# Essays on Household Economics:

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# Essays on Household Economics

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**Essays on Household Economics**

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Abstract:

The dissertation consists of three essays on different aspects of the collective household models in the household economics literature.

The first essay estimates a collective household model for evaluating the Supplemental Nutrition Assistance Program (SNAP) among older households. I use longitudinal Homescan data to identify SNAP-eligible food. I find that husbands have relatively stronger preferences for food than wives, and that household demand is affected by bargaining power (i.e., control over resources) within households. Failure to account for this difference in preferences and control 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 replacing SNAP with a cash transfer program. I find that most eligible older households spend more on SNAP-eligible food than would be allowed by their SNAP benefits. Their spending patterns suggest that their poor diet is mainly due to low income rather than tastes. Overall these findings imply that a SNAP comparable cash transfer can be an effective tool to achieve the goals of the SNAP program.

The second essay is joint work with my advisor Arthur Lewbel. We first prove identification of coefficients in a class of semiparametric models. We then apply these results to identify collective household consumption models. We extend the existing literature by proving point identification, rather than the weaker generic identification, of

all the features of a collective household (including price effects). Moreover, we do so in a model where goods can be partly shared, and allowing children to have their own preferences, without observing child specific goods. We estimate the model using Japanese consumption data, where we find new results regarding the sharing and division of goods among husbands, wives, and children.

The third essay is a joint paper with Tomoki Fujii. We study the intra-household inequality in resource allocation and bargaining within Japanese couples without children. We exploit a unique Japanese dataset in which individual private expenditures, savings, and time use information are available. From the data, we find that on average, the husband enjoys 1.5 times more purely private expenditures than the wife. However, the data only provides resource allocation on purely private expenditures, while 68 percent of household expenditures are devoted to the family, i.e., joint expenditures. We refer to the collective household literature in order to recover the unobserved sharing of total household expenditures, including both private and public goods. We find that the model-predicted sharing pattern is moderately consistent with the individual expenditure data. However, the intra-household inequality would be underestimated if we only use the sharing in purely private expenditures from the data. We find that Japanese wives are relatively disadvantaged to their husbands, no matter in purely private expenditures, total household expenditures, or gains from marriage. The findings in this paper provides certain external validity in terms of the collective household model of consumption, which we argue should be widely adopted in analyzing individual welfare in multi-person households.

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# 1 Chapter 1

# SNAP and Food Consumption among Older Adults: A Collective Household Approach with Homescan Data

## 1.1 Introduction

Many welfare programs are designed in part to change household consumption behavior, using, e.g., taxes, subsidies, and cash or in-kind transfers. There exists a large literature based on natural experiments that evaluate the effectiveness of these programs. However, these analyses are possibly limited in scope due to problems such as non-random selection into the program, inability to directly evaluate and compare alternative policy designs, and mixed evidence due to different samples studied. Furthermore, the resulting causal estimate only tells us the marginal, rather than the full response to those programs, which are often non-marginal in nature.[1]

To address these concerns, the first contribution of this paper is to adopt a structural approach to evaluate a particular program, e.g., the Supplemental Nutrition Assistance Program (SNAP). I overcome the above concerns by looking at SNAP-eligible households rather than only participants, estimating a structural demand model, and conducting a counterfactual experiment of an alternative policy design of SNAP, that is, replacing the current in-kind transfer with a cash transfer program. This allows me to directly answer the policy debate on in-kind versus cash transfers, and estimating the full demand response to the cash transfer. Few if any papers evaluate SNAP using a structural model. This is the first to do so using a structural collective household model. Unlike the large literature that investigates whether SNAP increases food spending more than a cash transfer would, this paper asks, "would a cash transfer be an effective tool to accomplish the goals of the SNAP program?"

To precisely estimate that switch, the second contribution of this paper is to model households consisting of multiple individuals, each with their own preferences and bargaining power, and they benefit from shared or joint consumption. In previous analyses, 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

[1] Hoynes and Schanzenbach (2009) argue that one should be cautious in interpreting the "marginal" calculation for food stamps income due to the "non-marginal" nature of the program design.

under the unitary approach are too restrictive. Household consumption outcomes are determined by heterogeneous individuals within the household, not by one representative agent.

In this paper, I address a particular limitation of the unitary approach for analyzing in-kind versus cash transfer programs. Transfers in kind encourage consumption of specific goods but discourage participation. The choice of best policy depends on whether the preferences of targeted households are such that, if given cash, they would buy the specific goods anyway. If enough households would buy the specific goods when given cash, then the cost of the in-kind program (in reduced participation) is not worth the benefit. The unitary approach will generally lead to a biased estimate of household preferences for the subsidized good when household members have asymmetric tastes and intrahousehold control, which in turn generates a bias in assessing the value of in-kind transfers.

I find this bias from the unitary model to be empirically relevant. I use longitudinal Homescan data to estimate a collective consumption model for older adults (widows, widowers, and couples) in the U.S.. The model is used to evaluate the impacts of SNAP, and of hypothetical changes to SNAP. The model accounts for intrahousehold preference heterogeneity, asymmetric bargaining, and joint consumption in older couples. I find that household members differ in tastes and household consumption is affected by bargaining power. If one did estimate a unitary model, it would be biased because it ignores husbands' stronger preferences for food. We would erroneously attribute too much of the variation in nutritional intake across older SNAP-eligible households to variation in preferences across households. As a result, the unitary model mistakenly overestimates the advantage of SNAP type in-kind transfers versus cash transfers. This is the first paper that borrows from the collective household literature to study demand estimation and demand responses to in-kind transfers using scanner data.

I focus on older adults for multiple reasons. First, food security and nutrition intake are among the largest concerns for the aging population.[2] 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 5 and 6 in the Appendix).[3] Third, 70 percent of goods in the scanner data are food-related, so the coverage of this data is particularly good

[2]For example, in the Nielsen Homescan data, I find that the SNAP-spending of 42 to 48 percent of SNAP-eligible households is below the program's needs standard (the cost of a minimal-cost, nutritious diet).

[3]Previous literature on the consumption retirement puzzle focuses explicitly on food among older adults. For example, Aguiar and Hurst (2007) use Homescan data and find that food expenditures are reduced while food consumption is not due to increased shopping intensity for lower prices and home production.

for this older population.

With the longitudinal Homescan data, I first estimate a collective demand model, accounting for within-household preference differentials, bargaining power, and joint (shared) consumption. The resulting elasticities of substitution are estimated across aggregate goods, household members, and between more public and less public goods.[4] Then, using information on household income, I select the SNAP-eligible older households and calculate their potential benefits. Finally, I conduct a counterfactual experiment of replacing SNAP benefits with a comparable cash transfer, and analyze the resulting demand responses, especially among constrained older households (e.g., households that, without SNAP, would consume less than the amount of nutritious food provided by SNAP).

I find in this older population that husbands prefer to spend a higher fraction of budget on food than wives, and that if one ignores this difference in tastes, then couples' overall demand for food is underestimated. This then biases downwards, both at the intensive and extensive margins, the estimates of older couples whose demand for food would be affected by cash transfers. And the underestimates would be mis-interpreted as evidence of preference difference on nutrition intake between poor and richer households, and would erroneously imply support for the in-kind transfer.

My findings here have important implications for the policy design of food subsidies provided to older adults. There is evidence that the in-kind transfer discourages SNAP participation, especially among older adults.[5] It is therefore important to know what the impact would be on households that would take up benefits if it were changed from an in-kind to a cash transfer program. The results here show that accurate evaluation of that switch requires accounting for the collective behavior of older couples.

My analysis uses Nielsen Homescan data covering 2004 - 2014. In this data, households use in-home scanners to record all purchased items, including prices, quantities, and coupon usage. The resulting rich price variation across households and over time enables more precise estimation of price elasticities and other preference parameters than is typically possible using expenditure

[4] Here public means public within the household. More public means more shared or more jointly consumed.

[5] According to USDA, SNAP serves more than 4 million seniors. Only 42 percent of eligible older individuals participate in SNAP, compared to 83 percent for all eligible people (Eslami 2016). The potential benefits for SNAP-eligible older nonparticipants are non-trivial. Average annual SNAP benefits are about $1,500, or about 15 percent of household income among the eligible (Center on Budget and Policy Priorities, 2017). Many older adults feel the weight of stigma or shame related to asking for help or receiving government benefits (Haider et al. 2003). Bartlett et al. (2004) use FoodAPS data and find that a third of eligible nonparticipating households respond positively to questions on stigma-related experiences.

survey data (like CEX or PSID). Individual goods are recorded at the bar-code level, which I use to identify SNAP-eligible food and spending.[6] This yields precise estimates of the fraction of households that are constrained by the SNAP in-kind transfers.[7]

I model household consumption decision as a Pareto efficient outcome among household members, each with their own preferences and bargaining power (or social welfare Pareto weights). Following the collective literature, I use resource shares (the share of total expenditures controlled by each individual household member) as a measure of each individual's relative bargaining power. A higher resource share implies that the couple's consumption behavior is represented more by one individual's preference. I also allow goods to each be partly shared, or partly jointly consumed. 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 economies of scale to consumption.

The model, based on the methodology developed by Browning, Chiappori, and Lewbel (2013) (hereafter BCL), identifies the separate preferences of each household member, their resource share, and the household's consumption economies of scale. The identification of wives and husbands respective preferences inside a couple comes from assuming older wives have similar preferences to widows, and that older husbands have similar preferences to widowers. Preferences for each are modeled using the Quadratic Almost Ideal Demand System developed by Banks et al. (1997). The responses of singles and couples to variation in prices, household expenditures, and household member characteristics are used to disentangle price effects, income effects, sharing (economies of scale to consumption), and heterogeneity in preferences.

Even though the data is at the bar-code level, which allows me to define narrow categories such as SNAP-eligible food, it is not feasible to identify and estimate demand systems for millions of goods. Instead, goods are aggregated based on categories defined by Nielsen. Namely, I focus on the categories: *1)* General Merchandise, *2)* Health and Beauty, *3)* Food Grocery, *4)* Non-food

[6] As an in-kind transfer program, SNAP benefits can not be spent on all kinds of food. The benefits can mainly be spent on four categories of food, including breads and cereals; fruits and vegetables; meats, fish and poultry; and dairy products.

[7] Households that are constrained by the SNAP in-kind transfers are more concerned by policymakers in welfare design because these households are more likely to live in deep poverty and less likely to spend enough on nutritious food. Hence, it is important to exactly identify those households from the policy perspective. These households are also the main target of the in-kind feature because it is often assumed that households who did not spend enough on nutritious food are also more likely to spend food subsidies on other non-food goods (Southworth 1945). Hence, estimates on the fraction of constrained households are often used as an indirect support for the in-kind design of food subsidies. Most of the existing literature that use expenditure survey data, such as the US Consumer Expenditure Survey (CEX) or Panel Study of Income Dynamics (PSID), often underestimate the fraction of constrained households because the data only has household spending on total food rather than SNAP-eligible food.

Grocery.[8] I construct Stone Price Indices for each aggregate good. Following a large literature in Industrial Organization, I address the price endogeneity problem using average prices in nearby areas to construct price instruments.

The results of the structural model are the following: I find strong evidence of preference heterogeneity inside older couples. Wives spend higher budget share on Health and Beauty and Non-food Grocery, while husbands spend higher budget share on Food Grocery and General Merchandise. The mean resource share of wives is 0.675, implying that the couple's consumption decision is represented more by wives' preference. Strong evidence of preference heterogeneity highlights the important role of bargaining power, in this case within households. In terms of consumption economies of scale, I find General Merchandise to be the most public, while Food Grocery and Health and Beauty are the least public. These results are intuitive, because General Merchandise is composed mainly of household appliances and small electronics, which can be highly shareable. The finding on food is consistent with the previous literature.

After structurally estimating the collective demand model, I conduct a counterfactual experiment of a SNAP comparable cash transfer. Even though the scanner data do not include information on SNAP eligibility or participation, the means-tested program feature of SNAP allows me to select SNAP-eligible households by using information on household income.[9] I also calculate potential household benefits following the current SNAP benefit formula.[10] I simulate what would happen if the SNAP in-kind benefits were replaced with a comparable cash transfer. One important basis for using in-kind transfers is the assumption that poor households have different preferences so that they might not spend all of their benefits, if given in cash, on nutritious food. I test that assumption directly by conducting the cash transfer experiment. These results allow me to calculate the full, rather than the marginal, propensity to consume SNAP-eligible food out of benefits or cash. This is in contrast to the previous literature based on reduced-form approaches, which can only obtain the marginal propensity to consume food (MPCF) out of

[8]Nielsen aggregates millions of bar-codes (Universal Product Codes or UPCS) into 10 departments. Because six of them are food-related, I aggregate those departments into one aggregate good — Food Grocery. I drop Alcohol due to the censoring problem. I follow the common practice in the literature of household demand and move Tobacco from department Non-food Grocery to Food Grocery.

[9]Households whose gross income is below 130 percent of the poverty line are eligible for SNAP. There are requirements on employment and household assets. However, the requirements do not apply to older adults population. Allcott et al. (2017) use Nielsen Homescan data to study the "food desert". They also select SNAP-eligible households using the same strategy here. Notice that I might overestimate preferences for food for the potential constrained SNAP participants in the Nielsen data set by ignoring that their budget constraint is binding by the SNAP in-kind design. I perform a robustness check in the counterfactual section and show that my baseline preferences estimates are not biased by the potential existance of SNAP participants in the data set.

[10]SNAP benefits are equal to the maximum allotment for a particular household size minus 30 percent of the difference between gross income and deductions.

benefits or cash. As pointed out by Hoynes and Schanzenbach (2009), one should be cautious in interpreting the "marginal" calculation for food stamps income due to the "non-marginal" nature of the program design.[11]

My counterfactual results show that both wives and husbands increase budget shares on Food Grocery and Non-food Grocery while decreasing budget shares on General Merchandise and Health and Beauty. However, husbands' increase in food budget share is 2.45 percent higher than wives'. This means that the couple's demand for food is reinforced by husbands' stronger preferences for food. The demand for food with SNAP might be underestimated without accounting for such preference heterogeneity. Further, I find that among SNAP-eligible older households (around 40% of older widows, 22% of older widowers, and 17% of older couples), the fraction of constrained older households is 42 to 48 percent, which is much higher than previous estimates by others that use total food expenditures to approximate SNAP-eligible spending.[12] Third, I find that 70 percent of constrained older couples, and 60-70 percent of constrained older widows and widowers, their SNAP-eligible spending, if given cash, is above their predicted benefit allotment; i.e., they are infra-marginal. This directly rejects the main argument of the in-kind design, that poor households would use most cash benefits to buy non-food goods. I further compare the spending pattern between constrained and unconstrained households, and SNAP-eligible versus ineligible households. I find the expenditure on SNAP-eligible-food-to-overall-food ratio to be around 80 percent for all of these households. By dividing food into healthy and unhealthy categories, I do not find that constrained households are more likely to eat unhealthy food. Next, by comparing the household income and food expenditures of infra-marginal versus extra-marginal households, I find the latter to be much poorer but to have similar total food expenditures. All of the suggestive evidence implies that older households are mostly constrained due to low income rather than tastes.[13] Lastly, the full propensity to consume SNAP-eligible food out of cash is 0.6 - 0.7 for infra-marginal older households, 0.5 - 0.6 for constrained older households, and only 0.15 - 0.2 for extra-marginal older widowhood households. This number is much higher than

[11] Banks et al. (1996) find that there exists substantial non-linearity in the demand estimation of certain consumption goods. Simple regressions that only obtain the marginal demand response to a tax reform will not show the full response to such reform and may lead to biased welfare implications.

[12] For example, Hoynes and Schanzenbach (2009) look at PSID and find that only 5 percent of food stamp recipients are observed to be constrained. They use total food spending (food-at-home and eating-out) and only look at non-elderly families. Hoynes et al. (2015) exploit CEX and show that 30 percent of recipients are constrained. They use food-at-home spending and focus on all demographic groups.

[13] A similar finding is obtained in Hoynes et al. (2015). They study the spending pattern between SNAP-eligible and SNAP-ineligible households in the CEX and do not find significant differences in budget shares of food and non-food goods between these two types of households.

the previous finding on the marginal propensity to consume food out of cash.[14] This finding highlights the danger in using the marginal response to transfers or taxes to do welfare analyses when these programs are non-marginal in nature.

The contributions of this paper are twofold. First, it extends the literature on collective consumption models to evaluate the demand responses of collective households to a transfer program. Many recent papers study the income-nutrition gradient (poor households consume less nutritious food than richer households), and they also use the scanner data for its rich price variation, available spending on disaggregated categories, and nutrition information (Dubois et al. 2014, Allcott et al. 2017, Amano 2018, Hastings and Shapiro 2018, Johnson et al. 2018, and Hasting et al. 2019). Consistent with the method in this paper, they adopt the structural model approach in order to simulate counterfactual experiments in which poor households are faced with the prices and incomes of richer households. However, they all use the unitary approach and ignore intrahousehold tastes and control. My paper is the one if any that evaluates SNAP with a structural approach, and more importantly, a collective household approach.[15] My results show that cost-benefit analyses of in-kind transfers are significantly affected by different household members having different tastes, and by asymmetric control of resources within households.

Second, I contribute to the literature on SNAP and food consumption by highlighting a problem with an implicit but rarely acknowledged assumption made by previous papers. This is the assumption that the value of in-kind transfer programs corresponds to the fraction of constrained households (e.g., Fraker 1990, Fraker et al. 1992, Ohls et al. 1992, Bitler 2015, and Hoynes and Schanzenbach 2009). The validity of this assumption depends on whether households are constrained due to low income itself or to preferences. If the former, then the assumption is not valid, and cash transfers can yield the same benefits as in-kind transfers without the added costs of the latter. I directly test this assumption using my structural model to evaluate the counterfactual impact of replacing SNAP with a comparable cash transfer. I find that older households are mostly constrained due to low income rather than tastes, and hence that the

[14] According to Hasting and Shapiro (2018), across a wide range of data (cross-sectional, time series) and econometric models, past estimates of MPCF out of cash are in a "quite tight" range from 0.03 to 0.17 for low-income populations. The latest estimate from Hasting and Shapiro (2018) on the MPCF out of SNAP is 0.5 - 0.6, which is very similar to my finding on the full propensity to consume SNAP-eligible food out of cash. However, they only look at SNAP-adaptors while I exploit SNAP-eligible older households. Their estimates only show the marginal response to SNAP while mine show the full response to cash.

[15] Previous literature on sNAP has also mentioned the role of intra-household behavior. For example, Hoynes and Schanzenbach (2009) hypothesize that people often find the marginal propensity to consume (MPC) food out of food stamps to be higher than the MPC food out of cash. It might be because the family member who controls food stamps is different from the member who controls cash. If the former member has stronger preferences for food, then the MPCs may differ. Hasting and Shapiro (2018) also try (as a robustness check) restricting their sample to single-adult households to limit the role of intrahousehold bargaining.

benefits of SNAP's in-kind transfers are lower than would be assumed given the observed fraction of constrained older households.

In terms of policy implications, my results first show the importance of accounting for a within-household preference differential and bargaining power when we estimate the household demand responses to transfer programs. Second, I find that hungry older households (i.e., constrained older households) do want to purchase more healthy food. Thus if a cash benefit program can achieve high participation, it can be an effective tool to reduce hunger that is not solved by SNAP, even with the same benefit size per person as the current SNAP program.

The remainder of this paper is organized as follows. Section 2 provides an overview of the related literature. Section 3 discusses the design of SNAP, its main objective, and particularly how a collective consumption model is appropriate in analyzing SNAP. Section 4 describes the data source and the construction of aggregate goods and prices. Section 5 presents the joint household model, its identification assumption, and the estimation. Section 6 describes the budget shares for individuals and the estimator. Section 7 reports the empirical results. Section 8 outlines the counterfactual experiment of a SNAP comparable cash transfer and its impact on household demand. Section 9 concludes.

## 1.2 Related Literature

This paper is related to two strands of literature: previous work on intrahousehold resource allocation, bargaining power, and consumption economies of scale; and the studies of in-kind transfer programs, in particular, of the impact of SNAP on food consumption.

Early literature on household consumption behavior often uses the so-called unitary approach, which assumes a household to be a single decision-making, utility-maximizing agent. Implications from this type of models include income pooling and symmetry of the Slutsky matrix, both of which were frequently rejected in empirical studies.[16] In contrast to the unitary approach, a number of papers focus on using the household-level expenditure data to recover the unobserved information about individual household members' preferences, control over resources, and consumption economies of scale. Building on Becker (1965, 1981) and Chiappori (1988, 1992), a number of papers adopt the collective approach, modeling a household consisting of multiple

[16] See Chiappori and Mazzocco (2017) for a summary of tests on the implications of the unitary approach.

members, each with their own preferences and among whom an intrahousehold bargaining process takes place. The only assumption in this type of models is Pareto efficiency. Applying standard decentralization results arising from Pareto efficiency, the latter papers show that regardless of the bargaining form or process, the behavior of a household is equivalent to the behavior of each household member who maximizes their own utility function, subject to shadow prices and shadow incomes that reflect the household chosen resource allocation method and sharing of goods.

Of particular interest in these models are *resource shares* (the share of total expenditures controlled by each individual household member). 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).[17] Calvi (2019), Tommasi (2019), and Penglase (2019) apply these methods to the studies on inequality and poverty within households in developing countries.

One limitation of the above papers is that they are based on household models that constrain goods to be purely public (like heat that are completely jointly consumed by all household members) or purely private (like food, e.g., no two can eat one pizza). To overcome this limitation, Browning, Chiappori, and Lewbel (2013) borrow from studies on the relationship between household expenditures and household composition (Barten 1964, Gorman 1976, Muellbauer 1977, and Lewbel 1985), and allow goods to be partly jointly consumed in the collective household models. They use the model to study individual welfare under different economic environments as measured by household size and composition. To do that, they propose the so-called indifference scale, i.e., the fraction of household total expenditure required by an individual household member purchasing goods privately, to be as well off materially as he or she is while living with others in a household that has joint income. Cherchye et al. (2012) apply BCL model to conduct an individual welfare analysis of older widows and widowers using Dutch data. Wewel (2017) applies

[17] Another strand of literature applies revealed preference theory and identifies resource shares by bound (e.g., Cherchye et al. 2012 and Cherchye et al. 2017).

BCL model to the PSID in the U.S. and studies the heterogeneity in gains from marriage for U.S. couples. This paper is the first one that applies BCL model to the scanner data and extends it to the evaluation of welfare programs.

Closely related to demand estimation in collective household models, demand responses to in-kind transfers have attracted much attention. Among these programs, SNAP has been widely studied.[18] A main debate on transfer programs is whether we should use in-kind or cash transfers. Early literature often finds that among constrained households (i.e., households that, without SNAP, would consume less than the nutritious food subsidized by SNAP) an in-kind transfer induces a larger increase in demand for the subsidized good than an equivalent cash transfer (Fraker 1990, Fraker et al. 1992, and Ohls et al. 1992). However, they often compare food spending between SNAP-participants and nonparticipants. The method suffers from the selection into the program problem, i.e., those who enroll might have different preferences from those who do not, and the unobserved preferences might be correlated with the regressor food spending (Bitler 2015). A recent exception in the literature is Hoynes and Schanzenbach (2009). They use a difference-in-difference approach and exploit county-level variation in the timing of adopting the food stamp program (FSP). They find that food stamps are equivalent to cash among most households. Another exception in the literature is Cunha (2014), who finds little distortion under the in-kind design in total food consumption, but large variation in distortion in individual foods. All of these reduced-form papers argue that the effectiveness of an in-kind transfer relative to an equivalent cash transfer relies on the fraction of constrained households, who are hypothesized to have different preferences and to dislike nutritious food (Southworth 1945). However, no studies have directly tested this assumption. As an indirect evidence, Hoynes et al. (2015) compare the expenditure pattern between SNAP-eligible and ineligible households using CEX and find no significant difference between them. I directly test this assumption by conducting a counterfactual experiment of a SNAP comparable cash transfer in order to explore whether poor households would spend more of the benefits, as given in cash, on non-food goods than richer households.

Many previous papers on demand estimation use expenditure survey data. A number of recent papers use scanner data, which have transaction records on detailed food categories, to study

[18] See Bitler (2015), Fox, Hamilton, and Lin (2004), and Hoynes et al. (2015) for a comprehensive literature on the effects of SNAP, and its predecessor the Food Stamp Program, on food spending.

nutrition intake, composition of food consumption, and demand responses to transfer programs. They include Dubois et al. (2014), Allcott et al. (2017), Amano (2018), Hastings and Shapiro (2018), Johnson et al. (2018), and Hasting et al. (2019). This is the first paper that borrows from the collective household literature to study demand estimation and demand responses to in-kind transfers using scanner data. My paper highlights the importance of accounting for within-household preference differentials and bargaining in order to precisely estimate price elasticities and demand responses to in-kind transfers in couples.

## 1.3 Supplemental Nutrition Assistance Program: The Design and its Main Objective

SNAP is the largest program in the domestic hunger safety net. According to the U.S. Department of Agriculture (USDA), its main objective is to increase food security and to reduce hunger by increasing access to food, a healthy diet, and nutrition education for low-income Americans. Besides its nation-wide coverage for poor households, SNAP plays an important role for seniors living in poverty. Specifically, SNAP provides 4.8 million seniors with the resources to afford an adequate diet. Seniors represent 11 percent of all SNAP recipients in 2015.[19] Moreover, seniors receiving SNAP benefits tend to live alone: only 1 in 4 live in households with other members.

I begin my empirical inquiry by describing the background of SNAP, particularly its objective and its chief characteristics of operation, i.e., the in-kind design. I then discuss the theoretical support for the in-kind design by distinguishing its impact on consumption between constrained and unconstrained households (defined by whether households that, without SNAP, would consume less than the amount of nutritious food provided by SNAP). I proceed to analyze the situations in which the theoretical predictions might not hold, in particular, where the in-kind design would be equivalent to a cash transfer, even for constrained households. Finally, I discuss why the collective approach matters for studying demand responses to cash transfers and how it alters the implications on in-kind versus cash transfers.

[19] Kelsey Farson Gray, Sarah Fisher, and Sarah Lauffer, "Characteristics of Supplemental Nutrition Assistance Program Households: Fiscal Year 2015," prepared for the Food and Nutrition Service, USDA, November 2016, https://www.fns.usda.gov/snap/characteristics-supplemental-nutrition-assistance-households-fiscal-year-2015

### 1.3.1 What Can SNAP Buy?

As an in-kind transfer program, SNAP benefits can only be used for food that recipients buy to prepare and eat at home. Because its goal is promoting nutrition among the poor population, SNAP mainly covers four categories of food: 1) breads and cereals; 2) fruits and vegetables; 3) meats, fish and poultry, and dairy products; 4) and seeds and plants that produce food for the household to eat. The subsidies exclude beer, alcohol, cigarettes, or tobacco. Hot food or deli is also not allowed. The 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.[20]

### 1.3.2 The Motivations of an In-Kind Transfer

This subsection describes the motivations behind an in-kind transfer. One main justification for an in-kind transfer is to promote the consumption of certain goods that are policy desired. It is also called the paternalistic motivations (Currie 1994 and Currie and Gahvari 2008). Many empirical studies have found that poor households have worse nutrition intake than richer households (e.g., Amano 2018). This naturally leads to the worrisome that recipients might spend benefits, if given in cash, on non-food goods. Given that, in-kind transfers would be more desired since they are more effective in increasing healthy food spending among poor households than cash transfers.[21]

To give a straightforward illustration of the motivation, Appendix Figure 1 to 3 show the impact of SNAP benefits on household budget constraints and SNAP-eligible food spending. In Figure 1, 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 1 to be unattainable under in-kind transfers.[22]

[20]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.

[21]The black market 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).

[22]The budget constraint in Figure 1 represents exactly the average constraint faced by older couples in Nielsen Homescan data. The budget constraint shifts outwards by an amount that is equal to the average benefits that I calculate for eligible older couples in Nielsen

The demand response to SNAP benefits among unconstrained households is illustrated in Figure 2. 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 $A_1^*$ given the in-kind transfers. And for them, in-kind transfers are equivalent to cash transfers.

The demand response to SNAP benefits among constrained households is more complicated and is illustrated in Figure 3. $B_0^*$ is the pre-treatment consumption choice. $B_1^*$ 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 and their post-treatment SNAP-eligible spending is above their SNAP benefits. In this case, in-kind transfers are equivalent to cash transfers, even for these very poor and constrained households. 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 $C$.

Constrained households are normally very poor households with household income below that of unconstrained households. Empirical evidence suggests that poor households eat less nutritious food than non-poor households. Hence, previous literature often assumes that poor households have different preferences: that they don't like nutritious food as much as non-poor households (Southworth 1945). This provides the main support for using in-kind transfers. However, households can be constrained due to low income itself or preferences. I address this question by conducting a counterfactual experiment of a SNAP comparable cash transfer. I further compare spending patterns and food composition between constrained and unconstrained households to support my counterfactual findings.

### 1.3.3 What Determines the Distorting Effect under an In-Kind Transfer?

Figure 3 in the previous section shows that the potential distorting effect of an in-kind transfer for constrained households is a function of the content of the in-kind transfer, the content of other goods shown in Figure 1, and the characteristics and preferences of the analyzed population.

Homescan data.

First, the content of an in-kind transfer is the extent of restrictions of a voucher, and is directly associated with the magnitude of distortion. The less limited the SNAP-eligible foods are versus total foods, the less an in-kind nature is a food stamp, and the less distorting is the impact of an in-kind design. Hence, it is crucial to clearly identify SNAP-eligible food in order to precisely determine the potential distorting effect for constrained households. I achieve this goal by using the Nielsen Homescan data with its bar-code level information on disaggregated goods.

Second, household preferences for SNAP-eligible food are also affected by other possible choices, i.e., the non-food goods. Nielsen Homescan data mainly consist of grocery-type goods, and 70 percent of the goods are food-related. This might lead my results to overstate the preferences for food and suggest the benefits to be infra-marginal. However, the problem is less serious because I focus on the older population, whose expenditures on transportation or clothing decrease dramatically after retirement. Instead, food remains a large portion of their budget.

Lastly, potentially the most important determinant of consumption choice is the characteristics and preferences of the analyzed population. Strong preferences for food would be evidence supporting cash transfers. The argument for cash transfers is even stronger for seniors due to their potential stigma problem and reduced participation with in-kind transfers. This last point leads to my argument: that the collective approach is critical in estimating older couples' preferences for food as discussed in the next subsection.

### 1.3.4 The In-kind Design: A Collective Household Approach

Given the theoretical motivations of an in-kind transfer, and its implications for the distorting effect, I proceed to demonstrate why the collective household approach is more appropriate than the unitary approach or the reduced-form approach for studying in-kind transfers for multi-person households (older couples specifically in this paper).

The collective approach allows for preference heterogeneity between wives and husbands. If one ignores that and if one partner has stronger preferences for food than the other, the overall household demand for food might be underestimated. This further biases downwards, at both the intensive and extensive margins, the number of households who would be affected under a cash transfer. Moreover, wives and husbands might have different preferences not only on aggregate goods but also on goods with different jointness or sharing degree. For example, a microwave is more attractive to an individual who lives within a couple than the same individual living alone because the former can share one microwave with his or her partner.

In short, the collective approach allows for elasticities of substitution not only across aggregate goods but also across household members, and between more public versus less public goods. It allows for counteracting or reinforcing preferences across households members; such preferences exist not only on aggregate goods but also on goods with different jointness. If one ignores these interactions, the resulting demand estimates may be biased, and this would further bias the demand responses to cash transfers. Eventually this would result in biased implications about the effectiveness of cash transfers.

Generally speaking, the collective demand model is a structural model, and hence allows me to conduct a counterfactual experiment of a SNAP comparable cash transfer. In the real-world, we only observe the outcomes under the SNAP in-kind transfer never under a counterfactual equivalent cash transfer. But relying only on the fraction of constrained households to show the effectiveness of in-kind transfers is also questionable, because the underlying assumption "that poor households have different preferences from richer households" is never verified. The collective approach allows me to both test the assumption directly and to simulate the outcomes under a cash transfer.

## 1.4 Nielsen Homescan Data

I use the Nielsen Homescan data covering 2004 to 2014. It is made available through the Kilts Center at the University of Chicago Booth School of Business. The Homescan data is particularly good for demand estimation as it provides detailed information on household consumption behavior and comprehensive household demographic characteristics.

The Nielsen Homescan data comprise 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 data set 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).[23] I use UPC and product interchangeably in this paper.

[23]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.

A key advantage of the data is that it has household-level price information. The rich price variation over time and across households allows me to precisely estimate price elasticities and other preference parameters than is typically possible using expenditure survey data.[24] Another advantage of the data is its highly disaggregated product structure (bar-code - product module - product group - department), which allows me to identify different food categories, especially the SNAP-eligible food.[25] Other consumption data are often cross-sectional, and hence 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.

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 Food Grocery. This yields a total of four aggregate goods in the demand estimation, and they are *1)* General Merchandise, *2)* Health and Beauty, *3)* Food Grocery, and *4)* Non-food Grocery.[26] Table 23 displays the three groups with the largest group shares under each of these four aggregate goods.

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. They account for nearly 20 percent of total food expenditure among older households. In other words, the expenditure on SNAP-eligible-food-to-overall-food ratio is around 80 percent for the older population. Because Food Grocery accounts for 70 percent of total spending in the data, that means overall around 56 percent of the total spending goes to SNAP-eligible products.

The largest aggregate good in Nielsen Homescan data is Food Grocery, which accounts for around 70 percent of the total expenditure tracked by Nielsen. The coverage of the data is particularly good for analyzing the older population because their expenditures on transportation or clothing decrease dramatically after retirement. Instead, food remains a large portion of their budget (shown in Figure 5 and Figure 6). This mitigates the concern that I might overestimate

[24] Previous literature on demand estimation often use expenditure survey data (CEX or PSID), which do not have price of goods purchased by households. Instead, the authors often use Consumer Price Indices (CPI) in the demand estimation. However, such indices are normally only available at more aggregate good or region level. They do not necessarily reflect the actual price faced by households.

[25] I classify products as SNAP-eligible or SNAP-ineligible based on a product taxonomy and the guidelines for eligibility published on the USDA website. Hasting and Shapiro (2018) also define SNAP-eligible food in a similar way as mine using the Nielsen Homescan data.

[26] Non-food Grocery include products like housekeeping supplies, smoking supplies, and pet food/services. 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.

household preferences for food and suggest the benefits to be infra-marginal due to the less comprehensive coverage of the Nielsen Homescan data.

How does Nielsen Homescan data 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 PSID. Appendix Table 24 shows the mapping of the four aggregate goods in this paper to the broad categories of goods in CEX. Table 25 compares the total food expenditure in Nielsen Homescan data with that in CEX, and the numbers are very closed. This gives some confidence on the coverage of products under Food Grocery in Nielsen Homescan data.

In the Appendix, I also 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 price, and sample attrition.

## 1.5 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) to account for gender asymmetries in preferences and bargaining power, as well as consumption economies of scale in the demand estimation of older couples. I then discuss the identification and estimation of the model.

### 1.5.1 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 the household faces a 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

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

$$x = x^f + x^m \tag{2}$$

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

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

Equation (1) is the weighted sum of household members' utility resulting from the Pareto efficiency assumption. $\mu$ refers to the Pareto weight of wives relative to husbands. It summarizes a member's bargaining power. A higher Pareto weight implies that the household demand is represented more by the member's preferences. In general, $\mu$ can depend on prices, total expenditures, and a vector $s$ of distribution factors (factors that only affect bargaining power but not preferences or budget constraint).[27]

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 68).

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 memebrs 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

[27] 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).

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 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 $\pi$ and a sharing rule $\eta$, 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 $\pi$ 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).

### 1.5.2 Identification

Given the model above, the goal here is to identify the parameters for individual members' preferences, Barten scales matrix $A$ and resource shares $\eta$ in equation (6). To do that, it requires that we know the Marshallian demand of wives $h(p/y)^f$ and that of husbands $h(p/y)^m$. However, we do not observe the demand of wives or husbands but only the demand of the households overall. To overcome the identification challenge, Browning et al. (2013) use single females' demand to represent wives' demand and single males' demand to represent husbands' demand. The implicit assumption is that singles' preferences are similar to married individuals.[28] The assumption is vulnerable to the selection into marriage problem, that is, those who get married might have different preferences compared to those who stay single.[29] Since my sample consists of only older adults, I assume older wives have similar preferences to older widows, and that older husbands have similar preferences to older widowers. These two groups of households are similar in terms of observed preference covariates (like demographic characteristics and budget share allocations, shown later in section 1.7). Furthermore, both widows and widowers were married before and hence the identification does not suffer from the "selection into marriage" problem.[30] The implicitly assumption here is that married individuals do not change their preferences on the goods covered by Nielsen Homescan data after the loss of their significant others.

### 1.5.3 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.

[28]Literature on collective household models often need to impose certain preference similarity assumptions in order to identify the model (e.g., Browning et al. 2013 and Dunber et al. 2013). It is because household demand is only observed at the household-level but not individual-level. Due to the same reason, it is not possible to test those assumptions. However, it is possible to test whether individuals, who enter and exit marriage, have similar preferences before and after the marriage. It is also possible to consider some very simple parameterizations of preference change resulting from marriage (Browning et al. 2013).

[29]Brugler (2016) looks at couples in the U.S. using Consumer Expenditure Survey and rejects the preference similarity assumption between singles and married individuals.

[30]The same identification strategy has been used in Cherchye, De Rock, and Vermeulen (2012).

The price in the data is at UPC or bar-code level while the goods in the demand estimation later 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 a large literature in demand estimation and construct Stone Price Indices for each aggregate goods. The details of the construction are discussed below.

The Nielsen Homescan data has information on the total money spent, the purchase date, and the store code for every shopping trip made by all households in a given year. For each shopping trip, households are instructed to scan all UPCs purchased during the trip. The scanned information includes a UPC number, the total price paid, coupon value, deal flag (1 = deal, 0 = no deal), and quantity. I calculate the unit price for each product (UPC) by dividing the coupon-subtracted total price paid by the quantity.

I then aggregate household-specific product-level prices to price indices for aggregate goods. One challenge in doing that is the fact that not all households purchased every UPC, and not all UPCs were available in each state. If I ignore this fact and simply aggregate price from UPC-level to 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 in the construction of 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 in the choice of product groups.

I formalize the above discussions by expressing the price construction 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 $s(h)$.

Instrument for price 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, such as Whole Foods, 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 $H'$.

## 1.6 Budget Shares for Individuals

I specify individuals preferences using the $QUAIDS$ demand system of Banks et al. (1997). 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 $\omega^{hi}$ denote the $J$-vector of budget shares $\omega_j^{hi}$ for $j = 1, ..., J$. Notice that we only observe budget shares $\omega_j^{hi}$ 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 $QUAIDS$ demand equation for an individual of type $i$ living in a household $h$ takes the $J$-vector form

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

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

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

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

Here, $\alpha^{hi}$, $\beta^{hi}$, and $\lambda^i$ are $J$-vector preference parameters, $\Gamma^i$ is $J \times J$ preference parameters. $\delta_0^{hi}$ is a scalar parameter which we set to equal to zero based on the insensitivity reported in Banks et al. (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 $\Gamma^i$ be a symmetric matrix.

I allow observable preference heterogeneity in $\alpha^{hi}$ and $\beta^{hi}$ by letting them to depend on demographic variables. The equation of $\alpha^{hi}$ 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 $M_\alpha$ and $M_\beta$ are the total number of such covariates I observe. Each $\alpha^{hi}$ and $\alpha^{hi}$ 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 8 region dummies, a Black/African American dummy, and a some college education dummy, making $M_\alpha = 10$. $d_{m,\beta}^{hi}$ includes a kitchen appliances (microwave, garbage disposal, and dishwasher owner) ownership dummy and an Internet ownership dummy, so $M_\beta = 2$. 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.

### 1.6.1 The Estimator for Older Widows and Widowers Living Alone

The demand functions for households $h$ consisting of only one member $i$ are given by equation (71). Such households will either have $i = f$ if the household is an older widow living alone or have $i = m$ if the household is an older widower 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 (older widow or widower), I append a $J$-vector valued error term $U^{hi}$ (consisting of elements $U_j^{hi}$ to equation 71). This introduces unobserved heterogeneity in the older 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 $\omega_j^{hi}$ minus the right hand side of equation (71), where $\theta^i$ is the vector of all the parameters in that equation. Note that $u_j^{hi}(\theta^i)$ is simply a function of $\omega_j^{hi}$ and all the regressors in the model. The moment condition for GMM estimation is $E(u_j^{hi}(\theta^i)\tau^{hi}) = 0$, where $\tau^{hi}$ 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 $\tau^{hi}$ for households consisting of one member (widow or widower) includes 8 region dummies, a Black/African American dummy, a some college education dummy, a kitchen appliances ownership dummy, an Internet ownership dummy, log relative prices plus log real total expenditure from the trip data (defined as the log of total expenditures divided by a Stone price Indices computed for the three nondurable goods), its square, and its interaction with the kitchen appliances ownership dummy and the Internet dummy. The number of moments therefore consist of $J - 1 = 3$ distinct demand equations times the number of elements in $\tau^{hi}$, 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 living alone. For $i = f$ and $i = m$, let $H^i$ denote the set of households that consist only one member (older widow or widower) 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 $\widetilde{\theta}^i = \arg\min_{\theta^i} v^i(\theta^i)' v^i(\theta^i)$.

The Joint Model For the empirical application of the joint model, I assume that older widows and widowers living alone 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 $1 - \eta$. $s$ and $q$ denote distribution factors and preference covariates, with $\delta$ and $\sigma$ 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 a dummy that the education of the female head is higher than that of the male head.[31] The preference covariates include a dummy for female with some college education and a dummy for male with some college education, a dummy of Black or African American, a dummy of kitchen appliances (microwave, garbage disposal, and dishwasher) ownership, a dummy of Internet ownership, and log real total expenditure (defined as the log of nominal total expenditure divided by a Stone Price Indice computed for the four aggregate goods).

With the consumption technology function (20) and the corresponding shadow prices (21), and the sharing rule (79), 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 $\omega_j^f$ and $\omega_j^m$ are the female head's and the male head's demand functions, estimated using equations (71) to (73).

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 $QUAIDS$ parameters for the widows' and widowers' budget shares, $\omega_j^f$ and $\omega_j^m$, 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.[32] I have 102 preference parameters ($18 \times 3 - 3 = 51$ symmetry constrained $QUAIDS$

[31] Previous literature also includes unemployment and wage ratio as potential distribution factors. However, the sample in this paper only consists of older adults, who age is either "55-64" or "65+". The majority households of the sample do not work (76 percent of older widows and 79 percent of older widowers, and more than 60 percent of the female and male heads in older couples do not work). Including employment status might cause multicollinearity problem in the estimation. Wage information is also not available in Nielsen Homescan data.

[32] 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

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 widowers and 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

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

where $c$ denote households of older couples, $\theta$ denote the full set of parameter values, and $W^m$ and $W^f$ are taken from $QUAIDS$ 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.

## 1.7 Empirical Results

In this section, I present the empirical results including the estimates for Barten scales and resource shares. I also analyze the individual welfare for older widows and widowers using indifference scales. I then conduct a counterfactual experiment of a SNAP comparable cash transfer and discuss the role of the collective household approach in the evaluation of the SNAP comparable cash transfer in the next section.

### 1.7.1 Sample Selection

I select older widows and widowers who are "ever-widowed households", i.e., who have been widowed at least once during the sample period. Older couples consist of only couples and no others present in the household. Older adults are defined as those who are 55 and above.[33] To mitigate the possible effects of outliers, I further trim the three samples with respect to key variables (yearly budget share of each aggregate good and log yearly total expenditure) by dropping observations in the lower and upper 5 percentiles.[34] I also drop observations if one of the household heads is a student.[35]

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. Hence, we focus on the one-step estimator.

[33]The elderly defined by SNAP are those who are 60 and above. However, the age bins for older adults in Nielsen Homescan data only include "55 - 64" and "65 and above". Hence, I choose "55 and above" to be the criteria for the elderly.

[34]This drops 14747 observations of older widows, 2926 observations of older widowers, and 44791 observations of older couples.

[35]This drops 42 observations for older widow and 291 observations for older couples. None of older widowers are students.

Summary statistics of the resulting samples are reported in Table 2.[36] Older widows' average household income is about 70 percent of older widowers'. Despite that, the total expenditure and the budget shares across the four aggregate goods are similar between older widows and widowers. older widows prefer slightly more of health and beauty and non-food groceries, while older widowers prefer slightly more of general merchandise and food groceries. Notice that the expenditure on SNAP-eligible-food-to-overall-food ratio is around 80 percent for all of the three samples.

**Table 1: Demographic Characteristics**

| | Older Widows | Older Widowers | Older Couples |
|---|---|---|---|
| Number of unique households | 5,455 | 1,092 | 23,807 |
| Household income | 24338.49 | 33555.20 | 46732.05 |
| Yearly expenditure (trip data) | 2968.27 | 2837.00 | 6425.16 |
| Yearly expenditure (purchase data) | 1933.45 | 1926.53 | 4256.22 |
| Budget share (health&beauty) | 0.13 | 0.10 | 0.12 |
| Budget share (general merchandise) | 0.09 | 0.09 | 0.10 |
| Budget share (food grocery) | 0.68 | 0.72 | 0.68 |
| Budget share (non-food grocery) | 0.10 | 0.08 | 0.10 |
| Yearly SNAP-eligible food spending | 1181.02 | 1200.74 | 2167.89 |
| Expenditure share (SNAP food / Food Grocery) | 0.79 | 0.77 | 0.81 |
| Female head age | 73.41 | - | 66.03 |
| Male head age | - | 75.60 | 68.66 |
| >= Graduated high school (Female) | 0.95 | - | 0.96 |
| >=Some College (Female) | 0.58 | - | 0.61 |
| >= Graduated high school (Male) | - | 0.95 | 0.93 |
| >=Some College (Male) | - | 0.70 | 0.66 |
| Microwave, Dishwasher, & Garbage Disposal | 0.23 | 0.25 | 0.22 |
| Regular & Pay Cable | 0.31 | 0.39 | 0.39 |
| Internet connection | 0.60 | 0.68 | 0.83 |
| Obs | 19,366 | 3,440 | 82,716 |

*Notes:* Values are mean. Yearly expenditure from the trip data is the total expenditure for each trip. Yearly expenditure from the purchase data is the sum of money spent on the scanned items by the panelists. The latter is smaller than the former due to missing scanned items or items were eaten on the way home.

To illustrate the differences in demands of older widow, widowers, and couples, Figure 7 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 (Engel curves are downward sloping ) while General Merchandise is a luxury good (Engel curve is upward sloping). The Non-food Grocery is a luxury good at low expenditure level and becomes a necessity at high expenditure level. The elasticities

[36]The sample size of older widows is about five times that of older widowers. This is consistent with the current widow-to-widower ratio in the U.S..

estimates of older widows and widowers are reported in Table 6.

### 1.7.2 The Sharing Rule

The main results for the joint model are displayed in Table 2. The upper panel shows the results on the mean wife's resource share and the sharing rule. In theory, the sharing rule can depend on both distribution factors and preference factors. I first try model (1), which includes only one distribution factor: a dummy variable that the education of the female head is higher than that of the male head. The significant positive coefficient implies that, on average, wives in households where her education is higher than her spouse enjoy 21.3% higher resource share. I then try model (2), which includes both distribution factors and preference factors. The significant positive coefficient of log real total expenditure suggests that wives in households with one unit higher log real total expenditure enjoy 27.3 % higher resource share. This finding is different from empirical results in previous literature, which often find log real total expenditure to not be significant in determining the sharing rule. For example, a key assumption in Dunbar et al. (2013) is that the resource share does not depend on total expenditures. Menon, Pendakur, and Perali (2012) test the assumption with Italian International Center of Family Studies (CISF) and do not reject the assumption. The different results here might be driven by the different samples used in this paper, which only focuses on older adults. It might also be due to that the total expenditure in this paper only covers grocery-type goods and hence is only a subset of total expenditures studied in previous literature. On the other hand, wives in households with Internet connection and microwave, dishwasher, and garbage disposal have 12.8% and 11.7% lower resource share, respectively. To further test whether log real total expenditure is significant in resource shares, I estimate model (3), which only includes the distribution factor that whether the education of the female head is higher than that of the male head, and the log real total expenditure. It turns out that log real total expenditure becomes insignificant in resource shares. And hence model (1) is more preferred to model (3). In all three models, I find that the mean resource share of wives is higher than that of husbands. This finding implies that couples' preferences are represented more by wives' preferences.[37] The finding is consistent with previous studies on the sharing rule in western developed countries. For example, Browning et al. (2013) study the Canadian couples and Cherchye et al. (2012) study older couples in Netherlands. They both find that wives has

[37] The finding here is also supported by the evidence that two thirds of grocery shoppers are women (Goodman 2008).

higher resource shares than husbands.

To select between model (1) and (2), I use the non-nested testing procedure proposed by Smith (1992).[38] The resulting Cox-type statistics is 0.0248. Hence, model (1) is not rejected. This implies that the preference covarites in model (2) do not have significant effects on resource shares. Hence in the following analysis, I choose estimates from model (1) as my baseline demand estimates.

**Table 2: Estimation Results on Sharing Rule and Barten Scales**

| | Model (1) | | Model (2) | | Model (3) | |
|---|---|---|---|---|---|---|
| Mean wife's share | 0.675 | | 0.824 | | 0.879 | |
| Distribution and Preference Factors | coef | Std error | coef | Std error | coef | Std error |
| Constant | 0.679*** | 0.042 | 0.074 | 0.707 | 0.275 | 1.060 |
| Female some college | | | -0.117 | 0.710 | | |
| Male some college | | | -0.291 | 0.860 | | |
| Difference in age (female - male) | | | 0.005 | 1.048 | | |
| Female education higher than male | 0.213*** | 0.043 | -0.001 | 0.503 | 0.491*** | 0.186 |
| Black or African American | | | -0.094 | 0.148 | | |
| Kitchen appliances | | | -0.117*** | 0.072 | | |
| Internet | | | -0.128*** | 0.059 | | |
| Log real total expenditure | | | 0.273*** | 0.100 | 0.222 | 0.143 |
| | Barten scale | Std error | Barten scale | Std error | Barten scale | Std error |
| General Merchandise | 0.669*** | 0.011 | 0.665*** | 0.014 | 0.768*** | 0.016 |
| Food Grocery | 0.785*** | 0.016 | 0.837*** | 0.023 | 0.951*** | 0.024 |
| Non-food Grocery | 0.780*** | 0.021 | 0.713*** | 0.020 | 0.964*** | 0.018 |
| Health & Beauty | 0.799*** | 0.013 | 0.834*** | 0.019 | 0.893*** | 0.018 |

*Notes:* The table displays the estimates of the joint model for older couples. Barten Scales are assumed to be homogeneous across all households. Model (1) includes only distribution factors in the sharing rule. Model (2) includes both distribution factors and preference factors in the sharing rule. Kitchen appliances is a dummy denoting whether the household owes microwave, garbage disposal, and dishwasher. Model (3) includes only the distribution factor that female's education higher than male's and log real total expenditure. $\star p < 0.10, \star\star p < 0.05, \star\star\star p < 0.01$.

### 1.7.3 Barten Scales

The lower panel of Table 2 shows the Barten scales for each of the four aggregate goods. The rankings in terms of jointness or sharing of good for each good are similar across three models. Food grocery and health and beauty are the least public, non-food grocery is public to some extent, and general merchandise is the most public. The finding on the Barten scale of food is consistent with that in previous literature (e.g., 0.77 in Browning et al. 2013 and 0.994 in Cherchye et al. 2012). The estimated Barten scale of General Merchandise is also intuitive

[38] In particular, the Cox-type statistics is constructed by examining the difference of the estimated GMM criterion functions for the model (1) $M_1$ and for the alternative model (2) $M_2$. 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 $M_1$ against $M_2$.

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

### 1.7.4 Poverty Analyses with Indifference Scales

Given the structural estimates of the sharing rule and Barten scales, I further study the welfare implications for wives and husbands in older couples. I use the so-called "indifference scales" developed by Browning el al. (2013). They use resource shares and Barten scales to construct indifference scales in order to compare the welfare of individuals living under different economic environments (mainly household size and composition). The indifference scale is defined as "the fraction of household expenditures that the wife (husband) needs to obtain the same utility of goods in marriage if she (he) is living alone, endowed with the fraction of resources in marriage and faced with market prices." For the older adults application here, the question would be that "How much income would a widow or widower living alone need to be materially as well as a member of an older couple?"

To conduct individual welfare analyses of older widows and widowers, I first construct the equivalent budget share (EBS) for widows and widowers. EBS is calculated as the wife' or the husband' QUAIDS budget share if she or he is faced with a resource share of 0.675 or 0.325 and the shadow price. The equivalent budget share represents the private good equivalents, that is, the quantities the female or male head consumes out of the purchased bundles. I then calculated their equivalent expenditures (the income required by the older widow or widower to live materially as well off as if she or he is living in an older couple). This allow me to calculate their indifference scales (their equivalent expenditures divided by the household total expenditure), and the overall scale economy (how much it would cost a couple more to buy the private equivalent goods they consumed in marriage if there had been no shared or joint consumption). The formal definitions of EBS, equivalent expenditures, indifference scales, and overall scale economy are given in equations (28) to (34) in the Appendix. The results for them are reported in Table 3, where the middle column reports the estimates if we assume wife's resource share to be 0.5, while the right column reports the estimates under the estimated wife's resource share 0.675. Comparing the estimates under these two columns tell us how much the welfare implications would be biased if we assume equal sharing (ignore intrahousehold inequality in resource allocation).

The upper panel of Table 3 reports the EBS for wives and husbands. The numbers of EBS represent how wives or husband allocates her or his budget across the four aggregate goods. Compared with husbands, wives demand less Food Grocery and General Merchandise but more Health and Beauty and Non-food Grocery. This pattern is consistent with the actual budget shares for older widows and widowers reported in Table 2. This gives some confidence on the estimates of the joint model.

The first two rows of the lower panel in Table 3 show the equivalent expenditures for wives and husbands. Equivalent expenditure is the amount of money that the member needs to attain the same indifference scales of goods in marriage while living alone, that is, being faced with full market price and their respective resource share. Given the definition, an individual has higher equivalent expenditure if she enjoys higher resource share or if she allocates more budget share to more public goods. I find that wives' mean equivalent expenditure (2842) is much higher than husbands' equivalent expenditure (1368.90), and this is mainly due to wive's higher resource share (0.675) compared to husbands' (0.325). If we assume equal sharing (as reported in the middle column), wives and husbands would have similar equivalent expenditures (2104.9 for wives and 2104.4 for husbands).

Wives' higher equivalent expenditures mean that they also have higher indifference scales. Wives on average require 76% of the household total expenditure to attain the same allocation of goods in marriage while living alone. That number is only 42% for husbands. It implies that wives on average abstract much more gains from marriage than husbands, and this is mainly due to that wives control more of the household total expenditure.

The last row of Table 3 reports the overall scale economy or the consumption economies of scale $R$, which is equal to 0.293. This means that it would cost an older couple 29.3 percent more to buy the (private equivalent) goods they consumed if there had been no shared or joint consumption. Notice that this estimate presents an upper bound of the total expenditure the couple needs if they live apart. The reason is that they can re-allocate purchases and attain more cheaply the same indifference curves that $x^f$ and $x^m$ lie on (Browning et al. 2013).

**Robustness Checks** To test the sensitivity of the empirical results, I compare the demand estimates using the collective household approach with the unitary approach, that is, estimate QUAIDS for widows, widowers, and couples. The goal is to select the model most consistent with the data among non-nested competing models. I again use the non-nested testing procedure

**Table 3: Implications of estimates**

| Wife's share | 0.500 | | 0.675 | |
|---|---|---|---|---|
| Equivalent budget share | female | male | female | male |
| General merchandise | 0.09 | 0.09 | 0.09 | 0.10 |
| Food grocery | 0.67 | 0.72 | 0.67 | 0.70 |
| Non-food grocery | 0.11 | 0.08 | 0.11 | 0.08 |
| Health and beauty | 0.13 | 0.10 | 0.12 | 0.11 |
| | | | | |
| Her equivalent expenditure | 2104.90 | | 2842.00 | |
| His equivalent expenditure | 2104.40 | | 1368.90 | |
| Actual couple's expenditure | 3256.70 | | 3256.70 | |
| Indifference scale for women | 0.65 | | 0.87 | |
| Indifference scale for men | 0.65 | | 0.42 | |
| Scale economy, R | 0.29 | | 0.29 | |

*Notes:* The table displays the estimates of the joint model for older couples. Barten Scales are assumed to be homogeneous across all households. Model (1) includes only distribution factors in the sharing rule. Model (2) includes both distribution factors and preference factors in the sharing rule. Kitchen appliances is a dummy denoting whether the household owes microwave, garbage disposal, and dishwasher. Model (3) includes only the distribution factor that female's education higher than male's and log real total expenditure. $\star p < 0.10, \star\star < 0.05, \star\star\star < 0.01$.

proposed by Smith (1992).[39] The resulting Cox-type statistics is 0.0098. Hence, the collective demand model is not rejected.

From Table 2, the household income of elderly widows are lower than that of elderly widowers and couples. This might challenge the preference similarity assumption between elderly widows and older wives. As another robustness check, I drop elderly widow households whose income was below $ 20,000. This gives me similar average household income between elderly widows and widowers. I then re-estimate the joint model (1) and (2). The resulting elasticities estimates for elderly widows and widowers sample are reported in Appendix Table 7. They are similar to Table 6 of the baseline estimates. The resulting estimates of the resource share and Barten scales are presented in Table 8, which is again similar to the baseline model estimates in Table 2.

Another concern is that how different are husbands' and wives' preferences? To answer this question, I estimate the model constraining men and women to have the same 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).

[39]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 $M_u$.

## 1.8 Counterfactual Exercises: A SNAP Comparable Cash Transfer

Given the estimates of preferences for older widows and widowers, and of older couples' demand that takes into account within-household preference heterogeneity and consumption economies of scale, I next perform a counterfactual experiment: replaceing SNAP with a comparable cash transfer.

The goal of this counterfactual exercise is to see what would happen if we replace the current SNAP in-kind transfer with a more convenient cash transfer. Notice that the convenience of cash transfers here implies not only lower administration cost but more importantly it might greatly encourage SNAP take-up, which is a major concern among older population. There is a large debate on whether using in-kind or cash transfers to subsidize policy-desired goods. They mainly rely on reduced-form studies that look at the fraction of households whose food spending is constrained by their benefits, and compare the spending between constrained and unconstrained households. These studies make an implicit assumption: constrained households, who are normally poorer, have different preferences from richer households. They would spend benefits, if given in cash, on non-food goods. Given this assumption, they argue that a higher fraction of constrained households lead to more support for in-kind transfers.

However, I first argue that this assumption has not been directly tested before. The structural model here allows me to directly test this assumption by conducting a counterfactual experiment of a SNAP comparable cash transfer. Second, previous studies that do use structural approach on demand estimation often ignores within-household preference heterogeneity and consumption economies of scale, both of which are important in precisely estimating preferences of multi-person households. Here I adopt the collective household approach to study demand responses to a SNAP comparable cash transfer for an alternative effective policy design of SNAP.

I first select SNAP-eligible older adults. To do that, I utilize the means-tested feature of SNAP and the availability of household income in Nielsen Homescan data. I then present the counterfactual outcome and its implications. The focus here would be on findings for the constrained households, who are the main target of in-kind transfers. In particular, I relate the implications to the motivations of using the collective household model in Section 1.3.

One thing I should be upfront is that I do not observe SNAP participation in the Nielsen data set. If some of the imputed SNAP-eligible households are already SNAP recipients while I take their budget constraint the same as equation (68) (that is, ignore that their budget might be binding by the SNAP in-kind design, or the distorted case shown in Figure 3), I will obtain biased demand estimates for these SNAP participants. I perform a robustness check at the end of this chapter to show that the baseline preferences for food are not biased by the potential existence of SNAP participants in the data set.

### 1.8.1 Sample Selection of SNAP-Eligible Older Households

As a means-tested program, SNAP selects eligible households based on the income and resources of household, household size, and employment status. However, households with people with disabilities or adults ages 60 and older are required to meet only the net monthly income requirement.[40] Given the availability of household income in Nielsen Homescan data, I select the sample of eligible older households (widows, widowers, and couples) according to the current SNAP eligibility scheme.[41]

The maximum gross income of a household to receive SNAP benefits is set at 130 percent of the poverty line.[42] Table 4 reports the maximum gross income and the maximum SNAP benefits for one-person and two-person households. I follow the SNAP benefit formula to calculate the potential benefits available to the eligible older households. Specifically, I calculate the net income, which is the gross income subtracted by certain deductions, and then multiply it by 30 percent.[43] That number is then subtracted from the maximum allotment, and the remaining amount is the potential SNAP benefit. The deductions include a 20-percent deduction from gross income, a standard deduction of \$160 for household sizes of 1 to 3 people, and a standard shelter deduction for homeless households of \$143.[44] Equation (25) summarizes the SNAP benefit formula.

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

[40] SNAP counts cash income from all sources, including earned income (before payroll taxes are deducted) and unearned income, such as cash assistance, Social Security, unemployment insurance, and child support.

[41] The income in Nielsen Homescan data is for 2 years prior to the panel year. Because I do not want to drop households in year 2004 - 2005 whose income is not available in the sample period, I assume the household current income is the same as the income 2 years ago.

[42] In most cases, a household must meet both the gross and net income limits. However, a household with an older or disabled person only has to meet the net income limit. This means that I might underestimate the number of eligible older households by following only this criteria. On the other hand, since I don't have information on household resources or assets, I might underestimate household total assets and hence overestimate the number of eligible older households.

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

[44] I exclude the dependent care deduction and the medical deduction since they are not available in the data. A dependent care deduction is the expenditure needed for work, training, or education. 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. Since my sample is restricted to older adults, and the poor older are more likely to have medical deductions, the resulting estimated benefits are likely to be underestimated.

The resulting sample of SNAP-eligible older households and summary statistics are reported in Table 9. The fraction of SNAP-eligible households among older widows, older widowers, and older couples are 40 percent, 22 percent, and 17 percent, respectively.[45] The fraction of constrained households is 42 percent to 48 percent.[46] Comparing Table 9 to Table 2, there are no significant differences in demographic characteristics between the eligibles and the entire samples, except that the eligibles have lower household income. Table 10 reports the summary statistics comparing constrained and unconstrained SNAP-eligible households. The budget share on SNAP-eligible food is similar between these two groups. Notice also that there is no evidence that constrained households are more likely to eat unhealthy foods.

Moreover, I follow Hoynes et al. (2015) in defining healthy foods, unhealthy foods, and sugar-sweetened beverages, and compare food spending by types of food between SNAP-eligible and ineligible older households.[47] The results are reported in Table 11. Again, the budget shares of health and unhealthy food are similar between the two groups. This is consistent with the finding in Hoynes et al. (2015), which also compares the expenditure pattern between eligible and ineligible households using Consumer Expenditure Survey. The finding here also provides suggestive evidence that poor older households are not more likely to eat unhealthy food. Their low total expenditure on food is mainly due to their low household income. This evidence will later support my counterfactual outcomes in section 1.8.3.

**Table 4: SNAP Eligibility Criteria and Maximum Benefits**

| Number of Household Members | Maximum Amount of Gross income for All Household Members | Maximum Food Stamp Benefits |
|---|---|---|
| 1 | \$1,307 | \$192 |
| 2 | \$1,760 | \$352 |

*Notes:* The table reports the maximum gross income and maximum allotment by household size of current SNAP eligibiligy and benefits scheme. Gross income is a household's total, non-excluded income, before any deductions have been made. Source: United States Department of Agriculture (USDA) Food and Nutrition Service

[45] According to USDA, 9 percent of U.S. seniors live below the poverty level. This number is much lower than the fraction of SNAP-eligible older households here because I only look at widowhood people living alone and older couples, and exclude households in which seniors live together with others. It is expected that widowhood households and older couples living by themselves are poorer than seniors living with others.

[46] This number is much higher than previous findings that use expenditure survey data and approximate SNAP-eligible spending with total food spending.

[47] 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 "unhealthy 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.

### 1.8.2 Counterfactual Budget Shares

Given the sample of SNAP-eligible households, I conduct a counterfactual experiment of a SNAP cash transfer among them. To do that, I add potential benefits as cash transfers to the total expenditure of SNAP-eligible 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

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

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

One caveat in the analyses that I should be clear about is that the demand in this paper is only modeled at the level of aggregate food. That is, I could only predict the counterfactual expenditure share for overall Food Grocery. Nonetheless, by assuming that the expenditure on SNAP-eligible-food-to-overall-food ratio is the same as in the baseline case (around 80 percent), I can back out the expenditures on SNAP-eligible food by multiplying the expenditure on SNAP-eligible-food-to-overall-food ratio with the counterfactual total food expenditure. I define the extra-marginal households as those whose SNAP-eligible food spending given the cash transfers is below their imputed SNAP benefits.

### 1.8.3 Counterfactual Results

In this subsection, I report the counterfactual results for older couples, constrained households, and unconstrained households. I first show the counterfactual results for older couples. In particular, I show the importance of accounting for unequal bargaining power between wives and husbands in order to precisely estimate couples' food demand responses to SNAP cash transfers. I then show the results for constrained and unconstrained households, with the focus on the former households. I show that the assumption that poor households prefer less nutritious food than richer households does not hold for the older population. And this finding might be overlooked if we ignore intrahousehold inequality in bargaining power and preference heterogeneity in the demand estimation of older couples.

### 1.8.4 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 0.675 or 0.5. The results are reported in Table 17. Tables 18 and 19 show the demand responses of wives and husbands, if they are faced with the shadow prices, and their respective resource share. In terms of food spending, the increase in budget share for food is 2.45 percent higher for husbands than wives. If we ignore wives' higher bargaining power and assume her resource share to be 0.5, we would overestimate the demand for food by 1.8 percent. On the other hand, without accounting for husbands' stronger preferences for food, we might underestimate the couple's increase in food spending. Both spouses increase spending on Food Grocery and decrease spending on General Merchandise and Health and Beauty. However, wives increases Non-food Grocery by 9.95 percent while husbands does not have a significant change in this category. Husbands decrease spending on General Merchandise by 14.69 percent while wives only decrease spending on it by 3.53 percent.

### 1.8.5 Counterfactual Results for Constrained Older Households

Constrained households are more concerned by policymakers, because they did not spend enough on nutritious food and have relatively low income. They are also the main target of an in-kind transfer because theory predicts that their preferences might be different: they might prefer other non-food necessities rather than nutritious food. Using an in-kind transfer is likely to distort their consumption to be at the kink point, as illustrated in Figure 3. However, it is not clear whether the main reason for being constrained is low income or preference differences. If giving them cash transfers can encourage them to spend all benefits on nutritious food, it implies that these households are constrained due to low income itself rather than preference. It also implies that cash transfers can be an effective tool in achieving the desired outcomes.

The counterfactual results for constrained older widows, widowers, and couples are reported in Table 12 and Table 15 respectively. Table 13 and Table 13 report the counterfactual results separately for extra-marginal and infra-marginal households among older constrained widows and widowers. For constrained older widows (Table 12), 42 percent of them are extra-marginal households, meaning that they do not spend all imputed SNAP benefits on SNAP-eligible food. However, even among those extra-marginal older widows, a large fraction spend 80 - 90 percent of imputed SNAP benefits on SNAP-eligible food (Figure 4). The results are similar for constrained older widowers (Table 14), among whom only 30 percent are extra-marginal and among them most spend 80 - 90 percent of imputed SNAP benefits on SNAP-eligible food (Figure 4). This finding implies that older constrained widows and widowers have strong preference for food, and for SNAP-eligible food. The cash transfers can yield the desired outcome, that is, promoting nutrition intake among the poor households.

For constrained older couples (Table 15), around 30% of households are extra-marginal. However, all older constrained couples' spending on aggregate food, given the cash benefits, is above their imputed SNAP benefits. Notice that the result would be different (I might find more extra-marginal households) if I assume equal sharing (bargaining power) in older couples. This is because I would ignore husbands' stronger preference for food than wives and underestimate the couple's overall demand for food.

These results suggest that constrained households are not necessarily equivalent to extra-marginal households. It rejects the theory's prediction on constrained households, that they have low preferences for food. Instead, when we compare the average household income between infra-marginal and extra-marginal households for older widows and widowers (last column in 12), we see that the income for the latter is much lower. Combining the suggestive evidence from before, that poor households are not more likely to eat unhealthy food compared to relatively rich households in the baseline summary statistics (Table 10), it seems that households are food insecure due to low income rather than different preferences.

I next calculate the full propensity to consume (FPC) SNAP-eligible food out of SNAP benefits (shown in panel B in Table 12 and Table 15 for widows, widowers, and couples respectively). The FPC SNAP-eligible food out of imputed SNAP benefits is 0.56, 0.61, and 0.59 for widows, widowers, and couples, respectively. If we look further into the FPC between extra-marginal and infra-marginal households for older widows and widowers (there are no extra-marginal households in older couples), the former is much lower (0.21 for widows and 0.15 for widowers), as shown in Table 13 and Table 14 . The extra-marginal households are those who live in deep poverty compared with infra-marginal households. For these households, it is likely that both low income and weaker preference for food explain low consumption of nutritious food. For them, in-kind transfers might be desirable and useful in terms of promoting nutritious food consumption. However, they still only constitute a small fraction of the eligible households, and they are more prevalent among widowhood households, not among older couples. On the other hand, we are not sure about the trade-off in in-kind transfers between promoting policy-desired goods consumption and creating stigma that deters take-up. It is not clear whether these extra-marginal households are also those who are more affected by stigma and less likely to take up in-kind benefits. To answer this questions, we will need both SNAP participation and eligibility data as well as the reasons for not taking up SNAP benefits among eligible households.

### 1.8.6 Counterfactual Results for Unconstrained Older Households

Table 16 panel $A$, $B$, and $C$ report the counterfactual results for unconstrained older widows, widowers, and couples, respectively. For them, the theory predicts that SNAP in-kind transfers are equivalent to cash transfers, in the sense that the food vouchers would simply replace one-to-one their out-of-pocket spending on SNAP-eligible food.

I find that for older unconstrained widows, SNAP cash transfers lead to higher expenditures on Food Grocery and an even larger increase in Non-food Grocery. The expenditures on Health and Beauty drop by a fairly large amount. For older unconstrained widowers, SNAP cash transfers lead to higher food expenditures and lower expenditures on General Merchandise and Health and Beauty. For older unconstrained couples, expenditures on Food and Non-food Grocery increase while expenditures on General Merchandise and Health and Beauty decrease, with or without assuming equal sharing. However, the increase in Non-food Grocery would be overestimated under equal sharing because it overlooks the small change in non-food groceries by husbands.

Panel B in Table 16 reports the full propensity to consume (FPC) food out of SNAP cash benefits, which is 0.76 - 0.83 for unconstrained widows, widowers, and couples. By assuming the same ratio of expenditure on SNAP-eligible food to expenditure on overall food (around 0.8), the full propensity to consume SNAP-eligible food out of SNAP cash benefits is 0.61-0.66. That number is much larger than the previous findings on the marginal propensity to consume (MPC) food out of cash based on the reduced-form approach.[48] This finding highlights the caveat in

[48] Previous literature normally finds the marginal propensity to consume food out of cash to be around 0.1. For example, Hoynes and (2009) estimate an MPC food out of cash income of 0.09 to 0.10. Beatty and Tuttle (2015) estimate an MPC food out of cash income of 0.15. Hastings and Shapiro (2018) estimate an MPC food out of cash income of no more than 0.1.

using the effect of a marginal change to infer the effect of a substantial change.[49] The results in this paper speak to the non-marginal design of SNAP and estimate the full response of demand to SNAP cash transfers.

**Robustness Checks** I performed a series of robustness checks to test the sensitivity of my counterfactual results to the possible error in the imputed SNAP benefits and the fact that some of the households in the data set are SNAP participants while I take them as nonparticipants. The details are presented below.

In order to overcome the potential measurement error in selecting the potential eligible households, I compare the income and expenditure characteristics of the eligible sample in this paper with that in previous literature as a robustness check. First, I re-calculate the fraction of constrained households using total food expenditures rather than SNAP-eligible spending. The fraction is around 30 percent, which is consistent with estimates from previous literature, e.g., Johnson et al. (2018) using Panel Study of Income Dynamics (PSID) data from 1977 to 2013.

Nielsen does not provide information on SNAP participation. Some households in the data set might already be SNAP recipients, and for those who are constrained, their consumption might be distorted to meet the SNAP's needs standard (the cost of a minimal-cost, nutritious diet). I might overestimate or underestimate their preferences for food because both the price and income effects would be biased if they are SNAP recipients.

First, how large is the fraction of households whose tastes for food could be overestimated? It is the fraction of households who are SNAP participants, as well as being constrained, while I could not identify them in the data set and count their SNAP-eligible spending as if it were without SNAP benefits. According to USDA, 42 percent of eligible older individuals participate in SNAP.[50] Dean and Flowers (2018) from AARP Public Policy Institute show that the majority of older adults who rely on SNAP live alone. In 2016, nearly 70 percent of SNAP households with adults age 50 - 59 were single-person households. Among households with adults ages 60 and above, over 80 percent live alone.

Hence, my sample here of SNAP eligible older widows and widowers are likely to contain SNAP participants while SNAP eligible older couples are mostly SNAP non-recipients. Therefore, it is likely that I would would get biased preferences estimates for the former sample.

[49]Similar argument is found by Banks et al. (1996). They find that demand estimation is important in order to precisely estimate the full response to a tax reform and obtain unbiased welfare implications.

[50]Source: USDA Support for Older Americans, Fact Sheet, https://www.fns.usda.gov/pressrelease/2015/020215

First evidence that I could test whether households are SNAP participants is that, I would expect to see many eligible households spend exactly the amount of their imputed benefits on SNAP-eligible food (if we assume that these participating households are also likely to be constrained and have low preferences for SNAP-eligible food). That is, their consumption would be binding by their SNAP benefits. To test that, I plot the distribution of the ratio between SNAP-eligible spending and imputed SNAP benefits across the three samples. They are reported in Appendix Figure 8. I do not find discontinuity in the SNAP-eligible spending over benefits ratio in the neighborhood of 1. This finding implies that it is less likely that a large number of households in the data set are SNAP participants.

To further test whether my baseline demand estimates were biased by potential unobserved SNAP participation, I re-estimate the joint model only for SNAP ineligible households and calculate the implied elasticities for ineligible widows and widowers (because 70 - 80% of SNAP elderly participants live alone, the estimation errors are most likely to occur for widowhood households in my sample). I compare that to the elasticities implied by my baseline estimates (obtained by estimating the joint model using the full sample) for ineligible widows and widowers. If the two sets of elasticities, especially budget elasticities of food, are similar, then it implies that I am not overestimating households' preferences for food.

The resulting two sets of elasticities estimates are presented in Table 20 and Table 21. They are similar in terms of both the sign and magnitude. In particular, the budget elasticities of Food Grocery, which reflect the household food spending in response to an income shock, are similar. This finding shows that my baseline estimates on household preferences for food are not biased by the potential SNAP participants in the data set.

The other concern on changing SNAP vouchers to cash is that recipients might spend the benefits on alcohol. Nielsen Homescan data set has expenditure information on alcohol. However, due to the censoring problem of alcohol consumption, I drop this department from the demand estimation. As a robustness check, I report the yearly alcohol expenses, yearly Food Grocery expenses, and the alcohol expenses to SNAP benefits ratio for SNAP-eligible older widows, widowers, and couples in Table 22. The ratio is 0.11, 0.14, and 0.30 for widows, widowers, and couples who are above the 90% of the observations. Hence, SNAP-eligible older widowers are more likely to spend SNAP benefits on alcohol. However, for over 80% of SNAP-eligible older widowers, their alcohol expenses to SNAP benefits ratio is equal to or below 0.1. Moreover, the sample size of SNAP-eligible widowers is small compared to that of widows or couples. It is less of a concern that the majority of the recipients would spend the benefits, if given in cash, on alcohol.

## 1.9 Conclusion

This paper considers the role of intrahousehold gender asymmetries in preferences and bargaining power in the evaluation of welfare programs. Specifically, I focus on the Supplemental Nutrition Assistance Program (SNAP), the largest anti-hunger program in the U.S.. By looking at older widows and widowers and couples, using the Nielsen Homescan data, I am able to identify SNAP-eligible food. I find strong evidence of heterogeneity in preferences, not only for aggregate goods but also for more versus less public goods. If one ignores that heterogeneity, then older adults couples' demand for food will be underestimated and this will further bias downwards, both at the intensive and extensive margin, the estimates of older couples whose demand for food would be affected by cash transfers. The observation of preference heterogeneity also highlights the important role of bargaining power, in this case within households.

I estimate a structural model of household demand that identifies wives' and husband's respective preferences and bargaining power and the extent to which goods are shared or jointly consumed. I find that husbands prefer to spend a higher fraction of their budget on Food Grocery and General Merchandise while wives prefer to spend a higher fraction of their budget on Health and Beauty and Non-food Grocery. General Merchandise is the most public while Food and Health and Beauty is the least public. The mean wife's resource share, that is the share of household expenditures enjoyed by an individual, is higher than husband's. This suggests that older couple's consumption decision is represented more by wives' preferences. Using a counterfactual SNAP cash transfer experiment, I find that 70 percent of constrained older couples, and 60-70 percent of constrained older widows and widowers, their spending on food given the cash transfer is above the program's needs standard (the cost of a minimal-cost, nutritious diet). Combing these results with household spending patterns, I argue that low income is the main reason for food insecurity among older households.

This paper is one of the few if any that demonstrates the importance of within-household preference differentials and bargaining power in evaluating welfare programs, the goal of which is to improve welfare by changing household consumption behavior. Future research should focus on the individual welfare analysis within households even though welfare programs are often targeted at household-level. One promising avenue of research is the investigation of household demand within families with children, where preferences are heterogeneous among both adults and children, the parents have caring preferences for children, and there are both adult-specific and child-specific goods.

## 1.10 APPENDIX 1.A: Additional Figures and Tables

**Figure 1: Impact of SNAP on Budget Constraint**

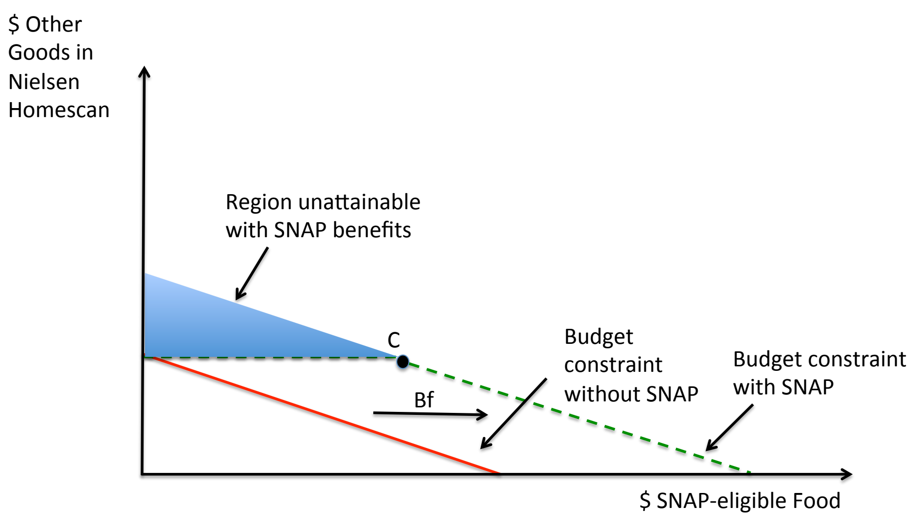



**Figure 2: Consumption Re-allocation for Unconstrained Households**

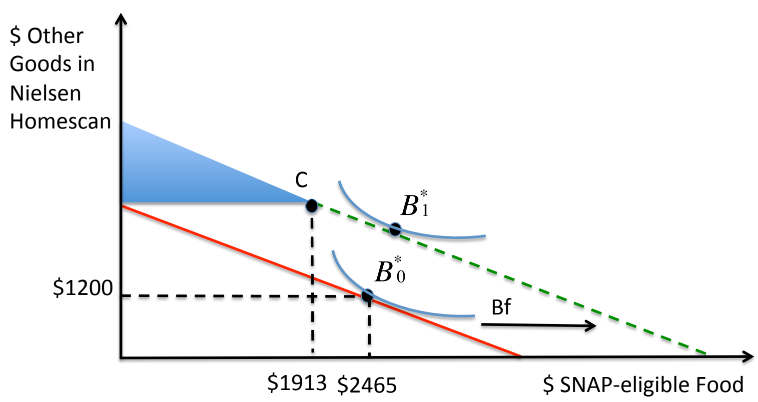
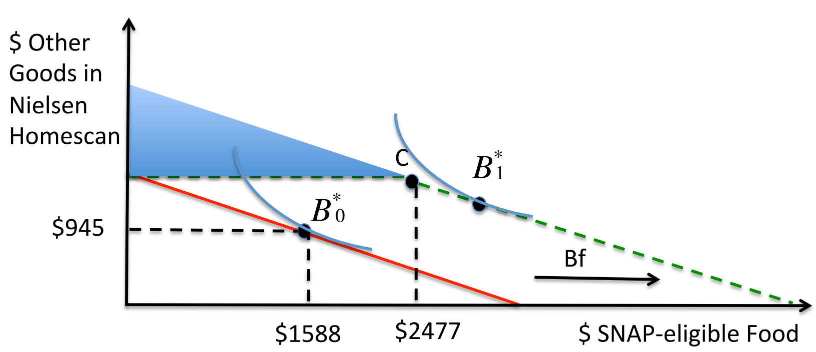
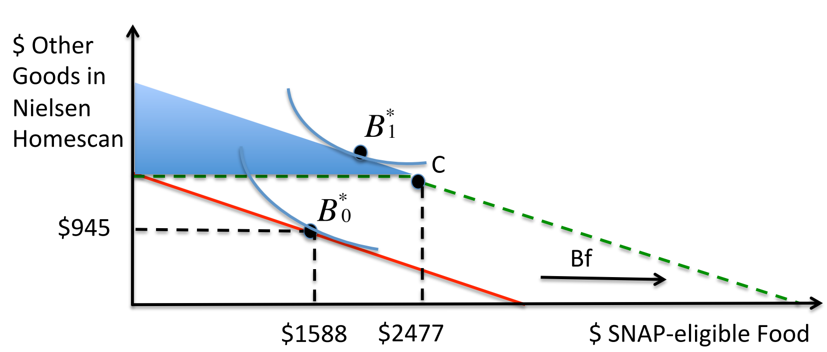



**Figure 3: Consumption Re-allocation for Constrained Households**

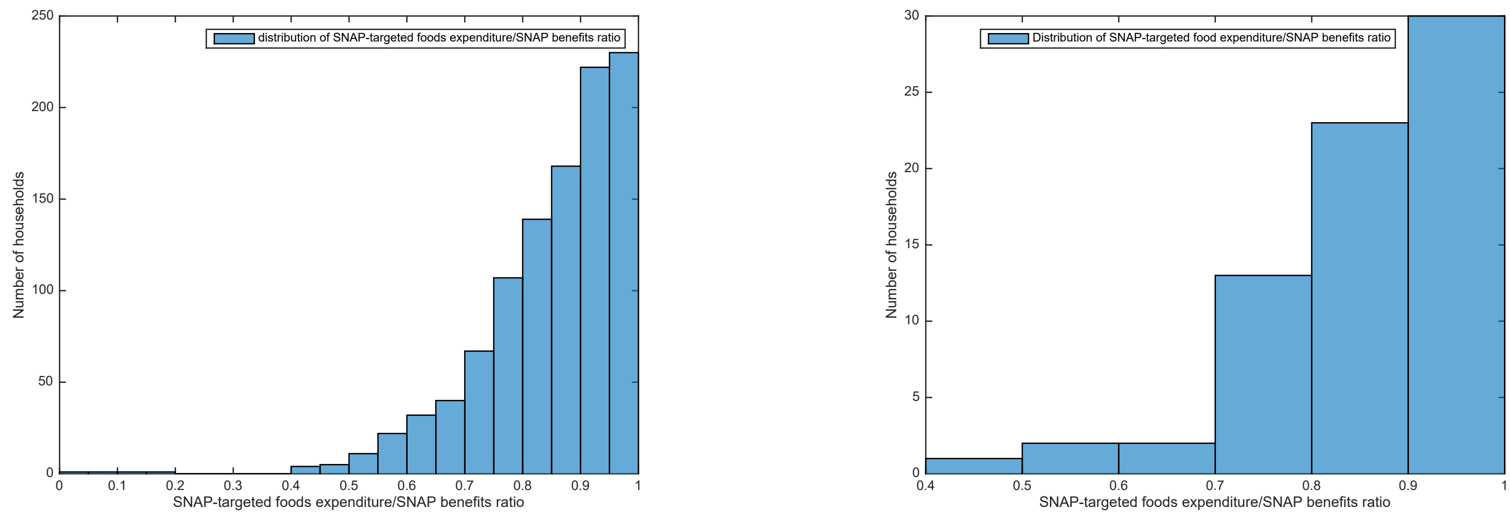



**(a)** Undistorted Case




**(b)** Distorted Case

## Figure 4: Baseline: SNAP-eligible Spending to SNAP Benefits Ratio




**(a)** Extra-marginal Older Widows

**(b)** Extra-marginal Older Widowers

## Figure 5: Mean Food Expenditures: by Age of Reference Person, 2013, CEX

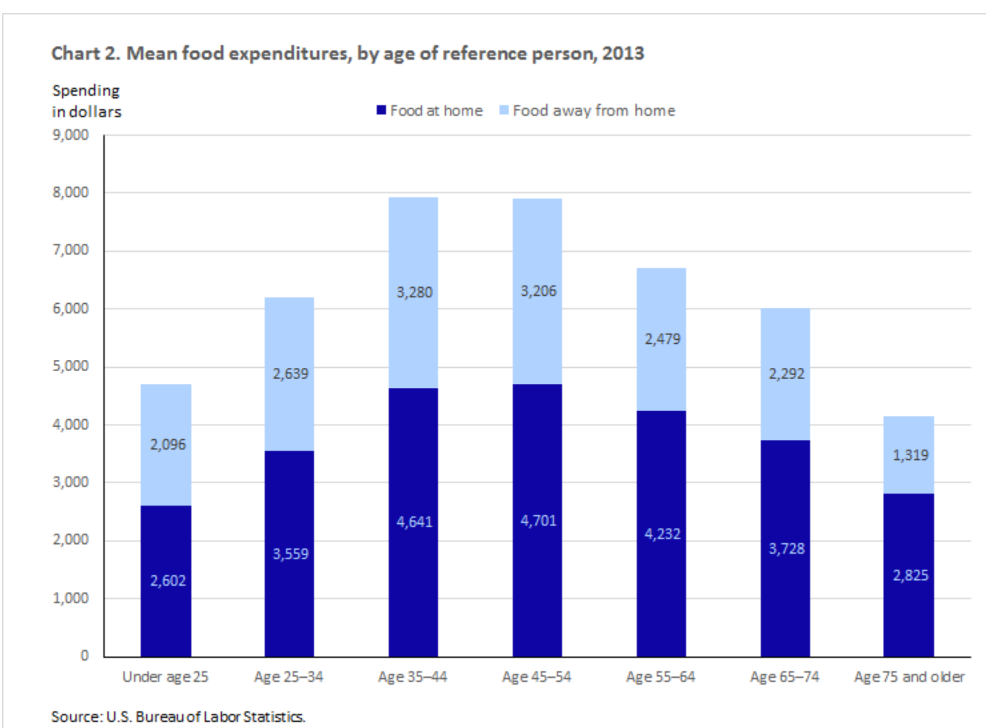


Figure 6: Other Non-food Expenditures: by Age of Reference Person, 2013, CEX

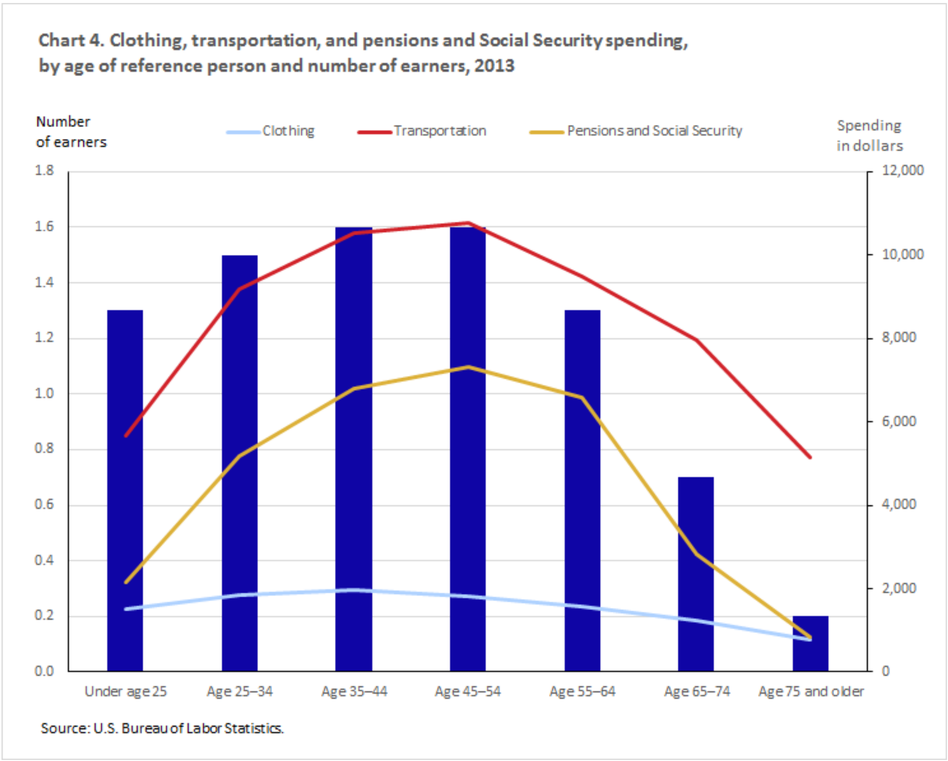
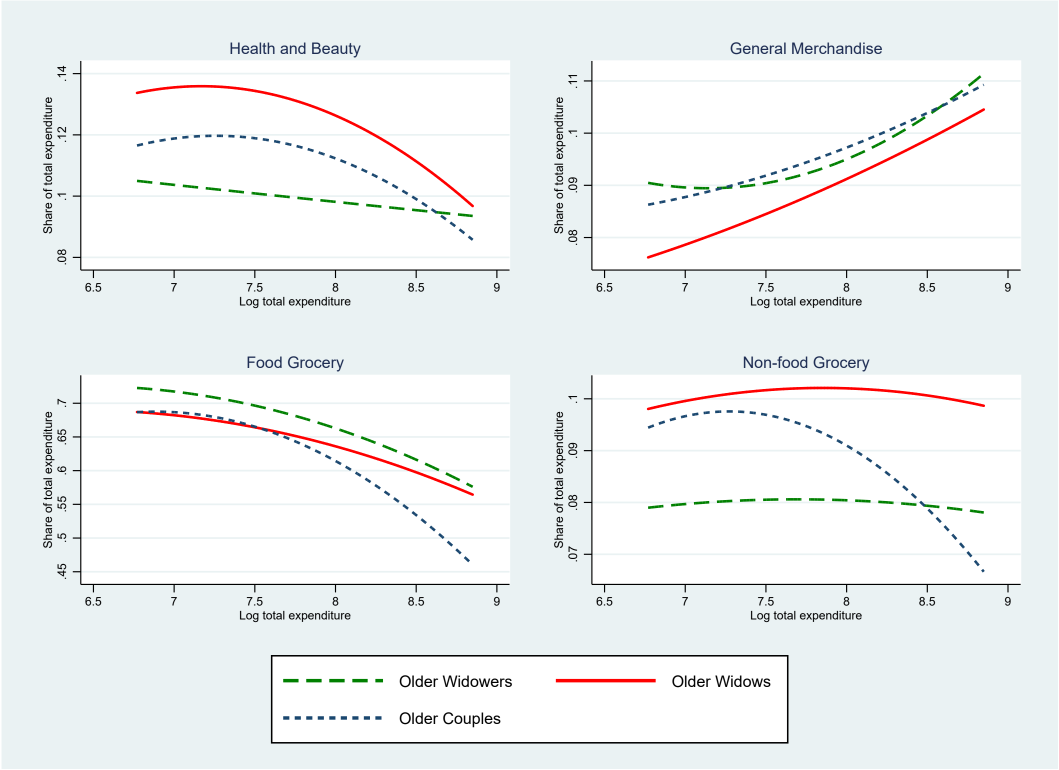
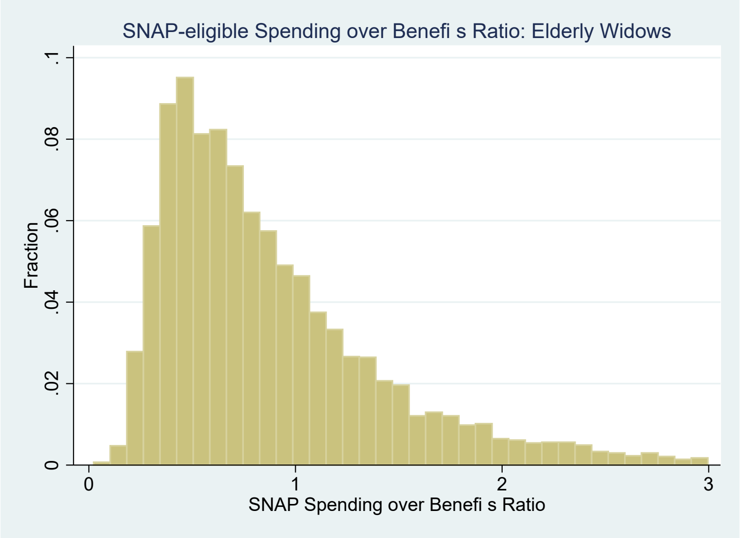
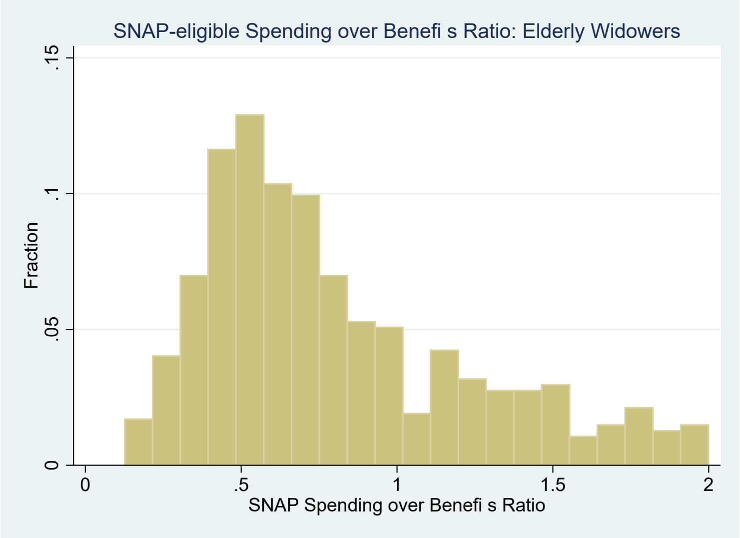


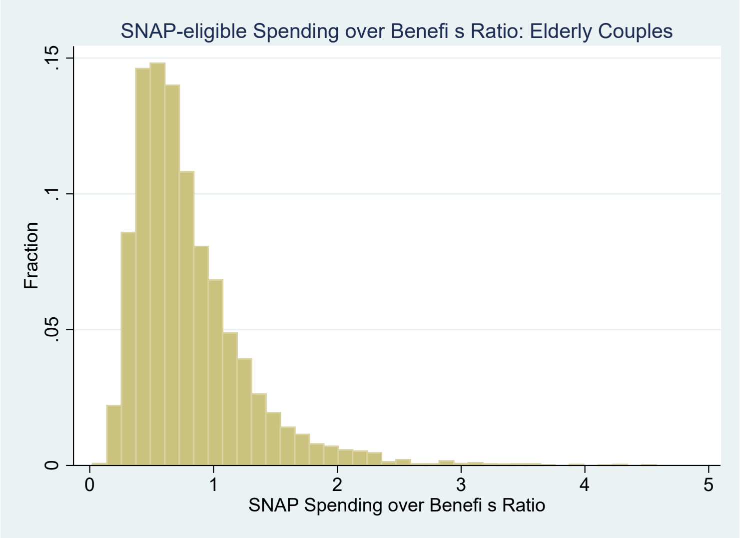

Figure 7: Engel Curves for Older Widows, Widowers, and Couples



## Figure 8: Counterfactual: SNAP-eligible Spending to SNAP Benefits Ratio




## Table 5: Top Three Groups under Each Aggregate Good

| General Merchandise | | Health Beauty | | Non-food Grocery | | Food Grocery | |
|---|---|---|---|---|---|---|---|
| Group | Percent | Group | Percent | Group | Percent | Group | Percent |
| Electronics, records, tapes | 29 | Vitamins | 34 | Tabacco and 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:* The table displays the groups with the top three largest shares under each departments: General Merchandise, Healthy Beauty, Non-food Grocery, and Food Grocery.

## Table 6: QUAIDS Elasticities Estimates

Budget Elasticities

| | Older Widows | Older Widowers |
|---|---|---|
| General Merchandise | 0.941 | 0.724 |
| Food Grocery | 1.051 | 1.070 |
| Non-food Grocery | 1.035 | 0.974 |
| Health and Beauty | 0.757 | 0.800 |

Uncompensated Price Elasticities (Older Widows)

| | General Merchandise | Food Grocery | Non-food Grocery | Health and Beauty |
|---|---|---|---|---|
| General Merchandise | -0.391 | -0.699 | -0.101 | -0.071 |
| Food Grocery | -0.066 | -0.833 | -0.007 | -0.153 |
| Non-food Grocery | -0.089 | 0.081 | -0.768 | -0.292 |
| Health and Beauty | -0.026 | -0.791 | -0.132 | -0.016 |

Compensated Price Elasticities/Slutsky Matrix (Older Widows)

| | General Merchandise | Food Grocery | Non-food Grocery | Health and Beauty |
|---|---|---|---|---|
| General Merchandise | -0.274 | -0.092 | -0.008 | 0.051 |
| Food Grocery | 0.026 | -0.115 | 0.102 | -0.010 |
| Non-food Grocery | 0.000 | 0.772 | -0.649 | -0.155 |
| Health and Beauty | 0.032 | -0.339 | -0.062 | 0.115 |

Uncompensated Price Elasticities (Older Widowers)

| | General Merchandise | Food Grocery | Non-food Grocery | Health and Beauty |
|---|---|---|---|---|
| General Merchandise | -0.975 | 0.683 | -0.425 | 0.173 |
| Food Grocery | 0.014 | -0.970 | 0.017 | -0.140 |
| Non-food Grocery | -0.437 | 0.370 | -0.897 | -0.031 |
| Health and Beauty | 0.254 | -1.297 | 0.043 | -0.131 |

Compensated Price Elasticities/Slutsky Matrix (Older Widowers)

| | General Merchandise | Food Grocery | Non-food Grocery | Health and Beauty |
|---|---|---|---|---|
| General Merchandise | -0.859 | 1.006 | -0.384 | 0.222 |
| Food Grocery | 0.116 | -0.193 | 0.107 | -0.027 |
| Non-food Grocery | -0.347 | 1.051 | -0.800 | 0.067 |
| Health and Beauty | 0.321 | -0.800 | 0.103 | -0.014 |

*Notes:* Elasticities calculated from parameter estimates based on the joint model (1).

## Table 7: QUAIDS Elasticities Estimates with Trimmed Older Widows Sample

Budget Elasticites

| | Older Widow | Older Widower |
|---|---|---|
| General Merchandise | 0.963 | 0.755 |
| Food Grocery | 1.041 | 1.079 |
| Non-food Grocery | 1.081 | 0.923 |
| Health and Beauty | 0.755 | 0.749 |

Uncompensated Price Elasticities (Older Widows)

| | General Merchandise | Food Grocery | Non-food Grocery | Health and Beauty |
|---|---|---|---|---|
| General Merchandise | -0.365 | -0.696 | -0.162 | -0.075 |
| Food Grocery | -0.068 | -0.773 | -0.023 | -0.182 |
| Non-food Grocery | -0.128 | -0.091 | -0.854 | -0.029 |
| Health and Beauty | 0.001 | -0.998 | 0.089 | -0.048 |

Compensated Price Elasticities/Slutsky Matrix (Older Widows)

| | General Merchandise | Food Grocery | Non-food Grocery | Health and Beauty |
|---|---|---|---|---|
| General Merchandise | -0.246 | -0.068 | -0.065 | 0.050 |
| Food Grocery | 0.022 | -0.062 | 0.085 | -0.041 |
| Non-food Grocery | -0.035 | 0.637 | -0.730 | 0.115 |
| Health and Beauty | 0.061 | -0.540 | 0.160 | 0.083 |

Uncompensated Price Elasticities (Older Widowers)

| | General Merchandise | Food Grocery | Non-food grocery | Health and Beauty |
|---|---|---|---|---|
| General Merchandise | -0.596 | 0.149 | -0.405 | -0.042 |
| Food Grocery | -0.017 | -1.033 | 0.064 | -0.105 |
| Non-food grocery | -0.436 | 0.965 | -1.194 | -0.208 |
| Health and Beauty | 0.027 | -0.871 | -0.080 | -0.139 |

Compensated Price Elasticities/Slutsky Matrix (Older Widowers)

| | General Merchandise | Food Grocery | Non-food grocery | Health and Beauty |
|---|---|---|---|---|
| General Merchandise | -0.477 | 0.522 | -0.358 | 0.014 |
| Food Grocery | 0.086 | -0.249 | 0.155 | 0.009 |
| Non-food grocery | -0.354 | 1.593 | -1.102 | -0.117 |
| Health and Beauty | 0.086 | -0.435 | -0.027 | -0.027 |

*Notes:* The elasticites are estimated based on model (1). The Older widows sample is trimmed by dropping households with income below $20,000 such that the resulting Older widows sample has similar average household income as Older widowers'.

**Table 8: Estimation Results of Sharing Rule and Barten Scales with Trimmed Widows Sample**

| | Model (1) | | Model (2) | | Model (3) | |
|---|---|---|---|---|---|---|
| Mean wife's share | 0.724 | | 0.841 | | 0.890 | |
| Distribution and Preference Factors | coef | Std error | coef | Std error | coef | Std error |
| Constant | 0.891*** | 0.042 | 0.057 | 0.890 | 0.339 | 1.039 |
| Female some college | | | -0.128 | 0.788 | | |
| Male some college | | | -0.152 | 0.951 | | |
| Difference in age (female - male) | | | -0.087 | 0.081 | | |
| Female education higher than male | 0.309*** | 0.051 | 0.047 | 0.564 | 0.497*** | 0.177 |
| Black or African American | | | -0.071 | 0.168 | | |
| Kitchen appliances | | | -0.042 | 0.076 | | |
| Internet | | | -0.028 | 0.059 | | |
| Log real total expenditure | | | 0.231*** | 0.117 | 0.228 | 0.141 |
| | Barten scale | Std error | Barten scale | Std error | Barten scale | Std error |
| General Merchandise | 0.648*** | 0.008 | 0.657*** | 0.023 | 0.764*** | 0.018 |
| Food Grocery | 0.807*** | 0.012 | 0.813*** | 0.032 | 0.953*** | 0.025 |
| Non-food Grocery | 0.768*** | 0.015 | 0.705*** | 0.029 | 0.948*** | 0.018 |
| Health & Beauty | 0.813*** | 0.010 | 0.817*** | 0.028 | 0.894*** | 0.019 |

*Notes:* The table displays the estimates of the joint model (1). Elderly widows whose income was below $20,000 were dropped from the sample such that the average income of older widows and widowers is similar. Barten Scales are assumed to be homogeneous across all households. Model (1) includes only distribution factors in the sharing rule. Model (2) includes both distribution factors and preference factors in the sharing rule. Kitchen appliances is a dummy denoting whether the household owes microwave, garbage disposal, and dishwasher. Model (3) includes only the distribution factor that female's education higher than male's and log real total expenditure. $\star p < 0.10, \star\star\star p < 0.05, \star\star\star p < 0.01$.

## 1.11 APPENDIX 1.B: Nielsen Homescan Dataset

The Nielsen Homescan Data represents a longitudinal panel of approximately 40,000 - 60,000 U.S. households who continuously provide information on what products they buy, when and where they make the purchase, and their household characteristics. The Nielsen provides in-home scanners for the panelists to record all of their purchases, intended for personal, in-home use.

Products recorded in Nielsen include all Nielsen-tracked categories of food and non-food items, in which food accounts for approximately 70 percent. Nielsen adopts four-tier hierarchy of product structure: UPC (3.2 million UPC Codes) – Product Module (1,075 Product Modules) – Product Group (125 Product Groups) – Department (10 Departments). Since 6 out of the 10 departments are food related, I aggregate those 6 department into category Food Groceries. The resulting four aggregate goods in this paper are Health and Beauty, Food Groceries, Non-food Groceries, and General Merchandise.

For each shopping trip, the participant scans every bar-code/Universal Product Code (UPC)

Table 9: Summary Statistics for SNAP-eligible Households

| | SNAP - eligible Older Widows | SNAP - eligible Older Widowers | SNAP - eligible Older Couples |
|---|---|---|---|
| Number of unique households | 2153 | 237 | 3976 |
| Fraction of constrained households: $ SNAP foods <SNAP benefits | 42% | 44% | 48% |
| Fraction of constrained households: $ Food Grocery <SNAP benefits | 28% | 26% | 31% |
| Household income | 11093.64 | 10977.35 | 15695.84 |
| Yearly expenditure (trip data) | 2678.25 | 2585.35 | 4615.00 |
| Yearly expenditure (purchase data) | 1800.14 | 1837.29 | 3159.79 |
| Budget share (health&beauty) | 0.13 | 0.09 | 0.11 |
| Budget share (general merchandise) | 0.08 | 0.09 | 0.09 |
| Budget share (food grocery) | 0.67 | 0.70 | 0.67 |
| Budget share (non-food grocery) | 0.09 | 0.07 | 0.09 |
| Yearly SNAP-eligible food spending | 924.76 | 1173.66 | 2044.70 |
| Expenditure share (SNAP food / Food Grocery) | 0.79 | 0.78 | 0.81 |
| Imputed SNAP benefits | 1222.36 | 1222.36 | 2329.80 |
| Female head age | 74.52 | - | 68.33 |
| Male head age | - | 75.27 | 71.45 |
| >= Graduated high school (Female) | 0.90 | - | 0.91 |
| >=Some College (Female) | 0.42 | - | 0.41 |
| >= Graduated high school (Male) | - | 0.86 | 0.82 |
| >=Some College (Male) | - | 0.53 | 0.43 |
| Microwave, Dishwasher, & Garbage Disposal | 0.15 | 0.12 | 0.13 |
| Regular & Pay Cable | 0.26 | 0.34 | 0.34 |
| Internet connection | 0.50 | 0.65 | 0.73 |
| Obs | 5,858 | 544 | 9,132 |

*Notes:* The values reported above are mean. The expenditures are deflated. Older adults are defined as those who are 55+. The constrained households are either defined as those whose expenditure on SNAP-eligible food is less than the imputed SNAP benefits or those whose expenditure on Food Grocery is less than the imputed SNAP benefits.

## Table 10: Summary Statistics for Constrained and Unconstrained SNAP-eligible Households

| | SNAP-eligible Older Widows | | SNAP-eligible Older Widowers | | SNAP-eligible Older Couples | |
|---|---|---|---|---|---|---|
| | Constrained | Unconstrained | Constrained | Unconstrained | Constrained | Unconstrained |
| Obs | 2,468 | 3,390 | 238 | 306 | 4,384 | 4,748 |
| Number of unique households | 1,158 | 1,523 | 130 | 148 | 2,214 | 2,536 |
| Household income | 9,045.27 | 12,584.90 | 8,806.19 | 12,666.04 | 13,285.49 | 17,921.40 |
| Yearly expenditure (trip data) | 2,077.77 | 3,115.42 | 2,050.97 | 3,000.99 | 3,728.44 | 5,433.59 |
| Yearly expenditure (purchase data) | 1,401.80 | 2,090.14 | 1,455.93 | 2,133.90 | 2,533.56 | 3,738.00 |
| budget share (health&beauty) | 0.14 | 0.13 | 0.09 | 0.09 | 0.11 | 0.11 |
| budget share (general merchandise) | 0.08 | 0.08 | 0.09 | 0.09 | 0.09 | 0.09 |
| budget share (food grocery) | 0.67 | 0.67 | 0.70 | 0.70 | 0.66 | 0.67 |
| budget share (non-food grocery) | 0.10 | 0.10 | 0.07 | 0.08 | 0.10 | 0.09 |
| Yearly SNAP-eligible food spending | 840.51 | 1321.62 | 903.54 | 1383.75 | 1588.59 | 2465.84 |
| Expenditure share (SNAP food / Food Grocery) | 0.78 | 0.80 | 0.77 | 0.79 | 0.80 | 0.81 |
| Imputed SNAP benefits | 1,555.98 | 979.48 | 1,540.01 | 885.26 | 2,477.22 | 1,913.35 |
| Female head age | 74.57 | 74.49 | - | - | 68.64 | 68.04 |
| Male head age | - | - | 74 | 76.26 | 71.87 | 71.07 |
| >= Graduated high school (Female) | 0.88 | 0.92 | - | - | 0.89 | 0.93 |
| >=Some College (Female) | 0.40 | 0.44 | - | - | 0.39 | 0.42 |
| >= Graduated high school (Male) | - | - | 0.85 | 0.86 | 0.79 | 0.85 |
| >=Some College (Male) | - | - | 0.53 | 0.53 | 0.41 | 0.44 |
| Microwave, Dishwasher, & Garbage Disposal | 0.12 | 0.16 | 0.08 | 0.15 | 0.13 | 0.13 |
| Regular & Pay Cable | 0.27 | 0.26 | 0.36 | 0.32 | 0.29 | 0.39 |
| Internet connection | 0.45 | 0.54 | 0.66 | 0.64 | 0.69 | 0.76 |
| Obs | 2,468 | 3,390 | 238 | 306 | 4,384 | 4,748 |

*Notes:* The values reported above are mean. The expenditures are deflated. Older adults are defined as those who are 55+. The constrained households are either defined as those whose expenditure on SNAP-eligible food is less than the imputed SNAP benefits or those whose expenditure on Food Grocery is less than the imputed SNAP benefits.

## Table 11: Spending Patterns between SNAP-eligible and Ineligible Households

| | SNAP-eligible Households | | SNAP-ineligible Households | |
|---|---|---|---|---|
| *Panel A: Spending Level* | Mean | Std dev | Mean | Std dev |
| Total expenditure in Nielsen Homescan dataset | 3159.79 | 1250.98 | 3497.63 | 1337.88 |
| Food grocery expenditure | 2582.95 | 1054.72 | 2733.33 | 825.39 |
| SNAP-eligible food spending | 1641.25 | 587.56 | 1778.58 | 629.10 |
| Spending on healthier foods | 2180.10 | 938.83 | 2300.78 | 972.46 |
| Spending on unhealthy foods | 276.94 | 155.59 | 299.91 | 165.20 |
| Spending on sugar-sweetened beverages | 125.91 | 114.83 | 132.64 | 113.50 |
| *Panel B: Spending as a Percent of Food Grocery Spending* | Mean | | Mean | |
| SNAP-eligible food | 63.54% | | 65.07% | |
| Healthier foods | 84.40% | | 84.17% | |
| Unhealthy foods | 10.72% | | 10.97% | |
| Sugar-sweetened beverages | 4.87% | | 4.85% | |

*Notes:* Std dev refers to standard deviation. 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 "unhealthy 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. The definitions follow Hoynes et al. (2015).

## Table 12: Counterfactual Results for Constrained Older Widows and Widowers

| | Constained Older Widows | | | Constained Older Widowers | | |
|---|---|---|---|---|---|---|
| *Panel A: Changes in Budget Shares among Constrained Older Widows* | Baseline | Counterfactual | % Change | Baseline | Counterfactual | % Change |
| General merchandise | 0.08 | 0.08 | -2.81% | 0.09 | 0.08 | -14.41% |
| Food grocery | 0.68 | 0.70 | 2.99% | 0.73 | 0.76 | 3.95% |
| Non-food grocery | 0.10 | 0.11 | 6.43% | 0.08 | 0.08 | 4.62% |
| Health & beauty | 0.14 | 0.10 | -25.99% | 0.10 | 0.08 | -19.90% |
| *Panel B: Full Propensity to Consume (FPC) SNAP-eligible Food out of SNAP Benefits* | | Mean | | | Mean | |
| Imputed SNAP benefits | | 1556.00 | | | 1540.00 | |
| Baseline Food Expenditure | | 929.08 | | | 999.36 | |
| Counterfactual Food Expenditure | | 2045.57 | | | 2214.61 | |
| Increase in Food Expenditure | | 1116.49 | | | 1215.25 | |
| FPC food out of SNAP benefits | | 0.72 | | | 0.79 | |
| Baseline spending on SNAP-eligible-food-to-overall-food ratio | | 0.78 | | | 0.77 | |
| FPC SNAP-eligible food out of SNAP benefits | | 0.56 | | | 0.61 | |
| Household Income | | 9045.20 | | | 8806.10 | |
| obs | | 2468 | | | 238 | |

*Notes:* Values are in mean. FPC food out of SNAP benefits is calculated as the average increase in food expenditures divided by the average SNAP benefits. FPC SNAP-eligible food out of benefits is calculated as FPC food out of SNAP benefits multiplied by the baseline spending on SNAP-eligible-food-to-overall-food ratio. Constrained households are defined as those whose pre-treatment expenditure on SNAP-eligible food is equal to or less than their imputed SNAP benefits.

## Table 13: Counterfactual Results for Extra-marginal and Infra-marginal Widows

| | Constrained Extra-marginal Widows | | | Constrained Infra-marginal Widows | | |
|---|---|---|---|---|---|---|
| *Panel A: Changes in Budget Shares* | Baseline | Counterfactual | % Change | Baseline | Counterfactual | % Change |
| General merchandise | 0.08 | 0.08 | 3.21% | 0.08 | 0.07 | -6.35% |
| Food grocery | 0.69 | 0.70 | 1.85% | 0.67 | 0.71 | 5.03% |
| Non-food grocery | 0.10 | 0.11 | 8.83% | 0.11 | 0.11 | 1.04% |
| Health & beauty | 0.13 | 0.11 | -18.67% | 0.14 | 0.11 | -20.79% |
| | | | | | | |
| *Panel B: Full Propensity to Consume (FPC) SNAP-eligible Food out of SNAP Benefits* | | Mean | | | Mean | |
| Imputed SNAP benefits | | 1682.80 | | | 1461.90 | |
| Baseline Food Expenditure | | 906.99 | | | 940.31 | |
| Counterfactual Food Expenditure | | 2098.40 | | | 2018.85 | |
| Increase in Food Expenditure | | 1191.40 | | | 1078.55 | |
| FPC food out of SNAP benefits | | 0.71 | | | 0.74 | |
| Baseline spending on SNAP-eligible-food-to-overall-food ratio | | 0.30 | | | 0.84 | |
| FPC SNAP-eligible food out of SNAP benefits | | 0.21 | | | 0.62 | |
| Household Income | | 3552.40 | | | 9566.80 | |
| obs | | 1051 | | | 1417 | |

*Notes:* Values are in mean. FPC food out of SNAP benefits is calculated as the average increase in food expenditures divided by the average SNAP benefits. FPC SNAP-eligible food out of benefits is calculated as FPC food out of SNAP benefits multiplied by the baseline spending on SNAP-eligible-food-to-overall-food ratio. Constrained households are defined as those whose pre-treatment expenditure on SNAP-eligible food is equal to or less than their imputed SNAP benefits.

## Table 14: Counterfactual Results for Extra-marginal and Infra-marginal Widowers

| | Constrained Extra-marginal Widowers | | | Constrained Extra-marginal Widowers | | |
|---|---|---|---|---|---|---|
| *Panel A: Changes in Budget Shares* | Baseline | Counterfactual | % Change | Baseline | Counterfactual | % Change |
| General merchandise | 0.09 | 0.08 | -9.50% | 0.09 | 0.07 | -16.54% |
| Food grocery | 0.75 | 0.76 | 0.96% | 0.73 | 0.77 | 5.27% |
| Non-food grocery | 0.08 | 0.08 | 8.66% | 0.08 | 0.08 | 2.90% |
| Health & beauty | 0.08 | 0.08 | -6.28% | 0.10 | 0.08 | -24.59% |
| | | | | | | |
| *Panel B: Full Propensity to Consume (FPC) SNAP-eligible Food out of SNAP Benefits* | | Mean | | | Mean | |
| Imputed SNAP benefits | | 1675.10 | | | 1482.60 | |
| Baseline Food Expenditure | | 980.26 | | | 1006.84 | |
| Counterfactual Food Expenditure | | 2262.38 | | | 2194.15 | |
| Increase in Food Expenditure | | 1282.12 | | | 1187.31 | |
| FPC food out of SNAP benefits | | 0.77 | | | 0.80 | |
| Baseline spending on SNAP-eligible-food-to-overall-food ratio | | 0.19 | | | 0.82 | |
| FPC SNAP-eligible food out of SNAP benefits | | 0.15 | | | 0.66 | |
| Household Income | | 2415.10 | | | 9108.20 | |
| obs | | 71 | | | 166 | |

*Notes:* Values are in mean. FPC food out of SNAP benefits is calculated as the average increase in food expenditures divided by the average SNAP benefits. FPC SNAP-eligible food out of benefits is calculated as FPC food out of SNAP benefits multiplied by the baseline spending on SNAP-eligible-food-to-overall-food ratio. Constrained households are defined as those whose pre-treatment expenditure on SNAP-eligible food is equal to or less than their imputed SNAP benefits.

## Table 15: Counterfactual Results for Constrained Older Couples

| *Panel A: Changes in Budget Shares among Constrained Couples* | Baseline | Counterfactual (collective approach) | | | |
|---|---|---|---|---|---|
| | | Wife's resource share = 0.5 | | Wife's resource share = 0.675 | |
| | Budget share | Budget share | % change | Budget share | % change |
| General merchandise | 0.09 | 0.08 | -12.71% | 0.08 | -9.90% |
| Food grocery | 0.69 | 0.73 | 4.96% | 0.71 | 3.10% |
| Non-food grocery | 0.10 | 0.10 | -2.49% | 0.11 | 5.86% |
| Health & beauty | 0.12 | 0.10 | -17.18% | 0.10 | -15.51% |
| *Panel B: Full Propensity to Consume (FPC) SNAP-eligible Foodamong Constrained Couples* | | Mean | | | |
| Imputed SNAP benefits | | 2762.50 | | | |
| Baseline food expenditure | | 1641.80 | | | |
| Counterfactual food expenditure | | 3667.20 | | | |
| Increase in food expenditure | | 2025.40 | | | |
| FPC food out of SNAP benefits | | 0.73 | | | |
| Baseline spending on SNAP-eligible-food-to-overall-food ratio | | 0.81 | | | |
| FPC SNAP-eligible food out of SNAP benefits | | 0.59 | | | |

*Notes:* Values are in mean. FPC food out of SNAP benefits is calculated as the average increase in food expenditures divided by the average SNAP benefits. FPC SNAP-eligible food out of benefits is calculated as FPC food out of SNAP benefits multiplied by the baseline spending on SNAP-eligible-food-to-overall-food ratio. Constrained households are defined as those whose pre-treatment expenditure on SNAP-eligible food is equal to or less than their imputed SNAP benefits.

## Table 16: Counterfactual Results for Unconstrained Older Households

| *Panel A: Changes in Budget Shares among Unconstrained Older Widows, Widowers, and Couples* | Unconstrained Older Widows | | | Unconstrained Older Widowers | | | Unconstrained Older Couples | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Baseline | Counterfactual | % Change | Baseline | Counterfactual | % Change | Baseline | Counterfactual wife's resource share = 0.5 | % Change | Counterfactual wife's resource share = 0.675 | % Change |
| General merchandise | 0.08 | 0.08 | 0.77% | 0.10 | 0.09 | -7.64% | 0.09 | 0.08 | -5.99% | 0.09 | -3.77% |
| Food grocery | 0.68 | 0.71 | 3.92% | 0.73 | 0.74 | 2.41% | 0.70 | 0.72 | 2.79% | 0.70 | 1.03% |
| Non-food grocery | 0.10 | 0.11 | 9.20% | 0.08 | 0.08 | 0.48% | 0.10 | 0.10 | 2.19% | 0.11 | 10.43% |
| Health & beauty | 0.14 | 0.10 | -25.99% | 0.09 | 0.08 | -11.25% | 0.12 | 0.10 | -13.70% | 0.10 | -11.74% |
| *Panel B: Full Propensity to Consume (FPC) SNAP-eligible Food out of SNAP Benefits* | | Mean | | | Mean | | | | Mean | | |
| Imputed SNAP benefits | | 979.00 | | | 835.00 | | | | 1913.00 | | |
| Baseline Food Expenditure | | 1376.54 | | | 1441.18 | | | | 2354.50 | | |
| Counterfactual Food Expenditure | | 2122.80 | | | 2135.58 | | | | 3882.80 | | |
| Increase in Food Expenditure | | 746.26 | | | 694.40 | | | | 1528.30 | | |
| FPC food out of SNAP benefits | | 0.76 | | | 0.83 | | | | 0.80 | | |
| Baseline spending on SNAP-eligible-food-to-overall-food ratio | | 0.80 | | | 0.79 | | | | 0.81 | | |
| FPC SNAP-eligible food out of SNAP benefits | | 0.61 | | | 0.66 | | | | 0.65 | | |

*Notes:* Values are in mean. FPC food out of SNAP benefits is calculated as the average increase in food expenditures divided by the average SNAP benefits. FPC SNAP-eligible food out of benefits is calculated as FPC food out of SNAP benefits multiplied by the baseline spending on SNAP-eligible-food-to-overall-food ratio. Constrained households are defined as those whose pre-treatment expenditure on SNAP-eligible food is equal to or less than their imputed SNAP benefits.

## Table 17: Counterfactual Results for Older Couples

| | Baseline | Counterfactual wife's resource share = 0.5 | | Counterfactual wife's resource share = 0.675 | |
|---|---|---|---|---|---|
| | Budget Share | Budget Share | % Change | Budget Share | % Change |
| General Merchandise | 0.09 | 0.08 | -9.26% | 0.08 | -6.70% |
| Food Grocery | 0.69 | 0.72 | 3.82% | 0.71 | 2.02% |
| Non-food Grocery | 0.10 | 0.10 | -0.10% | 0.11 | 8.15% |
| Health & Beauty | 0.12 | 0.10 | -15.37% | 0.10 | -13.60% |

*Notes:* Values are in mean. The table shows the changes in budge shares for older couples given the SNAP-like cash transfer. Column (2) shows the counterfactual budget shares if we assume equal sharing. Column (3) shows the counterfactual budget shares if we use the estimated sharing rule (wife's resource share = 0.675) from the collective model.

**Table 18: Counterfactual Results for Wives**

| | Baseline | Counterfactual | |
|---|---|---|---|
| | Equivalent Budget Share | Equivalent Budget Share | % Change |
| General Merchandise | 0.09 | 0.08 | -3.53% |
| Food Grocery | 0.68 | 0.69 | 1.40% |
| Non-food Grocery | 0.11 | 0.12 | 8.85% |
| Health & Beauty | 0.12 | 0.10 | -13.39% |

*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 wives are calculated as wife's QUAIDS estimates of budget shares if she is faced with 0.675 resource share and the shadow prices.

**Table 19: Counterfactual Results for Husbands**

| | Baseline | Counterfactual | |
|---|---|---|---|
| | Equivalent Budget Share | Equivalent Budget Share | % Change |
| General Merchandise | 0.10 | 0.08 | -14.69% |
| Food Grocery | 0.71 | 0.74 | 3.85% |
| Non-food Grocery | 0.08 | 0.08 | -0.25% |
| Health & Beauty | 0.11 | 0.10 | -11.80% |

*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 QUAIDS estimates of budget shares if he is faced with 0.325 resource share and the shadow prices.

so that information, such as price, quantity, deal or coupon used, date of shopping trip, and total amount spent on the trip, are recorded. Prices are either recorded as the weighted average price for the bar-code that week in that particular store, if Nielsen has point of sale data of the store. Otherwise, the participant is instructed to enter the total price paid for the bar-code (prior to any coupon or deal used). Information on store locations is not revealed up to the 3 digit zip code. Neither is the retailer name. Only the retailer channel type (drug store or convenience store) is revealed.

Information on household characteristics are collected through an annual questionnaire in which households report household size, composition, marital status, race, education, age, region, and zip code. Employment hours are collected only into three ranges of hours (under 30, 30-34, 35+, or not employed).Broadly defined occupations (12 types) are also collected. It also provides information on household ownership of TV items, cable, internet connection, and kitchen appliances.

Certain issues should be mentioned about the quality of the data, especially the price information. Since all data are collected by participants themselves within the home, they might suffer from common recording error. Items might be eaten on the way home or the participant might forget or scan the wrong item (Please see Einav, Leibtag, and Nevo (2010) for a more detailed

**Table 20: QUAIDS Elasticities Estimates for SNAP-ineligible Widows and Widowers (Estimates obtained from Estimating the Joint Model (1) on SNAP-ineligible Households)**

| Budget Elasticities | | |
|---|---|---|
| | Elderly Widow | Elderly Widower |
| General Merchandise | 0.897 | 0.746 |
| Food Grocery | 1.063 | 1.065 |
| Non-Food Grocery | 1.048 | 0.982 |
| Health and beauty | 0.714 | 0.813 |

| Uncompensated Price Elasticities (Older Widows) | | | | |
|---|---|---|---|---|
| | General Merchandise | Food Grocery | Non-food Grocery | Health and Beauty |
| General Merchandise | -0.386 | -0.711 | -0.069 | 0.003 |
| Food Grocery | -0.068 | -0.867 | -0.014 | -0.122 |
| Non-food Grocery | -0.071 | 0.003 | -0.715 | -0.311 |
| Health and Beauty | -0.002 | -0.506 | -0.160 | -0.189 |

| Compensated Price Elasticities/Slutsky Matrix (Older Widows) | | | | |
|---|---|---|---|---|
| | General Merchandise | Food Grocery | Non-food Grocery | Health and Beauty |
| General Merchandise | -0.280 | -0.146 | 0.019 | 0.117 |
| Food Grocery | 0.021 | -0.140 | 0.098 | 0.024 |
| Non-food Grocery | 0.016 | 0.709 | -0.593 | -0.170 |
| Health and Beauty | 0.050 | -0.094 | -0.095 | -0.064 |

| Uncompensated Price Elasticities (Older Widowers) | | | | |
|---|---|---|---|---|
| | General Merchandise | Food Grocery | Non-food Grocery | Health and Beauty |
| General Merchandise | -0.798 | 0.251 | -0.341 | 0.187 |
| Food Grocery | -0.019 | -0.919 | 0.006 | -0.142 |
| Non-food Grocery | -0.362 | 0.242 | -0.875 | -0.009 |
| Health and Beauty | 0.248 | -1.270 | 0.059 | -0.159 |

| Compensated Price Elasticities/Slutsky Matrix (Older Widowers) | | | | |
|---|---|---|---|---|
| | General Merchandise | Food Grocery | Non-food Grocery | Health and Beauty |
| General Merchandise | -0.679 | 0.602 | -0.296 | 0.242 |
| Food Grocery | 0.085 | -0.149 | 0.096 | -0.028 |
| Non-food Grocery | -0.270 | 0.929 | -0.778 | 0.092 |
| Health and Beauty | 0.318 | -0.756 | 0.121 | -0.040 |

## Table 21: QUAIDS Elasticities Estimates for SNAP-ineligible Widows and Widowers (Estimates obtained from Estimating the Joint Model (1) on the Baseline Sample)

Budget Elasticities

| | Older Widow | Older Widower |
|---|---|---|
| General Merchandise | 0.935 | 0.727 |
| Food Grocery | 1.052 | 1.070 |
| Non-food Grocery | 1.033 | 0.974 |
| Health and Beauty | 0.758 | 0.803 |

Uncompensated Price Elasticities (Older Widows)

| | General Merchandise | Food Grocery | Non-food Grocery | Health and Beauty |
|---|---|---|---|---|
| General Merchandise | -0.354 | -0.709 | -0.101 | -0.069 |
| Food Grocery | -0.066 | -0.833 | -0.007 | -0.153 |
| Non-food Grocery | -0.087 | 0.079 | -0.772 | -0.285 |
| Health and Beauty | -0.025 | -0.781 | -0.131 | -0.022 |

Compensated Price Elasticities/Slutsky Matrix (Older Widows)

| | General Merchandise | Food Grocery | Non-food Grocery | Health and Beauty |
|---|---|---|---|---|
| General Merchandise | -0.246 | -0.105 | -0.007 | 0.052 |
| Food Grocery | 0.022 | -0.114 | 0.104 | -0.010 |
| Non-food Grocery | -0.002 | 0.770 | -0.651 | -0.147 |
| Health and Beauty | 0.032 | -0.326 | -0.059 | 0.109 |

Uncompensated Price Elasticities (Older Widowers)

| | General Merchandise | Food Grocery | Non-food grocery | Health and Beauty |
|---|---|---|---|---|
| General Merchandise | -0.975 | 0.680 | -0.424 | 0.172 |
| Food Grocery | 0.014 | -0.970 | 0.017 | -0.141 |
| Non-food grocery | -0.431 | 0.364 | -0.897 | -0.031 |
| Health and Beauty | 0.247 | -1.263 | 0.042 | -0.144 |

Compensated Price Elasticities/Slutsky Matrix (Older Widowers)

| | General Merchandise | Food Grocery | Non-food grocery | Health and Beauty |
|---|---|---|---|---|
| General Merchandise | -0.857 | 1.003 | -0.382 | 0.223 |
| Food Grocery | 0.118 | -0.196 | 0.108 | -0.026 |
| Non-food grocery | -0.340 | 1.043 | -0.801 | 0.070 |
| Health and Beauty | 0.316 | -0.762 | 0.103 | -0.026 |

## Table 22: Alcohol Expenses for SNAP-eligible Older Widows, Widowers, and Couples

| *Panel A: Yearly Alcohol and Food Grocery Expense* | | Mean | Std. Dev. | Min | Max | Obs |
|---|---|---|---|---|---|---|
| | Older Widows | 52 | 153 | 0 | 2418 | 5852 |
| Yearly Alcohol Expense | Older Widowers | 102 | 242 | 0 | 1868 | 541 |
| | Older Couples | 109 | 334 | 0 | 4829 | 410 |
| | Older Widows | 1222 | 495 | 1677 | 2304 | 5852 |
| Yearly Food Grocery Expense | Older Widowers | 1178 | 568 | 22 | 2304 | 541 |
| | Older Couples | 2602 | 520 | 1677 | 4224 | 410 |

| *Panel B: Alcohol Expense to SNAP Benefits Ratio* | | Older Widows | Older Widowers | Older Couples |
|---|---|---|---|---|
| | Percentiles | | | |
| | 50% | 0.00 | 0.01 | 0.00 |
| | 75% | 0.02 | 0.07 | 0.02 |
| | 90% | 0.14 | 0.30 | 0.11 |
| | 95% | 0.30 | 0.52 | 0.23 |
| | 99% | 0.76 | 1.40 | 0.48 |

*Notes:* Samples of older couples here are those who are eligible for SNAP in 2004. Samples of older widows and widowers are those who are eligible for SNAP for the entire sample period 2004 - 2014.

analyses on the recording error of Nielsen home-scan data). Weekly average store price might overestimate the actual price that the consumer would have paid with a loyalist card. It leads to measurement errors in price. However, Einav, Leibtag, and Nevo (2010) finds that attrition in price in Nielsen Homescan data is not more serious than that in other consumption surveys, such as the Current Population Survey (CPS). As long as recording errors are not systematically different across participants, the results should not be severely impacted.

### 1.11.1 Compare Nielsen Homescan Dataset to CEX

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 Homescan data to those in the Consumer Expenditure Survey (CES).[51] 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 A2 compares the mean food expenditure in Nielsen with CEX among older adults population. The definition of food and total expenditures on food among older adults are similar between CEX and Nielsen Homescan data. It implies that food products included in the Nielsen Homescan data is complete.

Note that goods such as heating, transportation, etc are not included in the paper. The implicit assumption in demand estimation is the separability assumption frequently made by previous literature. Here I assume that older adults make separate spending decisions between grocery-type goods and other goods. Readers can also think of it as a two-stage budget problem. That is, older adults first make decisions on how much to spend on housing, utilities, transportation, and grocery goods. In the second stage, they decide the consumption allocation within grocery goods.

Moreover, the problem of not having comprehensive goods is less serious when I only consider

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

older adults population. Figure 5 and 6 show food and non-food expenditures by age the reference person in CEX in 2013. Note that households whose reference person is middle-age are likely to have both adults and children. The average consumer units per household is 3. Household food expenditures decrease moderately after aging, while non-food expenditures such as clothing, transportation, and pensions and social security decrease dramatically after retirement age.[52] Hence, even though Nielsen tracked only a subset of goods compared to other more comprehensive datasets, food constitutes a larger chunk of their budget among older adults population compared to the younger population.

**Table 23: 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 aggregateg good in Nielsen Homescan data set.

**Table 24: Definitions of Aggregate Goods: Nielsen Homescan versus CEX**

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

**Table 25: Food Expenditures: Nielsen Homescan versus CEX**

| | Nielsen Homescan | CEX |
|---|---|---|
| Yearly Food Expenditure | 6425 | 6066 |

*Notes:* Values are in mean. The food expenditure here for Nielsen Homescan is that among older couples, in which both spouses are aged 55 and above. The food expenditure for CEX is among the households in which the age of the reference age is 55 and above. The source for CEX data is from U.S. Bureau of Labor Statistics.

## 1.12 APPENDIX 1.C: Individual Welfare Measures

The private good equivalents are given by:

[52] Previous finding by Aguiar and Hurst (2007) shows that older population decrease total expenditures on food but increase time on food preparation, cooking, and shopping intensity. Hence, their overall food consumption does not decrease after aging.

$$x_k^f = \frac{\eta \omega_k^f(\pi/\eta)}{\pi_k} = \frac{\omega_k^f}{A_k}\eta y \tag{28}$$

$$x_k^m = \frac{(1-\eta)\omega_k^m(\pi/(1-\eta))}{\pi_k} = \frac{\omega_k^m}{A_k}(1-\eta)y \tag{29}$$

The equivalent expenditures for each are given by:

$$x^f = \sum_k x_k^f = \eta y \sum_k \frac{\omega_k^f}{A_k} \tag{30}$$

$$x^m = \sum_k x_k^m = (1-\eta)y \sum_k \frac{\omega_k^m}{A_k} \tag{31}$$

The indifference scales for each are given by:

$$IS^f = \frac{x^f}{y} = \eta \sum_k \frac{\omega_k^f}{A_k} \tag{32}$$

$$IS^m = \frac{x^m}{y} = (1-\eta) \sum_k \frac{\omega_k^m}{A_k} \tag{33}$$

The relative economies of scale to consumption, $R$, are defined as

$$R = \frac{p'(x_f + x_m)}{y} - 1 = \frac{p'(x_f + x_m - z)}{p'z} \tag{34}$$

If all goods are public (private), then $R = 1$ ($R = 0$).

# 2 Chapter 2

# Identification of Semiparametric Model Coefficients, With an Application to Collective Households

## 2.1 Introduction

There is a long literature on the identification and estimation of Pareto efficient collective household models of consumption. These are households with multiple members, each of whom maximizes a utility function, subject to their claims on the household's resources and a household budget constraint. Almost all of the theoretical results in this literature either show point identification of just a subset of the model's features (e.g., identifying resource shares but not economies of scale), or only establishes generic identification rather than point identification. In this paper we extend existing collective household identification theorems by proving point identification of all the features of the household's optimization problem, including resource shares, economies of scale, indifference scales, price, and income effects. Moreover, we do so in a model that allows goods in the household to be partly shared, and we identify the extent to which each good is shared. Further, our model reduces data requirements relative to some existing theorems, such as identifying the complete demand functions of children without observing any child specific goods.

To obtain these identification results, we first propose and apply some general methods for proving identification of coefficients in a class of semiparametric function. A few alternative sets of identifying assumptions are provided, thereby giving researchers multiple means by which such models can be identified. We then apply these results to identification of collective household models.

After establising identification, we parameterize and empirically estimate a collective household model using Japanese consumption data on single men, single women, and couples with zero to four children. Among other empirical results, we find that multi-person households save the equivalent of about one fourth of their total expenditures through shared and joint consumption of goods, that wives consume between one fourth to one half of household resources (depending on factors like number of children), and that, to provide for the children, wives forgo far more resources relative to husbands when there are children in the household. Failure to account for the extent to which goods are shared, and hence consumed jointly, leads to underestimates of the decrease in the wife's resources relative to that of the husband's when the number of children increases.

We also find that a single adult would need to spend between one third to two thirds as much as a family to attain the same standard of living by themselves as they could attain as a member of a multi-person household (the exact amount depends on the composition of the household). We find that adding one more child to a household with one or two children requires increasing household expenditures by about 8 percent to maintain the children's standard of living.

We begin by considering models of the form $M(p, s) = G(a_{s1}p_1, ..., a_{sJ}p_J)$ where the function $M$ is known or identified (e.g., $M$ could be a conditional mean function estimated by nonparametric regression), $p = (p_1, ..., p_J)$ is a vector of observed covariates (prices in our application), and $s$ is an observed discrete variable or index. We wish to identify the vector of coefficients $a_s = (a_{s1}, ..., a_{sJ})$ for each value that $s$ can take on. It is important to note that this is NOT an index model. Many results exist for identifying the relative values of coefficients $a_{sj}/a_{s1}$ in linear index models, i.e., models that are functions of $a_{s1}p_1 + ... + a_{sj}p_j$. But those results are not applicable to this context. Here each $p_j$ appears separately and potentially nonlinearly in the function $G$, though each $p_j$ appears with a coefficient $a_{sj}$ that varies by the observed discrete $s$. The relative terms we will be identifying are terms like $a_{sj}/a_{1j}$, not terms like $a_{sj}/a_{s1}$.

We first give some alternative sets of assumptions that suffice to point identify the relative coefficients $a_{sj}/a_{tj}$ for $j = 1, ..., J$, or equivalently to identify the coefficients $a_{sj}$ in cases where $a_{tj}$ for some $t$ can be normalized to equal one. These identification results employ variants of methods described by Matzkin (2003, 2007, 2012), Lewbel (1998, 2018), and Lewbel and Pendakur (2017). A useful feature of these identification results is that they do not impose monotonicity on $G$.

The collective household models we consider have a more general structure than the above $G$ function. In our application, we will have an observable vector of household demand functions that depend on a $J$-vector of prices of goods $p$, and where the vector $a_s$ is a set of coefficients that summarize how much goods are shared or jointly consumed. In addition, the household's demands will depend on terms like $\widetilde{\eta}_s^k(p)y$ where $\widetilde{\eta}_s^k(p)$ is a resource share function for household member $k$, and the index $s$ is a generalization of what the collective household consumption literature calls "distribution factors." In our collective household application, we will need to identify the functions $\widetilde{\eta}_s^k(p)$ as well as the coefficients $a_{sj}$. The identification of this household model will proceed in multiple steps that repeatedly apply and extend the above general coefficient identification results involving $M$ and $G$.

Expenditure surveys generally collect consumption data at the level of households. Standard poverty and welfare measurements based on such data are also typically calculated at the household level. But well-being and utility apply to individuals, not households. The empirical collective household consumption literature deals with identifying and estimating features of the behavior and well-being of individuals within households. These models generally start with the assumption that household members each have their own utility functions over goods, and that households allocate goods to their members in some way that is Pareto efficient. Important early examples of such models are Becker (1965, 1981) and Chiappori (1988, 1992). Applying standard decentralization results arising from Pareto efficiency, the latter papers show that, regardless of the bargaining or social welfare process the household uses to allocate resources, the behavior of the household is equivalent to the behavior of each household member maximizing his or her own utility function, subject to shadow prices and shadow incomes that reflect the household's chosen allocation of resources.

Of particular interest in these models are resource shares, defined as the fraction of the household's total expenditures (i.e., its budget) that is allocated to each household member. The earlier literature on such models, including Browning, Bourguignon, Chiappori, and Lechene (1994), Browning and Chiappori (1998), Vermeulen (2002), and Chiappori and Ekeland (2006, 2009), showed that, even if one knew all of the demand functions of a household (that is, how much the household would buy of every good as a function of prices, income, and other observed covariates), without additional information one still cannot identify the level of each household member's resources.[53] However, this earlier work also shows that one can usually identify how these resource shares would change in response to a change in observed covariates called distribution factors. Distribution factors are variables that affect the bargaining power of household members, and so affect their resource shares, but do not affect the tastes of household members. Papers that make use of this identification result include Bourguignon and Chiappori (1994), Chiappori, Fortin, and Lacroix (2002), and Blundell, Chiappori, and Meghir (2005).

[53]These results are often presented in terms of Pareto weights (the weights placed on the utility functions of each household member in the household's optimization problem) rather than resource shares. Likewise, distribution factors can be equivalently defined in terms of such weights rather than in terms of resource shares. However, as Browning, Chiappori, and Lewbel (2013) show, resource shares are monotonic in Pareto weights and vice versa, so each, along with individual member utility functions, contain comparable information about the household. However, resource shares have both more direct economic implications, and do not depend on the arbitrary cardinalization of utility functions.

One limitation of these earlier resource share identification theorems is that they are based on household models that constrain goods to be either purely private or purely public within a household, meaning that each good is either completely jointly consumed by all household members (like heat) or completely privately consumed (like food, e.g., no two people can eat the same apple). We relax this restriction by working with a more general model based on Browning, Chiappori, and Lewbel (2013) (hereafter BCL), that allows goods to be partly shared. An example of a partly shared good could be gasoline, which is privately consumed when one person uses a car by him or herself, but is jointly consumed by more than one household member when those members ride in the car together.

A second limitation of these earlier resource share identification theorems is that they only prove generic identification. Roughly, generic identification means that models are usually identified, but there can exist rare situations where identification fails (see McManus 1992 and Lewbel 2019 for the formal definition of generic identification).

Our first collective household identification theorem extends the classical resource share identification theorem (proving identification of changes in resource shares in response to changes in distribution factors) in three ways. First, we show point identification rather than just generic identification. Second, we prove this point identification result in a model (the BCL framework) that allows goods to be partly shared. And third, we allow covariates to simultaneously affect both resource shares, and the extent to which goods are shared.

In response to the results from the earlier literature that only changes in resource shares and not levels can be identified from household data, a more recent literature has focused on adding additional assumptions to the model to identify the levels of resource shares.[54] For example, in a model without children, BCL obtain generic identification by assuming common preferences over goods for individuals whether single or married. Other papers that impose additional functional form or behavioral restrictions to gain point identification include Lewbel and Pendakur (2008), Couprie, Peluso, and Trannoy (2010), Bargain and Donni (2009, 2012), Lise and Seitz (2011), and Dunbar, Lewbel, and Pendakur (2013).

All of the above past results that obtained point identification, rather than just generic iden-

[54] One response to the nonidentification of resource share levels has been the collection of costly (and hence small) data sets of extremely detailed within household consumption. Examples of constructing resource share estimates using such detailed data include Menon, Perali, and Pendakur (2012) and Cherchye, De Rock, and Vermeulen (2012). Another response has been to construct revealed preference based set identification bounds on resource shares. Examples include Cherchye, De Rock, and Vermeulen (2011), Cherchye, De Rock, Demuynck, and Vermeulen (2017), and Cherchye, De Rock, Lewbel, and Vermeulen (2015).

tification, either depended on very strong functional form restrictions, or only showed point identification of some features of the household's behavior (e.g., identifying resource shares but not economies of scale or price effects). Our second collective household identification theorem point identifies all the features of the household's behavior, again allowing for partial sharing of goods. The theorem includes point identification of the demand functions and resource shares of children, without requiring observation of any child specific goods.

## 2.2 The Collective Household Model With Cooperation Factors

Resource shares are functions that describe the allocation of a household's total budget to each of the household's members. A distribution factor is a covariate that affects resource shares, but does not affect household member's tastes for goods. Lewbel and Pendakur (2019) propose a generalization of distribution factors called "cooperation factors." A cooperation factor affects both resource shares and the extent to which each good the household consumes is shared or jointly consumed.[55] Earlier collective household models maintained the unrealistic assumption that all goods were either purely public or purely private within a household. These models therefore could not permit any variation across households in how much each good was shared or jointly consumed, and so could not contain cooperation factors.

The covariate $s$ in our model is the value of a cooperation factor. An example of a cooperation factor might be the number of children in the household, where we assume a single utility function for all children. The sharing of goods within a household varies with the number of children, as does the fraction of the household's total resources that are devoted to children.

One economic motivation for uncovering the unobserved resource share and allowing goods to be partly shared is to enable individual-level welfare analysis. In particular, we are interested in comparing individuals' welfare under different economic environments (like household size and composition). An example of such comparisons are the so-called "indifference scales" proposed by BCL. The indifference scale for a household member $k$ is defined as the fraction of the household's total expenditures $y$ that would be required by member $k$ if he or she were living alone to be as well off materially as he or she is in the household. This is in contrast to the earlier notions of "equivalence scales", which attempted to directly compares the welfare of

[55]In Lewbel and Pendakur (2019), cooperation factors can also directly affect the utility functions of household members. That additional feature of cooperation factors is irrelevant for the present paper, because that feature only affects the value of $s$, but does not affect the household's demand functions or resource shares as functions of $p$, $y$, and $s$.

an individual to the welfare of a household. Equivalence scales have the drawback of requiring cardinal utility comparisons, and requires that utility be defined for a households, not just for individuals. Indifference scales do not suffer from these drawbacks. Indifference scales can be used for poverty, life insurance, and wrongful death calculations. For example, Cherchye et al. (2012) apply indifference scales to Dutch data to study the poverty and economic well-being among the elderly widows and widowers.

This section summarizes our collective household consumption model. Our model is the Barten scale consumption technology model in BCL,[56] with the following modifications: 1. BCL assumes households are couples, and that the observable data includes both the demand functions of couples and the demand functions of singles (i.e., it assumes data from men and women each living alone, as well as living together). Our model assumes any number of members K, and we do not assume we can see the demand functions of singles (so, e.g., our model can include children). 2. Instead of assuming we can observe the demand functions of singles, we impose the constraints that assignable goods can be observed for some household members, and we assume that the resource share functions do not depend on y (as discussed elsewhere, other papers provide empirical evidence supporting these assumptions). 3. BCL implicitly allows for distribution factors, while we explicitly let the model depend on cooperation factors, which include distribution factors as a special case. In particular, we let the resource share functions $\widetilde{\eta}_s^k(p)$ for household member $k$ and Barten coefficients $a_{sj}$ for good $j$ each depend on cooperation factors $s$.

A household consists of $K$ members. Let subscript $j$ denote a good and superscript $k$ denote a household member. Let $z$ index the continuous quantities of goods purchased by the household. The household solves the following optimization problem

$$\max_{x^1,\ldots,x^K} \sum_{k=1}^{K} \mu^k(p/y)U^k(x^k) \tag{35}$$

$$\text{such that } z = Ax,\ x = \textstyle\sum_{k=1}^{K} x^k,\ p'z = y$$

$U^k$ is member $k$'s utility function. We allow household members to have different preferences.

[56]The consumption technology is called a Barten technology after Barten (1956), who proposed an analogous construction to model preference heterogeneity across consumers in unitary (not collective) models.

$\mu^k$ is the so-called "Pareto weight" of each member. It summarizes the member's bargaining power in a collective model. A higher Pareto weight implies that the household demand is represented more by the member's preferences. $p'z = y$ is the household's budget constraint.

Each member's utility function depends on the private good equivalents that the member consumes. $x^k = (x_1^k, ..., x_J^k)$ is the vector of member $k$'s private equivalent consumption of goods. They are the quantities of transformed goods that are consumed by each member. $x$ is the sum of private good equivalents for all members, i.e., $x = \sum_{k=1}^{K} x^k$. $z = Ax$ is the household "consumption technology function". The difference between $z$ and $x$ is due to the sharing and jointness of consumption. The square matrix $A$ summarizes how much goods are shared or jointly consumed. The diagonal elements of $A$ represents how much each good can be shared by itself. For example, suppose that the first element of $x^k$ is the quantity of gasoline consumed by member $k$. If all household members shared their car (riding together) by 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 $z_1 = (2/3)(g_1^1 + g_1^2)$. In this example, the upper left corner of matrix $A$ would be 2/3 and the remaining first row and first column of $A$ would be zero. The off-diagonal element of $A$ represents how much the sharing of one good depends on the consumption of another good. For example, a household that consumes more public transportation will have a lower degree of sharing in gasoline. For simplicity, we assume the off-diagonal elements of $A$ to be zero.

The key assumption in the collective household literature is that the household outcomes 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 is equivalent to a two-stage process. In stage one, household's total expenditure is divided between members according to some sharing rule. The resource share for member $k$, denoted $\widetilde{\eta}_s^k(p)$, is defined as the fraction of the household's resources $y$ that are consumed by member $k$. In stage two, each member $k$ chooses her or his private equivalent consumption $x^k$ to maximize her or his own utility $U^k$ given a Lindahl (1958) type shadow price vector and his or her own resource share. The Lindahl shadow price of a good $j$ is the market price $p_j$ discounted by the degree of sharing or jointness of consumption, that is, the shadow price is $a_{sj}p_j$. The second stage of the household's optimization problem takes the form

$$\max_{x^k} U^k(x^k) \text{ such that } (a_{s1}p_1, ..., a_{sJ}p_J)x^k = \widetilde{\eta}_s^k(p)y \tag{36}$$

which has the solution vector

$$x^k = g^k(a_{s1}p_1, ..., a_{sJ}p_J, \widetilde{\eta}_s^k(p)y) \tag{37}$$

The function $g^k$ is the Marshallian demand function for member $k$, obtained by maximizing member $k$'s utility function $U^k(x^k)$ subject to a linear budget constraint.

From this derivation, the household's demand functions have the form

$$\omega_j\left(p, s, y\right) = \sum_{k=1}^{K} \widetilde{\eta}_s^k(p) h_j^k\left(a_{s1}p_1, ..., a_{sJ}p_J, \widetilde{\eta}_s^k(p)y\right) \tag{38}$$

The function $\omega_j\left(p, s, y\right)$ is the household's demand function for good $j$, defined as the total expenditures of the household on good $j$, divided by the household's expenditures on all goods $y$. $h_j^k$ is member $k$'s demand function for good $j$, defined as the member's expenditure on good $j$, if faced with the shadow price and resource share, divided by the member's control of resources $\widetilde{\eta}_s^k(p)y$.

The household's resource share functions $\widetilde{\eta}_s^k(p)$ and the Barten scales $a_{sj}$ vary by $s$. Since each $a_{sj}$ must be strictly positive, and the functions $\widetilde{\eta}_s^k$ can vary with $s$, we can without loss of generality define resource share functions $\eta_s^k$ such that

$$\eta_s^k(a_{s1}p_1, ..., a_{sJ}p_J) = \widetilde{\eta}_s^k(p) \tag{39}$$

Writing resource shares in the form of $\eta_s^k$ rather than $\widetilde{\eta}_s^k$ simplifies some of our later identification proofs.

Recall that $A_s$ is a diagonal matrix with the vector of coefficients $(a_{s1}, ..., a_{sJ})$ on the diagonal. We can then rewrite equation (38) as

$$\omega_j\left(p, s, y\right) = \sum_{k=1}^{K} \eta_s^k(A_s p) h_j^k\left(A_s p, \eta_s^k(A_s p)y\right). \tag{40}$$

The general problem to be considered is identification of the Barten scales $a_{sj}$, the resource share functions $\eta_s^k$, and the individual member demand functions $h_j^k$, given the observable (or consistently estimable) household demand functions $\omega_j$. Note that if the functions $\eta_s^k$ and the vector of Barten coefficients $(a_{s1}, ..., a_{sJ})$ are identified, then the alternative way to represent resouce shares given by the functions $\widetilde{\eta}_s^k$ are also immediately identified by equation (39).

For both identification and estimation, we make use of the concept of assignable goods. A good is assignable if it is only consumed by one household member. Suppose, e.g., that for some household member $k$, good $j = k$ is assignable to member $k$. Then for $j = k$, equation (40) simplifies into

$$\omega_k\left(p, s, y\right) = \eta_s^k(A_s p) h_k^k\left(A_s p, \eta_s^k(A_s p) y\right) \tag{41}$$

Chiappori and Ekeland (2009) show that, without partially shared goods, one can obtain generic identification of the model given assignable goods, but they cannot show point identification. Similarly, BCL show only generic identification of their model. Dunbar, Lewbel, and Pendakur (2013) combine having assignable goods with some preference similarity restrictions to point identify resource shares, but not other features of the model, e.g. they cannot identify economies of scale to consumption, and because they use Engel curve data, they cannot identify price effects. In contrast, we point identify all the features of the collective household model.

## 2.3 Semiparametric Coefficients Identification

Before we tackle the general problem of identifying the components of equation (40), we first consider a simpler problem. Let $a_s = (a_{s1}, ..., a_{sJ})$ be a $J$-vector of coefficients we wish to identify. Let $A_s$ be the $J$ by $J$ diagonal matrix that has the vector $a_s$ on the diagonal. Let $P = (P_1, ..., P_J)$ be a $J$-vector of continuous covariates and let $S$ be a discrete covariate.

Assume we can identify a function $M\left(P, S\right)$, e.g., $M\left(P, S\right)$ might be a conditional mean, conditional density, or conditional quantile function that we could consistently estimate. In our applications, $P$ is a vector of prices, $S$ is a so-called cooperation factor, and $M$ is derived from household demand functions that can be estimated from observed consumption data. The goal is to identify the unknown vector of coefficients $a_s = (a_{s1}, ..., a_{sJ})$ in the model

$$M(p,s) = G(a_{s1}p_1, ..., a_{sJ}p_J) = G(A_s p) \tag{42}$$

for some unknown function $G$.

In this section we provide a theorem that gives three alternative sets of conditions, each of which suffice for point identification of the vector of coefficients $(a_{s1}, ..., a_{sJ})$ for each value $s$ that $S$ can equal. An attractive feature of these identification results is that they do not impose monotonicity on the function $G$. These relatively simple results will form alternative building blocks that we can then use to identify the collective household model. These results are based on identification methods described by Matzkin (2003, 2007, 2012), Lewbel (1998, 2019), and Lewbel and Pendakur (2017).

ASSUMPTION A1: Let the support of $(P, S)$ be $\Omega_p \times \Omega_s$. For each $(p,s) \in \Omega_p \times \Omega_s$, equation (42) holds for some unknown function $G$ and some vector of constants $a_s = (a_{s1}, ..., a_{sJ})$. The function $M(p,s)$ is identified for all $(p,s) \in \Omega_p \times \Omega_s$.

ASSUMPTION A2: Assume for some $t \in \Omega_s$ that $a_{tj} = 1$ for $j = 1, ..., J$.

Assumption A1 essentially just lays out the model. Assumption A2 is a scale normalization. In some contexts, Assumption A2 can be made without loss of generality (as long as $a_{tj}$ is not identically zero). This is because, if $a_{tj} \neq 1$ then we can redefine the function $G$ to make $a_{tj} = 1$, by replacing $G$ with $\widetilde{G}$ defined by $\widetilde{G}(p) = G(a_{t1}p_1, ..., a_{tJ}p_J)$ and replacing each $a_{sj}$ with $\widetilde{a}_{sj}$ defined by $\widetilde{a}_{sj} = a_{sj}/a_{tj}$.

We will propose three assumptions (Assumption A3, A4, and A5), each of which can be used to obtain identification. Assumption A3 is a high level assumption, which may therefore be hard to verify in practice. Assumption A4 is more restrictive, but is simple and low level, and therefore could be easier to verify or justify in applications. Assumption A5 is discussed below.

ASSUMPTION A3: Assume $G(p)$ is continuously differentiable. Let $m_j(p,s) = \partial M(p,s)/\partial p_j$ and let $g_j(p) = \partial G(p)/\partial p_j$. For any $J$-vector $\alpha = (\alpha_1, .., \alpha_J)$, define the $J$-vector valued function $\zeta(\alpha, p, s)$ as having the elements

$$\zeta_j(\alpha, p, s) = \frac{m_j(p,s)}{g_j(\alpha_1 p_1, ..., \alpha_J p_J)} \text{ for } j = 1, ..., J$$

For each $s \in \Omega_s$, assume there exists a $\widetilde{p} \in \Omega_p$ such that $A_s\widetilde{p} \in \Omega_p$ and $\zeta_j(\alpha, p, s)$ is a contraction on $a$.

ASSUMPTION A4: Assume $\Omega_p$ includes a neighborhood of zero, and that $G(p)$ is continuously differentiable for all $p$ in that neighborhood of zero. Assume $\partial G(p)/\partial p_j$ does not equal zero when $p = 0$.

In Assumption A4, the neighborhood of $\Omega_p$ containing zero can be one sided, by just using one sided derivatives and limits in the proof of Lemma 1 below. So, e.g., $p$ in our later application will be prices, which are nonnegative. But if arbitrarily low prices (relative to expenditure levels) can be observed in theory, then Lemma 1 can be applied, taking one sided limits and derivatives as $p$ goes to zero.

Define the random vector $V$ by $V = (V_1, ..., V_J)$ where $V_j = a_{Sj}P_j$. Let $\Omega_v$ denote the support of $V$.

LEMMA 1: Let Assumptions A1 and A2 hold. If either Assumption A3 or Assumption A4 also holds then the coefficients $a_{s1}, ...a_{sJ}$ and the function $G(v)$ are point identified for all $v \in \Omega_v$ and $s \in \Omega_s$.

The identification in Lemma 1 is what Khan and Tamer (2010) call "thin set" identification. Thin set identification is when identification is based on a measure zero subset of the support of the data. In this example, identification is based either on the point $p$ that makes Assumption A3 hold, or the point $p = 0$ for Assumption A4. Either such point is observed with probability zero if $P$ is continuous. The more well known concept of "identification at infinity" as in Chamberlain (1986) and Heckman (1990) is another example of thin set identification. Many of the identification theorems given in Matzkin (2003, 2007, 2012) assume a normalization that otherwise unknown functions take on known values at one point, such as zero. Such normalizations typically imply thin set identification. In practice, estimators of parameters that are only thin set identified will usually converge at slow rates[57].

One way to avoid thin set identification is to assume that Assumption A3 holds at a mass point $p$. Another way would be to assume that Assumption A3 holds for all points $p$ in some

[57]See Khan and Tamer (2010) and Lewbel (2018) for details regarding thin set identification.

convex positive measure subset of $\Omega_p$. However, this is an additional strong high level assumption that could be difficult to verify.

To avoid issues associated with thin set identification, we now give an alternative identification result that integrates over the support of $p$. This identification however, requires a large support assumption. However, unlike identification at infinity or other thin set identification (and associated convergence rate issues), here the large support assumption is only needed to avoid the presence of boundary terms in a change of variables argument.

For a given function $\psi_j$, define $c_j$ by

$$c_j = \int_0^\infty ... \int_0^\infty \psi_j \left[G\left(p\right)\right] p_1^{-1}...p_{j-1}^{-1}p_{j+1}^{-1}...p_J^{-1} dp_1...dp_J \tag{43}$$

ASSUMPTION A5: Assume $\Omega_p$ is the positive orthant. $G\left(p\right)$ is continuous for all $p \in \Omega$. All $a_{sj}$ are positive. For each $j \in \{1, ..., J\}$, we can find a continuous function $\psi_j$ such that the constant $c_j$ defined by equation (43) exists, is finite, and non-zero.

Having $\Omega_p$ be the positive orthant is the large support assumption. The assumption that all $a_{sj}$ are positive is testable, using the estimated average derivatives with respect to $p_j$ of $M\left(p, s\right)$ relative to average derivatives of $M\left(p, t\right)$. In our empirical application, the $a_{sj}$ coefficients will be sharing parameters that are positive by construction. It is assumed that we can find a continuous function $\psi_j$ that makes the integral given by equation (43) convergent. Note that $G\left(p\right)$ is identified by $G\left(p\right) = M\left(p, t\right)$, so knowing $G$, the assumption is that we can construct a continuous function $\psi_j$ that goes to zero sufficiently quickly whenever any element of $P$ goes to zero, and grows sufficiently slowly, or not at all, when any element of $P$ goes to infinity. [58]

LEMMA 2: If Assumptions A1, A2, and A5 hold, then the coefficients $a_{s1}, ...a_{sJ}$ and the function $G\left(v\right)$ are point identified for all $v \in \Omega_v$ and $s \in \Omega_s$.

Both Lemmas 1 and 2 have proofs by construction, so semiparametric estimators could be readily constructed by mimicking the steps of either proof. Combining Lemmas 1 and 2, and separately considering the scale normalization of Assumption A2 gives us our first identification theorem.

[58] A similar construction appears in Lewbel and Pendakur (2017), who also provide some examples. However, their application involved much stronger conditions than ours, because in their model the coefficients were random rather than constants.

THEOREM 1: Let Assumption A1 hold. If either Assumption A3, A4, or A5 also holds, then the relative coefficients $a_{s1}/a_{t1},...,a_{sJ}/a_{t1}$ are point identified for all $v \in \Omega_v$, $s \in \Omega_s$, and $t \in \Omega_s$. If Assumption A2 also holds then the coefficients $a_{s1},...,a_{sJ}$ and the function $G(v)$ are point identified for all $v \in \Omega_v$ and $s \in \Omega_s$.

## 2.4 Identification of the Collective Household Model

We now consider identification of the collective household model. The results here are variants and applications of Theorem 1. As with Theorem 1, we will present pairs of results that allow us to obtain point identification either making use of large support assumptions or entailing possible thin set identification.

ASSUMPTION B1: Household budget share demand functions $\omega_j(p,s,y)$ for $j=1,...,J$ are given by equation (40), where for all $(p,s,y) \in \Omega_p \times \Omega_s \times \Omega_y$, the functions $h_j^k(p,y)$ and $\eta_s^k(p)$ are continuous for each member $k$ and cooperation index $s$. The Barten technology constants $a_{sj}$ are bounded and strictly positive for each cooperation index $s$ and good $j$.

Assumption B1 essentially lays out the collective household model as discussed in the previous section. The continuity conditions follow naturally from smooth utility and household bargaining or social welfare functions. Similarly, having Barten scales be bounded and positive follows from physically feasible sharing.

Our first goal is to identify the Barten constants $a_{s1}$,...,$a_{sJ}$. We cannot immediately apply Theorem 1 to equation (40) or equation (41) (taking $G$ to be any of the household demand functions $\omega_j$), because the resource shares $\eta_s^k(A_s p)$ vary by $s$. We therefore will first construct a function $G$ out of a demand function $\omega_j$ using Theorem 2 below, and then apply Theorem 1 to the result.

Assumptions B2, B3, and B4 below are alternatives; only one needs to hold for Theorem 2. These assumptions each resemble either Assumption A3 or A5 from Theorem 1, and Theorem 2 correspondingly uses similar machinery to that of Theorem 1. But instead of directly identifying coefficients, Theorem 2 is used to modify the demand function of equation (40) into a form needed to apply Theorem 1.

ASSUMPTION B2: Assume that $\Omega_y$ includes a neighborhood of zero. Assume there exists a good $j$ that is assignable to some household member $k$. Assume that for this assignable good $j$, for all $(p, s) \in \Omega_p \times \Omega_s$, the function $M(p, s)$ defined by the following equation is finite and nonzero

$$M(p, s) = \lim_{y \to 0} \frac{1}{\omega_j(p, s, y)^2} \frac{\partial \omega_j(p, s, y)}{\partial y}$$

ASSUMPTION B3: Assume that $\Omega_y$ includes $(0, \infty)$. Assume there exists a good $j$ that is assignable to some household member $k$. Assume that for this assignable good $j$, for all $(p, s) \in \Omega_p \times \Omega_s$, the function $M(p, s)$ defined by the following equation is finite and nonzero for some real nonzero constant $c$.

$$M(p, s) = \int_0^\infty [\omega_j(p, s, y)]^c y^{c-1} dy.$$

ASSUMPTION B4: Assume that $\Omega_y$ includes $(0, \infty)$. Assume there exists a good $j$ such that, for all $(p, s) \in \Omega_p \times \Omega_s$, the function $M(p, s)$ defined by the following equation is finite and nonzero.

$$M(p, s) = \int_0^\infty \omega_j(p, s, y) \, dy.$$

THEOREM 2: Let Assumptions B1 hold. If Assumption B2 or B3 or B4 also holds, then there exists a function $G(p)$ such that $M(p, s) = G(A_s p)$.

COROLLARY 1: Let Assumption B1 hold. If Assumption B2 or B3 or B4 also holds, and if corresponding $M(p, s) = G(A_s p)$ equation from Theorem 2 satisfies Assumption A1 and either Assumption A3 or A4 or A5, then $a_{sj}/a_{tj}$ is identified for every $s \in \Omega_s$, every $t \in \Omega_s$ and every $j \in \{1, ..., J\}$.

Theorem 2 shows that equation (42) holds, and so Theorems 1 and 2 can be combined as in Corollary 1. Corollary 1 shows that all the relative Barten scales $a_{sj}/a_{tj}$ are identified. In this context the scale normalization of Assumption A2 is not a free normalization, because each $a_{sj}$ has a physical economic meaning as the extent to which good $j$ is shared in a household with cooperation factor $s$. However, we will later use additional information to identify the levels of the Barten scales and not just their relative values.

Note for Theorem 2 that Assumptions B2 and B3 require an assignable good, while B4 does not. However, our identification of resource shares below will require an assignable good regardless, so B4 is mainly useful if the primary goal is just identification of the Barten scales, or if some other mechanism like functional form restrictions are used to identify the resource shares. Assumption B4 is weaker than B3 in that it doesn't require an assignable good, but is stronger in that it requires the constant $c$ to equal one.

Assumption B2 implicitly assumes that for the given good $j$, $\lim_{y\to 0}\omega_j(p,s,y)$ is nonzero. This limit would be zero if $\omega_j$ was a quantity, but $\omega_j$ is a budget share. This condition is not a strong constraint for a budget share, and so would hold if, e.g., the budget share for good $j$ was bounded away from zero for $y>0$ (given continuity). We can expect this condition to hold for most goods, but in particular for necessities, since such goods are, definitionally, necessary and hence comprise a nonzero share of the household's budget.

A notable feature of Theorem 2 is that it gets identification from the demand function of just one good that the household consumes. Since we can estimate household demand functions for many goods, we can expect the Barten scales to be greatly over identified in practice. Another feature is that these results do not require monotonicity of demands, which is useful because empirically the effects of both $p$ and $y$ on budget shares can change signs.

Given identification of the Barten technology, our next goal is identification of relative resource shares. Define the vector $\phi_{st}(p)$ to be the vector of elements $\phi_{stj}(p_j)$ defined by

$$\phi_{stj}(p_j)=\frac{p_j}{a_{sj}/a_{tj}}$$

where $t\in\Omega_s$ is any nonzero cooperation factor value chosen by the econometrician.

ASSUMPTION C1: Assume that $\Omega_y$ includes a neighborhood of zero, that there exists a good $j$ that is assignable to some household member $k$, and for that good $j$ the budget share function $\omega_j(s,\phi_{st}(p),0)$ is finite and nonzero for all $(p,s)\in\Omega_p\times\Omega_s$.

ASSUMPTION C2: Assume that $\Omega_y$ includes $(0,\infty)$, that there exists a good $j$ that is assignable to a household member $k$, and for that good $j$, for all $(p,s)\in\Omega_p\times\Omega_s$, the function

$m(p,s)$ defined by the following equation is finite and nonzero for some real constants $c_1$ and $c_2$ where $c_2 \neq c_1 - 1$ and $c_1 \neq 0$.

$$m(p,s) = \int_0^{\infty} \left[\omega_j\left(s, \phi_{st}(p), y\right)\right]^{c_1} y^{c_2} dy.$$

THEOREM 3: Let the Assumptions of Corollary 1 hold for some $s \in \Omega_s$ and let them also hold replacing $s$ with some other value $r \in \Omega_s$. If in addition either Assumption C1 or C2 holds, then the relative values of resource shares $\eta_s^k(A_t p)/\eta_r^k(A_t p)$ are identified for all $p$ such that $(a_{s1}\phi_{st1}(p_1), ..., a_{sJ}\phi_{stJ}(p_J))$ and $(a_{r1}\phi_{rt1}(p_1), ..., a_{rJ}\phi_{rtJ}(p_J))$ lie in $\Omega_p$. If $\Omega_p$ is the positive orthant, then $\eta_s^k(A_t p)/\eta_r^k(A_t p)$ is identified for all $p \in \Omega_p$.

The classical identification result in the collective household literature discussed earlier, and given in its most general form by, e.g., Chiappori and Ekeland (2006, 2009) is that, without additional information, the level of resource shares were not identified, but the changes in the resource shares resulting from changes in distribution factors are generically identified. However, this classical model required that all goods be either completely private within the household, or completely public. Theorems 2 and 3 together generalize this classical result to the model where goods can be partly shared as in BCL, and where the extent to which goods are shared can vary across households. In particular, these theorems show identification of relative Barten scales and relative resource shares, and so show that changes in these functions are identified given a change in the cooperation factor $s$. Moreover, these theorems here give explicit conditions for point identification of these relative values, rather than just the generic identification of earlier results (see, e.g., Lewbel 2019 for the difference between point and generic identification).

One potential limitation of Theorem 3 is that, if $\Omega_p$ is not the positive orthant, there could exist values of $p$ for which identification of the relative resource shares is not shown. However, the identification in Theorem 3 uses just the demand function of one good for each household member. Since the demand functions for many goods are observed, as with Theorem 2 we can in general expect substantial overidentification, based on information in the other goods the household consumes.

For many applications, identification of relative values, particularly of resource shares, does not suffice to answer some questions of economic significance. E.g., as stressed by Dunbar, Lewbel, and Pendakur (2013), identification of poverty rates and of relative bargaining power of household members requires identifying the levels of resource shares, not just their relative values.

Therefore, for the last part of this section, we consider using additional information to obtain identification of the entire model, including levels of resource shares, levels of Barten scales, and the demand functions of each household member. These results will also allow us to relax the assumption that a private assignable exists for every household member.

ASSUMPTION D1: For some household member $k \in \{1, ..., K\}$ assume there exists an assignable good $j$. Without loss of generality let $j = k$. Assume that the demand function $h_k^k(p, y)$ is identified.

Letting $j = k$ in Assumption D1 is a free index normalization. What Assumption D1 says is that the demand function for one household member's assignable good is identified. The easiest way for Assumption D1 to hold is if our data includes single person households, and the demand function for an assignable good consumed by member $k$ is the same whether that person lives alone or with other people. For example, if member $k$ is a middle aged man, then let $s_k$ denote the value of $s$ that indexes households consisting of a middle aged man living alone. Since there is no one to share with when living alone, $\eta_{s_k}^k$ must equal one and $a_{s_k j}$ must equal one for all goods $j$. It follows that $\omega_k(p, s_k, y) = h_k^k(p, y)$, which then identifies $h_k^k(p, y)$.

THEOREM 4: Let the Assumptions of Corollary 1 hold for all $s \in \Omega_s$, let either Assumption C1 or C2 hold, and let Assumption D1 hold. Then the Barten constants $a_{s1}$,...,$a_{sJ}$ are identified for all $s \in \Omega_s$, and the relative resource shares $\eta_s^k(p)/\eta_r^k(p)$ are identified for all $p \in \Omega_p$. If in addition Assumption D1 holds for $k = 1, ..., K-1$, then each $\eta_s^k(p)$ function is identified for $k = 1, ..., K$.

COROLLARY 2: Let the Assumptions of Corollary 1 hold for all $s \in \Omega_s$. If either Assumption C1 or C2 holds, and if Assumption D1 holds for $k = 1, ..., K-1$, then the entire model is identified.

What we mean by the entire model being identified in Corollary 2 is that all the Barten scales $a_{sj}$, all the resouce share functions $\eta_s^k(p)$, and all the demand functions $h_j^k(p, y)$ are identified. Note that Corollary 2 follows immediately from Theorem 4, because once all the Barten constants and resource share functions are identified, we may then from equation (40) obtain the demand functions $h_j^k(p, y)$ for each good $j$.

By Theorem 4, only one assignable good for one household member is needed to identify the levels of the Barten constants. To identify the levels of the resource shares, and hence identify the entire model by Corollary 2, we require $K-1$ assignable goods. So, e.g., if $K=3$ where $k=1$ is the father, $k=2$ is the mother, and $k=3$ is the children, then we only need to have one identified, assignable good for the mother and for the father. As discussed above, these could come from observing single men and single women, assuming that one's taste for the assignable good does not differ between those living with others versus those living alone. In this example we do not need to observe or identify any child assignable goods, which is very useful because we would not expect to observe households consisting of children living alone (the original BCL model did not include children because, unlike the present paper, it did not overcome this obstacle to identification with children).

## 2.5 Empirical Application

### 2.5.1 Japanese Expenditure Data

We use Japanese household expenditures and demographic data. The data come from the Keio Household Panel Survey (KHPS) and the Japan Household Panel Survey (JHPS), made available to us by the Panel Data Research Center at Keio University. The KHPS has been implemented continuously since 2004, and consists of 4,000 households and 7,000 individuals nationwide. An additional survey on a cohort of about 1,400 households and 2,500 individuals was initiated in 2007. In 2009, the Panel Data Research Center at Keio University began implementing the JHPS, a new survey targeting 4,000 male and female subjects nationwide in parallel with the KHPS.

The survey questionnaires cover comprehensive topics such as household structure, individual attributes, academic background, employment or education status, distribution of living hours, and matters related to cohabitation with parents, etc. Households are asked the following questions regarding household expenditures, "Enter the amount your household spent on each of the following living expenditures last month (January)." The expenditure categories that we include in this paper are food (at-home or eating-out and school lunches), utilities, clothing and shoes, transportation, communication, and entertainment, giving us a total of $J=6$ different goods.

The consumption data separately reports household expenditures (in January) on clothing and shoes for the household head, spouse(s), and children. The sum of expenditures on clothing and shoes for each household member type (men, women, and children) are our private assignable goods. Note that while the data include assignables for all $K = 3$ types of household members, our identification theory only requires observation of $K - 1 = 2$ assignable goods. This provides over identifying information.

We select households (single men, single women, and married couples) according to the following criteria: (1) couples with children aged 15 or over are excluded (since adult clothing purchases could be consumed by older children); (2) for married couples, households with members over 50 are excluded; (3) single women and men are restricted to be between 22 to 65 years old; (4) households with members as students are excluded; (5) observations where expenditures on four or more of the six goods is zero are excluded; (6) To mitigate the possible effects of outliers, we further trim the three samples with respect to key variables (the budget share of each aggregate good and log real total expenditure) by dropping observations in the lower and upper 1 percentile. After applying these criteria, we are left with a sample consisting of 277 single women, 361 single men, and 1070 married couples having from zero to four children.

### 2.5.2 Price Data

We use price data from the 2015 based Consumer Price Index (CPI) available from e-Stat, the Portal Site of Official Statistics of Japan. The goal is to construct a price index for each aggregate good for each household in our sample. It is challenging to merge this CPI data into the JHPS/KHPS because the two datasets divide the country somewhat differently. JHPS/KHPS provides the region and city size of the residence of each household. The CPI divides Japan into 10 regions, whereas the JHPS/KHPS divides it into 8 regions. We first reduce the number of regions in the CPI by merging some of the CPI regions to match the definitions in JHPS/KHPS. While most prefectures belong to the same region between the CPI and JHPS/KHPS data after merging, the three prefectures of Yamanashi, Nagano, and Mie are classified to different regions between the CPI and JHPS/KHPS data.[59]

In addition to regional prices, the CPI dataset provides price data for each "designated city,"

[59]To match the JHPS/KHPS definition of Kyushu region (Fukuoka, Saga, Negasaki, Miyazaki, Kagoshima, Kumamoto, Oita, and Okinawa prefectures), we merged Kyushu and Okinawa regions in CPI. To match the JHPS/KHPS definition of Chubu region (Yamanashi, Nagano, Niigata, Fukui, Toyama, Ishikawa, Shizuoka, Gifu, and Aichi prefectures), we also merge Hokuriku and Tokai prefectures. With these merging, most prefectures belong to the same region between the JHPS/KHPS and CPI datasets with the following exceptions: Yamanashi and Nagano prefectures belong to Kanto [Chubu] region in CPI [JHPS/KHPS] dataset, and Mie prefecture belongs to Chubu [Kinki] region in CPI [JHPS/KHPS] dataset. About 3.7 percent of the Japanese population live in these three prefectures, according to the 2015 population census. See also, http://www.stat.go.jp/english/data/kokusei/2015/final_en/final_en.html. This procedure follows Fujii and Lin (2018).

## Table 26: Summary Statistics, JHPS/KHPS 2004 - 2016

| | Single Men | Single Women | Couples with | | | |
|---|---|---|---|---|---|---|
| | | | 0 child | 1 children | 2 children | 3 - 4 children |
| Number of observations | 1,194 | 830 | 379 | 711 | 1,376 | 396 |
| Number of unique households | 361 | 277 | 195 | 281 | 458 | 139 |
| Household income | 346.37 | . | 750.01 | 590.89 | 652.72 | 640.20 |
| Total expenditures (month) | 124.17 | 114.43 | 182.80 | 180.35 | 192.35 | 201.81 |
| Budget share (food) | 0.45 | 0.40 | 0.34 | 0.35 | 0.36 | 0.38 |
| Budget share (clothing) | 0.05 | 0.08 | 0.09 | 0.08 | 0.07 | 0.07 |
| Budget share (communication) | 0.11 | 0.12 | 0.12 | 0.13 | 0.12 | 0.13 |
| Budget share (entertainment) | 0.18 | 0.16 | 0.23 | 0.22 | 0.23 | 0.22 |
| Budget share (transportation) | 0.08 | 0.09 | 0.09 | 0.09 | 0.07 | 0.07 |
| Budget share (utility) | 0.13 | 0.15 | 0.13 | 0.14 | 0.14 | 0.14 |
| Husband clothing&shoes share | - | - | 0.04 | 0.02 | 0.01 | 0.01 |
| Wife clothing&shoes share | - | - | 0.06 | 0.02 | 0.02 | 0.01 |
| Children clothing&shoes share | - | - | 0.00 | 0.03 | 0.04 | 0.04 |
| Female age | - | 47.13 | 38.33 | 37.79 | 38.36 | 38.25 |
| Female unemployed | - | 0.11 | 0.10 | 0.23 | 0.23 | 0.22 |
| Female college graduate or above | - | 0.20 | 0.07 | 0.10 | 0.10 | 0.07 |
| Female some college | - | 0.40 | 0.33 | 0.30 | 0.28 | 0.21 |
| Male age | 48.05 | - | 39.23 | 39.10 | 39.89 | 39.29 |
| Male unemployed | 0.46 | - | 0.01 | 0.00 | 0.00 | 0.00 |
| Male college graduate or above | 0.19 | - | 0.07 | 0.10 | 0.07 | 0.10 |
| Male some college | 0.46 | - | 0.39 | 0.27 | 0.26 | 0.30 |
| Child 1 age | - | - | - | 6.79 | 9.71 | 11.42 |
| Child 2 age | - | - | - | - | 6.50 | 8.69 |
| Child 3 age | - | - | - | - | - | 5.35 |
| Child 4 age | - | - | - | - | - | - |
| Child average age | - | - | - | 6.79 | 8.11 | 8.34 |
| Home ownership | 0.36 | 0.41 | 0.49 | 0.59 | 0.73 | 0.80 |

*Notes:* Income and expenditures are in thousand yen. JHPS/KHPS covers years 2004 - 2016. Expenditures are for January. Definition of aggregate goods in JHPS/KHPS: food expenditure includes eating out. Transportation includes automobile expenses, fares, commuting passes, taxes, and tolls. Communications includes postage, fixed-line, and mobile phone charges. Culture amusement includes stationery, sporting goods, travel, hobbies. Utility includes electricity, gas, water (supply sewage). Clothing includes both clothese and shoes. All sources of income are before tax in the past year. "." means observations are all missing for this variable. "-" means information not available/not applicable. For education variable, college graduate or above in JHPS/KHPS includes junior college or technical college, univeristy, or graduate school. Household income refers to annual take-home income (after tax and social insurance deductions).

that is, each major city with a population of more than half million that is designated as such by order of the Cabinet of Japan.[60] Combining these city level prices using CPI weights, we construct price indices for designated cities within each of the eight regions, except for the Shikoku region where there is no designated city. Using each regional price index and the price indices for designated cities, we additionally back out price indices for the areas outside each designated city in each region. Thus, for each aggregate good, we obtain price data for 15 (8 regions $\times$ 2 (designated city or not) $-$ 1 (no designated city in Shikoku region)ïŒ combinations of regions and city sizes, which we then assign to households in the JHPS/KHPS dataset.

In the food category, the CPI dataset has separate price indices for food-at-home and eating-out. We construct household-level price indices for food using a Stone price index, by taking a weighted average of the log of the price of eating-out and the log price of food-at-home, where the weights are the household's food budget shares of eating-out and of food-at-home. By employing each household's own within food relative consumption weights, this construction more accurately reflects the price for food faced by individual households than the total food index provided by the CPI.

#### 2.5.3 Model Specification

We have proven identification of the model where all the component functions are nonparametric. However, these functions are high dimensional, so nonparametric estimation is not practical with modest sample sizes. We will therefore instead estimate the model parametrically, but make use of relatively flexible functional forms. Estimation will be based on moments implied by the model, and so will not entail specifying or estimating the distribution of error terms.

#### 2.5.4 Budget Shares for Individuals

Our model starts with a utility derived functional form for the budget shares of individuals. We specify individual preferences using the Quadratic Almost Ideal Demand System (QUAIDS) developed by Banks et al. (1997).

Let $p$ denote the $J$-vector of price indices of aggregate consumption goods. In our application, $J = 6$. Let $y$ denote total expenditures. Let $h$ index households, and let $k$ denote a household member. The household member types $k$ are $f$ for female, $m$ for male, and $c$ for children. For

[60] There are 20 designated cities in Japan as of January 1, 2019.

member $k$ of household $h$, let $\omega^{jhk}$ denote the fraction of member $k$'s total resources in the household that he/she spends on good $j$, and let $\omega^{hk}$ be the $J$-vector of budget shares $\omega^{jhk}$ for $J = 1, ..., J$. Note that we can only observe $\omega^{jhk}$ in households $h$ that have just one member $k$ (since for those households observed purchased budget shares equal the shares consumed by member $k$).

The QUAIDS demand system, for a single individual of type $k$, living in the household $h$, takes the $J-$ vector form

$$\omega^{hk}\left(\frac{p}{y^h}\right) = \alpha^{hk} + \Gamma^k \ln p + \beta^{hk}[\ln(y^h) - c^{hk}(p)] + \frac{\lambda^k}{b^{hk}(p)}[\ln(y^h) - c^{hk}(p)]^2. \tag{44}$$

Here $b^{hk}(p)$ and $c^{hk}(p)$ are price indices defined as

$$\ln[b^{hk}(p)] = (\ln p)'\beta^{hk}, \tag{45}$$

$$c^{hk}(p) = c_0^{hk} + (\ln p)'\alpha^{hk} + \frac{1}{2}(\ln p)\Gamma^{k\prime}\ln p, \tag{46}$$

$\alpha^{hk}$, $\beta^{hk}$, and $\lambda^k$ are $J$-vectors of preference parameters, $\Gamma^k$ is a $J \times J$ matrix of preference parameters, and $c_0^{hk}$ is a scalar parameter which we set to equal to zero based on the insensitivity reported in Banks et al. (1997). By definition, budget shares must add up to one, i.e., $\mathbf{1}'_J\omega^{hk} = 1$ for all $p/y$, where $\mathbf{1}_J$ is a $J$-vector of ones. This, in turn, implies that $\mathbf{1}'_J\alpha^{hk} = 1$, $\mathbf{1}'_J\beta^{hk} = 0$, $\mathbf{1}'_J\lambda^k = 0$, and $\Gamma^{k\prime}\mathbf{1}_J = \mathbf{0}_J$, where $\mathbf{0}_J$ is a $J$-vector of zeros. Slutsky symmetry requires that $\Gamma^k$ be a symmetric matrix.

As the indices above show, we let the parameter vectors $\alpha^{hk}$ and $\beta^{hk}$ vary by household $h$ as well as by individual $k$. In particular, we specify these parameter vectors by

$$\alpha^{hk} = \alpha_0^k + \sum_{m=1}^{M_\alpha} \alpha_m^k d_{m,\alpha}^{hk} \tag{47}$$

$$\beta^{hk} = \beta_0^k + \sum_{m=1}^{M_\beta} \beta_m^k d_{m,\beta}^{hk}, \tag{48}$$

where $d_{m,\alpha}^{hk}$ and $d_{m,\beta}^{hk}$ are observed demographic characteristics, and $M_\alpha$ and $M_\beta$ are the number of such covariates we observe. Each $\alpha^{hk}$ and $\beta^{hk}$ is a $J$-vector, which from the above adding up restrictions must satisfy $\mathbf{1}'_J\alpha_0^k = 1$, $\mathbf{1}'_J\alpha_m^k = 0$ for $m = 1, ..., M_\alpha$, and $\mathbf{1}'_J\beta_m^k = 0$ for $m = 0, ..., M_\beta$.

In our application $d^{hk}_{m,\alpha}$ consists of 7 region dummies and the age of member $k$, making $M_\alpha = 8$, while $d^{hk}_{m,\beta}$ is an indicator for homeownership, so $M_\beta = 1$. Taken together, we have 17 preference parameters for each of $J-1=5$ distinct equations, yielding a total of 85 parameters for each type of individual $k$. Note that the model for households with more than one member will also have additional parameters associated with resource shares and Barten scales.

### 2.5.5 The Estimator for Singles

The demand functions for households $h$ consisting of just a single man or a single woman are given by equation (44). Such households have either $k = f$ if the household $h$ is a single woman or $k = m$ if the household $h$ is a single man (there are of course no single children households). In this subsection we describe how these demand functions for singles are estimated. The demand functions and associated estimators for households consisting of multiple members are given in the next subsection.

For households $h$ consisting of singles, we append a $J$-vector valued additive error term $U^{hk}$ (consisting of elements $U^{jhk}$) to equation (44). This introduces unobserved heterogeneity in the singles' demand functions. We assume that the error vectors $U^{hk}$ are uncorrelated across households. Adding up requires $\mathbf{1}'_J U^{hk} = 0$, which implies that nonzero correlations must exist among the elements of each $U^{hk}$, that is, across goods $j$. We estimate the budget share demand equations for single men and for single women separately using GMM, allowing for arbitrary correlations in the errors across goods.

Let $u^{jhk}\left(\theta^k\right) = U^{jhk}$ denote $\omega^{jhk}$ minus the $j$'th element of the right hand side of equation (44), where $\theta^k$ is the vector of all the parameters in that equation. Note that $u^{jhk}\left(\theta^k\right)$ is implicitly a function of $\omega^{jhk}$ and of all the regressors in the model. The moments used for GMM estimation take the form $E\left(u^{jhk}\left(\theta^k\right)\tau^{hk}\right) = 0$, with $\tau^{hk}$ being a vector of covariates as defined below. To impose the adding-up constraints we apply the standard practice of dropping one demand equation, and we recover the estimated parameters for that last equation using the adding-up constraints. The choice of which demand equation to drop is numerically irrelevant, because by the adding-up constraints, the parameters of the dropped equation are all deterministic functions of the parameters in the remaining equations. The full set of moments for estimating the model of singles of type $k$ is therefore $E\left(u^{jhk}\left(\theta^k\right)\tau^{hk}\right) = 0$ for $j = 1, ..., J-1$. Letting $u^{hk}\left(\theta^k\right)$ be the $J-1$ vector of elements $u^{jhk}\left(\theta^k\right)$ for $j = 1,...,J-1$, we equivalently write these moments as

$E\left(\left(I_{J-1} \otimes \tau^{hk}\right) u^{hk}\left(\theta^{k}\right)\right) = 0.$

The set of covariates $\tau^{hk}$ (for single households $h$) consists of region dummies, age, log relative prices, log real total expenditure (defined as the log of total expenditures divided by a Stone price index computed for our six nondurable goods) and its square, and the product of log real total expenditures with the home ownership dummy and with log prices. The number of moments therefore consists of $J-1=5$ distinct demand equations times the number of elements of $\tau^{hk}$, which is 22, for a total of 110 moments for $k=f$ and for $k=m$.

We apply GMM for estimation separately for single women and for single men. For $k=f$ and for $k=m$, let $H^k$ denote the set of households that consist of a single member of type $k$, and let $n_k$ denote the number of elements of $H^k$. Denote the sample moments for GMM estimation by

$$v^k(\theta^k) = \frac{1}{n_k} \sum_{h \in H^k} \left(I_{J-1} \otimes \tau^{hk}\right) u^{hk}\left(\theta^k\right), \tag{49}$$

the GMM criterion function is then

$$\widehat{\theta}^k = \arg\min_{\theta^k} v^k(\theta^k)' W^k v^k(\theta^k) \tag{50}$$

where $W^k$ is a weighting matrix. We apply standard two step GMM, where $W^k$ is an estimate of the efficient GMM weighting matrix, given by

$$W^k = \left(\frac{1}{n_k} \sum_{h \in H^k} \left(I_{J-1} \otimes \tau^{hk}\right) u^{hk}\left(\widetilde{\theta}^k\right) u^{hk}\left(\widetilde{\theta}^k\right)' \left(I_{J-1} \otimes \tau^{hk}\right)\right)^{-1} \tag{51}$$

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

Although we do not use it for our main analysis, in addition to estimating the above model for single men and for single women, we for comparison also estimated if for other households (couples with 0-4 children). For multiple member households, this corresponds to what is known in the collective household literature as a unitary model, that is, a model that treats a household as if it was a single maximizing agent. We provide this unitary model just for comparison to singles, and to our later collective model estimates. Iillustrating the differences in demands of single women, single men, and other households, Figure 1 presents fitted Engel curve plots for our six goods, with total expenditures $y$ ranging from the 1st to the 99th percentile. We shift the plots for couples with 0-4 children to the left in these figures to make them comparable to the singles plots. We find that food (at home and eating-out), utility, and communication are necessities while clothing and shoes, transportation, and entertainment are luxuries. Single women have a steeper Engel curve slope for clothing and shoes compared to other households. Couples with 0-4 children have a steeper Engel curve slope for entertainment compared to singles. Elasticity estimates for single women and single men are reported in Table 1 in Appendix B.

#### 2.5.6 The Joint Model

For our empirical application of the joint model, we assume that men, women, and children each have demands given by the QUAIDS functional form described in the previous section. The Barten type linear consumption technology for households with multiple members is

$$z_j = a_{sj} x_j \tag{52}$$

for each good $j$, or equivalently, $z = Ax$ with a diagonal matrix $A$. For households having total expenditure level $y$ and facing market prices $p$, the resulting shadow prices for this technology are

$$\pi(p/y) = \frac{A'p}{y}. \tag{53}$$

We parameterize each household member's resource shares with the functional form

$$\eta^f = \frac{\exp(\delta^{f\prime} s)}{1 + \exp(\delta^{f\prime} s) + \exp(\delta^{m\prime} s)}, \tag{54}$$

$$\eta^m = \frac{\exp(\delta^{m\prime} s)}{1 + \exp(\delta^{f\prime} s) + \exp(\delta^{m\prime} s)}, \tag{55}$$

where $f$ denotes female and $m$ denotes male, and the children's resource share is $1 - \eta^f - \eta^m$. If there are no children in the household, then

$$\eta^f = \frac{\exp(\delta^{f\prime} s)}{1 + \exp(\delta^{f\prime} s)}, \tag{56}$$

and the husband's share is $1 - \eta^f$.

We allow the same cooperation factors $s$ to affect the resource shares of every household member (wives, husbands, and children). The vectors of coefficients of $s$ are $\delta^f$ and $\delta^m$. The vector of cooperation factors $s$ consists of the difference in age between the wife and husband, the difference in log income between the wife and husband, number of children, the minimum age of children less 5, the age of the wife less 39 (the average age of wives in the sample), and indicators of whether the wife has some college education, and whether the husband has some college education.

With the technology function (52), the corresponding shadow prices (69), and the sharing rule (54) and (55), we end up with the following expression for the budget shares of couples with one to four children:

$$\omega_j^h(p, s^h, y^h) = \eta_{s^h}^{hf} \omega_j^{hf} \left( \frac{\pi}{\eta_{s^h}^{hf}} \right) + \eta_{s^h}^{hm} \omega_j^{hm} \left( \frac{\pi}{\eta_{s^h}^{hm}} \right) + (1 - \eta_{s^h}^{hf} - \eta_{s^h}^{hm}) \omega_j^{hc} \left( \frac{\pi}{1 - \eta_{s^h}^{hf} - \eta_{s^h}^{hm}} \right). \quad (57)$$

Couples with no children have the same expression but with $\omega^{h_j^c}$ (the budget share demand function of children $c$ for good $j$) set equal to zero.

Equation (57) shows that the budget share of couples with zero to four children is equal to a weighted average of the budget share of its members (wives, husbands, and children), evaluated at shadow prices, with weights given by their respective resource share. The resource share $\eta_s^{hk}$ represents both the fraction of the total expenditures controlled by member $k$ and the extent to which the household's demand is represented by that member's preferences.

Unlike singles, who have budget share equations for six goods, couples have budget shares $\omega_j^h(p, s^h, y^h)$ for seven or eight goods, since they include men's clothes, women's clothes, and (when present) children's clothes as separate goods, while singles just consume one type of clothing.

The parameters of the joint model consists of all the QUAIDS parameters of budget shares, $\omega^{hf}$, $\omega^{hm}$, and $\omega^{hc}$, the Barten scales $A_j$, and the parameters of the sharing rules $\eta_{s^h}^{hf}$ and $\eta_{s^h}^{hm}$. We jointly estimate all the parameters of the model using data from both singles and couples.

We have 150 preference parameters (5 $\times$ 17 - 10 = 75 symmetry constrained QUAIDS parameters for each of men and women). We also have 6 Barten scale parameters and 16 sharing rule parameters (the 7 listed above plus the constant for each of men and women); this gives a total of 172 parameters. We have 335 instruments (for each of the 5 goods there are 22 instruments for single men, 22 for single women, and 23 for couples), giving a maximum degrees of freedom of 163 for the most general model. The GMM weighting matrices for singles, $W^f$ and $W^m$, are obtained from the QUAIDS estimates for singles in the previous subsection; see equation (51). The weighting matrix for children, $W^c$ is derived using two-step GMM on the full system, starting with an initial identity weighting matrix. The GMM criterion is:

$$\min_{\theta}(v^c(\theta)'W^c v^c(\theta) + v^f(\theta)'W^f v^f(\theta) + v^m(\theta)'W^m v^m(\theta)), \tag{58}$$

where $\theta$ is the full parameter vector of the joint model and the instrument matrices are defined as in equation (49).

### 2.5.7 Resource Shares and Barten Scales

The main results for our preferred model are displayed in Table 3. Panel A in Table 3 reports the estimates of sharing rule parameters. We find that wives' resource share decreases significantly with the number of children. In terms of percent change, as the number of children increases by 1, the wife's resource share decreases by 35.7%. In contrast, the number of children does not significantly affect the husband's resource share. Dunbar et al. (2013) similarly found that husband's resource shares were little affected by the number of children.

We find that education is a significant cooperation factor. Specifically, the resource share of wives who have some college education is 92.5% higher than those who do not. Even in families where husbands have some college education, wives enjoy a 52.4% higher resource share than in families where husbands do not have any college education.

The estimated resource shares for each type of household member (wives, husbands, and children) are reported in Table 28. The mean value of the wife's resource share is 0.51 in couples without children, 0.3 in couples with 1 child, 0.24 in couples with 2 children, and 0.17 in couples with 3 or 4 children. The mean value of the husband's resource share is 0.49 in couples without children, 0.24 in couples with 1 child, and stays almost constant as the number of children increases to 3 or 4. The results suggest that when there are no children present in the household, wives and husbands have similar resource shares or bargaining power. However, when the number of children rises, mothers on average devote much more of their own resource shares to children

Table 27: **Estimation Results: the Sharing Rule and Barten Scales**

| | Wife | | Husband | |
|---|---|---|---|---|
| ***Panel A: the Sharing Rule*** | Coef | Std Error | Coef | Std Error |
| Constant | -0.701*** | 0.239 | -0.913** | 0.434 |
| Difference in log income (female - male) | -0.069 | 0.057 | -0.106 | 0.075 |
| Difference in age (female - male) | -0.003 | 0.009 | 0.017 | 0.013 |
| Number of children | -0.357*** | 0.058 | -0.101 | 0.181 |
| Minimum child age less 5 | -0.375 | 0.256 | -0.151 | 0.306 |
| Female age less 39 | 0.223 | 0.152 | 0.409 | 0.244 |
| Wife some college | 0.925*** | 0.333 | -0.869 | 0.793 |
| Husband some college | 0.524** | 0.247 | 0.347 | 0.343 |

| ***Panel B: Estimates of Barten Scales*** | Barten scale | Std Error |
|---|---|---|
| Food | 0.838*** | 0.017 |
| Clothing and shoes | 1.000 | - |
| Communication | 0.845*** | 0.020 |
| Entertainment | 0.665*** | 0.015 |
| Transportation | 0.760*** | 0.014 |
| Utility | 0.562*** | 0.014 |

*Notes:* Barten Scales are assumed to be homogeneous across all households. The Barten scale of clothing and shoes is assumed to be 1. $\star p < 0.10, \star\star < 0.05, \star\star\star < 0.01$.

compared to fathers.

Table 29 reports wives' resource share conditional on household characteristics. The benchmark household are ones in which neither the wife nor the husband has college education and are renters with median total expenditure. The first row shows that at our benchmark values, wives' resource share is 0.21. Rows 2 and 3 suggest that the education of both wives and husbands has a strong impact on wives' resource share. Wives in households who are home owners have slightly lower resource share. This is because home-owner households also tend to have children, and wives' resource share is lower in families with children.

For identification in their model, Dunbar et al. (2013) required that resource shares not depend on total expenditures. Our model does not require this restriction, and so can be used to test if it is valid. The last two rows of Table 29 show that resource shares do not change by total expenditure, providing empirical support to the assumption required by Dunbar et al. (2013). Our finding is also consistent with Menon, Pendakur, and Perali (2012) who find that the assumption also holds with data from the Italian International Center of Family Studies (CISF).

Estimates of Barten scales are reported in Panel B of Table 3. We restrict Barten scales to be between 0.5 and 1, as in BCL. Because we assume clothing and shoes to be private assignable

**Table 28: Estimated Resource Shares**

| | | Zero child | One child | Two children | Three/four children | All households |
|---|---|---|---|---|---|---|
| Woman | Mean | 0.51 | 0.30 | 0.24 | 0.17 | 0.28 |
| | Std Dev | 0.12 | 0.11 | 0.10 | 0.07 | 0.14 |
| | Min | 0.25 | 0.14 | 0.11 | 0.08 | 0.08 |
| | Max | 0.80 | 0.56 | 0.49 | 0.38 | 0.80 |
| Man | Mean | 0.49 | 0.24 | 0.25 | 0.27 | 0.28 |
| | Std Dev | 0.12 | 0.10 | 0.10 | 0.10 | 0.13 |
| | Min | 0.20 | 0.06 | 0.07 | 0.07 | 0.06 |
| | Max | 0.75 | 0.43 | 0.45 | 0.45 | 0.75 |
| Children | Mean | - | 0.45 | 0.50 | 0.56 | 0.43 |
| | Std Dev | - | 0.07 | 0.07 | 0.07 | 0.19 |
| | Min | - | 0.27 | 0.30 | 0.36 | 0.00 |
| | Max | - | 0.69 | 0.75 | 0.76 | 0.76 |

**Table 29: Sharing Rule Implications**

| **Household Characteristics** | **Wife's resource share** |
|---|---|
| | All households |
| Benchmark | 0.21 |
| Wife with some college education | 0.45 |
| Husband with some college education | 0.32 |
| Home owner | 0.19 |
| First quantile total expenditure | 0.21 |
| Third quantile total expenditure | 0.21 |

goods, we set their Barten scales equal to 1. We find that food and communication are highly private (having Barten scales close to one), while communication and utility are highly public (with Barten scales well below one). Transportation is found to be partially public. Note that transportation here includes both private cars and public transportation, where the former is more public and the latter is less public (here public means within households). The findings on Barten scales here are generally consistent with findings from previous literature, including BCL, Cherchye et al. (2012), Solvejg (2016), Lin (2018), and Fujii and Lin (2018).

#### 2.5.8 External Validation of Model Predictions

The estimated resource shares are unobserved, and may suffer from measurement error or estimation error due to possible model misspecification (see, e.g. Calvi et al. 2019). To verify our results, we compare our estimated resource shares to individual private consumption given by the Japanese Panel Survey of Consumers (JPSC).

A unique feature of JPSC is that it asks the individual expenses and savings of each household member. Specifically, JPSC asks the following question (answered for both the wife and husband):

How much expenditure, savings (including life insurance premiums etc.), and loan repayments did you pay this September? The answers are divided into : i) expenses/savings for all of my family ii) expenses/savings for me iii) expenses/savings for my husband iv) expenses/savings for my children v) expenses/savings for the others.

Categories ii), iii), and iv) are measures of private consumption for wives, husbands, and children. Category i) represents expenditures on goods that can be jointly consumed (like heat or gasoline). Previous studies have used inequality in private consumption to infer intra-household inequality in resource allocation.[61] However, these types of estimates, at best based on data like the JPSC, are incomplete, in the sense that they do not account for the potentially large role that shared goods may have in the actual resources consumed by each family member. In the JPSC data, over two thirds of expenditures are listed as shared goods.[62]

Comparing our results to the JPSC data, first consider children's shares. Our model predicts children's resource shares in the range of 0.45 to 0.56. This is consistent with the JPSC data, being above what JPSC reports for private children's consumption, and below the sum of JPSC's private children plus shared household expenditures. Second, our model estimates are that wives and husbands have roughly equal resource shares when there are no children present in the household. But the resource share of husbands increases up to around 1.6 times that of wives as the number of children in the household increases. This number is close to the ratio of private expenditures between husbands and wives, 1.5 - 2.3, found in the JPSC data. Taken together, these results provide evidence that our estimates are at least in ranges consistent with existing direct (albeit incomplete) measures of resource shares.

Finally we compare implications that one might draw about intra-household inequality from the JPSC data to estimates based on our model that accounts for and allocates expenditures on shared goods. Our estimates are that increasing the number of children decreases the wive's share by 35 percent while the husband's share decreases by only 10 percent. In the JPSC data, these numbers are 47 percent and 15 percent (based on summary statistics reported in Table 1 of Fujii

[61] Lise and Yamada (2014) look at JPSC households and find that there is a substantial difference between private consumption devoted to the wife, 6.3 percent, versus the husband, 15 percent. On average, 21.3 percent of the household expenditures are reported as the private consumption of either the wife or the husband, leaving 78.7 percent of household expenditures as public (expenditures for the family, children, and others). Fujii and Lin (2018) look at JPSC couples without children and also find similar patterns. The average private consumption devoted to the wife is 10 percent, versus the husband, 15 percent. 68 percent of household expenditures are devoted to the family. The remaining 4 percent of household expenditures are devoted to others. The previous findings imply that if we only consider private expenditures, the husband's resources are about 1.5-2.3 times of the wife's. The public expenditures, including both children and family expenditures, are around 70-80 percent of total household expenditures.

[62] Note, however, that expenditures for the family in the JPSC data include some durables that our data excludes, like furniture and electronics spending.

and Ishikawa 2013). By failing to allocate shared goods, the JPSC appears to underestimate the relative contribution of wives vs. husbands to children's resources.

### 2.5.9 Indifference Scales and Economies of Scale

We next consider the private equivalent expenditures for household members in multi-person households, and the resulting household's economies of scale to consumption, and household member's indifference scales. The private good equivalent of good j by member k in household h, $x_j^{hk}$, is the quantity of good j that member k consumes, accounting for the extent to which that good is shared with other members. The more public a good is, and hence the more that good is shared, the lower is its Barten scale, and the greater is the sum of $x_j^{hk}$ across household members k, relative to $z_j$, the household's purchased quantity of good j.

The household's economies of scale to consumption is how much more it would cost to buy every member's private good equivalents at market prices, relative to the household's actual total expenditure level. A member's indifference scale is defined to be the cost, at market prices, of the cheapest bundle of goods that gets member j to the same utility level (i.e., the same indifference curve over goods) that the member attains in the household by consuming his or her own vector of private good equivalents. See BCL for more details on these definitions.

Given our estimates of budget shares for singles, resource shares, and Barten scales, the private good equivalent quantities for each household member $k$ for each good $j$ are given by

$$x_j^{hk} = \frac{\eta_{s^h}^{hk}\omega_j^{hk}(\pi/\eta_{s^h}^{hk})}{\pi_j} = \frac{\omega_j^{hk}}{a_{s^h j}}\eta_{s^h}^{hk}y^h. \tag{59}$$

Let $\widetilde{V}^k\left(\pi/\eta_{s^h}^{hk}\right)$ denote the QUAIDS indirect utility function of member $k$, so the function $\widetilde{V}^k$ is defined by $\widetilde{V}^k\left(\pi/\eta_{s^h}^{hk}\right) = U^k(x_1^{hk}, ..., x_J^{hk})$ where $U^k$ is member $k$'s utility function. The indifference scale $IS^{hk}$ for each member $k$ is defined as the solution to

$$IS^{hk} = \widetilde{V}^k\left(\frac{p/y}{IS^{hk}}\right) = \widetilde{V}^k\left(\frac{\pi}{\eta_{s^h}^{hk}}\right). \tag{60}$$

The relative economies of scale to consumption, $R$, are defined as

$$R = \frac{p'(\sum_k x^{hk})}{y^h} - 1 = \frac{p'(\sum_k x^{hk} - z)}{p'z}. \tag{61}$$

Table 4 reports the estimates of members' private good equivalent expenditures $x^k$, indifference scales $IS^k$, and the overall economies of scale $R$. Row 6 in Table 4 reports the indifference scale for wives. This indifference scale can be interpreted as the fraction of the household's total expenditures that a wife would need when living alone (i.e., as a single) to attain the same indifference curve over goods that she reaches as a member of the household. The table shows that, on average, wives would require 67% of the couple's total expenditures to be as well off living alone as she is in the couple, when there are no children. This drops to only 23% in families with 3 to 4 children, reflecting how much less, relatively, women consume when children are present. The corresponding numbers for husbands (in row 7 of Table 4) are 66% without children, dropping to 36% when 3 to 4 children are present.

The interpretation of an indifference scale as the relative cost of living alone is not relevant for children, however, indifference scales for children still provide a measure of the savings in costs of children that household's attain by sharing consumption, and it is meaningful to compare the relative values of children's indifference scales in households of different compositions. Children's indifference scales are reported in row 8 of Table 4.

The second to the last row in Table 4 gives household's overall economies of scale. On average, it ranges between 0.33 to 0.36 across different household types. This implies that it would cost families 33% to 36% more to buy the (private equivalent) goods they consumed if there had been no shared or joint consumption.

## 2.6 Conclusions

The previous literature on collective household models shows point identification of some model features (like resource shares), but only generic identification of the entire model. We show point identification, rather than the weaker generic identification, of all the features of a collective household's optimization problem. Moreover, we do so in a model that allows goods to be partly shared, and that includes identifying the demand functions and resource shares of children, without observing any child specific assignable goods.

We apply our model to Japanese data consisting of single men, single women, and married couples with zero to four children. We find that wives and husbands have similar control over

**Table 30: Implications of Estimates**

| | Couples with | | | |
|---|---|---|---|---|
| | 0 child | 1 child | 2 children | 3 - 4 children |
| Wife's resource share | 0.51 | 0.30 | 0.24 | 0.17 |
| | | | | |
| Wife's equivalent expenditure | 121.66 | 69.79 | 59.71 | 45.15 |
| Husband's equivalent expenditure | 119.80 | 56.47 | 62.58 | 69.09 |
| Children's equivalent expenditure | - | 107.47 | 126.26 | 148.15 |
| Actual couple's expenditure | 181.82 | 173.31 | 183.40 | 192.64 |
| Indifference scale for women | 0.67 | 0.40 | 0.32 | 0.23 |
| Indifference scale for men | 0.66 | 0.33 | 0.34 | 0.36 |
| Indifference scale for children | - | 0.62 | 0.69 | 0.77 |
| Scale economy, R | 0.33 | 0.35 | 0.35 | 0.36 |
| Number of Observations | 379 | 704 | 1369 | 392 |

*Notes:* Values are in mean. Equivalent budget share is the budget share of the wife (husband) if she (he) is endowed with the fraction of resources and faced with shadow prices (market prices discounted by the Barten scales). The equivalent expenditure is the expenditure that the wife (husband) needs to obtain the same private good equivalents in marraige if she (he) is living alone, endowed with the fraction of resources in marriage and faced with market prices. Scale economy means it would cost the couple R percent more to buy the (private equivalent) goods they consumed if there had been no shared or joint consumption. The expenditures are in thousand yen.

resources when there are no children in the household. However, wives devote much more of their resources to children relative to husbands when there are children in the household. Around half of the household total expenditure is devoted to children. We find that it is important to allow goods to be partly shared because failure to account for that leads to underestimates of the decrease in wives' resources relative to husbands' when the number of children rises. In terms of individual welfare analysis, wives need two thirds of household total expenditure to live alone while being materially as well as living in the household. That number drops to only one fourth in households with 3-4 children. However, husbands still need one third of household total expenditure to live along while being materially as well as living in a 3-4 children household. One more child in a 1-2 children household will need an additional 7-8% of household total expenditure in order to maintain the current living standard of all children.

Our findings have important policy implications for the welfare analysis of children in multi-person households. For example, one potential application of our model is to calculate appropriate levels of compensation for children, to maintain their standard of living, if parents separate or a parent dies. Also, since we identify (ordinally) the utility functions of children and their parents, the framework can be used to evaluate the impact of welfare programs (e.g., taxes or subsidies) on the individual welfare of mothers, fathers, and children.

Finally, our general theorem on nonparametric identification of coefficients in nonlinear models may be applicable to a variety of other contexts. for example variation in the quality of inputs in production functions would have a comparable form to our Barten scales of prices in demand functions.

## 2.7 APPENDIX 2.A: Proofs

PROOF of LEMMA 1: The function $G(p)$ is identified for all $p \in \Omega_p$ by $G(p) = M(p,t)$, where $t$ is defined in Assumption A2. Also, the functions $m_j(p,s)$ and $g_j(p)$ are identified (where the derivatives defining these functions exist) for all $p \in \Omega_p$ by construction because they are derivatives of identified functions.

Now let Assumption A3 hold. Since $m_j(p,s) = g_j(a_{s1}p_1, ...a_{sJ}p_J)$, we have that

$$\zeta_j(\alpha, \widetilde{p}, s) = a_{sj} \frac{g_j(a_{s1}\widetilde{p}_1, ...a_{sJ}\widetilde{p}_J)}{g_j(\alpha_1\widetilde{p}_1, ...\alpha_J\widetilde{p}_J)} \text{ for } j = 1, ..., J \tag{62}$$

Since this mapping is a contraction, by the Banach fixed point theorem there exists is a unique $\alpha$ such that $\alpha = \zeta(\alpha, \widetilde{p}, s)$. This unique $\alpha$ is identified, because the value of the function $\zeta(\alpha, \widetilde{p}, s)$ is identified. But by equation (62), $a_s = \zeta(a_s, \widetilde{p}, s)$, and therefore the unique identified $\alpha$ is the desired coefficient vector $a_s$.

Next, suppose instead that Assumption A4 holds. For all $p$ in the neighborhood of zero given by Assumption A2, let $m_j(p,s) = \partial M(p,s)/\partial p_j$ and let $g_j(p) = \partial G(p)/\partial p_j$. These functions are identified by construction given that $M(p,s)$ and $G(p)$ are identified. Then, it follows from equation (62) that $a_s$ is identified by $a_{sj} = \zeta_j(0,0,s) = \lim_{p\to 0} m(p,s)/g_j(p)$, noting that $m_j(p,s)$ and $g_j(p)$ now exist for $p$ in a neighborhood of zero.

Finally, given identification of each $a_s$, the function $G(z)$ is identified not just for all $z \in \Omega_p$ but for all $z \in \Omega_z$ by $G(a_{s1}p_1, ...a_{sJ}p_J) = M(p,s)$ for all $(p,s) \in \Omega_p \times \Omega_s$.

PROOF of LEMMA 2:

First observe that, given $\Omega_p$ is the positive orthant and all $a_{sj}$ are positive, it follows that $\Omega_z$ is also the positive orthant, and therefore $G(z)$ for all $z \in \Omega_z$ by $G(p) = M(p,0)$. It follows that $c_j$ defined by equation (43) is also identified, since $G(p)$ is identified over the positive orthant and the function $\psi_j$ is chosen. Next define constants $C_{sj}$ by

$$C_{sj} = \int_0^\infty ... \int_0^\infty \psi_j[M(p,s)]\, p_1^{-1}...p_{j-1}^{-1}p_{j+1}^{-1}...p_J^{-1} dp_1...dp_J.$$

Each $C_{sj}$ is identified, since $M(p,s)$ is identified for all $p$ over the positive orthant and all $s \in \Omega_s$, and the function $\psi_j$ is chosen. Notice that $c_j = C_{0j}$. Then, using the change of variables $\phi_i = a_{si}p_i$

for each good $i$,

$$\begin{aligned}
C_{sj} &= \int_0^\infty ... \int_0^\infty \psi_j \left[ G\left(a_{s1}p_1, ...a_{sJ}p_J\right)\right] p_1^{-1}...p_{j-1}^{-1}p_{j+1}^{-1}...p_J^{-1}dp_1...dp_J \\
&= \int_0^\infty ... \int_0^\infty \psi \left[ G\left(\phi_1, ...\phi_J\right)\right] \frac{a_{s1}}{\phi_1}...\frac{a_{s,j-1}}{\phi_{j-1}}\frac{a_{s,j+1}}{\phi_{j+1}}...\frac{a_{sJ}}{\phi_J}\frac{d\phi_1}{a_{s1}}...\frac{d\phi_J}{a_{sJ}} \\
&= \int_0^\infty ... \int_0^\infty \psi \left[ G\left(\phi_1, ...\phi_J\right)\right] \frac{1}{\phi_1}...\frac{1}{\phi_{j-1}}\frac{1}{\phi_{j+1}}...\frac{1}{\phi_J}d\phi_1...d\phi_J\frac{1}{a_{sj}} = \frac{c_j}{a_{sj}}
\end{aligned}$$

so $a_{sj}$ is identified for each $s \in \Omega_s$ and $j \in \{1, ..., J\}$ by $a_{sj} = c_j/C_{sj}$.

PROOF of THEOREM 1: This follows immediately from Lemmas 1 and 2, noting that without the normalization of Assumption A2, the coefficients $a_{sj}$ in the proofs of Lemmas 1 and 2 correspond to $a_{sj}/a_{tj}$ for some $t \in \Omega_s$ where the function $G(p)$ in these proofs corresponds to $G\left(a_{t1}p_1, ...a_{tJ}p_J\right)$

PROOF of THEOREM 2: If Assumption B2 holds then without loss of generality let $j = k$. Let $h_k^{k\prime}(p, y) = \partial h_k^k(p, y)/\partial y$. Then

$$\begin{aligned}
M(p, s) &= \lim_{y \to 0} \frac{\partial\left[\eta_s^k(A_sp)h_k^k\left(A_sp, \eta_s^k(A_sp)y\right)\right]/\partial y}{\eta_s^k(A_sp)^2 h_k^k\left(A_sp, \eta_s^k(A_sp)y\right)^2} \\
&= \lim_{y \to 0} \frac{\eta_s^k(A_sp)\partial\left[\eta_s^k(A_sp)h_k^k\left(A_sp, \eta_s^k(A_sp)y\right)\right]/\partial\left[\eta_s^k(A_sp)y\right]}{\eta_s^k(A_sp)^2 h_k^k\left(A_sp, \eta_s^k(A_sp)y\right)^2} \\
&= \lim_{y \to 0} \frac{h_k^{k\prime}\left(A_sp, \eta_s^k(A_sp)y\right)}{h_k^k\left(A_sp, \eta_s^k(A_sp)y\right)^2} \\
&= \frac{h_k^{k\prime}\left(A_sp, 0\right)}{h_k^k\left(A_sp, 0\right)^2} = G\left(A_sp\right)
\end{aligned}$$

where the last equality above defines the function $G$.

Alternatively, If Assumption B3 holds then again without loss of generality let $j = k$ and we have

$$M(p, s) = \int_0^\infty \left[\eta_s^k(A_sp)\right]^c \left[h_k^k\left(A_sp, \eta_s^k(A_sp)y\right)\right]^c y^{c-1}dy$$

Now do the change of variables $\tau = \eta_s^k(A_sp)y$

$$\begin{aligned}
M(p, s) &= \int_0^\infty \left[\eta_s^k(A_sp)\right]^c \left[h_k^k\left(A_sp, \tau\right)\right]^c \left[\frac{\tau}{\eta_s^k(A_sp)}\right]^{c-1} \frac{d\tau}{\eta_s^k(A_sp)} \\
&= \int_0^\infty \left[h_k^k\left(A_sp, \tau\right)\right]^c \tau^c d\tau = G\left(A_sp\right)
\end{aligned}$$

where the last equality above defines the function $G$.

Finally, if Assumption B4 holds then

$$M(p,s) = \int_0^\infty \left( \sum_{k=1}^{K} \eta_s^k(A_s p) h_j^k\left(A_s p, \eta_s^k(A_s p) y\right) \right) dy$$
$$= \sum_{k=1}^{K} \int_0^\infty \eta_s^k(A_s p) h_j^k\left(A_s p, \eta_s^k(A_s p) y\right) dy$$

Now do the change of variables $\tau = \eta_s^k(A_s p) y$ in each of the $K$ integrals above.

$$M(p,s) = \sum_{k=1}^{K} \int_0^\infty \eta_s^k(A_s p) h_j^k(A_s p, \tau) \frac{d\tau}{\eta_s^k(A_s p)}$$
$$= \sum_{k=1}^{K} \int_0^\infty h_j^k(A_s p, \tau)\, d\tau = G(A_s p)$$

where the last equality above defines the function $G$.

PROOF of THEOREM 3:

By Corollary 1, the relative Barten technology parameters $a_{sj}/a_{tj}$ and $a_{rj}/a_{tj}$ are identified for given $r$, $s$, and $t$ elements of $\Omega_s$. Let $A_{st}$ be the diagonal matrix that has elements $a_{sj}/a_{tj}$ on the diagonal. Given Assumption C1, define the identified function $m$ by $\eta_s^k(A_{st} p) h_k^k\left(A_{st} p, \eta_s^k(A_{st} p) y\right)$

$$m(p,s) = \omega_j(s, \phi_{st}(p), 0) = \eta_s^k(A_t p) h_j^k\left(A_t p, \eta_s^k(A_t p) 0\right). \tag{63}$$

It then follows that relative values of resource shares are identified by

$$\frac{m(p,s)}{m(p,r)} = \frac{\eta_s^k(A_t p) h_j^k(A_t p, 0)}{\eta_r^k(A_t p) h_j^k(A_t p, 0)} = \frac{\eta_s^k(A_t p)}{\eta_r^k(A_t p)}.$$

Alternatively, given Assumption C2,

$$m(p,s) = \int_0^\infty \left[\eta_s^k(A_t p)\right]^{c_1} \left[h_j^k\left(A_t p, \eta_s^k(A_t p) y\right)\right]^{c_1} y^{c_2} dy$$

Now do the change of variables $\tau = \eta_s^k(A_t p)y$

$$m(p,s) = \int_0^\infty \left[\eta_s^k(A_t p)\right]^{c_1} \left[h_j^k(A_t p, \tau)\right]^{c_1} \left[\frac{\tau}{\eta_s^k(A_t p)}\right]^{c_2} \frac{d\tau}{\eta_s^k(A_t p)} \tag{64}$$
$$= \left[\eta_s^k(A_t p)\right]^{c_1-c_2-1} \int_0^\infty \left[h_j^k(A_t p, \tau)\right]^{c_1} \tau^{c_2} d\tau$$

and it then follows that relative values of resource shares are identified by

$$\left[\frac{m(p,s)}{m(p,r)}\right]^{1/(c_1-c_2-1)} = \frac{\left[\left[\eta_s^k(A_t p)\right]^{c_1-c_2-1} \int_0^\infty \left[h_j^k(A_t p, \tau)\right]^{c_1} \tau^{c_2} d\tau\right]^{1/(c_1-c_2-1)}}{\left[\left[\eta_r^k(A_t p)\right]^{c_1-c_2-1} \int_0^\infty \left[h_j^k(A_t p, \tau)\right]^{c_1} \tau^{c_2} d\tau\right]^{1/(c_1-c_2-1)}} = \frac{\eta_s^k(A_t p)}{\eta_r^k(A_t p)}.$$

PROOF of THEOREM 4:

Let $k = 1$ be a household member that satisfies Assumption D1, and let the private assignable good for member $k = 1$ be the good $j = 1$. We have that each $a_{sj}/a_{tj}$ and each $\eta_s^k(A_t p)/\eta_r^k(A_t p)$ is identified from Corollary 1 and Theorem 2. Let household type $t \in \Omega_s$ be a household that only contains member $k = 1$. Then for that $t$, $a_{tj} = 1$ for $j = 1, ..., J$ and $A_t$ is the $J$ by $J$, identity matrix. Substituting those values into $a_{sj}/a_{tj}$ and $\eta_s^k(A_t p)/\eta_r^k(A_t p)$ shows that each $a_{sj}$ and each $\eta_s^k(p)/\eta_r^k(p)$ is identified. In addition, If Assumption C1 holds then for each assignable $k$, equation (63) simplifies to $m(p,s) = \eta_s^k(p) h_k^k(p, 0)$, which we can solve for, and thereby identify, $\eta_s^k(p)$. Alternatively, if Assumption C2 holds then equation (64) simplifies to

$$m(p,s) = \left[\eta_s^k(p)\right]^{c_1-c_2-1} \int_0^\infty \left[h_k^k(p, \tau)\right]^{c_1} \tau^{c_2} d\tau$$

which again we can solve for, and thereby identify, $\eta_s^k(p)$. Finally, if we have identified $\eta_s^k(p)$ for $k = 1, ..., K-1$, then we can identify $\eta_s^K(p)$ by $\eta_s^K(p) = 1 - \sum_{k=1}^{K-1} \eta_s^k(p)$.

## 2.8 APPENDIX 2.B: Figures and Tables

## Table 1: Elasticities Estimates of Single Men and Women

**Budget Elasticities**

| | Single women | Single men |
|---|---|---|
| Food | 0.74 | 0.81 |
| Clothing | 1.45 | 1.20 |
| Communication | 0.78 | 0.76 |
| Entertainment | 1.45 | 1.53 |
| Transportation | 1.13 | 1.24 |
| Utility | 0.54 | 0.43 |

**Uncompensated Price Elasticities (single women)**

| | Food | Clothing | Communication | Entertainment | Transportation | Utility |
|---|---|---|---|---|---|---|
| Food | -1.01 | 0.21 | -0.59 | 0.95 | -0.04 | -0.23 |
| Clothing | 0.71 | -1.69 | 0.91 | -6.26 | 4.36 | 0.83 |
| Communication | -2.57 | 0.97 | -0.37 | 1.61 | 0.56 | -1.05 |
| Entertainment | 2.77 | -4.01 | 0.98 | -3.07 | -0.27 | 3.45 |
| Transportation | -0.30 | 5.48 | 0.77 | -0.53 | -5.67 | 4.08 |
| Utility | -1.37 | 1.03 | -0.92 | 4.51 | 2.25 | -5.14 |

**Compensated Price Elasticities/Slutsky Matrix (single women)**

| | Food | Clothing | Communication | Entertainment | Transportation | Utility |
|---|---|---|---|---|---|---|
| Food | -0.72 | 0.29 | -0.51 | 1.08 | 0.03 | -0.13 |
| Clothing | 1.35 | -1.44 | 1.11 | -5.92 | 4.56 | 1.06 |
| Communication | -2.33 | 1.05 | -0.26 | 1.74 | 0.64 | -0.96 |
| Entertainment | 3.50 | -3.78 | 1.21 | -2.69 | -0.06 | 3.72 |
| Transportation | 0.18 | 5.63 | 0.91 | -0.28 | -5.48 | 4.25 |
| Utility | -1.25 | 1.07 | -0.89 | 4.58 | 2.29 | -5.05 |

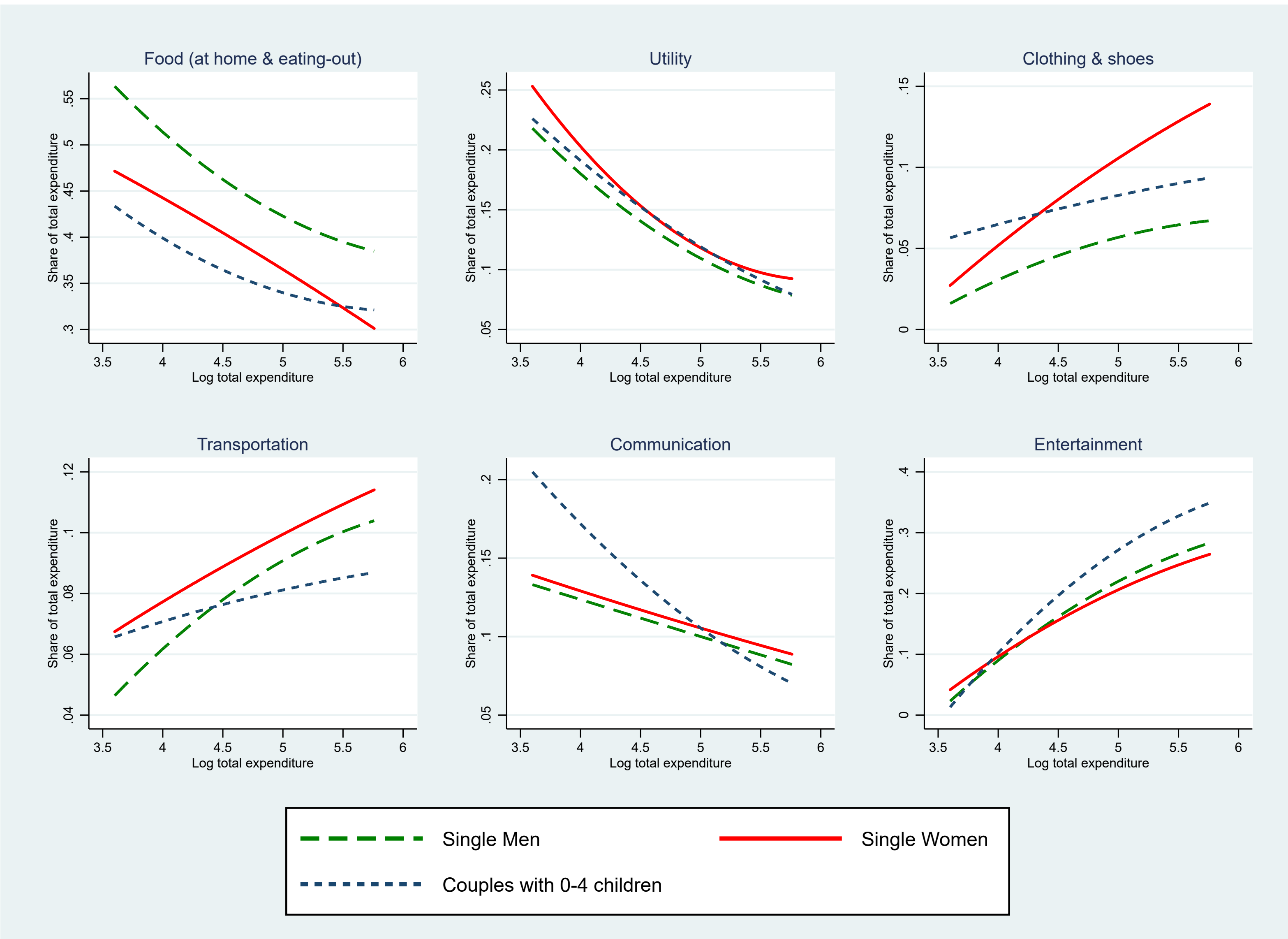
**Uncompensated Price Elasticities (single men)**

| | Food | Clothing | Communication | Entertainment | Transportation | Utility |
|---|---|---|---|---|---|---|
| Food | -1.29 | -0.31 | -0.42 | 1.60 | 0.18 | -0.53 |
| Clothing | -2.44 | -0.42 | -0.10 | 1.21 | -0.21 | 0.13 |
| Communication | -1.85 | -0.25 | -1.67 | 2.89 | -0.02 | 0.46 |
| Entertainment | 3.69 | -1.92 | 1.56 | -4.30 | -0.04 | 1.18 |
| Transportation | 0.99 | 5.38 | -0.05 | -0.21 | -3.82 | -1.27 |
| Utility | -2.11 | 0.60 | 0.16 | -1.27 | 2.67 | -0.45 |

**Compensated Price Elasticities/Slutsky Matrix (single men)**

| | Food | Clothing | Communication | Entertainment | Transportation | Utility |
|---|---|---|---|---|---|---|
| Food | -0.93 | -0.25 | -0.34 | 1.76 | 0.26 | -0.44 |
| Clothing | -1.87 | -0.28 | 0.05 | 1.51 | -0.07 | 0.29 |
| Communication | -1.59 | -0.19 | -1.57 | 3.03 | 0.05 | 0.53 |
| Entertainment | 4.50 | -1.76 | 1.78 | -3.89 | 0.15 | 1.41 |
| Transportation | 1.60 | 5.49 | 0.11 | 0.11 | -3.63 | -1.10 |
| Utility | -2.01 | 0.62 | 0.18 | -1.22 | 2.69 | -0.39 |

**Figure 1: QUAIDS fits for singles and couples with 0-4 children**



# 3 Chapter 3

# Individual Welfare Analysis in Japanese Couples without Children

## 3.1 Introduction

Welfare analysis and poverty evaluation should be conducted ideally at the individual level rather than at the household level. However, measuring welfare through consumption expenditure at the individual level is difficult for a number of reasons. Food is often prepared for the entire household and consumed together, making it difficult to assign the consumption expenditure to each household member. Further, depending on the household, a variety of goods and services—such as utilities, transportation, and even clothes in some cases—are shared among household members. The presence of such "intra-household public goods" makes it a challenge to measure welfare at the individual. As such, expenditure surveys are normally conducted at the household level, which makes it impossible to conduct direct individual-level welfare and poverty calculations from these surveys.

Against this backdrop, economists have started to combine structural model approach with household-level consumption data to uncover the unobserved intra-household resource allocation and savings from joint consumption, building on two seminal papers by Chiappori (1988, 1992) and a series of subsequent works such as Chiappori et al. (2013) (BCL hereafter). In particular, Chiappori et al. (2013) provide the identification of both the resource share and publicness of goods by combining couples' and singles' consumption data. However, since both estimates are unobserved in the data, it is hard to verify how realistic the estimates are. Further, the resource share only captures the share of total expenditures, leaving savings and time use unexplained. It is possible that an individual enjoys a relatively low share of total expenditures but enjoys a lot of leisure time and controls most of the savings. Therefore, even though the resource share is often used as an indirect measure of bargaining power, it is unclear whether the resource share actually reflects the bargaining power of individuals within a household. Hence, it is important to understand the relationships of the resource share with savings and individual time allocation, such as leisure, work (outside home), and housekeeping.

In this paper, we study these relationships by exploiting a unique dataset from Japan, the

Japanese Panel Survey of Consumers (JPSC), which has detailed individual-level expenditure, saving, and time use information. The data is composed of a panel of households, either single women or married women, observed up to 20 years. In each year, the survey asks information on the private consumption expenditures for the wife and husband, the expenditures for everyone in the households, and the savings for the wife and husband. We also have information on the time spent on work, housework, and leisure for both the wife and husband. Individual wages and incomes are also available along with other demographic characteristics.

We first estimate the collective household model developed by Browning et al. (2013, BCL hereafter). A household is composed of the wife and husband, each is endowed with their own preferences and bargaining power. The only assumption in the collective household model is Pareto efficiency of outcomes. Given the assumption, the household consumption decision can be modeled as a two-stage process. In stage one, household resources are divided between the wife and husband according to some sharing rule. The share of each household member is called their respective resource share, which is an indirect measure of bargaining power. It serves as an individual's weight in the household consumption decision process. In stage two, each household member chooses their own consumption by maximizing their individual utility subject to the resources they each gets. Moreover, some goods can be jointly consumed, such as gasoline and heating. A nice feature in Browning et al. (2013) is that they do not assume goods to be purely private or purely public. By adopting the Barten type consumption technology, they are able to identify the Barten scales of goods. To identify both the resource share and Barten scales, we follow Browning et al. (2013) and combine singles' and couples' data. That is, we impose the preference similarity assumption between singles and individuals inside couples in order to uncover the preferences of wives and husbands. A limitation of Browning et al. (2013) is that children's preferences or bargaining power are not identified.[63] Hence we apply the model only to married couples without children. We assume individual preferences to have the Quadratic Almost Ideal Demand system (QUAIDS) developed by Banks et al. (1997). The variation in prices, total expenditures, and demographic variables allow us to disentangle price effects, income effects, and observed heterogeneity in consumption behavior. Prices are taken from the Japanese Consumer Price Index.

[63]The main identification strategy in Browning et al. (2013) is to approximate the preferences of individuals in married couples by that of singles. However, since we do not observe children living alone, we can not identify the preferences or bargaining power of children. Children can be modeled as public goods in multi-person families.

Given the estimates, we next study the correlation between the model-predicted resource share and the observed individual expenditures, savings, and time use. We find that the resource share is positively correlated with individual expenditures. That is, when the resource share for the wife predicted from the model is low, she tends to be disadvantaged against her husband in the allocation of the expenditure on pure private goods. This provides strong evidence in support of the predictive power of the resource share as an indirect measure of bargaining power. On the other hand, the correlation, even though positive, is small in magnitude. One plausible reason is that resource share identified from the collective approach not only reports the sharing of purely private expenditures but also joint consumption. It also takes into account of intra-household preference heterogeneity and bargaining power. The low correlation instead highlights the potential importance of using the collective household model to comprehensively reveal intra-household inequality in both the resource allocation and the bargaining. In terms of the savings and time use, we find that the correlation between the estimated resource shares and these two variables to be closed to zero. We do not argue that the estimated resource shares can be good predictors for intra-household resource allocation in savings and time use.

We perform a series of robustness checks to validate our empirical application. Since JPSC data only include single women and married couples, but not single men, we also use Japan Household Panel Survey (JHPS/KHPS)[64] in order to estimate the preferences of single men. Both JPSC and JHPS/KHPS have similar sampling and survey designs. In particular, they ask almost the same set of questions about total household expenditures,[65] and the definition of goods are also comparable between these surveys. The distribution of demographic characteristics of women and couples between the two surveys are also very similar. Moreover, the expenditure pattern/budget share allocations are also similar between the two surveys for a given type of households. In term of estimating BCL, we tried three alternative methods: 1) single and couples are all taken from the JHPS/KHPS, 2) single females and males and taken from JHPS/KHPS, while couples are taken from JPSC. The specifications give similar results in terms of the mean resoure share and Barten scales.

Given the external validation of our estimates on resource share, we further conduct an indi-

[64] JHPS/KHPS refers to the former Japan Household Panel Survey and former Keio Household Panel Survey, which have very similar designs and are now simply called the Japan Household Panel Survey. See https://www.pdrc.keio.ac.jp/en/paneldata/datasets/jhpskhps/ for details.

[65] Both surveys ask expenditures on food, clothing, communication, transportation, utility, healthcare, education, entertainment, rent, and furniture.

vidual welfare analysis for men and women in Japanese couples without children. In particular, we construct the indifference scale, that is, the fraction of household total expenditures that a married individual needs to live materially as well as living alone, for both men and women. This measure implies the economic gains from marriage, which results from both the sharing of total resources and savings through joint consumption. On average, married men extracts more gains from marriage then married women. The mean IS for men is 0.70 while that for women is 0.58. It means that wives on average need 58 percent of the household total expenditures to live alone while attaining all the private good equivalents in marriage. The number is 70 percent for men. The overall scale economy is 0.28. It suggests that it would cost the couple 28 more percent to buy the (private equivalent) goods they consumed if there had been no shared or joint consumption (in other words, if they live separately). The findings are different from other studies in developed countries. They normally find the wife to enjoy a higher resource share and extract more gains from marriage. This highlights the difference in social norms between Asian and western developed countries, where the former is more conservative in terms of the gender norms (See Bertrand et al. (2016) for a discussion of gender norms differences across OECD countries).

This paper is the first to apply the collective household model of consumption to a developed country in Asia, which has very different social norms compared to western countries. This is also among the first few external validations of the collective household model. The only other paper that we know is Bargain et al. (2018), who applied Dunbar et al. (2013), a simplified version of Browning et al. (2013), to Bangladesh data with individual private expenditures. Different from their study, the resource share found in this paper captures the sharing of both private and public goods. It provides an external validation of resource share in terms of not only household expenditures, but also individual savings. Moreover, we explore the relationship between intra-household sharing and time use. The results in this paper provide a more comprehensive picture in terms of intra-household allocation, savings decisions, and time allocation.

## 3.2 Related Literature

This paper is related to previous work on intra-household resource allocation, bargaining power, and consumption economies of scale.

Early literature on household consumption behavior often models a household as a single utility-maximizing and decision-making agent. This so-called "unitary approach" ignores household members having different preferences or bargaining. The implications from the unitary model include income pooling and symmetry of Slutsky matrix, both of which have been frequently rejected empirically. Building on two seminal papers by Becker (1965, 1981) and Chiappori (1988, 1992), a number of papers adopt the collective approach, which models a household as composed of several members, each of whom having different preferences and among whom a bargaining procedure takes place. The only assumption in this type of model is Pareto efficiency of outcomes. Applying the decentralization results from Pareto efficienty, the latter papers show that the household optimization problem is equivalent to a two stage process. In stage one, household resources are allocated across household members. In stage two, each household member maximizes their own utility function given the shadow income and shadow price that reflect the household chosen allocation of resources and sharing of goods.

Of particular interest in collective household models are resource shares. They measure the fraction of resources controlled by each household member. Early literature only identifies the change in resource shares with respect to the change in distribution factors (factors that affect bargaining power only, but not preferences or budget constraints). They include Chiappori (1992), Browning, et al. (1994), Browning and Chiappori (1998), Chiappori, et al. (2002), and 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).[66] A number of papers apply these models to developing countries and find substantial inequality in resource allocation within households (Calvi 2019, Tommasi 2019, and Penglase 2019).

One caveat of the above literature is that they all assume goods to be either purely private or purely public. However, households of different size and compositions can certainly have different sharing technologies that give rise to different consumption economies of scale. To address this issue, Browning et al. (2013) point-identifies both resoure shares and the sharing of goods by assuming that singles and married individuals have similar preferences. They model the consumption economies of scale of each good in the fashion of Barten type (Barten 1964, Gorman

[66] Another strand of literature applies revealed preference theory and identifies resource shares by bound (Cherchye et al. 2012 and Cherchye et al. 2017).

1976, and Lewbel 1985). The main motivation and implication of their paper is to compare individual welfare under different economic environments (defined by size and composition) that lead to different sharing of income and goods within households. For example, Cherchye et al. (2012) apply BCL to Dutch data and study the individual welfare of elderly widows and widowers. Solvejg (2018) applies BCL to Panel Study of Income Dynamics (PSID) and studies the heterogeneity in gains from marriage in U.S. married couples. Lin (2019) applies BCL to the Nielsen Homescan data to evaluate the impact of Supplemental Nutrition Assistance Program on food consumption among older households. She finds that household total food demand and the implied responses to a cash transfer would be underestimated if we ignore the difference in preferences and control between husbands and wives.

## 3.3 A Structural Analysis of Household Demand

In this section, we first summarize a structural model of household demand. In particular, it follows the spirit of Browning et al. (2013) to allow for household members having different preferences, asymmetric bargaining, and shared or joint consumption of goods. We then discuss the identification and estimation of the model.

### 3.3.1 The Collective Household Model

We consider a couple, which is a household composed of wife $f$ and a husband $m$.[67] There are $j = 1, ..., J$ consumption goods in the model. Let $z$ denote the $J$-vector of purchased bundle of goods.

Each individual has a monotonically increasing, continuously twice differentiable, and strictly quasi-concave utility function $U^i(x)$ over a bundle of $J$ private equivalent consumption of goods $x^i = (x^i_1, ..., x^i_J)', i = f, m$. The couple facing the market price vector $p$ and the total expenditure $y$ solves the following program:

$$\max_{x^f, x^m} \mu(p/y)U^f(x^f) + U^m(x^m) \quad \text{subject to the following constraints:} \tag{65}$$

$$x = x^f + x^m \tag{66}$$

[67] Children may be present but they are modeled as public goods.

$$z = F(x) = Ax \tag{67}$$

$$p'z = y \tag{68}$$

Equation (65) is the overall household utility, which is equal to a weighted average of the husband's and wife's utility. $\mu$ represents the relative Pareto weight of the wife to the husband. It measures the bargaining power of the wife in terms of consumption decision-making. A higher value of $\mu$ implies that the household's consumption is more represented by the wife's preferences. Equation (66) says that the household private consumption is equal to the sum of the wife's private consumption and the husband's private consumption. Equation (67) describes the household consumption technology. The different between $z$ and $x$ summarizes the sharing or joint consumption of goods. The square matrix $A$ is a Barten-type technology matrix and summarizes how much goods are shared or jointly consumed. The diagonal element of $A$ summarizes how much each good can be shared by itself. For example, suppose a couple shared 1/3 of their total travelling distance by riding together. 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 $z_1 = (2/3)(g_1^1 + g_1^2)$. Here, the upper left corner element of matrix $A$ would be 2/3, which summarizes how much gasoline is shared, and the remaining elements of the first row and first column of $A$ would be zero. We assume the off-diagonal elements of $A$ to be zero. That is, a good can only be shared or jointly consumed by itself. For purely private goods (like food), their Barten scale would be one, while for purely public goods (like heating), their Barten scale would be one half. Equation (68) is the household's budget constraint.

The main assumption in the collective household literature is Pareto efficiency. Given this and according to the second welfare theorem, the household program is equivalent to a two-stage process. In stage one, the household divides resources according the sharing rule such that the wife gets $\eta$ fraction of the total expenditures and the husband gets $1 - \eta$ fraction of the total expenditures. In stage two, each household member maximizes their own utility subject to the shadow prices of goods and their respective shadow income (resource shares multiplied by the total expenditure). The shadow prices are the market prices discounted by the Barten scales. To summarize, under Pareto efficiency, there exists a shadow price $\pi$ and a sharing rule $\eta$, with

$0 \leq \eta \leq 1$, such that

$$\pi(p/y) = \frac{A'p}{y} \tag{69}$$

$$z = h(p/y) = Ah^f\left(\frac{A'p}{y}\frac{1}{\eta(p/y)}\right) + Ah^m\left(\frac{A'p}{y}\frac{1}{1-\eta(p/y)}\right) \tag{70}$$

Equation (69) represents the shadow prices of goods. Equation (70) is the main identifying equation. It says that the couple's Marshallian demand $z$ is a weighted average of the wife's Marshallian demand $h^f$ and husband's Marshallian demand $h^m$, where the weight is given by their resource share respectively.

### 3.3.2 Identification

Given the model above, the goal here is to identify equation (70) such that we get estimates of the preferences of wives and husbands $h^f$ and $h^m$, the Barten scales $A$, and resource shares $\eta$. The challenge in identifying (70) is that we do not observe wives' or husbands' demand but only the couples' demand in the data. To overcome that challenge, we follow the identification assumption in BCL and assume that wives have similar preferences to single females, and that husbands have similar preferences to single males. We also implicitly assume that singles do not change preferences upon marriage.

### 3.3.3 Estimators of Budget Shares for Individuals

We specify individual preferences using the QUAIDS demand system of Banks et al. (1997). Let $p$ denote the $J$-vector of price indices of aggregate consumption of goods. We have $J = 6$ in total. Let $h$ index a household and $i$ index a household member. The household member types here are $i = f$ for wives and $i = m$ for husbands. For member $i$ in household $h$, let $\omega^{hi}$ denote the $J$-vector of budget shares $\omega_j^{hi}$ for $j = 1, ..., J$. Notice that we only observe budget shares $\omega^{hi}$ for households of only one member, that is, single females and males in this paper (this is because for single households, there is no sharing or joint consumption and the household budget shares are the budget shares by themselves).

The QUAIDS demand system for an individual $i$ in a household $h$ takes the following $J$-vector form

$$\omega^{hi}(\frac{p}{y}) = \alpha^{hi} + \Gamma^i \ln(p) + \beta^{hi}[\ln(y) - c^{hi}(p)] + \frac{\lambda^i}{b^{hi}(p)}[\ln(y) - c^{hi}(p)]^2 \tag{71}$$

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

$$\ln[b^{hi}(p)] = (\ln p)' \beta^{hi} \tag{72}$$

$$c^{hi}(p) = \delta_0^{hi} + (\ln p)' \alpha^{hi} + \frac{1}{2}(\ln p)' \Gamma^i \ln p \tag{73}$$

Here $\alpha^{hi}$, $\beta^{hi}$, and $\lambda^{hi}$ are $J$-vector of preference parameters. $\Gamma$ is an $J \times J$ matrix of preference parameters. $\delta_0^{hi}$ is a scalar parameter which we set to equal to zero based on the insensitivity reported in Banks et al. (1997). By definition, budget shares must add up to one, i.e., $\mathbf{1}_J' \omega = 1$ 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 $\Gamma^i$

be a symmetric matrix.

We allow all the QUAIDS preference parameters of $\alpha^{hi}$, $\beta^{hi}$, $\lambda^{hi}$, and $\Gamma^{hi}$ to be heterogeneous across individuals by allowing them to depend on observable demographic characteristics. Specifically, we allow $\alpha^{hi}$ and $\beta^{hi}$ to vary between $f$ and $m$ as well as some other observable variables in the the following manner:

$$\alpha^{hi} = \alpha_0^i + \sum_{m=1}^{M_\alpha} \alpha_m^i d_{m,\alpha}^{hi} \tag{74}$$

$$\beta^{hi} = \beta_0^i + \sum_{m=1}^{M_\beta} \beta_m^i d_{m,\beta}^{hi} \tag{75}$$

where $d_{m,\alpha}^{hi}$ and $d_{m,\beta}^{hi}$ are observed demographic characteristics, and $M_\alpha$ and $M_\beta$ are the total number of such covariates I observe. Each $\alpha^{hi}$ and $\alpha^{hi}$ 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, the covariates $d_{m,\alpha}^{hi}$ for $\alpha$ include 7 region dummies and age, making $M_\alpha = 8$, and $d_{m,\beta}^{hi}$ includes an indicator for home owners, so $M_\beta = 1$. Taken together, we have 16 preference parameters for each of $J - 1 = 5$ distinct equations, yielding a total of 80 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.

### 3.3.4 Estimators for Singles

The demand functions for households consisting of only one member are given by equation (71). Such households are either single females or single males. In this subsection, we describe how the demand functions of singles are estimated. The demand functions and associated estimators for couples are given in the next subsection.

For households consisting of only one member, we add an $J$-vector valued error term $U^{hi}$ to equation (71). This introduces unobserved preference heterogeneity in the demand function of singles. We assume that the error terms 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, errors are correlated across goods within households. We estimate the demand functions of singles using GMM, allowing for arbitrary correlation across goods.

Let $u_j^{hi}(\theta^i)$ denote $\omega_j^{hi}$ minus the right hand side of equation (71), where $\theta^i$ is the vector of all the parameters in that equation. The moment condition for GMM estimation is $E(u_j^{hi}(\theta^i)\tau^{hi}) = 0$, where $\tau^{hi}$ is vector of all the covariates defined below. Following the common practice in demand estimation, we drop one equation or good in the estimation. We then recover the parameters for that good or equation using the adding up condition. The choice of good to be dropped is irrelevant because the adding up condition implies that the determinants of the preference parameters of the dropped good is a deterministic function of the parameters of the remaining goods. The full set of moments used in the 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 $\tau^{hi}$ for singles includes 7 region dummies, age, an indicator for home owners, 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 nondurable goods), its square, and its interaction with the home ownership dummy. The number of moments therefore consist of $J - 1 = 5$ distinct demand equations times the number of elements in $\tau^{hi}$, which is 17, for a total of 85 moments for $i = f$ and for $i = m$.

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

$$v^i(\theta^i) = \frac{1}{n^i}\sum_{h\in H^i}(I_{J-1}\tau^{hi}) \otimes U^{hi}(\theta^i) \tag{76}$$

The GMM criterion is then

$$\min_{\theta_i}(v^i(\theta^i)'W^i v^i(\theta^i)) \tag{77}$$

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

$$W^i = (\sum_{h\in H^i}(I_{J-1} \otimes \tau^{hi})u^{hi}(\widetilde{\theta^i})u^{hi}(\widetilde{\theta^i})'(I_{J-1} \otimes \tau^{hi}))^{-1} \tag{78}$$

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

#### 3.3.5 The Joint Model

For the empirical application of the joint model, we assume singles have preferences given by equation (71). For couples, we assume a Barten-type technology function such that the shadow prices are given by equation 69.

Browning et al. (2013) proves the generic identification of Barten scales and resource shares. In the empirical application here, the wife's resource share is parametrically estimated with the functional form

$$\eta^f = \frac{\exp(\delta' s^h)}{1 + \exp(\delta' s^h)}, \tag{79}$$

and the husband's resource share is simply $1 - \eta^f$.

$s^h$ denotes distribution factors for household $h$, and $\delta$ represents parameters. The logistic form bounds the resource share to be between 0 and 1. If none of the distribution factors are significant, then the resource share of the wife will be 0.5. The distribution factors are chosen such that they affect bargaining power but not the preferences or budget constraint. The candidates for distribution factors include difference in age between the wife and husband, difference in log income between the wife and husband, a dummy indicator of the wife not working, a dummy indicator of the husband not working, log real household total income, and log real total expenditures. These variables are commonly used as distribution factors by previous literature (e.g., Browning et al. (1994)).

With the shadow prices defined by equation (69) and the resource shares given by equation 79, we end up with the simple expression for the couples' budget share equations:

$$\omega^c\left(\frac{p^h}{y^h}\right) = \eta^h\omega^f\left(\frac{\pi^h}{\eta^h}\right) + (1-\eta^h)\omega^m\left(\frac{\pi^h}{1-\eta^h}\right), \tag{80}$$

where $\omega^f$ and $\omega^m$ are the demand functions for females and males expressed in budget shares estimated with equations (71)-( ). $\omega^c$ denotes the $J$-vector budget shares of couples.

The above equation says that the couple' budget share function is a weighted average of the wife's and husband's budget share functions, if each is faced with the shadow prices and their shadow income.

The baseline parameters of the joint model consist of the $QUAIDS$ parameters for singles' budget shares, $\omega_j^f$ and $\omega_j^m$; distribution factors and preference factors of the sharing rule, and 6 parameters of the Barten scales. We follow the suggestion in Browning et al. (2013) and use a one-step estimator. That is, we estimate the preference parameters jointly with the consumption technology and sharing parameters.[68] We have 150 preference parameters ($17 \times 5 - 10 = 75$ symmetry constrained $QUAIDS$ parameters for each of single females and males), 6 Barten scales parameters, and 6 sharing rule parameters, giving a total of 86 parameters to estimate. We have 250 instruments (for each of the five goods there are 17 instruments for each of single females and males and 18 instruments for couples), giving a maximum degrees of freedom of 88 of the most general model.

The joint model is estimated by GMM using the following criterion

$$\min_{\theta}(v^c(\theta)'W^c v^c(\theta) + v^f(\theta)'W^f v^f(\theta) + v^m(\theta)'W^m v^m(\theta)) \tag{81}$$

where $c$ denotes households of couples, $\theta$ denote the full set of parameter values, and $W^m$ and $W^f$ are taken from $QUAIDS$ 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.

[68]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. Hence, we focus on the one-step estimator.

## 3.4 Data

To estimate BCL, we need information on expenditures for both singles and married couples. To validate the estimates on sharing rule and Barten scales, we need information on individual expenditures, savings, and time use. A unique dataset that satisfies these requirements is the Japanese Panel Survey of Consumers (JPSC). However, since JPSC only contains information of single and couples, we also refer to the Japan Household Panel Survey(JHPS/KHPS) in order to estimate single males' preferences. We also utilize JHPS/KHPS single women and couples to estimate BCL as another robustness check.

### 3.4.1 Description of JPSC Data

We use the JPSC data covering years 1993 - 2015. It is designed to examine the lifestyles of young women by looking at a wide spectrum of factors including income, expenditures, savings, work patterns, and family relationships. The women in the sample may experience significant changes in their family life as they go from graduating school to getting a job, getting married and having children, while others may remain single. The data comprises five cohorts: Cohort A consisting of a group of young women aged between 24 and 34 who were selected from across Japan in 1993 for an in-home questionnaire survey, Cohort B, consisting of women aged between 24 and 27, cohort C, consisting of women aged between 24 and 29, cohort D, consisting of women aged between 24 and 28, and cohort E, consisting of women aged between 24 and 28, were added respectively in 1997, 2003, 2008 and 2013. The location of residence of each household is available at the level of the prefectures.[69]

We observe the following information for single women and both spouses in married couples: i) their demographic characteristics, such as household composition and size, age, and education; ii) the household overall expenditures and savings and the individual expenditures and savings; iii) individual time allocation across leisure, market work, and housework; iv) their wages, individual income, and household total income.

The JPSC asks the following questions regarding household expenditures: Please write down your household expenditure in September this year. (Including not only cash purchases, but also purchases with the credit loan(s), or those charged to your bank/post office account.)

[69]There are 47 prefectures in Japan and prefectures are the largest administrative unit in Japan. While prefectures are often grouped into regions, there is no uniform definition of regions even within the government.

The expenditure categories include foods (at-home or eating-out), utilities, clothing and shoes, transportation, communication, culture and entertainment, house rent, land rent and home repairs, furniture and housekeeping equipments, healthcare, education, social expenses, allowance or pocket money for your and your husband's parent(s), and other expenses. To avoid modeling the demand of durable goods, we only keep expenditures on the first six categories.

Regarding household finance, JPSC asks the following question (answered for both the wife and husband): How much expenditure, savings (including life insurance premiums etc.), and loan repayments did you pay this September?

The answers are break-downed to : i) expenses/savings for all of my family ii) expenses/savings for me iii) expenses/savings for my husband iv) expenses/savings for my children v) expenses/savings for the others.

Regarding individual income, JPSC asks: How much were the annual incomes that you (wife), your husband, and your household member(s) other than you, your husband and child(ren) obtained in the past year (January 2007 - December 2007), including revenues from assets, social insurance benefits, and remittances from your and your husband's parents (answered for both the wife and husband)?

Regarding time use, JPSC provides relatively detailed information by asking the following question (answered for both the wife and husband): How many hours do you or does your husband spend in total per workday and day off for each of 6 activities listed below (answered for both the wife and husband)? If you or your husband has two or more activities in the same period of time, choose the most important of the two. 1) For commuting 2) For work 3) For schoolwork (studies) 4) For housekeeping and child care 5) For hobby, leisure, social interaction, etc 6) For other activities such as sleeping, meals, taking a bath, etc.

### 3.4.2 Description of JHPS/KHPS Data

Since JPSC data only comprises women and married couples, we refer to JHPS/KHPS Data in order to estimate single males' preferences. We use JHPS/KHPS covering years 2004 to 2016. The Keio Household Panel Survey (KHPS) has been implemented continuously since 2004 on 4,000 households and 7,000 individuals nationwide. An additional survey on a cohort of about 1,400 households and 2,500 individuals was initiated from 2007. The Japan Household Panel Survey (JHPS) is a new survey targeting 4,000 male and female subjects nationwide in parallel with the KHPS. In addition to economic status and employment status, the JHPS collects data focused on education and health/ healthcare. JHPS/KHPS data provide the location of residence by the combination of eight regions of Japan and city size.

The sampling method and survey questions are very similar between JPSC and JHPS/KHPS. In particular, they ask information of expenditures on the same categories. I restrict the age range of males and females in JHPS/KHPS in order to match between JPSC. We construct single females/males by selecting the households whose marital status is single and who lives alone. The married couples are those whose marital status is married and the household size is two. We further trim the three samples with respect to key variables (yearly budget share of each aggregate good and log yearly total expenditure) by dropping observations in the lower and upper 1 or 5 percentiles. Table 2 compares the summary statistics between JPSC and JHPS/KHPS. Households in JPSC and JHPS/KHPS are similar in terms of spending and demographic characteristics. The only difference is that households in JHPS/KHPS are relatively younger than those in JPSC. That is why households in JPSC have relatively lower budget share in food and rent compared to those in JHPS/KHPS. We do control for age in the QUAIDS estimation.

#### 3.4.3 Price Data

In addition to the JPSC and JHPS/KHPS datasets, we also use the 2015-Base Consumer Price Index (CPI) available from e-Stat, the Portal Site of Official Statistics of Japan.[70] The CPI data are available for each month and at various geographic levels, but geographic areas used in the CPI data are different from those JPSC data or JHPS/KHPS data. Therefore, it is necessary to make some assumptions or adjustments to merge the CPI data into JPSC and JHPS/KHPS datasets.

To merge CPI into JPSC data, we assume that the prices that each household faces can be represented by the CPI in the capital of the prefecture of residence. This is the best approximation we can get, because the CPI dataset neither provide spatially disaggregated prices within each prefecture nor contain the prices representative of the whole prefecture. While the price gap between urban and rural areas may be a concern, the prices in the capital of the prefecture would be still reasonable because Japan is a highly urbanized country.

Merging CPI into JHPS/KHPS data is more challenging, because JHPS/KHPS provides only

[70] http://www.e-stat.go.jp

**Table 2: Summary Statistics, JPSC (Year 1993 - 2015) and JHPS/KHPS (Year 2004 - 2016)**

| | JHPS/KHPS | | | JPSC | |
|---|---|---|---|---|---|
| | Single Men | Single Women | Couples | Single Women | Couples |
| Obs | 1,087 | 512 | 2,399 | 2,102 | 2731 |
| Number of unique households | 382 | 192 | 858 | 573 | 853 |
| Household income | 372.7 | . | | 323.7 | 716.8 |
| Wife employment income | - | - | 193.3 | - | 192.3 |
| Wife total income | - | - | 211.7 | - | 208.4 |
| Husband employment income | - | - | 517.1 | - | 523.8 |
| Husband total income | - | - | 532.9 | - | 544.0 |
| Total expenditures (month) | 192.2 | 190.1 | 281.8 | 162.2 | 258.4 |
| Budget share (food) | 0.29 | 0.24 | 0.24 | 0.20 | 0.21 |
| Budget share (utility) | 0.08 | 0.09 | 0.09 | 0.07 | 0.07 |
| Budget share (rent & home repairs) | 0.20 | 0.22 | 0.13 | 0.29 | 0.18 |
| Budget share (clothing) | 0.03 | 0.06 | 0.05 | 0.07 | 0.04 |
| Budget share (transportation) | 0.06 | 0.06 | 0.06 | 0.06 | 0.07 |
| Budget share (communication) | 0.07 | 0.07 | 0.08 | 0.07 | 0.07 |
| Budget share (culture & amusement JHPS) | 0.04 | 0.04 | 0.04 | 0.04 | 0.03 |
| Budget share (entertaining ) | 0.09 | 0.08 | 0.13 | 0.09 | 0.05 |
| Budget share (allowances for parents) | - | - | - | - | 0.13 |
| Budget share (pocket money for you/husband) | - | - | - | - | 0.00 |
| Budget share (remittance and gifts) | 0.02 | 0.02 | 0.03 | - | - |
| Budget share (furniture) | 0.02 | 0.02 | 0.03 | 0.02 | 0.02 |
| Budget share (education) | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| Budget share (medical) | 0.03 | 0.03 | 0.04 | 0.03 | 0.03 |
| Budget share (other) | 0.06 | 0.07 | 0.07 | 0.07 | 0.08 |
| Female age | - | 39.49 | 42.21 | 33.22 | 35.78 |
| Female unemployed | - | 0.05 | 0.12 | 0.06 | 0.21 |
| Female college graduate or above | - | 0.31 | 0.19 | 0.58 | 0.55 |
| Female some college | - | 0.48 | 0.29 | - | - |
| Male age | 40.65 | - | 43.52 | - | 38.01 |
| Male unemployed | 0.06 | - | 0.01 | - | 0.02 |
| Male college graduate or above | 0.27 | - | 0.21 | - | 0.53 |
| Male some college | 0.51 | - | 0.36 | - | - |
| Home ownership | 0.32 | 0.25 | 0.56 | 0.11 | 0.39 |
| Car ownership | 0.56 | 0.59 | 0.84 | 0.42 | 0.85 |

*Notes:* Income and expenditures are in thousand yen. JHPS/KHPS covers years 2004 - 2016. JPSC covers years 1993 - 2015. The expenditure data in JHPS is for January. The expenditure data in JPSC is for September. Definition of aggregate goods in JHPS/KHPS: food expenditure includes eating out. Transportation includes automobile expenses, fares, commuting passes, taxes, and tolls. Communications includes postage, fixed-line, and mobile phone charges. Culture amusement includes stationery, sporting goods, travel, hobbies. Utility includes electricity, gas, water (supply sewage). Clothing includes both clothese and shoes. Definition of aggregate goods in JPSC: foods includes eating-out/food-dispensing. Utilities includes light, fuel, water and sewerage. Clothing and shoes Transportation includes the purchase of an automobile, fuel, or commuter pass. Communication includes postal fees, telephone, the Internet, etc. Culture and entertainment includes lessons except for those for entrance exams or supplementary tutoring, or durable goods for culture and entertainment. Clothing includes both clothese and shoes. Household income in JPSC is calculated as the sum of wife's and husband's annual total income. The income includes earnings from employment, revenue from assets, social security benefits, and other income (remittances or pin money from parents). All sources of income are before tax in the past year. "." means observations are all missing for this variable. For education variable, college graduate or above in JHPS/KHPS includes junior college or technical college, univeristy, or graduate school. In JPSC, it includes junior college, specialized school, four-year college, or graduate school. In JPSC, it includes junior college, specialized school, four-year college, or graduate school. Husband/Wife's total income includes employment income and other income such as rent, interest, remittances, public pension, unemployment benefits, welfare benefits etc. For car ownership of JHPS/KHPS female sample, only 32 out of 512 observations have non-missing values.

the region and city size of the residence. Further, the CPI data divides Japan into 10 regions, whereas the JHPS/KHPS data divide it into 8 regions. Therefore, we first reduce the number of regions in CPI data by merging some CPI regions to match the definition of regions in the JHPS/KHPS data. While most prefectures belong to the same region between the CPI and JHPS/KHPS data after merging, the three prefectures of Yamanashi, Nagano, and Mie are classified to different regions between the CPI and JHPS/KHPS data.[71]

In the food category, the CPI dataset has separate price indices for food-at-home and eating-out. While JPSC only has household total food expenditure, JHPS/KHPS does have expenditure information for these two categories. We therefore construct household-level price indices for food using a Stone price index, by taking a weighted average of the log of the price of eating-out and the log price of food-at-home, where the weights are the household's food budget shares of eating-out and of food-at-home. By employing each household's own within food relative consumption weights, this construction more accurately reflects the price for food faced by individual households than the total food index provided by the CPI.

The CPI dataset also provide the price data for each "designated city" or a major city with a population of more than half million and designated as such by order of the Cabinet of Japan.[72] Therefore, by combining with the CPI weights, we can construct the price index for desginated cities within each of the eight regions, except for the Shikoku region where there is no designated city. Further, it is also possible to back out the price index for areas outside the designated city in each region from the regional price index and price index for the designated city in that region. Thus, we have price data for $15(=8(\textit{regions}) \times 2(\textit{designated city or not}) - 1(\textit{no designated city in Shikoku region}))$ combinations of regions and city sizes, which is merged into the JHPS/KHPS dataset.

[71] To match the JHPS/KHPS definition of Kyushu region (Fukuoka, Saga, Negasaki, Miyazaki, Kagoshima, Kumamoto, Oita, and Okinawa prefectures), we merged Kyushu and Okinawa regions in CPI. To match the JHPS/KHPS definition of Chubu region (Yamanashi, Nagano, Niigata, Fukui, Toyama, Ishikawa, Shizuoka, Gifu, and Aichi prefectures), we also merge Hokuriku and Tokai prefectures. With these merging, most prefectures belong to the same region between the JHPS/KHPS and CPI datasets with the following exceptions: Yamanashi and Nagano prefectures belong to Kanto [Chubu] region in CPI [JHPS/KHPS] dataset, and Mie prefecture belongs to Chubu [Kinki] region in CPI [JHPS/KHPS] dataset. About 3.7 percent of the Japanese population live in these three prefectures, according to the 2015 population census. See also, http://www.stat.go.jp/english/data/kokusei/2015/final_en/final_en.html

[72] There are 20 designated cities in Japan as of January 1, 2019.

## 3.5 Empirical Results

In this section, we first present the estimation results of BCL. The parameters of interest are the resource share and Barten scales. We then present the implications from the model, that is, we drive the individual welfare of the wife and husband by constructing their respective indifference scales and the household overall scale economy. Lastly, we utilize the information on individual expenditures, savings, and time use to validate the results of the model.

### 3.5.1 Sharing Rule and Barten Scales

Because JPSC dataset only contains couples and single women, we have to refer to JHPS/KHPS dataset to utilize its single male sample. As a robustness check, we try three different models with different samples of singles and couples to test the sensitivity of the estimated resource shares to sample selection. The corresponding QUAIDS elasticities for each model are reported in table **??** in the appendix.

We include one distribution factor, that is, the difference in age between the female and male head in the sharing rule. Estimation results are reported in Table 3. The sharp difference occurs between model (1) versus (2) or (3). In model (1), wives on average have higher resource shares than husbands. However, we should be careful in interpreting this result because in this model, both couples and women sample are from the JPSC dataset. The higher resource share of women might simply reflect that the underlying sample or consumption patterns between couples and women are similar because they come from the same survey/dataset.

In model (2) and (3), where both single men and women are from the same dataset, we find that wives on average have lower resource share than husbands. We are more confident that model (2) and (3) reflect the true underlying resource allocation within Japanese couples. In both models, the covariate "difference in age between the female and male head" has a negative sign, implying that wives in families where they are older than their husbands tend to have lower resource shares. Estimated Barten scales in model (2) and (3) are similar except for Clothing. It is 0.542, which is closed to public goods in model (2), versus 0.948, which implies a purely private good in model (3). According to previous literature, clothing is normally assumed to be a purely private good. Estimates from the collective household literature also imply that it can not be jointly consumed (Cherchye et al. 2012, Browning et al. 2013, and Lewbel and Lin 2019).

Table 3: Estimation Results: Sharing Rule and Barten Scales

| | Model (1) | | Model (2) | | Model (3) | |
|---|---|---|---|---|---|---|
| | **JHPS men JPSC couples and single women** | | **JPSC couples JHPS single women and men** | | **JHPS couples and singles** | |
| **Mean wife's share** | 0.6356 | | 0.324 | | 0.334 | |
| ***Panel A: the Sharing Rule*** | Coef | Std error | Coef | Std error | Coef | Std error |
| Constant | 0.557 | 0.117 | -0.747 | 0.061 | -0.713 | 0.148 |
| Difference in age (female - male) | 0.000 | 0.005 | -0.004 | 0.002 | -0.016 | 0.008 |
| ***Panel B: Estimates of Barten Scales*** | Barten scale | Std error | Barten scale | Std error | Barten scale | Std error |
| Food (at home and eating out) | 0.987 | 0.079 | 0.946 | 0.403 | 0.862 | 0.081 |
| Clothing | 0.868 | 0.075 | 0.542 | 0.205 | 0.948 | 0.074 |
| Communication | 0.904 | 0.068 | 0.739 | 0.341 | 0.638 | 0.028 |
| Entertainment | 0.521 | 0.051 | 0.551 | 0.256 | 0.650 | 0.030 |
| Transportation | 0.640 | 0.038 | 0.557 | 0.243 | 0.818 | 0.046 |
| Utility | 0.966 | 0.084 | 0.931 | 0.426 | 0.718 | 0.073 |

*Notes:* Model (1) uses JHPS/KHPS men and JPSC couples and single women. Model (2) uses JPSC couples and JHPS/KHPS single women and men. Model (3) uses JHPS/KHPS couples and singles.

Estimates from model (2) are more trustful than that from model (3). However, because model (3) only uses JHPS/KHPS dataset, which does not has information on private expenditures, savings, or time use for men and women, we can not do the validity check between out model estimates on the sharing rule and the private expenditures and savings patterns from the JPSC dataset, we later refer to model (2) to do the validity check.

### 3.5.2 Indifference Scales (IS) and the Scale Economy

Given the estimates on the sharing rule and Barten scales, we then study the individual welfare of married couples by constructing the respective indifference scales of the wife and husband. Indifference scale answers the question that how much income would an individual living alone need to attain the same indifference curve that the individual attains as a member of the household. A higher indifference scale implies that the individual extracts more gains from marriage. The scale economy measures how much more, as a fraction of the total expenditures, the couple need to buy the (private equivalent) goods they consumed if there had been no shared or joint consumption. The equations for calculating indifference scales and the scale economy are in the appendix.

Table 4 presents the implications of estimates. The left panel shows the implications of the model if we ignore bargaining power asymmetry and assume that wife has a share of 0.5. The right panel shows the implications under the model predicted resource share 0.32. The mean wife's indifference scale is 0.62, implying that the wife would need 58 percent of the household's total expenditures to live alone while attaining the same indifference curve in marriage. The IS of the husband is 0.67, which is higher than that of the wife. The results suggest that on average,

**Table 4: Implications of Estimates**

| Wife's resource share | 0.50 | 0.32 |
|---|---|---|
| Her equivalent expenditure | 88.69 | 68.87 |
| His equivalent expenditure | 83.56 | 74.70 |
| Actual couple's expenditure | 118.67 | 118.67 |
| Indifference scale for women | 0.75 | 0.62 |
| Indifference scale for men | 0.70 | 0.67 |
| Scale economy, R | 0.45 | 0.29 |

*Notes:* Values are in mean. Estimates are based on model (2). Equivalent budget share is the budget share of the wife (husband) if she (he) is endowed with the fraction of resources and faced with shadow prices (market prices discounted by the Barten scales). The equivalent expenditure is the expenditure that the wife (husband) needs to obtain the same private good equivalents in marraige if she (he) is living alone, endowed with the fraction of resources in marriage and faced with market prices. Scale economy means it would cost the couple R percent more to buy the (private equivalent) goods they consumed if there had been no shared or joint consumption. The expenditures are in thousand yen.

the husband extracts more gains from marriage. The overall scale economy is 0.29, suggesting that it would cost the couple 29 percent more to buy the private equivalent goods they consumed if there had been no shared or joint consumption. The difference between the left and right panel highlights the importance of accounting for intra-household inequality. In particular, if we assume equal sharing, then we would overestimate wife's indifference scale and the scale economy.

The findings on mean resource share and indifference scales in this paper are quite different from previous findings in western developed countries (e.g., Browning et al. (2013) studies Canada, Cherchye et al. (2012) studies Dutch data, and Solvejg (2018) studies the U.S.). They normally find the wife to have higher bargaining power and higher indifference scale. However, we find the Japanese wife to have lower bargaining power and lower indifference scales than their husband. We hypothesize that the gender norms play an important role in terms of intra-household bargaining. In Japan, the social norms are conservative and men still prefer women to perform housework and earn less than their husbands.[73] In the next section, we will compare the predicted shares from the model directly to the empirical evidence on individual expenses, savings, and time use in JPSC. The exercise would provide strong validity check for our model.

[73] Bertrand et al. (2016) looks at the percentage of individuals who agree with the argument that "Men's job is to earn money, while women's job is to look after home" across countries. East Asia (mainly South Korea and Japan) has the highest percentage (around 0.4 in 2002 and around 0.3 in 2012) of individuals who agree with this argument. The gender norm in East Asia, even though gradually changing, is still the most conservative compared to western developed countries.

**Table 5: Summary Statistics on Individual Expenses and Savings, JPSC 1993 - 2015**

| | Expenditures | | Savings | |
|---|---|---|---|---|
| Total | 235.13 | | 84.63 | |
| For the family | 160.34 | 68% | 55.93 | 66% |
| For the wife | 23.68 | 10% | 12.54 | 15% |
| For the husband | 35.26 | 15% | 12.68 | 15% |
| For others | 9.90 | 4% | 1.98 | 2% |

*Notes:* Savings and expenses are for September and in thousand yen.

### 3.6 Validation of the Collective Household Model

Given the estimates on resource share and Barten scales, we next validate the results by exploiting the relationship between model-predicted resource share and observed individual expenditures, savings, and time use in JPSC. We first present the summary statistics on those observed information and then correlate them with the predictions of our model.

The summary statistics on individual expenses and savings are reported in table 5. The average private consumption devoted to the wife is 10 percent, versus the husband, 15 percent. 68 percent of household expenditures are devoted to the family. The individual private expenditure data can only tells the intra-household inequality in purely private expenditures, which only constitutes 30 percent of total household expenditures. This highlights the importance of using the collective household approach in order to obtain the intra-household inequality in resource allocation in the remaining 68 percent joint expenditures.

The summary statistics on individual time use for couples in JPSC are reported in table 6. Each row reports the average number of minutes spent for a particular activity in a week. The first three rows relate to work-related activities such as commuting, work, and schoolwork. Housekeeping includes only includes domestic chore but child care is negligible since we only use a sample of couples without children here. Leisure includes both hobby, leisure, social interaction and other activities such as sleeping, meals, taking a bath, etc. On average, the husband does more market work while the wife does more house work. However, the wife has much less leisure compared to the husband. If we only count hobby, leisure, and social interaction, the husband enjoys 30 percent more leisure than the wife.

**Correlation between Observed and Estimated Resource Share** We next examine whether the predictions on resource allocation from the collective model is consistent with the

**Table 6: Individual Time Allocation, JPSC couples 1993 - 2015**

| | Wife | | Husband | |
|---|---|---|---|---|
| | mins | percent | mins | percent |
| For commuting | 47 | 2% | 71 | 2% |
| For work | 359 | 12% | 623 | 22% |
| For schoolwork | 35 | 1% | 40 | 1% |
| For housekeeping | 420 | 15% | 80 | 3% |
| For hobby, leisure, social interaction, etc | 585 | 20% | 658 | 23% |
| For other activities such as sleeping, meals, taking a bath, etc | 1431 | 50% | 1407 | 49% |
| Total | 2877 | | 2879 | |

*Notes:* The sample here is restricted to couples without children. the left column for wife/husband shows the total minites (mins) spend in total per workday and day off for each of 6 activities. We sum the total minutes for workday and day off. Values are in mean. The upper panel shows the time spent on each activity. The lower panel combines the disaggregated activities in the upper panel into three main categories. Work-related includes commuting, work, and schoolwork. Housework corresponds to housekeeping and child care in the upper panel. Leisure includes both hobby, leisure, social interaction and other activities such as sleeping, meals, taking a bath, etc.

empirical evidence in the JPSC data. To do that, we correlate resource share with individual private expenditures, savings, market work, house work, and leisure. Our goals are the following. First, the resource share is defined as the share of total expenditures enjoyed by a member. it includes not only purely private expenditures but also the part of joint expenditures that are consumed exclusively by a member. We expect a positive correlation between resource share and individual private expenditures from the data, but not necessarily a large magnitude because the data does not report the sharing of joint consumption while the model does. That is also why we need a collective household model in order to reveal the unobserved share of total resources, both privately and jointly consumed. Second, household total resources include not only expenditures but also savings. Resource share estimated from the model only tells the intra-household allocation in expenditures. Hence, it has been a concern that resource share might not fully reflect the bargaining power since a member who controls a low fraction of total expenditures might control most of the savings. Out correlation studies will directly speak to this concern in order to explore how well resource share is as an indirect measure of bargaining power. Third, it is interesting to explore the relationship between resource share and time allocation. We might want to ask whether people gets higher resource share because they work more (house work or market work)?

Table 7 presents the correlation estimates between the estimated resource share and observed resource allocation and time use. First, resource share is positively correlated with individual expenses even though the magnitude is not large. This is consistent with our hypothesis because the resource share not just reflects the individuals' share in private expenditures but more im-

**Table 7: Correlation: Individual Resource Share, Expenses, Savings, and Time Use**

| | Wife's estimated resource share |
|---|---|
| Wife's share of private expenses | 0.11 |
| Wife's share of private savings | -0.04 |
| Wife's share of work-related time | 0.06 |
| Wife's share of leisure time | -0.04 |
| Wife's share of housekeeping time | -0.08 |

*Notes:* Values are correlation estimates. Work-related time combines work (including schoolwork) and commuting time. Leisure includes both hobby, leisure, social interaction, and other activities such as sleeping, meals, taking a bath, etc.

portantly their share in joint consumption. The low magnitude in correlation actually points out that it would be misleading to simply use the naive share, i.e., the individual's share in purely private expenditures, to reflect intra-household inequality. Second, the correlation between the estimated resource shares and individual savings or time use is small in magnitude.

## 3.7 Conclusion

We apply the collective household model developed by Browning et al. (2013) to the Japanese Panel Survey of Consumers (JPSC) and Japan Household Panel Survey (JHPS/KHPS) in order to study the individual welfare and intra-household resource allocation in Japanese couples without children. We validate the predicted resource share from the model by correlating it with the observed individual private expenses, savings, and time use in JPSC. We find that the model predicts the intra-household resource allocation well. The inequality predicted by the model-predicted resource share is consistent with that from the private expenditure data. However, the former provides a more comprehensive view of individual inequality because it reflects individual share in not only purely private expenditures but also joint expenditures, which constitutes a large chunk of the household expenditures.

Along with Bargain et al. (2018), this paper provides the first validation of the collective household model of consumption in developed countries in Asia. Different from their paper, which only calculates the resource share of the private expenditures of households, we calculate the resource share of both private and joint expenditures. The analysis in this paper provides a more comprehensive view of the prediction power of resource share in terms of intra-household resource allocation. Moreover, we validate the model by not only correlating the resource share with individual private expenditures but also correlating it with individual savings and time use. One concern about the resource share is its prediction power in terms of household expenditures.

However, resource share is more importantly used as an indirect measure of bargaining power. The bargaining power should reflect not only power in consumption decisions but also decisions in savings and time use. Another concern about the resource share is its prediction in terms of total household resources, including both expenditures and savings. We validate the second concern by studying the relationship between the estimated resource share and individual savings by using the unique dataset JPSC, which provides such information. We find that the estimated resource share supports the empirical evidence in savings and time use.

The findings in this paper provide certain external support of the collective household approach in analyzing intra-household resource allocation and bargaining. Future research should draw more attention to individual-level welfare analysis and intra-household inequality in resource allocation. We argue that the collective household approach should be widely applied in order to achieve the above two goals.

## 3.8 APPENDIX 3.A: Individual Welfare Measures

The private good equivalents for good $k \in \{1, \ldots, n\}$ are given by:

$$x_k^f = \frac{\eta \omega_k^f(\pi/\eta)}{\pi_k} = \frac{\omega_k^f}{A_k} \eta y \tag{82}$$

$$x_k^m = \frac{(1-\eta)\omega_k^m(\pi/(1-\eta))}{\pi_k} = \frac{\omega_k^m}{A_k}(1-\eta) y \tag{83}$$

The equivalent expenditures for each are given by:

$$x^f = \sum_k x_k^f = \eta y \sum_k \frac{\omega_k^f}{A_k} \tag{84}$$

$$x^m = \sum_k x_k^m = (1-\eta) y \sum_k \frac{\omega_k^m}{A_k} \tag{85}$$

The indifference scales for each are given by:

$$IS^f = \frac{x^f}{y} = \eta \sum_k \frac{\omega_k^f}{A_k} \tag{86}$$

$$IS^m = \frac{x^m}{y} = (1-\eta)\sum_k \frac{\omega_k^m}{A_k} \tag{87}$$

The relative economies of scale to consumption, $R$, are defined as

$$R = \frac{p'(x_f + x_m)}{y} - 1 = \frac{p'(x_f + x_m - z)}{p'z} \tag{88}$$

If all goods are public (private), then $R = 1$ ($R = 0$).

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