perfect. Pass-through formulas imply that the effect of energy costs on retail prices is just the cost share of energy costs. The 2009 economic census estimates that the share of electricity, purchased fuels, and other utility payments is 5.5% of operating expenses. Given a gross margin of around 30% in the grocery sector based on the Annual Retail Trade Survey, this implies an upper bound of about $0.055 \times 0.3 = 0.0165$ for the cost share of energy costs. Therefore, we use 0.02 as our back-of-the-envelope estimate of the direct effect of the IV on retail prices, which is denoted as δ. When $\delta = 0.02$, our estimated coefficient is 0.066 and remains statistically significant at the 1% level.

[63] The posted price is actually recorded as a weekly unit value for Saturday-ending weeks. DVG highlight that this feature creates a slight aggregation bias but the bias is relatively small for state-level shocks in their calibrations.

We show that our results remain robust to a wide range of values of δ up to at least 0.04 in Appendix Figure O10, which is double our back-of-the-envelope estimate. To illustrate this, we plot the estimated coefficients and their confidence intervals against different levels of δ under various methods in Conley et al. (2012). The three methodologies are the union of confidence interval approach with a support of $[0, 0.08]$, the local-to-zero approach with a standard deviation of 0.02, and the local-to-zero approach with a standard deviation of δ.[64]

F Auxiliary Data

Population data are available from the Census Bureau. Data on housing prices are obtained from the Federal Housing Finance Agency (FHFA), which produces housing price indices at the state level from 2006 to 2015. County housing-price indices from 2006 to 2015 are also obtained from CoreLogic through the Fama-Miller Center at the University of Chicago Booth School of Business. Results are presented using state-level housing prices from FHFA, whereas results are robust to using county level housing prices. Labor force and demographic variables are obtained from the BLS and the Census. Tobacco tax data are available from the industry-funded annual report *Tax Burden on Tobacco, 2017* and are assembled by *Campaign for Tobacco-Free Kids*. SNAP-recipient characteristics are obtained from SNAP QC data described above. Energy controls, which include annual state-level total energy, electricity, LPG, and natural gas quantities consumed and prices for the residential sector, are obtained from the State Energy Data System (SEDS) maintained by the US Energy Information Administration (EIA). Data on monthly temperature by state are obtained from Berkeley Earth. Data on policy controls refer to state-year measures of amounts paid out by transfer programs available from the BEA. The transfer amounts are logged and these programs include social security, other retirement and disability insurance transfers, Medicare, Medicaid and other vendor payments, military medical insurance, SSI, EITC, other income maintenance programs such as TANF and WIC, state unemployment insurance, other unemployment insurance, Veterans' benefits, education and training assistance, other government transfers, transfers from nonprofit institutions, and transfers from businesses. Measures of grocery industry concentration, which include the number of establishments per population and the HHI, are obtained from the County Business Patterns (CBP) made available by the Census Bureau. The HHI is calculated using the mid-point of available employment size brackets.

G Graphical Evidence

We present some graphical evidence that suggests the identifying assumption of parallel trends is satisfied as an alternative graphical illustration of parallel pre-trends. Appendix Figure O3 plots the revenue-weighted average grocery store price indices by the quantile of change in residualized log synthetic benefits per population, our IV, for states above and below the median, respectively. To obtain these quantiles, a state-month panel of log synthetic benefits per population is regressed on the set of control variables as well as

[64] To implement the local-to-zero approach, we dropped a few control variables to ensure the covariance matrix would remain non-singular. The point estimates are robust to such changes in the set of controls.

state and period fixed effects, then the total change in the residualized log synthetic benefits per population during the Farm Bill and the ARRA for each state is used to separate the states into quantiles. The first quantile denotes the 24 states with larger changes in residualized log synthetic benefits per population and the second quantile denotes the 24 states with smaller changes. The figure shows the pre-trends are parallel and the price indices, which are normalized to 1 in January 2006, diverge just around the Farm Bill and become roughly parallel again after the ARRA, implying price growth in states with larger changes in synthetic benefits per population is around 2%-3% larger than states with smaller changes. Likewise, we plot these figures for population-weighted averages of housing prices and unemployment rates in Appendix Figure O4 to check how observable economic covariates vary across quantiles. Both housing-price and unemployment-rate trends look nearly identical across the two quantiles, implying the variation generated by the IV is largely uncorrelated with observable economic variables.[65]

H Within-Chain Price Rigidity

To understand why the pass-through elasticity estimates are heterogeneous across store types as shown in Appendix Table N10, we first show the proportion of revenue generated by each of five product departments across store types in Appendix Table N9. Drug stores earn most of their revenue from health and beauty care products, whereas both grocery and merchandise stores earn most of their revenue from food, although grocery stores earn a lot more from food at around 77%. If consumers respond to SNAP-benefit increases mostly by changing demand for products such as food but not other types of products as shown in Section 4.2, we would see smaller price responses in drug and merchandise stores, both of which do not derive the majority of their revenue from selling food.

Next, we follow DVG to measure the extent of price rigidity for each of the retail chains in the data. First, we pick the top UPC from each of 12 product modules with high revenue: canned soup, cat food, chocolate, coffee, cookies, carbonated soft drinks, yogurt, orange juice, bleach, toilet tissue, paper towel, and tooth cleaners. Next, we calculate the weekly correlation in prices for each store pair as a similarity measure, first demeaning the price at the store-quarter-product level before calculating the correlations over all weeks and products that are not missing both store pairs. For each chain, we define the flexibility measure as the percentage difference between the average correlation for store pairs within the same state and the average correlation for store pairs across different states. The closer the flexibility measure is to zero, the more rigid the chain pricing. Because multiple product modules exist, we take either the mean or median flexibility measure across product modules for each chain. DVG perform the same exercise using an alternative similarity measure.

The pass-through elasticity estimated from local variation in SNAP benefits per population should be affected by the extent to which chains are pricing rigidly. Chains that price flexibly across states as well as chains that price rigidly but are located primarily in one state should exhibit local pricing and react to local shocks, whereas chains that price rigidly and locate across many states should exhibit national pricing and will not react to

[65]In fact, the slight divergence in trends implies the states with smaller changes in the IV have slightly better economic outcomes, creating, if any, a slightly negative bias in our results.

local shocks. we plot the distribution of flexibility measures as well as number of states each chain is in across stores by store type in Appendix Figure O11. Both drug and merchandise stores belong to a few large chains that price rigidly, whereas a large amount of grocery stores belong to chains that price flexibly or chains that are located only in a few states. Over 50 grocery chains are in the sample whereas both drug and merchandise stores come from around five retail chains each.[66] This implies most grocery stores are engaging in local pricing, whereas drug and merchandise stores are not.

I Firm Dynamics and Market Structure

To investigate the impact of SNAP-benefit changes on firm dynamics and market structure, we use two additional data sets. First, we use FNS data on a yearly panel of retail stores that participate in SNAP from 2006 to 2015. For each store, we observe the years in which it is contained in the sample, that is, registered with the FNS to sell to SNAP consumers. We also observe the exact authorization date, the name and address of the store including the county it is located in, and the store type. To focus on the grocery industry, we restrict our sample to stores that are classified as grocery stores, supermarkets, or superstores. We then construct five county-level outcomes of interest from the data: (1) authorization rate, the number of newly authorized stores per month divided by the total number of stores, (2) entry rate, the number of new stores in the sample each year divided by the total number of stores, (3) exit rate, the number of stores that exit the sample the next year divided by the total number of stores the previous year, (4) reallocation rate, the sum of entry and exit rates, and (5) log count per population, the log of the total number of stores per population. Second, we use County Business Patterns (CBP) data from the Census Bureau to obtain two additional annual outcomes at the county-level: (6) log establishments per population, the log of the number of establishments per population, and (7) HHI, the sum of squared market shares calculated using employment size as a measure of firm size.[67] We then estimate equation (3) at the county-month level using the seven outcomes, again using data from 2007 to 2010 to focus on the periods in which SNAP benefits were increased.

As shown in Appendix Table N11, the estimated effect on entry and exit is positive but almost all of the estimates are statistically insignificant except the reallocation rate, suggesting that SNAP-benefit changes had little impact on entry and exit margins and market structure. A 10% increase in benefits per population increases the reallocation rate by 0.01, compared to a mean of around 0.17 for grocery stores in the SNAP panel. One possible reason for these small effects is that most grocery stores already accepted SNAP before our sample period. Many non-grocery stores also started accepting SNAP at the chain level over this time period so the competitive landscape may have changed in ways not fully captured in our analysis.

[66]Data from the Economic Census also show the grocery store industry is much less concentrated and less dominated by chains than the drug and merchandise store industries. For example, market share of the 4 largest firms is 30.7%, 54.4%, and 73.2% for grocery stores, drug stores, and merchandise stores respectively in 2007.

[67]Since the CBP only provides employment size in 13 size brackets, we use the mid-point of each bracket to construct the HHI.

J Graphical Illustration

We graphically illustrate how economic incidence changes in a simple partial-equilibrium framework under different assumptions about the food market in Appendix Figure O12. For simplicity, we begin with an example in which all consumers receive SNAP benefits. In Appendix Figure O12a, we assume a perfect competitive market with a flat supply curve. A SNAP-benefit increase shifts the demand curve out from D to D', and prices remain constant while quantities consumed increase from Q to Q'. Assuming no income effects or a parallel shift in demand, we evaluate incidence under the original demand curve. All of the surplus generated goes to the consumer as consumer surplus increases by $PBCP^{S'}$. In Appendix Figure O12b, we again assume perfect competition but let the supply curve be upward-sloping. Prices now increase from P to P' when SNAP benefits increase. The increase in surplus is now divided between the producer and the consumer, with producer surplus increasing by $P'ABP$ and consumer surplus increasing by $PBCP^{S'}$. In Appendix Figure O12c, we assume the firm is a monopolist with a constant marginal cost. A SNAP-benefit rise increases prices from P to P' because the firm raises its markup and sells at a more inelastic portion of the demand curve. The increase in surplus is again split between the producer and the consumer, with producer surplus increasing by $P'ABCDEP$ and consumer surplus increasing by $PEBP^{S'}$. Therefore, either an upward-sloping supply or market power would shift a portion of the benefits generated by the transfer from SNAP recipients to producers.

We then extend the framework to allow for SNAP and non-SNAP consumers. We illustrate the framework graphically under perfect competition and monopoly. The setup of the theoretical framework is analogous to that for a consumer unit subsidy by the government given to a specific product in partial equilibrium. We first graphically illustrate the case under perfect competition in Appendix Figure O13. Consider the market-demand curve D for SNAP-eligible products in the retail sector, which is obtained by the horizontal summation of demand of SNAP recipients D^S and non-SNAP recipients D^{NS}. Equilibrium price P and quantity Q are obtained by the intersection of demand D and supply S. The government then disburses SNAP benefits to recipients, shifting the demand curve of SNAP recipients up to $D^{S'}$. Equilibrium price increases to P' and quantity increases to Q' by the intersection of new market demand D' and supply S. We now evaluate the changes in welfare as a result of SNAP. The increase in price and quantity leads to increased producer surplus of $P'CDP$. Assuming either no income effects or a parallel shift in demand, we evaluate the welfare of SNAP recipients under their old demand curve D^S. SNAP recipients now act as if they face lower prices of $P^{S'}$ and quantity demanded increases to $Q^{S'}$ due to the disbursement of benefits, and hence their consumer surplus increases by $PGFP^{S'}$. On the other hand, non-SNAP consumers now face a higher price P', and their consumer surplus decreases by $P'BEP$. To consider the deadweight loss of the program, we first observe that the loss in non-SNAP consumer surplus $P'BEP$ directly transfers to a gain in producer surplus. The remaining producer surplus $BCDE$ from SNAP consumers is equal in area to $P'AGP$. The cost of SNAP benefits to the government is $P'AFP^{S'}$, which implies the deadweight loss of the program is GAF. This deadweight loss is a result of SNAP consumers buying marginal units they value at less than the marginal cost for producers.

Next, we graphically illustrate the case under monopoly in Appendix Figure O14.

Likewise, the market-demand curve D for SNAP-eligible products is obtained by the horizontal summation of demand of SNAP recipients D^S and non-SNAP recipients D^{NS}. Equilibrium price P and quantity Q are now obtained by the intersection of marginal revenue MR that is obtained from demand D and marginal cost given by supply curve S. We now assume marginal cost is constant based on evidence on retailers by Stroebel and Vavra (2019). If the supply curve is flat under perfect competition, the price response is zero. On the other hand, we illustrate that the price response could be large with market power. The government then disburses SNAP benefits to recipients, shifting the demand curve of SNAP recipients up to $D^{S'}$. Equilibrium price increases to P' and quantity increases to Q' by the intersection of new marginal-revenue curve MR' and supply S. We now evaluate the changes in welfare as a result of SNAP. The increase in price and quantity leads to increased producer surplus of $P'CDEFP$. SNAP recipients now act as if they face lower prices of $P^{S'}$ and quantity demanded increases to $Q^{S'}$ due to the disbursement of benefits, and hence their consumer surplus increases by $PMJP^{S'}$. On the other hand, non-SNAP consumers now face a higher price P', and their consumer surplus decreases by $P'BGP$. To consider the deadweight loss of the program, we first observe that the loss in non-SNAP consumer surplus $P'BGP$ directly transfers to a gain in producer surplus. The remaining producer surplus $BCFG$ from SNAP consumers is equal in area to $P'AMP$. The cost of SNAP benefits to the government is $P'AJP^{S'}$, which implies part of the deadweight loss of the program is MAJ. However, this deadweight loss is offset by the change in producer surplus $FCDE$. To better understand the change in total surplus, note that $FCDE$ is identical in area to $MAKL$ minus $BGHI$. Therefore, the change in total surplus of $FCDE$ minus MAJ is equivalent to $MJKL$ minus $BGHI$. In other words, the change in deadweight loss of the program is given by the decrease in deadweight loss when the monopolist sells more to SNAP consumers and the increase in deadweight loss when the monopolist further restricts output to non-SNAP consumers.

K Derivations

K.1 Pass-through Formulas

Under perfect competition, we can obtain the benefit pass-through elasticity $\varepsilon_\rho \equiv \frac{dp}{db}\frac{b}{p}$ by differentiating the equilibrium condition with respect to benefits b. Quantity demanded Q^D, the sum of demands by SNAP consumers $Q^{D,S}$ and non-SNAP consumers $Q^{D,NS}$, is equal to quantity supplied Q^S, as follows:

$$\begin{aligned}
Q^D(p,b) = Q^{D,S}(p,b) + Q^{D,NS}(p) &= Q^S(p) \\
\frac{\partial Q^{D,S}(p,b)}{\partial p}\frac{dp}{db} + \frac{\partial Q^{D,S}(p,b)}{\partial b} + \frac{\partial Q^{D,NS}(p)}{\partial p}\frac{dp}{db} &= \frac{\partial Q^S(p)}{\partial p}\frac{dp}{db} \\
\rho \equiv \frac{dp}{db} &= \frac{\frac{\partial Q^{D,S}(p,b)}{\partial b}}{\frac{\partial Q^S(p)}{\partial p} - \frac{\partial Q^D(p,b)}{\partial p}} \\
\varepsilon_\rho \equiv \frac{dp}{db}\frac{b}{p} &= \left(1 - \frac{1}{1+\frac{-\varepsilon_D}{\varepsilon_S}}\right)\frac{\varepsilon_{Q^{D,S},b}}{-\varepsilon_D}\frac{pQ^{D,S}}{pQ}. \qquad (24)
\end{aligned}$$

As discussed in detail in Section 5.2 along with each term's significance, the formula depends on the unit-subsidy pass-through elasticity, $1-\frac{1}{1+\frac{-\varepsilon_D}{\varepsilon_S}}$, and the shift magnitude, $\frac{\varepsilon_{Q^{D,S},b}}{-\varepsilon_D}\frac{pQ^{D,S}}{pQ}$.

We next derive the benefit pass-through elasticity under symmetric imperfect competition with market conduct parameter $\theta \equiv -[(p-mc)/p]\varepsilon_D$. For simplicity, we assume that θ reduces to a constant, which represents a broad range of models such as Bertrand competition, Cournot competition, monopolistic competition, and monopoly as shown in Weyl and Fabinger (2013). In addition, we support this assumption by the fact that we find that market conduct does not respond significantly to benefit changes as discussed in Appendix Section I.

First, we start from the profit-maximization condition—in which producers set Q and p is determined in equilibrium—and differentiate it with respect to the amount of benefits. We obtain an expression for the quantity response to benefits as follows:

$$
\begin{aligned}
p(Q,b)+\theta\frac{\partial p(Q,b)}{\partial Q}Q-c'(Q)&=0\\
MR(Q,b)-MC(Q)&=0\\
\left(\frac{\partial MR}{\partial Q}-\frac{\partial MC}{\partial Q}\right)\frac{dQ}{db}+\frac{\partial MR}{\partial b}&=0\\
\frac{dQ}{db}&=-\frac{\frac{\partial MR}{\partial b}}{\frac{\partial MR}{\partial Q}-\frac{\partial MC}{\partial Q}}\\
\frac{dQ}{db}&=-\frac{\theta\frac{\partial^2 p}{\partial b\partial Q}Q+\frac{\partial p}{\partial b}}{\frac{\partial MR}{\partial Q}-\frac{\partial MC}{\partial Q}}.
\end{aligned}
\tag{25}
$$

Next, we use the above expression to obtain the benefit pass-through formula:

$$
\begin{aligned}
\frac{dp}{db}&=\frac{\partial p}{\partial Q}\frac{dQ}{db}+\frac{\partial p}{\partial b}\\
&=\left(1-\frac{\frac{\partial p}{\partial Q}}{\frac{\partial MR}{\partial Q}-\frac{\partial MC}{\partial Q}}\right)\frac{\partial p}{\partial b}+\left(-\frac{\frac{\partial p}{\partial Q}}{\frac{\partial MR}{\partial Q}-\frac{\partial MC}{\partial Q}}\theta\frac{\partial^2 p}{\partial b\partial Q}Q\right)\\
\varepsilon_\rho\equiv\frac{dp}{db}\frac{b}{p}&=\left(1-\frac{\frac{\partial p}{\partial Q}}{\frac{\partial MR}{\partial Q}-\frac{\partial MC}{\partial Q}}\right)\frac{\varepsilon_{Q^{D,S},b}}{-\varepsilon_D}\frac{pQ^{D,S}}{pQ}+\frac{\frac{\partial p}{\partial Q}}{\frac{\partial MR}{\partial Q}-\frac{\partial MC}{\partial Q}}\frac{\theta}{-\varepsilon_D}\varepsilon_{|p'|,b}\\
&=\left(1-\frac{1}{1+\frac{-\varepsilon_D-\theta}{\varepsilon_S}+\frac{\theta}{\varepsilon_{ms}}}\right)\frac{\varepsilon_{Q^{D,S},b}}{-\varepsilon_D}\frac{pQ^{D,S}}{pQ}+\left(\frac{1}{1+\frac{-\varepsilon_D-\theta}{\varepsilon_S}+\frac{\theta}{\varepsilon_{ms}}}\right)\frac{\theta}{-\varepsilon_D}\varepsilon_{|p'|,b}.
\end{aligned}
\tag{26}
$$

where $|p'|=\left|\frac{\partial p}{\partial Q}\right|$ represents the slope of the inverse demand; and ε_{ms} the inverse marginal-consumer-surplus elasticity, which reflects the curvature of demand.[68,69,70]

[68]Note that $\theta=-[(p-c)/p]\varepsilon_D \Rightarrow \frac{c}{p}=\frac{\theta+\varepsilon_D}{\varepsilon_D}\Rightarrow \frac{\partial c^2}{\partial Q^2}/\frac{\partial p}{\partial Q}=-\frac{\varepsilon_D}{\varepsilon_S}\frac{c}{p}=\frac{-\varepsilon_D-\theta}{\varepsilon_S}$.

[69]$(ms)^{-1}\equiv(-p'q)^{-1}$ denotes the level of demand at which a marginal expansion in quantity would generate a given level of marginal consumer surplus. As shown by Weyl and Fabinger (2013), $\frac{1}{\varepsilon_{ms}}=1+\frac{p''Q}{p'}$.

[70]We can additionally show $\varepsilon_{|p'|,b}=\frac{\varepsilon_{Q^{D,S},b}}{-\varepsilon_D}\frac{pQ^{D,S}}{pQ}-\varepsilon_{|\varepsilon_D|,b}-\frac{dQ}{db}\frac{b}{Q}\left(|\varepsilon_D|-1/\varepsilon_{ms}\right)$. We do not explore this

A key relation we need to use en route to obtaining the formula above is $\frac{\partial p}{\partial b} = -\frac{\partial Q}{\partial b}\frac{\partial p}{\partial Q}$. This is the identity that allows us to express the shift magnitude in terms of the benefit elasticity of demand and the price elasticity of demand. The proof for this identity is as follows: $\frac{dp(Q(p,b),b)}{db} = \frac{\partial p}{\partial Q}\left(\frac{\partial Q}{\partial b} + \frac{\partial Q}{\partial b}\frac{dp}{db}\right) + \frac{\partial p}{\partial b} \Rightarrow \frac{\partial p}{\partial b} = -\frac{\partial Q}{\partial b}\frac{\partial p}{\partial Q}$.[71] A key assumption needed in the proof is $\frac{\partial p}{\partial Q} = 1/\frac{\partial Q}{\partial p}$, which in our multivariate case (p is a function not only of Q but also of b) requires that p is continuously differentiable and the total derivative is invertible within our domain of analysis.

The quantity response can be shown to depend on the benefit pass-through formula from an application of the chain rule:

$$\frac{dQ}{db} = \frac{\partial Q}{\partial p}\frac{dp}{db} + \frac{\partial Q}{\partial b}$$
$$\frac{dQ}{db}\frac{b}{Q} = \varepsilon_D\varepsilon_\rho + \varepsilon_{Q^{D,S},b}\frac{pQ^{D,S}}{pQ}. \tag{27}$$

K.2 Incidence

The change in consumer surplus can be derived from the construction of consumer surplus as the integral of the market demand curve, $\int_{p(Q,b)}^{\infty} Q^D(x,b)dx$. To make the analysis tractable, we additionally assume that the inverse aggregate-market-demand curve $p(Q,b)$ shifts up by a constant amount in response to an increase in benefits.[72] The change can then be decomposed into that for SNAP consumers and non-SNAP consumers:

$$\begin{aligned} CS(p) &= \int_{p(Q,b)}^{\infty} Q^D(x,b)dx \\ \frac{dCS}{db} &= -\frac{dp}{db}Q + \int_p^{\infty}\frac{\partial Q^D(x,b)}{\partial b}dx \\ &= -\rho Q + \frac{\partial p}{\partial b}Q \\ &= \left(-\varepsilon_\rho + \frac{\varepsilon_{Q,b}}{-\varepsilon_D}\right)\frac{pQ}{b} \\ &= \left(\frac{\varepsilon_{Q^{D,S},b}}{-\varepsilon_D} - \varepsilon_\rho\right)\frac{pQ^{D,S}}{b} + \left(-\varepsilon_\rho\right)\frac{pQ^{D,NS}}{b}, \end{aligned} \tag{28}$$

where the last step uses the relation, $\varepsilon_{Q,b} = \varepsilon_{Q^{D,S},b}\frac{pQ^{D,S}}{pQ}$.[73]

---

result in more depth for brevity.

[71] This is a technique similar to showing Roy's identity.

[72] That is, we assume the shift magnitude $\frac{\partial p(x,b)}{\partial b}$ is constant in x, so that $\frac{dCS}{db} = -\rho Q + \int_p^{\infty}\frac{\partial Q^D(x,b)}{\partial b}dx = -\rho Q + \int_0^Q \frac{\partial p(x,b)}{\partial b}dx = -\rho Q + \frac{\partial p}{\partial b}Q$. A related finding is that of HS, who do not find substantial heterogeneity across households in their estimates of the MPCF out of SNAP.

[73] Note $\frac{\partial Q}{\partial b}\frac{b}{Q} = \frac{\partial Q^{D,S}}{\partial b}\frac{b}{Q^{D,S}}\frac{Q^{D,S}}{Q} + \frac{\partial Q^{D,NS}}{\partial b}\frac{b}{Q^{D,NS}}\frac{Q^{D,NS}}{Q} \Rightarrow \varepsilon_{Q,b} = \varepsilon_{Q^{D,S},b}\frac{pQ^{D,S}}{pQ} + \varepsilon_{Q^{D,NS},b}\frac{pQ^{D,NS}}{pQ} = \varepsilon_{Q^{D,S},b}\frac{pQ^{D,S}}{pQ}$, since $\varepsilon_{Q^{D,NS},b} = 0$.

Under perfect competition, the change in producer surplus can be written as follows:

$$\begin{aligned} PS(p) &= \int_0^{p(Q,b)} Q^S(x)dx \\ \frac{dPS}{db} &= \rho Q = \varepsilon_\rho \frac{pQ}{b}. \end{aligned} \tag{29}$$

Since supply is a function solely of price, we only concern ourselves with the change to the upper bound of the integral.

We can extend our results to the case of symmetric imperfect competition assuming a constant marginal cost. The expression for $\frac{dCS}{db}$ remains unchanged whereas the change in producer surplus can be rewritten as follows:

$$\begin{aligned} PS &= (p-c)Q \\ \frac{dPS}{db} &= \rho Q + (p-c)\frac{dQ}{db} \\ &= \left(\varepsilon_\rho + \frac{p-c}{p}\frac{dQ}{db}\frac{b}{Q}\right)\frac{pQ}{b} && (30) \\ &= \left[\rho + \theta\left(\frac{\partial p}{\partial b} - \rho\right)\right]Q \\ &= \left[\varepsilon_\rho + \theta\left(\frac{\varepsilon_{Q,b}}{-\varepsilon_D} - \varepsilon_\rho\right)\right]\frac{pQ}{b} && (31) \\ &= \left[\varepsilon_\rho + \theta\left(\frac{\varepsilon_{Q^{D,S},b}}{-\varepsilon_D}\frac{pQ^{D,S}}{pQ} - \varepsilon_\rho\right)\right]\frac{pQ}{b}. && (32) \end{aligned}$$

K.3 Multi-Product Pricing

We extend pass-through formulas to a multi-product setting. In the case of perfect competition, we rewrite the equilibrium condition with demand $Q_j^D(p)$ for good j as a function of a vector of prices $p = (p_1, ..., p_n)$, split into demands by SNAP consumers $Q^{D,S}$ and non-SNAP consumers $Q^{D,NS}$, with the sum equal to supply Q^S:

$$Q_j^D(p,b) = Q_j^{D,S}(p,b) + Q_j^{D,NS}(p,b) = Q_j^S(p)$$

$$\sum_{i=1}^n \frac{\partial Q_j^{D,S}(p,b)}{\partial p_i}\frac{dp_i}{db} + \frac{\partial Q_j^{D,S}(p,b)}{\partial b} + \sum_{i=1}^n \frac{\partial Q_j^{D,NS}(p)}{\partial p_i}\frac{dp_i}{db} = \sum_{i=1}^n \frac{\partial Q_j^S(p)}{\partial b}\frac{dp_i}{db}$$

$$\rho_j \equiv \frac{dp_j}{db} = \frac{\frac{\partial Q_j^{D,S}(p,b)}{\partial b} + \sum_{i\neq j}\frac{\partial Q_j^{D,S}(p,b)}{\partial p_i}\frac{dp_i}{db} - \sum_{i\neq j}\frac{\partial Q_j^S(p,b)}{\partial p_i}\frac{dp_i}{db}}{\frac{\partial Q_j^S(p)}{\partial p_j} - \frac{\partial Q_j^D(p,b)}{\partial p_j}}$$

$$\varepsilon_{\rho_j} \equiv \frac{dp_j}{db}\frac{b}{p_j} = \left(1 - \frac{1}{1 + \frac{-\varepsilon_j^D}{\varepsilon_j^S}}\right)\left(\frac{\varepsilon_{Q_j^{D,S},b}}{-\varepsilon_j^D}\frac{p_j Q_j^{D,S}}{p_j Q_j} + \sum_{i\neq j}\frac{\varepsilon_{j,i}^D - \varepsilon_{j,i}^S}{-\varepsilon_j^D}\varepsilon_{\rho_i}\right). \tag{33}$$

Rather than writing the pass-through elasticity of each product in terms of the pass-through elasticity of other products, we can solve for each of the pass-through elasticities explicitly using a system of n equations in n unknowns, as follows:

$$\underbrace{\begin{bmatrix} \frac{\partial Q_1^D}{\partial p_1} - \frac{\partial Q_1^S}{\partial p_1} & \cdots & \frac{\partial Q_1^D}{\partial p_n} - \frac{\partial Q_1^S}{\partial p_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial Q_n^D}{\partial p_1} - \frac{\partial Q_n^S}{\partial p_1} & \cdots & \frac{\partial Q_n^D}{\partial p_n} - \frac{\partial Q_n^S}{\partial p_n} \end{bmatrix}}_{\mathbf{A}} \begin{bmatrix} \frac{dp_1}{db} \\ \vdots \\ \frac{dp_n}{db} \end{bmatrix} = \underbrace{\begin{bmatrix} -\frac{\partial Q_1^D}{db} \\ \vdots \\ -\frac{\partial Q_n^D}{db} \end{bmatrix}}_{\mathbf{b}}.$$

By Cramer's rule, the pass-through can be written as follows:

$$\frac{dp_i}{db} = \frac{det(\mathbf{A_i})}{det(\mathbf{A})}, \tag{34}$$

where $det(\cdot)$ is the determinant of a matrix and $\mathbf{A_i}$ is the matrix formed by replacing the i'th column of $\mathbf{A}$ by $\mathbf{b}$.

In the case of symmetric imperfect competition, consider the profit function for a firm with n products and the resulting first-order condition with respect to product i:

$$\pi = \sum_{j=1}^{n} p_j(q_1, \dots, q_n, b)q_j - c(q_1, \dots, q_n) \tag{35}$$

$$\frac{\partial \pi}{\partial q_i} = \underbrace{p_j(q_1, \dots, q_n, b) + \sum_{j=1}^{n} \theta_i q_j \frac{\partial p_j}{\partial q_i}}_{MR_i(q_1,\dots,q_n,b)} - \underbrace{\frac{\partial c}{\partial q_i}}_{MC_i} = 0. \tag{36}$$

Assuming the marginal costs do not depend on benefits, differentiating the first-order condition with respect to benefits, we have:

$$\sum_{j=1}^{n} \frac{\partial MR_i}{\partial q_j}\frac{dq_j}{db} + \frac{\partial MR_i}{\partial b} = 0. \tag{37}$$

Similar to the perfect competition case, we can solve for each of the quantity responses using a system of n equations in n unknowns, as follows:

$$\underbrace{\begin{bmatrix} \frac{\partial MR_1}{\partial q_1} & \cdots & \frac{\partial MR_1}{\partial q_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial MR_n}{\partial q_1} & \cdots & \frac{\partial MR_n}{\partial q_n} \end{bmatrix}}_{\mathbf{C}} \begin{bmatrix} \frac{dq_1}{db} \\ \vdots \\ \frac{dq_n}{db} \end{bmatrix} = \underbrace{\begin{bmatrix} -\frac{\partial MR_1}{db} \\ \vdots \\ -\frac{\partial MR_n}{db} \end{bmatrix}}_{\mathbf{d}}.$$

Note that the marginal revenue responses to quantities and benefits can be further written as follows, assuming the market conduct parameter is constant to simplify the exposition:

$$\frac{\partial MR_i}{\partial q_k} = \frac{\partial p_i}{\partial q_k} - \sum_{j=1}^{n} \theta_i \frac{\partial ms_{ji}}{\partial q_k} \tag{38}$$

$$\frac{\partial MR_i}{\partial b} = \frac{\partial p_i}{\partial b} + \sum_{j=1}^{n} \theta_i q_j \frac{\partial^2 p_j}{\partial b \partial q_i}, \tag{39}$$

where marginal surplus $ms_{ji} \equiv q_j \frac{\partial p_j}{\partial q_i}$.

By Cramer's rule, the quantity responses can be written as follows:

$$\frac{dq_i}{db} = \frac{det(\mathbf{C_i})}{det(\mathbf{C})}, \tag{40}$$

where $det(\cdot)$ is the determinant of a matrix and $\mathbf{C_i}$ is the matrix formed by replacing the i'th column of $\mathbf{C}$ by $\mathbf{d}$.

The pass-through of product i can be written as a function of the quantity responses as follows:

$$\frac{dp_i}{db} = \sum_{j=1}^{n} \frac{\partial p_i}{\partial q_j} \frac{dq_j}{db} + \frac{\partial p_i}{\partial b}. \tag{41}$$

We write out the pass-through formula for product 1 when the number of products $n = 2$ as follows:

$$\begin{aligned}\frac{dp_1}{db} = &\left(\frac{\frac{\partial p_1}{\partial q_1}}{\frac{\partial MR_1}{\partial q_1} - \underbrace{\frac{\frac{\partial MR_1}{\partial q_2}\frac{\partial MR_2}{\partial q_1}}{\frac{\partial MR_2}{\partial q_2}}}_{\text{Additional term 1}}} + \underbrace{\frac{\frac{\partial p_1}{\partial q_2}}{\frac{\partial MR_1}{\partial q_2} - \frac{\frac{\partial MR_1}{\partial q_1}\frac{\partial MR_2}{\partial q_2}}{\frac{\partial MR_2}{\partial q_1}}}}_{\text{Additional term 2}} \right)\left(-\frac{\partial MR_1}{\partial b}\right) + \frac{\partial p_1}{\partial b} \\ &+ \underbrace{\left(\frac{\frac{\partial p_1}{\partial q_1}}{\frac{\partial MR_2}{\partial q_1} - \frac{\frac{\partial MR_1}{\partial q_1}\frac{\partial MR_2}{\partial q_2}}{\frac{\partial MR_1}{\partial q_2}}} + \frac{\frac{\partial p_1}{\partial q_2}}{\frac{\partial MR_2}{\partial q_2} - \frac{\frac{\partial MR_1}{\partial q_2}\frac{\partial MR_2}{\partial q_1}}{\frac{\partial MR_1}{\partial q_1}}} \right)\left(-\frac{\partial MR_2}{\partial b}\right)}_{\text{Additional term 3}}. \end{aligned} \tag{42}$$

Note that there are now three additional terms in the pass-through formula, which relate to the cross-marginal-revenue effects, the inverse cross-price effects, as well as the effect of benefits on the marginal revenue of the other product.

We can further extend equation (42) by using equations (38) and (39). Note that since $p_i = p_i(q_1, q_2, b)$, by total differentiation, we can write $\frac{\partial p_i}{\partial b} = -\frac{dq_1}{db}\frac{\partial p_i}{\partial q_1} - \frac{dq_2}{db}\frac{\partial p_i}{\partial q_2}$, so we can estimate $\frac{\partial p_i}{\partial b}$ as a function of MPCs and inverse demand slopes. Therefore, the pass-through formula can be written as a function of four "shift" terms and four "slope" terms as follows:

$$
\begin{aligned}
MR_{ij} &\equiv \frac{\partial MR_i}{\partial q_j} - \frac{\frac{\partial MR_i}{\partial q_{-j}}\frac{\partial MR_{-i}}{\partial q_j}}{\frac{\partial MR_{-i}}{\partial q_{-j}}}, \text{ where } -i \text{ is the other product, i.e. not } i \\
\frac{dp_1}{db} &= \left(1 - \frac{\frac{\partial p_1}{\partial q_1}}{MR_{11}} - \frac{\frac{\partial p_1}{\partial q_2}}{MR_{12}}\right)\frac{\frac{dq_1}{db}}{-\frac{\partial q_1}{\partial p_1}} + \left(1 - \frac{\frac{\partial p_1}{\partial q_1}}{MR_{11}} - \frac{\frac{\partial p_1}{\partial q_2}}{MR_{12}}\right)\frac{\frac{dq_2}{db}}{-\frac{\partial q_2}{\partial p_1}} \\
&\quad + \left(\frac{\frac{\partial p_1}{\partial q_1}}{MR_{21}} + \frac{\frac{\partial p_1}{\partial q_2}}{MR_{22}}\right)\frac{\frac{dq_1}{db}}{\frac{\partial q_1}{\partial p_2}} + \left(\frac{\frac{\partial p_1}{\partial q_1}}{MR_{21}} + \frac{\frac{\partial p_1}{\partial q_2}}{MR_{22}}\right)\frac{\frac{dq_2}{db}}{\frac{\partial q_2}{\partial p_2}} \\
&\quad + \left(\frac{\frac{\partial p_1}{\partial q_1}}{MR_{11}} + \frac{\frac{\partial p_1}{\partial q_2}}{MR_{12}}\right)\theta_1\frac{\partial ms_{11}}{\partial b} + \left(\frac{\frac{\partial p_1}{\partial q_1}}{MR_{11}} + \frac{\frac{\partial p_1}{\partial q_2}}{MR_{12}}\right)\theta_2\frac{\partial ms_{21}}{\partial b} \\
&\quad + \left(\frac{\frac{\partial p_1}{\partial q_1}}{MR_{21}} + \frac{\frac{\partial p_1}{\partial q_2}}{MR_{22}}\right)\theta_1\frac{\partial ms_{12}}{\partial b} + \left(\frac{\frac{\partial p_1}{\partial q_1}}{MR_{21}} + \frac{\frac{\partial p_1}{\partial q_2}}{MR_{22}}\right)\theta_2\frac{\partial ms_{22}}{\partial b}.
\end{aligned} \tag{43}
$$

L Pass-through Rates and Demand Curvature

As seen above, the unit-subsidy pass-through rate under symmetric imperfect competition with constant market conduct is given by the following expression:

$$1 - \frac{\frac{\partial p}{\partial Q}}{\frac{\partial MR}{\partial q} - \frac{\partial MC}{\partial q}} = 1 - \frac{1}{1 + \frac{-\varepsilon_D - \theta}{\varepsilon_S} + \frac{\theta}{\varepsilon_{ms}}}. \tag{44}$$

Given Stroebel and Vavra (2019) find evidence that marginal costs in the retail sector are not responsive to demand shocks, we assume supply is perfectly elastic, so the pass-through rate can now be rewritten as:

$$1 - \frac{1}{1 + \frac{\theta}{\varepsilon_{ms}}}. \tag{45}$$

The pass-through rate is now dependent only on market conduct and the curvature of demand. As mentioned in Section 5.3, we can obtain demand elasticities by regressing log real sales on log price indices for both SNAP-eligible and -ineligible goods with store and period fixed effects. Results are similar using Hausman IVs following DVG, where price instruments are other stores in the same chain outside of the own store's market. To obtain an estimate of the curvature of demand, we first show log real sales against log price in a binned scatter plot in Appendix Figure O15 for both SNAP-eligible and -ineligible goods. Both groups exhibit log-concave demand, and we quantify the degree of log-concavity by regressing log real sales on log prices as well as additional polynomial terms of log prices. Results are similar by adding either a quadratic or cubic term, so we present results using a quadratic term only. More specifically, we estimate the following equation with either $m = 2$

or $m = 3$:

$$lnQ_{it} = \alpha + \sum_{k=1}^{m} \beta_k (lnP_{it})^k + \alpha_i + \alpha_{zt} + \varepsilon_{it}. \tag{46}$$

We can then obtain an estimate of the inverse elasticity of marginal surplus, which can be written as:

$$\frac{1}{\varepsilon_{ms}} = -\frac{\sum_{k=1}^{m} \beta_k k(k-1)(lnP_{it})^{k-2} - \sum_{k=1}^{m} \beta_k k(lnP_{it})^{k-1}}{\left(\sum_{k=1}^{m} \beta_k k(lnP_{it})^{k-1}\right)^2}. \tag{47}$$

We show the estimation results in Appendix Table N16. Plugging in the mean of lnP_{it} and assuming a market conduct parameter of 0.2 and 0.5 for eligible and ineligible goods, respectively, we calculate a unit-subsidy pass-through rate of 0.49 and 0.15, respectively.

M Multi-Product Pricing Models

M.1 A Simple Example

We first illustrate using the simple example in Chen and Rey (2012) how we can generate the following result: as the valuation of one product increases, the price of the other product increases. We then extend this to the baseline model in the next section. We follow their setup and assume that there are two types of retailers. The first retailer is a large firm L with a broader product range that monopolizes product A and also sells product B. The second type of retailers are a fringe of small firms S that only sell product B in the competitive market. Consumers have unit inelastic demand for both products A and B to rule out cross-subsidy motives based on demand elasticity differences. Consumers incur a shopping cost s for visiting a store. Applied to our setting, product A is a SNAP-ineligible good (non-food) whereas product B is a SNAP-eligible good (food). Almost all retail stores in our data sell both food and non-food and belong to retail chains so they are considered as "large" firms. Small firms may be small discount grocers that specialize in selling food only.

A numerical example can illustrate the intuition. Suppose that L can supply A at no cost and B at unit cost $c = 4$, while consumers value A at $u_A = 10$ and B at $u_B = 6$. Suppose half of the consumers face shopping cost $s = 4$ and half shop at no cost. If L were alone, it would supply all consumers at a total price (slightly below) $p^m = u_A + u_B - s = 12$, yielding a monopoly profit $\Pi^m = 12 - 4 = 8$: L would thus extract all surplus from high-cost consumers but leave the others with a surplus of 4.

Suppose now that B is also offered by a competitive fringe S at a price $\hat{p} = 2$. S cannot attract high-cost consumers, who can only obtain $u_B - \hat{p} - s = 0$; L can therefore still charge them at a total price of p^m, e.g. $p_B = 4$ and $p_A = 8$. L would then sell A only to low-cost consumers who become "multi-stop shoppers" and yet obtain the monopoly margin on both types of consumers: $p^m - c = p_A = 8$. However, the presence of small rivals opens a door for screening consumers according to their shopping costs, which is best achieved by selling B below cost; keeping the total price equal to p^m, lowering the price for B down to $\hat{p} = 2$, and increasing the price for A to $\hat{p}_A = 10$. This does not affect the shopping behavior of high-cost consumers who still face a total price of p^m but increases the margin earned on multi-stop shoppers since $\hat{p}_A > p_A$. This loss-leading strategy allows L to charge the monopoly price to one-stop shoppers and actually extracts here the full value of A from multi-stop shoppers; as a result, it earns a total profit of $\Pi = 10 + 0.5 \cdot (2 - 4) = 9 > 8$.

Now suppose that u_B increases. For example, let $u_B = 8$. Now for firm L, $p^m = 10 + 8 - 4 = 14$, so with $p_A = 10$ and $p_B = 4$, L earns profits $\Pi = 10 + 0.5 \cdot (4 - 4) = 10$. However, if it again loss-leads on B by charging $p_A = 12$ and $p_B = 2$, L can now earn more profits with $\Pi = 12 + 0.5 \cdot (2 - 4) = 11 > 10$. Therefore, the increase in u_B results in the same $p_B = 2$ which is constrained by the competitive fringe S, but markups increase even more for A with p_A increasing by the change in u_B by 2 from 10 to 12. Therefore, in this simple example, any increase in u_B completely translates into an increase in p_A while both p_B and the costs remain unchanged.

M.2 Baseline Model

We now illustrate how the baseline model in Chen and Rey (2012) can generate the following result: as the valuation of one product increases, the price of the other product increases. We follow their setup and assume that there are two types of retailers. The first retailer is a large firm L with a broader product range that monopolizes product A and also sells product B of variety B_L in the competitive market. The second type of retailers are a fringe of small firms S that sells product B of variety B_S in the competitive market. Once again, applied to our setting, product A is a SNAP-ineligible good (non-food) whereas product B is a SNAP-eligible good (food). Almost all retail stores in our data sell both food and non-food and belong to retail chains so they are considered as "large" firms. Small firms may be small discount grocers that specialize in selling food only.

Consumers have unit inelastic demand for both products A and B, and value A, B_L, and B_S at u_A, u_L, and u_S, respectively, whereas producers face unit costs of c_A, c_L, and c_S, respectively. S supplies B_S at cost ($p_S = c_S$). For each unit of B_S, consumer surplus v_S equals total surplus w_S of $u_S - c_S$. Suppose $w_S > w_L \equiv u_L - c_L > 0$ to ensure multi-stop shopping. This can be driven either by the fact that $c_S < c_L$, where small firms are hard discounters, or $u_S > u_L$, where small firms are specialists. Likewise, define total surplus for a unit of A as $w_A \equiv u_A - c_A > 0$ and total surplus from buying a unit of both A and B_L as $w_{AL} \equiv w_A + w_L$.

Shopping cost s is drawn from a cumulative density function $F(\cdot)$ and density function $f(\cdot)$. Let $r_{AL} \equiv p_A - c_A + p_L - c_L$ be the producer surplus of a unit of A and $v_{AL} \equiv u_A + u_L - p_A - p_L = w_{AL} - r_{AL}$ be the consumer surplus from buying a unit of A and B_L each. One-stop shoppers prefer L to S if $v_{AL} \geq v_S = w_S$ and patronize L as long as $v_{AL} \geq s$. Consumers will multi-stop shop if $\tau \equiv v_S - v_L = w_S - (w_L - r_L) \geq s$, that is, the extra cost of visiting S is exceeded by the extra value it offers. Profits of L are then given by the following equation:

$$\pi_L = r_{AL}(F(v_{AL}) - F(\tau)) + r_A F(\tau) = r_{AL} F(v_{AL}) - r_L F(\tau). \tag{48}$$

The mass of one-stop shoppers is $F(v_{AL}) - F(\tau)$, whereas the mass of multi-stop shoppers is $F(\tau)$. Now we consider the optimal pricing strategy of firm L. Assume the inverse hazard rate $h(\cdot) \equiv F(\cdot)/f(\cdot)$ is strictly increasing to ensure quasi-concavity of L's profit function.

The first order condition for r_L and r_{AL} gives the following equations:

$$\begin{aligned} r_L^* &= -h(\tau^*) < 0 && (49)\\ \tau^* &\equiv l^{-1}(w_S - w_L) > 0 && (50)\\ r_{AL}^m &= h(v_{AL}^m) && (51)\\ v_{AL}^m &\equiv l^{-1}(w_{AL}), \end{aligned}$$

where $l(s) \equiv s + h(s)$ and $l' > 0$. As long as $v_{AL}^m \geq w_S$, the optimal strategy of the firm is to charge r_{AL}^m for the bundle and $r_L^* = -h(\tau^*)$ for B_L.

M.3 Pass-through

Now suppose the valuations u_L and u_S for product B_L and B_S increase due to an exogenous increase in SNAP benefits. Again assume that marginal costs are unchanged. Then the price and quantity responses can be written as follows:

$$\begin{aligned} r_A &= r_{AL}^m - r_L = h(l^{-1}(w_{AL})) + h(\tau^*)\\ \frac{dp_A}{db} &= h'(l^{-1})'\frac{d(u_A + u_L)}{db} + h'(l^{-1})'\frac{d(u_S - u_L)}{db} && (52)\\ \frac{dp_L}{db} &= -h'(l^{-1})'\frac{d(u_S - u_L)}{db} && (53) \end{aligned}$$

$$\begin{aligned} \frac{dq_A}{db} &= \frac{dF(v_{AL})}{db}\\ &= f(v_{AL})\frac{d(u_L + u_A - p_L - p_A)}{db}\\ &= f(v_{AL})\left(1 - h'(l^{-1})'\frac{d(u_A + u_L)}{db}\right) && (54)\\ \frac{dq_L}{db} &= \frac{d\left(F(v_{AL}) - F(\tau^*)\right)}{db}\\ &= f(v_{AL})\left(1 - h'(l^{-1})'\frac{d(u_A + u_L)}{db}\right) - f(\tau)(l^{-1})'\frac{d(u_S - u_L)}{db}. && (55) \end{aligned}$$

Therefore, based on this model, there are at least two reasons for the large pass-through elasticity for SNAP-ineligible products. For exposition, assume that $u_S - u_L$ remains unchanged. First, because SNAP benefits lead to a rise in disposable income for SNAP consumers, demand for SNAP-ineligible products could increase, i.e. $\frac{du_A}{db} > 0$, since $h(\cdot)$ and $l'(\cdot)$ are increasing functions.

Second, because of the multi-product nature of all grocery stores in our data, food and non-food products can become complementary due to shopping costs. Multi-product retailers with asymmetric market power over food and non-food can leverage this complementarity to raise markups on non-food products when SNAP benefits increase. Even if u_A remains unchanged with benefit increases, p_A still increases since u_L increases, i.e. $\frac{du_L}{db} > 0$. q_A is negatively correlated with the price response of A, consistent with our empirical results. How

p_L varies depends on how $u_S - u_L$ changes. If $\frac{d(u_S - u_L)}{db}$ decreases, both prices and quantities of l would increase, consistent with our empirical results, while tempering the increase in p_A.

Chen and Rey (2012) show that their results on loss leading can be extended to heterogeneous valuations for B as well as imperfect competition among large retailers and heterogeneous valuations for A, both of which relax the degree of asymmetric market power between food and non-food markets. The result that an increase in valuation for the more competitive product will lead to a rise in price of the less competitive one can be extended similarly.

M.4 Multi-product Pass-through Formula Example

In addition, we can use this model as an example to illustrate the intuition behind the multi-product pass-through formula for two products in equation (42). We can write out the demand and inverse demand as follows:

$$q_A = F(v_{AL})$$
$$q_L = F(v_{AL}) - F(v_S - v_L)$$
$$p_A + p_L = -F^{-1}(q_A) + u_A + u_L \tag{56}$$
$$p_L = F^{-1}(q_A - q_L) + u_L - u_S + c_S \tag{57}$$
$$p_A = -F^{-1}(q_A) + u_A - F^{-1}(q_A - q_L) + u_S - c_S. \tag{58}$$

With these equations, we can observe that $\frac{\partial q_L}{\partial p_A} = \frac{\partial q_A}{\partial p_L} = \frac{\partial q_A}{\partial p_A} = -f(v_{AL})$ and $\frac{\partial q_L}{\partial p_L} = -f(v_{AL}) - f(\tau)$. Therefore, A and L are complements. In addition, we have equations for the inverse demand and hence the response of marginal revenues to quantities and benefits, as follows:

$$\frac{\partial p_A}{\partial q_A} = -(F^{-1})'(q_A) - (F^{-1})'(q_A - q_L) \tag{59}$$
$$\frac{\partial p_A}{\partial q_L} = (F^{-1})'(q_A - q_L) \tag{60}$$
$$\frac{\partial p_L}{\partial q_A} = (F^{-1})'(q_A - q_L) \tag{61}$$
$$\frac{\partial p_L}{\partial q_L} = -(F^{-1})'(q_A - q_L) \tag{62}$$

$$R = p_A(q_A, q_L)q_A + p_L(q_A, q_L)q_L \tag{63}$$
$$MR_A = \frac{\partial p_A}{\partial q_A}q_A + p_A + \frac{\partial p_L}{\partial q_A}q_L \tag{64}$$
$$MR_L = \frac{\partial p_A}{\partial q_L}q_A + p_L + \frac{\partial p_L}{\partial q_L}q_L \tag{65}$$

$$\begin{aligned}
\frac{\partial MR_A}{\partial q_A} &= \frac{\partial^2 p_A}{\partial q_A^2} q_A + 2\frac{\partial p_A}{\partial q_A} + \frac{\partial^2 p_L}{\partial q_A^2} q_L \\
&= -(F^{-1})''(q_A)q_A - 2(F^{-1})'(q_A) + \frac{\partial MR_L}{\partial q_L} \qquad (66)\\
\frac{\partial MR_A}{\partial q_L} &= \frac{\partial^2 p_A}{\partial q_L \partial q_A} q_A + \frac{\partial p_A}{\partial q_L} + \frac{\partial p_L}{\partial q_A} + \frac{\partial^2 p_L}{\partial q_L \partial q_A} q_L \\
&= (F^{-1})''(q_A - q_L) + 2(F^{-1})'(q_A - q_L) - (F^{-1})''(q_A - q_L)q_L \qquad (67)\\
\frac{\partial MR_L}{\partial q_A} &= \frac{\partial^2 p_A}{\partial q_A \partial q_L} q_A + \frac{\partial p_A}{\partial q_L} + \frac{\partial p_L}{\partial q_A} + \frac{\partial^2 p_L}{\partial q_A \partial q_L} q_L \\
&= \frac{\partial MR_A}{\partial q_L} = -\frac{\partial MR_L}{\partial q_L} \qquad (68)\\
\frac{\partial MR_L}{\partial q_L} &= \frac{\partial^2 p_A}{\partial q_L^2} q_A + 2\frac{\partial p_L}{\partial q_L} + \frac{\partial^2 p_L}{\partial q_L^2} q_L \\
&= -(F^{-1})''(q_A - q_L)q_A - 2(F^{-1})'(q_A - q_L) + (F^{-1})''(q_A - q_L)q_L \qquad (69)\\
\frac{\partial MR_A}{\partial b} &= \frac{\partial^2 p_A}{\partial q_L^2} q_A + 2\frac{\partial p_L}{\partial q_L} + \frac{\partial^2 p_L}{\partial q_L^2} q_L \\
&= \frac{du_A}{db} + \frac{du_S}{db} \qquad (70)\\
\frac{\partial MR_L}{\partial b} &= \frac{\partial^2 p_A}{\partial b \partial q_L} q_A + \frac{\partial p_L}{\partial b} + \frac{\partial^2 p_L}{\partial q_L \partial b} q_L \\
&= \frac{du_L}{db} - \frac{du_S}{db} \qquad (71)
\end{aligned}$$

$$\begin{aligned}
\frac{dp_A}{db} = &\left(\frac{\frac{\partial p_A}{\partial q_A}}{\frac{\partial MR_A}{\partial q_A} - \frac{\frac{\partial MR_A}{\partial q_L}\frac{\partial MR_L}{\partial q_A}}{\frac{\partial MR_L}{\partial q_L}}} + \frac{\frac{\partial p_A}{\partial q_L}}{\frac{\partial MR_A}{\partial q_L} - \frac{\frac{\partial MR_A}{\partial q_A}\frac{\partial MR_L}{\partial q_L}}{\frac{\partial MR_L}{\partial q_A}}} \right) \left(-\frac{\partial MR_A}{\partial b} \right) + \frac{\partial p_A}{\partial b} \\
&+ \left(\frac{\frac{\partial p_A}{\partial q_A}}{\frac{\partial MR_L}{\partial q_A} - \frac{\frac{\partial MR_A}{\partial q_A}\frac{\partial MR_L}{\partial q_L}}{\frac{\partial MR_A}{\partial q_L}}} - \frac{\frac{\partial p_A}{\partial q_L}}{\frac{\partial MR_L}{\partial q_L} - \frac{\frac{\partial MR_A}{\partial q_L}\frac{\partial MR_L}{\partial q_A}}{\frac{\partial MR_A}{\partial q_A}}} \right) \left(-\frac{\partial MR_L}{\partial b} \right).
\end{aligned} \qquad (72)$$

Assuming u_A and $u_S - u_L$ remain unchanged as benefits increase,

$$\begin{aligned}\frac{dp_A}{db} &= -\left(\frac{\frac{\partial p_A}{\partial q_A}}{\frac{\partial MR_A}{\partial q_A} - \frac{\partial MR_L}{\partial q_L}} + \frac{\frac{\partial p_A}{\partial q_L}}{\frac{\partial MR_A}{\partial q_A} - \frac{\partial MR_L}{\partial q_L}}\right)\left(\frac{du_A}{db} + \frac{du_S}{db}\right) + \left(\frac{du_A}{db} + \frac{du_S}{db}\right) \\ &\quad + \left(\frac{\frac{\partial p_A}{\partial q_A}}{\frac{\partial MR_A}{\partial q_A} - \frac{\partial MR_L}{\partial q_L}} - \frac{\frac{\partial p_A}{\partial q_L}}{\left(\frac{\partial MR_A}{\partial q_A} - \frac{\partial MR_L}{\partial q_L}\right)\frac{\frac{\partial MR_L}{\partial q_L}}{\frac{\partial MR_A}{\partial q_A}}}\right)\left(\frac{du_S}{db} - \frac{du_L}{db}\right) \\ &= h'(l^{-1})'\frac{du_L}{db}. \end{aligned} \tag{73}$$

From the above equation, we see that due to the complementarity of A and L for the large retailer, the response of the marginal revenue of A responds to changes in the valuation of S and hence L as well given they both rise together. This term, $\frac{du_L}{db}$, is then multiplied by the pass-through rate, which is composed of a combination of marginal revenues and inverse demand slopes $1 - \frac{\frac{\partial p_A}{\partial q_A}}{\frac{\partial MR_A}{\partial q_A} - \frac{\partial MR_L}{\partial q_L}} - \frac{\frac{\partial p_A}{\partial q_L}}{\frac{\partial MR_A}{\partial q_A} - \frac{\partial MR_L}{\partial q_L}}$, and is equal to $h'(l^{-1})'$, consistent with equation (52).

Regarding other models, Zhou (2014) finds that multi-product search effect can generate both loss leading and cross-category pricing in a multi-product sequential-search model. In his model, a rise in valuation for one good can lead to an increase in price for the other. Other models include Rhodes (2015), who highlights an alternative mechanism in which a firm's optimal advertising strategy can give rise to loss leading. Johnson (2017) points to a different mechanism that leads to loss leading in which asymmetric multi-product retailers compete for consumers who make unplanned purchases. These models have different predictions on whether prices will rise together when one product category is shocked, and we leave a more detailed analysis of the implications of these models to future work.

N Tables

Table N1: Decomposing variance in percentage changes in synthetic benefits per population, Farm Bill and ARRA

	(1)			(2)		
VARIABLES	% change in IV, FB	Covariance share	R2 share	% change in IV, ARRA	Covariance share	R2 share
Log average gross income	7.105***	0.260	0.101	6.851***	-0.0978	0.148
	(1.402)			(0.946)		
Log average rent	-1.433	-0.0711	0.025	-2.285***	0.260	0.065
	(0.932)			(0.464)		
Log average household size	4.656	-0.0795	0.028	1.769	0.0534	0.045
	(2.945)			(1.747)		
Share elderly/disabled	5.219	0.0680	0.027	-1.251	0.00691	0.019
	(3.239)			(1.703)		
Share homeless	13.95	-0.00325	0.005	-0.415	0.000459	0.007
	(13.04)			(7.692)		
Log SUA	-2.114***	-0.0594	0.039	-3.318***	0.831	0.453
	(0.570)			(0.307)		
% change in SUA	0.159***	0.685	0.458	-0.00602	0.0254	0.036
	(0.0150)			(0.00846)		
Other Controls		-0.0198	0.045		-0.0227	0.087
Energy Controls		0.179	0.271		-0.138	0.141
Residual		0.0406			0.0819	
Observations	48			48		
R-squared	0.959			0.918		
Prob > F	0.000			0.000		

Notes: Robust standard errors are in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1. % change in IV refers to the percentage change in synthetic benefits per population, FB refers to the Farm Bill in 2008m10, ARRA refers to the American Recovery and Reinvestment Act in 2009m4. Covariance share refers to the share of the variance in the outcome explained by each variable. R2 share refers to the share of R-squared explained by each variable following Huettner and Sunder (2012). This measure uses Shapley and Owen values, which calculates the average marginal contribution of each regressor over all possible orderings. All variables are measured in 2006 except for two variables. Log standard utility allowance (Log SUA) is measured the month before the event of interest, and the percentage change in the standard utility allowance (% change in the SUA) is measured at the Farm Bill only because the SUA did not change during the ARRA. Other controls include annual state-level changes in housing prices, unemployment rate, average wage, tobacco tax, average SNAP recipient household gross income and rent, and average personal current transfer receipts from various government policies. Energy controls refer to annual changes in state-level total energy, electricity, LPG, and natural gas quantities consumed and prices for the residential sector. We sum up the covariance share of these variables to obtain their total covariance shares.

Table N2: Effect of SNAP-benefit changes on prices, first stage

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Log benefits per population					
Log synthetic benefits per population	1.376	1.832***	1.892***	1.706***	1.727***	1.692***
	(0.857)	(0.490)	(0.448)	(0.375)	(0.380)	(0.377)
Log housing price		-0.556***	-0.514***	-0.503***	-0.500***	-0.491***
		(0.132)	(0.118)	(0.112)	(0.111)	(0.0889)
Log unemployment rate			0.0911***	0.0912***	0.0879***	0.0741***
			(0.0199)	(0.0198)	(0.0191)	(0.0154)
Log population			0.355*	0.351*	0.336*	0.335**
			(0.181)	(0.182)	(0.182)	(0.162)
Log average wage			0.0151	0.0160	0.0128	0.0147
			(0.0201)	(0.0201)	(0.0203)	(0.0198)
Log tobacco tax				0.0236	0.0232	0.0196
				(0.0204)	(0.0205)	(0.0191)
Log SNAP average gross income					-0.101	-0.102
					(0.0872)	(0.0897)
Log SNAP average rent					0.0226*	0.0220*
					(0.0119)	(0.0126)
Observations	382560	382560	382560	382560	382560	382524
R-squared	0.979	0.986	0.987	0.987	0.987	0.988
Prob > F	0.115	0.000	0.000	0.000	0.000	0.000
Number of units	7970	7970	7970	7970	7970	7970
Number of clusters	48	48	48	48	48	48
Energy controls						X

Notes: Robust standard errors are in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1. Store and period fixed effects are included. Energy controls refer to annual state-level total energy, electricity, LPG, and natural gas quantities consumed and prices for the residential sector.

Table N3: Effect of SNAP-benefit changes on prices, reduced form

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES				Log price index		
Log synthetic benefits per population	0.319***	0.288***	0.281***	0.201***	0.204***	0.139***
	(0.0698)	(0.0596)	(0.0586)	(0.0477)	(0.0467)	(0.0375)
Log housing price		0.0382**	0.0421**	0.0465***	0.0479***	0.0350***
		(0.0162)	(0.0159)	(0.0135)	(0.0137)	(0.0113)
Log unemployment rate			0.00550	0.00555	0.00542	0.00224
			(0.00417)	(0.00413)	(0.00395)	(0.00258)
Log population			-0.0930	-0.0947	-0.0947	-0.116***
			(0.0608)	(0.0578)	(0.0567)	(0.0394)
Log average wage			0.00979*	0.0102*	0.0100*	0.00869
			(0.00562)	(0.00544)	(0.00560)	(0.00561)
Log tobacco tax				0.0102***	0.0101***	0.00679***
				(0.00201)	(0.00194)	(0.00161)
Log SNAP average gross income					-0.00804	-0.00198
					(0.00873)	(0.00464)
Log SNAP average rent					-0.00246	-0.00310
					(0.00337)	(0.00271)
Observations	382560	382560	382560	382560	382560	382524
R-squared	0.893	0.896	0.897	0.899	0.899	0.904
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
Number of units	7970	7970	7970	7970	7970	7970
Number of clusters	48	48	48	48	48	48
Energy controls						X

Notes: Robust standard errors are in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1. Store and period fixed effects are included. Energy controls refer to annual state-level total energy, electricity, LPG, and natural gas quantities consumed and prices for the residential sector.

Table N4: Effect of SNAP-benefit changes on prices, no housing controls and contiguous counties

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Log price index					
Log benefits per population	0.112**	0.109***	0.111*	0.0810***	0.0886**	0.0671*
	(0.0459)	(0.0383)	(0.0553)	(0.0253)	(0.0413)	(0.0385)
Log benefits p.p., other states in same chain						0.0200
						(0.0291)
Observations	382524	555072	555072	210240	210240	345468
R-squared	0.881	0.933	0.931	0.926	0.926	0.904
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
Number of units	7970	2706	2706	1372	1372	7198
Number of clusters	48	47	47	42	42	48
First stage F-stat	9.832	13.952	4.411	7.188	2.441	4.073
Housing controls		X		X		
Contiguous counties		X	X	X	X	
Same CZ				X	X	

Notes: Robust standard errors are in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1. Control variables from our preferred specification as well as store and period fixed effects are included. Contiguous counties refers to a specification with county pair fixed effects, where county pairs are pairs of adjacent counties that straddle state borders. Same CZ are county pairs in the same commuting zone as constructed in Autor and Dorn (2013). Log benefits p.p., other states in same chain, refers to average log benefits per population for each store at the retail chain level, weighted by store revenue in the pre-period of 2006, excluding stores in the same state.

Table N5: Effect of SNAP-benefit changes on prices, robustness checks

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Log price index										
Log benefits	0.0849***	0.0924***									
	(0.0251)	(0.0286)									
Log benefits per population			0.0863***	0.0656***	0.0811***	0.0711***	0.0704**	0.0855***	0.101***	0.0866***	0.0893***
			(0.0224)	(0.0206)	(0.0212)	(0.0229)	(0.0323)	(0.0240)	(0.0259)	(0.0244)	(0.0233)
Observations	382524	382524	382524	382524	2301	307750	836631	382524	382524	353712	353712
R-squared	0.898	0.895	0.899	0.888	0.963	0.883	0.931	0.901	0.899	0.900	0.900
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of units	7970	7970	7970	7970	48	6429	7153	7970	7970	7369	7369
Number of clusters	48	48	48	48	48	1050	48	48	48	42	42
First stage F-stat	17.328	15.502	19.798	43.623	19.874	21.093	21.529	20.753	33.105	12.518	12.518
No population controls		X									
Store revenue weights			X								
Population weights				X							
State population weights					X						
County-level benefits						X					
Full sample							X				
Remove disaster payments								X			
Policy controls									X		
Recalculate SUA										X	
Update SUA											X

Notes: Robust standard errors are in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1. Control variables as well as store and period fixed effects are included. Weights are fixed to the pre-period of 2006m1. Population weights refer to regressing with county-level population weights. State population weights refer to collapsing observations to the state-level and regressing with state population weights. County-level benefits refer to using county-level benefits and county-level synthetic benefits for the set of states that report benefits at the county-level. Full sample refers to using the entire sample from 2006-2015. Removing disaster payments refers to removing any variation in both benefits and participants due to disaster relief events. Policy controls refer to state-year measures of amounts paid out by transfer programs available from the BEA. The transfer amounts are logged and these programs include social security, other retirement and disability insurance transfers, Medicare, Medicaid and other vendor payments, military medical insurance, SSI, EITC, other income maintenance programs such as TANF and WIC, state unemployment insurance, other unemployment insurance, Veterans' benefits, education and training assistance, other government transfers, transfers from nonprofit institutions, and transfers from businesses. Recalculate the SUA and update the SUA refer to the estimated effects from a specification in which benefits per population are interacted with an indicator whether states recalculate the SUA using utility data, or update the SUA relative to a base each year using the fuel CPI respectively.

Table N6: Effect of SNAP-benefit changes on prices, alternative price indices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Method	Default	Alternative weights	Tornqvist	One-stage	Geometric	Fixed	Fixed, posted price	NCP
VARIABLES	Log price index							
Log benefits per population	0.0740***	0.0813***	0.0700***	0.0786***	0.0767***	0.0800***	0.0777***	0.0838***
	(0.0216)	(0.0234)	(0.0213)	(0.0240)	(0.0234)	(0.0273)	(0.0245)	(0.0244)
Observations	382524	382524	382524	382524	382524	352188	352188	331119
R-squared	0.919	0.915	0.917	0.915	0.899	0.891	0.882	0.860
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of units	7970	7970	7970	7970	7970	7338	7338	6899
Number of clusters	48	48	48	48	48	48	48	48
First stage F-stat	20.194	20.194	20.194	20.194	20.194	18.680	18.680	18.714

Notes: Robust standard errors are in parentheses, clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1. Control variables as well as store and period fixed effects are included. Details on each of the index construction methods used above are shown in Appendix Section D.

Table N7: SNAP participation and effect of SNAP-benefit changes on prices by product department, grocery stores

	(1)	(2)	(3)	(4)	(5)
Product department	Health & Beauty Care	Food	Non-food Grocery	Alcohol	General Merchandise
VARIABLES			Log price index		
Baseline					
Log benefits p.p.	0.0747**	0.0741***	0.163***	0.0910	-0.0116
	(0.0357)	(0.0267)	(0.0451)	(0.0544)	(0.0286)
Interaction					
Log benefits p.p.	0.0660**	0.0667**	0.148***	0.0893	-0.0169
	(0.0326)	(0.0277)	(0.0453)	(0.0537)	(0.0279)
x Participation rate	0.140***	0.117***	0.247***	0.0260	0.0857**
	(0.0481)	(0.0397)	(0.0688)	(0.0728)	(0.0372)
Observations	381612	382140	381900	364044	380988
Number of units	7951	7962	7957	7585	7938
Number of clusters	48	48	48	48	48
Revenue share	0.0512	0.768	0.0949	0.0653	0.0206

Notes: Robust standard errors are in parentheses, clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1. Controls refer to the full set of controls including log housing prices, log unemployment rate, log employment to population ratio, log population, log average wage, poverty rates at both the state and county levels, as well as log SNAP participants at the state level. Store and period fixed effects are also included. Log benefits p.p. refers to log benefits per population. Participation refers to the ratio of SNAP participants to population in each county fixed to the pre-period of 2006.

Table N8: SNAP participation and effect of SNAP-benefit changes on real sales by product department, grocery stores

Product department	(1) Health & Beauty Care	(2) Food	(3) Non-food Grocery	(4) Alcohol	(5) General Merchandise
VARIABLES	Log real sales				
Baseline					
Log benefits p.p.	0.00913	0.0613	-0.265*	-0.199	0.0385
	(0.145)	(0.108)	(0.138)	(0.280)	(0.160)
Interaction					
Log benefits p.p.	0.00337	0.0387	-0.247*	-0.199	0.0320
	(0.143)	(0.103)	(0.132)	(0.264)	(0.156)
x Participation rate	0.0918	0.358***	-0.276	0.00306	0.104
	(0.200)	(0.118)	(0.188)	(0.399)	(0.184)
Observations	381612	382140	381900	364044	380988
Number of units	7951	7962	7957	7585	7938
Number of clusters	48	48	48	48	48
Revenue share	0.0512	0.768	0.0949	0.0653	0.0206

Notes: Robust standard errors are in parentheses, clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1. Controls refer to the full set of controls including log housing prices, log unemployment rate, log employment to population ratio, log population, log average wage, poverty rates at both the state and county levels, as well as log SNAP participants at the state level. Store and period fixed effects are also included. Log benefits p.p. refers to log benefits per population. Participation refers to the ratio of SNAP participants to population in each county fixed to the pre-period of 2006.

Table N9: Proportion of revenue earned by each product department by store type

Store Type	Product department				
	Health & Beauty Care	Food	Non-Food Grocery	Alcohol	General Merchandise
Drug	0.479	0.216	0.171	0.052	0.083
Food	0.053	0.765	0.094	0.065	0.023
Merchandise	0.219	0.312	0.225	0.008	0.237

Notes: This table lists the proportion of revenue earned by each product department by store type across all stores from 2006 to 2015.

Table N10: Effect of SNAP-benefit changes on prices and real sales, drug and merchandise stores

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Store Type	Drug				Merchandise			
Specification	OLS	IV	OLS	IV	OLS	IV	OLS	IV
VARIABLES	Log price index		Log real sales		Log price index		Log real sales	
Log benefits per population	0.00113	0.0250	-0.0155	0.198*	0.00567	0.0311*	0.00950	-0.0646
	(0.00651)	(0.0251)	(0.0363)	(0.113)	(0.00408)	(0.0175)	(0.0236)	(0.0754)
Observations	445467	445467	445467	445467	385527	385527	385527	385527
R-squared	0.912	0.912	0.977	0.976	0.915	0.914	0.991	0.991
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of units	9281	9281	9281	9281	8032	8032	8032	8032
Number of clusters	48	48	48	48	49	49	49	49
First stage F-stat		21.167		21.167		14.903		14.903

Notes: Robust standard errors are in parentheses, clustered by state. Control variables as well as store and period fixed effects are included. *** p<0.01, ** p<0.05, * p<0.1.

Table N11: Effect of SNAP-benefit changes on grocery store firm dynamics and market structure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	SNAP stores					All stores	
VARIABLES	Authorization	Entry	Exit	Reallocation	Log count p.p.	Log est. p.p.	HHI
Log benefits p.p.	0.0319	0.0525	0.0481	0.101**	0.0778	-0.0237	0.00716
	(0.0330)	(0.0362)	(0.0430)	(0.0487)	(0.0697)	(0.0817)	(0.00733)
Observations	149178	149178	149178	149178	144342	146562	146562
R-squared	0.497	0.438	0.398	0.526	0.978	0.968	0.980
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of units	3108	3108	3108	3108	3023	3070	3070
Number of clusters	49	49	49	49	49	49	49
First stage F-stat	22.822	22.822	22.822	22.822	22.878	22.846	22.846

Notes: Robust standard errors are in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1. Control variables as well as county and period fixed effects are included. Authorization refers to the authorization rate, that is, the number of newly authorized stores per month divided by the total number of SNAP-authorized grocery stores in each county. Entry and exit refers to the entry and exit rates, that is, the number of entering and exiting stores in a particular year divided by the total number of SNAP-authorized grocery stores in each county. Reallocation is the sum of entry and exit rates. Log count p.p. refers to the log of the total number of SNAP-authorized grocery stores per population in each county. Log est. p.p. refers to the log of the total number of grocery establishments per population in each county. HHI refers to a county-level measure of HHI, using the number of employees as the measure of firm size for the grocery industry.

Table N12: Effect of SNAP-benefit changes on consumption of households, weekly

	(1)	(2)	(3)	(4)
Specification	OLS, log-log	IV, log-log	OLS, level-level	IV, level-level
VARIABLES		Consumption		
Both ineligible	0.105**	0.287**	0.0281*	0.0321
	(0.0501)	(0.125)	(0.0166)	(0.0404)
Household eligible only	0.0508	0.239*	0.00297	0.00526
	(0.0778)	(0.139)	(0.0210)	(0.0403)
Product eligible only	0.0174	0.223*	0.0221*	0.0273
	(0.0393)	(0.113)	(0.0121)	(0.0375)
Both eligible	0.158***	0.348***	0.0521**	0.0563
	(0.0491)	(0.118)	(0.0229)	(0.0434)
Both ineligible x fraction issued	0.00846	0.0101	0.00717	0.00410
	(0.0248)	(0.0294)	(0.0117)	(0.0136)
Household eligible only x fraction issued	0.0380	0.0396	0.0436***	0.0404**
	(0.0252)	(0.0300)	(0.0131)	(0.0153)
Product eligible only x fraction issued	0.00561	0.00724	0.00801	0.00485
	(0.0247)	(0.0293)	(0.0116)	(0.0135)
Both eligible x fraction issued	0.0439*	0.0455	0.0796***	0.0765***
	(0.0242)	(0.0291)	(0.0125)	(0.0152)
Observations	6797627	6797627	6798234	6798234
R-squared	0.271	0.271	0.270	0.270
Prob > F	0.000	0.000	0.000	0.000
Number of units	23789	23789	23789	23789
Number of clusters	49	49	49	49
First stage F-stat		6.840		8.643

Notes: Robust standard errors are in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1. Each coefficient comes from a regression of (log) weekly consumption on (log) monthly SNAP benefits per recipient, interacted with four group indicators and the fraction issued. Both ineligible refers to expenditures by SNAP-ineligible households on SNAP-ineligible products, household eligible only refers to expenditures by SNAP-eligible households on SNAP-ineligible products, product eligible only refers to expenditures by SNAP-ineligible households on SNAP-eligible products, and both eligible refers to expenditures by SNAP-eligible households on SNAP-eligible products. Fraction issued refers to the fraction of days out of a month in which SNAP benefits are issued during that week. Only the first four weeks of each month are kept in the sample. Control variables as well as household-month and year-month-week fixed effects are also included. Observations are weighted by sampling weights.

Table N13: Effect of SNAP-benefit changes on shopping behavior of households

Specification	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
VARIABLES	Coupon share		Deal share		Store brand share		Log trips	
Both ineligible	0.00394	0.0272**	-0.00605	0.00485	-0.0301**	-0.107**	-0.0384	-0.00719
	(0.00323)	(0.0107)	(0.0122)	(0.0555)	(0.0112)	(0.0469)	(0.0325)	(0.165)
Household eligible only	-0.00732*	0.0161	-0.0687***	-0.0589	-0.0461***	-0.123**	-0.0360	-0.00918
	(0.00374)	(0.00995)	(0.0184)	(0.0557)	(0.0156)	(0.0493)	(0.0514)	(0.179)
Product eligible only	0.00314	0.0269**	0.0210	0.0376	-0.0290**	-0.108**	-0.0449	-0.0157
	(0.00235)	(0.0102)	(0.0133)	(0.0557)	(0.0121)	(0.0461)	(0.0319)	(0.163)
Both eligible	-0.00569**	0.0177	0.00192	0.0195	-0.0542***	-0.132***	-0.0441	-0.0185
	(0.00266)	(0.0106)	(0.0194)	(0.0588)	(0.0143)	(0.0462)	(0.0520)	(0.183)
Observations	2044662	2044662	2044662	2044662	2044662	2044662	2044666	2044666
R-squared	0.624	0.623	0.734	0.734	0.454	0.454	0.770	0.770
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.011	0.000
Number of units	23911	23911	23911	23911	23911	23911	23911	23911
Number of clusters	49	49	49	49	49	49	49	49
First stage F-stat		12.258		12.258		12.258		12.258

Notes: Robust standard errors are in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1. Each coefficient comes from a regression of the outcome on log SNAP benefits per recipient, interacted with four group indicators. Both ineligible refers to outcomes by SNAP-ineligible households on SNAP-ineligible products, household eligible only refers to outcomes by SNAP-eligible households on SNAP-ineligible products, product eligible only refers to outcomes by SNAP-ineligible households on SNAP-eligible products, and both eligible refers to outcomes by SNAP-eligible households on SNAP-eligible products. Control variables as well as household-month and period fixed effects are also included. Observations are weighted by sampling weights.

Table N14: SNAP participation and effect of SNAP-benefit changes on prices, ARRA expiration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Specification	OLS	IV	OLS	IV	OLS	IV	OLS	IV
VARIABLES	Log price index							
Log benefits p.p.	0.0366***	0.101	-0.00252	-0.0441	0.0250	0.0895	0.00389	-0.0431
	(0.0122)	(0.0901)	(0.0127)	(0.0492)	(0.0159)	(0.113)	(0.0156)	(0.0612)
x Participation rate					0.0775	0.0629	-0.0427	-0.00699
					(0.0537)	(0.147)	(0.0780)	(0.0954)
Observations	85836	85836	321885	321885	85836	85836	321885	321885
R-squared	0.972	0.971	0.915	0.914	0.972	0.971	0.915	0.914
Prob > F	0.000	0.000	0.000	0.004	0.000	0.000	0.000	0.002
Number of units	7153	7153	7153	7153	7153	7153	7153	7153
Number of clusters	48	48	48	48	48	48	48	48
First stage F-stat		5.182		9.670		2.632		4.952
Sample	2013	2013	2012-2015	2012-2015	2013	2013	2012-2015	2012-2015

Notes: Robust standard errors are in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1. Control variables as well as store and period fixed effects are also included. Log benefits p.p. refers to log benefits per population. Participation refers to the ratio of SNAP participants to population in each county fixed to the pre-period of 2011.

Table N15: Effect of SNAP-benefit changes on consumption of households, ARRA expiration

	(1)	(2)	(3)	(4)
Specification	OLS, log-log	IV, log-log	OLS, log-log	IV, log-log
VARIABLES	Consumption			
Both ineligible	-0.0641	-0.452	0.0141	0.217
	(0.121)	(0.489)	(0.0926)	(0.308)
Household eligible only	-0.0302	-0.142	-0.123	0.0915
	(0.250)	(0.535)	(0.154)	(0.335)
Product eligible only	-0.144	-0.525	-0.0681	0.202
	(0.106)	(0.526)	(0.0954)	(0.277)
Both eligible	0.207	0.220	-0.0182	0.304
	(0.269)	(0.701)	(0.182)	(0.318)
Observations	518146	518146	1943066	1943066
R-squared	0.510	0.510	0.467	0.467
Prob > F	0.000	0.000	0.000	0.000
Number of units	24748	24748	24748	24748
Number of clusters	49	49	49	49
First stage F-stat		0.936		6.693
Sample	2013	2013	2012-2015	2012-2015

Notes: Robust standard errors are in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1. Each coefficient comes from a regression of (log) consumption on (log) SNAP benefits per recipient, interacted with four group indicators. Both ineligible refers to expenditures by SNAP-ineligible households on SNAP-ineligible products, product eligible only refers to expenditures by SNAP-ineligible households on SNAP-eligible products, household eligible only refers to expenditures by SNAP-eligible households on SNAP-ineligible products, and both eligible refers to expenditures by SNAP-eligible households on SNAP-eligible products. Control variables, household-month and period fixed effects are also included. Observations are weighted by sampling weights.

Table N16: Estimates of demand elasticity, demand curvature, and pass-through rates for SNAP-eligible goods

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Log real sales								
Log price	-0.605***	-0.659***	-0.709***	0.214	-0.118	-0.144	0.442	0.306	0.389
	(0.185)	(0.222)	(0.233)	(0.370)	(0.457)	(0.485)	(0.422)	(0.446)	(0.469)
(Log price)^2				-2.042**	-1.389	-1.491	-3.631	-4.830***	-5.858***
				(0.842)	(0.899)	(0.949)	(2.335)	(1.661)	(1.679)
(Log price)^3							2.920	6.505***	8.286***
							(3.650)	(2.390)	(2.519)
Observations	838260	837168	827388	838260	837168	827388	838260	837168	827388
R-squared	0.934	0.946	0.954	0.934	0.946	0.954	0.934	0.947	0.955
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of units	7004	6995	6914	7004	6995	6914	7004	6995	6914
Number of clusters	48	48	48	48	48	48	48	48	48
Time FE	X			X			X		
DMA x Time FE		X			X			X	
Zip3 x Time FE			X			X			X
Implied rate				0.740	0.522	0.489	0.767	0.480	0.597

Notes: Robust standard errors are in parentheses, clustered by state. *** p<0.01, ** p<0.05, * p<0.1. Control variables as well as store and specified period fixed effects are included. DMA refers to Nielsen designated market areas. Zip3 refers to 3-digit zip codes. Implied rate refers to the unit-subsidy pass-through rates implied by the estimated coefficients assuming markups are 0.3, which implies a market conduct of about 0.16. The coefficients are used to calculate the elasticity of marginal surplus at the mean log price.

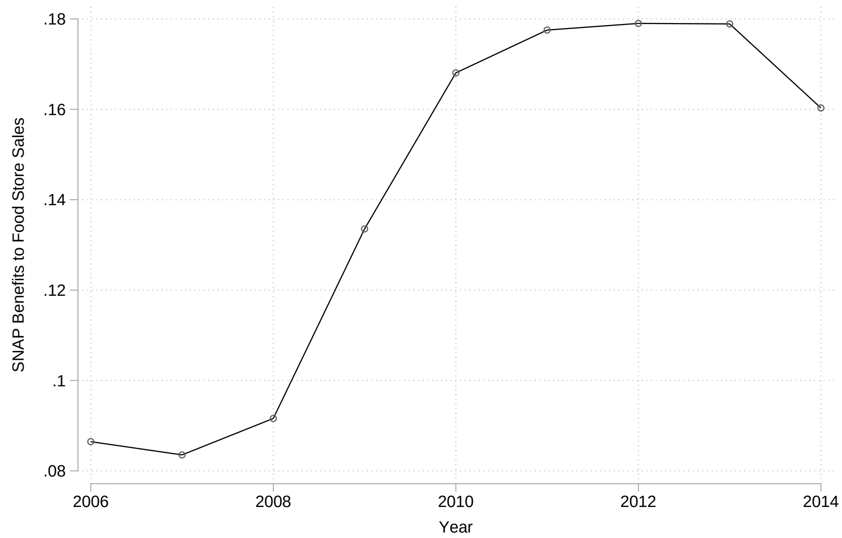
Table N17: Incidence of an additional dollar of SNAP benefits for SNAP-ineligible goods

MPC elasticity	Pass-through elasticity	Shift magnitude	PS	CS	CS (SNAP)	CS (non-SNAP)
0.1182	0.0898	0.009	0.098	-0.1608	-0.013	-0.148

Notes: MPC elasticities are obtained from Section 4.2. A market conduct parameter of 0.5 is assumed using markups as shown in Hottman (2016). Demand elasticity is estimated using panel variation as described in Section 5.3. Proportion of SNAP sales of 0.168 is obtained from USDA data. Pass-through elasticity is obtained from Section 4.1 and the shift magnitude is the predicted pass-through elasticity obtained using equation (8) assuming a unit-subsidy pass-through rate of 1. Surplus calculations are changes in surplus per marginal dollar of SNAP disbursed. PS refers to producer surplus and CS refers to consumer surplus, CS(SNAP) and CS(non-SNAP) refers to consumer surplus for SNAP consumers and consumer surplus for non-SNAP consumers, respectively.

O Figures

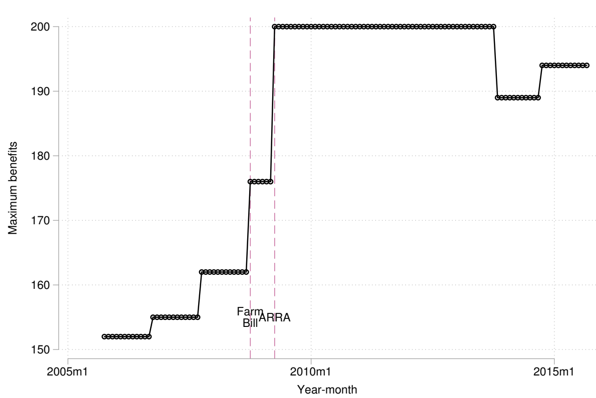
Figure O1: SNAP benefits as a proportion of total food-at-home sales in food stores, 2006-2014



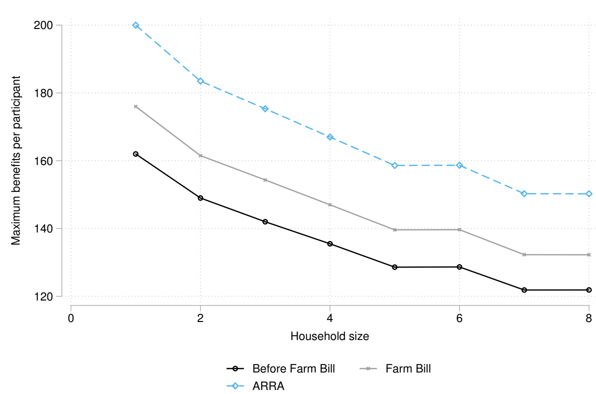
Notes: This figure plots the ratio of SNAP benefits to total food-at-home sales at food stores, as defined by the USDA ERS, from 2006-2014 using data from the USDA ERS and FNS.

Figure O2: Changes in maximum benefits

(a) Maximum benefits, single-person household

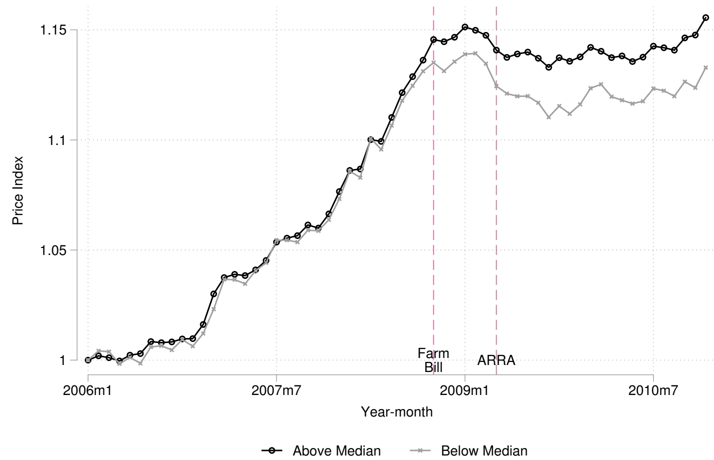


(b) Maximum benefits per participant by household size



Notes: This figure plots out the maximum benefits for a single-person household over time in Figure O2a, and the maximum benefits by household size before the Farm Bill, after the Farm Bill, and after the ARRA in Figure O2b.

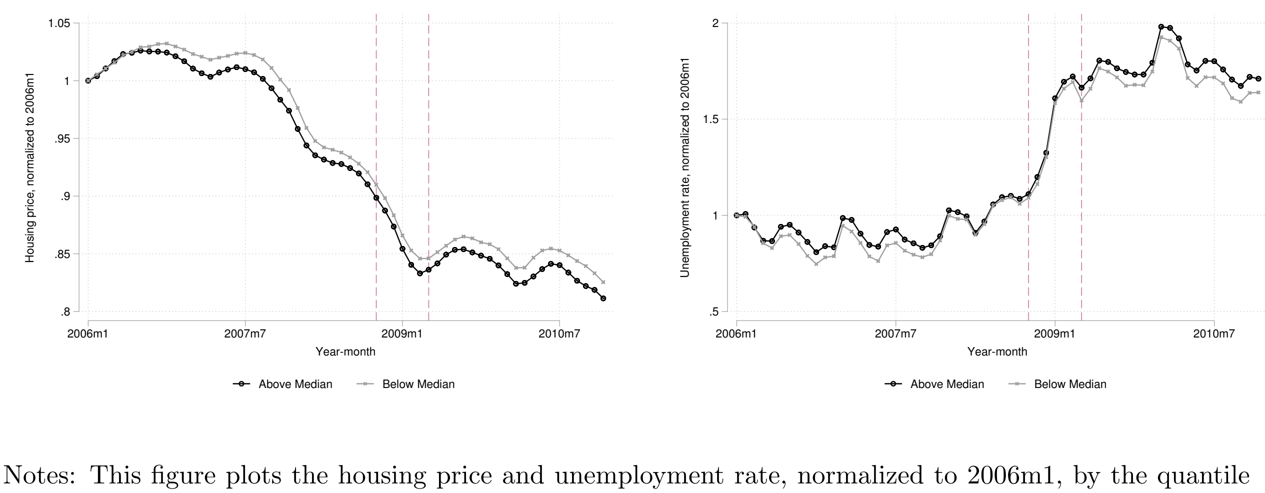
Figure O3: Grocery store price indices by quantile of change in log synthetic benefits per population, 2006-2010



Notes: This figure plots the revenue-weighted average grocery store price indices by the quantile of change in log synthetic benefits per population for the first and second quantile, respectively. To obtain these quantiles, the total change in the log synthetic benefits per population during the Farm Bill and the ARRA for each state, residualized by control variables, is used to separate the states into quantiles. The first quantile denotes the 24 states with the largest changes in residualized log benefits per population, and the second quantile denotes the 24 states with the smallest changes.

Figure O4: Housing price and unemployment rate by quantile of change in log synthetic benefits per population, 2006-2010

(a) Housing price (b) Unemployment rate

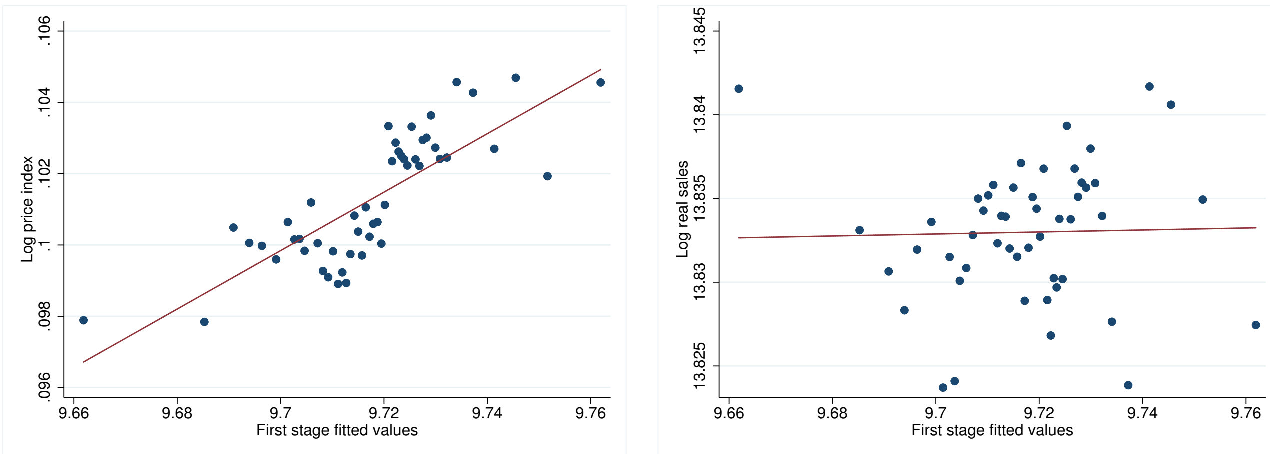


Notes: This figure plots the housing price and unemployment rate, normalized to 2006m1, by the quantile of change in log synthetic benefits per population for the first and second quantile, respectively. To obtain these quantiles, the total change in the log synthetic per population during the Farm Bill and the ARRA for each state, residualized by control variables, is used to separate the states into quantiles. The 1st quantile denotes the 24 states with the largest changes in residualized log benefits per population, and the 2nd quantile denotes the 24 states with the smallest changes.

Figure O5: Effects of SNAP-benefit changes on prices and real sales

(a) Log price index on fitted log benefits per population

(b) Log real sales on fitted log benefits per population

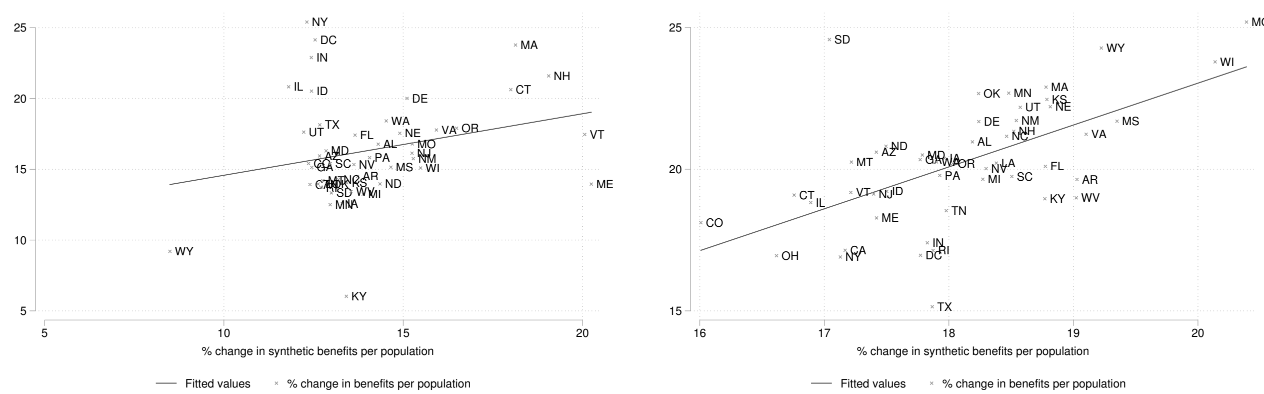


Notes: This figure plots the log price index against the fitted values of log benefits per population as predicted by the IV. Both variables are residualized by regressing on a set of controls, store fixed effects, and period fixed effects. For each store-year-month observation, the first-stage fitted values are calculated and grouped into 50 quantiles. The x-axis displays the mean of the residualized first-stage fitted values in each quantile. The y-axis shows the mean of the residualized log price index in each quantile. The line of best fit is obtained from the regression using all observations in each sample. The slopes are 0.082 (0.023) and 0.00597 (0.109), respectively.

Figure O6: Changes in SNAP benefits per population against changes in synthetic benefits per population, Farm Bill and ARRA

(a) Farm Bill

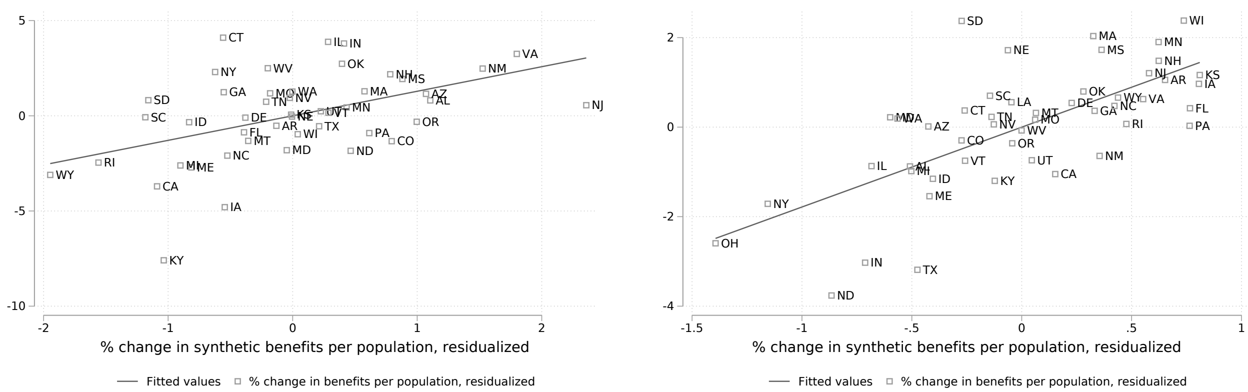
(b) ARRA



Notes: This figure plots the changes in SNAP benefits per population against changes in synthetic benefits per population during the Farm Bill and the ARRA. The slopes are 0.43 (0.27) and 1.48*** (0.28), respectively. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Ohio and Louisiana are dropped during the Farm Bill due to disaster-relief events.

Figure O7: Changes in residualized SNAP benefits per population against residualized changes in synthetic benefits per population, Farm Bill and ARRA

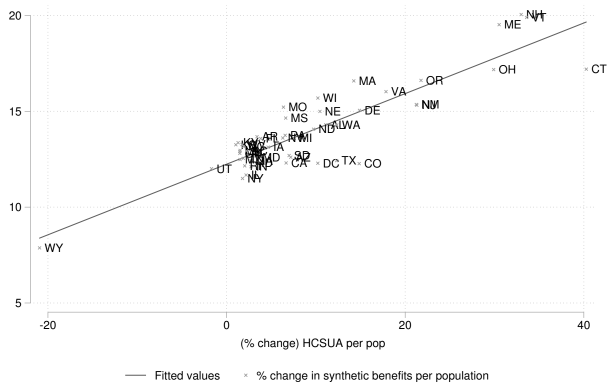
(a) Farm Bill (b) ARRA



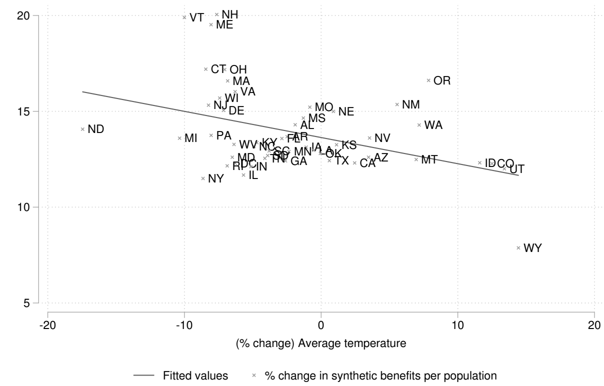
Notes: This figure plots the changes in residualized SNAP benefits per population against residualized changes in synthetic benefits per population during the Farm Bill and the ARRA. The slopes are 1.29*** (0.35) and 1.78*** (0.44), respectively. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Ohio and Louisiana are dropped during the Farm Bill due to disaster-relief events.

Figure O8: Changes in synthetic SNAP benefits per population, SUA, energy usage and prices, and temperature by state, Farm Bill

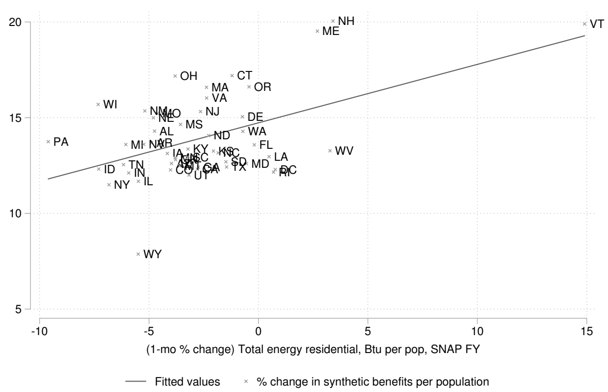
(a) Changes in synthetic benefits per population and HCSUA, Farm Bill



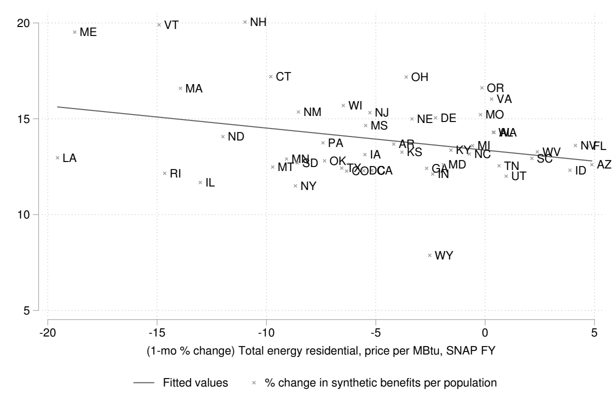
(b) Changes in synthetic benefits per population and temperature, Farm Bill



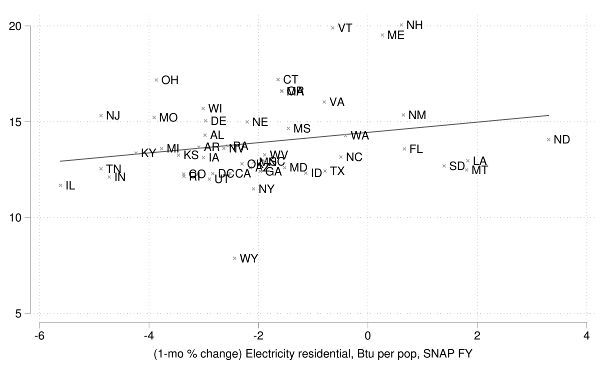
(c) Changes in synthetic benefits per population and total residential energy usage per population, Farm Bill



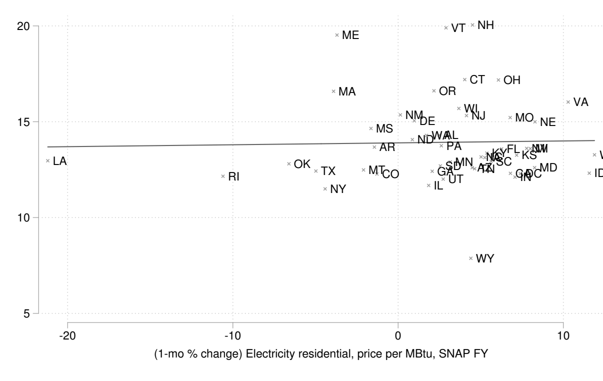
(d) Changes in synthetic benefits per population and residential energy prices, Farm Bill



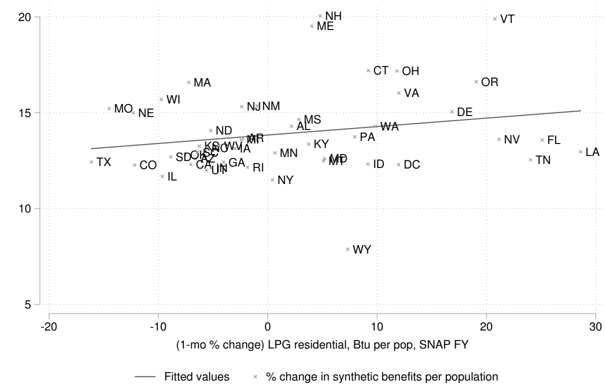
(e) Changes in synthetic benefits per population and electricity usage per population, Farm Bill



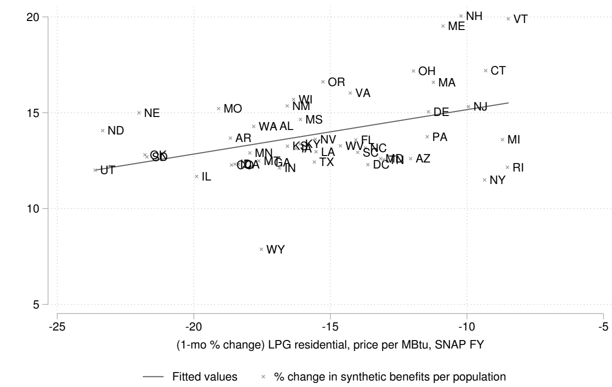
(f) Changes in synthetic benefits per population and electricity prices, Farm Bill



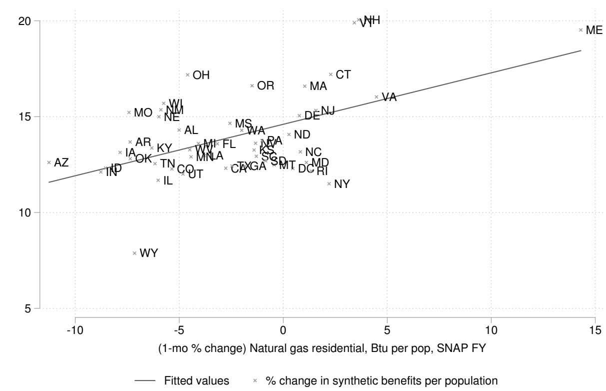
(g) Changes in synthetic benefits per population and LPG usage per population, Farm Bill



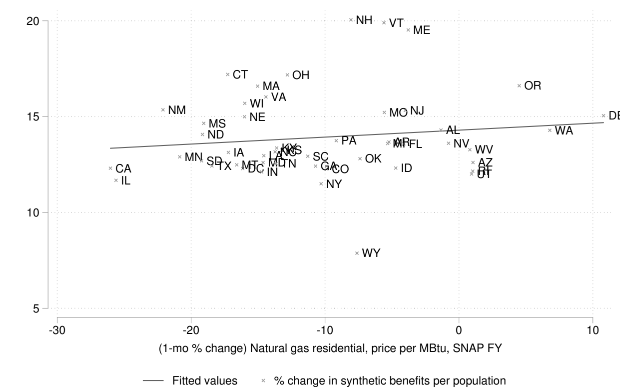
(h) Changes in synthetic benefits per population and LPG prices, Farm Bill



(i) Changes in synthetic benefits per population and natural gas usage per population, Farm Bill

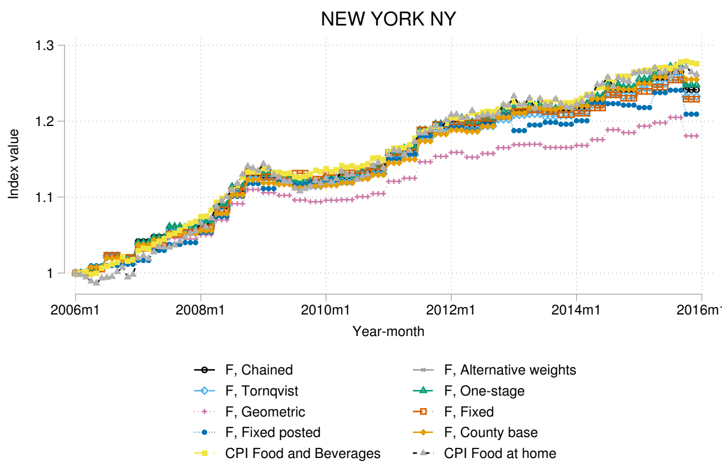


(j) Changes in synthetic benefits per population and natural gas prices, Farm Bill



Notes: This figure plots the changes in synthetic SNAP benefits per population, SUA per population, energy usage per population and prices for the residential sector and different fuel types, and temperature by state during the Farm Bill.

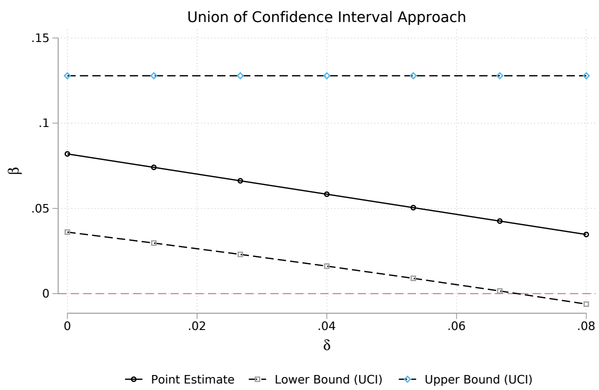
Figure O9: Comparison of Nielsen price indices with CPI, grocery stores



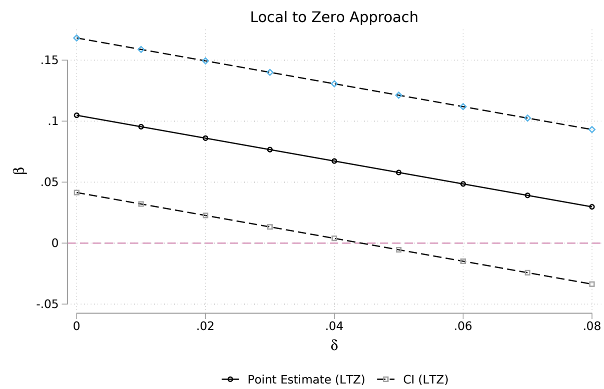
Notes: This figure plots city-level price indices from 2006 to 2015 constructed using Nielsen retail scanner data with alternative methods against those used by the BLS to construct the CPI. F correspond to Nielsen price indices for drug stores, grocery stores, and mass merchandise stores respectively. Nielsen price indices are first constructed at the store level, and aggregated to the city level by taking a sales-weighted average.

Figure O10: Plausible Exogeneity

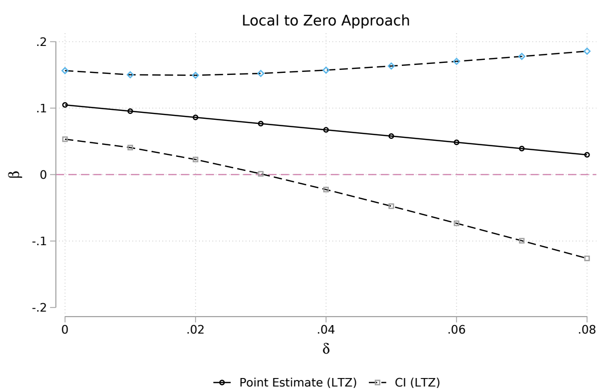
(a) Union of Confidence Intervals



(b) Local-to-Zero: Standard Deviation = 0.02



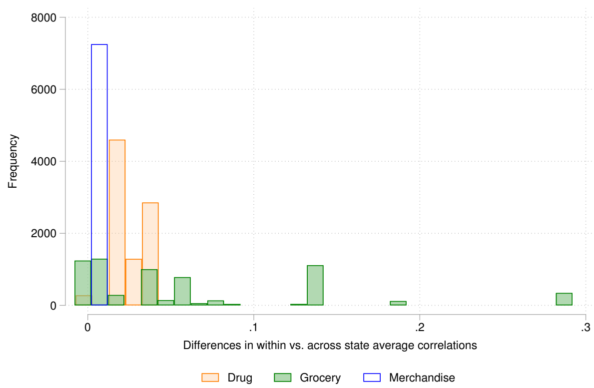
(c) Local-to-Zero: Standard Deviation = δ



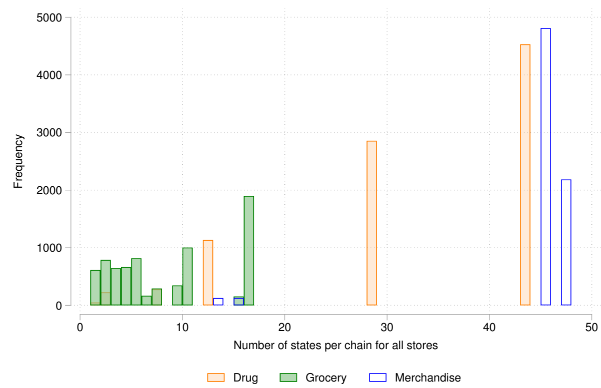
Notes: This figure plots the estimated coefficients and their confidence intervals against different levels of δ, the effect of the instrument on the outcome, under various methods in Conley et al. (2012). The three methodologies are the union of confidence interval approach with a support of $[0, 0.08]$, the local-to-zero approach with a standard deviation of 0.02, which is our back-of-the-envelope estimate of δ, and the local-to-zero approach with a standard deviation of δ.

Figure O11: Distribution of flexibility measures across store types

(a) Flexibility measures

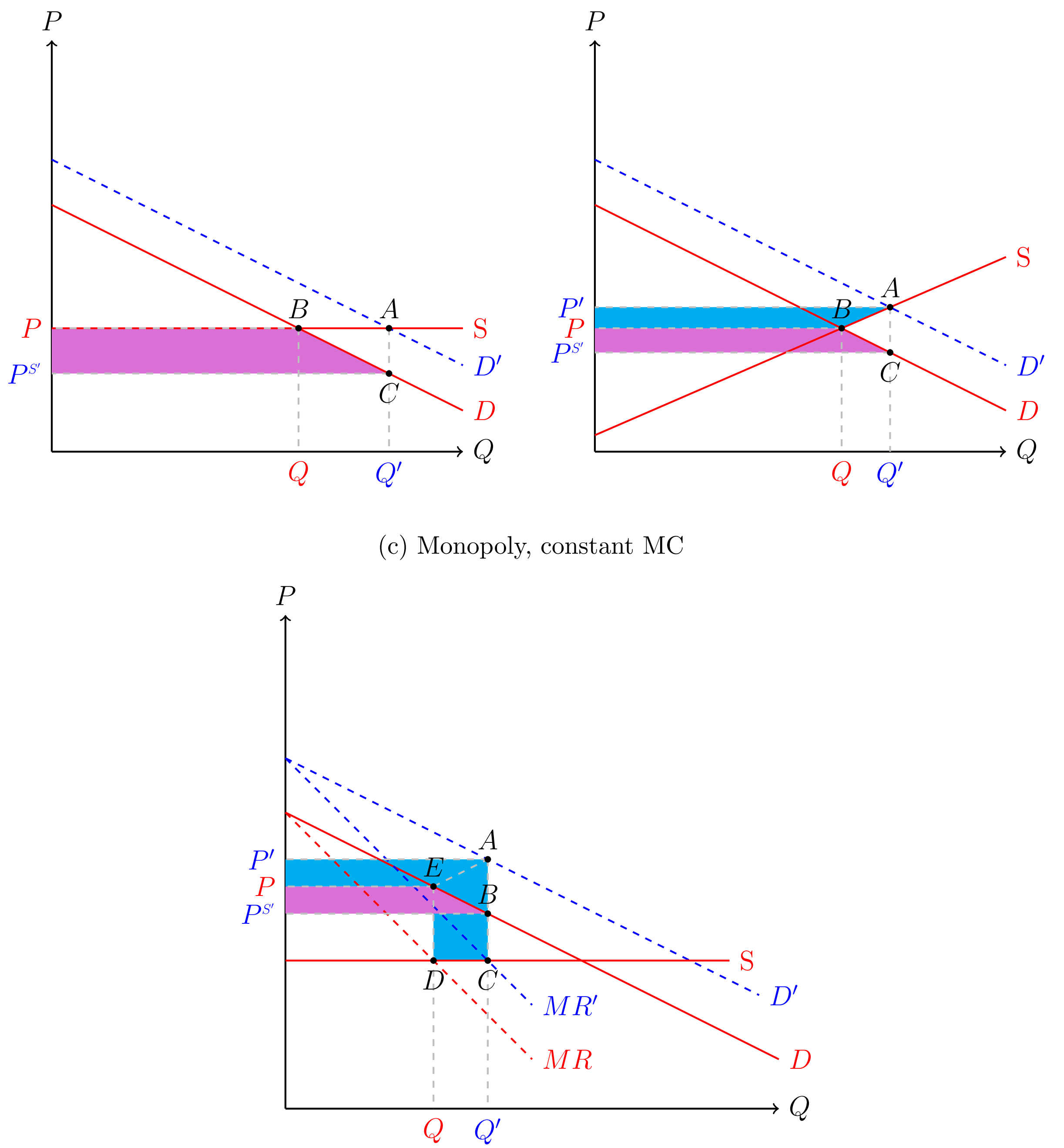


(b) Number of states in each chain for all stores



Notes: This figure plots the chosen flexibility measure, differences in within vs. across state average correlations, as illustrated in Appendix Section H, and also the number of states in each chain for all stores.

Figure O12: Incidence under different assumptions



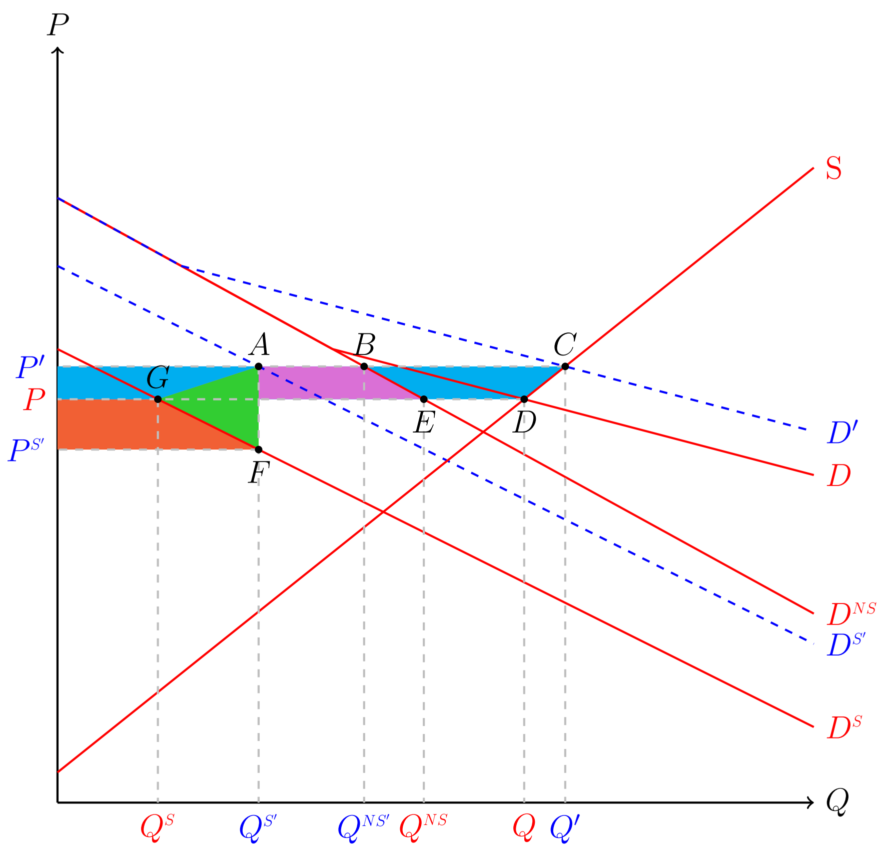
(a) Perfect competition, flat supply

(b) Perfect competition, upward-sloping supply

(c) Monopoly, constant MC

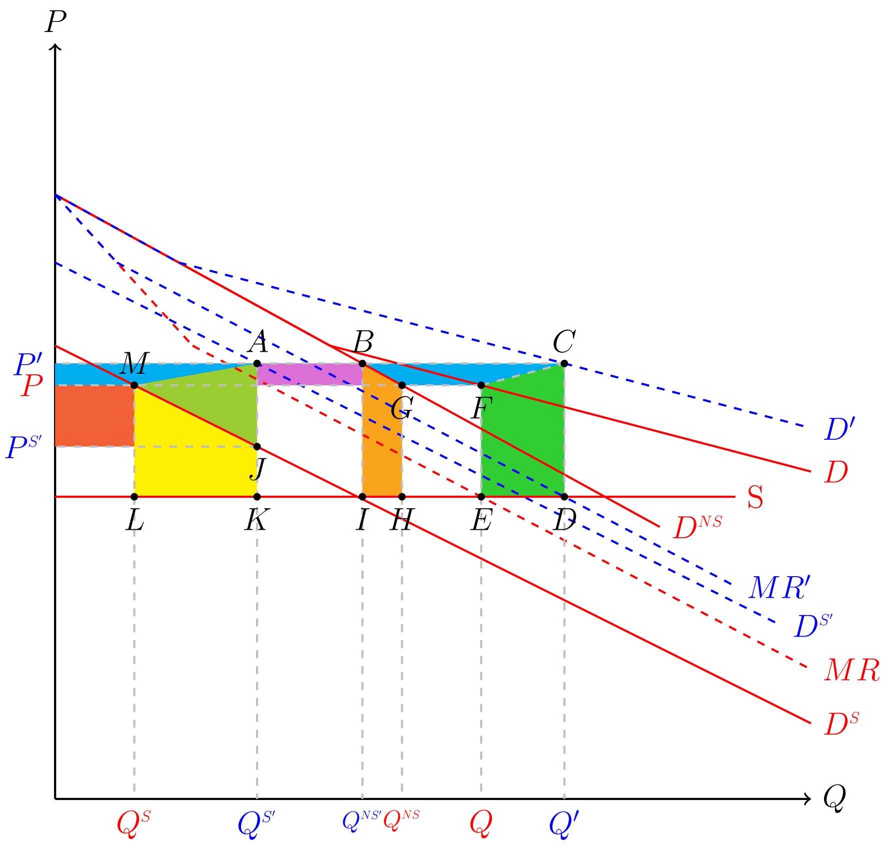
Notes: In this figure, we graphically illustrate how economic incidence changes in a simple partial-equilibrium framework under different assumptions about the food market. For simplicity, we begin with an example in which all consumers receive SNAP benefits. In Figure O12a, we assume a perfect competitive market with a flat supply curve. A SNAP-benefit increase shifts the demand curve out from D to D', and prices remain constant while quantities consumed increase from Q to Q'. Assuming no income effects or a parallel shift in demand, we evaluate incidence under the original demand curve. All of the surplus generated goes to the consumer as consumer surplus increases by $PBCP^{S'}$. In Figure O12b, we again assume perfect competition but let the supply curve be upward-sloping. Prices now increase from P to P' when SNAP benefits increase. The increase in surplus is now divided between the producer and the consumer, with producer surplus increasing by $P'ABP$ and consumer surplus increasing by $PBCP^{S'}$. In Figure O12c, we assume the firm is a monopolist with a constant marginal cost. A SNAP-benefit rise increases prices from P to P' because the firm raises its markup and sells at a more inelastic portion of the demand curve. The increase in surplus is again split between the producer and the consumer, with producer surplus increasing by $P'ABCDEP$ and consumer surplus increasing by $PEBP^{S'}$.

Figure O13: Full incidence of SNAP benefits under perfect competition



Notes: This figure illustrates the incidence of increased SNAP benefits in a partial-equilibrium setting under perfect competition. Market-demand curve D for SNAP-eligible products is obtained by the horizontal summation of demand of SNAP recipients D^S and non-SNAP recipients D^{NS}. Equilibrium price P and quantity Q are obtained by the intersection of demand D and supply S. The government then disburses SNAP benefits to recipients, shifting the demand curve of SNAP recipients up to $D^{S'}$. Equilibrium price increases to P' and quantity increases to Q' by the intersection of new market demand D' and supply S. The increase in price and quantity leads to increased producer surplus of $P'CDP$. Assuming no income effects or a parallel shift in demand, we evaluate the welfare of SNAP recipients under their old demand curve D^S. SNAP recipients now act as if they face lower prices of $P^{S'}$ and quantity demanded increases to $Q^{S'}$ due to the disbursement of benefits, and hence their consumer surplus increases by $PGFP^{S'}$. On the other hand, non-SNAP consumers now face a higher price P', and their consumer surplus decreases by $P'BEP$. To consider the deadweight loss of the program, we first observe that the loss in non-SNAP consumer surplus $P'BEP$ directly transfers to a gain in producer surplus. The remaining producer surplus $BCDE$ from SNAP consumers is equal in area to $P'AGP$. The cost of SNAP benefits to the government is $P'AFP^{S'}$, which implies that the deadweight loss of the program is GAF. This deadweight loss is a result of SNAP consumers buying marginal units they value at less than the marginal cost for producers.

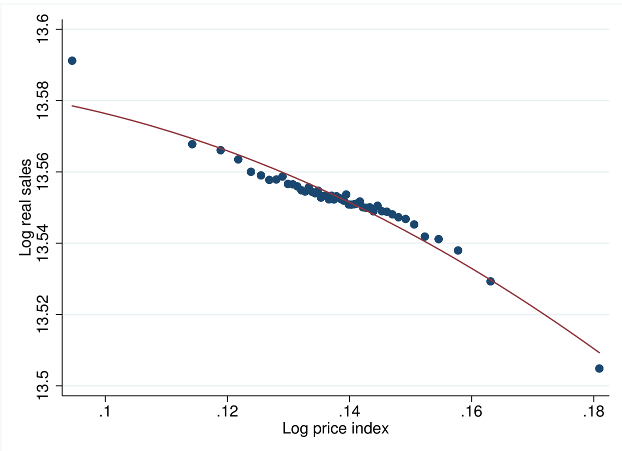
Figure O14: Full incidence of SNAP benefits under monopoly



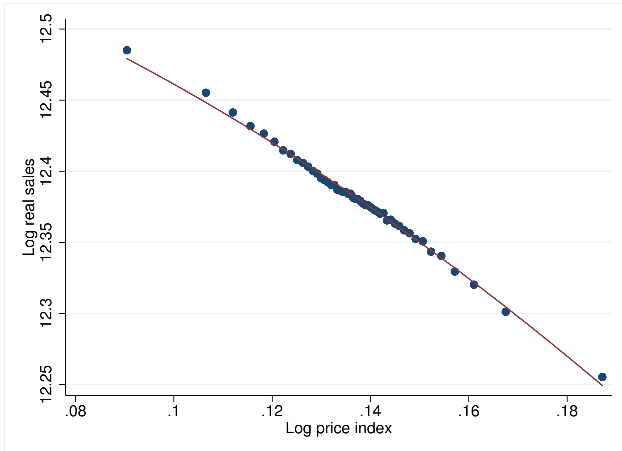
Notes: This figure illustrates the incidence of increased SNAP benefits in a partial-equilibrium setting under monopoly. The market demand curve D for SNAP-eligible products is obtained by the horizontal summation of demand of SNAP recipients D^S and non-SNAP recipients D^{NS}. Equilibrium price P and quantity Q are now obtained by the intersection of marginal revenue MR that is obtained from demand D and marginal cost given by supply curve S, which we assume is constant, based on evidence by Stroebel and Vavra (2019). The government then disburses SNAP benefits to recipients, shifting the demand curve of SNAP recipients up to $D^{S'}$. Equilibrium price increases to P' and quantity increases to Q' by the intersection of new marginal-revenue curve MR' and supply S. We now evaluate the changes in welfare as a result of SNAP. The increase in price and quantity leads to increased producer surplus of $P'CDEFP$. SNAP recipients now act as if they face lower prices of $P^{S'}$ and quantity demanded increases to $Q^{S'}$ due to the disbursement of benefits, and hence their consumer surplus increases by $PMJP^{S'}$. On the other hand, non-SNAP consumers now face a higher price P', and their consumer surplus decreases by $P'BGP$. To consider the deadweight loss of the program, we first observe that the loss in non-SNAP consumer surplus $P'BGP$ directly transfers to a gain in producer surplus. The remaining producer surplus $BCFG$ from SNAP consumers is equal in area to $P'AMP$. The cost of SNAP benefits to the government is $P'AJP^{S'}$, which implies part of the deadweight loss of the program is MAJ. However, this deadweight loss is offset by the change in producer surplus $FCDE$. To better understand the change in total surplus, note that $FCDE$ is identical in area to $MAKL$ minus $BGHI$. Therefore, the change in total surplus of $FCDE$ minus MAJ is equivalent to $MJKL$ minus $BGHI$. In other words, the change in deadweight loss of the program is given by the decrease in deadweight loss when the monopolist sells more to SNAP consumers and the increase in deadweight loss when the monopolist further restricts output to non-SNAP consumers.

Figure O15: Binned scatter plot of log real sales on log prices, SNAP-eligible and ineligible goods

(a) Eligible goods



(b) Ineligible goods



Notes: This figure plots the log real sales against the log price index for SNAP-eligible and ineligible goods. Both variables are residualized by regressing on a set of controls, store fixed effects, and 3-digit zip code x period fixed effects. For each store-year-month observation, log prices are grouped into 50 quantiles. The x-axis displays the mean of the residualized log price in each quantile. The y-axis shows the mean of the residualized log real sales in each quantile. The quadratic curve of best fit is obtained from the regression using all observations.