DEMAND AND WELFARE ANALYSIS WHEN PRODUCTS AND CONSUMERS ARE DIFFERENT

by

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(Under the Direction of Chen Zhen)

ABSTRACT

In this study, we show how to estimate large consumer demand and household collective models using big microdata in an efficient way. The dissertation is composed of three chapters, where we reduce aggregation bias in consumer demand systems, nest heterogeneous habit in household's demand models, and evaluate the degree of intrahousehold inequality within 2-3 person households in the United States.

In Chapter 1, we show how inferential errors due to inconsistent aggregation bias can be properly reduced. To manage dimensionality in consumer demand estimation, researchers' common practice is to aggregate elementary products to a higher level prior to econometric estimation. Inconsistent product aggregation, however, introduces bias to econometric estimates and policy-relevant inferences. We propose two alternative strategies for bias reduction. The first strategy uses the relative prices of elementary products as control variables in the aggregate demand. The second uses a residual-based instrumental variable method to achieve independence between the instrument and the residual.

In Chapter 2, we study the heterogeneity of habit strength in households' demand for regular carbonated sweetened beverages (CSBs) and beer in the United States. A demand model that nests a smooth transition function is used to describe habit-based consumption patterns, revealing heterogeneous strengths of habits among households. We find that more habitual consumers, those with a strong preference for a particular product, are not as sensitive to price or expenditure as the aggregate population.

In Chapter 3, we examine the degree of intrahousehold inequality within 2-3 person households in the United States. Using structural collective model and household scanner data, we estimate the fraction of household resources that are consumed by husbands, wives and children. We find intrahousehold inequality exists in two-person (i.e. husband and wife) households but not in three-person (i.e. parents and one child under 5-year-old) households. The policy implication of this finding is two-fold: 1) this empirical finding suggests the current household income eligibility threshold for the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC Program, a social welfare program targeting at women and children) should be increased for two-person households so that women who are currently not eligible for WIC Program but should have been can be covered; 2) Cost-efficient public policies can be achieved by allowing eligibility thresholds to vary by household demographics (e.g. education level, employment status, etc.).

INDEX WORDS: Product Aggregation, Heterogeneity, Habit Strength, Resource Share, Collective Model

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DEDICATION

I dedicate this dissertation to my grandparents for raising me up with affections and love and their unlimited support for my life.

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CHAPTER 1

TWO SIMPLE STRATEGIES FOR REDUCING AGGREGATION BIAS IN DEMAND SYSTEM MODELS

1. Introduction

In recent years, measuring the price elasticities of food demand—a traditional area of research for agricultural economists—is of growing interest to the broader community of public policy. The newfound interest in food demand is a response to the ever-increasing policy calls for using price (dis)incentives to improve diet and reduce obesity and nutrition-related noncommunicable diseases in the United States and globally. Many of the policy scenarios concern taxes or subsidies that target finely defined food and beverage categories differentiated by nutrient contents (e.g., sugary vs. diet beverages). The need for predicting and comparing outcomes of these policy alternatives fuels the drive toward estimating highly disaggregated food demand systems.

Thanks to greater accessibility of scanner data, researchers now have the liberty of disaggregating demand to a level as detailed as the barcode (Broda and Weinstein 2010). However, unless one is willing to use restrictive functional forms such as the constant elasticity of substitution demand, a degree of product aggregation is necessary to make estimation practical. This is especially true for flexible functional form systems where there are at least as many price variables per equation as the number of goods in the system. Even if we impose the symmetry, homogeneity and adding up restrictions, the number of parameters would still be too high to estimate them for a large system. Aggregating to fewer product categories would reduce the dimension of the parameter space but at the potential cost of creating bias if aggregation is inconsistent. From an economist's perspective, an aggregation scheme is consistent if the aggregated categories maximize a utility function given aggregate price indexes and income. The canonical approach to reducing aggregation bias is to test the sufficient conditions for consistent aggregation. There are two alternative types of conditions. The first is a set of equality restrictions on product-level price and income elasticities implied by separable utility (Blackorby, Primont, and Russell 1977; Blackorby, Davidson, and Schworm 1991; Moschini, Moro, and Green 1994). This requires first estimating the product-level demand system and then determining if certain products can be aggregated into separable groups based on tests of the equality constraints. As prices of similar products tend to be highly collinear, thereby producing imprecise coefficient estimates, test of separability may have low power. Moreover, if a product-level demand system can be estimated to credibly test the separability restrictions, it obviates the need for aggregating products into fewer groups. The alternative condition for consistent aggregation concerns movement of product prices in the same group. The Hicks-Leontief composite commodity theorem states that products whose prices are perfectly correlated can be consistently aggregated into a group. This requires within-group product prices to move in perfect synchronization, which is empirically unlikely.

In a seminal paper, Lewbel (1996) extended the Hicks-Leontief theorem into an empirically more plausible generalized composite commodity theorem (GCCT) that only requires the deviation of product prices from its group price be independent of the group price. The significance of Lewbel's GCCT is that its mild restrictions on price variation rationalize some of the common product groupings that were previously untested or rejected by separability tests (e.g., Davis, Lin, and Shumway 2000; Capps and Love, 2002; Reed, Levedahl, and

Hallahan 2005; Schulz, Schroeder, and Xia 2012; Heng, House, and Kim 2018). Indeed, Shumway and Davis (2001) found that GCCT tests had the lowest frequency of rejection among all types of aggregation tests in a survey of 22 peer-reviewed studies. There is a concern, however, that the low rejection rates may be an artifact of size distortions and power problems associated with time-series unit root and cointegration tests in small samples (Davis 2003). Although multiple aggregation tests are available, most demand studies do not test for consistent aggregation. Rather, aggregation decisions are guided by research questions, constrained by data availability, and often follow convention, intuition or even convenience. For example, the literature on sugar-sweetened beverage taxes has either aggregated all sugary drinks into a single category (Lin et al. 2011; Allcott, Lockwood and Taubinsky 2019) or up to three product types (Dharmasena and Capps 2012; Zhen et al. 2014). One factor in the infrequent deployment of aggregation tests in demand analysis may be time. Testing an exhaustive list of potential cointegrating relationships under the GCCT framework can be time-consuming even with a large number of elementary products.[1] Given that aggregation decisions are not formally tested in most studies, it will be useful to develop a practical approach that reduces bias when the chosen aggregation schemes violate the GCCT.

The objective of this study is to propose two alternative strategies for reducing aggregation bias. The first strategy uses the log relative (to the group) product prices as control variables in the group demand equations. Although Lewbel (1996) had used essentially the same procedure as a test for separability in a consistently aggregated demand system, its ability in

[1] The time-consuming aspect of the GCCT test arises from the fact that there are a large number of alternatives to combine elementary products into groups. The combinations with at least two nonstationary product-level prices need to be tested for cointegrating relationships. The final aggregation scheme can be especially difficult to choose if some unit root and cointegration test results are indeterminate.

reducing bias from inconsistent aggregation was not previously recognized. The second strategy uses linear regression to project each log group price onto the log relative prices of elementary products and a residual. The residual is then used as an instrument for the group price. Both the control variables method and the residual-based instrumental variables method are simple enough for use in any flexible demand systems where bias from inconsistent aggregation is of concern. To address the issue of low power in time-series unit root tests, we conduct the GCCT tests in a panel data setting. This is the first application of panel unit root tests to the GCCT. In an example application to fruit and vegetable demand, the more powerful panel tests rejected aggregation schemes at a much higher rate than time-series tests. The preferred bias-reduction method reduced aggregation bias in elasticity estimates by up to 67% for fruit and 91% for vegetables.

The next section briefly reviews the GCCT, where we motivate bias from inconsistent aggregation as a special case of the omitted variable problem. We then discuss using the panel unit root tests to examine the GCCT with more power. This is followed by an empirical illustration of the proposed methods using retail scanner data on fruit and vegetable from 72 US markets over the 2008–2012 period. The final section summarizes and discusses an extension of the methods.

2. Composite Commodity Theorems

For ease of exposition, we discuss Lewbel's GCCT in the context of a linear approximate almost ideal demand system. All results apply to other functional forms. Let the product-level demand system be

(1) $$w_i = \alpha_i + \sum_{j=1}^{n} \beta_{ij} \ln p_j + \theta_i \ln y + \varepsilon_i$$

where elementary products are indexed by $i \in D = \{1,2,\dots,n\}$, w_i is the budget share of product i, p_j is the price of product j, y is total expenditure in real terms, α, β, and θ are parameters, and ε_i is the orthogonal residual term. We suppress the time and market subscripts to simplify notation in this section. They are introduced in later sections to properly denote variables in panel setting.

To aggregate the n products into N groups, define an aggregate indexing set $I = \{I_{\mathrm{r}}\}_{r=1}^{N}$, where $I_r \subseteq D$ for any $r = 1,\dots,N < n$. Let the aggregate price index for group r be P_r. The log ratio of p_j to P_r is calculated as

(2) $$\ln\left(p_j/P_r\right) = \rho_j \ , j \in I_r$$

where the relative price ρ_j measures the deviation of the log product price from its group price index and can be considered as an aggregation error. Replacing $\ln p_j$ in Eq. (1) with $\ln P_r$ and ρ_j yields

(3) $$w_i = \alpha_i + \sum_{r=1}^{N} \psi_{ir} \ln P_r + \sum_{j\notin I} \beta_{ij} \ln p_j + \theta_i \ln y + \sum_{j\in I} \beta_{ij}\rho_j + \varepsilon_i \,,$$

where $\psi_{ir} = \sum_{j\in I_r} \beta_{ij}$. Aggregating Eq. (3) of products $i \in I$ into N group share equations yields the following demand system:

(4a) $$W_s = \mathrm{A}_s + \sum_{r=1}^{N} \Psi_{sr} \ln P_r + \sum_{j\notin I} \mathrm{B}_{sj} \ln p_j + \Theta_s \ln y + \sum_{j\in I} \mathrm{B}_{sj}\rho_j + \mathrm{E}_s \,,\ \ s = 1,2,\dots,N$$

(4b) $$w_k = \alpha_k + \sum_{r=1}^{N} \psi_{kr} \ln P_r + \sum_{j\notin I} \beta_{kj} \ln p_j + \theta_k \ln y + \sum_{j\in I} \beta_{kj}\rho_j + \varepsilon_k \,,\ \ k \notin I$$

where W_s is the aggregate budget share of group s, w_k is the budget share of product k not aggregated into one of the N groups, $A_s = \sum_{i\in I_s} \alpha_i$, $\Psi_{sr} = \sum_{i\in I_s} \psi_{ir}$, $\mathrm{B}_{sj} = \sum_{i\in I_s} \beta_{ij}$, $\Theta_s = \sum_{i\in I_s} \theta_i$, and $E_s = \sum_{i\in I_s} \varepsilon_i$. If all n products are allocated into the N groups, the system (4a-b) reduces to Eq. (4a).

The Hicks-Leontief composite commodity theorem states that products can be consistently aggregated into groups if product prices within each group r are *perfectly* correlated, that is, ρ_j being constant over time for $\forall\ j \in I_r$. This allows $\sum_{j\in I} \mathrm{B}_{sj}\rho_j$ in (4a) and $\sum_{j\in I} \beta_{kj}\rho_j$ in (4b) be combined with A_s and α_k, respectively, to form the new intercepts for the system (4a-b). Independence of the residuals E_s and ε_k from P_r $(r = 1, \dots, N)$ and p_k $(k \notin I)$ ensures consistent estimation of Ψ_{sr}, B_{sj} $(j \notin I)$, and Θ_s in (4a) and ψ_{kr}, β_{kj} $(j \notin I)$, and θ_k in (4b). Unfortunately, the Hicks-Leontief theorem does not hold empirically because it requires prices of all products within a group move in absolute synchronization.

Lewbel's key insight is that consistent estimation of the slope coefficients in the system (4a-b) does not actually require constancy of ρ_j, only that the distribution of ρ_j be independent of P_r and p_k $\forall j, r, k$. To see this, without loss of generality, let ρ_j be a zero-mean random variable. This would be the case if both p_j and P_r, $j \in I_r$, are indexes normalized to 1 at the base, which is set to the sample mean of each variable. Then the new composite residuals of (4a) and (4b) are $\sum_{j\in I} \mathrm{B}_{sj}\rho_j + \mathrm{E}_s$ and $\sum_{j\in I} \beta_{kj}\rho_j + \varepsilon_k$, respectively. Both would have an expected value of 0 and are independent of P_r and p_k if the GCCT holds. The GCCT relaxes the empirically untenable Hicks-Leontief theorem into a more plausible requirement on how product prices move within a group. Lewbel (1996, p. 526-527) showed that, under the GCCT if the adding up, symmetry and homogeneity conditions hold for the product-level Eq. (1), then the aggregate system (4a-b) would also possess these properties. In addition, elasticities derived from the system (4a-b) are the best unbiased estimates of group demand elasticities that would be obtained from estimation of Eq. (1) using disaggregate data (Lewbel 1996, p. 528).

As noted earlier, in most cases, aggregation into groups is driven by the specific needs of the analysis as opposed to the GCCT test results. If the selected aggregation scheme violates the

GCCT, omission of the relative prices ρ_j from the system (4a-b) will cause the composite residuals to be correlated with the group prices P_r and, thereby, bias the coefficient estimates on group prices. This can be seen as a special case of the omitted variable problem in two aspects. First, unlike a standard case of omitted variables,[2] conventional instrumental variables will not help reduce the endogeneity bias attributed to inconsistent aggregation. Given that ρ_j is inversely related to P_r, it will be difficult to identify a naturally-occurring instrument that is strongly correlated with P_r but independent of ρ_j except in the trivial case of ρ_j being independent of P_r. Second, unlike endogeneity bias due to unobserved heterogeneity, the relative prices are perfectly observed by the econometrician. The latter distinction leads to two surprisingly simple strategies for reducing bias in the group price coefficients Ψ_{sr} and ψ_{kr} in an inconsistently aggregated system.

The first strategy uses the relative prices $\rho_j \; \forall j \in I$ as control variables in the system (4a-b). The second, called residual-based instrumental variables, is implemented by regressing each group price on all relative prices and using the residual as instruments for group prices in the aggregate demand. By design, the residual-based instrument is orthogonal to the relative prices and produces consistent estimates of the group price coefficients.

3. Panel GCCT Tests

Aggregation according to the GCCT entails testing the independence between the ρ's and the P's. If prices are nonstationary, as they often appear to be, ordinary covariances and correlations

[2] Many standard sources of endogeneity bias are fundamentally an omitted variable problem. For example, classical demand-supply simultaneity bias in demand analysis is caused by unobservable (to the econometrician) demand shocks that are omitted from the demand regression. In the absence of direct measures of the unobserved demand shocks, supply-side variables are often used as instruments for the endogenous prices.

cannot be used to test independence. There are a few complications associated with detecting nonstationarity and testing for independence among nonstationary prices. Unit root tests, such as the augmented Dickey-Fuller (ADF) test (Dickey and Fuller 1979), are problematic in that they are not very powerful in distinguishing highly persistent stationary processes from nonstationary processes, especially in short time series. Schwert (1987) and Lo and MacKinlay (1989) documented that tests for a unit root (the null) have low power in finite samples against the local alternative of a root close to but below unity. Cochrane (1991) decomposed a unit root process into a stationary and a random walk component. He argued that because the random walk component can have arbitrarily small variance, a test of the null hypothesis of a unit root has arbitrarily low power against the alternative of trend stationarity in finite samples. To address the power issue in unit root tests, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al. 1992) switched the null to trend stationarity against the alternative of a unit root. However, Caner and Kilian (2001) showed that the use of conventional asymptotic critical values for stationarity tests may cause extreme size distortions, if the model under the null hypothesis is highly persistent. In essence, the size distortion of stationarity tests is the mirror image of the low power of unit root tests. If prices are indeed nonstationary, multivariate cointegration tests are necessary to determine independence. However, studies (Haug 1996; Ho and Sørensen 1996) have shown that the Engle and Granger (1987) cointegration test has power problems similar to those of the unit root tests. To confront these issues, Davis (2003) proposed modified Bonferroni procedures to strengthen the time series GCCT test. Davis et al. (2000) provided additional strategies to more powerfully test the GCCT using time series data.

Inspired by the increasing availability of scanner panels, we take a different approach to strengthening the GCCT test. Testing unit roots using panel data is driven by the desire to gain power over tests for single time series (Levin et al. 2002; Im et al. 2003; Breitung 2000). Since the low power problem is most severe in small samples, one can increase the sample size by pooling time series data across the cross-sectional units. That said, it is important to account for cross-sectional dependence when conducting panel unit root tests. Neglecting this common feature of panel data is shown to lead to severe power reduction and size distortion (O'Connell 1998). For this reason, we chose Pesaran's (2007) cross-sectionally augmented Im-Pesaran-Shin (CIPS) test to test for panel nonstationarity.

4. An Application

We illustrate the two bias reduction strategies with an example of fruit and vegetable demand that is of continuing interest to agricultural economists. Estimates of fruit and vegetable elasticities have been used to explain the farm-retail price spread (Wohlgenant 1989), understand the role of farm policy in the obesity epidemic (Okrent and Alston 2012), and predict the effects of prices on food waste (Hamilton and Richards 2019), among other applications. We selected 15 fruits and 15 vegetables for analysis (see table 1 for a list). These tend to be the most commonly available fruit and vegetables at retail. We call each fruit or vegetable a product. The GCCT tests are used to determine whether these products may be consistently aggregated into fewer groups. We compare test results from the time series unit root tests with those from the panel tests to highlight the differences in aggregation scheme suggested by each type of tests. The demand system with GCCT-consistent aggregation scheme is treated as the benchmark model. We evaluate the performance of the bias reduction methods in a GCCT-inconsistent aggregate system by comparing the bias-adjusted estimates with the benchmark estimates.

The Demand Model

We choose the quadratic almost ideal demand (QUAID) (Banks et al. 1997) as the functional form. Compared with the almost ideal demand, QUAID has more flexible Engel curves but retains exact aggregation over consumers. The group-level budget share equation for group s is

$$(5) \quad W_{mst} = A_{mst} + \sum_r \Psi_{sr} \ln P_{mrt} + \Theta_{1s} \ln\left[\frac{x_{mt}}{a(P_{mt})}\right] + \frac{\Theta_{2s}}{b(P_{mt})}\left\{\ln\left[\frac{x_{mt}}{a(P_{mt})}\right]\right\}^2 + \mathrm{e}_{mst}$$

where the subscripts m and t denote the cross-sectional unit and time period, respectively; x_{mt} is total nominal income; $\ln a(P_{mt}) = A_0 + \sum_s A_{s0} \ln P_{mst} + 0.5 \sum_s \sum_r \Psi_{sr} \ln P_{mst} \ln P_{mrt}$; $b(P_{mt}) = \prod_s P_{mst}^{\Theta_{1s}}$; e_{mst} is the residual; and the A's, Ψ's, and Θ's are parameters. The intercept A_{mst} is specified as $A_{mst} = A_{s0} + \mathbf{z}_{mst}\boldsymbol{\delta}_s$, where $\mathbf{z}_{mst}$ is a row vector of control variables and $\boldsymbol{\delta}_s$ is the corresponding column vector of parameters.

Eq. (5) is the quadratic counterpart of group-level demand in Eq. (4a). To avoid notational clutter, we have assumed all products are aggregated into some groups so that Eq. (4b) drops out. This is a harmless assumption because if group r consists of a single product then the group price P_{mrt} and budget share W_{mrt} equal those of the product.

Data and Variable Construction

Information on fruit and vegetable sales comes from the IRI InfoScan retail scanner data that the USDA Economic Research Service acquired to support food market and policy research. Our sample covers 65 quadweeks (i.e., 4-weekly periods) between January 6, 2008 and December 29, 2012. In InfoScan, there are 65 markets and 8 standard whitespaces (i.e., remaining Areas of the contiguous United States). We dropped the Green Bay, WI market from the sample due to insufficient retail data for the study period. This gives a balanced panel with 4,680 market-quadweek observations. Some InfoScan-participating retailers provided data at the store level but others only at the retail marketing area (RMA) level (Muth et al. 2016). The geographical coverage of RMA varies across retailers, but a typical RMA contains a cluster of counties. We aggregated store-level data to the IRI market level. For RMA-only retailers, IRI reports the number of stores and addresses in each RMA. To estimate IRI market-level sales for these retailers, we divided RMA-level sales by store number to get average sales per store and allocate RMA sales to each IRI market based on the number of stores the retailer has in each IRI market.

Compared to traditional budget surveys, the detailed product information in scanner data allows the researcher to better control for the unit value bias. A unit-value price is calculated as the expenditure on a good divided by its purchase quantity. Bias may arise if the construct of the demand model is abstract from the quality decision while the unit-value price encompasses both the quality and quantity dimensions of consumer choice (Deaton 1988; Cox and Wohlgenant 1986). To differentiate quality among varieties within a fruit or vegetable, we define variety at the type (up to two types per fruit/vegetable, e.g., romaine vs. leafy lettuce), brand (name brand, no brand, private label), organic (organic, nonorganic), and form (fresh, frozen, canned) level. This yields up to 36 unique varieties per product.[3] We then constructed the superlative Fisher Ideal price index for fruit or vegetable product j as follows

$$(6) \quad p_{mjt} = \sqrt{\left(\frac{\sum_k (p_{mt}^k q_0^k)}{\sum_k (p_0^k q_0^k)}\right)\left(\frac{\sum_k (p_{mt}^k q_{mt}^k)}{\sum_k (p_0^k q_{mt}^k)}\right)}$$

where the subscripts m and t index market and period, respectively; p_{mt}^k and q_{mt}^k are the price and volume sales of variety k, respectively, and p_0^k and q_0^k are the base price and volume of variety k set at their sample means. The Fisher Ideal price index is superlative because it approximates the true cost of living index for a class of expenditure function (Diewert 1976). It allows the researcher to account for within-product substitution without estimating a variety-

[3] Our maintained hypothesis is that the ≤36 varieties can be consistently aggregated into a single fruit or vegetable.

level demand system. Davis (1997) developed a test for unit value bias and found important differences in estimates and policy implications between a demand model using superlative price indexes and a model using unit-value prices.

To construct the price index for the numéraire good, we multiplied annual Regional Price Parities for 2008-2009 from the Bureau of Economic Analysis with monthly Consumer Price Index from the Bureau of Labor Statistics to obtain a panel of the cost-of-living index for metropolitan statistical areas. The index numbers were then weighted by county population to construct the numéraire price index at the IRI market level.

Price endogeneity is a concern, even with consistent aggregation, because of demand-supply simultaneity and unobserved heterogeneity. We created a Hausman-type (Hausman et al. 1997) instrument p_{-mjt} for each fruit or vegetable price p_{mjt}, where p_{-mjt} is the average price of j in the five IRI markets closest to market m in distance. Identification of the price coefficients in the demand model relies on 1) there be common supply shocks across nearby markets, and 2) the restriction that unobserved demand shocks be uncorrelated across markets after accounting for market, year and seasonal fixed effects in the $\mathbf{z}_{mst}$ vector. Using the nearest markets is designed to increase the strength of p_{-mjt} in explaining the variations in p_{mjt}. We used the same approach to create instruments for group prices.

For the residual-based instrumental variables method, we use the following linear regression to generate the instrument

(7) $\ln P_{-mrt} = a_r + \sum_{j \in I} b_{rj} \rho_{mjt} + u_{mrt}, \qquad r \in I$

where P_{-mrt} is the Hausman instrument for group price P_{mrt} of group r, the a's and b's are parameters, and u_{mrt} is the residual. The fitted residual $\hat{u}_{mrt}$ serves as the residual-based instrument for group price P_{mrt}.

Aggregation Scheme

We take a food-group based approach to aggregating the 30 fruits and vegetables into groups. Because much of the recent food demand literature has a nutrition policy focus, we follow the food categorization scheme used in MyPlate–the current USDA nutrition guide based on the recommendations of the *Dietary Guidelines for Americans*. According to MyPlate, the 15 fruits are categorized into three groups: berries, melons, and other fruits. Similarly, the 15 vegetables are categorized into four groups: dark-green vegetables, red and orange vegetables, starchy vegetables, and other vegetables. Table 1 presents the composition of each group.

Consistent product aggregation requires the relative product price ρ_j to be independent of the group price P_r. Therefore, testing whether an aggregation scheme is consistent with the GCCT is equivalent to testing whether ρ_j and P_r are independent of each other. Tests depend on the time series properties of the data. The procedure consists of two steps: (1) determine the stationarity of each ρ_j and P_r using unit root tests and (2) based on the results of step 1, test independence between ρ_j and P_r. There are three alternative scenarios in step 2. First, if both ρ_j and P_r are stationary, a correlation test is appropriate. Second, if ρ_j and P_r are both nonstationary, a cointegration test should be conducted. Third, if ρ_j is stationary but P_r is nonstationary or vice versa, then no test of independence is necessary because the two series cannot be cointegrated, which is evidence for independence (Lewbel 1996, p. 532).

Davis (2003) correctly pointed out that the GCCT require testing independence of each ρ_i from all of the P_r's, not just price of the group comprising product i as was done in Lewbel (1996) and virtually all published work on GCCT. One reason for limiting the scope of the independence test is the power and size problems of multivariate cointegration tests. Additionally, given evidence for cointegration vectors, exclusion restriction tests are required to determine whether the cointegration is between ρ_i and the P_r's, or among the P_r's (Davis 2003, p. 479). The test workload can quickly become unwieldy as the number of elementary products and aggregation schemes increases. For these reasons, we confine the independence test to between ρ_j and its own group price P_r ($j \in I_r$), which is most likely to correlated or cointegrated with ρ_j among all group prices.

Time Series Test Results

We conducted the ADF and KPSS tests on the relative product prices and group prices. The null hypothesis of the ADF test is the presence of a unit root, while the null of the KPSS is stationarity. Reversing the null and alternative hypotheses is designed to manage the power issue of time series GCCT tests (Davis et al. 2000). When results from the two tests are conflicted, inferences based on the joint confirmation hypothesis (JCH) of a unit root are used (Carrion-i-Silvestre et al. 2001). If the group price P_r and relative price ρ_j are both nonstationary, we used the Engle-Granger test to examine the null hypothesis of no cointegration between the two series. The Spearman's rank test is used to test for correlation when the two series are stationary, with a null hypothesis that the two series are not correlated.

Table 1 reports the test results on fruit and vegetable grouping. The price indices of all groups, bar dark-green vegetables, are nonstationary, and so are 7 of the 30 relative prices. Of the 5 nonstationary relative prices whose group indexes are also nonstationary, the Engle-Granger test failed to reject the null of no cointegration between each relative price and its group price. This confirms independence of the 30 relative prices from their corresponding group prices and consistent aggregation of these products into seven fruit and vegetable groups. This finding is consistent with previous time-series tests of the GCCT that found low rates of rejection of the proposed aggregation schemes (Shumway and Davis 2001).

Panel Test Results

We hypothesize that rejection of consistent aggregation is more frequent in panel-based tests because of the increased power of panel unit roots tests. The null hypothesis of the CIPS panel unit root test is that all units of the panel contain unit roots. The alternative hypothesis is that at least some units are stationary. In contrast to the time-series results that found unit roots in all but one group prices, the panel test (table 2) indicates that only the group prices of berries and starchy vegetables contain unit roots. Tests of independence found that the relative prices of 21 fruits and vegetables are significantly correlated with their group prices and, hence, cannot be consistently aggregated into the MyPlate-based groups.[4] Berries and starchy vegetables, each containing two elementary products, are the only GCCT-consistent groups. Thus, without a bias-reduction method, the researcher has to estimate the remaining 13 fruits and 13 vegetables as individual goods in a demand system to avoid inferential errors due to inconsistent aggregation.

Demand Specifications and Results

To evaluate the empirical performance of the two bias-reduction strategies, we estimate the following four versions of the demand system Eq. (5) separately for fruit and for vegetables:

Model 1 uses the consistent aggregation schemes suggested by the panel test results. The demand estimates are set as the benchmark.

Model 2 follows MyPlate grouping which is not fully supported by the panel test. The differences between Model 2 and Model 1 estimates measure the degree of bias attributable to inconsistent aggregation.

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[4] A cointegration test is not applicable here because there is not a single case where the relative price and its group price are both nonstationary. Otherwise, we could use Westerlund's (2007) test, which accounts for cross-sectional dependence, to examine panel cointegration.

Model 3 follows the same grouping as Model 2 but includes the relative prices as control variables in the **z** vector so that the inconsistently aggregated group prices remain orthogonal to the error term e in Eq. (5). Comparing the differences in elasticity estimates between Model 3 and Model 1 with those between Model 2 and Model 1 provides empirical evidence on the efficacy of the control variable method.

Model 4 again follows the same grouping as Model 2 but uses the residual-based price instruments. We expect Model 4 to produce bias reduction comparable to Model 3 in magnitude.

We estimated each model using full information maximum likelihood (FIML). Models 1-3 use the Hausman-type instruments to control for price endogeneity. Model 4 uses the residual-based instruments to control for both price endogeneity and aggregation bias. The budget share equation for the numéraire was not estimated. Instead, we recovered its parameters using estimates from the fruit and vegetable budget share equations through the parametric restrictions implied by the adding up, homogeneity, and symmetry conditions. We calculated elasticities at the sample mean. The standard error for each point estimate is generated by taking 100 random draws from a multivariate normal distribution of the model parameters with the mean and covariance set to their estimated values (Krinsky and Robb 1990). These are the more policy-relevant unconditional elasticities because they are not conditional on total fruit and vegetable expenditures that are likely endogenous with prices.

Tables 3a and 3b present the Marshallian price elasticities of fruit and vegetable demand, respectively. All own-price elasticities are negative and statistically significant. Lemons/limes, tomatoes, and onions are the least price elastic with own-price elasticities at around −0.3. Many cross-price effects are consistent with a priori expectations. For example, we found statistically significant substitution between romaine/leafy lettuce and iceberg lettuce, between grapefruit, tangerines and oranges, and between cherries and the berries group. Using the individual fruit and vegetable elasticities, we simulated the aggregate demand elasticity for group s with respect to the aggregate price of group r by changing the prices of all products in r by the same percentage. The resulting group demand elasticities, shown in tables 4a and 4b, are the *benchmark* because they derive from the Model 1 estimates that are GCCT-consistent.

Table 5a presents group demand elasticities estimated by the group demand Model 2, 3, and 4 for fruit. Comparing tables 4a and 5a indicates that the fruit cross-price elasticities of Model 2 and 3 agree in sign but differ from the benchmark in sign between berries and other fruits. By contrast, Model 4, which used the residual-based instruments, correctly estimated the substitutive relationship between berries and other fruits.

Turning now to comparing the vegetable results in table 5b with the benchmark in table 4b. Model 3 and 4 correctly estimated the complementarity between dark-green vegetables and red and orange vegetables, while Model 2 incorrectly suggested substitution. Meanwhile, the substitution between starchy vegetables and red and orange vegetables is correctly predicted by Model 2 and 3 but not by Model 4. Finally, Model 4 is the only aggregate demand that estimated substitution between starchy vegetables and other vegetables.

Table 6 summarizes these comparisons. In terms of the magnitude of the bias, Model 3 and 4 performed better than Model 2, as expected, with the exception of the (unweighted) average own-price elasticity of Model 4 that is more biased than that of Model 2. This is entirely driven by the larger difference in own-price elasticity for berries, which account for 9% of total pound purchased. After weighting the bias by purchase quantity, Model 4 performs 67% better than Model 2 in terms of own-price elasticities. In general, the degree of bias reduction achieved by Model 3 is smaller than that of Model 4, and we observe a more significant bias reduction in own-price elasticities than in cross-price elasticities, and in vegetable demand than in fruit demand.

To further measure the difference between the elasticity matrix of the aggregate demand model and that of the benchmark model, we calculated the Euclidean norm, also known as the L_2 norm, which measures the distance between two matrices in an N dimensional space. The smaller Euclidean norm is, the closer the two matrices are. Table 7 presents the results. For both fruit and vegetables, the elasticity matrix produced by Model 4 has the smallest Euclidean norms with respect to the elasticity matrix produced by the benchmark model, which means elasticity matrix of Model 4 more closely resembles that of the benchmark model. As such, we find that comparing with the model with aggregation bias (Model 2), both control variable model (Model 3) and instrumental variable model (Model 4) produces less biased estimates, and Model 4 is preferred empirically.

5. Conclusion

Users of flexible demand systems usually aggregate many elementary products into fewer groups and estimate consumer preferences at the group level. This is done for practical reasons of avoiding the curse of dimensionality and customizing the analysis to answer specific research questions. The chosen aggregation scheme is frequently justified by tests of the GCCT―the most empirically plausible aggregation theorem of all. Using more powerful panel unit root tests, we showed that the low rejection rates of GCCT-consistent aggregation schemes in past studies are likely caused by the low power of time-series unit root tests. Rejection of a proposed aggregation scheme can be inconvenient because estimation at a more disaggregated level may not be practical due to multicollinearity and constraint on computing resources.[5] With these in mind, it is of significant practical value to develop an approach that reduces bias in an inconsistently aggregated demand system. This would allow practitioners to continue using the aggregation schemes best suited for addressing their specific research questions.

Our approach is motivated by noting a simple fact: the relative prices of elementary products, whose correlation with the group prices is the root cause for aggregation bias, are observable to the econometrician. One strategy is to include these relative prices as control variables in the aggregate demand model such that the group prices are no longer correlated with the regression error. Another strategy is to regress each group price on all relative prices and use the residual, which is free from correlation with the relative prices, as instrumental variables for the group prices in the aggregate demand.[6] We call the latter strategy the residual-based instrumental variable method.

Theory predicts that both strategies produce a similar degree of bias reduction. However, in the application to fruit and vegetable demand, we found the residual-based instrumental variable method to outperform the control variable method. In practice, there may be other reasons to prefer the former method to the latter. For example, when there is a large number of elementary relative product prices, it may not be practical to include all as control variables in the aggregate demand system, especially if the system is nonlinear. The stepwise nature of the residual-based instrumental variable method means that it can be implemented with ease

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[5] In our experience estimating large demand systems, the highest consumption of computer memory lies in imposing the cross-equation parametric restrictions of homogeneity and symmetry.

[6] As shown in our empirical illustration, if unobserved demand shocks and heterogeneity exist, one can regress a conventional price instrument on all relative prices and use the residual as the instrument in the aggregate demand.

regardless how many elementary products are aggregated into groups. This method is even more appealing in situations where the researcher is already planning to use instrumental variables to account for, in addition to aggregation bias, conventional sources of price endogeneity such as supply-demand simultaneity and unobserved heterogeneity.

Finally, although we illustrated the approach using market-level data, the methodology is equally applicable to demand system estimated on household-level data. For micro data applications of demand systems, another key motivation for product aggregation is to reduce the number of zeros. Accounting for these corner solutions introduces additional nonlinearity and, hence, complexity to the estimation. It will be straightforward to integrate the residual-based instrumental variable method into, for example, the extended Amemiya generalized least squares estimator for censored micro demand systems (Zhen et al. 2014) to correct for both aggregation bias and conventional price endogeneity.

Table 1. Time-Series GCCT Test Results

Group and relative prices	ADF Test H_0: I(1)[a]	KPSS Test H_0: I(0)[b]	I(1) or I(0)[c]	Engle-Granger Test[d]: H_0: Not Cointegrated	Consistent Aggregation (Yes/No)
P (Berries)	-2.23 (10)	0.17*	I(1)		
$\rho_{\text{strawberries}}$	-3.09 (7)	0.18*	I(1)	-1.69 (2)	yes
$\rho_{\text{blueberries}}$	-3.53 (7)*	0.12	I(0)	n/a	yes
P (Melons)	3.10 (4)	0.17*	I(1)		
$\rho_{\text{watermelon}}$	-7.59 (8)*	0.13*	I(0)	n/a	yes
$\rho_{\text{cantaloupe}}$	-6.35 (10)*	0.13*	I(0)	n/a	yes
P (Other Fruits)	-1.55 (2)	0.15*	I(1)		
$\rho_{\text{grapefruit}}$	-7.76 (5)*	0.12*	I(0) (JCH)	n/a	yes
ρ_{apples}	-4.84 (1)*	0.15*	I(0) (JCH)	n/a	yes
ρ_{grapes}	-5.41 (1)*	0.08	I(0)	n/a	yes
$\rho_{\text{lemons/limes}}$	-3.21 (1)*	0.12*	I(1) (JCH)	-1.83 (1)	yes
ρ_{peaches}	-5.37 (4)*	0.10	I(0)	n/a	yes
ρ_{avocado}	-3.18 (1)*	0.08	I(0)	n/a	yes
ρ_{pears}	-4.96 (1)*	0.14*	I(0) (JCH)	n/a	yes
ρ_{cherries}	-6.74 (8)*	0.09	I(0)	n/a	yes
$\rho_{\text{tangerines}}$	-5.59 (5)*	0.10	I(0)	n/a	yes
ρ_{oranges}	-2.92 (10)	0.14*	I(1)	-1.49 (10)	yes
$\rho_{\text{pineapple}}$	-6.02 (2)*	0.10	I(0)	n/a	yes
P (Dark-Green Vegetables)	-3.19 (1)*	0.12	I(0)		
ρ_{broccoli}	-3.10 (0)	0.17*	I(1)	n/a	yes
$\rho_{\text{lettuce (romaine/leafy)}}$	-3.14 (0)	0.16*	I(1)	n/a	yes
P (Red and Orange Vegetables)	-2.93 (1)	0.09	I(1) (JCH)		
ρ_{tomatoes}	-5.00 (5)*	0.11	I(0)	n/a	yes
$\rho_{\text{bell peppers}}$	-4.03 (0)*	0.09	I(0)	n/a	yes
$\rho_{\text{sweet potatoes}}$	-5.88 (1)*	0.09	I(0)	n/a	yes
ρ_{carrots}	-3.39 (1)*	0.09	I(0)	n/a	yes

Table 1. Continued

Group and relative prices	ADF Test H_0: I(1)[a]	KPSS Test H_0: I(0)[b]	I(1) or I(0)[c]	Engle-Granger Test[d]: H_0: Not Cointegrated	Consistent Aggregation (Yes/No)
P (Starchy Vegetables)	-2.07 (0)	0.11	I(1) (JCH)		
ρ_{corn}	-5.68 (3)*	0.12	I(0)	n/a	yes
$\rho_{potatoes}$	-4.55 (1)*	0.12	I(0)	n/a	yes
P (Other Vegetables)	-2.52 (0)	0.07	I(1) (JCH)		
ρ_{onions}	-2.51 (3)	0.09	I(1) (JCH)	-2.87 (4)	yes
$\rho_{lettuce\ (iceberg)}$	-3.41 (3)*	0.07	I(0)	n/a	yes
ρ_{celery}	-5.63 (1)*	0.07	I(0)	n/a	yes
$\rho_{cucumbers}$	-4.12 (1)*	0.07	I(0)	n/a	yes
$\rho_{mushrooms}$	-2.66 (0)	0.12	I(1) (JCH)	-2.67 (0)	yes
$\rho_{cabbage}$	-3.74 (1)*	0.07	I(0)	n/a	yes
$\rho_{green\ beans}$	-5.90 (1)*	0.10	I(0)	n/a	yes
10% Critical Value	-3.17	0.12	(–3.64, 0.07)	-3.11	

Notes: * denotes rejection of the null at the 0.10 significance level.

[a] The test statistic of the null hypothesis of I(1) is the augmented Dickey-Fuller (1979) (ADF) t-statistic of the coefficient on the lagged level variable in the regression of the first-difference on a constant, a time trend, the lagged level, and lagged differences of variables appended to the regression. The number of lags of first differences is reported in parentheses and determined by Eviews 10.

[b] The test statistic of the null hypothesis of I(0) is the Kwaitkowski et al. (1992) (KPSS) t-statistic. The t-statistic is the sum of the squared partial sums of residuals divided by an error variance estimator. The residuals are computed from a model in which the series is regressed on a constant and a time trend. For the correction of the error term, a Bartlett window with ten lags was used to ensure the variance matrix was well behaved.

[c] Inferences based on the joint confirmation hypothesis (JCH) of a unit root are used when the ADF and KPSS tests are in conflict (Carrion-i-Silvestre et al., 2001). The joint critical values of (–3.60, 0.07) represent the midpoint of critical values for 50 and 100 observations for the ADF and the KPSS (with Bartlett kernel) tests with trend. They are interpreted as follows. If the value of the ADF statistic is less (greater) than –3.60 and the value of the KPSS statistic is less (greater) than 0.07 then the series is considered (at 90% probability of joint confirmation) stationary (nonstationary). Otherwise, the series cannot be confirmed to have a unit root and is therefore considered stationary.

[d] The test statistic is for the Engle-Granger test of the null hypothesis that the kth relative price ρ_k and its group price P_r ($k \in I_r$) are not cointegrated. The entries are ADF tests of I(1) residuals formed from regressing the relative price on its integrated group price. The 10% critical values reported for the individual tests are based on 65 observations. The number of lags of the first-differenced residuals in the residual regression is determined by Eviews 10 and reported in parentheses.

Table 2. Panel GCCT Test Results

Group and relative prices	CIPS Test: H_0: I(1)[a]	I(1) or I(0)	Correlation Test[b]: H_0: Not correlated	Consistent Aggregation (Yes/No)
P (Berries)	-2.41	I(1)		
$\rho_{strawberries}$	-5.34*	I(0)	n/a	yes
$\rho_{blueberries}$	-5.32*	I(0)	n/a	yes
P (Melons)	-4.90*	I(0)		
$\rho_{watermelon}$	-5.47*	I(0)	0.71*	no
$\rho_{cantaloupe}$	-5.33*	I(0)	0.74*	no
P (Other Fruits)	-5.03*	I(0)		
$\rho_{grapefruit}$	-5.11*	I(0)	-0.11*	no
ρ_{apples}	-4.84*	I(0)	0.08*	no
ρ_{grapes}	-6.15*	I(0)	-0.07*	no
$\rho_{lemons/limes}$	-4.02*	I(0)	-0.05	yes
$\rho_{peaches}$	-5.07*	I(0)	0.14*	no
$\rho_{avocado}$	-4.43*	I(0)	-0.19*	no
ρ_{pears}	-4.87*	I(0)	0.30*	no
$\rho_{cherries}$	-5.67*	I(0)	0.04	yes
$\rho_{tangerines}$	-5.40*	I(0)	0.34*	no
$\rho_{oranges}$	-2.33	I(1)	n/a	yes
$\rho_{pineapple}$	-4.44*	I(0)	-0.08*	no
P (Dark-Green Vegetables)	-4.40*	I(0)		
$\rho_{broccoli}$	-4.74*	I(0)	0.37*	no
$\rho_{lettuce\ (romaine/leafy)}$	-4.49*	I(0)	-0.36*	no
P (Red and Orange Vegetables)	-4.75*	I(0)		
$\rho_{tomatoes}$	-5.02*	I(0)	-0.28*	no
$\rho_{bell\ peppers}$	-4.61*	I(0)	-0.27*	no
$\rho_{sweet\ potatoes}$	-4.79*	I(0)	0.28*	no
$\rho_{carrots}$	-4.87*	I(0)	0.50*	no

Table 2. Continued

Group and relative prices	CIPS Test: H_0: I(1)[a]	I(1) or I(0)	Correlation Test[b]: H_0: Not correlated	Consistent Aggregation (Yes/No)
P (Starchy Vegetables)	-2.19	I(1)		
ρ_{corn}	-4.86*	I(0)	n/a	yes
$\rho_{potatoes}$	-4.24*	I(0)	n/a	yes
P (Other Vegetables)	-4.43*	I(0)		
ρ_{onions}	-4.33*	I(0)	-0.34*	no
$\rho_{lettuce\ (iceberg)}$	-4.23*	I(0)	-0.22*	no
ρ_{celery}	-4.34*	I(0)	-0.29*	no
$\rho_{cucumbers}$	-4.53*	I(0)	-0.20*	no
$\rho_{mushrooms}$	-2.28	I(1)	n/a	yes
$\rho_{cabbage}$	-4.87*	I(0)	0.03	yes
$\rho_{green\ beans}$	-4.24*	I(0)	0.32*	no
10% Critical Value	-2.53			

Notes: * denotes rejection of the null at the 0.10 significance level.

[a] Pesaran (2007)'s cross-sectionally augmented Im-Pesaran-Shin (CIPS) test regresses, for each unit m in the panel, the first difference on a constant, a time trend, the lagged level and its cross-sectional mean, the first difference of the cross-sectional mean and its lags, and the lagged first differences. The CIPS statistic is the cross-sectional average of the t-statistics on the lagged level. The null hypothesis is I(1) for all units. The `xtcips` command in Stata 14 was used to perform the CIPS test. The maximum number of lags included in the model is set to ten for each cross-section.

[b] Spearman's correlation coefficient which can take values from -1 to 1. The closer the test statistic is to zero, the weaker the association between the group price and the relative price. The `spearman` command in Stata 14 was used to perform the test.

Table 3a. Price Elasticities of Fruit Demand (Model 1, aggregation supported by panel GCCT tests)

		With respect to the price of														
			Melons		Other Fruits											
Elasticity of demand for		Berries	Watermelon	Cantaloupe	Grapefruit	Apples	Grapes	Lemons/Limes	Peaches	Avocado	Pears	Cherries	Tangerines	Oranges	Pineapple	Numeraire
	Berries	**-1.836**	0.001	-0.020	0.013	0.061	-0.046	-0.040	0.062	-0.005	0.016	0.121	-0.016	-0.009	-0.030	1.582
		(-30.910)	(-0.077)	(-1.682)	(2.734)	(-1.342)	(-1.216)	(-4.433)	(2.485)	(-0.436)	(0.723)	(3.868)	(-5.349)	(-0.511)	(-1.961)	(9.871)
Melons	Watermelon	0.004	**-1.678**	0.157	-0.022	-0.169	0.095	-0.057	-0.140	-0.005	-0.043	0.046	0.122	-0.062	-0.071	1.779
		(-0.076)	(-23.164)	(-6.019)	(-2.428)	(-2.250)	(1.661)	(-4.029)	(-3.352)	(-0.203)	(-3.568)	(0.717)	(2.673)	(-1.637)	(-2.539)	(5.585)
	Cantaloupe	-0.122	0.286	**-1.743**	0.045	-0.042	-0.048	-0.048	0.178	-0.022	0.023	0.164	0.230	0.021	-0.120	1.543
		(-1.672)	(-5.980)	(-33.256)	(2.856)	(-0.377)	(-0.709)	(-2.363)	(3.182)	(-0.662)	(0.833)	(3.542)	(4.097)	(0.362)	(-2.631)	(5.649)
Other Fruits	Grapefruit	0.200	-0.098	0.113	**-1.290**	0.109	0.026	-0.257	-0.304	0.037	0.328	-0.015	0.044	0.330	0.142	0.441
		(2.762)	(-2.373)	(2.855)	(-23.354)	(1.052)	(0.539)	(-4.737)	(-4.090)	(0.725)	(5.66)	(-0.091)	(0.739)	(5.607)	(2.622)	(2.399)
	Apples	0.051	-0.044	-0.006	0.006	**-0.497**	-0.025	-0.030	-0.034	-0.044	-0.003	-0.021	-0.008	0.048	0.003	0.651
		(-1.295)	(-2.197)	(-0.368)	(1.066)	(-9.983)	(-0.790)	(-3.223)	(-1.360)	(-3.210)	(-0.187)	(-0.820)	(-0.270)	(2.214)	(0.152)	(5.327)
	Grapes	-0.054	0.035	-0.009	0.002	-0.035	**-1.111**	-0.005	0.002	-0.009	0.008	0.125	-0.009	0.050	0.009	0.809
		(-1.196)	(1.687)	(-0.711)	(0.540)	(-0.811)	(-25.018)	(-0.707)	(0.072)	(-0.974)	(1.213)	(4.334)	(-0.240)	(3.124)	(0.772)	(4.811)
	Lemons/Limes	-0.220	-0.096	-0.044	-0.095	-0.194	-0.024	**-0.302**	-0.039	-0.101	-0.024	-0.022	-0.090	0.021	-0.093	1.142
		(-4.409)	(-4.117)	(-2.354)	(-4.778)	(-3.246)	(-0.706)	(-8.876)	(-0.907)	(-4.341)	(-0.85)	(-0.742)	(-2.545)	(0.699)	(-3.143)	(7.928)
	Peaches	0.233	-0.156	0.110	-0.075	-0.145	0.008	-0.026	**-1.650**	-0.105	0.055	-0.187	0.189	0.077	-0.013	1.723
		(2.523)	(-3.35)	(3.168)	(-4.091)	(-1.361)	(0.087)	(-0.899)	(-15.149)	(-2.961)	(2.087)	(-3.908)	(2.870)	(1.386)	(-0.337)	(6.387)
	Avocado	-0.017	-0.005	-0.014	0.009	-0.196	-0.027	-0.070	-0.108	**-0.946**	0.022	-0.082	0.057	-0.191	0.023	1.455
		(-0.404)	(-0.184)	(-0.656)	(0.728)	(-3.232)	(-0.957)	(-4.322)	(-2.997)	(-31.805)	(1.516)	(-2.930)	(1.326)	(-5.643)	(0.641)	(10.539)
	Pears	0.035	-0.077	0.023	0.129	-0.017	0.039	-0.025	0.086	0.035	**-1.511**	0.058	0.072	0.017	0.028	1.092
		(0.769)	(-3.569)	(0.839)	(5.68)	(-0.184)	(1.236)	(-0.844)	(2.101)	(1.521)	(-32.177)	(2.102)	(1.947)	(0.438)	(0.655)	(8.276)
	Cherries	0.508	0.059	0.114	-0.004	-0.104	0.443	-0.017	-0.213	-0.091	0.041	**-2.930**	0.104	0.128	0.076	1.529
		(3.929)	(0.717)	(3.568)	(-0.095)	(-0.844)	(4.172)	(-0.757)	(-3.972)	(-2.946)	(2.091)	(-18.241)	(1.423)	(2.472)	(1.960)	(3.236)
	Tangerines	-0.642	0.173	0.179	0.014	-0.044	-0.037	-0.077	0.240	0.070	0.057	0.116	**-1.932**	0.462	0.143	0.810
		(-5.205)	(2.694)	(3.984)	(0.732)	(-0.289)	(-0.255)	(-2.506)	(2.823)	(1.316)	(1.927)	(1.445)	(-13.373)	(6.479)	(3.145)	(1.891)
	Oranges	-0.028	-0.063	0.012	0.075	0.189	0.142	0.013	0.070	-0.171	0.009	0.104	0.335	**-1.066**	-0.069	0.212
		(-0.5)	(-1.615)	(0.366)	(5.627)	(2.193)	(3.098)	(0.696)	(1.369)	(-5.627)	(0.431)	(2.519)	(6.419)	(-21.803)	(-1.83)	(1.285)
	Pineapple	-0.117	-0.084	-0.077	0.037	0.014	0.031	-0.066	-0.014	0.023	0.019	0.070	0.119	-0.078	**-1.045**	1.049
		(-1.942)	(-2.562)	(-2.635)	(2.605)	(0.149)	(0.778)	(-3.135)	(-0.342)	(0.641)	(0.652)	(1.954)	(3.118)	(-1.832)	(-18.567)	(6.150)
	Numeraire	0.005	0.002	0.001	0.000	-0.002	0.000	0.000	0.001	0.001	0.000	0.001	0.000	-0.001	0.000	**-1.031**
		(6.953)	(4.837)	(3.605)	(-2.185)	(-2.607)	(-0.082)	(2.647)	(3.481)	(4.679)	(0.990)	(2.422)	(0.686)	(-3.588)	(1.119)	(-364.677)

Notes: Elasticities and t-values (in parentheses) calculated at sample mean. Own-price elasticities in bold font.

Table 3b. Price Elasticities of Vegetable Demand (Model 1, aggregation supported by panel GCCT tests)

Elasticity of demand for		With respect to the price of														
		Dark Greens		Red and Orange Vegetables					Other Vegetables							
		Broccoli	Lettuce (Romaine/ Leafy)	Tomatoes	Bell Peppers	Sweet Potatoes	Carrots	Starchy Vegetables	Onions	Lettuce (Iceberg)	Celery	Cucumbers	Mushrooms	Cabbage	Green Beans	Numeraire
Dark Greens	Broccoli	**-0.952**	0.078	0.141	0.013	-0.055	-0.089	-0.038	0.020	0.139	-0.038	0.046	0.203	-0.198	-0.024	0.650
		(-14.125)	(1.577)	(2.621)	(0.182)	(-1.086)	(-1.192)	(-0.525)	(0.487)	(3.852)	(-1.042)	(1.375)	(2.329)	(-6.555)	(-0.389)	(4.366)
	Lettuce (Romaine/ Leafy)	0.112	**-0.860**	0.055	0.004	-0.085	-0.106	-0.091	0.024	0.121	0.004	0.011	0.379	0.087	-0.048	-0.171
		(1.573)	(-14.290)	(0.851)	(-0.016)	(2.127)	(0.111)	(-1.619)	(0.629)	(3.300)	(0.011)	(0.268)	(3.927)	(2.279)	(-0.818)	(-0.968)
Red and Orange Vegetables	Tomatoes	0.036	0.010	**-0.368**	0.019	-0.012	-0.075	-0.107	-0.158	-0.043	0.009	0.007	-0.057	-0.007	0.019	0.563
		(2.623)	(0.863)	(-7.736)	(0.653)	(-0.429)	(-3.912)	(-2.660)	(-7.330)	(-3.612)	(0.370)	(0.459)	(-1.409)	(-0.882)	(1.098)	(4.497)
	Bell Peppers	0.011	0.002	0.061	**-0.957**	0.099	0.082	-0.107	-0.002	0.043	-0.030	0.003	0.471	0.089	-0.021	-0.025
		(0.176)	(-0.017)	(0.645)	(-12.81)	(2.093)	(1.797)	(-1.291)	(-0.116)	(1.555)	(-0.619)	(0.155)	(4.912)	(3.824)	(-0.583)	(-0.117)
	Sweet Potatoes	-0.106	-0.113	-0.092	0.233	**-2.742**	-0.080	0.462	0.371	0.042	-0.045	-0.059	0.176	0.134	-0.244	1.436
		(-1.089)	(2.139)	(-0.438)	(2.081)	(-22.976)	(-0.781)	(2.810)	(2.594)	(0.891)	(-0.480)	(-0.763)	(0.789)	(2.348)	(-3.205)	(3.727)
	Carrots	-0.075	0.003	-0.247	0.085	-0.035	**-1.155**	0.047	-0.038	-0.079	0.064	0.155	-0.044	-0.174	0.089	1.204
		(-1.195)	(0.113)	(-3.900)	(1.797)	(-0.779)	(-13.051)	(0.764)	(-0.796)	(-2.315)	(1.465)	(3.340)	(-0.302)	(-4.596)	(1.679)	(6.480)
	Starchy Vegetables	-0.005	-0.007	-0.051	-0.016	0.029	0.007	**-0.801**	-0.025	0.016	0.013	-0.004	0.033	0.005	0.000	0.655
		(-0.553)	(-1.614)	(-2.685)	(-1.29)	(2.868)	(0.753)	(-21.188)	(-1.426)	(-3.831)	(2.224)	(-0.413)	(1.722)	(1.537)	(0.012)	(5.322)
Other Vegetables	Onions	0.013	0.011	-0.409	-0.002	0.127	-0.029	-0.137	**-0.330**	-0.028	-0.016	-0.006	0.012	0.031	-0.017	0.574
		(0.480)	(0.633)	(-7.450)	(-0.115)	(2.598)	(-0.797)	(-1.420)	(-4.667)	(-1.334)	(-0.590)	(-0.329)	(0.238)	(1.987)	(-0.647)	(2.503)
	Lettuce (Iceberg)	0.200	0.120	-0.245	0.076	0.032	-0.135	0.188	-0.061	**-0.399**	0.060	0.003	-0.075	0.044	-0.055	0.330
		(3.840)	(3.313)	(-3.636)	(1.557)	(0.896)	(-2.315)	(-3.841)	(-1.338)	(-10.368)	(2.091)	(0.122)	(-0.876)	(1.324)	(-1.087)	(2.197)
	Celery	-0.066	0.004	0.059	-0.063	-0.040	0.133	0.185	-0.041	0.072	**-0.540**	-0.146	-0.056	-0.012	0.047	0.221
		(-1.047)	(0.012)	(0.366)	(-0.618)	(-0.477)	(1.463)	(2.216)	(-0.598)	(2.085)	(-7.565)	(-1.733)	(-0.322)	(-0.342)	(0.623)	(0.834)
	Cucumbers	0.067	0.011	0.039	0.005	-0.045	0.268	-0.046	-0.013	0.003	-0.123	**-0.657**	0.491	0.046	-0.175	-0.197
		(1.369)	(0.270)	(0.450)	(0.154)	(-0.765)	(3.330)	(-0.428)	(-0.331)	(0.121)	(-1.731)	(-8.055)	(3.816)	(1.083)	(-2.831)	(-1.042)
	Mushrooms	0.065	0.084	-0.070	0.185	0.029	-0.017	0.091	0.006	-0.016	-0.010	0.107	**-0.897**	0.070	-0.021	0.294
		(2.329)	(3.904)	(-1.398)	(4.974)	(0.791)	(-0.298)	(1.760)	(0.248)	(-0.864)	(-0.321)	(3.836)	(-9.346)	(3.946)	(-0.735)	(1.632)
	Cabbage	-0.531	0.161	-0.068	0.291	0.186	-0.553	0.112	0.126	0.082	-0.019	0.084	0.587	**-1.527**	0.212	0.773
		(-6.540)	(2.285)	(-0.876)	(3.817)	(2.353)	(-4.609)	(1.571)	(1.986)	(1.326)	(-0.341)	(1.082)	(3.932)	(-18.295)	(2.614)	(4.037)
	Green Beans	-0.026	-0.036	0.082	-0.027	-0.138	0.116	0.004	-0.028	-0.042	0.030	-0.131	-0.073	0.087	**-1.393**	1.547
		(-0.389)	(-0.809)	(1.110)	(-0.572)	(-3.200)	(1.686)	(0.071)	(-0.639)	(-1.081)	(0.626)	(-2.810)	(-0.731)	(2.624)	(-18.503)	(11.325)
	Numeraire	0.000	-0.001	-0.002	-0.002	0.001	0.001	-0.001	-0.001	0.000	-0.001	-0.001	-0.003	0.000	0.001	**-1.024**
		(-1.931)	(-5.939)	(-2.599)	(-4.209)	(2.417)	(2.429)	(-1.095)	(-1.324)	(-2.822)	(-2.743)	(-4.886)	(-4.294)	(-0.797)	(5.119)	(-258.136)

Notes: Elasticities and t-values (in parentheses) calculated at sample mean. Own-price elasticities in bold font.

Table 4a Benchmark Fruit Group Demand Elasticities Derived from Model 1 Estimates

	With respect to the price of			
Elasticity of group demand for	Berries	Melons	Other Fruits	Numeraire
Berries	**-1.836**	-0.019	0.125	1.582
Melons	-0.021	**-1.504**	-0.168	1.731
Other Fruits	0.035	-0.013	**-1.007**	0.900
Numeraire	0.005	0.002	0.001	**-1.031**

Notes: The group demand elasticities are simulated by changing individual fruit prices in Model 1 by the same percentage at the sample mean. Own-price elasticities in bold font.

Table 4b Benchmark Vegetable Group Demand Elasticities Derived from Model 1 Estimates

	With respect to the price of				
Elasticity of group demand for	Dark-Green Vegetables	Red and Orange Vegetables	Starchy Vegetables	Other Vegetables	Numeraire
Dark-Green Vegetables	**-0.773**	-0.104	-0.080	0.492	-0.006
Red and Orange Vegetables	-0.032	**-0.470**	-0.012	-0.019	0.717
Starchy Vegetables	-0.012	-0.031	**-0.801**	0.038	0.655
Other Vegetables	0.081	-0.076	0.022	**-0.502**	0.579
Numeraire	-0.001	-0.002	-0.001	-0.005	**-1.024**

Notes: The group demand elasticities are simulated by changing individual vegetable prices in Model 1 by the same percentage at the sample mean. Own-price elasticities in bold font.

Table 5a Price Elasticities of Fruit Group Demand

	With respect to the price of			
Elasticity of group demand for	Berries	Melons	Other Fruits	Numeraire
	Model 2 (aggregation rejected)			
Berries	**-1.778**	0.072	-0.047	1.356
	(-47.151)	(3.079)	(-0.702)	(13.472)
Melons	0.152	**-1.674**	0.083	1.133
	(3.092)	(-37.489)	(0.726)	(6.756)
Other Fruits	-0.011	0.010	**-0.980**	0.819
	(-0.633)	(0.750)	(-20.612)	(12.539)
Numeraire	0.004	0.001	0.000	**-1.027**
	(8.603)	(2.991)	(-0.227)	(-548.108)
	Model 3 (relative prices used as control variables)			
Berries	**-1.703**	0.062	-0.047	1.317
	(-35.868)	(2.400)	(-0.614)	(11.407)
Melons	0.129	**-1.613**	0.075	1.092
	(2.409)	(-28.135)	(0.641)	(5.755)
Other Fruits	-0.011	0.010	**-1.017**	0.871
	(-0.557)	(0.674)	(-18.006)	(12.385)
Numeraire	0.004	0.001	0.000	**-1.028**
	(6.359)	(2.494)	(0.244)	(-501.682)
	Model 4 (residual-based instruments)			
Berries	**-1.573**	0.062	0.197	0.899
	(-45.933)	(2.642)	(2.847)	(8.950)
Melons	0.130	**-1.493**	-0.160	1.229
	(2.658)	(-33.813)	(-1.209)	(7.209)
Other Fruits	0.052	-0.019	**-0.972**	0.784
	(2.921)	(-1.184)	(-17.449)	(11.093)
Numeraire	0.002	0.001	-0.001	**-1.024**
	(3.617)	(3.532)	(-0.847)	(-525.866)

Notes: Elasticities and t-values (in parentheses) calculated at sample mean. Own-price elasticities in bold font.

Table 5b Price Elasticities of Vegetable Group Demand

	With respect to the price of				
Elasticity of group demand for	Dark-Green Vegetables	Red and Orange Vegetables	Starchy Vegetables	Other Vegetables	Numeraire
	Model 2 (aggregation rejected)				
Dark-Green Vegetables	**-0.812**	0.072	-0.054	0.289	0.328
	(-20.662)	(1.861)	(-1.714)	(4.768)	(3.844)
Red and Orange Vegetables	0.017	**-0.521**	-0.047	-0.203	0.533
	(1.845)	(-14.574)	(-1.695)	(-5.775)	(7.932)
Starchy Vegetables	-0.011	-0.039	**-0.857**	-0.062	0.723
	(-1.751)	(-1.712)	(-28.182)	(-2.588)	(9.692)
Other Vegetables	0.062	-0.177	-0.064	**-0.258**	0.286
	(4.776)	(-5.738)	(-2.533)	(-5.38)	(4.077)
Numeraire	-0.001	-0.003	0.000	-0.008	**-1.021**
	(-6.885)	(-4.145)	(-0.660)	(-9.563)	(-416.958)
	Model 3 (relative prices used as control variables)				
Dark-Green Vegetables	**-0.772**	-0.132	-0.075	0.331	0.517
	(-15.196)	(-2.22)	(-2.148)	(4.268)	(6.046)
Red and Orange Vegetables	-0.033	**-0.544**	-0.059	-0.144	0.601
	(-2.231)	(-10.102)	(-2.09)	(-3.992)	(6.621)
Starchy Vegetables	-0.016	-0.049	**-0.844**	-0.021	0.692
	(-2.193)	(-2.119)	(-24.246)	(-1.178)	(8.109)
Other Vegetables	0.071	-0.125	-0.021	**-0.491**	0.411
	(4.271)	(-3.987)	(-1.13)	(-9.099)	(5.268)
Numeraire	-0.001	-0.003	-0.001	-0.006	**-1.024**
	(-4.224)	(-3.018)	(-0.889)	(-6.105)	(-347.559)
	Model 4 (residual-based instruments)				
Dark-Green Vegetables	**-0.786**	-0.113	-0.043	0.441	0.333
	(-19.811)	(-1.810)	(-1.242)	(6.354)	(3.161)
Red and Orange Vegetables	-0.028	**-0.466**	0.018	-0.046	0.284
	(-1.819)	(-8.164)	(0.851)	(-0.905)	(3.292)
Starchy Vegetables	-0.009	0.014	**-0.782**	0.081	0.435
	(-1.284)	(0.840)	(-21.730)	(2.796)	(4.789)
Other Vegetables	0.095	-0.039	0.087	**-0.515**	0.206
	(6.351)	(-0.889)	(2.836)	(-8.491)	(2.448)
Numeraire	-0.001	-0.006	-0.004	-0.008	**-1.013**
	(-5.405)	(-5.910)	(-4.413)	(-8.228)	(-344.672)

Notes: Elasticities and t-values (in parentheses) calculated at sample mean. Own-price elasticities in bold font.

Table 6 Elasticity Differences between Each Aggregate Demand and the Benchmark

	Average absolute difference						Percent improvement over Model 2			
	Model 2 (a)		Model 3 (b)		Model 4 (c)		Model 3 1-(b)/(a)		Model 4 1-(c)/(a)	
Elasticity	Fruit	Veg	Fruit	Veg	Fruit	Veg	Fruit	Veg	Fruit	Veg
Own-Price										
Unweighted	0.09	0.10	0.08	0.03	0.10	0.01	11%	70%	-11%	90%
weighted[a]	0.09	0.11	0.06	0.03	0.03	0.01	33%	73%	67%	91%
Cross-Price										
Unweighted	0.13	0.08	0.12	0.05	0.06	0.03	8%	38%	54%	63%
weighted[a]	0.11	0.07	0.11	0.04	0.04	0.03	0%	43%	64%	57%

Notes: The group demand elasticities derived from Model 1 estimates are set as the benchmark. The comparisons exclude all numeraire demand and price elasticities. [a]Purchase quantities used as weights.

Table 7 Euclidean Norm between Each Aggregate Demand and the Benchmark

	Distance to Benchmark Elasticity Matrix					
	Model 2 (a)		Model 3 (b)		Model 4 (c)	
	Fruit	Veg	Fruit	Veg	Fruit	Veg
Euclidean Norm	0.408	0.453	0.380	0.245	0.325	0.127

Notes: The group demand elasticities derived from Model 1 estimates are set as the benchmark. The comparisons exclude all numeraire demand and price elasticities.

CHAPTER 2

THE IMPLICATIONS OF HETEROGENEOUS HABIT IN CONSUMER BEVERAGE PURCHASES ON SODA AND SIN TAXES

1. Introduction

There are numerous studies that analyze consumer responses and welfare effects due to government policies related to products with habit effects. This type of research is specifically targeted at unhealthy and habit-forming products, such as sugary beverages, junk food, alcohol, and tobacco, etc. (Andreyeva et al., 2010; Goryakin et al., 2017; Härkänen et al., 2014; Lin et al., 2017; Pacula, 1998).The models employed to study such policies consider price and income as the main determinants of consumption. A general question is whether increasing the cost would, in fact, decrease the consumption of unhealthy products and break consumers' original habits, thus improving health outcomes. To answer such questions, a common practice is to estimate an econometric model for consumer demand under habit formation. Then, the associated economic impact under different tax or subsidy policies is simulated with the estimated model to assess such policies (Duffy, 2003; Haden, 1990; Herzfeld et al., 2014; Zhen et al., 2014, 2011; Zheng et al., 2017).

Over decades, demand models have evolved to better describe people's behavior as well as to be consistent with economic theory. Models have been greatly improved by considering nonlinear income effects, endogeneity, dynamics, and censoring, etc. But one strict econometric assumption, homogeneity, has rarely been relaxed. Andreyeva et al. (2010) reviews all US-based studies on the price elasticities of demand for major food categories. Most of these studies obtain price elasticity estimates from traditional homogeneous models. By assuming all consumers react equally to changes, such models might yield biased estimates of aggregate responses if heterogeneous responses are not symmetrically distributed. Moreover, intuition tells us there exists extreme variation in preference over specific goods, such as tobacco, alcohol, and sweetened beverages, which severely undermines the assumption of homogeneous responses. In the last decade, incorporating consumer heterogeneity in demand models has received increasing attention. The most prominent examples are Bertail and Caillavet (2008) and Wang (2015). Bertail and Caillavet (2008) studied the heterogeneity of fruit and vegetable consumption patterns in France. A finite mixture of AIDS models is used to describe food demand patterns revealing different preferences. Six different clusters which reflect specific socio-demographic characteristics and different income and price elasticities are obtained. Wang (2015) provides estimates of the relevant price elasticities based on a random coefficient dynamic demand model that addresses unobservable persistent heterogeneous tastes. It is found that traditional static analyses tend to overestimate the long-run own-price elasticity of regular soda by 60.8%, leading to an overestimated consumption reduction of sugar-sweetened soft drinks of up to 57.9%.

As exploring the role of heterogeneity in explaining household demand is important especially from marketing and policy perspectives, and to extend earlier research in incorporating heterogeneity in demand estimation, this paper takes an innovative approach that combines a Panel Smooth Transition Regression (PSTR) model (González et al., 2017) with an ECON transition function (Hood and Dorfman, 2015) to investigate the demand for regular carbonated sweetened beverages (CSBs) and beer. Specifically, our research seeks to determine the extent to which heterogeneous habit strength characterizes households' heterogeneous responses to price or income changes. At the final stage, an assessment of the potential effects of soda and beer taxes is implemented. Our policy simulation finds that households with more habit-based consumption are more insensitive to price or income changes. Since a higher habit level is significantly associated with higher consumption on CSBs and beer,[7] the overall effects of a sin tax would be highly over-estimated if heterogeneous consumer responses are not considered. Specifically, the forecast aggregate declines in soda and beer consumption due to a one-cent per ounce tax increase are found to be 20% and 26% larger, respectively, with homogeneous habit strength than with a model incorporating heterogeneity in habit strength. Because the top 10% of consumers in habit strength account for 18% and 23% of total consumption for CSBs and beer, respectively, it is important to account for their differential behavior in optimal policy design. Public health gains would come more from reductions in consumption from heavy users than occasional drinkers; thus, the tax rates may need to be raised further or alternative policies should be targeted at the more habitual and high-consumption consumers in order to meet public health goals.

In this paper, we make three major contributions to the empirical literature on demand analysis. First and foremost, this study contributes to the existing literature by introducing a new approach to relaxing the homogeneity assumption in demand estimation with habit effects. The proposed model allows continually varying household price/income elasticities as habit strength varies across households. The model can be easily extended to include other exogenous variables representing household heterogeneity and can also be applied to more sophisticated demand systems. Second, habit is generally explained as a repeated behavior pattern. The underlying hypothesis is that current consumption of one product is substantially affected by consumption of

[7] Pearson's correlation coefficient, ρ, between mean habit strength (see equation 1) and mean consumption by household are calculated for CSBs and beer: $\rho_{CSBs} = 0.53$ (p-value < 0.0001); $\rho_{beer} = 0.51$ (p-value < 0.0001).

the same product in the previous period. Lagged purchases are usually included in demand models to demonstrate habits. An issue of this approach is that lagged response variables could suppress the explanatory power of other explanatory variables. Consequently, it may become difficult to identify the relationship between quantity and each explanatory variable independently because lagged purchase and other independent variables tend to change in unison. Moreover, the inference of price and income elasticities will be less precise, which weakens the statistical power of the model and the results of policy evaluation. This can be solved by including a smooth transition function of past purchases in the demand model, as we do here. Third, we introduce variance as a co-measurement of habit. Habitual consumption behavior refers to situations where a consumer's demand for a bundle of goods reveals very few differences across periods. Those loyal or even addicted consumers show different economic behavior than "normal" consumers and are more important in policy analysis due to their higher levels of consumption. A common practice in previous literature was to use only the sum of purchases in past periods, which does not take variation in past purchases into account when measuring habit. Occasional large purchases do not reflect a household buying for its own consumption the same as steady, consistent purchases. In previous models, both kinds of consumption might be classified equally as habitual behavior. Given this consideration, our variable of habit strength for a household is defined as the sum of consumption in the last eight quarters divided by the standard deviation of quarterly purchases. Thus, a large standard deviation due to inconsistent consumption behavior will lead to a lower habit strength. Incorporating variation in transition variables helps better measure customers' habitual behavior and allows us to better characterize individual policy responses, leading to better estimates of the aggregate response. Moreover, with each household's habit strength and demographics available, we are able to find the common characteristics of the habitual household thus helping with better targeted policies.

The outline of the paper is as follows. We lay out our research design and data description in Section 2 and 3, followed by the empirical demonstration in Section 4 that applies the heterogeneous habit model to both regular CSBs and beer in the United States, finding strong evidence for heterogeneity in both price and income elasticities across households. Finally, some policy implications and conclusions are provided.

2. Empirical Strategy

To examine the household's heterogeneous responses to price or income changes, this paper extends previous literature by proposing an ECON-PSTR model combined with simple demand functions to model habit strength that is heterogeneous across households.

Habit Strength

Numerous studies have incorporated habit in demand models. It is well recognized among economists that demand in one period may depend on demand decisions in other periods (Becker and Murphy, 1988; Boyer, 1983). The literature has provided evidence of habit in not only addictive goods such as tobacco and alcohol but also non-addictive consumer goods (Arnade et al., 2008; Fuhrer, 2000; Heien and Durham, 1991; Holt and Goodwin, 1997). Particularly relevant here, Zhen et al. (2011) found the presence of habit in demand for nine categories of non-alcoholic beverages.

Different than the common practice in previous literature that habit is measured by purchases in past periods, we proposed a new index for habit strength, s_{ijt}, defined as:

(1) $s_{ijt} = \frac{(\sum_{d=1}^{8} Q_{ijt-d})}{v_{ij}}$

where Q_{ijt} is the consumption of product *j* in quarter *t* for household *i* and ν_{ij} is the standard deviation of $\left(Q_{ijt-1}, Q_{ijt-2}, \ldots, Q_{ijt-8}\right)$. Accordingly, habitual behavior is indexed by the sum of quarterly consumptions in the last two years over the standard deviation of those eight lagged values. Both quantity and variation are incorporated to depict past consumption behavior such that habit strength is strictly increasing in past consumption but is decreasing in consumption volatility. Given the same aggregate consumption in the past two years, a household with a more consistent purchasing pattern is considered to have greater habit strength in our model than a household with a volatile purchasing history. This formulation of habit strength is inspired by careful inspection of the data which reveals occasional spikes in household CSB consumption leading to large aggregate consumption that may, in fact, may be caused by activities such as parties where CSBs were not necessarily consumed by the household alone. Including volatility of past consumption in our habit measure attempts to capture this feature of the data and more accurately measure true habitual consumption.

For each consumer, we calculate the mean habit strength over the sample period and plot histograms for CSBs and beer consumers, shown in Figure 1 and Figure 2. Both histograms show a highly right-skewed pattern, due to extremely high habit strength in a small minority of consumers with consistent and large purchases over the sample period.

ECON-PSTR Model Specification

Economists have increased their interest in the modeling of heterogeneity by such methods as latent class models and clustering analysis (Baker and Burnham, 2001; Bertail and Caillavet, 2008; Kikulwe et al., 2011; Ortega et al., 2011). These approaches can work well, but they reduce the modeling of heterogeneity down to a set of discrete values or groups. In contrast, we essentially create an infinite number of latent classes to represent the range of possible strengths of habit in beverage demand by using a demand model that nests a smooth transition function. Each household is treated differently based on the value of an index variable that summarizes the strength of habit in their household beverage purchasing decisions.

The Smooth Transition Regression (STR) model, initially developed by Bacon and Watts (1971), can be seen as a generalized regime switching model in such a way that the transition from one extreme regime to the other is not discrete, but smooth, with a function of the continuous transition variable. The PSTR model is a newly developed type of STR model in the first version of González et al. (2017) and Fok et al. (2005). Since its first appearance in 2005, the PSTR model has been applied to a wide variety of statistical and economic studies (e.g. Cheng and Wu, 2013; Delatte et al., 2012; Espinoza et al., 2012; Fok et al., 2005; Geng, 2011; Omay et al., 2018; Seleteng et al., 2013). In this paper, to estimate the impact of food tax policies on consumption, we use the PSTR approach to model continuous habit regimes, thus introducing heterogeneity in habit strength to demand studies. The PSTR model in this paper has a structure similar to Lundbergh et al. (2003), but is modified in a panel setting. The model is specified as follows:

(2) $lnQ_{ijt} = \mu_i + \lambda_t + f\left(x, \theta^{(1)}\right)\left[1 - G\left(s_{ijt}, c_{jt}, \sigma_{jt}; \gamma\right)\right] + f\left(x, \theta^{(2)}\right)G\left(s_{ijt}, c_{jt}, \sigma_{jt}; \gamma\right) + \varepsilon_{ijt}$

where μ_i represent individual household fixed effects and λ_t represents quarter and year fixed effects, respectively, ε_{ijt} are the errors, lnQ_{ijt} is the natural logarithm of demand for product j at time t of household i, G is a smooth transition function, x is a vector of intercept and regressors including, prices, expenditures, and social demographics, θ is a vector of coefficients, and $f\left(x, \theta^{(k)}\right)$ is the demand equation for regular CSBs or beer. Making things concrete, in the application that follows,

(3) $f\left(x, \theta^{(k)}\right) = x'\theta^{(k)} = \theta_1^{(k)} + \theta_2^{(k)} lnP_{jt} + \theta_3^{(k)} lnY_{it} + \theta_4^{(k)} Gender_i + \sum_{h=1}^{3} \theta_{5,h}^{(k)} Race_{hi} + \theta_6^{(k)} Edu_i + \theta_7^{(k)} Chd_{it}, \quad k = 1,2$

where lnP_{jt} is the Törnqvist panel price index of product *j* at time *t*, $lnY_{i,t}$ is the natural logarithm of expenditure of household i at time t, $Gender_i$ is coded as 1 if the household head is male and zero otherwise, the $Race_{hi}$ are a set of binary indicators for the race of the household head (h =1 for white, h = 2 for black, and h = 3 for Hispanic) with other races (Asian, American Indian, multiracial Americans, etc.) as the reference group. Edu_i is an indicator for the household head having at least a college degree, and $CHD_{i,t}$ is an indicator for household *i* having at least one child at time *t*.

The $f\left(x, \theta^{(1)}\right)$ and $f\left(x, \theta^{(2)}\right)$ are demand functions in two extreme regimes. Regime One represents the households who do not consume product *i* based on habit at all, implemented through the vector of parameters $\theta^{(1)}$, whereas, Regime Two represents households who have a strong habit of consistently consuming product *i* or are even addicted to it, expressed through a vector of parameters $\theta^{(2)}$. Most consumers behave consistent with some state in between the two extremes, with an infinite number of such regimes lying on that continuum and their location on the continuum expressed by the value of *G*. If consumers overall display little heterogeneity in the strength of their habits they will show similar responses to price or income changes; that is, the parameter vectors $\theta^{(1)}$ and $\theta^{(2)}$ will be similar. In this case, estimation results will be similar to those of a standard regression without a transition function.

Among numerous variations of the transition function *G*, the logistic STAR (LSTAR) model and the exponential STAR (ESTAR) model are the most commonly used. The transition function employed in this paper follows the ECON-STAR model (Hood and Dorfman, 2015), which is a variant of ESTAR model. In the ECON-STAR model, the transition function takes the form

(4) $G(s_t, v_t; \gamma, c, d) = 1 - exp\left\{-\gamma\left[\left(\frac{s_t - c}{\sigma_s}\right)\left(\frac{v_t - d}{\sigma_v}\right)\right]\right\}$

where the speed-of-adjustment parameter $\gamma > 0$ is required, s_t and v_t are transition variables (such as rolling averages of past values of an economic indicator) in two adjacent regions, c and d are the minimum transition variable values over time for each location thus ensuring $(s_t - c)$ and $(v_t - d)$ are non-negative. Also, $(s_t - c)$ and $(v_t - d)$ are normalized by their standard deviations, σ_s and σ_v, respectively. With this specification, the value of the $\mathrm{G}(\cdot)$ function will be zero at least once when $s_t = c$ or $v_t = d$.

In this paper, we generalize the transition function into a panel setting and offer modest improvements. The function $G(s_{ijt}, c_{jt}, \sigma_{jt}; \gamma)$ is a continuous and smooth function of s_{ijt}, c_{jt} and σ_{jt}, taking the form:

(5) $G(s_{ijt}, c_{jt}, \sigma_{jt}; \gamma) = 1 - exp\left\{-\gamma\left[\Phi\left(\frac{s_{ijt} - c_{jt}}{\sigma_{jt}}\right)\right]\right\}$

where $\gamma > 0$ is required, s_{ijt} is the habit strength as defined in Equation (1), c_{jt} is the mean value of s_{ijt} across households, and σ_{jt} is the standard deviation of s_{ijt}, $s_{ijt} - c_{jt}$ is normalized by σ_{jt} to make the speed-of-adjustment parameter γ unit free, and $\Phi(\cdot)$ is the cumulative density function (cdf) of the standard normal distribution. Embedding the term $\frac{s_{ijt} - c_{jt}}{\sigma_{jt}}$ in the cdf of the standard normal distribution gives an almost linear shape for values of s_{ijt} within 2 standard deviations about zero but has flatter tails as the value of s_{ijt} goes to extremes when compared with the linear term $\frac{s_t - c}{\sigma_s}$ in Equation (4). This property enables coefficient estimates to be less influenced by extreme values of s_{ijt}, thus yielding more robust coefficient estimates. In addition,

$\Phi\left(\frac{s_{ijt}-c_{jt}}{\sigma_{jt}}\right)$ also satisfies the positivity requirement thus keeping the value of transition function bounded between 0 and 1 when combined with the imposed restriction of $\gamma > 0$.

The Estimation of a PSTR model

The estimation of the PSTR model is accomplished by a two-step procedure (González et al., 2017). The first step is eliminating fixed effects (μ_i and λ_t) by subtracting the individual- and time-specific means on both sides of the equation. The second step is to estimate the model with the transformed data by nonlinear least squares (NLS). To simplify algebra and without loss of generality, we define a PSTR demand model with only one product for household i at time t:

(6) $lnQ_{it} = \mu_i + \lambda_t + x_{it}'\theta^{(1)}G(z_{it};\gamma) + x_{it}'\theta^{(2)}[1 - G(z_{it};\gamma)] + \varepsilon_{it}$

where $z_{it} = \frac{s_{it}-c_t}{\sigma_t}$. First, we subtracted the mean for each household over time and the mean for each time period across all households from the dependent variable and the residuals to construct centered variables, ${Q_{it}}^c$ and ${\varepsilon_{it}}^c$:

(7) ${Q_{it}}^c = lnQ_{it} - \overline{lnQ_\iota} - \overline{lnQ_t}$

(8) ${\varepsilon_{it}}^c = \varepsilon_{it} - \overline{\varepsilon_\iota} - \overline{\varepsilon_t}$

where $\overline{lnQ_\iota} = \frac{1}{T_i}\sum_{t=1}^{T_i} lnQ_{it}$, $\overline{lnQ_t} = \frac{1}{N_t}\sum_{i=1}^{N_t} lnQ_{it}$, $\overline{\varepsilon_\iota} = \frac{1}{T_i}\sum_{t=1}^{T_i} \varepsilon_{it}$, $\overline{\varepsilon_t} = \frac{1}{N_t}\sum_{i=1}^{N_t} \varepsilon_{it}$, T_i is the number of time periods that household i was observed in the panel, and N_t is the number of households observed at time t. For the terms $x_{it}'G(z_{it};\gamma)$ and $x_{it}'[1 - G(z_{it};\gamma)]$, we make the following transformations:

(9) ${A_{it}}^c(z_{it};\gamma) = x_{it}'G(z_{it};\gamma) - \overline{A_\iota}' - \overline{A_t}'$

(10) ${B_{it}}^c(z_{it};\gamma) = x_{it}'[1 - G(z_{it};\gamma)] - \overline{B_\iota}' - \overline{B_t}'$

where $\overline{A_\iota} = \frac{1}{T_i}\sum_{t=1}^{T_i} x_{it}G(z_{it};\gamma)$, $\overline{A_t} = \frac{1}{N_t}\sum_{i=1}^{N_t} x_{it}G(z_{it};\gamma)$, $\overline{B_\iota} = \frac{1}{T_i}\sum_{t=1}^{T_i} x_{it}\,[1 - G(z_{it};\gamma)]$, and

$\overline{B_t} = \frac{1}{N_t}\sum_{i=1}^{N_t} x_{it}[1 - G(z_{it};\gamma)]$. Therefore, each row of the new centered design matrix becomes

${x_{it}}^c(z_{it};\gamma)' = [{A_{it}}^c(z_{it};\gamma)'; {B_{it}}^c(z_{it};\gamma)']$.

After eliminating fixed effects by data transformation, we can apply nonlinear least squares (NLS) to estimate the coefficients that minimize the concentrated sum of squared errors:

(11) $$SSE^c(\gamma) = \sum_{i=1}^{N}\sum_{t=1}^{T}\left[{Q_{it}}^c - {x_{it}}^c(z_{it};\gamma)'\hat{\theta}(\gamma)\right]^2$$

where $\hat{\theta}(\gamma)$ is obtained by ordinary least squares (OLS) at each iteration in the non-linear optimization and is strongly dependent on the quality of initial values. A grid search for the parameter γ in the transition function $G(z_{it};\gamma)$ is applied to obtain the starting value of γ.[8]

3. Data

Data Description

Our primary source of data is the Nielsen Homescan household panel for the years 2008 to 2015. More than 100,000 households across the U.S. record information on shopping trips and purchased items using an optical scanner on a weekly basis over a period of at least a year. Every recorded transaction contains information including the Universal Product Code (UPC), quantity, price paid, size, single or multipack, and brand. The Nielsen Homescan data is available to academic researchers through a partnership between Nielsen and USDA-Economic Research Service (ERS). The biggest advantage of the Homescan panel data set is that the sample is nationally representative. The participating households reside in fifty-two Nielsen markets and nine remaining areas in the United States. Household survey weights provided by Nielsen can be

[8] The Model and NLIN procedures in SAS 9.4 are used for model estimation. For future researchers who are interested in applying PSTR models, an R package (PSTR) written by Y. Yang provides a useful tool for model setup, estimation, and evaluation.

used to create national estimates of household purchases. Further, the Homescan dataset includes almost all U.S. retailers including mass merchants such as Walmart.

To analyze heterogeneous demand responsiveness, we focus on CSBs and beer products. CSBs is one of the four categories included in Sugary-sweetened beverages (SSBs), which is a common target of soda tax policies. The other three categories are regular non-diet fruit juices, non-diet sports and energy drinks, and all other SSBs. Among the four categories of SSBs, regular CSBs are the most prevalent SSB type across all years for all age groups except children (for whom fruit drinks were the most prevalent in 1999 and 2005) (Han and Powell, 2013). We choose only CSBs as our research subject since it is the most representative group and analyzing the effect of soda tax on the full categories of SSBs would generally involve product aggregation or estimation of a system of demand equations, which is out of the research scope of this paper.

We apply the following screens to ensure the data used consist only of households who consistently recorded their purchasing sometime between 2008 and 2015. Households who fail to satisfy any of the following criteria are excluded from the dataset:

(i) Each household must be on the panel for at least nine quarters since we track household habits based on two years of purchasing history.

(ii) Each household must have at least one shopping trip per quarter. A quarter is considered long enough to identify that the household has stopped recording its purchases.

(iii) The consumption of regular CSBs or beer by the household must be positive for at least one quarter because the target population in our study is CSBs or beer consumers.

We also deleted observations with abnormally large or small prices. Specifically, we deleted transactions in which unit price for a specific product was more than five times or less than one-fifth of the sample mean price.

Summary Statistics

Table 8 summarizes the demographics of the households of different habit strength levels. For each product, CSBs and beer, the households are classified into four groups, with Group 1 representing the quartile of households with the greatest habit strength, that is, the most habitual households, Group 2 representing the second most habitual households, and so on.

For CSBs, the most habitual consumers are associated with a smaller household size, a lower annual household income, a higher probability of having a male and white household head without college degree, and a higher probability of having one or more children, on average, than other consumers. We do not find a significant difference in mean household size between any two of Group 1, 2, and 3. However, mean household size of Group 4 is significantly larger than each of Group 1 to 3, although the largest difference is only 0.14, indicating the least habitual households are associated with a slightly larger household size on average. Similarly, significant differences in mean income are found only between Group 1 and 3, and between Group 1 and 4, with the most habitual households associated with the lowest mean income in the sample. The most habitual households are more likely to have a male household head than any of the other groups, and the least habitual households are less likely to have a male household head than any of the other groups. A more habitual household is associated with a higher probability of having a white household head, hence a lower probability of having a non-white household head and is also associated with a higher probability of having at least one child. Last but not least, the heads of the most habitual households are found to be least likely to hold a college degree or higher while the heads of the least habitual households are the most likely to have a college or higher degree.

Similarly, for beer, the most habitual consumers are associated with a smaller household size, lower annual household income, a higher probability of having a male and white household head without college degree, and a lower probability of having one or more children, on average, than the other consumers. Specifically, statistically significant differences in mean household size are found between Group 1 and each of Group 2 to 4, although the largest difference is only 0.2, indicating the most habitual households are associated with a slightly smaller household size on average. The mean annual household income of Group 1 is found to be the lowest among the four groups. As with CSBs consumers, the most habitual households are found to be the most likely to have a male household and the least habitual households are the least likely to have a male household head among all the groups. Also, Group 1 is associated with the highest probability of having a white household head, and Group 4 with the least. Moreover, more habitual households are found to have a lower probability of having at least one child, and a lower probability of holding a college degree or higher.

Price Index

To reduce the unit value bias (Cox and Wohlgenant, 1986; Deaton, 1988), we created a quarterly superlative Törnqvist price index for product *j* for each state. Let an entity be a unique combination of location and time. For example, the same location (e.g., a county) in period t and period $t + 1$ is considered as two distinct entities in index formulas. The Törnqvist price index is defined as

(6) $p_T^{0k} = exp\{0.5 \sum_{v \in 0k}(s_v^0 + s_v^k) \ln(p_v^k / p_v^0)\}$

where p_v^k is the is the price of product *v* in entity *k*; p_v^0 and q_v^0 are the base price and quantity of product *v*, respectively; v_{0k} demotes the common set of items sold in both base *0* and entity *k*, and s_v^0 and s_v^k are budget shares of product *v* in base *0* and entity *k*.

4. Empirical Results

This section presents demand estimation for regular CSBs and beer, respectively, with both homogeneous and heterogeneous habit strength, followed by a simulation of demand change when soda and beer taxes are imposed. We assess a sin tax effect because taxes on energy-dense, low-nutrient foods such as sugar-sweetened beverages (SSBs) is the most commonly proposed anti-obesity policy (Cawley, 2015). From the policy maker's perspective, the stated goal of the soda tax is to reduce consumption of these beverages, stem the obesity epidemic, fund health-related initiatives, and raise much-needed revenue to offset a large state budget deficit (New York State Department of Health, 2010).

Carbonated Sweetened Beverages

First, the linear demand model in equation (3) is estimated for regular CSBs. As shown in Table 9, the coefficient on lnP_{jt}, β_1, is estimated to be -1.055 and statistically significant, indicating that a one percent increase in prices would result in a 1.055% decrease in quantity consumed. Next, the ECON-PSTR model of heterogeneous habit strength is estimated. The fourth column of Table 9 presents the PSTR model results, which are further illustrated in Figure 4. In Figure 4, the x-axis represents the value of *G*, which is bounded between 0 (no habit at all) and 1 (addiction). Based on our estimation, the value of *G* ranges across households from 0.07 to 0.99. The solid line shows a household's own-price elasticity decreases in magnitude from -1.422 to -0.410 as a household's habit strength increases from 0.07 to 0.99. Thus, for the more habitual consumers, who are the primary target of public health policy makers, sin tax style policies are not as effective as for those who are not as habitual in consumption. The dotted line represents the expenditure elasticity of each household under different habits. The expenditure elasticity increases from 0.276 to 0.365 as a household's habit level increase from 0.07 to 0.99. These findings are in line with expected behavior. Habitual consumers would allocate more spending on goods they are most habituated to as their total expenditure increases. Additionally, model selection criteria (AIC and BIC) are smaller when the PSTR model is applied, providing evidence in favor of the heterogeneous habit model for these data. Figure 3 plots the value of G functions against mean habit strength of CSBs and beer consumers.

To understand the influence of a soda tax on consumption, we simulate a scenario where a one-cent per ounce tax[9] is levied on regular CSBs. We assume that the tax is fully passed through to retail prices. Applying the parameters of the homogeneous habit model, the estimated decrease in purchases of each household is illustrated in Figure 5, where blue bars and orange bars indicate demand drop under homogeneous and heterogeneous habit strength assumptions, respectively. With a model of homogeneous habit, the percentage change is the same across households given equal price elasticities. Consequently, the absolute decrease in purchases of habitual households is larger than for non-habitual households when facing the same percentage increase in prices. Based on the reactions simulated for each household with homogeneous habit, the one-cent per ounce soda tax would result in an aggregate 28.84% decrease in household CSBs.

From the results of the heterogeneous habit strength model, the own-price elasticity ranges from -1.422 to -0.410. As the orange bar in Figure 5 indicates, the net decrease in purchases of habitual households is not much larger than that of non-habitual households because the households with the largest purchases tend to be more price inelastic. Based on this simulation, a one-cent per ounce soda tax would result in a 24.11% decrease in overall consumption. Thus, the

[9] Some past literature used half-cent per ounce soda tax in policy simulations (Dharmasena and Capps, 2012; Lin et al., 2011; Zhen et al., 2014, 2011). In the November 4, 2014 election, Berkeley, California, enacted the first soda tax in the United States, establishing one-cent per ounce tax on sugary drinks. To make the simulations more relevant to current public policy, we use one-cent per ounce as the proposed soda tax.

demand response to a soda tax when heterogeneous habit strength is allowed for in the model is considerably less than under the standard, homogeneous habit model. In fact, when individual heterogeneity is ignored, the overall decrease in household regular CSBs demand would be overestimated by 4.73 percentage points.

Beer

To further demonstrate the importance of allowing heterogeneity in habit, we perform a second simulation, this time applied to beer purchasing behavior. Similar results will suggest that the specific product chosen has not biased our results. Intuitively, beer is a more habit-forming product than regular CSBs. As before, first, a constant habit regression for beer demand is conducted using equation (3). The coefficient on lnP_{jt} is estimated to be -1.089 and statistically significant, indicating that a one percent increase in prices would result in a 1.089% decrease in average consumption of beer. Linear regression results are presented in the fifth column of Table 9.

Next, we estimate our heterogeneous habit PSTR model for beer. Column 6 in Table 9 presents the nonlinear regression results, and Figure 6 shows the relationship between habit, price elasticity, and income elasticity. Similar to Figure 4, the x-axis measures the level of habit, which ranges from 0.21 to 0.99, suggesting that even the least habitual consumers in the dataset have a moderate level of habit in purchasing beer. The absolute own-price elasticity decreases from 1.323 to 0.357 and the expenditure elasticity increases slightly from 0.643 to 0.679 as a household's habit level increases. Additionally, model selection statistics (AIC and BIC) are again smaller when the PSTR model is applied, indicating that incorporating heterogeneous habit is the preferred model specification. The shape of G functions with respect to mean household habit strength of beer consumers is illustrated in Figure 3.

We again simulate a scenario of an additional one-cent per ounce tax being implemented and fully passed through to retail prices. Based on the results of the homogeneous habit model, with its price elasticity of -1.089, the tax would result in a 15.76% decrease in overall beer sales. The decrease in purchases among consumers with different habit strengths when habit strength is modeled as constant is illustrated by the blue bar in Figure 7. Under our heterogeneous habit model, a one-cent per ounce beer tax would result in only a 12.49% decrease in overall sales of beer. The reduced purchases among consumers at different habit levels when heterogeneous habit strength is modeled are illustrated by the orange bar in Figure 7. The figure makes clear that beer is a more habitual product, and the more habitual a household is, the less sensitive to price changes they are. Like the results from regular CSBs, the net decrease from more habitual households is quite similar to less habitual households. If individual heterogeneity is ignored, the overall decrease in household beer demand would be overestimated by 3.27 percentage points. In other words, with the stronger habit of beer demand across the spectrum, incorporating heterogeneous habit leads to estimates of responsiveness to a beer tax only 80% of that suggested by the uniform habit model.

5. Conclusions and Policy Implications

Previous food demand research typically has found an own-price elasticity of -1.05 to -1.1 for the category of regular CSBs (Bergtold et al., 2004; Heien and Wessells, 1990; Pittman, 2005). An estimated own-price elasticity of -1.2 was applied by Yale University's Rudd Center to calculate the tax revenues generated by a soda tax (Rudd Center for Food Policy and Obesity, 2010). More recently, Zhen et al., (2014) estimated that the price elasticity of regular CSBs as -1.035 based on the Nielsen Homescan Dataset (also used here). With previous published estimates of price elasticities, the percentage drop in aggregated purchase of regular CSBs due to a one-cent per ounce soda tax is between the interval of 28.71% to 32.81% given our calculated CSBs prices, which contains our simulated results (28.84%) in the homogeneous habit model. Compared with the more general and realistic heterogeneous habit strength model, assuming constant habit strength leads to significant overestimation of the effect of a soda tax on CSBs purchases.

In this paper, we proposed an innovative procedure to investigate the demand for regular CSBs and beer under heterogeneous habit strength. To demonstrate how important this model generalization is for policy analysis, we reported an analysis of the potential effects of a one-cent per ounce soda tax and a one-cent per ounce beer tax. Our results shed light on the importance of incorporating individual heterogeneity when conducting research on public food policies. Habitual consumers have the strongest preference for a particular product and are less price sensitive than those with weaker habit effects. Because those with stronger habit effects have more inelastic demands and consume larger than average quantities, ignoring the heterogeneity of habit leads to an aggregation bias that could lead to faulty policy analyses. Consequently, the welfare measurement of the policy may be inaccurate due to price and expenditure insensitivity of highly habitual consumers. Table 8 provides possible criteria related to demographics to screen the highly habitual consumers at whom a more specific policy could target.

The ECON-PSTR model of habit strength introduced here reveals heterogeneous consumption patterns for regular CSBs and beer, leading to different responses to public policy among people. If individual heterogeneity in habit strength is ignored, the overall effect of soda tax and beer tax would be overestimated by 4.73 and 3.27 percentage points respectively. In other words, the aggregate declines in soda and beer consumption are over-estimated by 20% and 26%, respectively, under the homogeneity assumption. This implies sin and food taxes will be less successful at discouraging consumption than predicted by constant-habit demand models. Our analysis also suggests food policies should be designed with consideration of heterogeneity in consumers' habits and their varying sensitivity to price and income changes. In particular, public health professionals and nutrition experts don't simply want to reduce consumption of sugar sweetened beverages and beer, they specifically want to reduce consumption among the heaviest consumers of these unhealthy beverages. Once heterogeneity of habit strength is accounted for, we find that sin taxes have less effect on exactly these targeted consumers. Thus, our results suggest that from a public health perspective, policies beyond simple price adjustments are needed to achieve the desired objectives.

Table 8 Homescan Sample Summary Statistics, by Products and Habit Strength Quartiles

	Group	Range of Habit Strength[a]	Number of Households	Mean Habit Strength	Mean Household Size	Mean Household Income[b]	Percentage of Male Household Head	Race of Household Head				At least one Child	Household Head holding at least College Degree
								White	Black	Hispanic	Others		
CSBs Households (N = 10921)	1	$> Q_3$	**2731**	**36.27**	**2.38**	**8.29**	**35.77%**	**92.27%**	**4.25%**	**3.22%**	**0.26%**	**22.38%**	**38.04%**
				(9.08)	(1.11)	(2.84)	(9.17e-3)	(5.11e-3)	(3.86e-3)	(3.38e-3)	(9.68e-4)	(7.98e-3)	(3.86e-4)
	2	$(Q_2, Q_3]$	**2730**	**24.40**	**2.37**	**8.36**	**30.11%**	**89.12%**	**6.23%**	**3.85%**	**0.81%**	**19.67%**	**40.55%**
				(1.74)	(1.15)	(2.94)	(8.78e-3)	(5.96e-3)	(4.62e-3)	(3.68e-3)	(1.71e-3)	(7.61e-3)	(9.40e-3)
	3	$(Q_1, Q_2]$	**2730**	**19.43**	**2.42**	**8.43**	**31.14%**	**88.10%**	**7.18%**	**4.18%**	**0.55%**	**17.47%**	**39.93%**
				(1.23)	(1.20)	(2.87)	(8.86e-3)	(6.20e-3)	(4.94e-3)	(3.83e-3)	(1.41e-3)	(7.27e-3)	(9.37e-3)
	4	$\leq Q_1$	**2730**	**14.79**	**2.51**	**8.44**	**29.08%**	**84.84%**	**9.19%**	**5.13%**	**0.84%**	**15.16%**	**41.43%**
				(1.85)	(1.30)	(2.97)	(8.69e-3)	(6.86e-3)	(5.53e-3)	(4.22e-3)	(1.75e-3)	(6.86e-3)	(9.43e-3)
Beer Households (N = 1613)	1	$> Q_3$	**404**	**30.19**	**2.03**	**8.27**	**44.42%**	**90.07%**	**5.46%**	**4.22%**	**0.25%**	**8.93%**	**33.75%**
				(9.90)	(0.91)	(2.91)	(2.47e-2)	(1.49e-2)	(1.13e-2)	(1.00e-2)	(2.48e-3)	(1.42e-2)	(2.35e-2)
	2	$(Q_2, Q_3]$	**403**	**17.80**	**2.14**	**8.78**	**41.69%**	**87.10%**	**8.68%**	**3.72%**	**0.50%**	**10.17%**	**35.48%**
				(1.58)	(0.92)	(2.51)	(2.46e-2)	(1.67e-2)	(1.40e-2)	(9.43e-3)	(3.50e-3)	(1.51e-2)	(2.38e-2)
	3	$(Q_1, Q_2]$	**403**	**13.40**	**2.22**	**9.02**	**42.43%**	**88.83%**	**6.20%**	**3.97%**	**0.99%**	**12.90%**	**42.93%**
				(1.08)	(1.03)	(2.69)	(2.46e-2)	(1.57e-2)	(1.20e-2)	(9.73e-3)	(4.94e-3)	(1.67e-2)	(2.47e-2)
	4	$\leq Q_1$	**403**	**9.62**	**2.23**	**9.13**	**40.94%**	**84.37%**	**11.17%**	**3.72%**	**0.74%**	**14.39%**	**47.15%**
				(1.34)	(0.95)	(2.67)	(2.45e-2)	(1.81e-2)	(1.57e-2)	(9.43e-3)	(4.28e-3)	(1.75e-2)	(2.49e-2)

[a] Q_1, Q_2, Q_3 represent the first, second, and third quartile of the habit strength, respectively.

[b] Household Income is a categorical variable where annual income ranges from $0 to $9,999 is coded as 1, $10,000 to $11,999 as 2, $12,000 to $14,999 as 3, $15,000 to $19,999 as 4, $20,000 to $24,999 as 5, $25,000 to $34,999 as 6, $35,000 to $44,999 as 7, $45,000 to $49,999 as 8, $50,000 to $59,999 as 9, $60,000 to $69,999 as 10, $70,000 to $99,999 as 11, and $100,000 and greater as 12.

Table 9 Parameter Estimates for Regular CSBs and Beer

	Parameter Estimates for Regular Carbonated Sweetened Beverages and Beer				
		Regular Carbonated Sweetened Beverages		Beer	
	Model	Linear Demand Model	PSTR Model	Linear Demand Model	PSTR Model
Scheme 1	*Intercept*	4.284*	3.002*	1.959*	0.002
		(0.061)	(1.012)	(0.531)	(0.003)
	Natural log of Price	**-1.055***	**-1.598***	**-1.089***	**-1.936***
		(0.082)	(0.197)	(0.128)	(0.154)
	Natural log of Expenditure	**0.347***	**0.261***	**0.677***	**0.620***
		(0.006)	(0.010)	(0.003)	(0.005)
	Gender of Household	0.055*	0.058*	0.198*	0.164*
		(0.013)	(0.020)	(0.001)	(0.006)
	Race1	0.103*	0.141*	0.213*	0.249*
		(0.037)	(0.053)	(0.001)	(0.013)
	Race2	-0.126*	-0.037*	-0.171*	-0.143*
		(0.043)	(0.062)	(0.001)	(0.018)
	Race3	-0.019	0.127	0.015*	0.194*
		(0.061)	(0.097)	(0.002)	(0.022)
	Education Level of Household Head	-0.096*	-0.045*	-0.266*	-0.253*
		(0.013)	(0.019)	(0.000)	(0.006)
	Two or more children in the household	0.121*	0.015	-0.220*	-0.233*
		(0.016)	(0.022)	(0.001)	(0.007)
Gamma	*Gamma*		**1.385***		**1.735***
			(0.044)		(0.036)
Scheme 2	*Intercept*		0.823*		7.301*
			(0.210)		(0.667)
	Natural log of Price		**-0.126***		**-0.191***
			(0.023)		(0.002)
	Natural log of Expenditure		**0.384***		**0.689***
			(0.015)		(0.138)
	Gender of Household		0.015		1.388*
			(0.028)		(0.227)
	Race1		-0.094		-1.705
			(0.076)		(1.335)
	Race2		-0.224*		-1.309
			(0.090)		(0.766)
	Race3		-0.254		-7.728*
			(0.132)		(0.951)
	Education Level of Household Head		-0.154*		-0.544*
			(0.027)		(0.231)
	Two or more children in the household		0.294*		-0.014
			(0.032)		(0.326)
	N	243859	243859	40291	40291
	SSE	181180	156250	57810	52330
	Number of Parameters	9	19	9	19
	AIC	-31446.77	-47104.58	6335.30	4612.66
	BIC	-31416.28	-47040.23	6358.75	4662.16

$*$ Significant at 5% significance level. Heteroscedasticity-consistent standard error in parenthesis.

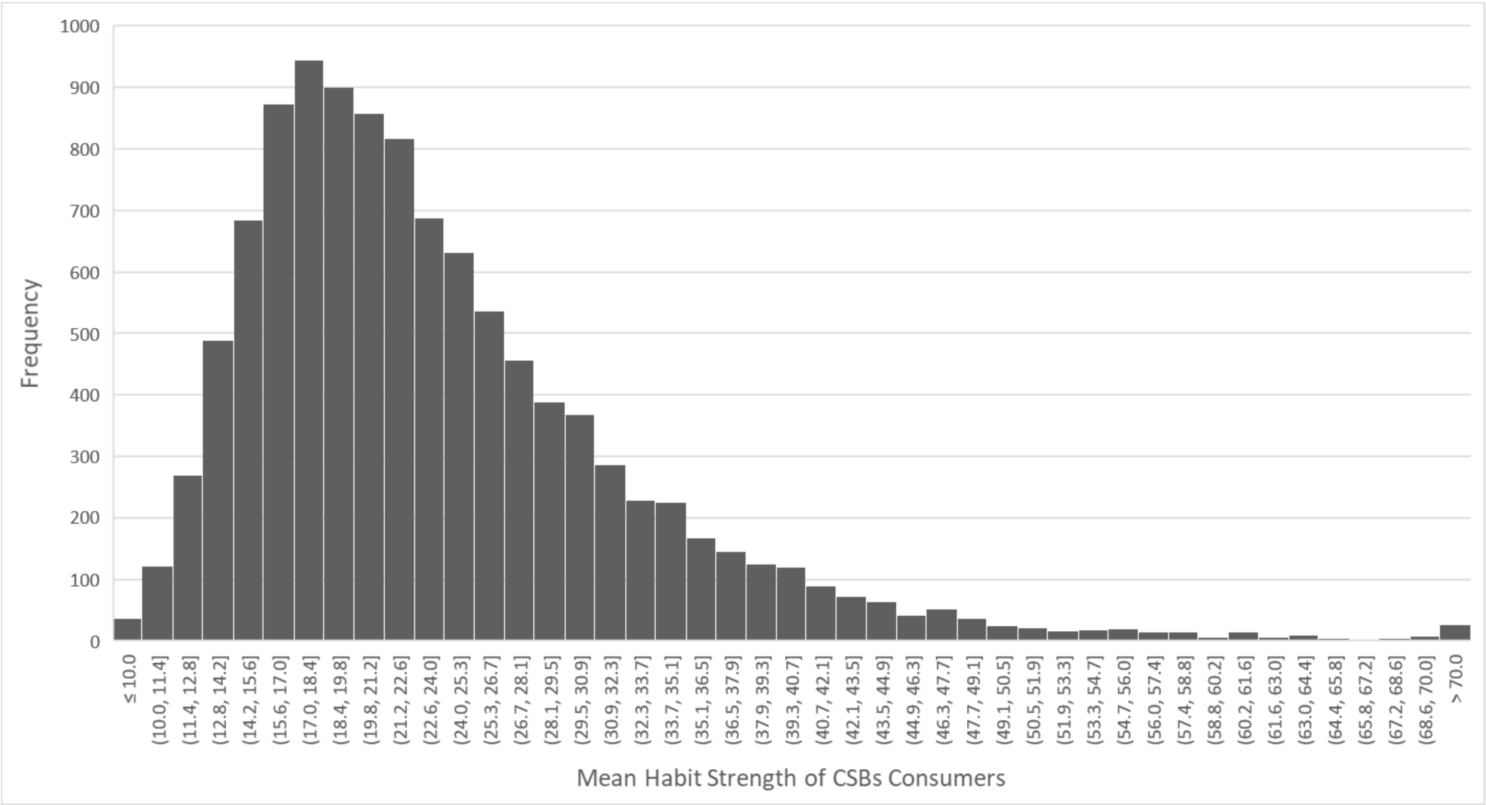

Figure 1 Histogram of Average Habit Strength over Sample Period - CSBs Consumers

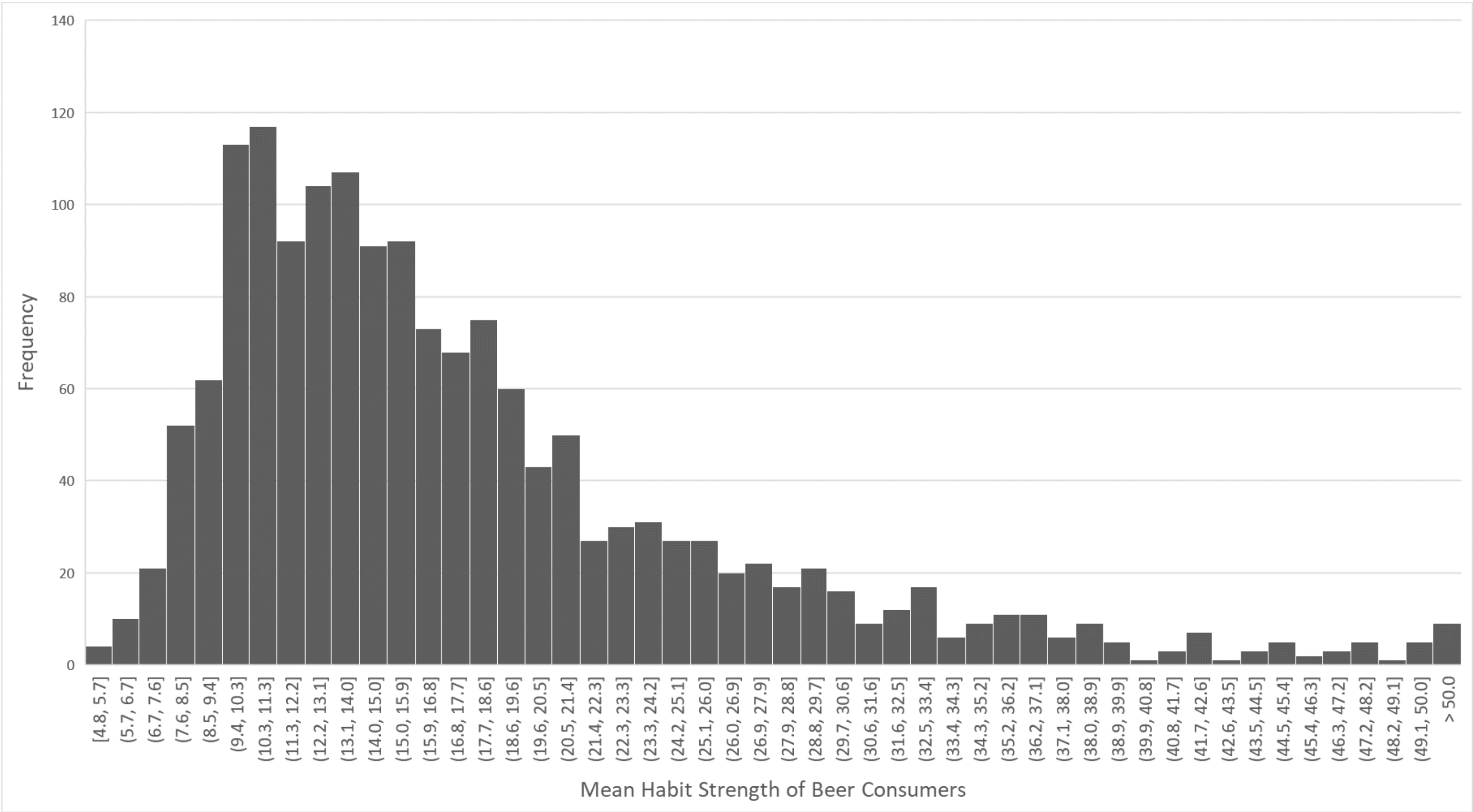

Figure 2 Histogram of Average Habit Strength over Sample Period - Beer Consumers

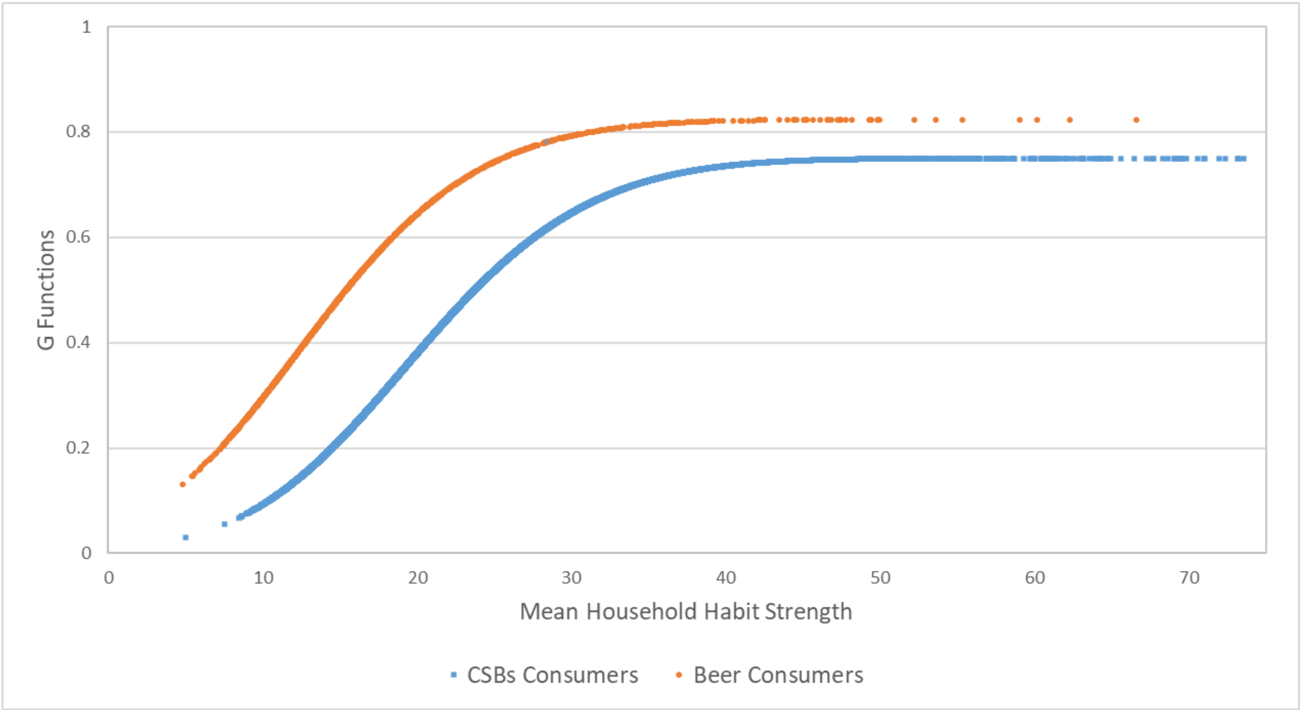

Figure 3 The Value of G - Functions Against Average Habit Strength over Sample Period

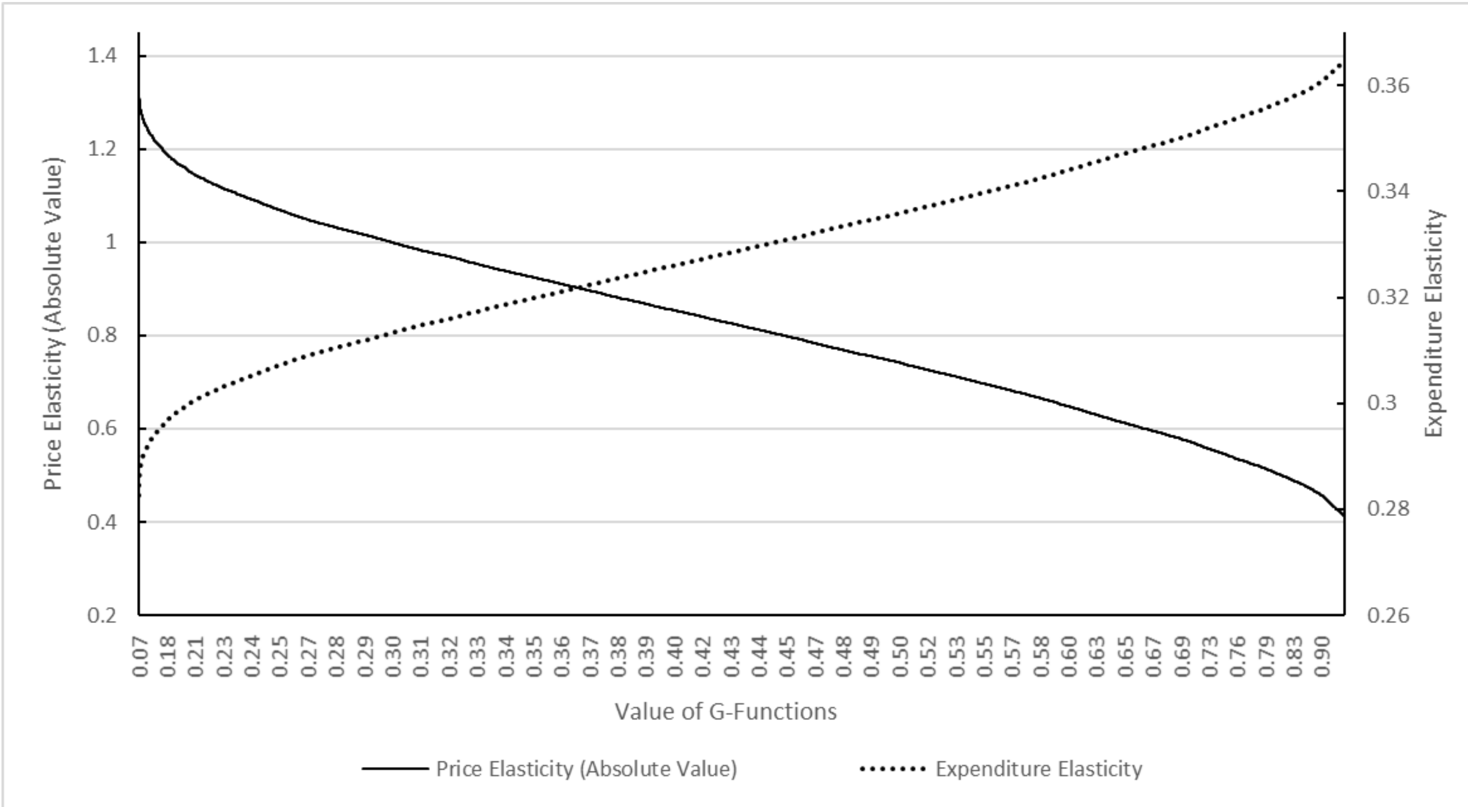

Figure 4 Habit, Price Elasticity and Expenditure Elasticity for Regular CSBs

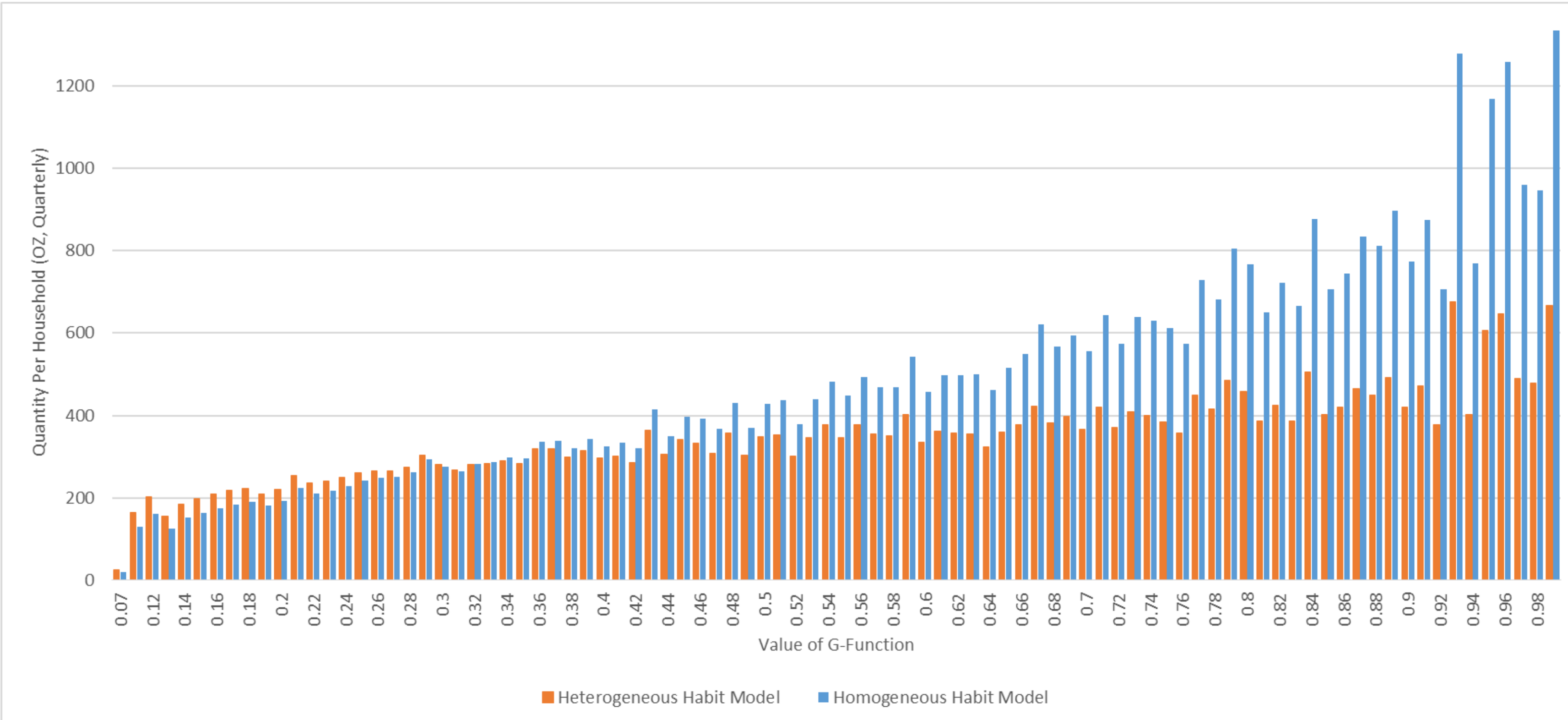

Figure 5 Decrease in Demand of Regular CSBs Due to Soda Tax under Both Heterogeneous and Homogeneous Habit Assumptions

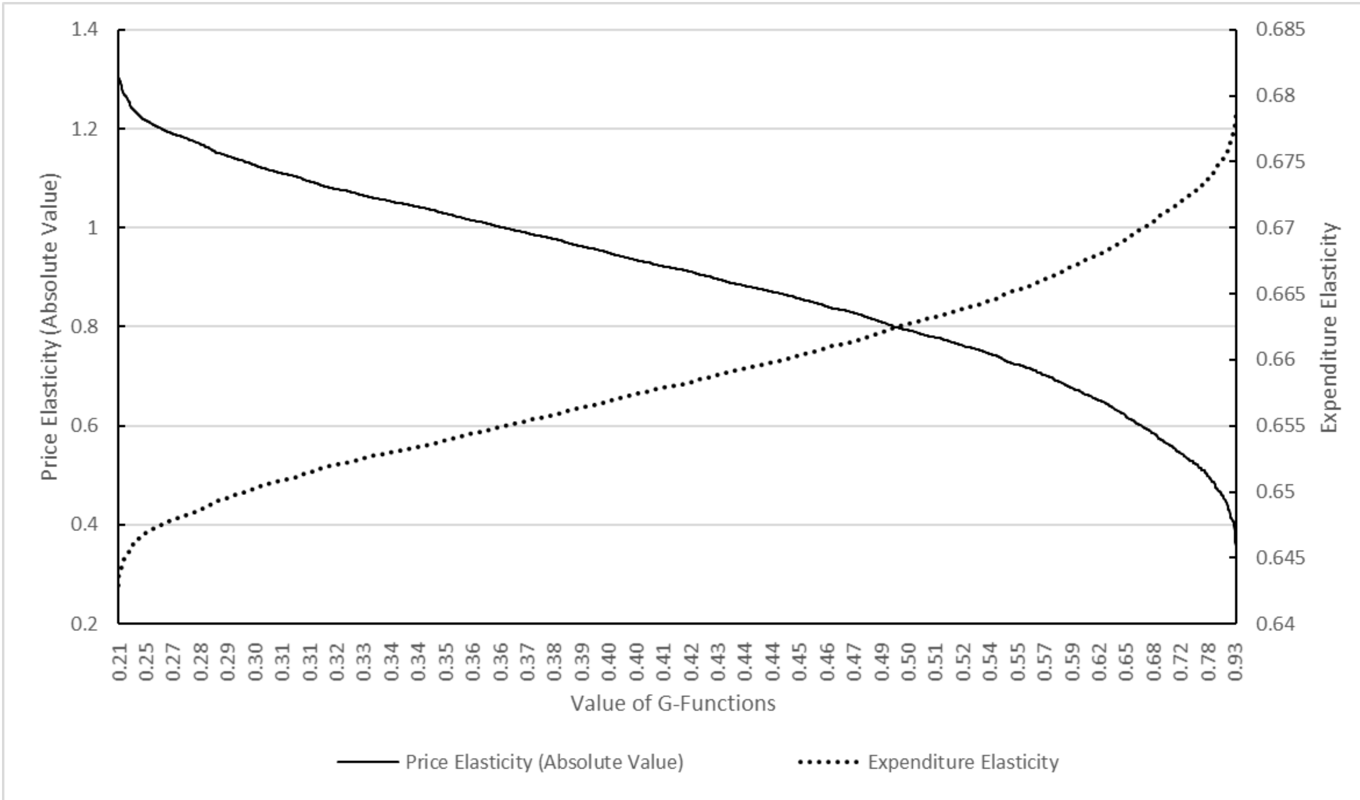

Figure 6 Habit, Price Elasticity and Expenditure Elasticity for Beer

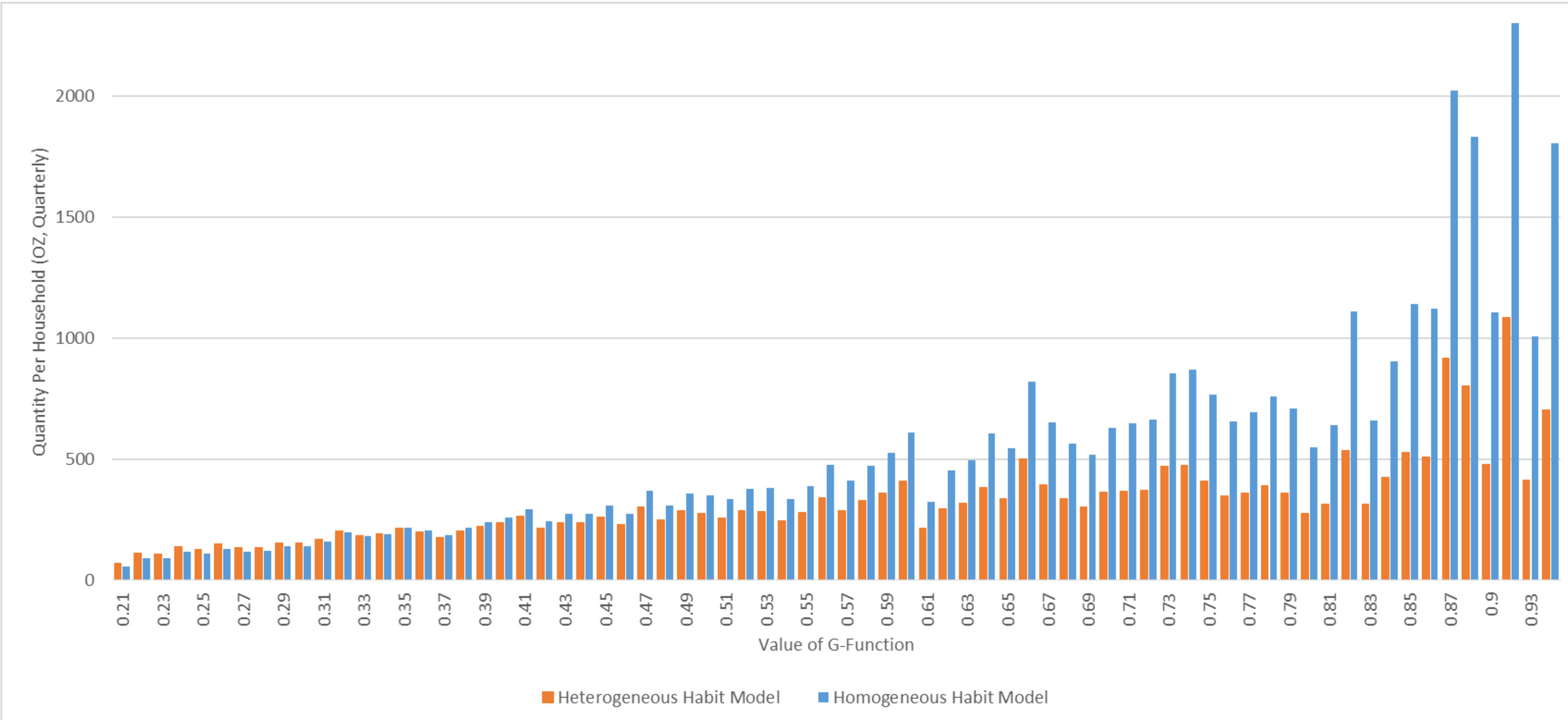

Figure 7 Decrease in Demand of Beer Due to Beer Tax under Both Heterogeneous and Homogeneous Habit Assumptions

CHAPTER 3

ARE RESOURCES EQUALLY SHARED WITHIN HOUSEHOLDS? – A COLLECTIVE MODEL APPROACH WITH SCANNER DATA.

1. Introduction

Intrahousehold inequality has been widely studied for developing countries but rarely for developed countries like the United States. Intrahousehold inequality can be assessed by each household member's individual consumption, and his/her consumption share within the total household. In practice, however, the consumption data at individual level is difficult to obtain and in fact, consumption data are usually collected at the household level. Nonetheless, Browning, Chiappori, and Lewbel (2013) (hereafter BCL), proposed a household collective model which makes possible the identification of individual-level consumption based on the consumption data from households which are composed of individuals, each with heterogenous preferences, symmetric bargaining power and joint consumption of public goods. Following their work, we examine the degree of the U.S. intrahousehold inequality among two types of households, two-adult no-child (Type I) households and two-adult one-child (Type II) households, in the United States by using the Nielsen household scanner data. Specifically, we estimated *resource shares*, defined as each member's share of total household consumption within the household using Engel curves. Our findings show that, in a Type I household, women command an average of 45% of the total household resources, 10 percentage points less than men's shares. As for Type II households, wives, husbands, and children are estimated to consume 39%, 41%, and 20% of the total resources on average, respectively. We conclude that resources are more “equally” shared within Type II households as the estimated shares are very close to the equal-division rule suggested by OECD (*i.e.* 38.5% for each of the parents and 23% for the child). Moreover, women’s full-time job, women’s education level, and men’s education level are found to be positively associated with resource shares for women. Additionally, age-related covariates are found to have significant impact on the share of women only from Type II households.

With above findings, we further examine the appropriateness of the current household income eligibility threshold for the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC Program), a public food assistance program aiming to provide supplemental foods, nutrition education and other related services to women and children from at-risk and low-income households. Based on the estimated household collective model, we suggest that the eligibility line of WIC program for the Type I household should be increased by 11% to ensure the intended purpose of the program to be achieved, and that the threshold for Type II households remain unchanged. Further, the household characteristics (e.g. level of women’s education, women’s employment status) that are found to have significant impact on women’s shares would enable policy makers to better identify and target the at-risk women, and to improve government spending efficiency.

The remainder of the paper is organized as follows. Section 2 provides an overview of the structural model and its identification assumption. Section 3 describes the data source and the construction dataset. Section 4 presents the structural estimation results. Section 5 concludes.

2. Structural Household Collective Model

Early literature on household consumption is often modeled as the outcome of a single decision-making, utility-maximizing agent, so called unitary models. However, empirical results argue that the assumptions under the unitary approach are too restrictive (Chiappori and Mazzocco, 2017). In contrast to the unitary approach, some other papers (e.g. Becker 1965, 1981; Chiappori 1988, 1992) adopt the collective approach, modeling a household consisting of multiple individuals, each with own preferences. The underlying assumption of the model is Pareto Efficiency, and 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 which reflect the sharing of goods.

The particular interest of the collective model is to estimate an individual's household resource share, Λ, defined as his/her share of total household consumption within the household. Consider a household comprised of J individuals indexed $j = 1, \ldots, J$ with total household expenditure y. Each household consumes K types of goods with prices $\boldsymbol{p} = (p^1, \ldots, p^K)$ and observed quantities $\boldsymbol{h} = (h^1, \ldots, h^K)$. Let $\boldsymbol{x_j} = (x_j^1, \ldots, x_j^K)$ be the vector of quantities, which are unobserved, of the K types of goods (referred to as *private good equivalents* hereafter) consumed by individual j if the individual lived alone. Under the assumption of Barten-type technology (BCL), the purchased quantities, h, by the household can be translated into private good equivalents, $\boldsymbol{x_j}$, by a $K \times K$ transformation matrix $\boldsymbol{A}$ such that $\boldsymbol{h} = \boldsymbol{A} \sum_{j=1}^{J} \boldsymbol{x_j}$.

We have provided here an example to illustrate how Barten-type consumption technology transfers household consumption, h, into private good equivalents, x. Suppose that individuals in a Type I household ride together and share the consumption of gasoline half of the time, and that the total household consumption of gasoline is 20 gallons per month. Therefore, if the two individuals lived alone, their total monthly consumption of gasoline (or private good equivalents, $x_f + x_m$) would have been 30 gallons, which are 1.5 times the quantity purchased at the household level. Assuming the consumption of gasoline (good *k*) does not depend on consumption of other goods, then the (k,k) element of $\boldsymbol{A}$ is $\frac{2}{3}$, representing the level of publicness of good k within the household, and the (k,j) elements of $\boldsymbol{A}$ are zeros, where $k \neq j$. In this way, the k^{th} element of h is $\frac{2}{3}\ (x_f + x_m)$.

Let $U_j(x_j)$ denote the consumption utility function of individual j over the vector of goods x_j, where $U(\cdot)$ is assumed to be monotonically increasing, twice continuously differentiable and strictly quasi-concave. We assume that each household member's total utility, $\widetilde{U}_j$, to be dependent on the utility of other household members and weakly separable over the consumption utility functions of all household members, and that direct consumption externalities are ruled out. Under above assumptions, the household member j who gets utility from the other family members' well-being as well as her own would have a utility function $\widetilde{U}_j = \widetilde{U}_j\left(U_1(\boldsymbol{x}_1), \dots, U_J(\boldsymbol{x}_J)\right)$.

At the household level, the consumption decision is modeled as a Pareto efficient outcome among household members, each with heterogenous preferences, and asymmetric bargaining power. The household maximizes a social welfare function, U_H, defined as

(1) $U_H\left(\widetilde{U}_1, \dots, \widetilde{U}_J, \boldsymbol{p}, y\right) = \sum_{j=1}^{J} \mu_j (\frac{\boldsymbol{p}}{y})\, \widetilde{U}_j$

where $\mu_j(\cdot)$ is a function that returns Pareto weights for individual j. The household's welfare maximization problem can be described as:

(2) $\max_{\boldsymbol{h}, \boldsymbol{x_1}, \dots, \boldsymbol{x_J}} \quad \sum_{j=1}^{J} \mu_j \left(\frac{\boldsymbol{p}}{y}\right) \widetilde{U}_j$

subject to

$\boldsymbol{h} = \boldsymbol{A} \sum_{j=1}^{J} \boldsymbol{x}_j$, $y = \boldsymbol{h}'\boldsymbol{p}$, and $\widetilde{U}_j = \widetilde{U}_j\left(U_1(\boldsymbol{x}_1), \dots, U_J(\boldsymbol{x}_J)\right)$

The solutions of this problem give the bundles of private good equivalents, $\boldsymbol{x}_j$, Pareto weights μ_j, and hence the resource share, λ_j, since there exists a monotonic correspondence between the pareto weights and resource share, and resource share is tractable as it is invariant to the cardinalization of utility functions (BCL).

Dunbar, Lewbel and Pendakur (2013), hereafter DLP, extended BCL to include children. They identify resource shares, λ_j, by using Engel curve curves for each *assignable private good* consumed by each household member type j. A private good, as opposed to public good (e.g. heat, TV, housing, etc), is defined to be a good that does not have any economies of scale in consumption (e.g. food and clothing), while an assignable private good is defined as a private good consumed exclusively by household members of known type - e.g., male/female/children clothing. Under the Barten-type consumption technology assumption, $\boldsymbol{A}_{kk} = 1$ and $\boldsymbol{A}_{kj} = 0$ $(k \neq j)$ for an assignable private good of type k, suggesting that the private good k do not have any economies of scale in consumption. The identification also assumes that resource shares and expenditure are independent, and preferences over the assignable private goods are similar among household members. The household demand functions for private assignable goods can be expressed as:

(3) $W_j(y, \boldsymbol{p}) = \lambda_j w_j(\boldsymbol{A}'\boldsymbol{p}, \lambda_j y)$

where w_j is the is the demand function of each household member of type j when facing her personal shadow budget constraint. Holding prices constant and given $W_j(\cdot)$ and y, the resource shares λ, can be implicitly inverted.

In this study, we select three assignable private goods: men's toiletries, women's cosmetics, and baby food for men, women, and children, respectively. To make sure that each category of assignable private products is exclusively used by a specific household member, we only focus on two types of households mentioned previously[10]. We choose the price independent generalized logarithmic (Piglog) functional form, which yields Engel curves that are linear in the logarithm of household expenditure. Like Calvi, 2019, we also allow preference parameters and resource shares to vary by household demographic characteristics. As such, the Engel curve systems for households with one child can be expressed as:

$$\begin{cases} W_f = \alpha_f \Lambda_f + \beta \Lambda_f \ln\left(\frac{\Lambda_f}{F}\right) + \beta \Lambda_f lny + \varepsilon_f & (4) \\ W_m = \alpha_m \Lambda_m + \beta \Lambda_m \ln\left(\frac{\Lambda_m}{M}\right) + \beta \Lambda_m lny + \varepsilon_m & (5) \\ W_c = \alpha_c \Lambda_c + \beta \Lambda_c \ln\left(\frac{\Lambda_c}{C}\right) + \beta \Lambda_c lny + \varepsilon_c & (6) \end{cases}$$

where

$$\alpha_f = \delta^0_{\alpha_f} + \delta^1_{\alpha_f} X_1 + \cdots + \delta^{12}_{\alpha_f} X_{12}$$

$$\alpha_m = \delta^0_{\alpha_m} + \delta^1_{\alpha_m} X_1 + \cdots + \delta^{12}_{\alpha_m} X_{12}$$

$$\alpha_c = \delta^0_{\alpha_c} + \delta^1_{\alpha_c} X_1 + \cdots + \delta^{12}_{\alpha_c} X_{12}$$

$$\beta = \delta^0_{\beta} + \delta^1_{\beta} X_1 + \cdots + \delta^{12}_{\beta} X_{12}$$

$$\Lambda_f = \delta^0_{\Lambda_f} + \delta^1_{\Lambda_f} X_1 + \cdots + \delta^{12}_{\Lambda_f} X_{12}$$

$$\Lambda_m = \delta^0_{\Lambda_m} + \delta^1_{\Lambda_m} X_1 + \cdots + \delta^{12}_{\Lambda_m} X_{12}$$

$$\Lambda_c = 1 - \Lambda_f - \Lambda_m$$

[10] In most datasets reporting household expenditures, individual consumption is not recorded. If future researchers are interested in including more household members, additional strong identifying assumptions must be imposed. For example, according to Calvi (2019), researchers need to assume the preferences to be the same for all household members of a specific type (i.e. common to all men, all women, and all children). One obstacle to our inclusion of more children in our model is that very few families in the household scanner dataset have more than one children under five at the same time.

where W_f, W_m and W_c are the budget shares spent on women's cosmetics, men's toiletries and children's baby food products, respectively, F, M, and C represent the number of women, men and children in a household, respectively, and y is the household total expenditure. $F = M = 1$ for Type I and $F = M = C = 1$ for Type II households. The vector $\boldsymbol{X} = (X_1, \ldots, X_{12})$ represents the socio-economic characteristics which may have impact on individual's preferences and hence resource shares. α_f, α_m and α_c, and β are preference parameters, and Λ_f, Λ_m and Λ_c are resource shares for women, men and children, respectively. For Type I households, the system contains only Engel curves (4) and (5). The system is estimated by non-linear Seemingly Unrelated Regression (SUR) approach. SUR is iterated until the estimated parameters and the covariance matrix settle.

3. Data

For this empirical exercise, we leverage the 2013-2017 weekly Homescan data, which is collected at household level by the Nielsen Company (US), LLC and made available for research purposes by the Kilts Marketing Data Center at The University of Chicago Booth School of Business. More than 100,000 households across the U.S. record information on shopping trips and purchased items using an optical scanner on a weekly basis over a period of at least a year. Every recorded transaction contains information including the Universal Product Code (UPC), quantity, price, size, brand, etc. The advantage of the Homescan panel dataset is that the sample is nationally representative since the participating households reside in fifty-two Nielsen markets and nine remaining areas in the United States and weights of observations are provided by Nielsen. Further, the Homescan dataset includes almost all U.S. retailers including mass merchants such as Walmart.

Based on the full dataset, we apply the following screens to ensure the data used consist only of households who consistently recorded their purchasing sometime between 2013 and 2017. Households who fail to satisfy any of the following criteria are excluded from the dataset:

(1) Each household must be on the panel for at least three consecutive years from 2013 to 2017.

(2) Each household must have non-zero aggregate spending on one of the private assignable products from 2013 to 2017.

(3) Each household must have an annual expenditure between 5th and 95th percentiles among the households of the same type to eliminate outliers.

Since WIC program targets on children under five-year-old, we only keep one-child households whose child is under five-year old. After filtering, our sample includes 970 one-child households, among which 131 have a single-parent, and 2760 no-child households, among which 799 are living alone. As for household demographics, we include the standardized age of the wife (X_1), the standardized age gap (X_2) between husband and wife (the age of husband minus the age of wife), indicators for the wife and husband having full-time jobs (X_3 and X_4, respectively), an indicator for wife having at least high school degree (X_5), an indicator (X_6) for the husband having higher education level than the wife. X_7 and X_8 are two binary indicators for the race identification of the household ($X_7 = 1$ for black, and $X_8 = 1$ for other races) with white as the reference group. X_9 is coded as 1 if the household is recognized having Hispanic origin, and X_{10} to X_{12} are three binary indicators for the statistical region indicators defined by The Census Bureau ($X_{10} = 1$ for the Northeast region, $X_{11} = 1$ for the Midwest region, and $X_{12} = 1$ for the South region) with the West as the reference group[11]. The demographic characteristics are

[11] Northeast Region: Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont, New Jersey, New York, and Pennsylvania.

summarized in Table 10. Compared with women in Type I households, women in Type II households are younger, and higher proportion of them have high school degrees, but lower proportion of them take full-time jobs. These differences are due to the fact that we only choose the households with children under 5-year-old, therefore, their mothers may be young, and it was the special stage in their life to dedicate themselves to kids and families.

4. Empirical Results

Table 11 reports the estimated coefficients on the covariates $X = (X_1, \ldots, X_{12})$ determining women's and men's resource shares (Λ_f and Λ_m, respectively). The results for Type I households and Type II households are presented in the second and third columns, respectively.

For Type I households, women's estimated resource share ($\widehat{\Lambda}_f$) will significantly increase if she holds at least high school degree and/or has a full-time job. The education level of the male is also found to be positively related to Λ_f. Ceteris paribus, the black households have lower resource shares devoted to women than white households, while women from the households whose races are not black or white have higher resource shares than those from white households. The age-related variables, male's employment, and location indicators are not statistically significant.

For Type II households, women's resource share ($\widehat{\Lambda}_f$) is positively associated with female's employment and males' education. The women in black households are found to have

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Midwest Region: Illinois, Indiana, Michigan, Ohio, Wisconsin, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota.

South Region: Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, District of Columbia, West Virginia, Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma, and Texas.

West Region: Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming, Alaska, California, Hawaii, Oregon, and Washington.

lower resource shares compared with those from white households. The age of female and the age gap are found to have positive impact on women's shares, and both are statistically significant at the 10% and 1% level, respectively. Specifically, one standard deviation increase in women's age (6.1 years) and age gap (2.1 years) are associated with a 1.2 and 1.7 percentage point increase in their resource shares. For the male household member, his estimated resource share ($\widehat{\Lambda}_m$) is positively related to female's age and is negatively correlated with women's education level. Men from black households have higher resource shares than those from white households. Other men's resource share covariates are not significant.

Estimated women's resource shares for Type I households are presented in Figure 8. We note that few women's household shares are below 18% or above 74%. And women's resource shares are less than or equal to Men's in 61% of the households, suggesting the existence of gender inequality in Type I households. The summary statistics are presented in Table 12. The average value of women 's household resource share is 45%, 10 percentage points less than men. With the current household income eligibility line, which is set under the assumption that each household member gets an equal share of resources, there exists a considerate number of households whose income is not eligible (i.e. income above the eligibility line) for the WIC program but whose female members are actually living in defined poverty due to gender inequality and should have been protected by the WIC program. As a result, to reach the intended purpose, the current eligibility line should be increased by at least $\frac{0.5}{0.45} * 100\% = 11\%$ to account for the derived gender inequality.

In Figure 9 and Figure 10, we show the estimated women's and children's resource shares in Type II households. In about 60% of the families, women 's resource share is below 40%, and few women hold more than half of the household resources. In 70% of the families, the children's resource share is higher than 15% and less than 30%. As indicated in Table 12, wives, husbands, and children are estimated to consume 39%, 41%, and 20% of the total resources on average, respectively. We conclude resources are more "equally" shared within Type II households as the estimated shares are very close to the equal-division rule suggested by OECD[12] (i.e. 38.5% for each of the parents and 23% for the child), and as such, revision of the eligibility line of the WIC program does not seem to be necessary for one-child households.

Among all the household demographic variables that are found to have significant impact on women's share in Type I households, we notice two can be possible criterial applied in policy making, which are indicators of women's high school degree and women's full-time job. Specifically, women have no high school degree or full-time job are more vulnerable than those who have and should be more likely to be targeted by assistance programs.

5. Conclusion

Many public welfare programs specifically target at people who are at risk, such as the elderly, women, and children. The eligibility criteria of these programs theoretically rely on the level of individual consumption of wives and children, but in practice are determined at household level under equal-share assumption due to data limitation.

In this paper, we estimated intrahousehold resource shares in two-person no-child and three-person one-child households by using the household scanner data and household collective models proposed by Browning et al. (2013) and Dunbar et al. (2013). Particularly, we backed out an estimate of the fraction of total household expenditure that is consumed by each family

[12] To account for the possibility that children may have lower needs than adults, following DLP, we use the OECD estimate of the relative needs of children (60 percent that of adults), and so the 'equal distribution' rule for the Type II households is 1:1:0.6 for man, woman and the child, which can be translated as '38.5% for each of the parents and 23% for the child'.

member on all goods they consume given household-level Engel curve data on private assignable goods.

We find the average value of women 's household resource share is 45% in a two-person no-child household, suggesting 10% difference in consumption shares between men and women. As a result, we suggest the eligibility income threshold of the WIC program should be increased by at least 11% to achieve the intended purpose. Intrahousehold consumption in three-person one-child households are found to be rather equal, which does not warrant an adjustment in eligibility line for the WIC program. Moreover, we propose two household traits in two-person no-child households that policy makers may leverage to make vulnerable women more likely to be targeted by those assistance programs. By doing this, the government welfare spending can be optimized.

Table 10 Homescan Sample Summary Statistics

	Type I Households	Type II Households
Age		
Female	49.28	35.09
	(8.67)	(6.10)
Gap (Male-Female)	1.12	2.07
	(4.87)	(4.53)
Full-time Employment		
Female	59.74%	46.63%
	(0.49)	(0.50)
Male	82.89%	95.70%
	(0.38)	(0.20)
Education		
Female (High School)	42.63%	65.07%
	(0.49)	(0.39)
Male (Higher Degree)	22.94%	18.09%
	(0.42)	(0.39)
Race and Origin		
White	76.46%	82.05%
	(0.42)	(0.38)
Black	13.58%	10.16%
	(0.34)	(0.30)
Other	9.96%	7.79%
	(0.30)	(0.27)
Hispanic Origin	8.25%	6.56%
	(0.28)	(0.25)
Region		
Northeast	16.97%	16.26%
	(0.38)	(0.37)
Midwest	27.92%	26.63%
	(0.45)	(0.44)
South	39.49%	39.31%
	(0.49)	(0.49)
West	15.62%	17.77%
	(0.36)	(0.38)
Number of Households	2760	970

Table 11 Determinants of Household Resource Shares

	Type I Households	Type II Households
Women		
Intercept ($\delta^0_{\Lambda_f}$)	0.236***	0.405***
	(0.062)	(0.057)
Female Age ($\delta^1_{\Lambda_f}$)	-0.002	0.012*
	(0.011)	(0.006)
Age Gap ($\delta^2_{\Lambda_f}$)	0.016	0.017***
	(0.010)	(0.006)
Female Employment ($\delta^3_{\Lambda_f}$)	0.237***	0.065***
	(0.038)	(0.011)
Male Employment ($\delta^4_{\Lambda_f}$)	0.002	0.004
	(0.031)	(0.012)
Female Education ($\delta^5_{\Lambda_f}$)	0.153**	0.017
	(0.033)	(0.018)
Male Education (Higher Degree) ($\delta^6_{\Lambda_f}$)	0.070***	0.060***
	(0.022)	(0.011)
Black ($\delta^7_{\Lambda_f}$)	-0.082***	-0.087**
	(0.040)	(0.035)
Other ($\delta^8_{\Lambda_f}$)	0.088*	0.052
	(0.046)	(0.041)
Hispanic Origin ($\delta^9_{\Lambda_f}$)	0.041	-0.038
	(0.240)	(0.032)
Northeast ($\delta^{10}_{\Lambda_f}$)	0.008	-0.018
	(0.043)	(0.031)
Midwest ($\delta^{11}_{\Lambda_f}$)	-0.013	-0.050*
	(0.040)	(0.027)
South ($\delta^{12}_{\Lambda_f}$)	0.021	-0.033
	(0.037)	(0.025)
Male		
Intercept ($\delta^0_{\Lambda_m}$)		0.478***
		(0.056)
Female Age ($\delta^1_{\Lambda_m}$)		0.028***
		(0.007)
Age Gap ($\delta^2_{\Lambda_m}$)		-0.001
		(0.007)
Female Employment ($\delta^3_{\Lambda_m}$)		0.001
		(0.012)

Male Employment ($\delta^4_{\Lambda_m}$)		0.283
		(0.371)
Female Education ($\delta^5_{\Lambda_m}$)		-0.038**
		(0.019)
Male Education (Higher Degree) ($\delta^6_{\Lambda_m}$)		0.016
		(0.015)
Black ($\delta^7_{\Lambda_m}$)		0.098***
		(0.037)
Other ($\delta^8_{\Lambda_m}$)		-0.022
		(0.042)
Hispanic Origin ($\delta^9_{\Lambda_m}$)		0.013
		(0.33)
Northeast ($\delta^{10}_{\Lambda_m}$)		0.032
		(0.032)
Midwest ($\delta^{11}_{\Lambda_m}$)		0.031
		(0.028)
South ($\delta^{12}_{\Lambda_m}$)		0.019
		(0.026)
Number of Households	2760	970

Note: $* p < 0.10$, $** p < 0.05$, $*** p < 0.01$. Robust standard errors are in parentheses.

Women's age and age gaps are standardized to ease computation.

Table 12 Summary Statistics of Estimated women's and children's Household Shares ($\widehat{\Lambda_f}$, $\widehat{\Lambda_c}$)

	Type I Households	Type II Households	
	Women ($\widehat{\Lambda_f}$)	Women ($\widehat{\Lambda_f}$)	Children ($\widehat{\Lambda_c}$)
Mean	0.45	0.39	0.20
Standard Deviation	0.15	0.06	0.10
Median	0.47	0.39	0.22

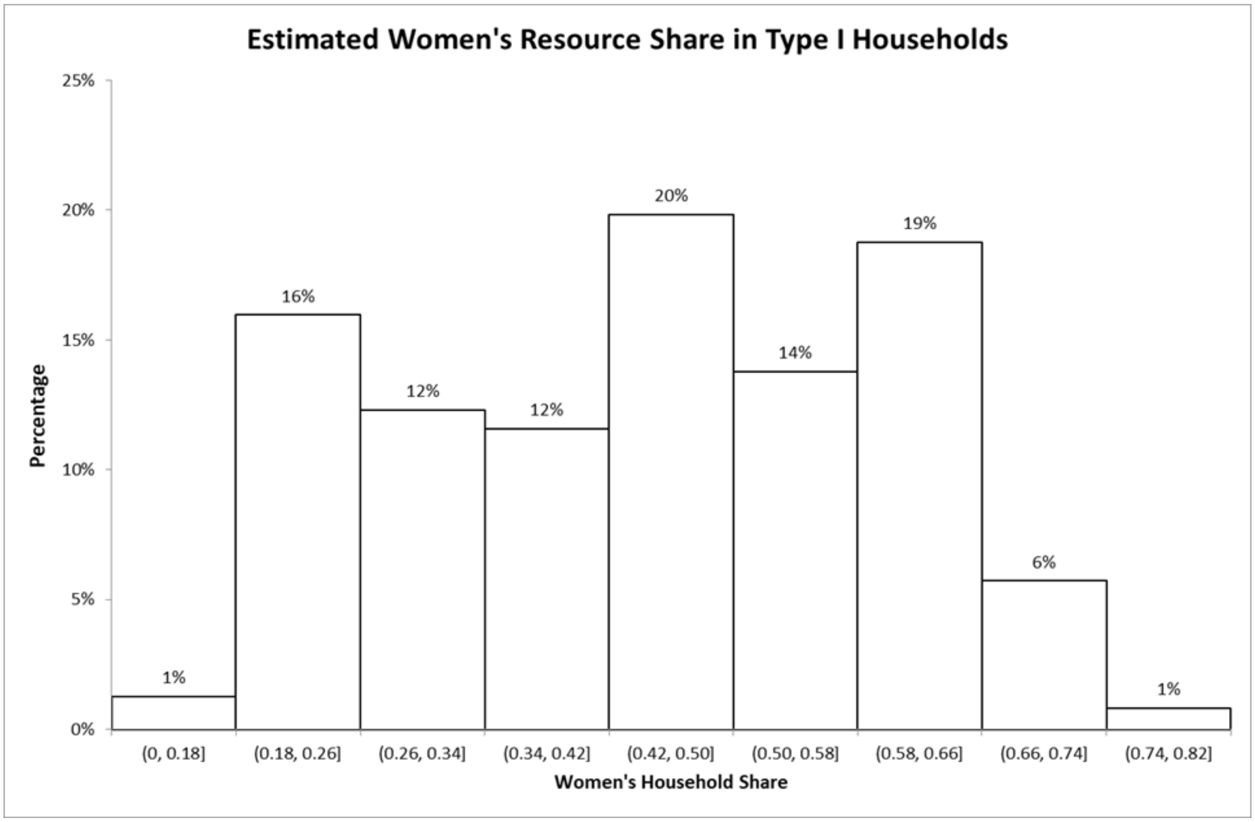

Figure 8 Estimated Women's Household Resource Share in Type I Households

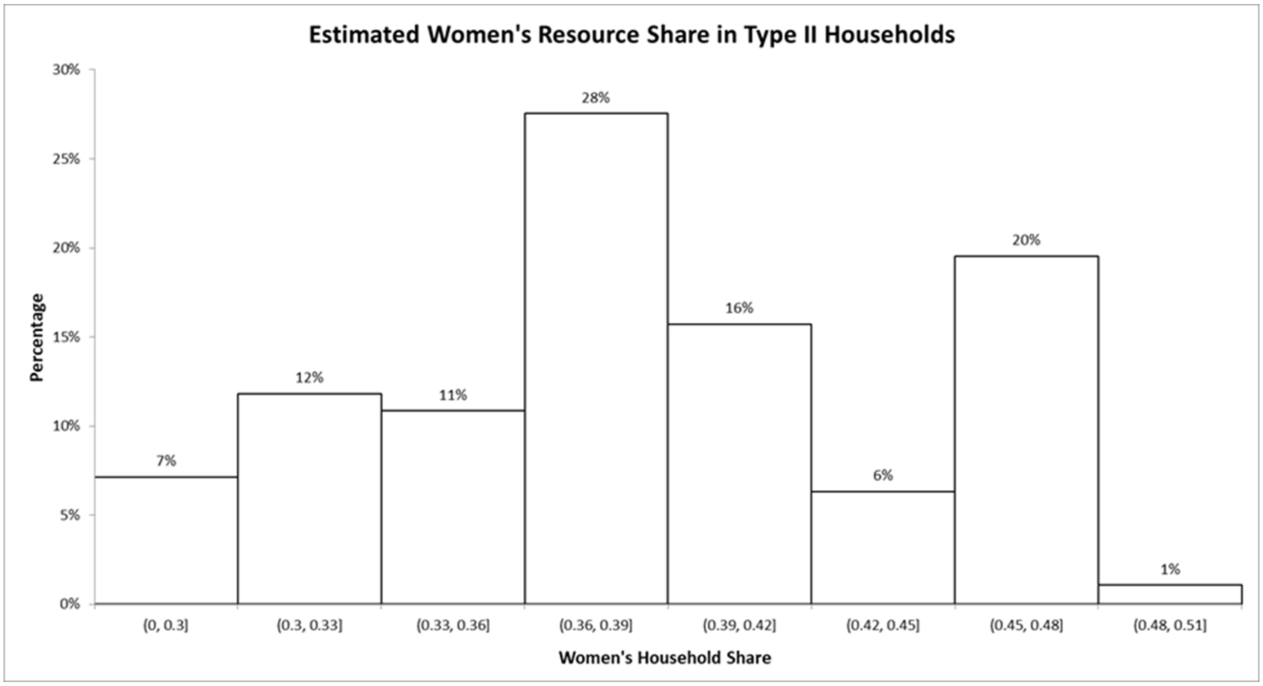

Figure 9 Estimated Women's Household Resource Share in Type II Households

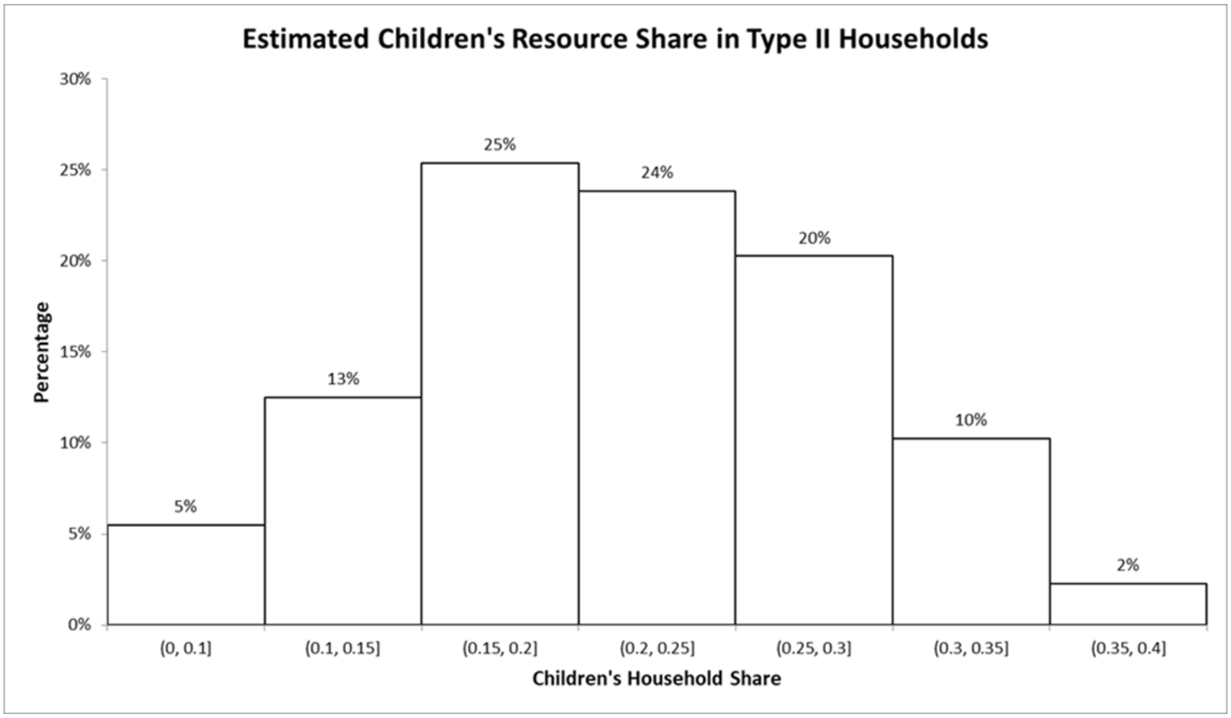

Figure 10 Estimated Children’s Household Resource Shares in Type II Households

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