Food Demand and Cash Transfers: A Collective Household Approach with Homescan Data

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Abstract

I study how individual preferences and bargaining power within older couples affects the impact of cash transfers on food demand. Using longitudinal Homescan data, I find that wives have stronger preferences for food than husbands, and that household demand patterns for food are affected by spouse's relative bargaining power. Failure to account for these effects leads to underestimates of older couples' total food demand, and of their implied response (at both intensive and extensive margins) to a counterfactual experiment of a cash transfer program with equivalent benefit size as the Supplemental Nutrition Assistance Program (SNAP). I find that the cash transfer can achieve the goals of SNAP to some extent (*JEL* D11, D12, D13, I31, I32, I38).

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1 Introduction

Many welfare programs are designed in part to change household consumption behavior, using, e.g., taxes, subsidies, and cash or in-kind transfers. To evaluate the effectiveness of these programs, household demand is often modeled as the outcome of a single decision-making, utility-maximizing agent (these are known as unitary models). However, the literature on collective households argues that the assumptions under the unitary approach are too restrictive (Chiappori 1988, 1992, Vermuelen 2002, Donni and Molina 2018). Household consumption outcomes are determined by heterogeneous individuals with different needs and tastes, not by one representative agent. Implications from the unitary model like income pooling have often been objected in the previous literature.[1] Moreover, as highlighted by Deaton and Paxson (1998), household scale economies arise through public goods that make larger families better off and release resources that can be spent on everything, public and private goods alike. The estimated demand and welfare responses to tax or transfer programs may be biased by failing to account for these within-household responses.[2]

Following the collective approach, this paper uses longitudinal Homescan data to estimate a collective consumption model for older adults (widows, widowers, and couples) in the US, and applies the model to evaluate a cash transfer with equivalent benefit size as the Supplemental Nutrition Assistance Program (SNAP) to low-income households.

I focus on older adults for three reasons. First, food security and nutrition intake are among the largest concerns for the aging population.[3] Second, for older adults, expenditures on other goods such as clothing and transportation decrease dramatically while food remains a large portion of their budget (Foster 2015, and see Figure A4 in the Appendix). Third,

[1]For example, see Thomas (1990), Thomas, Contreras, and Frankenbe (2002), Quisumbing and Maluccio (2003), Duflo (2003), and Attanasio and Lechene (2002).

[2]For example, see Adams, Cherchye, De Rock, and Verriest (2014), Cherchye, De Rock, Griffith, O'Connell, Smith and Vermeulen (2017), Fortin and Lacroix (1997), Browning and Chiappori (1998), and Cherchye and Vermuelen (2006).

[3]The elderly population is an under-studied group with regard to food insecurity. This may be a result of tradition (the elderly were primarily cared for by family or institutions) or of the perception that income support programs, such as Social Security, assure that the elderly are food secure (Ziliak and Gundersen 2011). However, food insecurity among older age groups increased substantially after 2007. By 2009, among adults age 50 and older, 15.6 million persons faced the threat of hunger (i.e. were marginally food insecure), 8.8 million faced the risk of hunger (i.e. were food insecure), and 3.5 million faced hunger (i.e. were low food secure). This is an increase of 66%, 79%, and 132%, respectively, from the levels of food insecurity in 2001 among this population (Ziliak and Gundersen 2011). The US Government Accountability Office (GAO 2011) found that following the economic downturn that began in late 2007, nearly 80% of senior-serving agencies reported an increased demand for nutrition assistance and 20% reported that they were unable to meet the increased demand. Moreover, 90% of low-income seniors who could not afford proper nutrition had no access to federal meal programs. The 2014 study Hunger in America reveals that a disproportionate number of individuals visiting food pantries are the elderly and that more than half of these individuals return monthly (Weinfield et al. 2014 and Arno et al. 2015).

70 percent of goods in the Homescan data are food-related, so the coverage of this dataset is particularly good for this older population.

SNAP is the largest anti-hunger program in the U.S.. As an in-kind transfer, SNAP provides subsidies that can only be spent on SNAP-eligible food.[4] A main support for the in-kind design is that low-income households have different preferences compared to high-income households. If given cash, they will spend the benefits on policy undesired goods. The first contribution of this paper is to directly test this assumption. This is achieved by the structural demand model and the resulting simulated cash transfer.

To precisely estimate the policy switch, the second contribution of this paper is to allow within-household preference heterogeneity, intra-household bargaining, and price effects due to joint consumption (public goods). I first show that among older couples, husbands and wives do indeed have different preferences, and this heterogeneity highlights the importance to account for intra-household bargaining. If we do not account for that, we would underestimate households' preferences for food, which may lead policy makers to underestimate the effectiveness of cash transfer programs. Second, I show that substantial household scale economies make public goods cheaper through sharing in older couples. Analyzing substitution across goods should also account for this feature in older couples.

I use Nielsen Homescan dataset covering year 2013 - 2018. The dataset comprises a demographically-representative set of consumers that use in-home scanners to record all purchased items for every shopping trip.[5] I observe prices, quantities, and coupon usage at the barcode-level. Detailed demographic information including household composition, income, education, race, and census tract allows me to incorporate rich observed heterogeneity into the demand estimation.

One main advantage of the data is its barcode-level information, which allows me to precisely calculate household spending on specific food categories, including those that are SNAP-eligible, i.e., SNAP-eligible food. A major limitation of previous papers that study household consumption and SNAP is that the data is often too aggregate in the sense that goods are on broad categories like food, housing, etc. For example, Consumer Expenditure

[4]SNAP benefits can mainly be spent on four categories of food, including breads and cereals; fruits and vegetables; meats, fish and poultry; and dairy products.

[5]Purchases from any department stores, grocery stores, drug stores, convenience stores, and other similar retail outlets

Survey (CEX) and Panel Study of Income Dynamics (PSID) are the most commonly used dataset, both of which do not have dis-aggregated household spending information. Second, the price information leads to more accurate price elasticities estimates compared to those using a regional Consumer Price Index (Blundell, Horowitz, and Parey 2020). Rich price variation is also a prerequisite for estimating the price effects due to joint consumption in collective household models. To avoid estimating a demand system of millions of barcode-level goods, which is impossible, I aggregate goods based on categories defined by Nielsen. Namely, they are: *1)* General Merchandise, *2)* Health and Beauty, *3)* Food Grocery, *4)* Non-food Grocery.[6]

I model household consumption decisions as a Pareto efficient outcome among household members, each with their own preferences and bargaining power. Following the collective literature, I use *resource shares* (i.e., the share of total expenditures controlled by each individual household member) as a measure of each individual's relative bargaining power. I also allow goods to each be partly shared. As a result, household members decide both how much to consume of each good, and how much to share each good (i.e., the degree to which goods are public within the household).

This sharing results in consumption economies of scale. I assume older couples have consumption technologies that define the extent of public nature of expenditures through *Barten scales*. For example, food can be nonshareable because the part eaten by one member can not be eaten by another. So if two members each eat 1 unit, the household must buy 2 units. In contrast, shareable goods (or public goods) have the property that the sum of the total quantities consumed by all members is greater than the total purchased quantities. For example, many goods under General Merchandise are household appliances (e.g., hair-drier) and can be highly shareable. The implication is that the *shadow* prices of those goods will be lower than their market prices. As a result, older couples save through sharing goods. Their consumption choices on food and non-food goods will be based on shadow prices rather than market prices. This aspect is completely ignored by literature on unitary demand models.

[6] I do not model only food categories but also the three other aggregate goods for two reasons. First, the other three goods contain a substantial amount of necessities that households might substitute food with. Second, those goods also have high degrees of consumption economies of scale and hence are important in a collective household setting.

I identify individual preferences and resource shares, and household's consumption economies of scale following the methodology developed by Browning, Chiappori, and Lewbel (2013, BCL hereafter).[7] Following BCL, preferences for each are modeled using the Quadratic Almost Ideal Demand System (QAIDS) developed by Banks, Blundell, and Lebwel (1997).[8] The responses of singles and couples to variation in prices, household expenditures, and household member characteristics are used to disentangle price effects, income effects, consumption sharing, and heterogeneity in preferences.

The results of the structural model are the following: First, I find strong evidence of preference heterogeneity inside older couples. This further leads to their different responses to the SNAP-like cash transfers. Second, the mean resource share of wives is 0.66, implying that the couple's consumption decision is represented more by the wife's preference. Strong evidence of preference heterogeneity highlights the important role of bargaining power, in this case within households. I do not find spouses' bargaining power to be affected by cash transfers. It is shown by the evidence that the household total expenditure is not a significant determinant in spouses' resource shares. Third, General Merchandise has the smallest Barten scale closed to 0.5, i.e., they are highly public. Food Grocery and Health and Beauty have the largest Barten scale closed to 1, implying that they are nonshareable. Non-food Grocery's Barten scale is in between, meaning it is shareable to some extent.

After structurally estimating the collective demand model, I simulate a counterfactual experiment of a SNAP comparable cash transfer. Specifically, I select the poorest part of the sample and simulate a cash transfer with equivalent benefit size as SNAP to them.[9] I find that the wife's increase in food budget share is 0.53 percent higher than the husband's. If we ignore wives' stronger preferences for food or assume equal bargaining power, we will underestimate (at both intensive and extensive margins) older couples' response to the

[7]Early literature only identifies the change in resource shares with respect to the change in *distribution factors*, that is, factors that only affect bargaining power of household members, but do not affect preferences or budget constraint (Chiappori 1992, Browning, et al. 1994, Browning and Chiappori 1998, Chiappori et al. 2002, Chiappori and Lechene 2006). Later literature point-identifies resource shares by imposing certain preference similarity assumptions (Lewbel and Pendakur 2008, Lise and Seitz 2011, Bargain and Donni 2009 and 2012, Browning et al. 2013, and Dunbar et al. 2013, Calvi 2019). Another strand of literature applies revealed preference theory and identifies resource shares by bound (e.g., Cherchye et al. 2012a and Cherchye et al. 2017). One limitation of the above papers is that they all constrain goods to be purely public or purely private. Instead, Browning et al. (2013) allow goods to be partly jointly consumed in the collective household models.

[8]A main advantage of QAIDS over the Almost Ideal Demand System (AIDS) by Deaton and Muellbauer (1980) is that it allows the curvature of Engel curve and hence the second-order effect of income transfers.

[9]SNAP's benefit formula is the maximum allotment conditional on household size minus 30% of household income.

SNAP cash transfer. Second, I find that for the majority of older low-income households, their preferences for food are strong such that they will buy SNAP-eligible food given cash transfers. For example, among the low-income households, constrained households are policymakers' main group of interest. Their SNAP-eligible food spending in the sample is lower than the imputed cash transfers. Hence, they are most likely to spend benefits on policy undesired goods. In Nielsen data, they account for around 30% of the poor sample. When I simulate a SNAP-like cash transfer to them, I find that only 4 - 12% of them increase SNAP-eligible food spending less than the cash transfers. In other words, cash transfers do work even for those who are most likely to spend cash on policy undesired goods.

This paper is in line with a number of papers that show that intrahousehold distribution of income and decision-making power matter, i.e., the "targeting" view.[10] Rather than focusing on the "targeting" view, I emphasize how the preference heterogeneity within couples and the cheaper prices of public goods will both affect the accuracy of demand elasticities and demand responses to cash transfers. Cherchye, De Rock, and Vermuelen (2012) also estimate BCL to study the economic well-being and poverty among the elderly and find that the poverty among women seems to be heavily underestimated. I complement to this strand of literature by applying such model, for the first time, to the Homescan data.[11]

This paper is also related to Hoynes and Schanzenbach (2009) and Hasting and Shapiro (2018). Hoynes and Schanzenbach (2009) use a difference-in-difference approach by exploiting the "program introduction" across states and find that in-kind and cash transfers achieve similar outcomes. Hasting and Shapiro (2018) use a large retail Homescan data and find that the marginal propensity to consume food (MPCF) out of cash is much smaller than the MPCF out of SNAP benefits. They attribute the reason to mental accounting. I complement to the literature by testing the fundamental supporting assumption for an in-kind design. The assumption is that low-income households have different preferences

[10]For example, see Thomas (1990), Schultz (1990), Browning et al. (1994), Lundberg, Pollak, and Wales (1997), Phipps and Burton (1998), Parker and Todd (2017), Attanasio and Lechene (2014), Martinelli and Parker (2003), and Duflo (2003).

[11]Papers that also use Homescan data include Hastings and Shapiro (2018), Johnson et al. (2018), Harding and Lovenheim (2017), Allcott, Taubinsky, and Lockwood (2019), and Dubois, Griffith, and Nevo (2014).

such that they will use cash benefits to buy non-food goods, or SNAP-ineligible food. My results reject the common assumption and suggest that cash transfers can achieve the goal of SNAP to some extent. My method is a structural approach and hence the estimated increase in SNAP-eligible food spending given the cash transfers can be interpreted as the *full* propensity to consume food (FPCF) out of cash. MPCF and FPCF can differ depending on the curvature of household preferences. For example, Banks, Blundell, and Lewbel (1996) also argue that demand estimation is necessary in order to precisely assess the effect of tax policy.

Papers that also use a structural demand model to simulate counterfactual tax or transfer experiments include Dubois, Griffith, and O'Connell (2020), Bonnet and Réquillart (2012), Harding and Lovenheim (2014), and ChernoZhukov, Hausman, and Newey (2019). I complement to these literature by focusing on intra-household welfare analyses.

The rest of this paper proceeds as follows. Section 2 presents the data. Section 3 presents the household model. Section 4 shows the estimation. Section 5 shows the estimation results. Section 6 presents the counterfactual SNAP cash transfer. Section 7 concludes.

2 Nielsen Consumer Panel Dataset

I use the Nielsen Consumer Panel Dataset covering 2013 to 2018. It is made available through the Kilts Center at the University of Chicago Booth School of Business. The dataset comprises a representative panel of households in the U.S. that use in-home scanners to record all of their purchases (from any department stores, grocery stores, drug stores, convenience stores, and other similar retail outlets) intended for personal, in-home use. Nielsen maintains a dataset of current prices for stores within its metropolitan area. Given the store and date information, Nielsen links the product scanned by the household to the actual price of the store that the product was sold. Each product has a Universal Product Code (UPC).[12] I use UPC and product interchangeably in this paper.

A key advantage of this dataset is that it has store-level price information. The rich price

[12]The Universal Product Code (UPC) is a bar-code symbol that is widely used in the United States, Canada, United Kingdom, Australia, New Zealand, in Europe and other countries for tracking trade items in stores. UPC (technically refers to UPC-A) consists of 12 numeric digits, that are uniquely assigned to each trade item.

variation over time and across households allows me to precisely estimate the price elasticity and other preference parameters than is typically possible using expenditure survey data.[13] Other consumption data are often cross-sectional, like the Consumer Expenditure Surveys. The identification of preferences often relies on enough price and expenditure variation across households. Instead, the preference parameters estimated from panel data not only reflect cross-household variation but also within-household variation. Moreover, the dataset has highly disaggregated product structure (bar-code - product module - product group - department), which allows me to identify different food categories, especially the SNAP-eligible food.

Nielsen aggregates millions of UPCs into 9 departments, 6 out of which are food-related, including dairy, deli, dry grocery, fresh produce, frozen food, and packaged meat. I aggregate these 6 departments into one aggregate good, which I call "Food Grocery". It accounts for around 70 percent of the total expenditure tracked by Nielsen. The resulting four aggregate goods in the demand estimation are *1)* General Merchandise, *2)* Health and Beauty, *3)* Food Grocery, and *4)* Non-food Grocery.[14] Table A13 displays the three groups with the largest group shares under each of these four aggregate goods. I drop Alcohol due to the censoring problem. I find that alcohol comprises only a small fraction of older low-income households' expenses.

I classify SNAP-eligible food based on product taxonomy and the eligibility guidelines provided by USDA website (FNS 2017a).[15] The products under Food Grocery in Nielsen while excluded by SNAP include prepared food (ready to serve, dry mixes, and frozen), pet food, ice, and deli. The resulting expenditure on SNAP-eligible-food-to-overall-food ratio is around 80 percent. In other words, around 56 percent of the total spending goes to SNAP-eligible products.

Given the high spending on SNAP-eligible-food-to-overall-food ratio, I do not divide the

[13] Many previous papers on demand estimation use expenditure survey data like CEX and PSID. A number of recent papers use Homescan data to study nutrition inequality. These include Dubois et al. (2014), Amano (2018), Hastings and Shapiro (2018), Johnson et al. (2018), Allcott et al. (2019), and Hasting et al. (2019).

[14] Non-food Grocery include products like housekeeping supplies, smoking supplies, and pet food/services. I follow the common practice in the literature of household demand and move Tobacco from department Non-food Grocery to Food Grocery. The products under General Merchandise are normally small household electronics, such as scissors and toasters. They are less of durable goods like refrigerator or television.

[15] Hasting and Shapiro (2018) also define SNAP-eligible food in a similar way using the Nielsen Consumer Panel Dataset.

aggregate Food Grocery into SNAP-eligible and SNAP-ineligible food when I model household demand. In the counterfactual cash transfer experiment, I assume the expenditure on SNAP-eligible-food-to-overall-food ratio to be the same as in the baseline case. I then back out household counterfactual spending on SNAP-eligible food by multiplying the counterfactual food spending with the baseline expenditure on SNAP-eligible-food-to-overall-food ratio. This assumption is not strong given the evidence in Hasting, Kessler, and Shapiro (2021), who find that the effect of SNAP participation on the composition of purchased foods is small relative to the cross-sectional variation. In other words, households barely change the types of food they purchase when they participate in SNAP.

How does Nielsen Consumer Panel Dataset compare to other consumption data such as CEX or PSID? Aguiar and Hurst (2007) point out that the life-cycle pattern of household expenditures recorded in Homescan data is roughly consistent with that reported for food expenditures at home in the PSID. Appendix Table A14 shows the mapping of the four aggregate goods in this paper to the broad categories of goods in CEX. The average total food expenditures in Nielsen dataset is $6425, and that in CEX is $6066. These findings give some confidence on the coverage of products under Food Grocery in Nielsen Consumer Panel Dataset. Einav, Leibtag, and Nevo (2010) study the accuracy of price information in Nielsen and conclude that the measurement error due to sales or attrition is not significantly different from other datasets.

Nielsen does not include spending on food-away-from-home (FAFH). Even though SNAP benefits can not be spent on FAFH, SNAP can enable households to incur less out-of-pocketing spending on food-at-home and to have more money available for FAFH. However, according to the USDA, low-income households spend much less in restaurants compared to high-income households (Saksena et al. 2018). There is neither empirical evidence showing that SNAP increases households spending on FAFH.

In the Appendix, I provide details on how Nielsen tracks prices. I also discuss a number of potential data quality issues with the Homescan data. These issues include: coverage of the goods scanned by households in Nielsen and its comparison between other commonly used survey data (e.g., CEX and PSID), measurement error in prices, and sample attrition.

3 A Structural Analysis of Household Demand

In this section, I summarize a structural model of household demand to study the effects of transfer programs on household consumption later. In particular, I follow the collective framework developed by Browning, Chiappori, and Lewbel (2013, BCL) to account for preference differentials and bargaining power, as well as consumption economies of scale within households. I then discuss the identification and estimation of the model.

3.1 A Collective Model of Households

I consider households consisting of two members (for older widows and widowers living alone, their demand would be modeled by the traditional unitary approach). Let f denote the wife and m denote the husband. Let superscript i denote individual household members, h refer to households, and subscript j index goods. There are J goods in the model, i.e., $j = 1, ..., J$. Let p denote the market price vector of purchased goods. y denotes the total expenditure. Let $U^i(x^i)$ refer to member i's direct utility function over the vector of goods $x^i = (x^i_1, ..., x^i_J)$. I assume that it is monotonically increasing, continuously twice differentiable, and strictly quasi-concave.

Now consider a household that faces the budget constraint $p'z = y$. Following the standard collective household literature, the key assumption regarding decision making within the household is Pareto efficiency of outcomes. A standard result of welfare theory (see e.g., Bourguignon and Chiappori 1994) is that, given ordinality, we can without loss of generality write Pareto efficient decisions as a constrained maximization of the following program

(1) $$\max \mu U^f(x^f) + U^m(x^m) \text{ such that}$$

(2) $$x = x^f + x^m$$

$$z = Ax \tag{3}$$

$$p'z = y \tag{4}$$

Equation (1) is the weighted sum of household members' utility resulting from the Pareto efficiency assumption. μ refers to the Pareto weight of wives relative to husbands and summarizes a member's bargaining power. A higher Pareto weight implies that the household demand is represented more by that member's preferences. In general, μ can depend on prices, total expenditures, and a vector d of distribution factors (factors that only affect bargaining power but not preferences or budget constraint).[16]

The household is subject to three constraints: the constraint (equation 2) that simply says individual members' private good equivalents add up to household private good equivalents, the consumption technology function (equation 3) that relates purchased goods with consumption goods, and the budget constraint (equation 4).

A key feature of the BCL model is that it allows goods to be jointly consumed, as represented by the consumption technology function (equation 3). The household purchases some bundle of vector z, but individual consumption of household members add up to some other bundle x (equation 2), with the difference due to sharing or joint consumption of goods. I assume a linear consumption technology function such that the outputs x can be produced by z through the square diagonal matrix A. The matrix is mathematically equivalent to Gorman's (1976) linear technology (a special case of which is Barten (1964) scaling). I assume the off-diagonal elements of A to be zero (the sharing of a good does not depend on other consumption goods). The diagonal elements of A represents how much each good can be shared by itself. For example, suppose the first diagonal element of A is

[16]Possible distribution factors include individual wages (Browning et al., 1994), non-labor income (Thomas 1990), sex ratio in the marrige market, and divorce legislation (Chiappori, Fortin and Lacroix 2002), etc. For a general discussion on distribution factors, see Chiappori and Ekeland (2005).

the sharing degree of gasoline. If a couple shares the car (by riding together) 1/3 of their time, then in terms of the total distance traveled by each household member, it is as if member 1 consumed a quantity of g_1^1 of gasoline and member 2 consumed a quantity of g_1^2, where $z_1 = (2/3)(g_1^1 + g_1^2)$. The diagonal element of A for purely public good would be 1/2 while that for purely private good would be 1.

As mentioned earlier, a key assumption in the collective household literature is that the household decisions are Pareto efficient. From the second welfare theorem, any Pareto efficient outcomes can be implemented as an equilibrium of the economy, possibly after some lump sum transfers between members. Hence, the duality of the above household program can be summarized as a two-stage process. In stage one, household's total expenditure is divided between wives and husbands according to some sharing rule $\eta(p/y, d)$, which is the fraction of resources controlled by wives. d denotes "distribution factors" (factors that only affect bargaining power but not tastes or budget constraint). Husbands then enjoy $1 - \eta(p/y, d)$ fraction of resources. In stage two, each member i chooses her or his private equivalent consumption x^f or x^m to maximize her or his own utility U^i given a Lindahl (Lindahl 1958) type shadow price vector (price discounted by the degree of sharing) and resource shares. To summarize, under Pareto efficiency, there exists a shadow price π and a sharing rule η, with $0 \leq \eta \leq 1$, such that

$$\pi(p/y) = \frac{A'p}{y} \tag{5}$$

$$z = h(p/y) = Ah^f(\frac{A'p}{y}\frac{1}{\eta(p/y)}) + Ah^m(\frac{A'p}{y}\frac{1}{1-\eta(p/y)}) \tag{6}$$

Shadow price π is determined by the Barten scales matrix A and the market price p. The smaller a good's Barten scale is, the greater the sharing degree of the good, and hence the lower the shadow price. $h(p/y)^i$ is the Marshallian demand function of member i. Equation (6) says that couples' Marshallian demand is a weighted average of wives'

Marshallian demand and husband's Marshallian demand, where the weight is given by their own resource share. The Marshallian demand of each household member is obtained by maximizing their own utility function if being faced with the shadow price and shadow income (i.e., control over resources).

3.2 Identification

Given the model above, the goal here is to identify the parameters for individual members' preferences, Barten scales matrix A and resource shares η in equation (6). To do that, it requires that we know the Marshallian demand of wives $h(p/y)^f$ and that of husbands $h(p/y)^m$. Browning, Chiappori, and Lewbel (2013, BCL) propose that by combining data from singles and couples via the assumption that preferences over goods do not change when individuals form a couple, they are able to completely identify the model.

However, a potential threat to this assumption is the "selection into marriage" problem. Instead, I use older widow(er)s' preferences to represent preferences of individuals in older couples. Also, the demand system does incorporate heterogeneity in observed demographic characteristics. Conditional on those covariates, we assume that older widow(er)s and individuals in couples have similar unobserved tastes. A supportive evidence is that these two groups of households have similar demographic characteristics and budget share allocations for the four goods. Another concern is that married couples likely engage in different activities (e.g., dine-out and travelling) than singles. Even though Nielsen does not have information on dining-out or travelling expenses, the evidence from the Consumer Expenditure Survey suggests that non-food expenditures decrease dramatically after aging while food constitutes a large fraction of older households' budget (Figure A4). I also allow preference shifters in the demand of older couples and do not find the results to be affected by it.

Previous literature on collective households exploit different ways to weaken the assumption. For example, Dunbar, Lewbel, and Pendakur (2013) use an Engel curve approach and impose a weaker preference similarity assumption. Mainly, they assume that either preferences are similar across types (men, women, and children) within households, or preferences are similar across people in different households. However, they can only identify resource shares but not Barten scales. That is, they do not identify cost savings in multi-person households. Another strand of literature applies revealed preference theory and identifies resource shares by bound (Cherchye et al. 2012a and Cherchye et al. 2017). However, they also constrain goods to be purely public or purely private. As Nielsen has rich price variation and many goods are shareable to different extent, exploiting the shadow prices of different goods is very interesting and important in demand analysis. This kind of analysis is also rare in the literature using scanner-type data.

4 Estimation

In this subsection, I summarize the estimation of the collective household model presented in the previous section. In particular, I discuss the construction of aggregate price indices and the instrument for price, the functional form chosen for budget shares for individuals and its estimators, and the estimation of the joint model. I proceed to present the empirical results in the next section.

4.1 Prices

The price observed in the dataset is at UPC level while the goods in the demand estimation is at aggregate goods level (there are four aggregate goods in total). I construct price indices for each of the four aggregate goods. I follow Banks, Blundell, and Lewbel (1997) to construct Stone Price Indices for each aggregate goods.

I first calculate the unit price for each product (UPC) by dividing the coupon-subtracted total price paid by the quantity. I then construct price indices for the four aggregate goods by using household-specific product-level prices. One challenge is that households did not purchase every UPC, either were all UPCs available in each state. If I ignore this fact and simply aggregate prices from the UPC level to the aggregate good level using the Stone Price Indices, I would end up with many households having zero or missing budget shares of products, and that is not allowed by Stone Price Indices. To deal with that, I utilize the multi-level product hierarchy in Nielsen (that is, UPC - product group - product module - department). Instead of aggregating from UPCs to aggregate goods, I first calculate the household yearly average price of product groups and then aggregate price from groups to aggregate goods. If a household does not purchase any products in a product group during a year, I use the average price of that group faced by other households who also live in the state that the household lives in to impute the price faced by this household for that group in that year. Ideally, to accurately reflect the price faced by a particular household, the weight for each product group in the Stone Price Indices should be the household's own budget share for that group. However, the more precise the weight is reflecting a household's choice of groups, the more likely that the price would be correlated with household unobserved heterogeneity in the demand equation. One common solution is to use nation-level expenditure shares as weights for product groups (Amano 2018). However, budget shares at the nation-level might also suffer from having not enough variation in the choice of product groups across households. As a middle ground, I choose the state-level expenditure share as weights. This construction mitigates the endogeneity problem while still reserving enough variation in households' tastes.

I formalize the above discussions by equations below. Let t denote purchase date, yr denote year, s denote state, g denote product group, and u denote UPC, I calculate the household average price per group $p_{g,h,yr}$ in year yr as

$$p_{g,h,yr} = \sum_{u \in g, t \in yr} \frac{total\ price\ paid_{u,h,t} - coupon_{u,h,t}}{quantity_{u,h,t}} \tag{7}$$

If a household does not purchase any products within a group, the imputed group price for this household is defined as

$$p_{g,h,yr} = \sum_{u \in g, t \in yr, h' \in s(h)} \frac{total\ price\ paid_{u,h',t} - coupon_{u,h',t}}{quantity_{u,h',t}} \tag{8}$$

where $s(h)$ is the state that household h lives in. h' is the other households that also live in the state $s(h)$ that household h lives in.

The yearly Stone Price Indices for an aggregate good c is defined as

$$SPI_{c,h,yr} = \sum_{g \in c} share_{g,s(h),yr} \times \log(p_{g,h,yr}) \tag{9}$$

where $share_{g,s(h),yr}$ is the state-level average budget share of a product group out of its corresponding aggregate good c among all the households who live in state $s(h)$. It is defined as below

$$share_{g,s(h),yr} = \frac{1}{H} \sum_{h \in s(h)} \frac{\sum_{h \in s(h), u \in g}(total\ price\ paid_{u,h,yr} - coupon_{u,h,yr})}{\sum_{h \in s(h), u' \in c}(total\ price\ paid_{u',h,yr} - coupon_{u',h,yr})} \tag{10}$$

where H is the total number of households that purchased at least one item in product group g in state $s(h)$.

Prices could be endogenous in the estimation of the demand function because the error term in the demand equation can have unobserved household tastes that are correlated with prices. For example, consumers might have different preferences in terms of stores at which they shop. The prices at a high-end supermarket will be different from the prices at a low-end supermarket. To account for this potential endogeneity, I use the "leave out" average prices paid for each product groups as instrument variables. Specifically, for each household i, the instrument of $p_{g,h,yr}$ will be calculated in the same way as in equations (7) and (8), but only for the households living in other counties that are in the same state in which household h lives in. The implicit assumption is that the unobserved preferences are not correlated across different markets (defined by counties). The "leave out" price for a group of a household is defined as

$$\pi_{g,h,yr} = \frac{1}{k} \sum_{h' \in H'} p_{g,h',yr} \tag{11}$$

where H' is the set of households that live in the same state $s(h)$ but different markets (counties) as household h lives in, and k is the number of elements of H'.

4.2 Budget Shares for Individuals

I specify individuals preferences using the $QAIDS$ demand system of Banks, Blundell, and Lewbel (1997).[17] Let p denote the J-vector of price indices of the aggregate consumption goods. I have $J = 4$ goods in total. Let y denote total expenditures. Let h index a household and let i denote a household member. The household member types are $i = f$ for women and $i = m$ for men. For member i of household h,let ω^{hi} denote the J-vector of budget shares ω_j^{hi} for $j = 1, ..., J$. Notice that we only observe budget shares ω_j^{hi} for households with only one member, that is, older widows and widowers living alone in this paper (this is because for members living alone their observed purchased budget shares are equivalent to the shares consumed by themselves).

The $QAIDS$ demand equation for an individual of type i living in a household h takes the J-vector form

$$\omega^{hi}(\frac{p}{y}) = \alpha^{hi} + \Gamma^i \text{ln}(p) + \beta^{hi}[\text{ln}(y) - c^{hi}(p)] + \frac{\lambda^i}{b^{hi}(p)}[\text{ln}(y) - c^{hi}(p)]^2 \tag{12}$$

where $b^{hi}(p)$ and $c^{hi}(p)$ are price indices defined as

$$\text{ln}[b^{hi}(p)] = (\text{ln}p)'\beta^{hi} \tag{13}$$

$$c^{hi}(p) = \delta_0^{hi} + (\text{ln}p)'\alpha^{hi} + \frac{1}{2}(\text{ln}p)'\Gamma^i\text{ln}p \tag{14}$$

[17] Browning, Chiappori, and Lewbel (2013, BCL) proves identification of the collective household model for the popular Almost Ideal and Quadratic Almost Ideal demand system. I focus on four aggregate goods and QAIDS is ideal for such demand analysis.

Here, α^{hi}, β^{hi}, and λ^{i} are J-vector preference parameters, Γ^{i} is $J \times J$ preference parameters. δ_0^{hi} is a scalar parameter which we set to equal to zero based on the insensitivity reported in Banks, Bluendell, and Lewbel (1997). By definition, budget shares must add up to one, i.e., $\mathbf{1}'_J\omega^{hi} = 1$ for all p/y where $\mathbf{1}_J$ is an J-vector of ones. This in turn, implies that $\mathbf{1}'_J\alpha^{hi} = 1$ and $\mathbf{1}'_J\beta^{hi} = \mathbf{1}'_J\lambda^{hi} = 0$ and $\Gamma^{i\prime}\mathbf{1}_J = \mathbf{0}_J$.

$\mathbf{0}_J$ is an J-vector of zeros. Slutsky symmetry requires that Γ^{i} be a symmetric matrix.

I allow observable preference heterogeneity in α^{hi} and β^{hi} by letting them to depend on demographic variables. The equation of α^{hi} is written as below

$$\alpha^{hi} = \alpha_0^i + \sum_{m=1}^{M_\alpha} \alpha_m^i d_{m,\alpha}^{hi} \tag{15}$$

$$\beta^{hi} = \beta_0^i + \sum_{m=1}^{M_\beta} \beta_m^i d_{m,\beta}^{hi} \tag{16}$$

where $d_{m,\alpha}^{hi}$ and $d_{m,\beta}^{hi}$ are observed demographic characteristics, and M_α and M_β are the total number of such covariates I observe. Each α^{hi} and α^{hi} is a J-vector, which from the above adding-up condition must satisfy $\mathbf{1}'_J\alpha_0^i = 1$, $\mathbf{1}'_J\alpha_m^i = 0$ for $m = 1, ..., M_\alpha$, and $\mathbf{1}'_J\beta_m^i = 0$ for $m = 1, ..., M_\beta$.

In the application, $d_{m,\alpha}^{hi}$ includes eight indicator variables for different regions, an indicator variable for Black/African American, an indicator variable for some college education, making $M_\alpha = 10$.[18] $d_{m,\beta}^{hi}$ includes an indicator variable for kitchen appliances (microwave, garbage disposal, and dishwasher owner) ownership and Internet ownership, so $M_\beta = 2$. I include these facilities ownership variables because I expect effect of total expenditures on budget shares can depend on households facilities ownership. For example, BCL include a car ownership indicator, which is not available in Nielsen. I also try including year fixed

[18] I do not include some intuitive demographic variables like age because I only focus on the elderly and Nielsen only has age information in bins. I include those who are "55 - 65" or "65 or above". I also exclude employment status as a preference shifters but include "Female unemployed" and "Male unemployed" as indicator variables in the sharing rule. I assume that these employment status variables are distribution factors but not preference shifters. This is very common practice in the collective household literature. I only include an indicator variable for "some college education" because 98 percent of the older widows and widowers graduated high school or above. 70 - 80 percent of them have some college education.

effects but the results are not significant. Since the model is complex and the estimation is challenging, I do not include them in my final estimation.

Taken together, I have 18 preference parameters for each of $J-1=3$ distinct equations, yielding a total of 54 preference parameters for each type of individual i. Note that for older couples, we will have additional parameters associated with Barten scales and resource shares.

4.3 The Estimator for Older Widows and Widowers

The demand functions for households h consisting of only one member i are given by equation (12). Such households will either have $i=f$ if the household is a female living alone or have $i=m$ if the household is a male living alone. In this subsection, I describe how the demand functions of older widows and widowers living alone are estimated. The demand functions and associated estimators for older couples are given in the next subsection.

For households consisting of only one member, I append a J-vector valued error term U^{hi} (consisting of elements U_j^{hi} to equation 12). This introduces unobserved heterogeneity in widows' and widowers' demand equations. I assume the error vectors U^{hi} are uncorrelated across households. Due to the adding-up condition $\mathbf{1}'_J\alpha_0^i=1$, there must exist nonzero correlations across elements of U^{hi}, that is, across goods j within households. I estimate older widows' and widowers' demand equations using GMM, allowing for arbitrary correlations in the error terms across goods.

Let $u_j^{hi}(\theta^i)$ denote ω_j^{hi} minus the right hand side of equation (12), where θ^i is the vector of all the parameters in that equation. Note that $u_j^{hi}(\theta^i)$ is simply a function of ω_j^{hi} and all the regressors in the model. The moment condition for GMM estimation is $E(u_j^{hi}(\theta^i)\tau^{hi})=0$, where τ^{hi} is the vector of covariates defined below. To implement the adding-up constraints, I follow the common practice in demand estimation and drop one good or equation, and then recover the parameters for that good or equation using the adding-up condition. The choice of good or equation to drop is numerically irrelevant because the adding-up condition implies that the parameters of that good or equation are deterministic functions of parameters in the remaining equations. The full set of moments used in estimation are $E(u_j^{hi}(\theta^i)\tau^{hi})=0$

for $j = 1, ..., J$. Let U^{hi} be the $J-1$-vector of elements $u_j^{hi}, j = 1, ..., J$. These moments can be equivalently written as $E((I_{J-1}\tau^{hi}) \otimes U^{hi}(\theta^i)) = 0$.

The full set of covariates τ^{hi} for households consisting of all demographic variables mentioned in Section 4.2, log relative prices plus log real total expenditure (defined as the log of total expenditures divided by a Stone price Indices computed for the three non-durable goods), its square, and its interaction with the indicator variables of facilities ownership.[19] The number of moments therefore consist of $J-1 = 3$ distinct demand equations times the number of elements in τ^{hi}, which is 20, for a total of 60 moments for $i = f$ and for $i = m$.

I apply GMM for estimation separately for older widows and widowers. For $i = f$ and $i = m$, let H^i denote the set of households that consist only one member and let n^i denote the number of elements of H^i. The sample moment conditions for GMM estimation is given by

$$v^i(\theta^i) = \frac{1}{n^i}\sum_{h\in H^i}(I_{J-1}\tau^{hi}) \otimes U^{hi}(\theta^i) \tag{17}$$

The GMM criterion is then

$$\min_{\theta_i}(v^i(\theta^i)'W^i v^i(\theta^i)) \tag{18}$$

where W^i is the weighting matrix. I apply standard two step GMM, where W^i is an estimate of the efficient GMM weighting matrix, given by

$$W^i = (\sum_{h\in H^i}(I_{J-1} \otimes \tau^{hi})u^{hi}(\widetilde{\theta^i})u^{hi}(\widetilde{\theta^i})'(I_{J-1} \otimes \tau^{hi}))^{-1} \tag{19}$$

where $\widetilde{\theta^i} = \arg\min_{\theta^i} v^i(\theta^i)'v^i(\theta^i)$.

[19]The covariates and interaction terms are chosen following BCL.

4.4 The Joint Model

For the empirical application of the joint model, I assume that older widows and widowers have the demand equations described in the previous section. For households of older couples, I assume a Barten type consumption technology function defined as

$$z_j = A_j x_j \tag{20}$$

The implied shadow price for this technology is

$$\pi_j = \frac{A_j p_j}{y} \tag{21}$$

where p is the market price faced by a household and y is the total expenditure of the household.

Browning et al. (2013) prove the generic identification of Barten scales and the sharing rule. In the empirical application, the wife's resource shares are parametrically estimated with the functional form

$$\eta^f = \frac{\exp(s'\delta + q'\sigma)}{1 + \exp(s'\delta + q'\sigma)} \tag{22}$$

and the husband's resource share is simply $1 - \eta$. d and q denote distribution factors and preference covariates, with δ and σ being the corresponding coefficient vectors. The logistic form bounds the resource share between 0 and 1. If none of the distribution factors or preference covariates are significant, then the resource share of wives will be 0.5. The distribution factors are chosen such that they affect bargaining power but not the preferences. The distribution factor candidates include difference in age between wives and husband and an indicator variable that the education of the female head is higher than that of the male head. The preference covariates include an indicator variable for some college education for the female and male each, an indicator variable for Black or African American, indicator variables for facilities ownership, and log real total expenditure.

With the consumption technology function (20) and the corresponding shadow prices (21), and the sharing rule (22), I end up with the following simple expression for the demand for households of older couples

$$\omega_j(p/y) = \eta\omega_j^f(\frac{\pi}{\eta}) + (1-\eta)\omega_j^m(\frac{\pi}{1-\eta}) \tag{23}$$

where ω_j^f and ω_j^m are the female head's and the male head's demand functions, estimated using equations (12) to (14).

The above equation shows that given the Barten-type consumption technology and the sharing rule, the demand functions for older couples are a weighted average of the budget shares of its members, where the weight is given by the member's resource share. The resource share here is an indirect measure of the member's bargaining power. It also represents to what extent the household's demand is represented by the member's preferences, when evaluated at the shadow prices.

The baseline parameters of the joint model consist of the $QAIDS$ parameters for the widows' and widowers' budget shares, ω_j^f and ω_j^m, distribution factors and preference factors of the sharing rule, and 4 parameters of the Barten scales. I adopt the one-step procedure by estimating the preference parameters of the widows and widowers jointly with the Barten scales and the sharing rule.[20] I have 102 preference parameters ($18 \times 3 - 3 = 51$ symmetry constrained $QAIDS$ parameters for each of older widows and widowers), 4 Barten scales parameters, and 9 sharing rule parameters, giving a total of 115 parameters to estimate. I have 183 instruments (for each of the three goods there are 20 instruments for each of older widows and widowersand 21 instruments for older couples), giving a maximum degrees of freedom of 68 of the most general model.

The joint model is estimated by GMM using the following criterion

[20] According to Browning et al. (2013), there are two options for estimation. One is a two-step estimator, where we first estimate the preference parameters using singles and then plug them into equation (6) to estimate the Barten scales and sharing parameters. The other option is the one-step estimator. Browning et al. (2013) found that the two-step procedure constantly gave a much worse fit than the one-step.

$$(24) \qquad \min_{\theta}(v^c(\theta)'W^c v^c(\theta) + v^f(\theta)'W^f v^f(\theta) + v^m(\theta)'W^m v^m(\theta))$$

where c denote households of older couples, θ denote the full set of parameter values, and W^m and W^f are taken from $QAIDS$ in the previous section. The weighting matrix W^c for the older couples is derived by using a two stage GMM for the full system, starting with an identity matrix.

5 Empirical Results

In this section, I present the empirical results including the estimates for resource shares and Barten scales. I then conduct a counterfactual experiment of a cash transfer with equivalent benefit size as SNAP.

The elderly defined by SNAP are those who are 60 and above. However, the age bins for older adults in the Nielsen Consumer Panel Dataset only include "55 - 64" and "65 and above". Hence, I choose "55 and above" to be the criteria for the elderly. I use marital status to choose widows and widowers. To mitigate the possible effects of outliers, I further trim the three samples with respect to yearly budget share of each aggregate good and log yearly total expenditure by dropping observations in the lower and upper 2 percentiles. Table 1 shows the summary statistics of the sample studied.

To illustrate the differences in demands of older widows, widowers, and couples, Figure A5 presents fitted demand (Engel curve) plots for the four goods, with total expenditures y ranging from the 1st to the 99th percentile. I shift the plots for older couples to the left in these figures to make them comparable to the widows' and widowers' plots. Across all three samples, health and beauty and food grocery are necessities while general merchandise is a luxury good. Non-food grocery is a luxury good at low expenditures level and becomes a necessity at high expenditures level. The elasticity estimates of older widows and widowers are reported in Table A1.

The main results for the joint model are displayed in Table 2. The first row shows that

Table 1: Demographic Characteristics

	Older Widows	Older Widowers	Older Couples
Number of unique households	11,906	4,395	20,735
Household income	36782.95	42662.64	61249.52
Total expenditures from trip data	4515.09	4152.87	7300.90
Total expenditures from purchase data	3244.10	3043.51	7300.90
Budget share (health&beauty)	0.13	0.09	0.12
Budget share (general merchandise)	0.14	0.13	0.13
Budget share (food grocery)	0.64	0.70	0.66
Budget share (non-food grocery)	0.09	0.06	0.08
Yearly SNAP-eligible food spending	1568.26	1568.61	2746.28
Spending on SNAP-eligible-food-to-overall-food ratio	0.76	0.75	0.79
Female head age	68.11	-	66.19
Male head age	-	66.93	68.56
Female education: graduated high school or above	0.98	-	0.98
Female education: some college or above	0.72	-	0.65
Male education: graduated high school or above	-	0.98	0.95
Male education: some college or above	-	0.79	0.67
Microwave, Dishwasher, & Garbage Disposal	0.11	0.11	0.11
Regular & Pay Cable	0.81	0.75	0.85
Internet connection	0.89	0.89	0.96
Obs	37,262	14,318	67,317

Notes: Values are mean. Observations are by household and year. Household income in the Nielsen Consumer Panel Dataset is in ranges and I take the middle value of each range. Total expenditures from the trip data is the total expenditure that appears at the bottom of each shopping trip receipt. Total expenditures from the purchase data is the author calculated total expenditure by summing up the expenditure of each scanned items. Total expenditures from the purchase data is smaller or equal to that from the trip data due to missing scanned items or items being eaten on the way home. Budget shares are calculated as the total expenditures of each aggregate good divided by total yearly expenditure from the purchase data.

the mean value of wives' resource share is 0.66. This result suggests that older couples' preferences are represented more by wives' preferences. The results are also consistent with that from previous studies, which normally find women have higher resource shares in western developed countries (Cherchye et al. 2012b, Browning et al. 2013, and Wewel 2017).

Table 2: The Sharing Rule Parameters and Barten Scales

Mean wife's resource share	0.66	
Panel A: The Sharing Rule	coef	std error
Constant	0.51	(0.39)
Female unemployed	-0.05	(0.09)
Male unemployed	-0.20	(0.07)
Female some college education	0.25	(1.01)
Male some college education	0.22	(1.06)
Difference in age (female - male)	-0.03	(0.16)
Panel B: Estimates of Barten Scales	coef	std error
General Merchandise	0.71	(0.03)
Food Grocery	0.91	(0.05)
Non-food Grocery	0.89	(0.05)
Health & Beauty	0.83	(0.04)

Notes: The first line displays the mean wife's resource share across the entire sample. Panel A displays the sharing rule, that is, the estimates of the covariates that affect the wife's resource share. Panel B displays Barten Scales, which are assumed to be homogeneous across all households.

Panel A in Table 2 reports the estimates of the sharing rule parameters. The employment status of men turns out to have a large impact on women's resource shares. On average, the resource share of wives whose husbands are unemployed is 20 percent lower than those whose husbands are employed.[21]

Panel B in Table 2 shows the Barten scales of the four aggregate goods. Barten scales range between 0.5 and 1, where 0.5 implies a good to be purely public and 1 implies a good to be purely private. I find that food and non-food grocery are the least public, health and beauty is public to some extent, and general merchandise is the most public. The estimated Barten scale of food is consistent with that from previous literature (e.g., 0.77 in Browning et al. 2013 and 0.994 in Cherchye et al. 2012b). The estimated Barten scale

[21]This is not the same as saying women who are unemployed tend to have lower resource shares compared to men. Instead, it is saying that women, regardless of her work status, have higher resource shares when their husbands are employed.

of General Merchandise is intuitive because General Merchandise is mainly composed of household appliances and small electronics, both of which are highly public.

Another important question is whether resource shares are affected by household total expenditures. If it does, then a cash or in-kind transfer will also change men's and women's resource shares and hence their bargaining power. To test this hypothesis, I include log real total expenditure as another sharing rule covariate in the joint model. The results are reported in Table A2. I find that log real total expenditure does not significantly affect wives' resource shares. This result is consistent with findings from previous literature (e.g., Menon et al. 2012 and Dunbar et al. 2013). Hence, I keep the wife' resource share as 0.66 in the SNAP cash transfer experiment.

One important question is how valuable it is to use a collective framework, as opposed to a unitary model, to study household food spending. The most straightforward answer is which model fits the data better. I compare the demand estimates using the collective household approach with the unitary approach, that is, estimate QAIDS for females, males, and couples. The goal is to select the model most consistent with the data among non-nested competing models. I use the non-nested testing procedure proposed by Smith (1992).[22] The resulting Cox-type statistics is 0.0098. Hence, the collective demand model is not rejected.

Robustness Checks From Table 1, the household income of older widows is lower than that of Older Widowers and couples. This might challenge the preference similarity assumption between older widows and older wives. As another robustness check, I drop older female households whose income was below \$ 20,000. This gives me similar average household income between older widows and widowers. I then re-estimate the joint model. The resulting elasticity estimates for older widows and widowers sample are similar to the baseline elasticity estimates.

Another concern is that how different husbands' and wives' preferences are? If they are not that different, then we do not need to employ the collective household approach. To answer this question, I estimate the model constraining men and women to have the same

[22] In particular, the Cox-type statistics is constructed by examining the difference of the estimated GMM criterion functions for the collective demand model M_c and for the alternative unitary demand model M_u. Normalized, standardized, and compared to a standard normal critical value, a large positive statistic in this one-sided goodness-of-fit test leads to the rejection of the null model M_c against M_u.

tastes, and then do a minimum Chi-squared test on the resulting constrained model to get a test statistic. The resulting statistic is much larger than the critical value and hence I reject the constrained model (the assumption of same tastes).

6 A SNAP-like Cash Transfer

Given the estimates of men's and women's preferences, the resource shares, and Barten scales, I next perform a counterfactual experiment of a cash transfer that has equal benefit size as the current SNAP program to low-income households.

I choose households who have net monthly income at 100 percent (or gross income at 130 percent) of the federal poverty line. This is also the eligibility criteria of SNAP. I follow the benefit formula (equation 25) of SNAP to impute the benefit amount for these households if they participate in SNAP. For more details about SNAP, please see Appendix section 2.

$$\text{Benefits} = \text{maximum allotment} - 30\% * (\text{gross income} - \text{deductions}) \tag{25}$$

The resulting sample of low-income older households and their summary statistics are reported in Table 3. The fraction of low-income households among older widows, widowers, and couples is 29 percent, 25 percent, and 13 percent, respectively. This implies that widows are in general poorer than widowers, and both widows and widowers are poorer than couples. The percentages are consistent with estimates from previous literature, e.g., Johnson et al. (2018) using Panel Study of Income Dynamics (PSID) data from 1977 to 2013. The income and expenditure characteristics of the low-income sample are also similar to previous findings.

Comparing Table 3 to Table 1, I find no significant differences in demographic characteristics between the low-income sample and the entire sample, except that the former has lower household income. In particular, the budget shares on the four aggregate goods and the spending on SNAP-eligible-food-to-overall-food ratio (around 80 percent) are similar between low-income households and the entire sample. As budget shares can reflect household tastes, this is the first evidence that low-income and high-income older households have similar preferences over the four aggregate goods and over SNAP-eligible food.

Another sample of households that attracts policy makers' interest is the so-called constrained households. These are the households whose SNAP-eligible food spending is lower than their potential SNAP benefits if they participate. They are likely to spend SNAP benefits on other policy undesired goods if they are given cash. Given the bar-code level spending information, I calculate household spending on SNAP-eligible food (e.g., SNAP-eligible food spending) and hence the fraction of constrained households. Table A4 reports their summary statistics. The fraction of constrained households for older widows, widowers, and couples is 29 percent, 29 percent, and 24 percent, respectively.[23] Comparing constrained to unconstrained households, I find that they have similar budget shares on aggregate goods and SNAP-eligible food. This finding directly rejects the hypothesis that constrained households are more likely to spend SNAP benefits, if given in cash, on policy undesired goods. Instead, they have similar preferences as unconstrained households or high-income households.

I further look at household spending on more dis-aggregated food categories and group them into "healthier foods", "SNAP-ineligible foods", and sugar-sweetened beverages following the method by Hoynes et al. (2015).[24] I compare the spending patterns on these goods between low-income and high-income households. The results are reported in Table A5. Again, they look very similar. This finding is also consistent with what has been found in Hoynes et al. (2015), who argue that SNAP participants or households eligible for SNAP are not overall more addicted to unhealthier foods or sugar-sweetened beverages.

In summary, the findings above provide suggestive evidence that low-income and high-income older households do not have different preferences, no matter on the more aggregated

[23]These numbers are similar to what has been found in previous literature. For example, Hoynes et al. (2015) find that 30 percent of SNAP recipients in CEX are constrained. I find that constrained households have lower household income and total expenditures than unconstrained households. This is also consistent with previous finding (e.g., Johnson et al. 2018).

[24]Notice that not all SNAP-eligible food are healthy because sugar sweetened beverages are also SNAP-eligible. The "healthier foods" category includes bread, poultry, fish and shellfish, eggs, milk, cheese, other non-ice cream dairy foods, fruit (excluding juice), vegetables, dried fruit, nuts, prepared salads and baby food. The "SNAP-ineligible foods" category comprises ice cream, candy, gum, hot dogs, potato chips and other snacks, and bakery goods and prepared desserts such as cakes, cupcakes, doughnuts, pies, and tarts. The sugar-sweetened beverages group includes colas, other carbonated drinks, and non-carbonated fruit-flavored and sports drinks.

Table 3: **Summary Statistics for Low-Income Households**

	Low-Income Older Widows	Low-Income Older Widowers	Low-Income Older Couples
Number of unique households	3,395	1,108	2,592
Household income	13656.07	12484.59	17860.60
Total expenditures from trip data	4113.51	3655.65	6527.93
Total expenditures from purchase data	3038.82	2753.49	4800.66
Budget share (health&beauty)	0.12	0.08	0.11
Budget share (general merchandise)	0.12	0.11	0.12
Budget share (food grocery)	0.67	0.73	0.68
Budget share (non-food grocery)	0.09	0.06	0.08
SNAP-eligible food spending	1522.99	1465.82	2505.67
Spending on SNAP-eligible-food-to-overall-food ratio	0.76	0.74	0.78
Female head age	69.03	-	67.00
Male head age	-	66.49	69.64
Female education: graduated high school or above	0.96	-	0.93
Female education: some college or above	0.57	-	0.45
Male education: graduated high school or above	-	0.96	0.85
Male education: some college or above	-	0.69	0.44
Microwave, Dishwasher, & Garbage Disposal	0.06	0.06	0.07
Regular & Pay Cable	0.74	0.62	0.76
Internet connection	0.83	0.84	0.90
Obs	8,014	2,845	5,342

Notes: Values are mean. Observations are by household and year. Household income in the Nielsen Consumer Panel Dataset is in ranges and I take the middle value of each range. Total expenditures from the trip data is the total expenditure that appears at the bottom of each shopping trip receipt. Total expenditures from the purchase data is the author calculated total expenditure by summing up the expenditure of each scanned items. Total expenditures from the purchase data is smaller or equal to that from the trip data due to missing scanned items or items being eaten on the way home. Budget shares are calculated as the total expenditures of each aggregate good divided by total yearly expenditure from the purchase data.

level goods, or more dis-aggregated level of specific food categories. I proceed to simulate a counterfactual exercise of an income transfer with equivalent benefit size as SNAP.

6.1 Counterfactual Budget Shares

Given the sample of low-income households, I conduct a counterfactual experiment of a cash transfer with SNAP-equivalent benefit size to them. To do that, I add the imputed benefits to the total expenditure of low-income households. The predicted expenditure shares of eligible widows and widowers are given by

$$\hat{\omega^i}(\frac{p^h}{y^h+b}) = \hat{\alpha^i} + \hat{\gamma^i}\ln p^h + \hat{\beta^i}[\ln(y^h+b) - \hat{c^i}(p^h)] + \frac{\hat{\lambda^i}}{\hat{b^i}(p^h)}[\ln(y^h+b) - c^i(p^h)]^2 \tag{26}$$

where b is the amount of benefits.

The predicted expenditure shares of eligible couples are given by

$$\hat{\omega}_j(\frac{p^h}{y^h+b}) = \hat{\eta}\hat{\omega}_j{}^f(\frac{\pi}{\hat{\eta}}) + (1-\hat{\eta})\hat{\omega}_j{}^m(\frac{\pi}{1-\hat{\eta}}) \tag{27}$$

where $\pi = \frac{Ap}{y^h+b}$.

6.2 Counterfactual Results for Older Couples

To highlight the importance of the collective approach, I compare the counterfactual results under unequal sharing with equal sharing, that is, whether we assume wives have resource share (bargaining power) of 0.66 or 0.5. The comparison is reported in Table A6. Under unequal sharing (wives' resource share = 0.66), older couples increase budget shares on food and non-food grocery while decrease budget shares on general merchandise and health and beauty. If we assume equal sharing (wives' resource share = 0.5), older couples increase budget shares on food and general merchandise while decrease budget shares on non-food grocery and healthy and beauty. The biggest difference in result between assuming equal and unequal sharing lies on the change in budget shares on non-food grocery, where we get completely opposite sign of the change. Moreover, assuming equal sharing also leads to a small underestimate of the increase in budget shares on food. Tables A7 and A8 report the predicted budget shares for wives and husbands if we assume that they live by themselves while still enjoying the shadow prices and resource shares in households. I find that wives increase food budget shares more than husbands. Hence, wives' higher bargaining power and stronger preferences for SNAP-eligible food have a great impact on older couples' overall food demand.

I further divide the low-income older couples into two groups: constrained and unconstrained households. The former group is those whose SNAP-eligible food spending is below my imputed cash benefits for them. They are mostly likely to spend cash on non-food goods and are the main target of an in-kind design. They constitute one fourth of the low-income older couples. Their household income is at lower bottom percentiles among all low-income households. In other words, they are the poorest sample in the data. Their spending on

SNAP-eligible food is also lower than that of the unconstrained households. I use this counterfactual exercise to test whether cash transfers can increase their SNAP-eligible food spending more than the transfer itself.

The results are reported in Table 4. Panel A shows that different from the common hypothesis, constrained households increase food budget shares by 2.97%, while unconstrained households decrease budget shares on food slightly. More specifically, constrained households increase budget shares on food and non-food grocery while decrease that on more luxury goods like general merchandise and healthy and beauty. In the contrast, unconstrained households increase spending on general merchandise by 5.6%. These findings suggest that constrained households do have strong preferences for food and when they are given cash, they will spend on SNAP-eligible food.

Panel B of Table 4 shows the full propensity to consume (FPC) SNAP-eligible food out of SNAP benefits. It is calculated as the change in SNAP-eligible food spending divided by the cash benefits. The FPC SNAP-eligible food out of SNAP benefits is 0.57 for constrained older couples. It means that if we give $100 cash to the constrained older couples, they will spend $57 on SNAP-eligible food. The FPC SNAP-eligible food out of SNAP benefits is 0.55 for unconstrained older couples. In other words, the propensities are very similar between the two groups.

Only around 20 percent of the constrained households increase SNAP-eligible food spending less than the imputed cash transfer. They can be thought of as the so-called *extra-marginal* households. However, their spending on SNAP-eligible-food-to-SNAP-benefits ratio is 80 to 90 percent, which is very high. In other words, the SNAP vouchers might only induce these 20 percent of constrained households to increase their spending on SNAP-eligible-food-to-SNAP-benefits ratio to 100 percent or above. Of course, SNAP vouchers might induce households to spend more on SNAP-eligible food than cash due to mental accounting etc (Hasting and Shapiro 2018). But the finding here points out that an easier cash transfer can achieve the goal of SNAP to a large extent.

Table 4: Counterfactual Results for Constrained and Unconstrained Older Couples

	Constrained Older Couples			Unconstrained Older Couples		
Panel A: Changes in Budget Shares	Baseline Budget Shares	Counterfactual Budget Shares	% change	Baseline Budget Shares	Counterfactual Budget Shares	% change
General merchandise	0.119	0.108	-9.56%	0.125	0.132	5.60%
Food grocery	0.683	0.703	2.97%	0.680	0.675	-0.74%
Non-food grocery	0.086	0.087	1.63%	0.082	0.084	1.70%
Health & beauty	0.112	0.102	-9.07%	0.113	0.109	-3.11%
Panel B: Full Propensity to Consume (FPC) SNAP-eligible Food out of SNAP Benefits	Mean			Mean		
Imputed SNAP benefits	3250			531.43		
Baseline food expenditure	2639			3,320.10		
Counterfactual food expenditure	5040			3,704.90		
Increase in food expenditure	2401			384.80		
FPC food out of SNAP benefits	0.74			0.72		
Baseline spending on SNAP-eligible-food-to-overall-food ratio	0.78			0.77		
FPC SNAP-eligible food out of SNAP benefits	0.57			0.55		
Number of Extra-marginal Households	218			0		
Obs	1069			4273		

Notes: Values are in mean. Constrained households are defined as those whose baseline SNAP-eligible food spending in Homescan data is lower than my imputed cash benefits for them using the SNAP benefit formula. The full propensity to consume (FPC) food out of cash is calculated as the increase in food expenditures divided by cash transfers. The FPC SNAP-eligible food out of benefits is calculated as the FPC food out of cash transfers multiplied by households' spending on SNAP-eligible-food-to-overall-food ratio.

6.3 Counterfactual Results for Older Widow(er)s

Table A9 and A11 show the counterfactual results for older widows and widowers. Both of them decrease budget shares on general merchandise and health and beauty. older widows increase food budget shares by 2.06 %, slightly more than that of widowers (1.37%).

Table A10 and A12 report the FPC SNAP-eligible food out of SNAP benefits for constrained and unconstrained older widows and widowers. The number is 0.55 for widows and 0.61 for widowers. It means that households will spend \$55 to \$61 on SNAP-eligible food when they are given \$100 cash. There is no large difference between constrained and unconstrained widow(er)s.

The fraction of extra-marginal households is 24 percent for widows and 20 percent for widowers. Figure A6 shows that similar to older couples, the majority of these households have SNAP-eligible food spending increased by over 80 - 90 percent of the imputed cash benefit. The results suggest that even among older widow(er)s, who have very low household income, they still have strong preferences for SNAP-eligible food such that a SNAP-like cash transfer can achieve the goal of SNAP.

7 Conclusion

I study the role of intra-household preference heterogeneity, bargaining power, and consumption economies of scale in the demand analysis for older widows, widowers, and couples. I use the demand estimates and simulate a counterfactual cash transfer with equivalent benefit size as the Supplemental Nutrition Assistance Program (SNAP). I test the assumption that supports the in-kind design of SNAP. That is, poor households have different preferences such that they will buy policy undesired goods when given cash subsidies. The results reject this hypothesis. More importantly, the demand responses would be underestimated, both at the intensive and extensive margins, if we ignore intra-household preference heterogeneity and bargaining power.

My demand model is based on Browning, Chiappori, and lewbel (2013) and I apply it for the first time to the Nielsen Homescan data. The framework allows me to not only identify individual preferences and bargaining power, but also consumption economies of scale of different goods. I find that different goods in Nielsen have different extent of economies of scale. It implies that previous literature that ignore the sharing of goods in household demand will have biased demand estimates. It also suggests that previous collective models literature that assume goods to be either purely public or purely private have too naive assumptions. The advantages of the model and the data give high credibility to my estimates on household demand and household responses to the cash transfer experiment.

A potential research question that is worth exploiting is whether cash and food vouchers can have different effects on intra-household bargaining power. If that is the case, then we can utilize the one that works to increase the power of the member who has stronger preferences for SNAP-eligible food. Another interesting question is to see whether taxes or subsidies on dis-aggregated goods in Nielsen can affect multi-person households' cost of saving through the sharing of goods. This will be an unintended policy consequence of commodity tax/subsidy.

Appendices

1 Additional Figures and Tables

Figure A1: Impact of SNAP on Budget Constraint

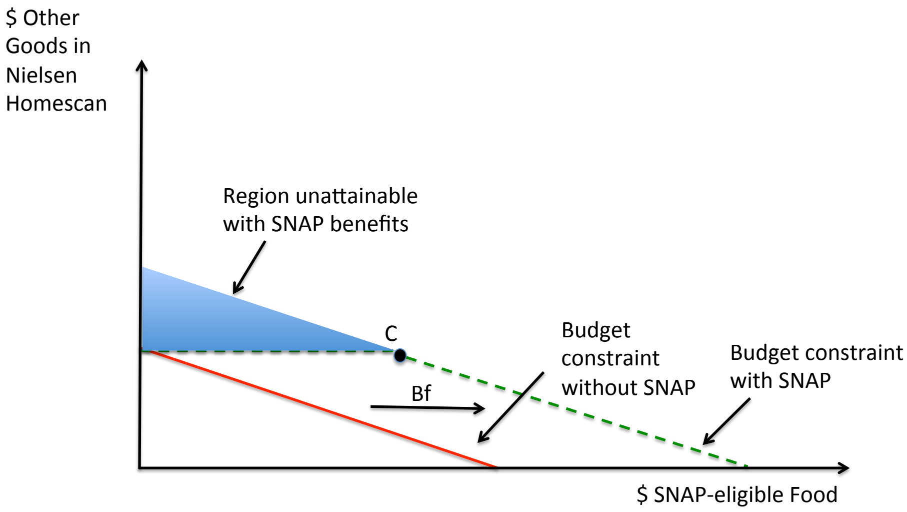


Figure A2: Consumption Re-allocation for Unconstrained Households

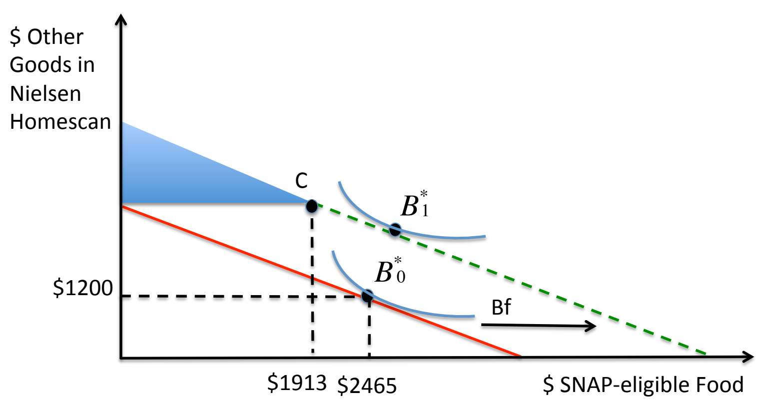
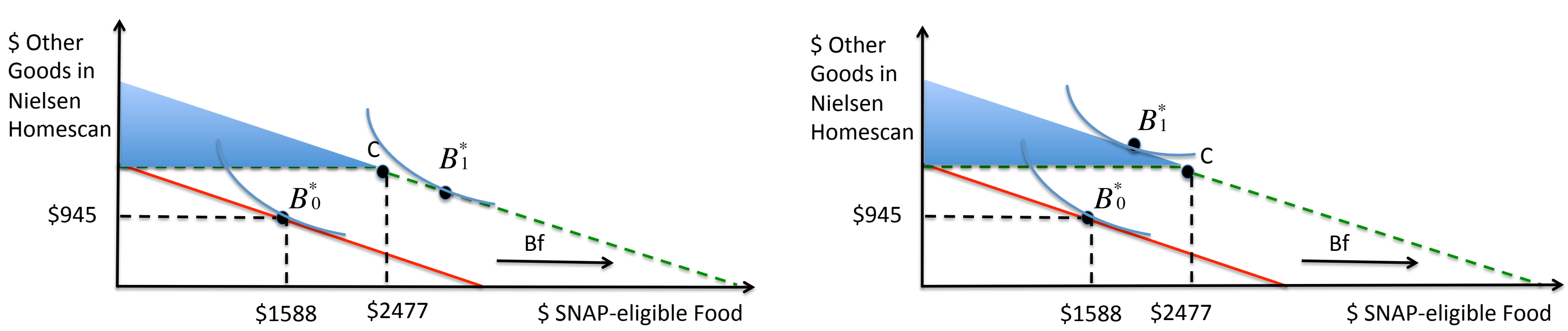
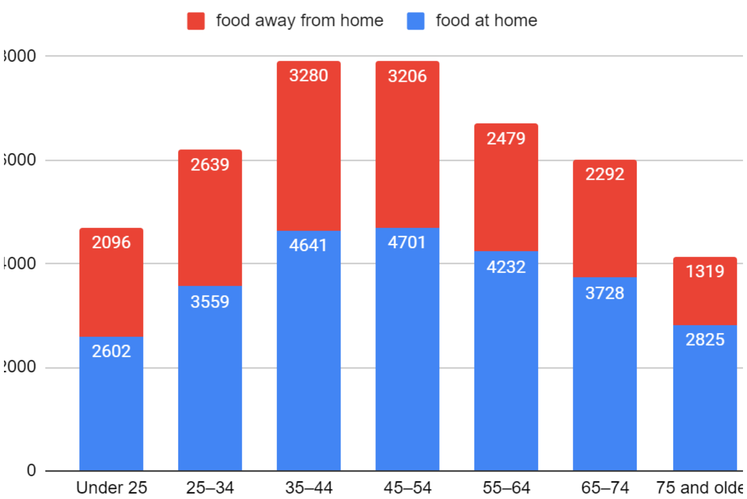


Figure A3: Consumption Re-allocation for Constrained Households

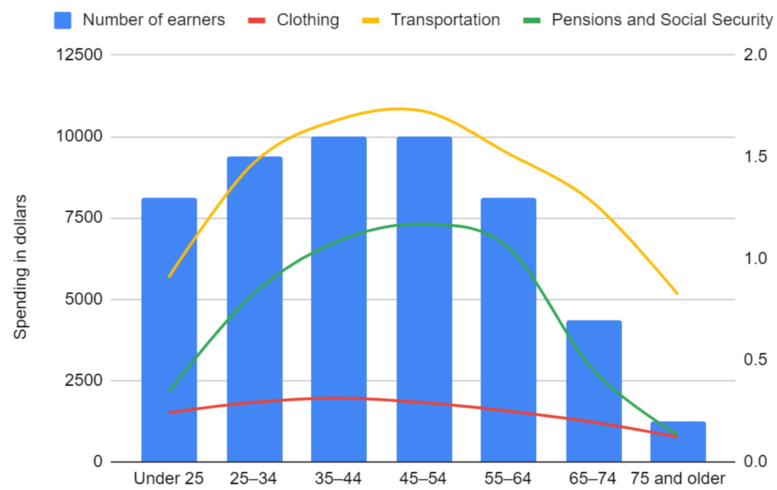


(a) Undistorted Case **(b)** Distorted Case

Figure A4: Mean Food and Non-food Expenditures: by Age of Reference Person, 2013, CEX



(a) Mean Food Expenditures



(b) Other Non-food Expenditures

Source:U.S. Bureau of Labor Statistics.

Figure A5: Engel Curves for older widows, widowers, and couples

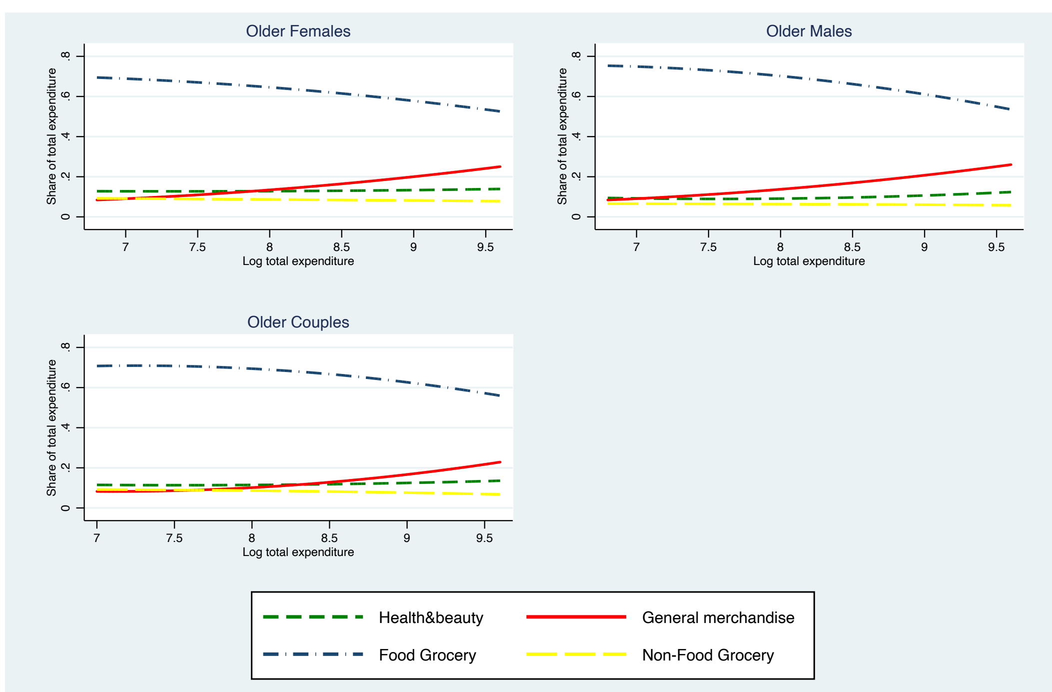
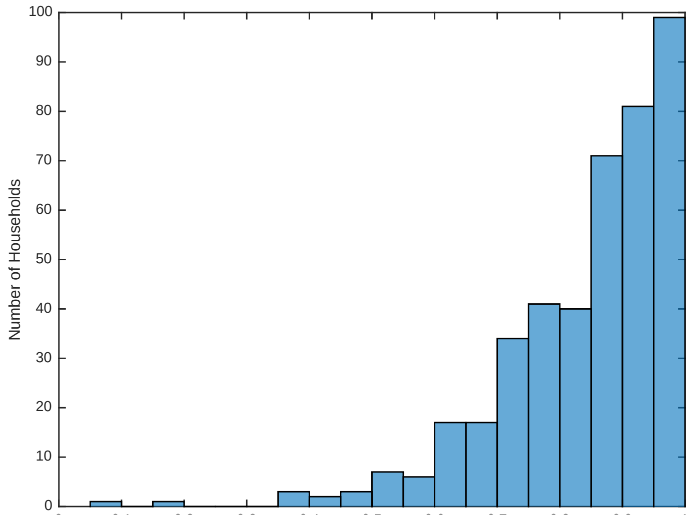
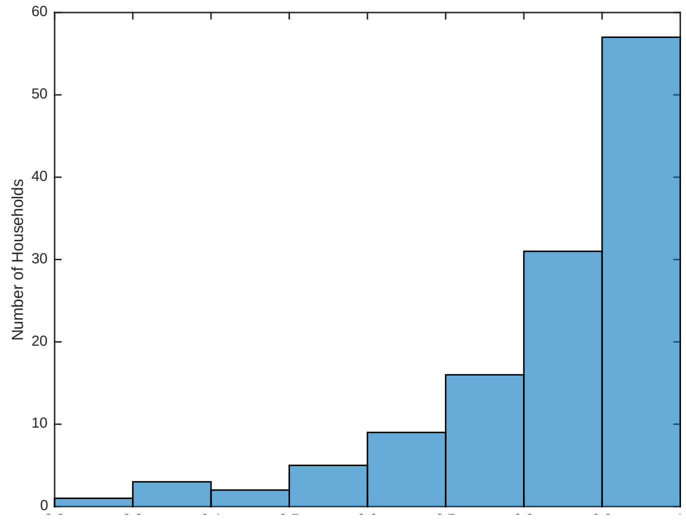


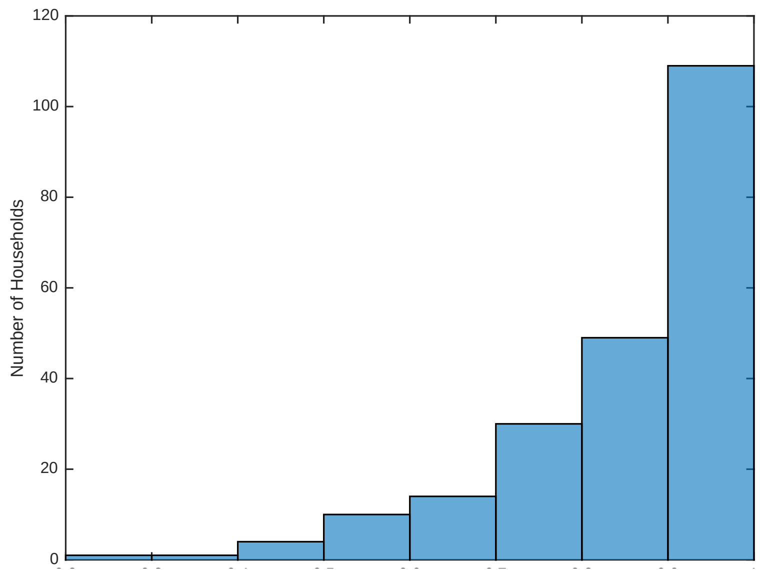
Figure A6: Ratio of SNAP-Eligible Food Spending to SNAP Benefits



(a) older widows



(b) Older Widowers



(c) Older Couples

Table A1: QAIDS Elasticities Estimates

Budget Elasticities		
	Single Females	Single Males
General Merchandise	0.867	0.724
Food Grocery	1.054	1.088
Non-Food Grocery	1.064	0.966
Health and beauty	0.844	0.820

Uncompensated Price Elasticities (Single Females)				
	General merchandise	Food Grocery	Non-Food Grocery	Health and beauty
General merchandise	-0.545	-0.678	-0.233	0.113
Food Grocery	-0.100	-0.712	-0.040	-0.207
Non-Food Grocery	-0.261	-0.343	-0.532	-0.058
Health and beauty	0.142	-1.329	-0.017	-0.022

Compensated Price Elasticities/Slutsky Matrix (Single Females)				
	General merchandise	Food Grocery	Non-Food Grocery	Health and beauty
General merchandise	-0.347	-0.295	-0.179	0.192
Food Grocery	0.045	-0.022	0.052	-0.071
Non-Food Grocery	-0.113	0.354	-0.422	0.081
Health and beauty	0.248	-0.831	0.052	0.129

Uncompensated Price Elasticities (Single Males)				
	General merchandise	Food Grocery	Non-food grocery	Health and beauty
General merchandise	-0.947	0.447	-0.171	0.558
Food Grocery	-0.047	-0.848	-0.043	-0.159
Non-food grocery	-0.192	-0.569	-0.473	0.037
Health and beauty	0.679	-2.076	0.058	-0.121

Compensated Price Elasticities/Slutsky Matrix (Single Males)				
	General merchandise	Food Grocery	Non-food grocery	Health and beauty
General merchandise	-0.753	0.240	-0.177	0.547
Food Grocery	0.104	-0.072	0.027	-0.056
Non-food grocery	-0.064	0.098	-0.391	0.125
Health and beauty	0.770	-1.622	0.102	0.002

Table A2: The Sharing Rule Parameters and Barten Scales

Mean wife's resource share	0.69	
Panel A: The Sharing Rule	coef	std error
Constant	0.15	(1.36)
Female unemployed	-0.08	(0.14)
Male unemployed	-0.30	(0.11)
Female some college education	0.03	(1.54)
Male some college education	0.13	(1.48)
Difference in age (female - male)	-0.02	(0.21)
Log real total expenditure	0.106	(0.17)
Panel B: Estimates of Barten Scales	coef	std error
General Merchandise	0.71	(0.03)
Food Grocery	0.90	(0.06)
Non-food Grocery	0.87	(0.05)
Health & Beauty	0.82	(0.05)

Notes: The first line displays the mean wife's resource share across the entire sample. Panel A displays the sharing rule, that is, the estimates of the covariates that affect the wife's resource share. Panel B displays Barten Scales, which are assumed to be homogeneous across all households.

2 Supplemental Nutrition Assistance Program: The Design and its Main Objective

SNAP is the largest anti-hunger program and the second largest means-tested program in the United States. Its main objective is to promote nutrition intake among the poor population. As an in-kind transfer, SNAP benefits mainly cover four categories of food: 1) breads and cereals; 2) fruits and vegetables; 3) meats, fish and poultry, and dairy products; 4) seeds and plants that produce food for the household to eat.[25] Participants use an electronic benefits card (EBT card), which is accepted at a broad range of businesses, including pharmacies, grocery stores, gas stations, and other small chains such as convenience stores.[26]

One main justification for an in-kind transfer like SNAP is to promote the consumption

[25]The subsidies exclude beer, alcohol, cigarettes, or tobacco. Hot food or deli is also not allowed.

[26]The Electronic Benefits Transfer (EBT) card is how Department of Transitional Service (DTA) delivers its core services: food and economic assistance. It works and looks like a debit card. The benefits are kept in a special account for participants. For SNAP participants, they can use the EBT card anywhere that displays a "Quest" logo and the participating store will have an EBT working machine. At check-out, the participant simply swipes the EBT card and tells the cashier how much money to enter or enter the purchase amount by self.

of certain goods that are policy desired, i.e., paternalistic motivations (Currie 1994, Currie and Gahvari 2008). Many empirical studies show that poor households have worse nutrition intake than richer households (e.g., Amano 2018). This naturally leads to the worry that recipients might spend benefits, if given in cash, on non-food goods.[27]

Appendix Figure A1 to A3 show the impact of SNAP benefits on household budget constraints and SNAP-eligible food spending. In Figure A1, the red line represents the original budget constraint. The dashed green line represents the post-transfer budget constraint. Without an in-kind design, SNAP benefits would be equivalent to income transfers in the sense that they shift out households' budget line. However, the in-kind design forces recipients to spend benefits only on SNAP-eligible food. This results in the upper triangle area in Figure A1 being unattainable under in-kind transfers.[28]

The demand response to SNAP benefits among unconstrained households is illustrated in Figure A2. For those households, since they have already spent at least the same amount of out-of-pocket expenditure as their potential SNAP benefits on SNAP-eligible food, the in-kind transfer would simply act like cash and replace, one-to-one, their out-of-pocket expenditure on SNAP-eligible food. Their resulting optimal consumption choice would change from A_0^* to A_1^*.

The demand response to SNAP benefits among constrained households is more complicated and is illustrated in Figure A3. B_0^* is households' consumption choice without SNAP. B_1^* in both the left and right panel represents the consumption choice under a cash transfer. The left panel (a) represents the situation in which constrained households have strong preferences for food such that their spending on SNAP-eligible food is more than SNAP benefits. In this case, in-kind transfers are equivalent to cash transfers. The right panel (b) represents the situation in which constrained households have stronger preferences for other non-food goods than for SNAP-eligible food, so that they spend most of their benefits on other goods. By giving them in-kind benefits, their consumption would be distorted to the kink point C.

[27] The black market of SNAP accounts for just over 1 percent of the total food stamp program, which is far less than fraud in other government programs like Medicare and Medicaid (Severson 2013).

[28] The budget constraint in Figure A1 to A3 represents exactly the average constraint faced by older couples in Nielsen Consumer Panel Dataset. The budget constraint was shifted outwards by the average benefits of eligible older couples.

As is shown by Figure A3, preferences of households play the most important roles in the justification of an in-kind design. In this paper, I show that precisely estimating the preferences of older couples requires that we account for the preference heterogeneity and bargaining power of individuals. Moreover, other goods like General Merchandise in a typical grocery store is important substitute of food while they also exhibit strong consumption economies of scale in older couples. Their shadow prices within households will be considered lower than market prices. It is necessary to take sharing of goods into account to accurately estimate price elasticities. Table A3 reports the maximum net income and the maximum SNAP benefits for one-person and two-person older households. I calculate the net income, which is the gross income subtracted by certain deductions,[29] and then multiply it by 30 percent.[30] That number is then subtracted from the maximum allotment, and the remaining amount is the potential SNAP benefits.

Table A3: SNAP Eligibility Criteria and Maximum Benefits for the Elderly

Number of Household Members	Maximum Amount of Net Income	Maximum Food Stamp Benefits
1	$1,041	$194
2	$1,410	$355

Notes: The table reports the maximum net income and maximum allotment by household size of the current SNAP eligibility and benefits scheme. Net income means gross income minus allowable deductions. Gross income means a household's total, non-excluded income, before any deductions have been made. Under Federal law, all income is counted to determine eligibility for SNAP unless it is explicitly excluded. For SNAP purposes, "income" includes both earned income such as wages and unearned income such as Supplemental Security Income (SSI) and veterans, disability, and death benefits. Source: United States Department of Agriculture (USDA) Food and Nutrition Service (2000)

[29] The deductions include a 20-percent deduction from gross income, a standard deduction of $167 for household sizes of 1 to 3 people, and a standard shelter deduction for homeless households of $152.06. Medical deductions are not accounted for here due to data limitation. For older or disabled members, medical expenses more than $35 for a month can be deducted if they are not paid by insurance or someone else. For shelter deductions, I refer to the standard deduction for homeless households due to data limitation. A more accurate shelter deduction rule is to first determine half of adjusted income, then determine if shelter costs are more than half of adjusted income, and finally subtract excess amount, but not more than the limit, from adjusted income.

[30] The households are expected to spend 30 percent of their gross income on food.

Table A4: Summary Statistics for Constrained and Unconstrained low-income households

	low-income older widows		low-income older Widowers		low-income older Couples	
	Constrained	Unconstrained	Constrained	Unconstrained	Constrained	Unconstrained
Number of unique households	991	3,198	319	921	620	2,202
Household income	6,543.03	14157.43	6048.33	14233.92	8074.01	20308.96
Total expenditures from trip data	3,136.50	4137.61	2798.93	3888.50	5677.23	6740.76
Total expenditures from purchase data	2,278.36	3074.25	2093.16	2932.96	3997.97	5001.47
Budget share (health&beauty)	0.12	0.12	0.07	0.09	0.11	0.11
Budget share (general merchandise)	0.11	0.12	0.11	0.11	0.12	0.12
Budget share (food grocery)	0.67	0.67	0.74	0.73	0.68	0.68
Budget share (non-food grocery)	0.09	0.09	0.06	0.06	0.08	0.08
SNAP-eligible food spending	1,101.82	1541.00	1093.59	1566.99	2079.99	2612.17
Expenditure share (SNAP food / Food Grocery)	0.74	0.76	0.73	0.74	0.78	0.77
Female head age	66.72	69.18	-	-	66.09	67.23
Male head age	-	-	64.55	67.02	68.53	69.92
Female education: graduated high school or above	0.95	0.96	-	-	0.91	0.94
Female education: some college or above	0.57	0.57	-	-	0.47	0.44
Male education: graduated high school or above	-	-	0.95	0.96	0.85	0.85
Male education: some college or above	-	-	0.70	0.68	0.48	0.43
Microwave, Dishwasher, & Garbage Disposal	0.05	0.06	0.07	0.06	0.10	0.06
Regular & Pay Cable	0.67	0.74	0.52	0.65	0.72	0.77
Internet connection	0.77	0.83	0.84	0.84	0.89	0.90
Obs	1,729	7,398	608	2,237	1,069	4,273

Notes: Values are mean. Observations are by household and year. Household income in the Nielsen Consumer Panel Dataset is in ranges and I take the middle value of each range. Total expenditures from the trip data is the total expenditure that appears at the bottom of each shopping trip receipt. Total expenditures from the purchase data is the author calculated total expenditure by summing up the expenditure of each scanned items. Total expenditures from the purchase data is smaller or equal to that from the trip data due to missing scanned items or items being eaten on the way home. Budget shares are calculated as the total expenditures of each aggregate good divided by total yearly expenditure from the purchase data.

Table A5: Spending Patterns between SNAP-eligible and Ineligible Households

	low-income households		**SNAP-ineligible Households**	
Panel A: Spending Level	Mean	Standard deviation	Mean	Standard deviation
Total expenditure in Nielsen	3159.79	1250.98	3497.63	1337.88
Food grocery expenditure	2582.95	1054.72	2733.33	825.39
SNAP food expenditure	1641.25	587.56	1778.58	629.10
Healthier foods	2180.10	938.83	2300.78	972.46
SNAP-ineligible foods	276.94	155.59	299.91	165.20
Sugar-sweetened beverages	125.91	114.83	132.64	113.50
	low-income households		**SNAP-ineligible Households**	
Panel B: Spending as a Percent of Food Grocery Spending	Mean		Mean	
SNAP foods	63.54%		65.07%	
Healthier foods	84.40%		84.17%	
SNAP-ineligible foods	10.72%		10.97%	
Sugar-sweetened beverages	4.87%		4.85%	

Notes: The definitions of healthier foods, SNAP-ineligible foods, and sugar-sweetened beverages follow Hoynes et al. (2015). The "healthier foods" category includes bread, poultry, fish and shellfish, eggs, milk, cheese, other non-ice cream dairy foods, fruit (excluding juice), vegetables, dried fruit, nuts, prepared salads and baby food. The "SNAP-ineligible foods" category comprises ice cream, candy, gum, hot dogs, potato chips and other snacks, and bakery goods and prepared desserts such as cakes, cupcakes, doughnuts, pies, and tarts. The sugar-sweetened beverages group includes colas, other carbonated drinks, and non-carbonated fruit-flavored and sports drinks.

Table A6: Counterfactual Results for Older Couples

	Baseline	Counterfactual			
		wives' resource share = 0.50		wives' resource share = 0.66	
	Older Couples' Budget Share	Older Couples' Budget Share	% Change	Older Couples' Budget Share	% Change
General merchandise	0.132	0.133	0.53%	0.127	-3.85%
Food grocery	0.667	0.680	1.98%	0.681	2.02%
Non-food grocery	0.083	0.080	-3.85%	0.084	1.44%
Health & beauty	0.117	0.107	-9.20%	0.108	-8.18%

Notes: Values are in mean. The table shows the changes in budge shares for older couples given the SNAP-like cash transfer. Baseline values are values of households in the Nielsen Consumer Panel Dataset. Counterfactual values are the predicted values of households given a SNAP-like cash transfer. Column (2) shows the budget shares of older couples in the Nielsen Consumer Panel Dataset. Column (3) shows the budget shares of older couples given the SNAP-like cash transfer if we assume equal bargaining power between wives and husbands. Column (5) shows the counterfactual budget shares if we use the estimated sharing rule (wife's resource share = 0.66) from the collective model.

Table A7: Counterfactual Results for Wives

	Baseline	Counterfactual	
	Equivalent Budget Share	Equivalent Budget Share	% Change
General merchandise	0.124	0.120	-3.40%
Food grocery	0.664	0.679	2.23%
Non-food grocery	0.090	0.091	1.33%
Health & beauty	0.122	0.110	-9.68%

Notes: Values are in mean. The table shows the changes in equivalent budge shares for wives given the SNAP-like cash transfer. Equivalent budget shares for husbands are calculated as husband's QAIDS estimates of budget shares if he is faced with 0.66 resource share and the shadow prices.

Table A8: Counterfactual Results for Husbands

	Baseline	Counterfactual	
	Equivalent Budget Share	Equivalent Budget Share	% Change
General merchandise	0.151	0.147	-3.10%
Food grocery	0.670	0.681	1.70%
Non-food grocery	0.069	0.069	-1.01%
Health & beauty	0.109	0.103	-5.49%

Notes: Values are in mean. The table shows the changes in equivalent budge shares for wives given the SNAP-like cash transfer. Equivalent budget shares for husbands are calculated as husband's QAIDS estimates of budget shares if he is faced with 0.34 resource share and the shadow prices.

Table A9: Counterfactual Results for older widows

	Baseline	Counterfactual	
	older widows' Budget Share	older widows' Budget Share	% Change
General merchandise	0.115	0.109	-5.30%
Food grocery	0.656	0.670	2.06%
Non-food grocery	0.101	0.101	0.40%
Health & beauty	0.128	0.120	-6.02%

Notes: values are in mean. The table shows the changes in budge shares for older widows given the SNAP-like cash transfer.

Table A10: Counterfactual Results for Constrained and Unconstrained Females

Panel A: Changes in Budget Shares	Constrained older widows			Unconstrained older widows		
	Baseline Budget Shares	Counterfactual Budget Shares	% change	Baseline Budget Shares	Counterfactual Budget Shares	% change
General merchandise	0.108	0.089	-17.53%	0.117	0.114	-2.57%
Food grocery	0.659	0.700	6.30%	0.656	0.663	1.05%
Non-food grocery	0.102	0.103	0.98%	0.100	0.101	0.20%
Health & beauty	0.131	0.108	-17.93%	0.127	0.123	-3.15%

Panel B: Full Propensity to Consume (FPC) SNAP-eligible Food out of SNAP Benefits	Mean	Mean
Imputed SNAP benefits	1730	352.50
Baseline food expenditure	1501	2,020.10
Counterfactual food expenditure	2780	2,261.00.90
Increase in food expenditure	1279	240.90
FPC food out of SNAP benefits	0.74	0.68
Baseline spending on SNAP-eligible-food-to-overall-food ratio	0.74	0.76
FPC SNAP-eligible food out of SNAP benefits	0.55	0.52
Number of Extra-marginal Households	423	0
Obs	1729	7398

Notes: Values are in mean. Constrained households are defined as those whose baseline SNAP-eligible food spending in Homescan data is lower than my imputed cash benefits for them using the SNAP benefit formula. The full propensity to consume (FPC) food out of cash is calculated as the increase in food expenditures divided by cash transfers. The FPC SNAP-eligible food out of benefits is calculated as the FPC food out of cash transfers multiplied by households' spending on SNAP-eligible-food-to-overall-food ratio.

Table A11: Counterfactual Results for Older Widowers

	Baseline	**Counterfactual**	
	Older Widowers' Budget Shares	Older Widowers' Budget Shares	% Change
General merchandise	0.123	0.116	-5.76%
Food grocery	0.723	0.733	1.37%
Non-food grocery	0.072	0.071	-1.11%
Health & beauty	0.082	0.080	-2.56%

Notes: values are in mean. The table shows the changes in budge shares for older widows given the SNAP-like cash transfer.

Table A12: Counterfactual Results for Constrained and Unconstrained Males

Panel A: Changes in Budget Shares	Constrained Older Widowers			Unconstrained Older Widowers		
	Baseline Budget Shares	Counterfactual Budget Shares	% change	Baseline Budget Shares	Counterfactual Budget Shares	% change
General merchandise	0.117	0.087	-25.72%	0.125	0.124	-0.56%
Food grocery	0.730	0.783	7.26%	0.721	0.719	-0.25%
Non-food grocery	0.071	0.074	4.53%	0.072	0.070	-2.63%
Health & beauty	0.082	0.056	-31.51%	0.082	0.086	5.24%

Panel B: Full Propensity to Consume (FPC) SNAP-eligible Food out of SNAP Benefits	Mean	Mean
Imputed SNAP benefits	1810	53.91
Baseline food expenditure	1504	2,116.20
Counterfactual food expenditure	3006	2,156.50
Increase in food expenditure	1502	40.30
FPC food out of SNAP benefits	0.83	0.75
Baseline spending on SNAP-eligible-food-to-overall-food ratio	0.73	0.74
FPC SNAP-eligible food out of SNAP benefits	0.61	0.55
Number of Extra-marginal Households	124	0
Obs	608	2237

Notes: Values are in mean. Constrained households are defined as those whose baseline SNAP-eligible food spending in Homescan data is lower than my imputed cash benefits for them using the SNAP benefit formula. The full propensity to consume (FPC) food out of cash is calculated as the increase in food expenditures divided by cash transfers. The FPC SNAP-eligible food out of benefits is calculated as the FPC food out of cash transfers multiplied by households' spending on SNAP-eligible-food-to-overall-food ratio.

3 Compare Nielsen Consumer Panel Datasetset to CEX

Table A13 displays the three groups with the largest group shares under each of these four aggregate goods. Nielsen estimates that approximately 30 percent of household consumption is accounted for by consumer panel data categories; however, they do not track other sources of consumer spending beyond the Nielsen-tracked categories. I compare the goods included in Nielsen Consumer Panel Dataset to those in the Consumer Expenditure Survey (CES).[31] To better understand the definitions and coverage of aggregate goods, I map the aggregate goods in Nielsen to aggregate goods and sub-categories in CEX, as reported in Table A1. The categories in CES that are beyond the Nielsen-tracked categories include rent, clothing, transportation, etc. Since a lot of services and goods, such as heating, housing, and transportation, are highly shareable, the resulting analyses on consumption savings through sharing public goods in this paper will be a lower bound for the actual total consumption savings through cohabitation.

Table A13: Top Three Groups under Aggregate Goods

General Merchandise		Health and Beauty		Non-Food Grocery		Food-Grocery	
Group	%	Group	%	Group	%	Group	%
Electronics, records, tapes	29%	Vitamins	34%	Tabacco & accessories	62%	Dry grocery	62%
Housewares, appliances	28%	Medications/remedies/health aids	33%	Paper products	32%	Dairy	15%
Stationary, school supplies	19%	Diet aids	19%	Pet care	23%	Frozen food	15%

Notes: Table displays the top three groups (with the largest group shares) under each aggregate good in Nielsen Consumer Panel Dataset set.

Table A14: Definitions of Aggregate Goods: Nielsen Homescan versus CEX

Aggregate Goods in Nielsen Consumer Panel Dataset	Aggregate Goods and Services in Consumer Expenditure Survey (CEX)
Health and Beauty	Healthcare: drugs, medical supplies Other expenditures: personal care products and services
Food Grocery	Food excluding food away from home Other expenditures: tabacco
Non-food Grocery	Entertainment: pets, pet food, pet services Other expenditures: smoking supplies Housing: housekeeping supplies (laundry and cleaning supplies)
General Merchandise	Housing: housekeeping supplies, household textiles, small appliances/miscellaneous housewares Transportation: maintenance and repairs Entertainment: Television, radio, and sound equipment, other entertainment equipment and services Other expenditures: education and reading (books, school supplies)

Notes: Table displays the four aggreagte goods in Nielsen and its corresponding goods and services in Consumer Expenditure Survey (CEX). Food in CEX includes spending on food at groceries, convenience stores, specialty stores, farmers markets and home delivery services, minus the cost of paper products, cleaning supplies, pet food and alcohol.

[31] For CES definition of goods and services, please visit the website of Bureau of Labor Statistics https://www.bls.gov/cex/csxgloss.htm

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