Consumer Demand Estimation for Heterogeneous U.S. Households[1]

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Abstract: The specification of the consumer demand system is important for estimating the economy-wide impacts of environmental regulation. In computable general equilibrium (CGE) models, household behavior is typically governed by a constant elasticity of substitution (CES) utility function, though it fails to realistically capture well-known patterns of consumer behavior. In addition, only a few CGE models econometrically estimate their own elasticities but are limited to a representative national level household. We empirically estimate a flexible consumer demand system for the U.S. economy and explore the sensitivity of estimates to regional and household income disaggregation. As part of this evaluation, we consider tradeoffs between different specifications with regards to complexity, regularity, the ability to capture cross-price elasticities, Engel curve flexibility, and the number of commodities that can be reasonably accommodated. We estimate price and income elasticities at the national level that are statistically significant and of the expected sign using a variety of empirical specifications. For the disaggregated results, we find that estimated elasticities are similar across U.S. Census regions but vary across income groups. Leisure is income elastic while other categories are income inelastic. Income-group and regional elasticity results are qualitatively similar to those at the national level, though magnitude varies by income group. All consumption categories and leisure are found to be price inelastic at the national level. Our estimated labor supply elasticities are within the expected range for price elasticities, though high for income elasticities. Finally, we test the regularity of the estimated demand system and find that the conditions are satisfied at the national level but not for all income groups and regions.

JEL Codes:

Disclaimer: The views expressed in this paper are those of the authors and do not necessarily reflect the views or policies of the U.S. EPA.

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1. Introduction

The U.S. EPA typically assesses the economic impacts of an environmental regulation as the difference between a baseline, or a representation of the economy without the regulation, and a policy case. The specification of consumer demand for goods and services can be an important determinant in multiple areas of this calculus. First, it can play a key role in the dynamic construct of the baseline (Cranfield, et al., 2002). While the functional form of consumer preferences is typically assumed to be time invariant, incomes and prices can change over time. It is important that the baseline growth path is consistent with these variations and rational consumer choice. Second, consumer preferences define the final good demand curves that help determine the ability to control pollution on the extensive margin through the output effect. In this role, the specification of consumer demand also helps determine the share of abatement costs borne by factors of production relative to consumers. Finally, the specification of consumer demand plays an important role in determining tax interaction effects, as it affects the estimated own-price and cross-price derivatives of demand, through which the optimal tax rates are determined (West and Williams III, 2007).

As regulatory agencies and researchers strive to improve their understanding of the costs of large environmental and energy policies, they have turned to computable general equilibrium (CGE) models to capture interactions between regulated sectors and other parts of the economy (Bergman, 2005; Nijkamp, et al., 2005). In CGE models, consumer behavior is governed by the utility function. Often, these models specify utility using some variant of the constant elasticity of substitution (CES) function, with substitution elasticities that are either based on heuristic arguments or calibrated to estimates in the literature. While there are several examples of CGE models that specify a more flexible consumer demand system and econometrically estimate their own elasticities (Jorgenson, et al., 2013; Yu, et al., 2004), they are relatively rare and have been limited to the case of a single representative household for the economy as a whole.

The continued use of homothetic CES utility functions in most CGE models is of concern given the failure of the CES specification to realistically capture well-known patterns of consumer behavior (Chen, 2017; Annabi, et al., 2006). For instance, the EPA's Science Advisory Board noted that specifying consumer demand as a CES function imposes unit income elasticities (Science Advisory Board, 2020). This violates Engel's Law for food demand, which has been confirmed by many studies in the empirical literature (Clements & Si, 2018; Taylor, 2009; Holcomb, et al., 1995).[3] Since household income is often expected to grow over time in the baseline, this assumption "imposes a baseline growth path at odds with historical experience" (Science Advisory Board, 2020).

In this paper, we empirically estimate several flexible consumer demand systems with an eye toward their eventual use in a CGE model of the U.S. economy with regional and household heterogeneity. As part of this evaluation, we consider tradeoffs between different specifications with regards to complexity, economic regularity (the consistency of a demand system with neoclassical economic theory in terms of positivity, monotonicity, and curvature of the utility function), the ability to capture cross-price elasticities, Engel curve flexibility, and the number of commodities that can be reasonably

[3] Engel's Law states that while consumers increase their expenditures for food products as their income grows, they do so at a decreasing rate.

accommodated. We estimate flexible functional forms including those that allow for non-monotonic income effects and heterogenous cross-price elasticities (e.g., Quadratic Almost Ideal Demand System). We combine the Consumer Expenditure Survey (CEX) micro public-use data with estimated price levels to generate prices and quantities that range from 2013 to 2017 at the state level for use in this estimation.

This study contributes to the literature by estimating a full consumer demand system (i.e., inclusive of leisure) for the United States while exploring heterogeneity across regions and household income groups. Consumption and labor supply are related through cross-price elasticities between leisure and five other consumption categories. These elasticities are useful in investigating the incidence of various energy and environmental policies while incorporating associated behavioral responses. Some previous studies have empirically estimated consumption and leisure demand, but they are either limited to very few consumption categories (West and Williams III, 2004) or only estimate elasticities at the national level (Jorgenson, et al., 2013).

The paper is organized as follows. Section 2 reviews the relevant literature. Section 3 provides information about the empirical framework employed by this study. The data and imputation challenges are explained in Section 4, followed by summary statistic of the data in Section 5. Finally, Section 6 discusses the results, and Section 7 presents the conclusions.

2. Literature Review

In economics, there is a long history of estimating consumer demand to investigate the impact of specific policies and their associated welfare impacts independent of any subsequent use in an economic model. Estimation strategies range from differential approaches (i.e., where no particular function is assumed for the utility function and the total differential of the logarithmic form of the Marshallian demand function is used) to parametric, semi-nonparametric (e.g. asymptotically globally flexible functional forms) and non-parametric approaches. Often, the focus is on consumer demand for a specific good or sector with no attempt to specify broader demand across all goods. For instance, there are many studies in the food and agricultural economics literature that use flexible functional forms such as a Quadratic Expenditure System (QES), the Rotterdam model, or a Quadratic Almost Ideal Demand System (QUAIDS) to estimate consumer demand for food (Härkänen, et al., 2014; Erdil, 2006).[4] One exception to this more focused approach is Taylor (2009), who estimates U.S. national-level income and price elasticities for six aggregate consumption categories using a flexible demand specification. However, Taylor doesn't include leisure in the estimation. Leisure is an important component of full consumption; its inclusion allows one to calculate labor supply elasticities and provides information on the relationship between consumer demand and labor supply.

In the context of environmental and energy policy, flexible demand systems also are sometimes estimated for use in welfare and policy analysis (Schulte and Heindl, 2017; West and Williams III, 2004; Cao, et al., 2020). However,, these studies are either focused on a specific sector of interest and therefore often consolidate the rest of consumer demand into one or two highly aggregated categories or do not include leisure in their estimation. West and Williams (2004) investigate the distributional

[4] The main properties of some of these specifications are explained in section 3.

impacts of gasoline taxes by estimating an Almost Ideal Demand System (AIDS) for the U.S. for gasoline, other goods, and leisure. Using their estimation results to investigate the incidence of environmental taxes, they find that ignoring these demand responses overestates the regressivity of gasoline taxes when there is no revenue recycling. Schulte and Heindl (2017) estimate demand for energy (electricity and heating) and six other aggregate categories (not including leisure) for Germany using a quadratic expenditure system (QES) that is disaggregated based on household size and expenditure quartiles. They find evidence of variation in estimated price and income elasticities when these heterogeneities are taken into account. Cao, et al. (2020) estimate a translog demand system for China that includes aggregate categories of food, consumer goods, services, and housing (but not leisure) to construct measures of social welfare and inequality for economy-wide policy evaluation. Unlike many of the papers from the food and agricultural economics literature, these studies utilize parametric demand systems that impose at least some regularity conditions. West and Williams' (2004) AIDS imposes homogeneity and symmetry conditions. Schulte and Heindl's (2017) QES demand system also satifies homogeneity and symmetry conditions by construction. To ensure consumer choice is rational, regularity conditions must hold. Specifically, a consumer demand system's associated indirect utility function needs to satisfy the following conditions to be regular: positivity, homogeneity of degree zero in prices and income, decreasing in prices, increasing in income, and strictly quasi-convex in prices (Caves and Christensen, 1980; Barnett and Serletis, 2008). In most cases, adding-up, homogeneity, and symmetry conditions are imposed in the estimation, but the curvature constraint is almost never evaluated or imposed because concavity properties, in general, cannot be imposed through parameter restrictions. Among the above studies, Schulte and Heindl (2017) test for positivity and negative semidefiniteness of the Slutsky matrix (curvature). Cao et al. (2020) also impose the curvature constraint when concavity (or curvature) does not hold for an estimated demand system.

Another strand of literature considers consumer demand systems for use in CGE models that are either empirically estimated or calibrated to existing parameter estimates. Specifying a consumer demand system in a CGE model is complicated by several factors. Unlike many of the empirical applications described above, goods and services must be aggregated to match the categories in the CGE model, which often also includes leisure to connect consumption decisions with labor supply.[5] In CGE applications, the demand system needs to be regular to ensure that the model is reliably solved (Perroni and Rutherford, 1995). In most cases, these issues are circumvented by calibrating simpler functional forms such as the constant elasticity of substitution (CES), linear expenditure system (LES), or constant difference in elasticity (CDE) to existing parameter estimates in the literature. This approach is typically justified by implementation and global regularity concerns that make more flexible functional forms challenging to use (Ho, et al., 2019).[6]

[5] Many CGE models assume that leisure is separable and labor supply is an exogenous function of population, while some CGE models explicitly model the labor-leisure tradeoff (e.g. ADAGE, EPPA-HE, and IGEM). See Ho, et al (2019).

[6] For instance, a CES utility function is used in CGE models such as the EPPA, ADAGE, and Rutherford models mainly due to its simplicity and regularity (Paltsev, et al., 2005; Ross, 2007; Rutherford, 1999). CGE models such as FARM, AIM CGE, EPPA (v6), GEM-E3, Globe, Imaclim-R, Mirage, and DART use LES elasticities (Sands, et al., 2017; Fujimori, et al., 2012; Capros, et al., 2013; McDonald, et al., 2007; Ho, et al., 2019). The CDE demand system is used in the GTAP model (Chen, 2016).

Inherent in these simplifying assumptions is a tradeoff between regularity and empirical validity. For instance, the CES functional form is commonly used in CGE modelling due to its regularity and other desirable computational and calibration properties (Ho, et al., 2019). However, it is particularly restrictive: it does not allow substitution elasticities to differ across pairs of goods and restricts the income elasticity of demand to be one. Some variants of the CES function such as LES and nested CES relax some of these restrictions while still maintaining regularity. However, while the budget shares from an LES function can differ with income level, income elasticities of demand approach one as income increases, which is inconsistent with empirical evidence for the Engle curve (Chen, 2016; De Boer and Paap, 2009). In addition, LES demand systems do not allow for the existence of inferior goods, elastic demand, or negative cross-price elasticities (Chung, 1994; Parks, 1969). Nested Nonseparable Constant Elasticity of Substitution (NNCES) functions introduced by Perroni and Rutherford (1995) are also globally regular, and they provide local flexibility through nested CES functions with latent goods (Perroni & Rutherford, 1995). The function allows price flexibility in the form of potentially different substitution relationships across goods, but it still does not allow for non-linear Engel curves. In CGE models with a fairly high level of aggregation, the chance of having elastic demand or an inferior good is expected to be low. However, the cross-price elasticity restriction remains a concern.

Calibration to available estimates in the literature also brings with it a host of complications. For example, it is important that the underlying behavioral assumptions in the estimating framework are consistent with model assumptions if adapting estimated parameters from the literature. Any inconsistencies can potentially lead to modeled responses that are not supported by the empirical literature. Moreover, available elasticity estimates in the literature are often not regularly updated, leading to empirical values based on data that are significantly older than what is used to specify the baseline and policy scenarios in an applied economic model. Hertel, et al. (2007) has also been critical of borrowing point estimates from the literature without considering their confidence intervals, their potential bias, and the effects of different aggregation levels in empirical estimates than what is used in the CGE model. A few modelers empirically estimate the parameters of a LES consumer demand function to ensure internal consistency with the consumer demand system in the CGE model (Gharibnavaz and Verikios, 2018; Jussila, Tamminen, and Kinnunen, 2012).

It is relatively rare to have a CGE model with a more flexible functional form that derives internally consistent elasticities from an estimated consumer demand system. Among U.S. CGE models, the IGEM model is unique in that it employs empirically estimated flexible demand systems for full consumption using rank two and rank three Translog (TL) functions for four aggregate goods at the national level: non-durables, capital services, consumer services, and leisure (Jorgenson, et al., 2013). Among global CGE models, Yu, et al. (2004) investigate using an estimated flexible demand system (e.g. a rank three AIDADS) and compare the CGE results to alternative rank two systems such as CDE and LES where the alternative functional forms are calibrated such that all systems start with the same income elasticity of demand. They show that using the more flexible functional form improves the results, particularly for predicted future demand for food.

3. Empirical Framework

Before laying out the framework we use to empirically estimate U.S. consumer demand, we first discuss several criteria that can be used to judge the properties of different functional forms. We then describe how a range of functional forms measure up against these criteria in order to systematically identify those specifications that likely best meet our needs while hopefully delivering reasonable elasticity estimates. We end the section with a description of our preferred approach, the QUAIDS consumer demand specification.

3.1. Selecting a Consumer Demand Functional Form

The main criteria in choosing a functional form for our demand system estimation are flexibility in the budget shares, flexibility in the own- and cross-price and income elasticities, regularity, and computational tractability. As previously mentioned, however, there is a trade-off between flexibility and regularity of demand functions; no functional form satisfies both global regularity and flexibility (McLaren and Yang, 2016). We discuss each of these criteria briefly below.

Regularity: Even when demand systems provide sensible results for the prices and quantities used in the estimation (i.e., the regularity properties for a rational consumer choice hold locally), they may not satisfy the regularity properties for large shocks to the price or income variables (i.e., they are not globally regular). Regularity is an important feature that is required when a demand system is used in welfare analyses and simulations that consider a wide range of different policy shocks. For instance, the utility functions are locally consistent with the income and price elasticities that are used for CGE modelling. However, this information is used to specify the full range of consumer responses in CGE models and therefore needs to be consistent with the utility functions beyond this local domain (Perroni and Rutherford, 1995). Regularity in terms of Marshallian demand systems means satisfying properties such as nonnegativity, adding up, homogeneity, and the symmetry and negative semi-definiteness of the Slutsky matrix (Deaton and Muellbauer, 1980). Many functional forms fail to satisfy the last constraint, known as the curvature or concavity condition. The other constraints are usually satisfied or imposed on a demand system.

Flexibility: The flexibility of a demand system is related to the number of constraints imposed on the income and price elasticities; demand systems with fewer constraints allow more income and price flexibility. Income flexibility allows for the existence of normal and inferior goods, while price flexibility allows for substitutes and complements to be reflected in cross-price elasticities. The rank of a demand system provides information about the degree of income flexibility of a demand system, and it describes “the maximum dimension of the function space spanned by the Engel curves of the demand system” (Lewbel, 1991). The more income flexible the demand system, the higher its rank. In addition, the budget share is constant across rank one demand systems, which means that the budget share does not change with income level. Higher rank demand systems allow flexibility in the budget share of goods as income changes.

A rank one demand system is compatible with a homothetic preference function such as CES where the Engle curve is linear and passes through the origin. Rank two demand systems are associated with linear Engle curves that don't necessarily pass through the origin. The most common rank two demand system is LES (Geary, 1950; Stone, 1954). Non-linear Engle curves correspond to a rank three demand system. Using subsamples of consumer expenditure data to assess the form of Engel curves implied by assumptions on the distribution of the data, Lewbel (1991) uses kernel regressions to show that while rank two demand systems are sufficient for samples without very low and very high expenditures, rank three demand systems are required when the sample includes such low- and high-expenditure households. Higher rank order demand systems, on average, are associated with more price flexibility. Rank three demand systems allow for non-constrained income and own price elasticities, but the degree of cross price flexibility varies across rank three demand systems.

Lastly, income flexibility also allows for flexibility in the budget share. Specifically, the budget share of consumption can change as income changes. This more accurately reflects the empirical data showing that low-income households spend a different share of their budget on some consumption categories than the high-income groups. Rank one demand systems do not provide budget share flexibility, while higher ranks of the demand system allow this flexibility.

Tractable computation: Computational tractability can be associated with either estimating the demand system itself or with solving a CGE model calibrated to a particular functional form. The former refers to issues such as failing to have precise parameter estimates in a flexible demand system because there are more parameters that need to be estimated. The latter refers to the computational challenges when solving a CGE model that is calibrated to a flexible functional form.

In this study, we restrict ourselves to functional forms that are at least rank two where the budget share of the consumption categories is not independent of the income level (Engle's Law). We also desire a demand system that allows for varying cross-price elasticities, while keeping an eye on the regularity of the demand system to allow for eventual use in a CGE model.

We do not review all possible functional forms, since previous studies give comprehensive reviews (Phlips, 2014; Huang, et al., 2013). However, Table 1 summarizes some common rank two and rank three demand systems estimated in the empirical literature with regards to regularity and flexibility, including LES (Linear Expenditure System), Rotterdam, Translog, AIDS (Almost Ideal Demand System), QES (Quadratic Expenditure System) AIDADS (An Implicitly Direct Additive Demand System), IAS (Indirect Addilog System), and QUAIDS (Quadratic Almost Ideal Demand System).

Table 1: Common rank two and rank three demand systems

Demand System	Rank Order	Benefits with regard to Regulatory and/or Flexibility	Restrictions/Limitations
LES	Two	- Adding-up, homogeneity, and Slutsky symmetry conditions satisfied. - Flexible budget share	- Linear Engel curve (constant marginal budget share) - No inferior goods, no complementary goods, and no elastic demand
Rotterdam	Two	- Adding-up condition satisfied. - Flexible budget share - Allows for cross-price elasticities.	- Linear Engel curve - Concern regarding integrability of the functional forms
Translog	Two/Three	- Allows different household types to have different demands. - Flexible budget share - Allows for cross-price elasticities. - Allows exact aggregation over households	- Linear Engel curve (relaxed in rank three Translog) - Number of goods is limited to <=5 - Failure in providing satisfactory cross-price elasticities consistent with the data
AIDS	Two	- Flexible budget share - Better suited than AIDADS when large price variation and when aggregation or cross-price effects are important. - Allows for exact (non-linear) aggregation over households. - Allows for cross-price elasticities.	- Linear Engel curve - Budget shares not constrained to unit interval
QES	Three	- Flexible budget share - Non-linear Engel curve - Flexible price elasticities	- Limited Engel-flexibility due to linear marginal expenditure
AIDADS	Three	- Flexible budget share and restricted to unit interval - Non-linear Engel curve (a generalized rank-three LES) - Better suited than AIDS when large variation in income - Flexible range of income and price elasticities	- Narrow range of cross-price elasticities - Maximum 10 commodities/sectors - Difficulty in demands aggregation across income levels - Constant subsistence levels (relaxed in Modified AIDADS)
IAS	Three	- Flexible budget share - Non-linear Engel curve - Adding-up, homogeneity, and Slutsky symmetry conditions satisfied. - Allows for inferior goods, elastic demand and negative cross-price elasticities.	- No independent cross-price elasticities
QUAIDS	Three	- Flexible budget share - Non-linear Engel curve - Flexible range of income and price elasticities	- Curvature condition can be rejected for very high-level expenditures.

Sources: Parks (1969), Chung (1994), Banks, et al. (1997) , Cranfield, et al. (2000), Yu, et al. (2000), Cranfield, et al. (2003), Yu, et al. (2004), Reimer and Hertel (2004), Lejour, et al. (2006), Erdil (2006), Barnett and Seck (2008), De Boer and Paap (2009), Preckel, et al. (2010), Chen (2016), (McLaren and Yang, 2016), Sommer and Kratena (2017), Ho, et al. (2019).

In general, rank two demand systems suffer from linearity of the Engel curve, while this constraint is relaxed in rank three functional forms. Price flexibility varies across different functional forms with QUAIDS providing flexibility in both own- and cross- price elasticities.

An important constraint for all these flexible functional forms is that they are not globally regular, mainly due to failing to maintain the curvature constraint globally (i.e., the violation of negative semi-definiteness of the Slutsky matrix). However, the range of prices and incomes/expenditures for which these functional forms are regular varies. While all of these functional forms satisfy regularity locally within the sample data space, the literature demonstrates that some demand systems are "effectively globally regular" (Cooper and McLaren, 1996). [7] This implies that the regularity region for these functional forms is an unbounded domain that includes all sample price and income/expenditure data points as well as any combination of price and nominal expenditures, which then allows higher levels of real expenditures than the minimum value in the sample (McLaren and Yang, 2016; Fisher, et al., 2001). Although not all of the functional forms summarized in Table 1 have been evaluated to see if they are effectively globally regular, studies demonstrate that demand systems such as LES, QES, AIDADS, and QUAIDS belong to this class (Reimer and Hertel, 2004; McLaren and Yang, 2016).

Because it is both effectively globally regular and offers a high degree of price and income flexibility, we explore the QUAIDS functional form for consumer demand in this study. Functional forms such as LES, QES, and AIDADS also have appealing regularity properties but are less flexible. In addition, Cranfield, et al., (2002) evaluate the performance of LES, AIDS, AIDADS, QUAIDS, and QES functional forms using a cross sectional sample of different income level countries and find that AIDADS, QUAIDS, and QES functional forms perform better than LES and AIDS based on both in-sample and out-sample criteria. We include AIDS in some of our regressions as a basis of comparison.

3.2. QUAIDS Empirical Framework

Since the QUAIDS is flexible and effectively globally regular, it is our preferred specification. Using a static framework, the QUAIDS has the following indirect utility function (Banks, et al., 1997):

$$ln\ v(\boldsymbol{p}, m) = [\left(\frac{\ln m - \ln a(\boldsymbol{p})}{b(\boldsymbol{p})}\right)^{-1} + \lambda(\boldsymbol{p})]^{-1} \tag{1}$$

We define a household's expenditure share for goods category i as $w_i \equiv \frac{p_i q_i}{m}$where m represents total household expenditures such that $\sum_{i=1}^{6} w_i = 1$.

Applying Roy's identity to the indirect utility function, the expenditure share, w_i , for each good category i and household h with the N-vector $\boldsymbol{p}$ (where N equals 6 in our case) has the following form:

$$w_i^h = \alpha_i + \sum_{j=1}^{6} \gamma_{ij} \ln p_j^h + \beta_i \ln \{\frac{m^h}{a(\boldsymbol{p})^h}\} + \frac{\lambda_i}{b(\boldsymbol{p})^h} [\ln \left\{\frac{m^h}{a(\boldsymbol{p})^h}\right\}]^2 \tag{2}$$

[7] The regular region is the set of income/expenditure and prices in which the indirect utility function satisfies regularity conditions.

For equation (2), p_i is the own price of good *i*, p_j is the price of other goods *j*, and $ln\ a(\boldsymbol{p})$ is a translog price index where $ln\ a(\boldsymbol{p}) = \alpha_0 + \sum_{i=1}^{6} \alpha_i \ln p_i + \frac{1}{2}\sum_{i=1}^{6}\sum_{j=1}^{6} \gamma_{ij} \ln p_i \ln p_j$, and $b(\boldsymbol{p}) = \prod_{i=1}^{6} p_i^{\beta_i}$.

We employ Pollak and Wales's (1981) translating approach to include household heterogeneity in the model. In this approach, sociodemographic variables (*s*) enter the model through α, where $\boldsymbol{\alpha}^h = \boldsymbol{A}\boldsymbol{s}^{\boldsymbol{h}}$ and $\boldsymbol{A} = (\boldsymbol{\alpha_i}'), \boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_6)'$. This allows the heterogeneity to appear in the model both linearly through the intercept and nonlinearly through the translog price index (Lecocq and Robin, 2015). Following Jorgenson, et al. (2013) and Cao, et al. (2020), we include age, education level, family size, number of children, and gender in the regression. We also include number of income earners and home ownership status as we expect these variables to impact the demand for categories such as housing and leisure. Finally, it is worth noting that the share equation reduces to the AIDS functional form if all λs are equal to zero.

Regularity requires that the consumer demand system satisfy the adding up, homogeneity in prices, symmetry and curvature/concavity constraints. The first three conditions require that:

$\sum_{i=1}^{6} \alpha_i = 1\ (adding\ up)$, (3a)
$\sum_{i=1}^{6} \beta_i = 0, \sum_{i=1}^{6} \lambda_i = 0, \sum_{j=1}^{6} \gamma_{ij} = 0\ (homogeneity)$, and (3b)
$\gamma_{ij} = \gamma_{ji}\ (symmetry)$ (3c)

The adding up constraint holds by construction. We test that the homogeneity and symmetry conditions are satisfied and then impose them as needed in the demand system.

The concavity constraint requires the Slutsky substitution matrix to be negative semidefinite. Using the Slutsky matrix in the form of elasticities, concavity is satisfied if (Barnett and Seck, 2008):

$$\varepsilon_{11}^c < 0 \text{ and } \det\begin{bmatrix} \varepsilon_{11}^c & \cdots & \varepsilon_{1j}^c \\ \vdots & \ddots & \vdots \\ \varepsilon_{i1}^c & \cdots & \varepsilon_{ij}^c \end{bmatrix} > 0, \quad (3d)$$

where ε_{ij}^c is the compensated elasticity for category *i* with respect to the price of category *j*. We test for the curvature of the estimated demand system.

The share equation (1) is simultaneously estimated for each expenditure category as a function of income, price levels, and other relevant explanatory variables. While coefficient estimates are not directly interpretable as elasticities, they can be calculated. The expenditure elasticity is defined as:

$$\eta_i = \frac{\mu_i}{w_i} + 1, \quad (4)$$

where μ_1 is first differential with respect to $\ln(m)$. The uncompensated price elasticity is defined as:

$$\epsilon_{ij} = \frac{\mu_{ij}}{w_i} - \delta_{ij}, \quad (5)$$

where δ_{ij} is the Kronecker delta (it equals 1 if *i = j* and 0 otherwise) and μ_{ij} is first differential of w_i with respect to $\ln p_j$. Finally, the compensated price elasticity is defined as:

$$\varepsilon_{ij}^{c} = \epsilon_{ij} + \eta_i w_j \ , \tag{6}$$

where μ_i and μ_{ij} are calculated as:

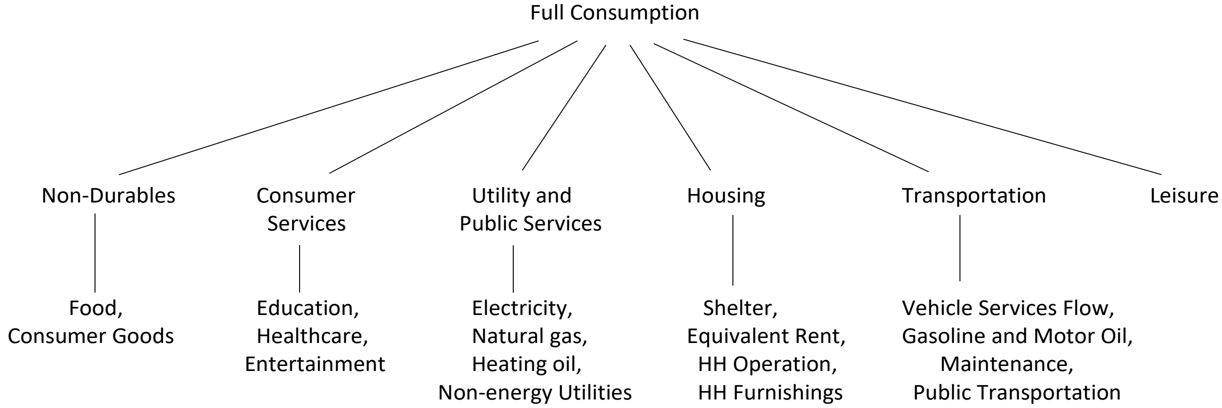
$$\mu_i = \frac{\partial w_i}{\partial \ln{(m)}} = \ \beta_i + \frac{2\lambda_i}{\prod_{i=1}^{6} p_i^{\beta_i}}\,[ln(\frac{m}{P(\boldsymbol{p})})]$$

$$\mu_{ij} = \frac{\partial w_i}{\partial \ln{(p_j)}} = \ \gamma_{ij} - \mu_i\big(\alpha_j + \gamma_j \boldsymbol{P}\big) - \lambda_i\beta_j \frac{[m-P(\boldsymbol{p})]^2}{\prod_{i=1}^{6} p_i^{\beta_i}}$$

Due to computational challenges associated with estimating a highly disaggregated demand system, it is common to conduct estimation for broad consumption categories. We employ a multistage budgeting approach to convert an exhaustive expenditure system to multiple stages. This approach addresses the empirical issue of estimating an extensive number of equations (parameters) and elasticities for full demand systems. In this approach, a model is estimated in different stages where the consumer is assumed to make a decision about aggregate expenditures followed by a decision about sub-aggregate expenditures in the next stage (Blundell, 1993). In this study, we only focus on estimating the top-level aggregate expenditures. Future work will examine modeling the consumer decision in the next stage as a function of aggregate expenditures and other factors.

The tiered structure of our final demand system for the U.S. households is shown in Figure 1. We estimate consumer demand for six categories, the top tier in the figure: non-durables, consumer services, housing, utilities and public services, transportation, and leisure. While much of the empirical consumer demand literature excludes leisure from the estimation, it is important for us to include because it provides information about the labor supply elasticities. In addition, consumption and labor supply are related through cross-price elasticities between leisure and the other consumption categories. These elasticities are important when investigating the incidence of various energy and environmental policies while incorporating the associated behavioral responses.

Figure 1: Consumer Demand Structure



This structure requires the implicit assumption of weak separability in the associated utility function. In addition, the aggregation is such that creating consistent price indices from available data is achievable. For instance, the price data upon which we rely provides price indices for food, apparel, transport, housing, education, entertainment, health care, and others. Some of these categories are the same as what we need at an aggregated level (e.g. housing and transportation); for the rest, sub-aggregate categories can be used to construct aggregate price indices for the associated categories (which is discussed in more detail in Section 4).

4. Data and Imputation Challenges

To estimate U.S. consumer demand, we combine the Bureau of Labor Statistics (BLS) Consumer Expenditure Survey (CEX) public-use microdata with estimated price levels to generate a pooled cross-sectional sample of quarterly prices at the state level and household-level expenditures from 2013-2017. We describe each of these data sources below, including how we address several data imputation challenges. We then define the key variables included in the demand specification.

4.1. Consumer Expenditure Survey data

The U.S. household expenditure data are from the U.S. Bureau of Labor Statistics' Consumer Expenditure Survey public use microdata, which also provide detailed information about households' income and demographic and socioeconomic characteristics. The data from individuals are reported in the form of Consumer Units (CUs) where CU members are either related by blood, marriage, or other legal arrangement, or they are financially dependent (i.e., live together and share the responsibility for some main expenditures in housing, food, and other living expenses). We assume that a CU is equivalent to a household, though they are not always the same.

The CEX data includes two different surveys, the Diary Survey and the Interview Survey.[8] To construct a panel, we use quarterly interview surveys that include data on large expenditures. The survey is a rotating panel that includes around 7,000 usable interviews for each calendar quarter of the year of which around one-fourth of the CUs are new to the survey. The data have been collected since 1980 but income tax data have only been available since 2013. The addition of these income tax data is important because they facilitate the calculation of after-tax wages and leisure values in our study. Interview surveys are designed as a representative sample of the entire U.S. civilian noninstitutional population.

For each of the six expenditure categories we include in our consumer demand specification, Table 2 shows the corresponding expenditures from the CEX. Most of the expenditures are directly available in the CEX data. For a few categories, namely leisure and the flow of vehicle services in transportation, we need to impute the expenditure values based on other information available in the CEX. We describe these processes in greater detail later in this section.

[8] The diary survey is designed to track frequent expenditures on a weekly basis at a highly disaggregated scale. For instance, within the food category it tracks expenses on types of fruit, milk, etc.

Table 2: Demand System Expenditures

Category	CEX Expenditures Included
Non-Durables	Food (Food, Alcoholic Beverages, Tobacco Products and Smoking Supplies), Consumer goods (Apparel, Personal Care, Reading)
Consumer Services	Education, Healthcare, Entertainment (including cable)
Utilities and public services	Electricity, Natural Gas, Heating Oil, Non-Energy Utilities and Public Services (excluding cable)
Housing	Shelter, Rental value of property (Owned Home, Time Share, Owned Vacation Home), Household Operations, Household Furnishings and Equipment
Transportation	Vehicle Services Flow (imputed), Gasoline and Motor Oil, Other Vehicle Expenses, Public Transportation
Leisure	Imputed

Expenditures cannot be negative in a demand system estimation. However, we find that the CEX reports a small number of negative expenditures for health care and housing. Health expenditures are negative for around 470 observations. This stems from the way the CEX treats reimbursements. According to CEX documentation, the CUs are asked to not include expenditures that they expect will be reimbursed by someone outside the CU, for example by an insurance company or employer. To address this issue, we remove reimbursements and gifts from the health care expenses category. In addition, housing expenditures are negative for 11 observations due to two expenditure categories: "Care for elderly, invalids, handicapped, etc." and "Adult day care centers." This may also be due to unreported subsidies or reimbursements, though we have no way to confirm this. We drop these observations from the sample. The average age for the 11 CUs that are dropped due to negative housing expenditures is 77, and they have low reported incomes.

In addition, we remove extreme outliers from the sample but take a conservative approach to this exercise. For instance, at the national level CUs with an hourly wage of more than $2,500 (14 observations) and quarterly housing expenditures of more than $162,562 (35 observations) are identified as outliers.[9] We also explore outliers within each income group. We classify 57 low-income CUs with leisure value greater than $382,610, 60 medium-income CUs with leisure value more than $645,919, and 53 high-income CUs with leisure value more than $821,998 as outliers and therefore drop them from our sample.[10]

West and Williams note that adults over 65 years old are expected to exhibit different labor market and consumption behavior than others (West and Williams III, 2004). For this reason, they exclude them from their sample. In determining the most appropriate cut off for the 2013-2017 CEX sample upon which we

[9] The outliers represent the 99.99 percentile and are more than two times greater than the next largest reported wage or expenditure.
[10] We also estimate the demand system without removing the outliers. We find that some elasticities are a bit higher, but the difference is very small. The standard errors are not sensitive to including these outliers.

rely, we find that, while adults between 65 and 70 years old are fairly evenly distributed across income groups, the majority of adults above 70 years old are in the low-income group. Data indicate that both income and expenditures begin to decline after age 65, with a particularly marked decline after age 70. Older adults also spend far less on transportation and clothing, but more on health care. This is true in spite of the fact that most expenditures on nursing home care are excluded from the CEX (Foster, 2015). To facilitate comparisons with existing estimates in the literature and also to retain some aspect of "representativeness," we exclude 15,548 CUs from the sample where the reference person is more than 70 years old.[11] We explore the sensitivity of the demand system results to different cut-offs, specifically excluding adults above 65 years old as well as excluding adults above 75 years old, in Section 6.1.

In addition, we exclude households with more than two adults from the sample. This is consistent with the prior consumer demand estimation literature. We exclude them for several reasons: We do not know have enough information to identify how consumer units with more than two adults make expenditure decisions – for instance, the degree to which they are made jointly or independently. The number of adults in a household also influences total leisure time and is expected to influence labor supply elasticities. CUs with more than two adults in them also may not be considered households from a tax perspective (for instance, roommates). A total of 16,182 CUs are dropped from the sample because they have more than two adults. Some of these CUs may also have a reference person that is older than 70 years old. Applying these constraints in tandem, we drop a total of 30,489 CUs to obtain our final sample of CUs with one or two adults and a reference person that is 70 years old or younger. The sensitivity of the results to including CUs with more than two adults is also presented in Section 5.2. While we exclude some CUs from the final sample for the demand system estimation, they are included in Heckman correction model and vehicle services estimates. This makes the imputation process the same for various subsamples so that the only difference is including them in the final demand system estimation.

4.1.1. Leisure Imputation

Leisure plays an important role in a CGE model because it connects consumption and production through the labor-leisure choice. Most CGE models calibrate the labor-leisure choice in one of two ways: by using estimated labor supply elasticities from the literature and calibrating the level of leisure such that it's consistent with the level of output and general labor supply characteristics in the economy(Fox, 2002), or by estimating the leisure/labor elasticities empirically. To pursue this latter approach, we include leisure explicitly in the consumer demand system. However, this requires information on both leisure price and quantity, which are not directly reported in the CEX. To impute these values for each CU, we use the after-tax hourly wage as a proxy for leisure price. We then multiply the leisure price by an estimate of leisure time to obtain leisure expenditures. We use the American Time Survey definition for leisure where leisure time includes activities such as socializing and communicating, watching TV, participating in sport, exercise, and recreation (Bureau of Labor Statistics, 2015).

We use the following formula to calculate the hourly after-tax wage for each reference person in a CU (i):

[11] A reference person is the consumer unit member who is reported by the respondent as the main person in charge of paying and/or making decision for major expenditures such as rent.

After-tax wage$_i$ = $\frac{reference\ \ person\,wagei}{hours\,worked\,by\,reference\ \ personi}$ ** (1 – federal marginal tax rate$_i$ – state marginal tax rate$_i$)* (7)

The federal and state marginal tax rates are reported in the CEX for each CU member. We then calculate the average marginal tax rates for each CU using the wage of each CU member as weights.

Quarterly leisure expenditures are calculated by multiplying the after-tax hourly wage by leisure time (i.e. time endowment - CU working hours) as shown below:

*leisure expenditure$_i$ = {[(90 * daily time endowment) *(no. of adults$_i$)] – total hours worked$_i$} * after-tax wage$_i$* (8)

where total hours worked is for all CU members during the past three months (i.e., 90 days). For the daily time endowment, we rely on an assumption borrowed from Fullerton and Rogers (1993), that each working adult in the United States has a time endowment of 4,000 hours per year or 10.96 hours per day on average that can then be distributed between work and leisure time. Assuming an eight hour work day implies an average leisure time for any adult of 2.96 hours per day. The time endowment is an important factor in determining the labor supply elasticity because it imposes a constraint on the degree to which labor supply can be increased (Ballard, 2000). We explore the sensitivity of our results to this assumption using different values of the time endowment including the average time endowment of 13.3 hours per year based on information from the American Time Use Survey.

Leisure and work time impact the magnitude of the compensated and uncompensated labor supply elasticities as follows:

$$(Un)Comp.\,labor\ supply\ elas. = -\left(\frac{leisure\ time}{work\ time}\right) * (Un)Comp.\,leisure\ demand\ elas. \qquad (9a)$$

Wage elasticities for labor supply are then calculated using the Slutsky formula:

$$Wage\ labor\ supply\ elas. = \frac{Comp.labor\ supply\ elas. - Uncomp.labor\ supply\ elas.}{expenditure\ share\ of\ leisure} \qquad (9b)$$

Some CUs report zero wages, which does not necessarily mean that the price of leisure is zero for them. The decision to not work is not random, but due to many factors such as a higher reservation wage, number of children, and marriage status (Ballard, 2000). We use the Heckman selection model (Heckman, 1979) to address the possibility of selection bias for reported wages. The model assumes the following equation exists where the dependent variable, y_i (here, wages), is observed if $z_i£ + u_{2i} > 0$ (selection equation). z_i includes variables that affect the probability of selection (here, working). Specifically, the consumer decides to work if the selection equation is positive (i.e., the wage data are available).

$$y_i = x_i\beta + u_{1i}\,, \qquad (10)$$

where u_{1i} and u_{2i} are normal and jointly distributed. When the correlation between the two error terms is not zero, estimating the regression equation and ignoring the selection problem creates biased results.

The Heckman correction model addresses this issue through a two-step approach. In our case, the first step is to estimate a probit model where the dependent variable indicates whether we observe a wage for a CU (i.e., they work). The selection equation includes both regression and selection variables to control for factors that affect the household's decision to work. We employ an approach similar to West and Williams (2004) where the after-tax hourly wage is estimated separately by gender for one-adult and more than one adult CUs. The separate estimation is mainly because on the decision regarding how much to working is expected to differ depending on the number of adults in the household. Previous work also shows that the labor supply elasticity is higher for females than males (Fuchs, et al., 1998; West & Williams III, 2007). However, some studies such as Heim (2007) show that labor supply elasticities for married women have decreased over time and tend to be closer to the elasticities for men in more recent years. For this reason, we only estimate the wage (leisure price) separately by gender; the demand system and the associated labor supply elasticities are not estimated separately in the main results. However, the results for when the demand system is estimated separately by gender are also presented in the sensitivity analysis section.

The wage equation is as follows where the selection variables are state-level unemployment rate, the number of children, and price of consumption categories. Education, age, marriage status, race, and geographic variables are also included as controls. Geographic variables include binary variables for the U.S. state in which a CU resides and whether a CU lives in an urban area.

$$\ln(wage_{it}) = \tau_1 age_{it} + \tau_2 \, age_{it}^2 + \tau_3 \, educa_{it} + \tau_4 \, marriage_{it} + \tau_5 \, white_{it} + \tau_6 urban_{it} + \tau_7 \, state_i + \epsilon_{it} \qquad (11)$$

In the case of CUs with more than one adult, the spouse's education level, age, and race are also added to the estimation. The spouse's education and age variables are missing for around 25% of two-adult CUs and we estimate a separate Heckman correction model for these CUs while we exclude these two variables from the estimation. We use the predicted hourly wage from this regression as the leisure price for CUs with zero wages.

4.1.2. Durable Good Purchases

Durable good purchases such as housing and vehicle purchases are large and infrequent. This means that not all households report expenditures on durable goods during the quarters in which they are surveyed. Because some sizable durable good expenditures are reported in the CEX data as one-time expenditures, we replace them with their quarterly service flows to allow for their inclusion in the consumer demand estimation.

For housing, the CEX reports equivalent rent, which is the rental value of the home in which the household currently resides. We use a broader definition of the equivalent rent of the property by adding together the estimated rental value of an owned home, as well as the value of any timeshare and vacation home that is available for rent.

For transportation expenditures, no such equivalent is directly reported in the CEX. Thus, we replace vehicle purchases with their vehicle service flow based on Slesnick (2001). Specifically, we define the quarterly vehicle service flow as:

$$S_t = 0.25(r_t + \delta)(1-\delta)^T P_0\,, \qquad (12)$$

where P_0 is the initial vehicle purchase price *T* years ago as defined by the CEX. r_t is an assumed value for the after-tax rate of return, and δ is the assumed depreciation rate. Data on the annual rate of return and vehicle depreciation rate are not available in the CEX data. We use the U.S. 20 Year Real Treasury Rate as a measure of the after-tax rate of return and scrappage rates summarized by Bento, et al. (2018) as a measure of the depreciation rate. These depreciation rates are assigned to each vehicle in the CEX data based on the age and type of vehicle.[12]

The vehicle purchasing price is missing for around 24% of the vehicles in our sample. To impute a value for these vehicles, we employ a similar approach to Meyer and Sullivan (2017). We first estimate the relationship between household and vehicle characteristics and the vehicle purchasing price for CUs with complete information in the CEX survey:

$$\ln(P_t) = v_1 veh\_age_{it} + v_2 fuel\_type_{it} + v_3 own\_use_{it} + v_4 veh\_new_{it} + v_5 family\_size_{it} + v_6 education_{it} + v_7\, age_{it} + v_8\, male_{it} + v_9\, region_{it} + v_{10}\, truck_i + v_{11} veh\_make_i + v_{12}\, veh\_year_i + \epsilon_{it}\,, \qquad (13)$$

where $own_{use}, veh_{new},$ and $truck$ are binary variables indicating whether the vehicle is for own use, is purchased as a new or used vehicle, and is a truck. We also include vehicle make, truck, and year fixed effects. We next impute the predicted vehicle purchasing price for households where this information is missing by multiplying the relevant vehicle and household characteristics for a CU-vehicle combination by the estimated coefficients. The imputed and reported vehicle purchasing prices are then used to calculate a vehicle services flow. Around 15% of the CUs do not own any vehicles, which implies a zero value of vehicle service flow for these households.

4.1.3. Zero Expenditures

Some households report zero expenditures on one or more consumption categories. These censored observations can occur due to factors such as affordability, non-preferences, or non-frequency, and raise a selection bias concern. Given that the censorship is not random, ignoring these observations creates selection bias. This selection issue is addressed by estimating the two-step Heckman correction model and using the estimated Inverse Mills ratios (as a measure of non-selection hazard) as right-hand-side variables in the demand system estimation (Heien and Wesseils, 1990). According to Shonkwiler and Yen (1999), this approach is biased if the number of censored observations is large. However, this is not a major concern in this study because we use highly aggregated consumption categories, of which a relatively low fraction of the top-level consumption expenditures is zero. with the category with the highest fraction of zero expenditures is consumer services, where less than five percent of observations are zero.

[12] The study provides average scrappage rates for passenger cars and light trucks in three time periods at ages 2 to 14 years old. We use the "passenger car" rates for automobiles and motorcycles and use the "light truck" rates for all other vehicle types. The depreciation rate for vehicles produced after 2014 are assumed to be the same as for 1987-2014, while we use the rates for 14 years old vehicles for older vehicles.

The Heckman correction model for each expenditure share includes number of children, home ownership status and the log of prices for other expenditure categories as selection variables.

$$\ln(w_i) = \delta_1\, age_{it} + \delta_2\, age_{it}^2 + \delta_3\, educa_{it} + \delta_4\, educa_{it}^2 + \delta_5\, white_{it} + \delta_6\, female_{it} + \delta_7\, adult_{it} + \delta_8\, marriage_{it} + \delta_9\, state_{it} + \delta_{10} year_{it} + \delta_{11}\, month_{it} + \epsilon_{it}\,, \qquad (14)$$

Control variables include age, education, race, gender, number of adults in the household, marriage status, state, and month and year of the interview. After estimating the Heckman correction model for each category, the Inverse Mills ratios are calculated for inclusion in the demand system estimation.

4.2. Consumption Price Data

This study employs two main sources of price data: Regional Price Parities (RPP) from the Bureau of Economic Analysis (BEA) and the Cost of Living Index (COLI) from the Center for Regional Economic Competitiveness. The CEX data reports a CU's expenditures for the past three months before the interview, which means that reported expenditures may span multiple calendar-defined quarters or even years. To match our price data with irregular interview dates, we construct three-month price indices that vary monthly. We use a combination of prices to capture important variation in expenditures for goods at the level of aggregation reported in Figure 1.

After creating monthly price indices for each state, the average past three months' price index for each consumption category is assigned to a household based on the time of the interview and the state of residence. Due to confidentiality, the CEX state variable is suppressed for around 11.5% of the observations in the CEX Public Use Micro data. For these observations, the state variable is replaced with a comparable state (e.g. Delaware might be replaced by New Jersey). We construct two aggregated price indices, one based on RPP data and the other based on CREC's COLI data. There are advantages and disadvantages associated with each set of price indices. For instance, RPPs are available for aggregated categories of expenditures but do not match all the categories that we need for our estimation. In addition, RPPs are calculated at the annual level and for each year separately. On the other hand, COLI prices are available quarterly and cover most of the required sub-aggregate categories, but they are not comprehensive. The higher frequency and time series aspect of the COLI data motivates us to use these data as the main source of price data. However, we also present the results based on RPPs.

We use quarterly MSA-level COLI data from 2013-2017. MSA-level price indices are aggregated to the state-level. The data are available for the first three quarters of each year. We use the average price indices of the first three quarters as the fourth quarter price index in each year. We use these data to derive monthly price indices (i.e., they will have the same value for months within a given quarter or year depending on the index utilized). We then re-aggregate to three-month periods that can be matched to the CEX expenditure data based on the CU's month and year of interview and its state of residence. COLI data does not include price indices for all categories, so we assign COLI price indices to each expenditure category as shown in Table 6.

Table 6: Cost of Living Index Assignment to Expenditure Categories

Expenditure Category	Assigned COLI Price Indices
Housing	Housing
Utilities	Utilities
Food	Grocery items
Transportation	Transportation
Health care	Health care
Beverages	Beer, Wine
Apparel	Men Dress Shirt, Man Denim Jeans, Boy Jeans, Men Slacks, Women Slacks
Personal Care	Haircut, Beauty Salon, Toothpaste, Shampoo, Dry Cleaning
Reading	Newspaper
Recreation	Movie, Tennis balls, Bowling

Since COLI price indices are only available for urban areas, we use "all goods" RPPs for nonmetropolitan versus metropolitan portions of each state to calculate non-urban RPP and COLI price indices for each consumption category.[13]

In addition, we use state-level RPPs from 2013-2017. These RPPs are annual and thus inherently they impose the same regional price parities across all months within a specific year. The RPP data includes the following consumption categories: rent, food, apparel, transport, housing, education, recreation, medical, and others. We use a multilateral aggregation method to calculate aggregated RPPs for non-durables and consumer services. For utilities prices (e.g., electricity, water), we use BLS monthly prices and State Energy Data System (SEDS) energy consumption data to calculate a weighted average aggregate utility price. Since we don't have state-level water and telephone prices, we assume their price variation is similar to the utilities' price variation for purposes of aggregation.

There is no direct RPP index for some of our aggregate consumption categories, such as consumers services and non-durables. We employ the Geary (also known as the Geary-Khamis) method (Geary, 1958; Khamis, 1972) to calculate aggregated price indices that maintain the multilateral properties of the price indices (Aten, et al., 2011). We follow Aten el. (2011) and use the following Geary formula to calculate aggregated price levels:

$$P_{ia}^{Geary} = \frac{e_{ia}(P_a)}{e_{ia}(P_n)}, \quad (15)$$

[13] The BEA has state-level RPP data separately for metropolitan and non-metropolitan portions for four categories: all items, goods, services, and rent. We use the (non-metropolitan RPP/metropolitan RPP) for *all items* as a weight to calculate a measure of non-urban price indices for each category.

where a and i represent geographic area and expenditure category, respectively. In general, the Geary price for area a and sub-category i can be calculated by dividing expenditures at area prices (P_a) by expenditures at national prices (P_n). Quantity in the nominator and the denominator is the same, so what remains is relative prices. Then, we can calculate price indices for our aggregated categories by adding expenditures at area prices divided by added expenditures at national prices (replaced with the above formula). For example, we calculate consumer services' RPP in area a as:

$$RPP_{cs,a} = \frac{e_{educ,a(P_a)}+e_{med,a(P_a)}+e_{rec,a(P_a)}}{\frac{e_{educ,a(P_a)}}{RPP_{educ,a}}+\frac{e_{med,a(P_a)}}{RPP_{med,a}}+\frac{e_{rec,a(P_a)}}{RPP_{rec,a}}}, \qquad (16)$$

where the expenditures for the education, medical, and recreation sub-categories for each area and year (at area prices) are from the CEX.

5. Demand System Estimation

After preparing the required price and expenditure variables for each expenditure category, the following budget share equation is estimated simultaneously for all categories using an iterated linear least-squares estimator.

$$w_i^h = \alpha_i + \sum_{j=1}^{6} \gamma_{ij} \ln p_j^h + \beta_i\{\ln m^h - (\alpha_0 + \sum_{i=1}^{6} \alpha_i \ln p_i + \frac{1}{2}\sum_{i=1}^{6}\sum_{j=1}^{6} \gamma_{ij} \ln p_i \ln p_j)\} + \lambda_i \frac{[\ln m^h - (\alpha_0 + \sum_{i=1}^{6} \alpha_i \ln p_i + \frac{1}{2}\sum_{i=1}^{6}\sum_{j=1}^{6} \gamma_{ij} \ln p_i \ln p_j)]^2}{\prod_{i=1}^{6} p_i^{\beta_i}} + u_i^h, \quad (17)$$

where, w_i^h is the budget share for good i in household h. The variable p indicates the price index for each good and m^h represents a household's total expenditures. The α's are linear combinations of demographic variables (s^h) such that $\boldsymbol{\alpha}^h = \boldsymbol{\alpha}_i' \, \boldsymbol{s}^h$ (Lecocq & Robin, 2015). The $\boldsymbol{s}^h$ vector includes reference person age, family size, number of income earners, race, home ownership status, number of children, region fixed effects, and the estimated inverse mills ratios from the Heckman correction model for each expenditure category.

Demand equations are often estimated using methods such as Seemingly Unrelated Regressions (SUR), Maximum Likelihood (ML), or Three-Stage Least Squares (3SLS). We employ the methodology developed in Lecocq and Robin (2015), which uses Blundell and Robin's (1999) iterated linear least-squares (ILLS) estimator.[14] The method is computationally less demanding than techniques such as nonlinear SUR but shares some common features. Operationally, the ILLS estimator consists of a series of iterations where a seemingly unrelated regression of expenditure shares is estimated in each iteration. The initial values for $ln\ a(\boldsymbol{p})$ and $\mathrm{b}(\boldsymbol{p})$ (Equation 2) are the Stone price index and the unit vector, respectively, and the price aggregators are updated in each iteration using the estimated parameters until numerical convergence (Lecocq and Robin, 2015).

Budget and price elasticities for each of the good categories are then calculated using the estimated parameters from the demand system as shown in equations (4) through (6).

[14] Practically, this is achieved using Stata's "aidsills" command.

6. Summary Statistics

Our final dataset includes a total of 75,266 CUs, limited to households with one or two adults and reference persons that are 70 years old or less. Tables 3 shows summary statistics for the CUs in our dataset for each of the six expenditure categories. By far, leisure has the highest share of total expenditures over the 2013-2017 timeframe with an average of 49 percent. This leisure share is 38 percent and 56 percent for one-adult and two-adult households, respectively. While West and Williams (2004) reported a similar average leisure share for two-adult household (55 percent), they report a markedly higher average leisure share for one-adult households (49 percent) over the 1996-1998 timeframe. The difference between the leisure shares compared to West and Williams (2004) is due to a variety of reasons: aside from the difference in the time frame, we assume a slightly lower time endowment and use reported wage instead of the Heckman corrected wage for the initial leisure value calculation.[15]

For the other expenditure categories, spending on housing and nondurables constitute about 16 and 15 percent of the total, respectively. The share of spending in other expenditure categories ranges from 9 percent (consumer services) to 6 percent (utilities). All the expenditure categories include some CUs that have zero expenditures within the reporting timeframe. The extent to which this occurs varies, with a larger proportion of CUs reporting zero expenditures for leisure due to missing wage information (20 percent) relative to 0.2 percent of CUs reporting zero expenditures for non-durables. Recall we address these missing values in the estimation. The large variation in leisure expenditures is mainly due to the wide range of the reported after-tax wages used in its derivation.

Table 3: Summary Statistics (Expenditures in US Dollars, 2013-2017)

Variable	N	Mean	SD	Min	Max	Expenditure Share Mean
Non-durable	75,266	2,538	1,825	0	37,430	0.15
Consumer services	75,266	1,848	3,135	0	98,710	0.09
Utilities	75,266	912	573	0	7,581	0.06
Housing	75,266	2,611	2,406	0	45,679	0.16
Transport	75,266	1,221	1,353	0	34,404	0.06
Leisure	75,266	16,562	27,105	0	811,598	0.49

In addition, Table 4 compares the average expenditure share for each of the six categories at the national level to those for three income groups (low, medium, and high)[16] and four Census regions. The expenditure share for each of the categories varies quite a bit across income groups, with particularly stark

[15] We use the Heckman corrected wage as the leisure price for CUs that report zero wages, but not for the leisure expenditures calculation. We instead use another Heckman correction model for leisure expenditures similar to what we do for other expenditures. West and Williams (2004) use the Heckman corrected wage (non-zero with smaller variance) for both leisure price and leisure expenditure value. The average hourly wage in our sample is 19.6 and 14.7 for the Heckman corrected wage and the reported wage, respectively.

[16] Income groups are defined by dividing the sample into three groups based on the households' equivalence-scale adjusted before-tax income where before-tax income is divided by $(adults + children)^{0.5}$ to adjust the value for the family size. We also check the sensitivity of the results to defining the income groups based on the households' equivalence-scale adjusted consumption expenditures. This is mainly because before-tax income might not be a good representative of a household's wealth. The results are shown in Table 20.

differences evident for leisure, non-durables, and housing. The leisure share increases with income, while other consumption categories' shares decrease with income. While expenditure values also vary across regions, the variation in relative shares is small. Based on these summary statistics, our expectation is that the estimated elasticities will exhibit greater variation across income groups than across census regions.

Table 4: Summary Statistics (Mean Expenditure Share)

	National	**Income Groups**			**Census Regions**			
		Low	*Medium*	*High*	*Midwest*	*Northeast*	*South*	*West*
Non-durable	0.15	0.20	0.13	0.11	0.15	0.15	0.16	0.14
Cons. services	0.09	0.09	0.08	0.09	0.09	0.09	0.08	0.08
Utilities	0.06	0.08	0.05	0.04	0.06	0.06	0.07	0.05
Housing	0.16	0.22	0.14	0.11	0.14	0.17	0.15	0.17
Transport	0.06	0.07	0.06	0.06	0.07	0.06	0.07	0.06
Leisure	0.49	0.33	0.53	0.59	0.49	0.48	0.48	0.50
Observations	75,266	23,881	24,357	27,028	27,028	13,942	27,423	19,041

Figures 2a and 2b show the average full consumption expenditure shares and average consumption expenditures across time between 2013 and 2017. While expenditures for categories such as housing and non-durables have increased over time, the consumption share doesn't show large variation across time. The largest change is in the transportation expenditure share, which decreased from 7.2% in 2013 to around 6% in 2017, on average.

Figure 2a: Average U.S. Households' Full Consumption Expenditure Shares

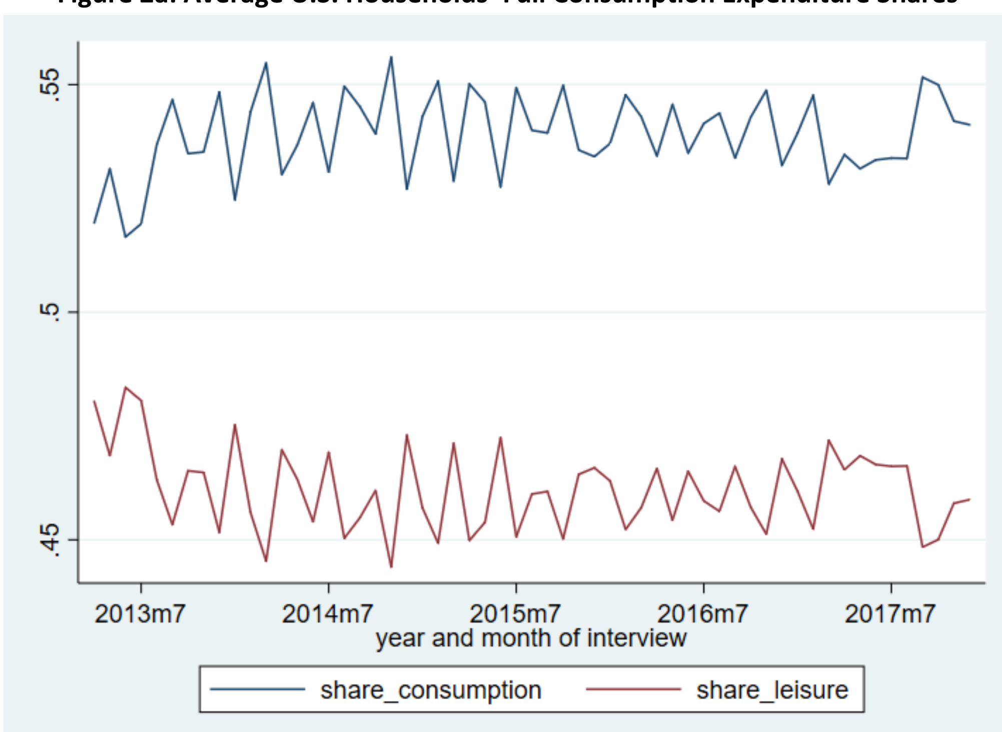


Figure 2b: Average U.S. Households' Consumption Expenditures

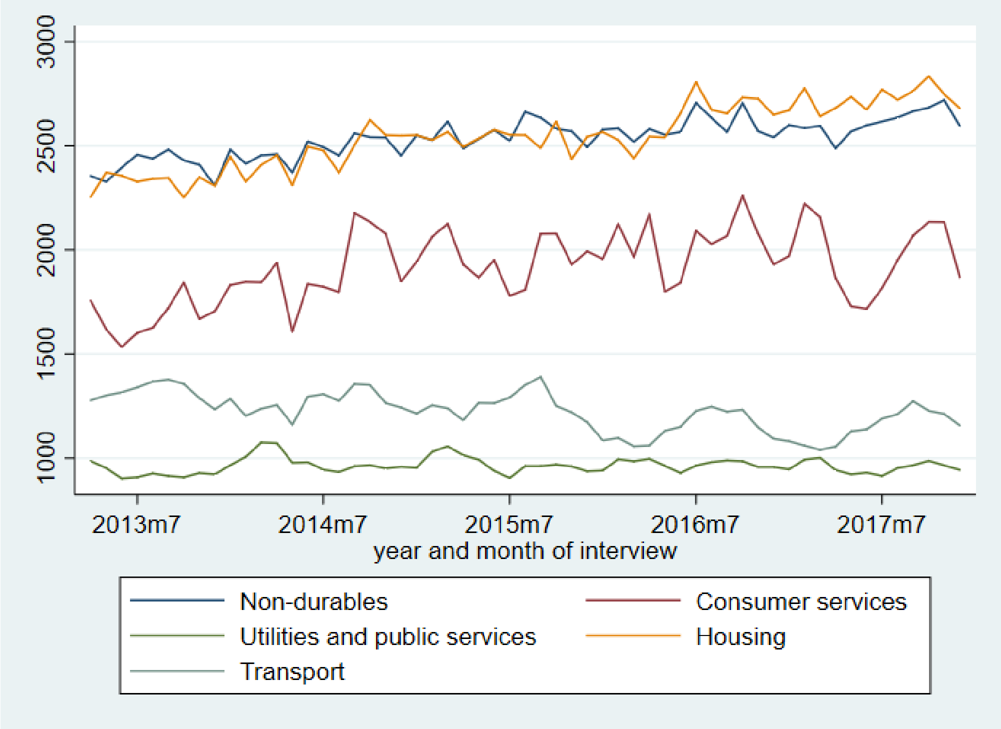


Table 5 reports summary statistics for the household demographic characteristics included in the consumer demand system estimation as controls. Note that working status of the reference person is a binary variable that is equal to one if the person is working. Variables such as female, white, married, and home ownership are also binary.

Table 5: Summary Statistics (Household demographics)

Variable	N	Mean	SD	Median	Min	Max
CU working status	75,266	0.80	0.40	1	0	1
CU annual income before taxes	75,266	72,531	73,888	51,126	-378,000	965,000
Age of reference person	75,266	45.79	14.32	46	18	70
Age of spouse	34,402	46.72	13.53	46	14	87
Education of reference person	75,266	13.58	1.75	13	0	16
Female (reference person)	75,266	0.52	0.50	1	0	1
White (reference person)	75,266	0.79	0.41	1	0	1
Married (reference person)	75,266	0.48	0.50	0	0	1
Number of children	75,266	0.65	1.08	0	0	11
Number of adults in CU	75,266	1.61	0.49	2	1	2
Number of members in CU	75,266	2.27	1.29	2	1	13
Home ownership	75,266	0.57	0.50	1	0	1

When possible, we compared these summary statistics to the 2013-2017 American Community Survey (ACS) Data Profile to check the broad representativeness of our data set. The CEX-derived data set that underlies our estimation has a similar percent who are married (48%) and female (52%) relative to the population as a whole (48 percent and 51 percent, respectively), while percent White is somewhat overrepresented in the dataset (79 percent) compared to the ACS (73 percent).

About 80 percent of CUs had at least one adult working at the time the CEX data were collected. The average annual before-tax income for a CU was $72,531 with a median of $51,126. Education level is defined as a categorial variable where zero signifies no school attendance and 16 means holding a graduate level degree. The median value of 13 implies that half of the reference persons have completed some college level studies with no degree (less than an Associate degree). On average, 57 percent of CUs owned a home. The average family size was 2.27 persons with a maximum number of 13 persons (recall that more than two-adult CUs and CUs with reference person above 70 years old are excluded from the main sample).

Figures 3-a and 3-b show the two sets of aggregated price indices for consumption categories where the price levels for each month are an average of the past three months' prices. These price indices do not show large variation across time; thus, this study is mainly using heterogeneity across individuals to derive elasticity estimates. As mentioned before, we rely on both price indices given their advantages and disadvantages with regards to comprehensiveness and sub-categorization. However, because COLI price indices are available quarterly, we use these price data in our main set of estimations and present the results using annual RPP price indices as a sensitivity. Given differences in terms of which sub-categories are included in the COLI versus RPP price indices, the aggregate values are not that close for some categories (e.g., COLI prices for categories such as non-durables and consumer services are lower than RPP prices). However, in general the ranking of expenditure categories is relatively consistent across the two price indices. Housing is the most expensive, followed by utilities, while consumer services has the lowest relative prices. While transportation and non-durables both fall somewhere in the middle, their relative ranking is not the same across indices.

Figure 3-a: COLI aggregated price indices

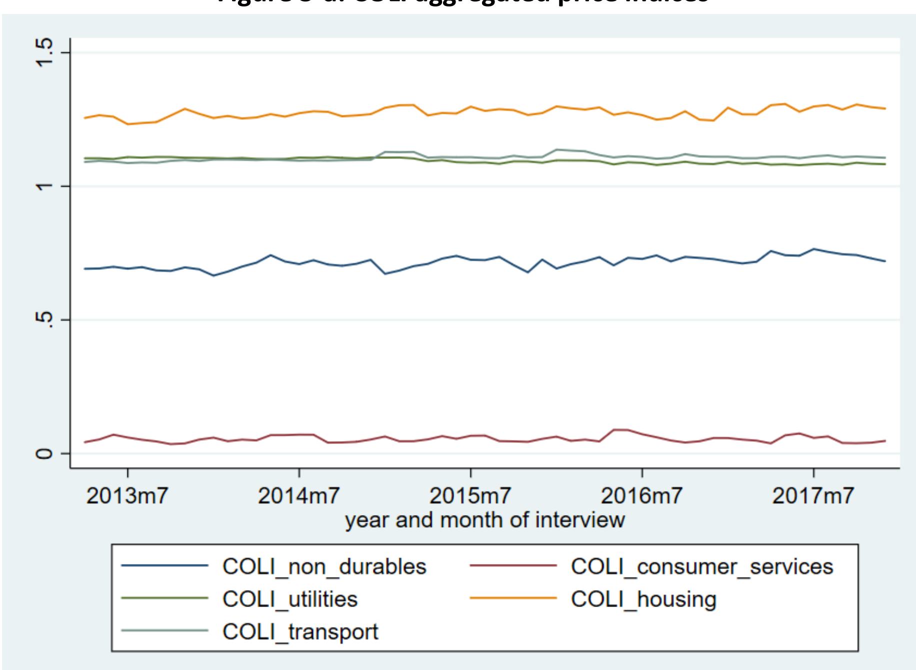
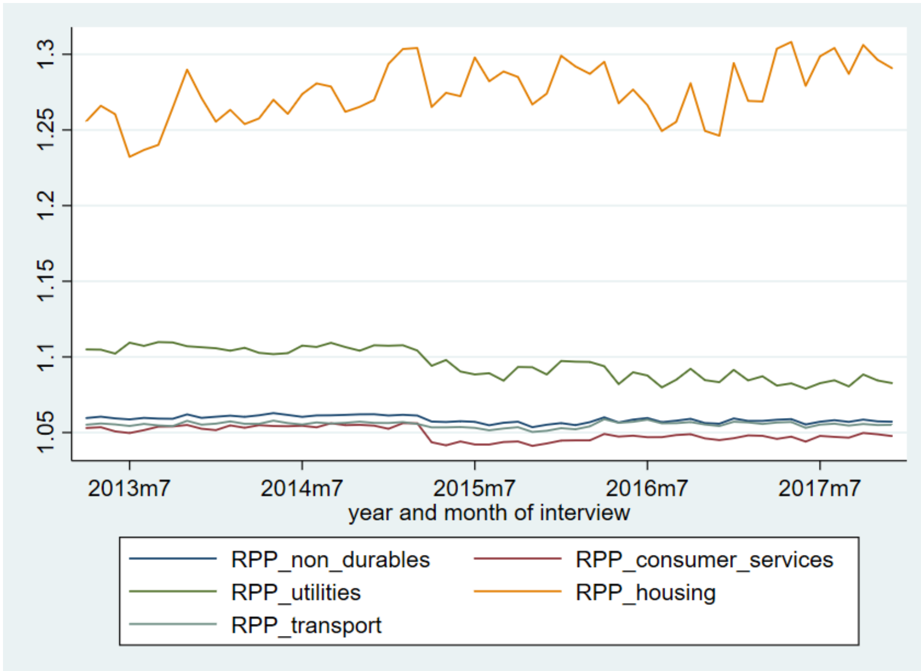


Figure 3-b: RPP aggregated price indices



7. Results

To estimate the demand system, we first need expenditure shares and prices for the six aggregate consumption categories. Section 7.1 presents the results for the vehicle services flow imputation and Heckman correction model for wage and expenditures, which then completes our estimation data set. Section 7.2 discusses the estimation results for the demand system at the national level followed by calculated elasticities. We also present the associated labor supply elasticities and the curvature tests in this section. The section also discusses the estimation results for the demand system differentiated by region and income. Finally, section 7.3 presents several sensitivities.

7.1 Vehicle services flow imputation and Heckman correction model results

To include vehicle services flow as part of the transportation expenditure category we first need to estimate the vehicle purchasing price for CUs who reported their vehicle information but omitted the vehicle purchasing price. Table 6 shows the estimation results based on CUs that reported the vehicle purchasing price using the Meyer and Sullivan (2017) approach described in Section 4.1.2. We present a naïve and fixed effect specification.

As expected, vehicle age has a negative impact on the purchasing price while, on average, vehicles that are purchased for own use, are new, or use gasoline as the fuel have a higher purchasing price. Household characteristics also affect the vehicle purchasing price. CUs that are larger, have higher income, have more education and have a male listed as the reference person tend to spend more on their vehicles. The average age of persons in the CU is also positively correlated with purchase price, but it is not a statistically significant determinant in the fixed effects specification.

Table 6: Vehicle purchasing price estimation for missing observations

VARIABLES	(1) Ln(purchase price)	(2) Ln(purchase price)
Vehicle age	-0.115***	-0.056***
	(0.001)	(0.002)
Fuel type	0.066***	0.097***
	(0.010)	(0.009)
Own use	0.211***	0.100***
	(0.029)	(0.025)
New vehicle	0.201***	0.262***
	(0.008)	(0.008)
Family size	0.004*	0.004*
	(0.002)	(0.002)
Age	0.001***	0.000
	(0.000)	(0.000)
Education	0.037***	0.012***
	(0.002)	(0.002)
Male	0.059***	0.026***
	(0.006)	(0.006)
No. of Observations	47,313	47,155
R-squared	0.496	0.665
Census Region	Yes	Yes
Fixed effects	No	Yes

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Fixed effect variables are truck dummy, vehicle make, and vehicle year

The vehicle purchasing price is predicted using the fixed effects estimation with an average of $12,560 while the average reported price is $19,588. Vehicles with a missing purchasing price are around two years older, on average. However, other statistics and household demographics are similar compared to the whole sample.

Using the predicted and reported vehicle purchasing price in addition to the other vehicle and household characteristics included in Equation 12, the quarterly vehicle services flow for each vehicle is calculated and added up for each CU (note that some CUs have multiple vehicles). Table 7 shows a summary of this variable where a zero value is used for non-owners.

Table 7: Total quarterly vehicle services

Variable	Observations	Mean	Std. Dev.	Min	Max
Quarterly vehicle services flow	75,266	207.27	179.72	0.00	4202.50
Number of vehicles	75,266	1.67	1.34	0.00	21.00

We find that the average quarterly vehicle services flow per CU is about $207 with a standard deviation of $180. Note, however, the existence of a long tail, which is driven by variation across observations in our sample both in terms of the number of vehicles owned or leased and the vehicle purchasing price.

Another variable needed for estimating the consumer demand system is leisure price. While we use the reported hourly wage to calculate a measure for leisure price for working CUs, we need to impute a value for non-working CUs. To accomplish this, we employ a Heckman correction model. We perform separate estimations based on the number of adults in the CU and the gender of the reference person. In general, we find intuitive results for most of the significant variables in the first-stage selection equation (see the Appendix for the table). For example, level of education and living in an urban area positively affect the likelihood that the reference person works, except in the case of two adult male-headed CUs where the relationship is estimated to be negative but insignificant. We find that the more children in a CU, the higher the likelihood that the reference person works, except in the case of one adult female-headed CUs where the relationship is estimated to be negative and significant. While age is positively related to the likelihood that a reference person works, the square term is negative and significant. A spouse's wage also has a positive impact on the likelihood that the reference person works. Other household and community characteristics are not consistent in terms of sign or significance across the specifications. Low p-values from the Wald test of independent equations imply that the error terms of the selection equation and the wage equation are not independent; that is, selection exists.

Table 8 shows the results for the wage equation when accounting for selection. Conditional on working, we find that older, more educated individuals earn higher wages. As is the case in the selection equation, the square term for age is negative and significant, indicating that the wage begins to decline for those who are either very young or old. We also find that the older and more educated the spouse, the higher the reference person's wage. Those living in urban areas and who are white also earn higher wages, except in the case of two adult male-headed CUs where living in urban areas has a negative but insignificant impact on wage.

Table 8: Heckman correction model results for wage (wage equation)

	(1)	(2)	(3)	(4)
VARIABLES	Ln(wage)	Ln(wage)	Ln(wage)	Ln(wage)
Age of reference person	0.077***	0.062***	0.070***	0.036***
	(0.004)	(0.004)	(0.005)	(0.006)
Squared age of reference person	-0.001***	-0.001***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Education of reference person	0.160***	0.190***	0.121***	0.141***
	(0.006)	(0.006)	(0.006)	(0.009)
Married	0.082**	0.042		
	(0.039)	(0.051)		
White	0.125***	0.062***	0.084**	0.018
	(0.022)	(0.020)	(0.042)	(0.037)
Urban area	0.354***	0.155*	-0.030	0.238***
	(0.077)	(0.082)	(0.077)	(0.089)
Education of spouse			0.070***	0.037***
			(0.006)	(0.007)
Age of spouse			0.003**	0.005**
			(0.002)	(0.002)
Gender of spouse (female)			0.082	0.223***
			(0.071)	(0.063)
Race of spouse (white)			0.054	0.036
			(0.042)	(0.037)
Observations	15,567	21,382	10,959	9,176
Number of adults	one	One	two	two
Gender	male	female	male	female
State fixed effects	yes	Yes	yes	yes
P_c	0.001	0.000	0.009	0.000

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Selection variables are state level unemployment rate and number of children and price of consumption categories.

P_c represents the P_value from Wald test of independent equations.

The predicted hourly wages for all reference persons in the data set, both working and non-working, from the Heckman correction models are summarized in Table 9. On average, the hourly wage for reference persons in two adult CUs is higher than it is in one-adult CUs, and the average hourly wage for a female reference person is lower than it is for a male reference person regardless of the number of adults in the CU. The predicted wage from the Heckman correction model differs by working status, where the average for working and non-working reference persons are $21.16 and $15.43 per hour, respectively.

Table 9: Predicted hourly wage from Heckman correction model

Variable	N	Mean	SD	Median	Min	Max
Hourly wage (one adult and male)	15,573	18.23	7.29	17.18	1.12	45.03
Hourly wage (one adult and female)	21,387	14.34	6.35	13.03	0.49	39.59
Hourly wage (two adult and male)	26,796	24.69	9.26	23.62	1.44	67.15
Hourly wage (two adult and female)	25,813	18.76	6.70	17.61	1.18	55.39

The final step before estimating the demand system is to estimate the Heckman correction model for each expenditure category to account for potential selection bias from zero expenditures. The results for the second stage are shown in Table 10. The low p-values in the last row of the table reject the null of no selection for all categories except for non-durables.

Conditional on having positive expenditures within a specific expenditure category, on average, CUs with higher income, or that are older, white, have more adults who are married, or with more children tend to have higher expenditures for virtually every category. One notable exception is that spending on leisure is inversely related to income and age. Housing expenditures also decline with age. Higher prices for one commodity category sometimes positively affect and other times negatively affect spending in another category. That said, we find that as leisure becomes more expensive, spending in other commodity categories also always increases, on average.

Table 10: Heckman correction model results for expenditure categories[17]

VARIABLES	(1) Non_durables	(2) Consumer services	(3) Utilities	(4) Housing	(5) Transport	(6) Leisure
Ln(income)	0.219***	0.390***	0.168***	0.200***	0.236***	-0.360***
	(0.003)	(0.006)	(0.003)	(0.003)	(0.004)	(0.003)
Age of reference person	0.010***	0.003**	0.031***	-0.022***	0.027***	-0.028***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Squared age of reference person	-0.000***	0.000***	-0.000***	0.000***	-0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White	0.113***	0.206***	0.032***	-0.031***	0.062***	0.007**
	(0.005)	(0.009)	(0.005)	(0.006)	(0.007)	(0.003)
Female	-0.034***	0.089***	0.050***	0.017***	-0.062***	0.030***
	(0.003)	(0.007)	(0.004)	(0.005)	(0.005)	(0.002)
Married	0.149***	0.336***	0.136***	0.065***	0.195***	0.181***
	(0.004)	(0.008)	(0.004)	(0.006)	(0.006)	(0.003)
Number of children	0.087***	-0.007*	0.099***	0.042***	0.032***	0.042***
	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)
Number of adults in CU	0.126***	0.049***	0.186***	-0.034***	0.115***	0.627***
	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)	(0.002)
Ln(price of non-durables)	-0.043*	-0.348***	-0.030	-0.112***	-0.476***	0.006
	(0.025)	(0.047)	(0.026)	(0.032)	(0.034)	(0.017)
Ln(price of consumer services)	-0.012	0.164***	0.003	0.002	-0.114***	0.003
	(0.009)	(0.018)	(0.010)	(0.012)	(0.013)	(0.007)
Ln(price of utilities)	-0.046	-0.242***	-0.099*	0.157**	0.186***	0.016
	(0.048)	(0.088)	(0.053)	(0.061)	(0.065)	(0.032)
Ln(price of housing)	0.146***	0.133*	0.050	0.290***	0.118**	-0.010
	(0.039)	(0.072)	(0.042)	(0.047)	(0.052)	(0.026)
Ln(price of transport)	0.267***	0.312***	0.291***	0.609***	-0.143**	-0.001
	(0.053)	(0.100)	(0.059)	(0.067)	(0.072)	(0.035)
Ln(price of leisure)	0.095***	0.208***	0.049***	0.100***	0.066***	1.304***
	(0.004)	(0.008)	(0.004)	(0.005)	(0.005)	(0.005)
Observations	105,515	105,515	105,515	105,515	105,515	105,515
State fixed effects	yes	Yes	yes	yes	yes	yes
Month fixed effects	yes	Yes	yes	yes	yes	yes
P_c	0.327	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Selection variable is home ownership (in addition to food stamp value for non-durables category).
The dependent variables are in the log form and conditional on having positive expenditures for the category.
P_c represents the P_value from Wald test of independent equations.

[17] Recall that for the purpose of comparison, we use the whole sample for Heckman correction models and vehicle services imputation. The final sample of excluding CUs with more than two adults and above 70 years old is used for the demand estimation.

7.2 Demand system estimation results

Using the expenditure shares and prices for each category and the CU demographic information in addition to the inverse mills ratios predicted from the Heckman correction models, we estimate a consumer demand system for U.S. households. Specifically, we estimate six expenditure share equations using an Iterated Linear Least Square method. Table 11 shows the estimation results at the national level using the QUAIDS functional form, state fixed effects, and COLI price data. We find evidence that flexibility in the functional form to allow for potential nonlinearities matters. As shown in the table, the λs are all statistically significant, indicating that an AIDS specification is insufficient for capturing demand responses. However, they are also estimated precisely at zero, so any nonlinearities appear to be quite small. While the demographic controls also are statistically significant, they, too, often have fairly small coefficient estimates. Our expectation then is that budget and price elasticities estimated using a QUAIDS or AIDS specification should be quite similar (See Table 12).

Table 11: Demand system estimation results (national level)

VARIABLES	(1) Non-durables share	(2) Consumer services share	(3) Utilities share	(4) Housing share	(5) Transport share	(6) Leisure share
γ_ln(p_non_dur)	-0.009**	-0.001	-0.006***	-0.004	-0.004	0.023***
	(0.004)	(0.004)	(0.002)	(0.005)	(0.003)	(0.008)
γ_ln(p_cons_serv)	-0.001	0.026***	-0.002**	-0.001	-0.005***	-0.017***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)
γ_ln(p_utility)	-0.006	-0.002	0.003	-0.011	0.014***	0.003
	(0.007)	(0.007)	(0.003)	(0.008)	(0.005)	(0.013)
γ_ln(p_housing)	-0.004	-0.001	-0.011***	0.011	-0.005	0.011
	(0.006)	(0.007)	(0.003)	(0.008)	(0.004)	(0.012)
γ_ln(p_transport)	-0.004	-0.005	0.014***	-0.005	0.009	-0.009
	(0.008)	(0.009)	(0.004)	(0.010)	(0.006)	(0.015)
γ_ln(p_leisure)	0.023***	-0.017***	0.003***	0.011***	-0.009***	-0.011***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)
β_ln(income)	-0.103***	-0.017***	-0.040***	-0.063***	-0.018***	0.241***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)
λ_ln(income)^2	0.003***	0.001***	-0.000	0.000	-0.001***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_age	-0.000	0.001***	0.000***	0.000***	0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_family_size	0.025***	0.009***	0.008***	0.006***	-0.000	-0.048***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
α_#of income earner	-0.014***	-0.026***	-0.006***	-0.021***	-0.003***	0.069***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
α_white	0.009***	0.001	-0.005***	0.010***	-0.001**	-0.013***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
α_own_home	0.019***	0.026***	0.015***	-0.069***	0.009***	-0.000
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)
α_#of child	-0.016***	-0.011***	-0.005***	-0.005***	-0.000	0.037***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)
Sample	National	National	National	National	National	National
Model	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS
Price data	COLI	COLI	COLI	COLI	COLI	COLI
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Inverse mills ratios	Yes	Yes	Yes	Yes	Yes	Yes
Observations	75,070	75,070	75,070	75,070	75,070	75,070

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Following the demand system estimation for each group, the income and price elasticities are calculated using the estimated parameters and Equations 4, 5, and 6. At the national level, the results in Table 12 indicate that all six expenditure categories are price inelastic with the un-compensated price elasticity ranging from -0.7 for consumer services to close to unity for leisure. All consumption categories except for leisure are also income inelastic. The non-durables category has the lowest income elasticity with a value of 0.5, while leisure has the highest elasticity at 1.49.

The price elasticity for utilities is close to estimates available in literature. For example, Alberini et al (2011) find that the own-price elasticity of demand for electricity is in the −0.86 to −0.67 range, and the own price elasticity of demand for gas is in the −0.69 to −0.57 range. However, it should be noted that the utilities category in this study includes non-energy utilities and public services in addition to electricity, natural gas, and heating oil. Our results for transport and housing are also broadly similar to available estimates in the literature. For instance, Fouquet (2012) estimates income and price elasticities for aggregate land transport services in the UK and finds values of 0.8 and -0.6, respectively. Albouy, et al. (2016) estimate price and income elasticities for housing are -0.67 and 0.67, respectively.

Table 12: Income and own-price elasticity results (national level)

	Budget Elasticity		**Un-compensated Price Elasticity**		**Compensated Price Elasticity**	
Non-durables	0.465***	0.452***	-0.841***	-0.846***	-0.768***	-0.773***
	(0.00)	(0.00)	(0.03)	(0.03)	(0.03)	(0.03)
Consumer services	0.921***	0.905***	-0.723***	-0.725***	-0.633***	-0.635***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Utilities	0.394***	0.391***	-0.864***	-0.865***	-0.838***	-0.839***
	(0.00)	(0.00)	(0.05)	(0.05)	(0.05)	(0.05)
Housing	0.618***	0.614***	-0.815***	-0.816***	-0.715***	-0.716***
	(0.00)	(0.00)	(0.05)	(0.05)	(0.05)	(0.05)
Transport	0.682***	0.686***	-0.832***	-0.834***	-0.785***	-0.787***
	(0.01)	(0.01)	(0.08)	(0.08)	(0.08)	(0.08)
Leisure	1.487***	1.505***	-0.973***	-0.979***	-0.310***	-0.315***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sample	National	National	National	National	National	National
Model	QUAIDS	AIDS	QUAIDS	AIDS	QUAIDS	AIDS
Price data	COLI	COLI	COLI	COLI	COLI	COLI
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	75,070	75,070	75,070	75,070	75,070	75,070

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

We next estimate the demand system for each income group and Census region. In our main result, we use the total equivalence-scale adjusted before-tax income to define the three income groups. Following West and Williams (2004), we divide before-tax income by $(adults + children)^{0.5}$ to adjust the value for family size. Results based on total equivalence-scale adjusted expenditures to define income groups are also presented as a sensitivity analysis in section 7.3.[18]

Table 13 provides the income elasticities estimated for different income groups and Census regions. While the income elasticities display some variation across different sub-categories, the results are qualitatively similar to the national level results in terms of leisure being income elastic and all other consumption categories being income inelastic. That said, there are some interesting differences in terms of their relative magnitude. For instance, the high-income group always has an income elasticity that is higher than the national estimate with the exception of the leisure category. Lower income groups have a lower income elasticity for all but consumer services and leisure. These variations stem from different expenditure shares across different income groups. For example, the high-income group, on average, has lower expenditure shares than the national level shares for all categories except leisure. Similarly, low-income CUs have higher expenditure shares than the national level shares for all categories except for consumer services and leisure.

The estimated income elasticities across Census regions demonstrate less variation than across income groups. Their magnitudes are fairly similar to the national-level results with the exception of utilities in Northeast, which have a higher income elasticity than the national results. The Northeast region has a higher income elasticity than at the national level in all categories except for non-durables.

Table 13: Income elasticity results

		Income Group			Census Region			
	National	Low	Medium	High	Midwest	Northeast	South	West
Nondurables	0.465***	0.259***	0.477***	0.604***	0.484***	0.309*	0.405***	0.480***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.03)	(0.15)	(0.11)	(0.01)
Consumer services	0.921***	1.071***	0.676***	0.949***	0.918***	0.994***	0.801***	0.918***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.08)	(0.01)
Utilities	0.394***	0.285***	0.360***	0.515***	0.358***	0.590***	0.406***	0.475***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.05)	(0.06)	(0.10)	(0.01)
Housing	0.618***	0.316***	0.577***	0.722***	0.603***	0.660***	0.636***	0.563***
	(0.00)	(0.02)	(0.01)	(0.01)	(0.03)	(0.06)	(0.07)	(0.01)
Transport	0.682***	0.575***	0.560***	0.693***	0.737***	0.715***	0.611***	0.642***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)	(0.08)	(0.10)	(0.02)
Leisure	1.487***	1.559***	1.646***	1.397***	1.473***	1.506***	1.455***	1.532***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.08)	(0.05)	(0.01)
Model	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS
Price data	COLI	COLI	COLI	COLI	COLI	COLI	COLI	COLI
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	75,070	23,703	24,351	27,016	14,834	13,900	27,360	18,976

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

[18] Note that the difference between results based on the AIDS vs. QAIDS specifications for income groups and Census regions are similar to those at the national level. The λs are statistically significant but very close to zero. Thus, the elasticity estimates based on AIDS are quite similar to those based on QUAIDS.

The price elasticity results demonstrate greater heterogeneity. Similar to the national level, uncompensated price elasticities for each income group are inelastic. However, categories such as leisure, housing and transportation are price elastic for some Census regions as shown in Table 14. The absolute value of the elasticity for consumption categories such as nondurables, consumer services, utilities, housing, and transport is lower for low-income households compared to medium- and high-income households.

Table 14: Uncompensated price elasticity results

		Income Group			Census Region			
	National	Low	Medium	High	Midwest	Northeast	South	West
Nondurables	-0.841***	-0.655***	-0.776***	-0.847***	-0.867***	-0.757***	-0.884***	-0.833***
	(0.03)	(0.07)	(0.04)	(0.03)	(0.06)	(0.10)	(0.05)	(0.06)
Consumer services	-0.723***	-0.644***	-0.730***	-0.679***	-0.713***	-0.705***	-0.643***	-0.744***
	(0.02)	(0.04)	(0.03)	(0.03)	(0.05)	(0.08)	(0.14)	(0.04)
Utilities	-0.864***	-0.794***	-0.825***	-0.929***	-0.804***	-0.929***	-0.744***	-0.980***
	(0.05)	(0.13)	(0.07)	(0.04)	(0.16)	(0.10)	(0.12)	(0.07)
Housing	-0.815***	-0.599***	-0.879***	-0.789***	-1.630***	-0.715***	-0.719***	-0.737***
	(0.05)	(0.14)	(0.07)	(0.06)	(0.22)	(0.10)	(0.13)	(0.07)
Transport	-0.832***	-0.572**	-0.913***	-0.887***	-1.157***	-1.116***	-0.032	-0.956***
	(0.08)	(0.19)	(0.12)	(0.10)	(0.22)	(0.19)	(0.33)	(0.12)
Leisure	-0.973***	-0.978***	-0.825***	-0.700***	-0.988***	-0.941***	-1.001***	-0.973***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)
Model	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS
Price data	COLI	COLI	COLI	COLI	COLI	COLI	COLI	COLI
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	75,070	23,703	24,351	27,016	14,834	13,900	27,360	18,976

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

The national level cross-price elasticities are presented in Table 15 The values on the diagonal present own price elasticities, which are identical to the reported un-compensated elasticities in Table 12.

Table 15: Uncompensated cross price elasticity results

	Non-durables	Consumer services	Utilities	Housing	Transport	Leisure
Non-durables	-0.841***	0.066***	0.05	0.146***	0.041	0.073***
	(0.03)	(0.01)	(0.05)	(0.04)	(0.05)	(0.01)
Consumer services	0.035	-0.723***	-0.004	0.02	-0.043	-0.206***
	(0.05)	(0.02)	(0.08)	(0.07)	(0.09)	(0.01)
Utilities	0.130***	0.046***	-0.864***	0.012	0.275***	0.006
	(0.03)	(0.01)	(0.05)	(0.05)	(0.06)	(0.01)
Housing	0.118***	0.042***	-0.01	-0.815***	0.012	0.035***
	(0.03)	(0.01)	(0.05)	(0.05)	(0.06)	(0.01)
Transport	0.06	-0.037*	0.247***	0.018	-0.832***	-0.139***
	(0.04)	(0.02)	(0.07)	(0.06)	(0.08)	(0.01)
Leisure	-0.136***	-0.101***	-0.072*	-0.128***	-0.077	-0.973***
	(0.02)	(0.01)	(0.03)	(0.03)	(0.04)	(0.00)

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

The labor supply elasticities can be calculated using the estimated leisure elasticities and the following formula.

*(Un)Compensated labor supply elasticity = - (leisure time/work time) * (Un)Compensated leisure demand elasticity* (18)

Price and income elasticities for labor supply are expected to be in the range of 0 to 0.3 and -0.1 to 0, respectively (McClelland and Mok, 2012). Although the price elasticities for labor supply we estimate are within the expected range, the income elasticities are quite high (Table 16). Note that the one other income elasticity estimated for use in a CGE model comes from Jorgenson (2013). However, the income elasticity estimated for a reference household is even higher (-2). One potential reason for high income elasticities is the time endowment assumed for each person. A smaller time endowment is expected to result in a smaller income elasticity. The next section shows the sensitivity of these labor supply elasticities to values other than 10.96 hours as the daily time endowment.

Table 16: labor supply elasticity (daily time endowment = 10.96 hours)

Sample	Income elasticity	Un-compensated elasticity	Compensated elasticity
National	-0.55	0.36	0.11
Low-income group	-0.58	0.36	0.08
Medium-income group	-0.61	0.31	0.05
High-income group	-0.52	0.26	0.03
Midwest region	-0.55	0.37	0.12
Northeast region	-0.56	0.35	0.12
South region	-0.54	0.37	0.10
West region	-0.57	0.36	0.12

Lastly, we examine the regularity of the demand system. The adding-up condition is imposed in Almost Ideal Demand Systems by construction. Homogeneity and symmetry conditions also are imposed when they are found to have failed after each iteration in the estimation. It should be noted that satisfying the symmetry condition ($\gamma_{ij} = \gamma_{ji}$ in Equation 2) in a flexible functional form does not necessarily imply that the cross-price elasticities are symmetric. To test the curvature condition, we check the constraints provided in 3(d) where the compensated own-price elasticities need to be negative and the determinant of the Slutsky matrix including compensated cross-price elasticities need to be positive. The former condition holds for all estimates. Table 17 shows the calculated determinant of the Slutsky matrix using the compensated price elasticities. Negative compensated own-price elasticities and positive determinants imply that the Slutsky matrix is negative semi-definite and the concavity condition is satisfied. We find that the curvature condition is satisfied at the national level. It also holds for the low- and medium-income groups and all of the Census regions.

Table 17: Slutsky matrix determinant

Sample	matrix determinant
National	-8.43E-05
Low-income group	-5.19E-05
Medium-income group	-3.90E-05
High-income group	1.94E-05
Midwest region	-2.37E-04
Northeast region	-9.22E-05
South region	-1.48E-06
West region	-1.97E-04

7.3 Sensitivity Analyses

To check the robustness of our results, we estimate the demand system using various specifications. They include replacing the COLI price indices with the RPP price indices (column 2 in the tables), converting nominal expenditures to real values (column 3), using alternative assumptions for the time endowment(columns 4 and 5), changing the age range and the number of adults that are excluded from the sample (columns 6 – 9), and estimating consumer demand without leisure (column 10). For purposes of the sensitivity analyses, we only report the national-level elasticity results in Tables 18 and 19. Recall that we assume 10.96 hours as the daily time endowment for our main estimates. The alternate value of 13.3 hours is borrowed from the American Time Survey where the average leisure time is reported as 5.3 hours per day. That implies a daily time endowment of 13.3 hours if individuals are working 8 hours per day. We also assume a daily time endowment of 15 hours to investigate the impact of using a time endowment that is close to the total number of nonsleeping hours available in a day.

We find that the national-level elasticities are similar across these various specifications except in the case of the budget elasticities when leisure is not included as a consumption category. In this case, as expected, the budget elasticities for the remaining expenditure categories are substantially higher. Importantly, the price elasticities are robust to the exclusion of leisure from the demand system. Note that many of the elasticity estimates for the RPP-based specification are not statistically significant. This is not surprising given that the RPPs are annual and demonstrate less frequency than the quarterly COLI price indices.

In addition, we estimate the demand system for different income groups using adjusted consumption expenditures to define the three income groups instead of adjusted before-tax income. Table 20 presents the results for this specification. Compared to the main income-group results, the income elasticity for categories such as nondurables, consumer services and transportation is lower for the low-income group. In addition, the income elasticity for leisure is higher for medium- and high-income groups. The price elasticities are relatively robust to this alternate specification.

Table 18: Results sensitivity: budget elasticity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Nondurables	0.465***	0.445***	0.464***	0.407***	0.370***	0.466***	0.441***	0.478***	0.452***	0.818***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.003)	(0.00)
Consumer services	0.921***	0.930***	0.921***	0.825***	0.773***	0.838***	0.957***	0.907***	0.871***	1.546***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.006)	(0.01)
Utilities	0.394***	0.371***	0.395***	0.359***	0.331***	0.362***	0.411***	0.384***	0.383***	0.577***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.004)	(0.00)
Housing	0.618***	0.596***	0.617***	0.553***	0.514***	0.657***	0.600***	0.625***	0.606***	1.046***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.004)	(0.00)
Transport	0.682***	0.668***	0.685***	0.632***	0.595***	0.644***	0.685***	0.685***	0.663***	0.994***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.005)	(0.01)
Leisure	1.487***	1.475***	1.489***	1.471***	1.465***	1.495***	1.471***	1.492***	1.497***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.003)	
Model	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS
Sample	National	National	National	National	National	National	National	National	National	National
Max no. of adults	2	2	2	2	2	n/a	2	2	n/a	2
Max age	70	70	70	70	70	n/a	65	75	70	70
Time endowment	10.96	10.96	10.96	13.3	15	10.96	10.96	10.96	10.96	10.96
Expenditures	Nominal	Nominal	Real	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal
Price data	COLI	RPP	COLI	COLI	COLI	COLI	COLI	COLI	COLI	COLI
Leisure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	75,070	75,070	75,070	75,070	75,070	105,748	67,649	80,318	89,991	75,070

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 19: Results sensitivity: un-compensated price elasticity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Nondurables	-0.841***	-1.003**	-0.847***	-0.848***	-0.848***	-0.848***	-0.843***	-0.845***	-0.832***	-0.864***
	(0.03)	(0.36)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.019)
Consumer services	-0.723***	-0.452	-0.720***	-0.725***	-0.724***	-0.690***	-0.726***	-0.719***	-0.713***	-0.826***
	(0.02)	(0.28)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.013)
Utilities	-0.864***	-0.820***	-0.833***	-0.824***	-0.821***	-0.836***	-0.852***	-0.838***	-0.874***	-0.887***
	(0.05)	(0.07)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.039)
Housing	-0.815***	-0.142	-0.817***	-0.808***	-0.803***	-0.868***	-0.815***	-0.831***	-0.835***	-0.943***
	(0.05)	(0.39)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.035)
Transport	-0.832***	-1.104*	-0.835***	-0.823***	-0.811***	-0.937***	-0.771***	-0.853***	-0.868***	-0.969***
	(0.08)	(0.53)	(0.08)	(0.09)	(0.09)	(0.07)	(0.09)	(0.08)	(0.07)	(0.065)
Leisure	-0.973***	-0.996***	-0.970***	-1.021***	-1.052***	-0.997***	-0.983***	-0.971***	-0.999***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Model	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS
Sample	National	National	National	National	National	National	National	National	National	National
Max no. of adults	2	2	2	2	2	n/a	2	2	n/a	2
Max age	70	70	70	70	70	n/a	65	75	70	70
Time endowment	10.96	10.96	10.96	13.3	15	10.96	10.96	10.96	10.96	10.96
Expenditures	Nominal	Nominal	Real	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal
Price data	COLI	RPP	COLI	COLI	COLI	COLI	COLI	COLI	COLI	COLI
Leisure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	75,070	75,070	75,070	75,070	75,070	105,748	67,649	80,318	89,991	75,070

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 20: Income-group results: using adjusted expenditures to define income groups

	Budget Elasticity			Un-compensated Price Elasticity			Compensated Price Elasticity		
Nondurables	0.107***	0.411***	0.593***	-0.696***	-0.765***	-0.832***	-0.681***	-0.694***	-0.708***
	(0.01)	(0.01)	(0.00)	(0.06)	(0.03)	(0.03)	(0.06)	(0.03)	(0.03)
Consumer services	0.456***	0.418***	0.812***	-0.790***	-0.771***	-0.692***	-0.761***	-0.725***	-0.553***

	(0.01)	(0.01)	(0.01)	(0.04)	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)
Utilities	0.275***	0.366***	0.535***	-0.756***	-0.994***	-0.878***	-0.735***	-0.967***	-0.839***
	(0.01)	(0.01)	(0.00)	(0.12)	(0.07)	(0.05)	(0.12)	(0.07)	(0.05)
Housing	0.328***	0.404***	0.669***	-0.595***	-0.832***	-0.843***	-0.543***	-0.760***	-0.694***
	(0.01)	(0.01)	(0.01)	(0.11)	(0.06)	(0.05)	(0.11)	(0.06)	(0.05)
Transport	0.366***	0.436***	0.673***	-0.683***	-0.747***	-0.847***	-0.660***	-0.713***	-0.779***
	(0.01)	(0.01)	(0.01)	(0.18)	(0.11)	(0.09)	(0.18)	(0.11)	(0.09)
Leisure	1.720***	1.946***	2.153***	-1.020***	-0.901***	-0.569***	-0.159***	-0.152***	-0.088***
	(0.00)	(0.01)	(0.02)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
Income group	Low	Medium	High	Low	Medium	High	Low	Medium	High
Model	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS
Max no. of adults	2	2	2	2	2	2	2	2	2
Max age	70	70	70	70	70	70	70	70	70
Time endowment	10.96	10.96	10.96	10.96	10.96	10.96	10.96	10.96	10.96
Expenditures	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal
Price data	COLI	COLI	COLI	COLI	COLI	COLI	COLI	COLI	COLI
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,667	24,827	26,576	23,667	24,827	26,576	23,667	24,827	26,576

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Finally, we calculate labor supply elasticities using the estimation results based on the different daily time endowment assumptions in Table 21. The labor supply elasticities are sensitive to the value assumed. The higher the time endowment parameter the larger the absolute value of the labor supply elasticity. This finding is consistent with Ballard's (2000) results and is of some importance since the labor supply elasticity can have a significant impact on welfare calculations in policy analyses. Note that the variation derives from the numerator in Equation 18 (leisure time), because the leisure elasticities are similar across different time endowment assumptions (as shown in columns 1, 4, and 5 in Tables 18 and 19).

Table 21: Results sensitivity: labor supply elasticity

Daily time endowment	Income elasticity	Un-compensated elasticity	Compensated elasticity
10.96	-0.55	0.36	0.11
13.3	-0.97	0.68	0.20
15	-1.28	0.92	0.26

Lastly, we estimate the demand system separately for CUs with a married male reference person and CUs with a married female reference person. The results are shown in Table 22. While the labor supply elasticities are lower for married female than married male reference persons, the difference is very small. In addition, the labor supply elasticities for CUs with a married reference person are higher than the average elasticities for all CUs.

Table 22: Labor supply elasticity by gender

Daily time endowment	Sample	Income elasticity	Un-compensated elasticity	Compensated elasticity
10.96	All	-0.55	0.36	0.11
10.96	Married male	-0.59	0.40	0.15
10.96	Married female	-0.60	0.39	0.14

8. Conclusion and Next Steps

In this study, we estimate a full demand system for U.S. households at the national level as well as by income group and Census region. We employ a flexible QUAIDS functional form to allow both income and price flexibility. We also include leisure as a component in consumer demand, which allows us to estimate labor supply elasticities. We find that all consumption categories except for leisure are income inelastic at the national level. This result also holds for each income group and Census region. Higher income groups have higher estimated income elasticities for consumption categories and a lower income elasticity for leisure. Uncompensated price elasticities are inelastic at the national level and for all income groups, but they are elastic for some consumption categories such as transportation and housing at the Census region level. In general, we find that the price elasticities are close to unity.

The estimated income elasticity for leisure is close to 1.5 no matter what value is chosen for the daily time endowment. However, the labor supply elasticity is strongly influenced by the choice of time endowment: the higher the time endowment, the higher the labor supply elasticity. A relatively small daily time endowment results in a labor supply elasticity that is still high but closer to the expected range. This finding confirms the importance of the time endowment choice when estimating labor supply elasticities, particularly when they are used in welfare analyses of various policies such as taxes.

Future work will calibrate a CGE model using the estimated elasticities from this study to explore the distributional implications of environmental policies. We also intend to explore estimating the demand system using less flexible but globally regular functional forms such as QES and LES to facilitate comparisons to other CGE models and to build a fuller understanding of the effects of different functional forms assumptions on estimates. Finally, we will assess the feasibility of estimating elasticities for some subcategories of goods such as electricity using a multistage budgeting approach.

Appendix

Table A1: Heckman correction model results for wage (selection equations)

VARIABLES	(1) Work	(2) Work	(3) Work	(4) Work
Age of reference person	0.062***	0.079***	0.165***	0.168***
	(0.005)	(0.004)	(0.015)	(0.016)
Squared age of reference person	-0.001***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Education of reference person	0.132***	0.143***	0.057***	0.097***
	(0.008)	(0.007)	(0.022)	(0.025)
Married	0.442***	-0.234***		
	(0.061)	(0.056)		
White	0.225***	0.173***	0.294*	0.450***
	(0.029)	(0.025)	(0.154)	(0.168)
Urban area	0.258**	0.605***	-0.066	0.345
	(0.117)	(0.107)	(0.262)	(0.325)
State unemployment rate	-0.016	-0.032***	-0.067**	0.053
	(0.012)	(0.011)	(0.032)	(0.035)
Number of children	0.161***	-0.040***	0.089**	0.039
	(0.039)	(0.013)	(0.040)	(0.034)
Price of non-durables	0.003	-0.002	0.013**	-0.009
	(0.002)	(0.002)	(0.006)	(0.006)
Price of consumer services	0.002	-0.000	0.001	0.015
	(0.003)	(0.003)	(0.010)	(0.010)
Price of utilities	-0.001	-0.001	-0.001	0.001
	(0.003)	(0.002)	(0.007)	(0.009)
Price of housing	-0.003*	-0.003**	0.005	0.002
	(0.002)	(0.001)	(0.007)	(0.004)
Education of spouse			-0.043*	-0.024
			(0.023)	(0.018)
Age of spouse			-0.002	-0.002
			(0.007)	(0.008)
Gender of spouse (female)			1.522***	-1.357***
			(0.210)	(0.185)
Race of spouse (white)			-0.127	-0.600***
			(0.154)	(0.204)
Log of spouse wage			0.431***	0.607***
			(0.036)	(0.041)
Observations	15,567	21,382	10,959	9,176
Number of adults	one	one	two	two
Gender	male	female	male	female
State fixed effects	yes	yes	yes	yes
P_c	0.001	0.000	0.009	0.000

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Selection variables are state level unemployment rate and number of children and price of consumption categories.
P_c represents the P_value from Wald test of independent equations.

Table A2: Heckman correction model results for expenditures (selection equations)

VARIABLES	(1) Non_durables	(2) Consumer services	(3) Utilities	(4) Housing	(5) Transport	(6) Leisure
Ln(income)	0.176***	0.272***	0.124***	0.240***	0.300***	0.937***
	(0.019)	(0.007)	(0.014)	(0.012)	(0.008)	(0.010)
Age of reference person	0.037***	-0.017***	0.057***	0.050***	0.015***	0.075***
	(0.007)	(0.003)	(0.003)	(0.005)	(0.002)	(0.002)
Squared age of reference person	-0.000***	0.000***	-0.001***	-0.000***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White	-0.037	0.209***	-0.117***	0.056	0.378***	0.009
	(0.061)	(0.017)	(0.025)	(0.037)	(0.015)	(0.011)
Female	-0.092*	0.101***	0.039*	0.079**	-0.062***	-0.096***
	(0.051)	(0.015)	(0.021)	(0.034)	(0.014)	(0.009)
Married	0.174*	0.120***	-0.012	-0.010	0.361***	-0.415***
	(0.093)	(0.019)	(0.029)	(0.051)	(0.020)	(0.012)
Number of children	-0.001	-0.012	0.234***	0.053**	0.021**	-0.113***
	(0.046)	(0.008)	(0.018)	(0.022)	(0.009)	(0.005)
Number of adults in CU	0.258***	0.015	0.202***	0.033	0.104***	0.165***
	(0.072)	(0.012)	(0.022)	(0.032)	(0.012)	(0.011)
Ln(price of non-durables)	-0.651*	-0.757***	-0.011	-0.354	-0.083	0.059
	(0.343)	(0.114)	(0.139)	(0.258)	(0.104)	(0.064)
Ln(price of consumer services)	-0.194*	-0.035	0.104**	0.037	0.066*	-0.003
	(0.117)	(0.041)	(0.051)	(0.085)	(0.038)	(0.024)
Ln(price of utilities)	0.144	0.444**	-0.277	-0.509	-0.089	-0.108
	(0.521)	(0.208)	(0.255)	(0.435)	(0.184)	(0.124)
Ln(price of housing)	-0.278	0.146	-0.145	-0.151	0.244*	-0.021
	(0.468)	(0.171)	(0.199)	(0.334)	(0.146)	(0.100)
Ln(price of transport)	-0.417	0.362	0.357	1.249**	0.726***	0.289**
	(0.685)	(0.221)	(0.287)	(0.520)	(0.205)	(0.137)
Ln(price of leisure)	-0.021	0.131***	-0.029*	-0.022	0.068***	-0.776***
	(0.030)	(0.011)	(0.016)	(0.023)	(0.012)	(0.013)
Home ownership	0.452***	0.346***	0.941***	5.716***	0.943***	0.003
	(0.069)	(0.019)	(0.031)	(0.140)	(0.018)	(0.009)
Food stamp value	-0.000**					
	(0.000)					
Observations	105,515	105,515	105,515	105,515	105,515	105,515
State fixed effects	yes	yes	yes	yes	yes	yes
Month fixed effects	yes	yes	yes	yes	yes	yes
P_c	0.327	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Selection variable is home ownership (in addition to food stamp value for non-durables category).
Dependent variables are binary variables for observance of each expenditure category.
The estimates include the whole sample.
P_c represents the P_value from Wald test of independent equations.

Table A3: Compensated price elasticity results

		Income Group			Census Region			
	National	Low	Medium	High	Midwest	Northeast	South	West
Nondurables	-0.768***	-0.619***	-0.698***	-0.745***	-0.786***	-0.719***	-0.824***	-0.759***
	(0.03)	(0.07)	(0.04)	(0.03)	(0.06)	(0.10)	(0.05)	(0.06)
Consumer services	-0.633***	-0.549***	-0.655***	-0.606***	-0.623***	-0.583***	-0.592***	-0.655***
	(0.02)	(0.04)	(0.03)	(0.03)	(0.05)	(0.05)	(0.12)	(0.04)
Utilities	-0.838***	-0.774***	-0.800***	-0.890***	-0.781***	-0.874***	-0.713***	-0.948***
	(0.05)	(0.13)	(0.07)	(0.04)	(0.16)	(0.10)	(0.11)	(0.07)
Housing	-0.715***	-0.555***	-0.783***	-0.670***	-1.540***	-0.589***	-0.623***	-0.634***
	(0.05)	(0.14)	(0.07)	(0.06)	(0.23)	(0.09)	(0.12)	(0.07)
Transport	-0.785***	-0.532**	-0.871***	-0.835***	-1.105***	-1.070***	0.007	-0.912***
	(0.08)	(0.19)	(0.13)	(0.10)	(0.21)	(0.20)	(0.32)	(0.12)
Leisure	-0.310***	-0.213***	-0.141***	-0.083***	-0.323***	-0.327***	-0.278***	-0.315***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.04)	(0.01)
Model	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS
Price data	COLI	COLI	COLI	COLI	COLI	COLI	COLI	COLI
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	75,070	23,703	24,351	27,016	14,834	13,900	27,360	18,976

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A4: Compensated cross price elasticity results

	Non-durables	Consumer services	Utilities	Housing	Transport	Leisure
Non-durables	-0.768***	0.112***	0.081	0.221***	0.073	0.280***
	(0.03)	(0.01)	(0.05)	(0.04)	(0.05)	(0.00)
Consumer services	0.181***	-0.633***	0.058	0.170*	0.021	0.204***
	(0.05)	(0.02)	(0.08)	(0.07)	(0.09)	(0.01)
Utilities	0.193***	0.085***	-0.838***	0.076	0.303***	0.181***
	(0.03)	(0.01)	(0.05)	(0.05)	(0.06)	(0.01)
Housing	0.216***	0.102***	0.031	-0.715***	0.055	0.310***
	(0.03)	(0.01)	(0.05)	(0.05)	(0.06)	(0.01)
Transport	0.169***	0.03	0.293***	0.129*	-0.785***	0.165***
	(0.04)	(0.02)	(0.07)	(0.06)	(0.08)	(0.01)
Leisure	0.100***	0.045***	0.027	0.113***	0.026	-0.310***
	(0.02)	(0.01)	(0.03)	(0.03)	(0.04)	(0.00)

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A5: Results sensitivity: compensated price elasticity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Nondurables	-0.768***	-0.935*	-0.773***	-0.789***	-0.797***	-0.776***	-0.774***	-0.769***	-0.761***	-0.628***
	(0.03)	(0.36)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.019)
Consumer services	-0.633***	-0.362	-0.630***	-0.650***	-0.656***	-0.607***	-0.636***	-0.627***	-0.630***	-0.566***
	(0.02)	(0.28)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.013)
Utilities	-0.838***	-0.796***	-0.807***	-0.802***	-0.801***	-0.812***	-0.825***	-0.813***	-0.849***	-0.816***
	(0.05)	(0.07)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.039)
Housing	-0.715***	-0.048	-0.717***	-0.726***	-0.731***	-0.761***	-0.720***	-0.729***	-0.738***	-0.641***
	(0.05)	(0.39)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.035)
Transport	-0.785***	-1.058*	-0.788***	-0.784***	-0.776***	-0.894***	-0.725***	-0.805***	-0.823***	-0.838***
	(0.08)	(0.53)	(0.08)	(0.09)	(0.09)	(0.07)	(0.09)	(0.08)	(0.07)	(0.065)
Leisure	-0.310***	-0.318***	-0.308***	-0.299***	-0.298***	-0.327***	-0.310***	-0.313***	-0.320***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Model	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS
Sample	National	National	National	National	National	National	National	National	National	National
Max no. of adults	2	2	2	2	2	n/a	2	2	n/a	2
Max age	70	70	70	70	70	n/a	65	75	70	70
Time endowment	10.96	10.96	10.96	13.3	15	10.96	10.96	10.96	10.96	10.96
Expenditures	Nominal	Nominal	Real	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal
Price data	COLI	RPP	COLI	COLI	COLI	COLI	COLI	COLI	COLI	COLI
Leisure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	75,070	75,070	75,070	75,070	75,070	105,748	67,649	80,318	89,991	75,070

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A6: Results sensitivity: income elasticity (low income)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Nondurables	0.259***	0.298***	0.264***	0.276***	0.244***	0.288***	0.282***	0.269***	0.310***	0.743***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.011)	(0.013)	(0.009)	(0.01)
Consumer services	1.071***	1.099***	1.074***	0.960***	0.900***	0.909***	1.078***	1.055***	0.955***	1.713***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.019)	(0.017)	(0.013)	(0.01)
Utilities	0.285***	0.363***	0.292***	0.346***	0.332***	0.266***	0.390***	0.259***	0.355***	0.590***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.011)	(0.014)	(0.009)	(0.01)
Housing	0.316***	0.386***	0.324***	0.369***	0.339***	0.442***	0.409***	0.310***	0.437***	0.972***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.012)	(0.015)	(0.009)	(0.01)
Transport	0.575***	0.610***	0.582***	0.577***	0.552***	0.561***	0.607***	0.581***	0.593***	1.051***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.012)	(0.015)	(0.010)	(0.01)
Leisure	1.559***	1.602***	1.565***	1.640***	1.638***	1.571***	1.597***	1.541***	1.637***	
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.007)	(0.005)	(0.006)	
Model	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS
Max no. of adults	2	2	2	2	2	n/a	2	2	n/a	2
Max age	70	70	70	70	70	n/a	65	75	70	70
Time endowment	10.96	10.96	10.96	13.3	15	10.96	10.96	10.96	10.96	10.96
Expenditures	Nominal	Nominal	Real	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal
Price data	COLI	RPP	COLI	COLI	COLI	COLI	COLI	COLI	COLI	COLI
Leisure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,703	23,703	23,703	23,703	23,703	35,264	20,926	26,122	27,138	23,703

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A7: Results sensitivity: income elasticity (medium income)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Nondurables	0.477***	0.443***	0.476***	0.411***	0.377***	0.450***	0.586***	0.484***	0.488***	0.840***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.016)	(0.006)	(0.005)	(0.01)
Consumer services	0.676***	0.673***	0.675***	0.584***	0.539***	0.581***	0.912***	0.659***	0.645***	1.583***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.029)	(0.010)	(0.009)	(0.01)
Utilities	0.360***	0.308***	0.363***	0.312***	0.289***	0.302***	0.435***	0.346***	0.379***	0.550***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.009)	(0.007)	(0.006)	(0.01)
Housing	0.577***	0.557***	0.576***	0.517***	0.479***	0.613***	0.641***	0.586***	0.589***	0.986***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.014)	(0.007)	(0.006)	(0.01)
Transport	0.560***	0.533***	0.564***	0.488***	0.453***	0.541***	0.586***	0.579***	0.563***	1.036***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.014)	(0.010)	(0.008)	(0.01)
Leisure	1.646***	1.617***	1.649***	1.620***	1.606***	1.586***	1.601***	1.618***	1.644***	
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.018)	(0.006)	(0.006)	
Model	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS
Max no. of adults	2	2	2	2	2	n/a	2	2	n/a	2
Max age	70	70	70	70	70	n/a	65	75	70	70
Time endowment	10.96	10.96	10.96	13.3	15	10.96	10.96	10.96	10.96	10.96
Expenditures	Nominal	Nominal	Real	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal
Price data	COLI	RPP	COLI	COLI	COLI	COLI	COLI	COLI	COLI	COLI
Leisure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,351	24,351	24,351	24,351	24,351	35,427	21,687	26,173	30,126	24,351

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A8: Results sensitivity: income elasticity (high income)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Nondurables	0.604***	0.598***	0.603***	0.586***	0.558***	0.545***	0.590***	0.614***	0.611***	0.928***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.009)	(0.006)	(0.006)	(0.01)
Consumer services	0.949***	0.967***	0.947***	0.775***	0.693***	0.811***	1.289***	0.869***	0.982***	1.474***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.045)	(0.013)	(0.014)	(0.02)
Utilities	0.515***	0.509***	0.516***	0.522***	0.505***	0.402***	0.500***	0.514***	0.514***	0.497***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.007)	(0.005)	(0.005)	(0.01)
Housing	0.722***	0.712***	0.720***	0.674***	0.641***	0.688***	0.707***	0.719***	0.721***	1.003***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.009)	(0.006)	(0.006)	(0.01)
Transport	0.693***	0.689***	0.697***	0.654***	0.621***	0.623***	0.688***	0.692***	0.685***	0.997***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.013)	(0.009)	(0.009)	(0.01)
Leisure	1.397***	1.416***	1.397***	1.425***	1.431***	1.511***	1.282***	1.480***	1.395***	
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.008)	(0.010)	(0.007)	
Model	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS
Max no. of adults	2	2	2	2	2	n/a	2	2	n/a	2
Max age	70	70	70	70	70	n/a	65	75	70	70
Time endowment	10.96	10.96	10.96	13.3	15	10.96	10.96	10.96	10.96	10.96
Expenditures	Nominal	Nominal	Real	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal
Price data	COLI	RPP	COLI	COLI	COLI	COLI	COLI	COLI	COLI	COLI
Leisure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,016	27,016	27,016	27,016	27,016	35,057	25,036	28,023	32,727	27,016

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A9: Results sensitivity: un-compensated price elasticity (low income)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Nondurables	-0.655***	-0.955	-0.667***	-0.675***	-0.655***	-0.719***	-0.682***	-0.673***	-0.669***	-0.778***
	(0.07)	(0.88)	(0.07)	(0.07)	(0.07)	(0.06)	(0.071)	(0.070)	(0.060)	(0.04)
Consumer services	-0.644***	-0.863	-0.638***	-0.658***	-0.661***	-0.649***	-0.611***	-0.663***	-0.650***	-0.859***
	(0.04)	(0.67)	(0.04)	(0.04)	(0.04)	(0.03)	(0.047)	(0.039)	(0.038)	(0.02)
Utilities	-0.794***	-0.740***	-0.764***	-0.743***	-0.730***	-0.743***	-0.779***	-0.750***	-0.828***	-0.854***
	(0.13)	(0.16)	(0.13)	(0.12)	(0.12)	(0.12)	(0.125)	(0.134)	(0.109)	(0.09)
Housing	-0.599***	0.599	-0.606***	-0.610***	-0.595***	-0.724***	-0.646***	-0.631***	-0.669***	-0.885***
	(0.14)	(0.99)	(0.14)	(0.12)	(0.13)	(0.11)	(0.132)	(0.139)	(0.110)	(0.08)
Transport	-0.572**	-1.065	-0.573**	-0.579***	-0.549**	-0.835***	-0.398*	-0.604**	-0.662***	-0.856***
	(0.19)	(1.10)	(0.19)	(0.17)	(0.18)	(0.15)	(0.179)	(0.185)	(0.161)	(0.12)
Leisure	-0.978***	-0.962***	-0.973***	-0.957***	-0.973***	-1.044***	-0.933***	-0.993***	-0.967***	
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.006)	(0.005)	(0.005)	
Model	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS
Max no. of adults	2	2	2	2	2	n/a	2	2	n/a	2
Max age	70	70	70	70	70	n/a	65	75	70	70
Time endowment	10.96	10.96	10.96	13.3	15	10.96	10.96	10.96	10.96	10.96
Expenditures	Nominal	Nominal	Real	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal
Price data	COLI	RPP	COLI	COLI	COLI	COLI	COLI	COLI	COLI	COLI
Leisure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,703	23,703	23,703	23,703	23,703	35,264	20,926	26,122	27,138	23,703

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A10: Results sensitivity: un-compensated price elasticity (medium income)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Nondurables	-0.776***	-1.038*	-0.776***	-0.775***	-0.777***	-0.815***	-0.767***	-0.797***	-0.768***	-0.876***
	(0.04)	(0.52)	(0.04)	(0.04)	(0.04)	(0.04)	(0.036)	(0.038)	(0.032)	(0.03)
Consumer services	-0.730***	-1.206**	-0.729***	-0.736***	-0.740***	-0.685***	-0.747***	-0.723***	-0.718***	-0.859***
	(0.03)	(0.40)	(0.03)	(0.02)	(0.02)	(0.02)	(0.025)	(0.025)	(0.022)	(0.02)
Utilities	-0.825***	-0.799***	-0.799***	-0.800***	-0.794***	-0.758***	-0.852***	-0.789***	-0.824***	-0.886***
	(0.07)	(0.09)	(0.07)	(0.07)	(0.07)	(0.07)	(0.059)	(0.071)	(0.057)	(0.06)
Housing	-0.879***	-1.315*	-0.881***	-0.857***	-0.853***	-0.953***	-0.889***	-0.918***	-0.889***	-1.026***
	(0.07)	(0.54)	(0.07)	(0.07)	(0.07)	(0.06)	(0.065)	(0.069)	(0.056)	(0.06)
Transport	-0.913***	-2.880***	-0.917***	-0.905***	-0.905***	-1.108***	-0.927***	-0.984***	-0.925***	-1.008***
	(0.12)	(0.82)	(0.12)	(0.13)	(0.13)	(0.12)	(0.116)	(0.129)	(0.107)	(0.11)
Leisure	-0.825***	-0.873***	-0.825***	-0.912***	-0.956***	-0.943***	-0.638***	-0.844***	-0.842***	
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.026)	(0.006)	(0.006)	
Model	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS
Max no. of adults	2	2	2	2	2	n/a	2	2	n/a	2
Max age	70	70	70	70	70	n/a	65	75	70	70
Time endowment	10.96	10.96	10.96	13.3	15	10.96	10.96	10.96	10.96	10.96
Expenditures	Nominal	Nominal	Real	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal
Price data	COLI	RPP	COLI	COLI	COLI	COLI	COLI	COLI	COLI	COLI
Leisure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,351	24,351	24,351	24,351	24,351	35,427	21,687	26,173	30,126	24,351

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A11: Results sensitivity: un-compensated price elasticity (high income)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Nondurables	-0.847***	-0.649	-0.847***	-0.837***	-0.839***	-0.857***	-0.824***	-0.851***	-0.839***	-0.972***
	(0.03)	(0.39)	(0.03)	(0.03)	(0.03)	(0.03)	(0.036)	(0.030)	(0.028)	(0.03)
Consumer services	-0.679***	0.683	-0.677***	-0.729***	-0.746***	-0.679***	-0.485***	-0.706***	-0.690***	-0.822***
	(0.03)	(0.50)	(0.03)	(0.03)	(0.03)	(0.02)	(0.064)	(0.028)	(0.028)	(0.02)
Utilities	-0.929***	-0.976***	-0.900***	-0.929***	-0.932***	-0.958***	-0.914***	-0.930***	-0.940***	-0.902***
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.038)	(0.039)	(0.035)	(0.05)
Housing	-0.789***	-0.189	-0.792***	-0.792***	-0.795***	-0.819***	-0.746***	-0.794***	-0.814***	-0.893***
	(0.06)	(0.42)	(0.06)	(0.05)	(0.05)	(0.05)	(0.064)	(0.052)	(0.047)	(0.05)
Transport	-0.887***	-0.506	-0.885***	-0.889***	-0.897***	-0.907***	-0.855***	-0.884***	-0.933***	-0.986***
	(0.10)	(0.60)	(0.10)	(0.09)	(0.09)	(0.09)	(0.112)	(0.092)	(0.083)	(0.10)
Leisure	-0.700***	-0.697***	-0.700***	-0.759***	-0.821***	-0.829***	-0.746***	-0.686***	-0.710***	
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.007)	(0.009)	(0.007)	
Model	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS	QUAIDS
Max no. of adults	2	2	2	2	2	n/a	2	2	n/a	2
Max age	70	70	70	70	70	n/a	65	75	70	70
Time endowment	10.96	10.96	10.96	13.3	15	10.96	10.96	10.96	10.96	10.96
Expenditures	Nominal	Nominal	Real	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal
Price data	COLI	RPP	COLI	COLI	COLI	COLI	COLI	COLI	COLI	COLI
Leisure	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,016	27,016	27,016	27,016	27,016	35,057	25,036	28,023	32,727	27,016

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

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