Energy Consumption of Urban Households in China

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Abstract

We estimate China urban household energy demand as part of a complete system of consumption demand so that it can be used in economy-wide models. This allows us to derive cross-price elasticities unlike studies which focus on one type of energy. We implement a two-stage approach and explicitly account for electricity, domestic fuels and transportation demand in the first stage and gasoline, coal, LPG and gas demand in the second stage. We find income inelastic demand for electricity and home energy, but the elasticity is higher than estimates in the rich countries. Demand for total transportation is income elastic. The price elasticity for electricity is estimated to be -0.5 and in the range of other estimates for China, and similar to long-run elasticities estimated for the U.S.

Keywords: Household energy consumption, demand price elasticity, China

1. Introduction

The rapid growth of energy consumption in China has generated a huge literature discussing its characteristics and environmental impacts. The residential portion of national energy use was only 12% in 2015, but is growing rapidly, at 6.0% per year during 2005-2015 compared to the 5.0% national energy growth rate. Residential electricity consumption is growing even faster than total residential energy, at 9.6% per year during that period. The ownership of automobiles among urban households went from 3.4 per 100 households in 2005 to 35 in 2016. Ownership of household appliances such as washing machines and refrigerators exceeded 90% since 2005 while air-conditioners rose from 0.81 per urban household in 2005 to 1.2 in 2016[1].

The prospects of such growth in household energy consumption, and the resulting impact on air pollution and greenhouse gas emissions, has prompted a large set of studies of household energy demand, its projection and conservation policies. For electricity consumption, Shi, Zheng and Song (2012), Zhou and Teng (2013), He and Reiner (2014)and Cao et al. (forthcoming) used household survey data to estimate price and income elasticities for electricity demand which Cao et al. then used to project electricity demand. Du et al. (2015) used the tier structure in electricity prices to estimate price elasticities while Murata et al. (2008) relates electricity consumption to the characteristics of appliances owned by households but do not consider price effects. Khanna et al. (2016) uses the CRECS survey of households to estimate the effectiveness of various demand side strategies to reduce electricity consumption[2].

For coal and gas demand there is little research based on household level data; Burke and Liao (2015) use total provincial coal consumption while Zhang et al. (2011) estimated price elasticities from aggregate national data. For residential gas demand Yu et al. (2014) used city average data. Only Cao, Ho and Liang (2016) used urban household data to

1 Energy consumption data is taken from the China Statistical Yearbook 2017, Tables 9-3 and 9-6, household goods ownership are from CSY 2017 Table 6-28.

2 The China Residential Energy Consumption Survey (CRECS) is conducted by Renmin University and is reported in Zheng et al. 2014.

estimate China coal and gas demand elasticities.

For gasoline and diesel demand, Lin and Zeng (2013) used provincial level data on fuel quantities and prices to estimate the price and income elasticities, this however, covers all liquid fuel demand, not just household use. Caron et al. (2017) estimated how household energy demand changes with income for various types of energy including liquid fuels, also using the CRECS household data.

The above studies have provided useful information about the demand characteristics and income and price elasticities. Such information is key for analysis of market-based energy and environmental policies such as gasoline taxes or carbon taxes. Estimating how much households would react to a carbon price depends heavily on these price elasticities. The studies cited, however, mostly focus on one type of energy, often using only the price of that energy type as an explanatory variable ignoring the prices of substitutes. The results of such methods may be appropriate for partial equilibrium analysis but less suitable for an economy-wide, general equilibrium, analysis of price and transfer policies. For example, Zhou and Teng (2013) only use the price of electricity while Murata et al. (2008) do not use any price data. Shi, Zheng and Song (2012), Du et al. (2015), He and Rainer (2014) and Khanna et al. (2016) use the prices of electricity and natural gas in their demand function for electricity. These specifications capture the most important variables but the broader energy demand literature also recognize key roles for housing and equipment in determining electricity demand and thus a more general specification should include the prices of housing and equipment.

For non-electrical energy, Zhang et al. (2011) estimated a VAR using national data on coal and oil, but only include the price of coal without other prices. Burke and Liao (2015) used the provincial price of coal and gasoline for estimating provincial coal demand, while Yu et al. (2014) has the richest price specification for city-level natural gas demand, using city prices of gas, LPG, electricity and coal. Lin and Zeng (2013) estimated of provincial gasoline demand uses the provincial price of gasoline, instrumented by the price of diesel.

Carron et al. (2017) study of 6 types of energy use at the household level is focused on income effects and use provincial level prices of the 6 types of energy, that is, they have a rich set of price variables, but the provincial aggregates somewhat limit the degree of variation. Cao, Ho and Liang (2016) is one of the few studies of China using a multiple equation system where the household demand for coal, gas, electricity and gasoline are simultaneously estimated using prices of all four energy types.

A contrast between these different specifications for energy demand is highlighted in a strand of papers in the general equilibrium modeling literature; Yu et al. (2004) and Bouet et al. (2014), for example, compare demand functions and show how simple forms such as the Linear Expenditure System (LES) or the Constant Elasticity of Substitution (CES) misses key features that more flexible forms capture. The LES and CES expresses the demand for a consumption item as a linear function of income and allows only one price elasticity, that is, there are no cross-price elasticities and in the case of the CES, a unit income elasticity is imposed. Flexible forms such as the Almost Ideal Demand System (AIDS) or translog specifies a complete system of demand for all commodities with a full range of cross-price effects and allowing non-unit income elasticities. In the empirical studies cited above, only Yu et al. (2014), Carron et al. (2017) and Cao, Ho and Liang (2016) allows a set of cross-price effects from substitutes, while four of the electricity studies consider only two prices – electricity and gas. We might also note that when the different energy types are estimated independently, as in Carron et al. (2017), there is no guarantee of global consistency; that is, ensuring income effects add to 1 and the budget constraint is satisfied. Modelers using such econometric estimates have to adjust them to ensure consistency, to ensure that expenditure shares add to 1.

Analysis of energy policies using economy-wide computable general equilibrium (CGE) models ideally take into account substitution between different forms of energy, and between energy and capital. It is also helpful to consider income elasticities that are not constrained to be one, or even non-linear or non-monotonic income effects; demand for potatoes, or coal, eventually fall when income rises. Many CGE models use the CES, the LES or other additive type utility functions that require only the own-price elasticities (some imposing unit income elasticities) and are easy to implement and may use the parameter estimates from the single-equation studies cited above but miss some of these desirable aspects[3]. Other CGE models use flexible demand systems that takes bundles of commodities into account with cross-price elasticities, for example, the use of a translog utility function in a U.S. model by Jorgenson et al. (2018) and in a China model by Cao et al. (2017), and an AIDS model for the EU by Sommer and Kratena (2017)[4]. There are, however, very few estimates of consumption demand systems covering all commodities in China that can be used in such CGE models. Cao et al. (2017) is one of the few papers using the system approach, it however, considers a 4-input function for food, consumer goods, services and housing; energy demand is part of services and part of housing and not explicitly identified at this stage. This means that the income and demographic effects for household energy demand are not well identified even if the price effects are given in the lower tiers of the consumption model (discussed further in the next sub-section).

Our paper thus has two aims. One is to develop a dataset of expenditures and prices that can be used for household demand analysis for detailed energy commodities. This provides far more detail than the residential energy studies noted above that rely on provincial or city-level averages. The second is to estimate a flexible demand system that will provide income and price elasticities, including cross-price elasticities, for electricity, other household energy (coal, LPG, gas, heat), and transportation for urban China. The demand function also relates energy use to household characteristics such as location, equipment ownership and characteristics of the household head. These elasticities are useful for both partial equilibrium analysis and those using CGE models.

[3] For example, the OECD Envisage model use LES functions; the family of GTAP models use additive CDE functions; MIT-EPPA (Chen et al. 2015) use CES functions with unit income elasticities.

[4] See also Savard (2010) who compared an AIDS model with the popular LES function in a CGE model by first estimating over a Philippines household survey data set. Bouet et al. (2014) discuss some experiments with Normalized Quadratic Expenditure Systems in the MIRAGE model.

Methods of modeling demand systems

Our approach draws on the household consumption estimation literature which is somewhat distinct from the energy demand literature cited above which are focused on single energy functions. For readers who may be less familiar with this large literature, we summarize here the key elements of modeling demand systems, that is, work focused on estimating utility functions with *n* commodities, $U(C_1^h,...,C_n^h;h)$ for household *h* consuming a quantity C_i^h of good *i*.

The flexible forms of demand systems would express the demand for good *i* as a function with independent effects from the *n* prices (e.g. eq. 2.3), in contrast to the CES with one common substitution elasticity for all prices. Since the number of cross-price elasticities increase with the square of the number of commodities in this approach, the strategy has been to use two-stage budgeting to represent the demand for a detailed set of commodities. As discussed in Jorgenson, Slesnick and Stoker (1988), there are two approaches to implementing a two-stage system given Gorman's (1971) characterization of restrictions on preferences.

The first approach (e.g. Hausman and Trimble 1984) has a utility function that is additive in the sub-utility function for all commodities; $U = U^I(C_1^I,...)+...+U^M(C_1^M,...)$. That is, "the group utility functions must correspond to indirect utility functions having the generalized Gorman polar form." This approach allows exact aggregation over consumers in the second stage, that is, derive national demand as a function of aggregate income and prices. However, there are restrictions on elasticities of demand in the first stage in this approach. This is the method also used in Cao, Ho and Liang (2016) estimation of China urban household energy demand where there is a Linear Expenditure System in the first stage for an energy bundle and a non-energy bundle, and an AIDS function in the second stage for the energy bundle as a function of electricity, coal, gas and gasoline.

In the second two-stage approach, the first-stage utility function is not required to be additive, but the sub-utility functions must be homothetic. This approach is implicit in the electricity demand models discussed by Aigner (1984) and explicit in Baker, Blundell and Mickelwright (1989) and Jorgenson et al. (1988). In Jorgenson et al. (1988) the first stage consists of a translog function of energy, food, consumer goods, capital services and services, and in the second stage the energy aggregate is homothetic function of electricity, gas, other home fuels, and gasoline.

To summarize, one has to essentially choose from the following options: (a) a simple 1-stage approach for many commodities such as the CES which imposes unit income elasticities and no cross-price effects, (b) a flexible 1-stage approach that has a full set of substitution elasticities but severely limit the number of commodities, (c) a 2-stage approach allowing more commodities but imposes unit income elasticities either in the first or second stages[5].

Our approach to modeling energy demands

We take a mixed approach where the first stage is a (flexible) translog function of electricity, other home energy, transportation, consumer goods and services. In the second stage, the other home energy bundle is allocated to coal, LPG, gas, and heat (from district central heating), and the transportation bundle is allocated to fuels and transportation services with homothetic functions. This method allows us to obtain cross-price elasticities for electricity, other home energy and the other three bundles, and at the same time allow for non-unitary income elasticities for these energy bundles. It also allows us to estimate the substitution among coal, LPG, gas, and heat, as well as the substitution between fuels (gasoline and diesel) and purchased transportation services (buses, taxis, etc.).

Our use of the Jorgenson et al. (1988) translog household indirect utility function in the first stage allows us to recognize the different characteristics of households, for example,

[5] There are other options discussed in Yu et al. (2006) and Bouet et al. (2016) such as AIDADS or the CDE, which have more flexible income effects than the CES but also do not allow a full set of cross-price elasticities.

allowing households with children to have a bigger share of expenditures allocated to food. It also allows us to derive an aggregate demand function where, say, the national demand for electricity depends only on prices and the distribution of national income across household types. This allows us to consider demographic changes when projecting future aggregate demand for energy. This aggregate demand function is also directly usable by CGE models to analyze policies without having to worry about aggregation consistency.

Our arrangement of the two stages means that we allow for non-unit income elasticity for the transportation bundle but imposes a homothetic function for the fuel and transportation services components of that bundle. Unlike Jorgenson et al. (1988) that has only one cross section of households and uses time series of aggregated prices to identify price effects, we follow Jorgenson and Slesnick (2008) in using repeated cross-sections of household data to identify both price and income elasticities in the first stage.

We combine expenditure data for 180,000 households from the Urban Household Income and Expenditure Survey (UHIES) and price information from the Consumer Price Index (CPI) from 1992 to 2009. We also use cross-sectional prices of detailed commodities in each region to identify regional differences in the benchmark year 2009. China has an unusually large share of owner-occupied housing, so we make an extra effort to impute rental equivalents using estimates of rent-to-price ratios and regional housing prices.

We find that an income elasticity of 0.7 for electricity, which is in the middle of a wide range of estimates in the literature. The own-price elasticity is -0.5 is consistent with the inelastic estimates of other research discussed below in Section 4. The income elasticity for other home energy (gas and coal) is 0.5 which is between some of the more elastic estimates for gas and the low elasticity estimates for coal. The income elasticity for transportation (own and purchased) is 1.2, which is consistent with the few estimates for gasoline demand in China. Our estimates of cross-price effects show that electricity is a substitute for transportation but a complement with other home energy and services (including housing services).

The paper is constructed as follows. We introduce the two-stage translog model of consumer behavior in Section 2. In Section 3, we discuss the data including rental equivalent imputations and cross-sectional prices that vary over regions and time. Section 4 reports the estimates and compares them to the literature.

2. Two-stage energy consumption model and econometric method

We follow the two-stage budgeting model of consumer behavior described in Jorgenson, Slesnick and Stoker (1988) and briefly summarize the main equations here. Households are assumed to be individual consuming units and maximize utility in two stages, conditional on leisure choice, location choice and the stock of durables including housing. We require that systems of demand functions from both stages be integrable. In the first stage total expenditures is allocated to electricity, other home energy, transportation, consumer goods and services. In the second stage, other home energy is allocated to coal, LPG, gas, and heat, and transportation is allocated to vehicle fuel and transportation services (fares and vehicle maintenance). Jorgenson et al. (1988) uses one cross section and a time-series of national prices, however, we employ the repeated cross-section econometric approach in Cao, Ho, Jorgenson and Hu (2017).

First stage

For the first stage we assume a translog indirect utility function for household *k*:

$$\ln V_k = \ln(\frac{p}{M_k})' \cdot \alpha_p + \frac{1}{2}\ln\left(\frac{p}{M_k}\right)' \cdot B \cdot \ln\left(\frac{p}{M_k}\right) + \ln\left(\frac{p}{M_k}\right)' \cdot B_A \cdot A_k \qquad (2.1)$$

where:

$V_k -$ indirect utility of household k,

$p = (p_1, p_2, \dots, p_N) -$ vector of prices of consumption bundles,

$x_k = (x_{1k}, x_{2k}, \dots, x_{Nk}) -$ vector of quantities consumed by household *k*,

$M_k = \sum_{n=1}^{N} p_n \cdot x_{nk} -$ total expenditures of household *k*,

$w_{nk} = p_n \cdot x_{nk}/M_k -$ expenditure share of the n-th commodity,

$w = (w_{1k}, w_{2k}, \dots, w_{Nk}) -$ vector of expenditure shares,

$A_k -$ vector attribute indicators.

The matrices α , B and B_A are constant parameters that are the same for all households. The five consumption bundles are index by:

n={1,2,3,4,5} = {electricity, other home energy, transportation, cons. goods, services}

In this form, the preference differences among households are introduced through the attribute vector A_k. These include household size, presence of children, region, ownership of durables, area of home, cooling degree days, heating degree days. There are other policy shocks or exogenous changes that may shift the demand curve beyond these characteristics such as product safety or energy efficiency regulations. Given the absence of detailed information on household equipment in the UHIES data we are unable to include these aspects.

As explained in Jorgenson et al. (1988), the conditions required for exact aggregation, (i.e. the restrictions needed so that an aggregate demand function is obtained by explicit aggregation over households) are that the expenditure shares be linear in functions of A_k and M_k . These conditions are:

$$\mathrm{i}' \cdot \mathrm{B} \cdot i = 0, \ \mathrm{i}' \cdot B_A = 0 \tag{2.2}$$

where i is a vector of 1's. In addition, homogeneity of the demand function allows us to choose a normalization:

$$\mathrm{i}' \cdot \alpha = -1$$

The vector of expenditure shares derived by Roy's identity is:

$$w_k = \frac{1}{D(p)}[\alpha + B \ln p - B_M \ln M_k + B_A A_k] \tag{2.3}$$

where the denominator takes the following form under the aggregation conditions:

$$D(p) = -1 + B_M{}' \cdot \ln p \tag{2.4}$$

$$B_M = B\iota$$

Integrability of the demand system also requires that the matrix of price substitution effects be symmetric and nonpositive definite:

$$B' = B \tag{2.5}$$

The second stage

In the second stage we assume that total other home energy (OHE) expenditures be allocated to coal, LPG, natural gas, and heat & all other household energy, and total transportation (T) expenditures be allocated to vehicle fuels (gasoline and diesel) and transportation services (fares, vehicle rentals, own-vehicle maintenance). These are allocated via homothetic translog utility functions, where the utility from bundle I is given by:

$$\ln I_k = \ln q^{I}{}'\gamma^I + \ln M_k^I + \tfrac{1}{2}\ln q^{I}{}'\Delta^I \ln q^I + \ln q^{I}{}'\Delta_A^I A_k, \qquad I = \{OHE, T\} \tag{2.6}$$

where:

$q^I = (q_1^I, \dots, q_N^I) -$ vector of prices; q_i^I is the price of item i in bundle I,

bundle OHE: $i \epsilon \{1,2,3,4\} = \{\text{coal, LPG, natural gas, heat\&other}\}$,

bundle T: $i \epsilon \{1,2\} = \{\text{vehicle fuel, transportation services}\}$,

$y_k^I = (y_{1k}^I, \dots, y_{Nk}^I) -$ vector of quantities y_{ik}^I consumed by household *k*,

$M_k^I = \sum_i q_i^I y_{ik}^I$ $-$ total expenditures on bundle I of household *k*,

$v_{ik}^I = q_i^I y_{ik}^I / M_k^I$ $-$ expenditure share of input i in bundle I,

The vector of expenditure shares of household *k* derived by Roy's Identity is:

$$-v_k^I = \gamma^I + \Delta^I \ln q^I + \Delta_A^I A_k \tag{2.7}$$

The conditions for exact aggregation – that expenditure shares are linear in functions of attributes and total expenditures – are satisfied by (2.7). We can express the price index of bundle I (the Other Home Energy and Transportation bundles in the top tier) as a ratio of nominal expenditures to the utility index given by the second stage utility functions:

$$\ln p_{Ik} = \ln M_k^I - \ln I_k$$
$$= -[\ln q^I{}'\gamma^I + \tfrac{1}{2}\ln q^I{}'\Delta^I \ln q^I + \ln q^I{}'\Delta_A^I A_k] \qquad \text{I=\{OHE, T\}} \qquad (2.8)$$

$$M_k^I = p_{Ik} * I_k = \sum_{I^i} q_{I^i k} y_{I^i k} \qquad (2.9)$$

Censored observations

The above system may be implemented if most households purchase all the items in the other home energy bundle and the transportation bundle. However, for our sample period 1992-2009, a large fraction of urban households in China do not own gasoline-using vehicles or consume coal or central district heat. We thus have to break the second stage into two steps: first whether to consume a specific item (e.g. owning a vehicle), and second, how much of it to consume. To correct for selection bias, we first estimate a probit function for having positive expenditures on the item I^i:

$$P(y_{ikt}^I > 0 \mid q_{ikt}^I, \ldots, q_{ikt}^I, M_{kt}^I, A_{kt}) = \Phi(y_{ikt}^I \cdot \upsilon) \qquad (2.10)$$

where Φ is the cumulative distribution function (CDF) of the standard normal distribution, and the selection function depends on prices, total expenditure on bundle I and demographic characteristics.

From the probit regression we may obtain the inverse Mills ratio, $\hat{\lambda}_{I^i kt} = \lambda(y_{I^i kt} \cdot \upsilon)$, where ϕ is the normal density function and:

$$\lambda_{I^i kt}(.) \equiv \frac{\phi_{I^i kt}(.)}{\Phi_{I^i kt}(.)}$$

To correct for sample selectivity, one would usually add this inverse Mills ratio on the right-hand side of the demand system (2.7). However, as noted by Shonkwiler and Yen (1999) and West and Williams (2004) this will result in a bias when there are many zero values. We thus follow them and Cao, Ho and Liang (2016) in using the following equation to correct for sample selectivity:

$$-v_{I^i kt}^I = \hat{\Phi}_{I^i kt} \cdot (\gamma^I + \Delta^I \ln q^I + \Delta_A^I A_k) + \xi \hat{\phi}_{I^i kt} + \upsilon_{1kt} \qquad (2.11)$$

Econometric method

For the first stage, we use the econometric method in Cao et al. (2017) which is based on Jorgenson and Slesnick (2008) use of repeated cross sections, pooling all years (1992-2009) with household observations, where prices vary across region and time[6]. That is, while we do not have prices unique to each household type k, we have prices for different regions in each province, denoted p_{rt}. These prices are explained in Section 3. We assume that the disturbances in the demand system (2.3) are additive so that the system of estimating equations is:

$$w_{kt} = \frac{1}{D(p_{rt})}[\alpha + B\ln p_{rt} - B_M \ln M_k + B_A A_k] + \tilde{\varepsilon}_{kt} \tag{2.12}$$

where the error vector $\tilde{\varepsilon}_{kt}$ is assumed to have mean zero. This disturbance may result from errors in implementing consumption plans or errors of measurement.

We drop one equation since the shares add to one, and express four prices relative to the fifth in the first stage. Let the error in the system of equations with the four shares be denoted by ε_{kt} and the variance-covariance matrix be Σ. We construct regional prices, p_{rt}, for each year 1992-2009, and estimate (2.12) as repeated cross-sections. The objective function to be minimized for the first stage is:

$$SSR(\delta) = \sum_{k,t} \varepsilon_{kt}{}' \hat{\Sigma}^{-1} \varepsilon_{kt} \tag{2.13}$$

where $\hat{\Sigma}$ is derived from a consistent estimate of the covariance matrix in a prior step and $\delta = \{\alpha, B, B_M, B_A\}$ denote the parameters to be estimated.

In the second stage, we similarly have to drop one equation. Using transportation as an example, we first estimate the probit equation (2.10) for Fuels. This gives us the fitted values for $\hat{\phi}_{1kt}$ and $\hat{\Phi}_{1kt}$. Equation (2.11) for the fuel share of total transportation has the

6 Jorgenson and Slesnick (2008) estimate both rank two and rank three demand systems but have only 4 consumption bundles. We have 5 consumption items and only estimate a rank two system.

disturbance term υ_{1kt}, and the $\hat{\phi}_{1kt}$ and $\hat{\Phi}_{1kt}$ terms for the correction for zero values. This equation is linear in the parameters unlike (2.13) and we may use weighted OLS.

We choose estimates that minimize the objective functions (2.13), subject to the constraints implied by integrability and concavity discussed above. The integrability constraints are given by (2.2) and (2.5), while the concavity constraints are discussed in detail by Holt and Goodwin (2009) and by Moschini (1999). We use maximum likelihood methods to estimate the system.

Holt and Goodwin (2009) also discuss the elasticities of translog demand systems. They derive the uncompensated price elasticity between input *i* and *j* as:

$$\eta_{ij} = -\delta_{ij} + \frac{\beta_{ij}/w_i - \beta_{Mi}}{-1+\sum_k \beta_{Mk} \cdot \ln(p_k/M)} \tag{2.14}$$

The expenditure elasticity for *i* is given by:

$$\eta_{iM} = 1 - \frac{\sum_j \beta_{ij}/w_i}{-1+\sum_k \beta_{Mk} \cdot \ln(p_k/M)} \tag{2.15}$$

where δ_{ij} is the Kronecker indicator. The compensated (Hicksian) price elasticities are:

$$\eta_{ij}^{C} = \eta_{ij} + w_j \eta_{iM} \tag{2.16}$$

The above η's denote the elasticities for the first stage. The elasticities for the second stage are derived in a similar way in the Appendix; the expenditure, uncompensated and compensated price elasticities for bundle I are, respectively:

$$\varphi_{ij}^{I} = -\delta_{ij} - \frac{\Delta_{ij}^{I}}{v_i^{I}} + v_j^{I}(1+\eta_{II}) \tag{2.17}$$

$$\varphi_{iM}^{I} = \eta_{iM}^{I} \tag{2.18}$$

$$\varphi_{ij}^{I,C} = \varphi_{ij}^{I} + v_j^{I}\omega_I \varphi_{iM}^{I} \tag{2.19}$$

3. Data Sources and price construction

3.1 UHIES data

In China, the only comprehensive source of information on household income, consumption expenditures on disaggregated items, demographics and housing is the Urban Household Income and Expenditure Survey (UHIES) conducted by the National Bureau of Statistics (NBS). The UHIES is conducted every year, using a stratified design and probabilistic sampling. One third of the sample households are replaced each year. The national sample size since 2001 is more than 40,000 annual observations. We group expenditures into five bundles:

1. Electricity (EL) – electricity.
2. Other home energy (OE) – coal, LPG, natural gas, heat and other energy in homes except electricity.
3. Transportation (TR) – vehicle fuels (gasoline and diesel), transportation services (bus, taxi, trains, etc.) and vehicle maintenance.
4. Goods (GD) – food (including in-kind and dining out), clothing, household equipment, medical goods, educational goods, transportation equipment, communications equipment, recreational goods, and other goods.
5. Services and Housing (SH) – expenditure on medical care, educational services, communication services, recreation services, other services, and rental equivalents of housing and water utilities.

These data are unfortunately not made available to researchers outside the NBS. We obtained a subsample of the UHIES through a special arrangement between the NBS and Tsinghua University covering 9 provinces from 1992 through 2009[7]. The 9 provinces were selected to represent all regions and income levels of China: Beijing, Liaoning, Zhejiang, Anhui, Hubei, Guangdong, Sichuan, Shaanxi and Gansu. After 2001, our sample covers about 90% of the cities in the 9 provinces, while only 60% are covered before that. The

[7] The National Bureau of Statistics provided this subsample to the China Data Center, Tsinghua University.

sample size is between 5,000 and 6,000 households per year before 2001, and 15,000-17,000 after that. In Cao et al. (2017) we compared the average expenditure shares in our sample to the national ones given in the China Statistical Yearbook and show that they are quite close[8].

As explained in Cao et al. (2017), we exploit the big differences in price levels between large and small cities within each province, and between provinces to help identify price elasticities. With this division between large versus small cities, our 9 provinces result in 17 distinct regions (Beijing is just one large city and thus not divided), and the price of commodity i in region r is denoted p_{irt}.

A key difficulty of measuring urban consumption is the high rate of home ownership (close to 90% in this period), and the lack of official rental imputations. We impute rentals equivalents as housing service flow, as described in Cao et al. (2017, Section 3.2), using the survey information on housing size, current value and location, and a separate set of estimates of house-rental ratios.

For consumer durables, one should ideally calculate annual service flows from data on stocks. Unfortunately, the UHIES data does not allow us to estimate the household stocks well; the survey only indicates the ownership of refrigerators, air-conditioners, TV's and vehicles, and gives the expenditures on durables only in the survey year. We approximate the service flow by noting that in the steady state households replace each type of durable when it has completely depreciated. We thus divide the purchases of durables by households in a given survey year to all households in the same decile group in that year. We allocate the households into deciles according to the expenditures on non-durable goods per capita within each region, in each year.

Total expenditures

Our final estimate of total expenditures for each household is thus the sum of spending

8 In that paper we also explained how we dealt with obvious errors and extreme values. Household weights are based on NBS sampling weight for each city and we rescale them to represent the whole sample.

on nondurables, services, the imputed service flows from consumer durables and owner-occupied housing. In Figure 1 we plot the five expenditure shares averaged over all households in the large cities[9]. There is a big fall in the share for consumer goods which include food, and an offsetting rise in the services-and-housing over the 1992-2009 period. During this period, per-capita GDP rose at 9.5% per year and the well-known income effects on food is quite clear. The shares for energy and transportation are small, less than 5%, and are given in greater detail in Figure 2.

Figure 2 shows the contrast in consumption between big and small cities. The share for transportation rises as gasoline expenditures rise with incomes in both types of cities, rising at a similar rate averaged over the 1992-2009 period. The share for electricity rose between 1992 and 2000 and then flattened out, with a bigger cumulative rise for the small cities. The other-home-energy share is essentially flat, with a much higher share for the small cities which are poorer on average than the big cities.

We should note the connection between the trends in these Figures and our choice of the consumption function in (2.3) and (2.7). The assumption is that the consumption function is stable and changes in shares over time as observed in Figures 1 and 2 are explained entirely by changes in prices and incomes. An alternative framework may be to assert that preferences or goods characteristics change over time. This is, however, difficult to distinguish from income effects since incomes have been rising steadily in this sample. We have thus followed the common approach of assuming a stable utility function.

We recognize that our sample period, 1992-2009, covering the publicly released household survey data does not capture the sizable changes in incomes between 2009 and today and plan use more recent surveys when they are made available to the public. We note that the official national urban consumption data show limited changes in the transportation and communication share even while the food and clothing shares fell

[9] The large cities are defined by the NBS, including 4 municipalities, capital cities in each province, and 5 Municipalities with Independent Planning Status (Dalian, Ningbo, Xiamen, Qingdao, and Shenzhen).

significantly between 2009 and 2017[10]: Food jumps from 36.5 to 28.6%, Housing from 10.0 to 22.8%, but Transport and Communications only changed from 13.72 to 13.59%, and Education and Recreation from 12.0 to 11.6%. This fall in food consumption is consistent with the estimated income elasticity in Cao et al. (2017) which used the same 1992-2009 sample period as this paper. That is, the 18 years of data we have generates income elasticities that are generally maintained beyond 2009.

[10] China Statistical Yearbooks, 2010 Table 10-5 and 2018 Table 6-6 gives the Urban Consumption by categories for these two years.

Figure 1. Expenditure shares of households in large cities, 1992-2009.

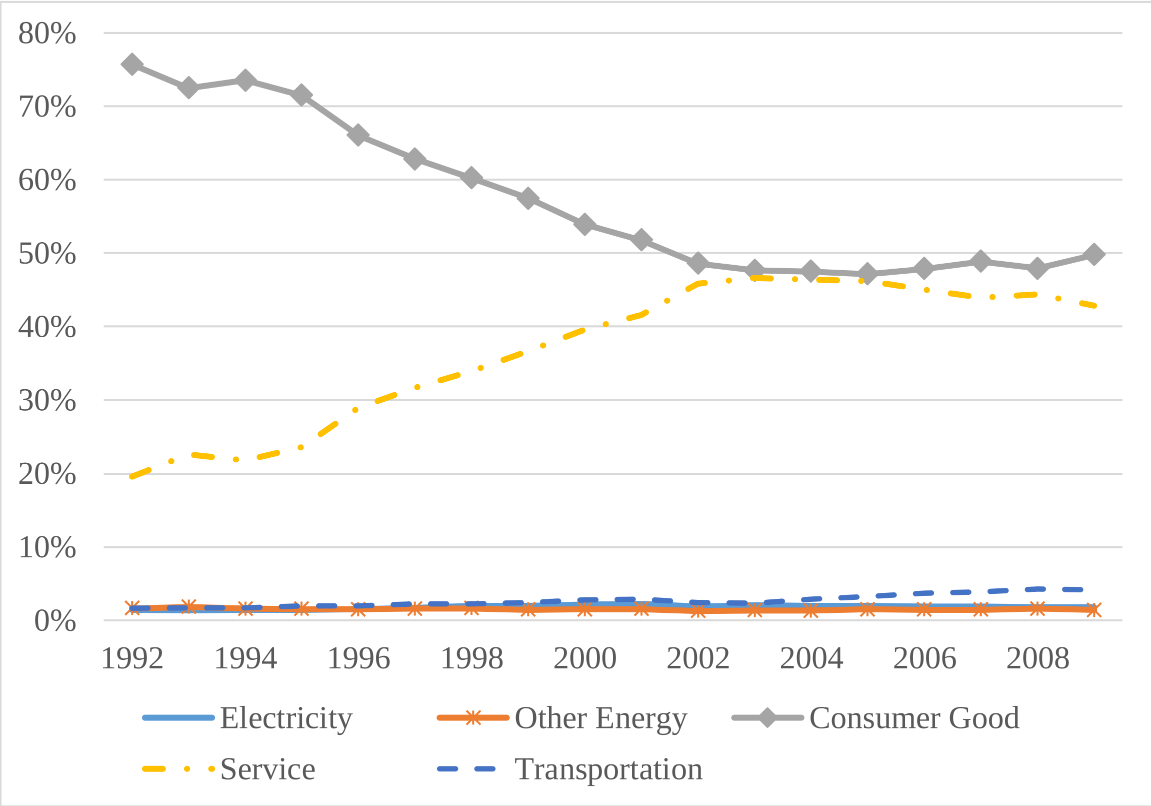
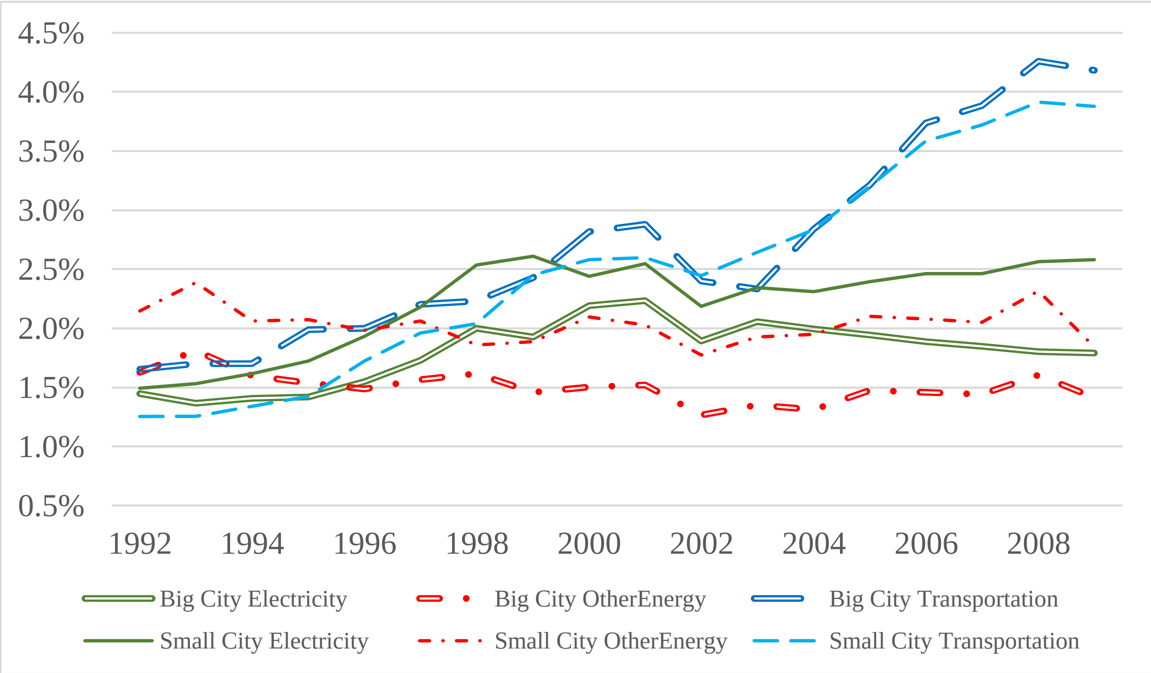


Figure.2 Energy Expenditure Shares (Small Cities Vs. Large Cities).



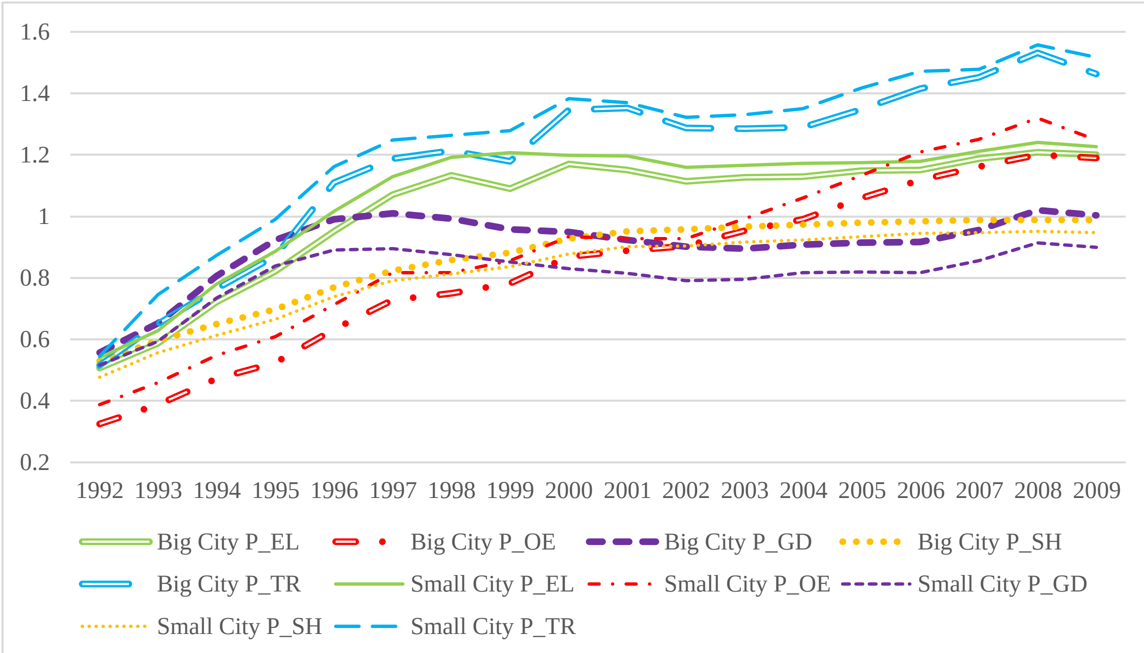
3.3 Measuring Price Levels in China

The UHIES records the RMB expenditures on hundreds of items, but quantities are only given for food, clothing, durable goods and energy. Many researchers use Brandt and Holz (2006) estimate of provincial price levels based on NBS data in 1990, a period when price controls were still widely in place and made such an exercise reasonable. Cao et al. (2017, section 3.3) explain how that data is no longer well suited for our study covering the 1992-2009 period and describe how we constructed an updated set of price levels from various sources. We supplemented the unit value data from the UHIES with data from National Development and Reform Commission (NDRC) surveys of prices in many cities, from the provincial DRC's and from companies[11]. For items such as communications equipment and electronic goods which are very heterogenous we assume that all regions face a common national price in 2015 and collected prices from the public webpages of retailers. These prices are then extrapolated back to 1992 using the provincial CPI's for each type of good.

Our price estimates are thus more detailed and recent compared to Brandt and Holz (2006). We use a chained basket of weights (instead of fixed 1990 weights) and use distinct prices from large and small cities (instead of only the provincial capital prices). Our price of housing is imputed from rental ratios (instead of relying only on prices of building materials). Our price indexes are Tornqvist indexes with chained weights, and they are relative to Beijing prices. For comparison between each province and the Beijing base price, the Tornqvist weights are the average of the two provinces' commodity shares.

[11] The provincial DRC's have web sites reporting prices of some services which are regulated, including health and education. Private companies such as tutoring also provided public prices.

Figure 3. Price of consumption bundles, big versus small cities.



The prices of the 5 bundles in the first stage are given in Figure 3 with thick lines for large cities and thin lines for small cities. The prices in large cities are higher relative to those in small cities for all bundles except for Transportation where the small city average is a few percentage points higher. The prices in the large and small cities have largely the same trends over this period, except for housing which is not disaggregated here but shown in Cao et al (2017, Figure 2). Service (including housing) prices rose rapidly during 1992-2001 but then decelerated. The price of the Consumer goods bundle, which include food, rose rapidly in the 1990s due the food inflation, but then fell with the falling prices of electronic equipment. The price of other-home-energy rose the most of these 5 bundles, while electricity prices were flat after the late 1990s.

A closer look at household energy shares, incomes and prices by province

The share demand equation 2.10 for the first stage is indexed by household (k) and time (t). As noted, we divide each province into a big-city group and a small-city group and obtained price estimates for each of 17 regions for our 9-province sample (Beijing is one province and not divided into regions). The prices on the right-hand side of 2.10 are thus given for each r, not k. The demographic term, $B_A A_k$, allows each household type to have its own intercept term. To show how important this flexibility is, we plot in Figure 4 the provincial average share of electricity in all home energy versus the log relative price of electricity. Each province is represented by a different marker, one point for each year in the sample period.

The provincial effects are clear, each set of markers is clustered and not scattered over the share-price plane. Some provinces exhibit a positive slope that one expects from a price-inelastic demand (Guangdong, Beijing, Gansu), others show negative relationship of a very price elastic response (Sichuan, Hubei, Anhui). If one were to ignore the provincial patterns then one would be estimating a flat curve, or a unit price elasticity.

Figure 4. Electricity share versus price by province and year (1992-2009).

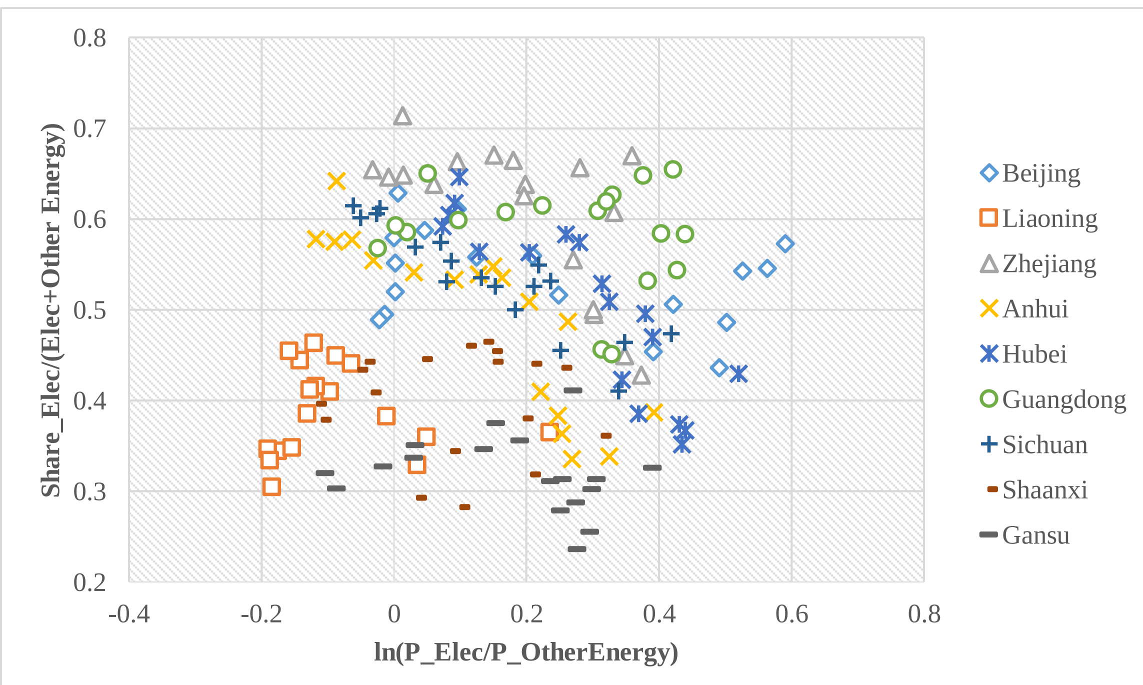


Figure 5. Electricity share versus total income.

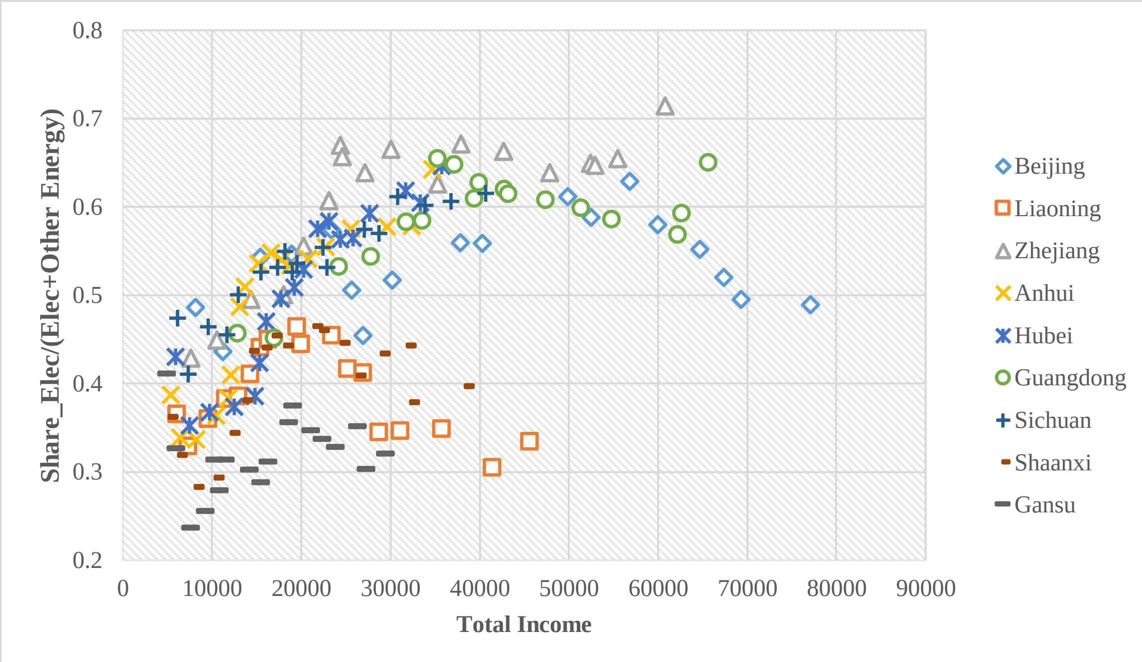


Figure 5 plots the shares versus average total income in each province and year. In this case we see how the provinces fit together to form a national income effect; the poor provinces of Gansu, Liaoning, Hubei on the left, and the rich provinces of Beijing, Guangdong and Zhejiang on the right. The share allocated to electricity rises as incomes rise within each province at low incomes but then flatten out and decline at high incomes.

4. The demand for energy

We estimate the parameters of the two-stage model using a demand system defined over five commodity groups described in the previous section. The demographic characteristics and durable ownership indicators used to control for heterogeneity in household behavior include:

1. Age of household head: Under 35, 35-55, Above 55.
2. Gender of household head: Female, Male.
3. Occupation of household head: Private Sector, Public Sector.

4. Education of household head: Less than Secondary School, Secondary School, and College (or above).
5. Has Child: A 0-1 indicator showing if there is someone under age 16 in the household.
6. Has Aged: A 0-1 indicator showing if there is someone aged 60 or older.
7. Number of members in the household: 1-2, 3, 3+.
8. Location: West, East and Middle.
9. Has Motorbike: A 0-1 indicator for a motorcycle in the household.
10. Has Car: A 0-1 indicator showing if there is a car in the household.
11. Number of TVs in the household: 0, 1, 2+.
12. Has PC: A 0-1 indicator showing if there is a computer in the household.
13. Number of Air Conditioners in the households: 0, 1, 2, 3+.
14. Cooling Degree Days[12]
15. Heating Degree Days
16. Area of the house

We included the employment type of the head of household since Cao et al. (2016) found a significant difference in consumption patterns between those who work in the public sector (including state-owned enterprises) and those who work in the private sector. Public sector workers are more often given in-kind payments and low-cost housing.

In Table 1 we present summary statistics of the variables used. There are 184,000 observations over 1992-2009, with about 15,000 per year in the recent years. On average, consumer goods comprise 58% of total expenditures (food alone is 34%), while services and housing comprise 35%. The shares for electricity, other-home-energy and transportation are all about 2%. Male-headed households account for over 75% of the sample and 31% of the household heads have college degrees. 22% have an elderly member

[12] The construction of cooling degree days and heating degree days is described in Cao et al. (forthcoming).

in the household and 44% has a child.

Averaged over the whole period, only 3.8% of urban households have a car, however, by 2009 it was 11%. About 90% of households have a washing machine and refrigerator, while 28% have two or more TV sets. 29% have only one air-conditioner while 16% have 2 or more.

Table 1. Sample summary statistics (Sample size: 183,564, 1992-2009)

Variable	Mean	Std. Dev.	Min	Max
Expenditure	31028.	24536	583	478351
Share_Elec	0.018	0.02	0	0.36
Share_OtherHomeEnergy	0.018	0.02	0	0.37
Share_ConsGoods	0.58	0.14	0.024	0.98
Share_Services	0.35	0.14	0.017	0.97
Share_Transport	0.022	0.03	0	0.70
Demographics. Share of households with a particular characteristic				
Age35-55	0.64	0.48	0	1
Age55+	0.20	0.40	0	1
Head_male	0.76	0.43	0	1
Head_public employment	0.60	0.49	0	1
Head_secondary school	0.62	0.48	0	1
Head_college	0.31	0.46	0	1
Has child	0.44	0.50	0	1
Has aged	0.22	0.41	0	1
HH size 3	0.59	0.49	0	1
HH size 4+	0.19	0.39	0	1
East China	0.49	0.50	0	1
Central China	0.24	0.43	0	1
Own Motorcycle	0.13	0.34	0	1
Car	0.04	0.19	0	1
Washing machine	0.91	0.29	0	1
Fridge	0.87	0.33	0	1
TV; 1 only	0.69	0.46	0	1
TV; 2+	0.28	0.45	0	1
PC	0.31	0.46	0	1
Air Conditioner: 1 only	0.29	0.46	0	1
Air Conditioner: 2	0.11	0.32	0	1
Air Conditioner: 3+	0.05	0.23	0	1
Cooling deg-days	277	222	0	919
Heating deg-days	3835	1944	273	7833
Home size (m_2)	72.4	41.2	5	2373

We use nonlinear full information maximum likelihood to estimate the system with the services equation omitted and subject to the constraints in (2.2, 2.5) and symmetry of B. Using the estimated values of the B matrix, we computed the Cholesky decomposition according to the formulas in Holt and Goodwin (2009) and find that they are concave for the share values and prices observed in the sample period. We thus did not need to explicitly constrain the values of B. It was also not necessary to impose any concavity restriction on Δ in the second stage.

The first-stage parameters estimated are presented in Appendix Table A1 and the second-stage in Tables A2 and A3. Table 2a gives the own-price and income elasticities derived from the estimated share elasticity matrix B (eqs. 2.14-2.16). The elasticities are calculated for the reference household in 2002: household size 3, with child, no aged member, East, and head of household is male, aged 35-55, secondary school educated, and employed in the private sector. Table 2b gives the cross-price elasticities.

The expenditure (income) elasticities are estimated with very small standard errors; Consumer Goods is slightly income inelastic (0.86) since it is a mix of inelastic food and more elastic electronic goods; Services, including housing is income elastic (1.23). Electricity and Other-home-energy have low income elasticities while Transportation which consist of motor fuels, daily passenger fares, and holiday travel, is elastic (1.23).

The own compensated price elasticities are negative for all bundles except for Consumer Goods. All the price elasticities are well estimated with small standard errors. The own-price (uncompensated) elasticity is negative for all goods; -0.49 for electricity and -0.35 for Other-home-energy, while transportation is the most price elastic with -0.71. We discuss how these estimates compare with others later in Table 5.

Table 2a. Price and Income Elasticities (standard errors in parenthesis)
(Reference Household: 35-55, Male, Private sector, Secondary School, Has Child, No Aged, Size 3, East)

Good	Uncompensated Price Elasticity	Compensated Price Elasticity	Expenditure Elasticity
First Stage			
Electricity	-0.491	-0.474	0.690
	(0.093)	(0.095)	(0.002)
Other Home Energy	-0.348	-0.337	0.492
	(0.087)	(0.084)	(0.001)
Transportation	-0.707	-0.671	1.225
	(0.085)	(0.088)	(0.002)
Consumer Goods	-0.497	-0.033	0.859
	(0.008)	(0.007)	(0.001)
Service & Housing	-0.500	-0.019	1.227
	(0.014)	(0.011)	(0.002)
Second Stage — Other Home Energy			
Coal	-0.406		
	(0.002)		
LPG	-0.608		
	(0.028)		
Natural Gas	-0.114		
	(0.013)		
Heat	-0.010		
	(0.007)		
Second Stage — Transportation			
Motor Fuels	-0.310		
	(0.022)		
Transportation Services	-0.155		
	(0.053)		

Table 2b. Uncompensated and compensated cross-price elasticities in first stage.

	Electricity	Other home energy	Transport-ation	Consumer Goods	Services & Housing
			Uncompensated Elasticity		
Electricity	-0.491	-0.133	0.201	0.678	-0.985
	(0.093)	(0.031)	(0.068)	(0.067)	(0.045)
Other-home-energy	-0.153	-0.348	0.640	0.753	-1.442
	(0.035)	(0.087)	(0.078)	(0.068)	(0.078)
Transportation	0.193	0.519	-0.707	-1.963	0.765
	(0.061)	(0.061)	(0.085)	(0.081)	(0.104)
Consumer Goods	-0.043	-0.044	-0.182	-0.497	-0.418
	(0.003)	(0.003)	(0.004)	(0.008)	(0.008)
Services & Housing	0.025	0.006	0.146	-0.381	-0.500
	(0.003)	(0.004)	(0.007)	(0.011)	(0.014)
			Compensated Elasticity		
Electricity	-0.473	-0.117	0.221	1.050	-0.715
	(0.095)	(0.034)	(0.071)	(0.068)	(0.048)
Other-home-energy	-0.140	-0.337	0.654	1.019	-1.249
	(0.036)	(0.090)	(0.081)	(0.074)	(0.085)
Transportation	0.225	0.547	-0.671	-1.302	1.245
	(0.063)	(0.064)	(0.087)	(0.081)	(0.107)
Consumer Goods	0.028	0.022	-0.154	-0.117	0.045
	(0.003)	(0.003)	(0.004)	(0.009)	(0.008)
Services & Housing	-0.054	-0.031	0.178	0.213	-0.069
	(0.003)	(0.004)	(0.007)	(0.011)	(0.015)

Note: Computed using (2.17) where *i* is the row and *j* is the column index.

The cross-price elasticities in Table 2b show some interesting patterns. Electricity is a substitute for Transportation and Consumer Goods but seems to be a complement with Other Home Energy and Services. This link with OHE may be due to the national electricity system that ties electricity prices to coal prices, or a technical linkage between gas and electricity (home ventilation systems that uses both gas and electricity). The complementarity with Services (including Housing) may be driven by the complementarity of home size and electricity use. The relationships of Other Home Energy with other bundles are the same as the ones for Electricity. Transportation is a substitute for Electricity, OHE and Services, but is a complement for Consumer Goods.

The uncompensated cross-price elasticity between Consumer Goods and Services is negative. Since these two bundles constitute about 90% of total expenditures, this is not surprising given the income effect of an increase in price. The compensated cross-price elasticities are 0.05 and 0.21 respectively, meaning these are substitutes.

Second Stage

The results of estimating the probit equation (2.10) are given in Appendix Tables A2 and A3 for OHE and Transportation, respectively. Using the normal density and CDF function values from the probit, we estimated the demand equation (2.11) and the results are given in Tables 3 and 4. The own-price coefficient is significantly negative, and the demographic terms are almost all significant at the 5% level.

The elasticities for this stage are computed using (2.17-19). The own-price (uncompensated) elasticities for coal, LPG, natural gas, heat are -0.41, -0.61, -0.11 and -0.01, respectively. Central district heating and natural gas are quite inelastic; once installed, they are unlikely to be replaced by other sources. On the other hand, coal and LPG are more elastic. Since we have to impose homotheticity in the second stage, the income elasticity is inherited from the stage one value for total other home energy, 0.49.

The own-price (uncompensated) elasticity for fuels (gasoline and diesel) in the Transportation bundle is -0.3, while that for transportation services is -0.16. The income elasticity is inherited from the stage one value for total transportation which is 1.23.

Table 3. Stage 2 demand function: Other Home Energy (Coal, LPG, Natural Gas, Heat)

Variable	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
	Coal		LPG		Natural Gas		Heat	
ln P(Coal)	-0.039	0.0001	-0.022	0.0001	-0.048	0.0002	-0.017	0.0001
ln P(LPG)	-0.002	0.0001	-0.040	0.0001	-0.026	0.0001	-0.013	0.0002
ln P(NGas)	0.006	0.0001	-0.172	0.0001	-0.198	0.0001	-0.006	0.0001
ln P(Heat)	-0.008	0.0001	-0.013	0.0001	-0.034	0.0001	-0.156	0.0001
Age35-55	-0.051	0.0001	0.009	0.0001	0.021	0.0001	0.021	0.0001
Age55+	-0.113	0.0001	0.034	0.0001	-0.026	0.0001	0.104	0.0001
hh_male	0.033	0.0001	0.002	0.0000	-0.080	0.0001	0.045	0.0001
hh_public	-0.117	0.0001	-0.005	0.0000	0.151	0.0001	-0.029	0.0001
hh_midschool	0.148	0.0001	-0.009	0.0001	-0.068	0.0002	-0.071	0.0001
hh_college	0.315	0.0001	-0.021	0.0001	-0.127	0.0002	-0.166	0.0001
has child	0.009	0.0001	0.001	0.0000	0.040	0.0001	-0.051	0.0001
has aged	-0.074	0.0001	0.020	0.0001	-0.044	0.0001	0.099	0.0001
hh size 3	0.046	0.0001	0.024	0.0001	-0.121	0.0001	0.050	0.0001
hh size 4+	-0.191	0.0001	0.046	0.0001	-0.065	0.0001	0.210	0.0001
east	0.359	0.0002	-0.189	0.0001	-0.004	0.0001	-0.166	0.0001
middle	0.146	0.0001	-0.302	0.0002	-0.168	0.0001	0.324	0.0001
CDD(1,000)	0.230	0.0002	-0.223	0.0002	-0.333	0.0003	0.326	0.0003
HDD(1,000)	-0.055	0.0000	0.050	0.0000	0.180	0.0000	-0.175	0.0000
Home Size (1,000m_2)	0.985	0.0005	-1.012	0.0004	-0.390	0.0007	0.418	0.0005

Table 4. Stage 2 demand function: Transportation (Fuels, Transportation Services)

	Estimate	SE
ln P(fuel/transp svc)	-0.167	0.0001
Age35-55	-0.027	0.0001
Age55+	0.046	0.0001
Head_male	-0.032	0.0000
Head_public employment	0.030	0.0000
Head_secondary school	-0.100	0.0001
Head_college	-0.112	0.0001
Has child	-0.080	0.0000
Has aged	0.035	0.0001
HH size 3	0.010	0.0001
HH size 4+	0.002	0.0001
East China	-0.117	0.0001
Central China	-0.040	0.0001

In the Introduction we noted estimates of China household energy demand in the literature using both household level and aggregated data, and using both single equation and equation systems approaches. Table 5 compares our income and price elasticities for each type of energy with these other studies including a few for other countries. These estimates cover quite a wide range of values which is not surprising given the different types of data and estimation methods.

For the studies on China, electricity has the largest number of studies among the various energy types; estimates of the income elasticity for electricity ranges from 0.1 from Zhou and Teng (2013) estimate using Sichuan data to 1.1 from Shi, Zheng and Song (2012) estimate using the 3 richest cities. Our estimate covering 9 provinces at different levels of development is 0.7. The income elasticities estimated for the richer countries are much lower. The estimates of price elasticity for electricity in China ranges from -0.1 (Shi et al.) to -0.5 (Khanna et al.) to -2.9 (He and Reiner 2014) compared to our -0.5. He and Reiner (2014) is also based on the 3 rich areas of Beijing, Shanghai and Guangdong, but includes dummy variables for 10 sets of income groups which may explain their unusually high elasticity. Three of the studies given in Table 5 distinguish between short- and long-run price elasticities in the rich countries, with short-run elasticities about -0.1 and long-run values about -0.5. Our use of repeated annual cross-sections should be interpreted as long-run elasticities.

Recall that our coal, LPG, natural gas and district heat elasticities are derived from the second stage function as part of the Other Home Energy (OHE) bundle. Coal is a small share of urban home energy use, less than 10% in our sample period. The expenditure elasticity for OHE is 0.49; for comparison, this is at the low end of the gas & coal elasticity of Cao, Ho and Liang (2016) which used the same urban household survey data as this paper. Burke and Liao (2015) use total provincial coal consumption instead of household data and estimated an aggregate income elasticity of 1.2 to 1.7. There are few studies of residential gas demand in China, Yu et al. (2014) use city average gas data and estimate an income elasticity of 0.21. The contrast in results from the coal and gas studies may be surprising given that coal is more often used by poorer households, but we emphasize that these two studies are not based on household data. The Cao et al. (2016) study using household data estimates a slightly lower income elasticity for gas compared to coal. Our OHE bundle that includes both coal and gas has an elasticity that is in between the two aggregated studies.

Our price elasticity for coal is -0.4 which is similar to Zhang et al.'s (2011) estimate of -0.3 using national data, but at the low end of the -0.4 to -0.9 range for coal & gas in Cao et al. (2016), and the -0.3 to -0.7 range for provincial coal price elasticity in Burke and Liao (2015).

Our price elasticity for LPG is -0.6 but only -0.1 for natural gas. This is much less elastic than the -1 to -2 range of gas price elasticity estimated for China from city average data by Yu et al. (2014). Gundimeda and Kohlin (2008) estimates for India are in the -0.5 to -1 range and cover our estimate for LPG.

Our transportation bundle consist of motor fuels and transportation services and vehicle maintenance and we estimate an income elasticity of 1.2. There are no directly comparable estimate that we can find. Fouquet (2012) examines the elasticities for passenger transportation (land and air) since 1850 for the UK and find that the income elasticity has fallen from 1.2 in 1970 to 1.0 in 2010. The income elasticity for fuels is inherited from the first stage estimate for the whole bundle (1.2). This is not far from the 1.0 estimated for gasoline by Lin and Zeng (2013) using total national demand but higher than the 0.7 to 0.9 range in Cao, Ho and Liang (2016) which used household data. Our price elasticity for motor fuels is -0.3 and is in the -0.5 to -0.2 range of Lin and Zeng but less elastic than Cao, Ho and Liang. The studies of the U.S. and OECD listed in Table 5 gives income elasticity estimates that are much lower, ranging from 0.1 to 0.4 as expected for richer countries. The price elasticities for gasoline in the rich countries range from -

0.02 to -0.6 (Wadud et al. 2010 and Flood et al. 2010).

Some of the studies of electricity demand also provide an estimate of the cross-price elasticity for natural gas. For the urban studies, Shi et al. (2016) report a cross-price coefficient of -0.49, He and Reiner (2014) report -1.36, while Khanna et al.'s study covering both rural and urban households report a positive value of 0.15; these are to be compared to our cross-price effect for Other Home Energy of -0.15 (Table 2b).

The above comparisons show that it is important to have more studies of energy demand using household level data. It is hard to draw firm conclusions by comparing household-based estimates with city-level or national-level estimates. The different household-based studies cited here use very different samples, with 2 studies focusing only on the rich cities.

Table 5. Estimates of energy demand elasticities in the literature.

Energy type	***Authors***	***Country***	***Price elasticity***	***Income elasticity***
Electricity	Paul et al. (2009)	U.S.	-0.11 to -0.15 (short-run)	0.11
			-0.32 to -0.52 (long-run)	
	Alberini and Filippini (2011)	U.S. Short run	-0.15	0.05
		Long run	-0.73	
	Fell et al. (2014)	U.S.	-0.5	0.01
	Blazquez et al. (2013)	Spain Short run	-0.07	0.23
		Long run	-0.19	0.61
	Bianco V. et al (2009)	Italy	-0.06	
	Hung and Huang (2015)	Taiwan-summer	-0.454	0.291
		non-summer	-0.857	0.205
	Gundimeda, Kohlin (2008)	India	-0.59 to -0.71	0.53 to 0.89
	Khanna et al. (2016)	China	-0.51	0.15
	He and Reiner (2014)	China	-2.91	
	Zhou and Teng (2013)	China	-0.35 to -0.50	0.14 to 0.33
	Shi, Zheng & Song (2012)	China	-0.15	1.06
	Cao, Ho and Liang (2016)	China	-0.57 to -0.49	0.64 to 0.80
	This study	**China**	**-0.491**	**0.690**
Other home energy	**This study**	**China**	**-0.348**	**0.492**
Gas	Solheim and Tveteras (2017)	OECD	-0.003 to -0.223	-0.26 to 1.59
	Meier and Rehdanz (2010)	U. K.	-0.34 to -0.56	0.01 to 0.06
	Maddala et al. (1997)	U.S.	-0.31 to -0.13	
	Gundimeda, Kohlin (2008)	India	-0.48 to -1.05	0.56 to 0.99
	Yu, Zheng, Han (2014)	China	-1.02 to -2.19	-0.19 to 0.23
	Cao, Ho and Liang (2016)	China coal & gas	-0.94 to -0.46	0.57 to 0.67
	This study	**China**	**-0.608 (LPG)**	
			-0.114 (NGas)	
Coal	Reddy (1975)	U.S.	-0.37 to -0.97	

	Goldstein & Smith (1975)	U.S.	-0.48 to -0.32	
	Zhang et al. (2011)	China	-0.34	
	Burke & Liao (2015)	China	-0.3 to -0.7	1.2 to 1.7
	Cao, Ho and Liang (2016)	China coal & gas	-0.94 to -0.46	0.76 to 0.94
	This study	**China**	**-0.406**	
Total Transport-ation	**This study**	**China**	**-0.707**	**1.225**
	Fouquet (2012, Passenger)	**UK**	**-0.6 to -0.7**	**1.0 to 1.2**
Gasoline	West and Williams (2004)	U.S.	-0.457	
	Wadud, Z. et al. (2010)	U.S.	-0.016 to -0.58	0.28 to 0.43
	Flood, L. et al.(2010)	OECD	-0.077 to -0.12	0.071 to 0.073
	Liu, W. (2014)	U.S.	-0.06 to -0.08	0.16 to 0.21
	Lin and Zeng (2013)	China	-0.50 and -0.20	1.01 and 1.05
	Cao, Ho and Liang (2016)	China	-0.95 to -0.85	0.76 to 0.94
	Cao and Hu (2018)	China	-0.466	1.307
	This study	**China**	**-0.310**	

5. Conclusion

Most estimates of household energy demand in China have focused on individual types of energy, most particularly electricity. While single-equation systems provide a great deal of flexibility, they do not give cross-price elasticities and are less suited for use in economy-wide models for policy analysis. We have estimated a two-stage household energy demand system that takes all consumption commodities into account, and the use of two stages allow us to explicitly identify demands for electricity, coal, gas, district central heating, vehicle fuels and transportation services. This system is internally consistent where the expenditure shares sum to 1. To implement this model, we have developed a set of provincial level price levels that allow us to exploit cross-sectional variation in prices to supplement the short time-series.

Our model allows different household types to have different consumption shares even if they have the same incomes and face the same prices. The function also can be consistently aggregated to give a national consumption function that depends only on prices, national income, and a demographic distribution parameter. This aggregate demand function may be easily used in economy-wide CGE models and used for projection of future energy demands that takes into account demographic changes (e.g. Jorgenson et al. 2018 application of a U.S. model to study carbon prices).

Our estimates of income inelastic demand for electricity matches most of the other research cited, while the -0.5 price elasticity is also close to some of the China estimates and close to the long-run estimates in the richer countries. The differences in sample size and scope make these electricity studies hard to compare directly as indicated by the range of values. The demand for coal, natural gas and home heating is price inelastic and we estimate an income elasticity of 0.5 for the home energy bundle. These estimates for coal, gas and heating contributes to the very few studies of China using household level data. The demand for vehicle fuels is part of the demand for transportation and we estimate an income elasticity of 1.2 which is much lower than the gasoline elasticity in rich countries but consistent with another China estimate. The estimates should be useful for various policy analysis especially those that would change energy prices significantly, using either partial equilibrium or general equilibrium methods.

The use of a flexible demand system allows us estimate cross-price elasticities and to estimate income effects in a consistent fashion, unlike single-equation methods. We find electricity and other home energy (coal, gas, district heating) to be complements, but substitutes for transportation. The cross-price effects for electricity and gas reported in the other studies span from positive to negative. The wide range of empirical estimates for both own and cross-price elasticities certainly indicate a need for more research given the key role these estimates play in evaluating policies.

While we have to employ various simplifying assumptions to implement a two-stage system, we believe that it would prove useful in policy analysis using CGE models. The results are statistically significant and accords with our expectations of own-price and income responses. One may extend the approach to cover more detailed energy types when more data becomes available.

We have seen income effects may be complicated and Lewbel (1991) has suggested the use of rank-3 systems to capture higher order effects[13]. In future work with longer time series we hope to use a rank 3 translog system in the manner of Jorgenson and Slesnick (2008).

[13] Lewbel (1991) explain the rank of a demand system as the number of independent price indexes needed to specify the corresponding indirect utility function. Rank 1 systems are homothetic functions while rank 2 have linear Engel curves that need not pass through the origin (such as the one used in this paper).

Appendix

Here we derive the price and expenditure elasticities in the second stage as given in equation (2.17). In the first stage the expenditure on bundle *I* is $p_I x_I$ which is also equal to the expression for the sum of components of *I* given in (2.9) for the second stage.

The cross-price elasticity of good i with respect to price j is defined as:

$$\varphi_{ij}^I = \frac{\partial \ln y_i^I}{\partial \ln q_j^I}$$

where the quantity is the value divided by the price:

$$y_i^I = \frac{v_i^I M^I}{q_i^I} = \frac{v_i^I p_I x_I}{q_i^I}$$

Thus, $\ln y_i^I = \ln v_i^I + \ln x_I + \ln p_I - \ln q_i^I$

and we have the price elasticity as:

$$\begin{aligned}
\varphi_{ij}^I &= \frac{\partial \ln v_i^I}{\partial \ln q_j^I} + \frac{\partial \ln x_I}{\partial \ln q_j^I} + \frac{\partial \ln p_I}{\partial \ln q_j^I} - \frac{\partial \ln q_i^I}{\partial \ln q_j^I} \\
&= \frac{1}{v_i^I}\frac{\partial v_i^I}{\partial \ln q_j^I} + \frac{\partial \ln x_I}{\partial \ln p_I}\frac{\partial \ln p_I}{\partial \ln q_j^I} + v_j^I - \delta_{ij} \\
&= \quad -\frac{\Delta_{ij}^I}{v_i^I} \quad + \quad \eta_{II} v_j^I \quad + v_j^I - \delta_{ij}
\end{aligned}$$

The first term comes from the share equation (2.7), the second term is the definition of the price elasticity of the first stage and δ_{ij} is the Kronecker indicator; the $\partial \ln p_I / \partial \ln q_j^I$ term may be approximated from the Tornqvist index of the price of bundle I:

$$\ln p_I = \sum_k \bar{v}_k^I \ln q_k^I$$

Table A1 reports the estimates of the first stage model estimated as repeated cross-sections over the period 1992-2009. Table A2 gives the Probit in the first step of the second stage for other home energy while Table A3 is the Probit for Transportation.

Table A1. Estimates of first-stage consumption function

Variable	Estimate	SE	Estimate	SE	Estimate	SE
	Electricity		Other energy		Transportation	
Constant	-0.0068	0.0078	-0.0118	0.0077	-0.0198	0.0077
Log P(elec)	-0.0134	0.0064	0.0032	0.0018	-0.0054	0.0038
Log P(other energy)	0.0032	0.0018	-0.0152	0.0020	-0.0149	0.0018
Log P(Transp)	-0.0054	0.0038	-0.0149	0.0018	-0.0084	0.0035
Log P(goods)	-0.0178	0.0027	-0.0175	0.0016	0.0573	0.0034
Log P(Services)	0.0253	0.0042	0.0328	0.0018	-0.0221	0.0050
Log Expenditure	-0.0080	0.0006	-0.0116	0.0006	0.0065	0.0006
Age35-55	-0.0011	0.0007	-0.0004	0.0007	0.0021	0.0007
Age55+	0.0000	0.0014	-0.0012	0.0014	0.0016	0.0014
Head_male	-0.0004	0.0005	-0.0006	0.0005	0.0006	0.0005
Head_public empl	0.0027	0.0005	0.0027	0.0005	-0.0007	0.0005
Head_secondary school	-0.0010	0.0015	-0.0003	0.0015	-0.0032	0.0015
Head_college	-0.0006	0.0018	-0.0001	0.0018	-0.0070	0.0018
Has child	0.0018	0.0004	0.0019	0.0004	-0.0003	0.0004
Has aged	-0.0011	0.0009	-0.0030	0.0009	0.0018	0.0009
HH size 3	-0.0010	0.0008	-0.0009	0.0008	0.0017	0.0008
HH size 4+	-0.0029	0.0011	-0.0043	0.0011	0.0019	0.0011
East China	0.0008	0.0009	0.0017	0.0009	0.0006	0.0009
Central China	-0.0034	0.0009	-0.0023	0.0009	0.0000	0.0009
Own Motorcycle	-0.0007	0.0008	0.0002	0.0008	-0.0090	0.0008
Car	0.0030	0.0030	-0.0005	0.0030	-0.0610	0.0030
Washing machine	-0.0003	0.0012	0.0000	0.0012	-0.0001	0.0012
Fridge	-0.0052	0.0009	0.0011	0.0009	-0.0017	0.0009
TV; 1 only	-0.0049	0.0024	-0.0021	0.0024	0.0015	0.0024
TV; 2+	-0.0061	0.0030	-0.0012	0.0030	0.0016	0.0030
PC	-0.0022	0.0008	-0.0022	0.0008	-0.0001	0.0008
Air Conditioner; 1 only	-0.0047	0.0007	0.0017	0.0007	0.0004	0.0007
AirConditioner; 2	-0.0060	0.0015	0.0017	0.0015	-0.0006	0.0015
AirConditioner; 3+	-0.0069	0.0025	0.0010	0.0025	-0.0016	0.0025
Cooling deg-days(1,000)	0.0003	8.49E-05	-0.0002	8.21E-05	0.0003	8.34E-05
Heating deg-days(1,000)	0.0073	6.20E-03	-0.0037	6.19E-03	0.0000	6.20E-03
Home size (1,000m2)	-0.0011	5.45E-05	-0.0083	5.50E-05	0.0721	5.49E-05

Table A1. Continued.

Variable	Estimate	SE	Estimate	SE
	Cons. goods		Services	
Constant	-0.6692	0.0077	-0.2924	0.0078
Log P(elec)	-0.0178	0.0027	0.0253	0.0042
Log P(other energy)	-0.0175	0.0016	0.0328	0.0018
Log P(Transp)	0.0573	0.0034	-0.0221	0.0050
Log P(goods)	-0.3125	0.0046	0.2144	0.0046
Log P(Services)	0.2144	0.0046	-0.1611	0.0096
Log Expenditure	-0.0761	0.0006	0.0892	0.0006
Age35-55	0.0157	0.0007	-0.0163	0.0007
Age55+	-0.0060	0.0014	0.0056	0.0014
Head_male	-0.0063	0.0005	0.0067	0.0005
Head_public empl	-0.0270	0.0005	0.0224	0.0005
Head_secondary school	0.0067	0.0015	-0.0022	0.0015
Head_college	0.0111	0.0018	-0.0035	0.0018
Has child	-0.0068	0.0004	0.0034	0.0004
Has aged	-0.0014	0.0009	0.0037	0.0009
HH size 3	0.0042	0.0008	-0.0040	0.0008
HH size 4+	-0.0047	0.0011	0.0100	0.0011
East China	0.0255	0.0009	-0.0285	0.0009
Central China	-0.0578	0.0010	0.0636	0.0009
Own Motorcycle	-0.0254	0.0008	0.0349	0.0008
Car	0.0169	0.0030	0.0415	0.0030
Washing machine	-0.0086	0.0012	0.0090	0.0012
Fridge	0.0083	0.0009	-0.0026	0.0009
TV: 1 only	0.0170	0.0024	-0.0115	0.0024
TV: 2+	0.0180	0.0030	-0.0123	0.0030
PC	0.0168	0.0008	-0.0123	0.0008
Air Conditioner: 1 only	0.0255	0.0007	-0.0229	0.0007
Air Conditioner: 2	0.0279	0.0015	-0.0231	0.0015
Air Conditioner: 3+	0.0285	0.0025	-0.0210	0.0025
Cooling deg-days(1,000)	-0.0029	8.18E-05	0.0025	8.49E-05
Heating deg-days(1,000)	-0.0235	6.19E-03	0.0198	6.22E-03
Home size (1,000m2)	0.7276	5.64E-05	-0.7868	5.38E-05

Table A2. Estimates of Probit for Other Home Energy (first-step of the second stage)

Variable	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
	Coal		LPG		Natural Gas		Heat	
ln P(Coal)	-0.069	0.00025	-0.271	0.00019	0.598	0.00018	-0.161	0.00028
ln P(LPG)	-0.407	0.00022	-0.305	0.00019	0.199	0.00018	0.530	0.00023
ln P(NGas)	0.037	0.00012	0.712	0.00010	-0.646	0.00010	-0.059	0.00013
ln P(Heat)	-0.074	0.00027	0.104	0.00015	-0.105	0.00015	-0.106	0.00030
Age35-55	-0.070	0.00014	-0.055	0.00012	0.108	0.00012	0.001	0.00015
Age55+	-0.008	0.00019	-0.031	0.00017	0.093	0.00017	0.040	0.00021
Head_male	0.081	0.00011	0.013	0.00010	-0.076	0.00010	0.038	0.00012
Head_public	-0.176	0.00012	0.039	0.00011	0.033	0.00010	-0.054	0.00013
Head_secondary school	-0.256	0.00018	-0.016	0.00018	0.210	0.00018	0.002	0.00022
Head_college	-0.510	0.00020	-0.125	0.00020	0.388	0.00019	-0.007	0.00024
Has child	0.013	0.00010	0.112	0.00009	-0.124	0.00009	-0.042	0.00011
Has aged	0.097	0.00015	-0.112	0.00014	0.142	0.00013	0.065	0.00016
HH size 3	0.023	0.00015	0.054	0.00013	0.014	0.00013	-0.002	0.00015
HH size 4+	0.259	0.00016	0.194	0.00015	-0.184	0.00015	0.091	0.00018
East China	-0.703	0.00016	0.648	0.00013	-0.271	0.00013	-0.069	0.00017
Central China	0.228	0.00024	1.261	0.00016	-0.812	0.00016	0.055	0.00026
CDD(1,000)	0.294	0.00041	0.064	0.00037	-0.138	0.00036	0.068	0.00046
HDD(1,000)	0.020	0.00006	0.011	0.00005	-0.008	0.00005	0.135	0.00006
Home size (1,000m_2)	2.809	0.00113	0.000	0.00056	0.000	0.00073	0.648	0.00126
M(1,000,000)	-20.600	0.00419	-9.320	0.00212	12.800	0.00219	1.120	0.00262
Cen_Heat*	0.130	0.00021	-0.321	0.00020	0.145	0.00019	0.445	0.00023

* CDD=Cooling degree days; HDD=Heating degree days; Cen_Heat= 0-1 indicator showing if the city has district central heating.

Table A3. Estimates of the Probit for Transportation

	Estimate	SE
ln P(fuel)/P(transp svc)	0.122	0.00014
Age35-55	-0.136	0.00012
Age55+	-0.375	0.00017
Head_male	0.079	0.00010
Head_public employment	-0.120	0.00010
Head_secondary school	-0.278	0.00017
Head_college	-0.348	0.00019
Has child	0.043	0.00009
Has aged	-0.137	0.00014
HH size 3	0.045	0.00013
HH size 4+	0.217	0.00015
East China	0.315	0.00012
Central China	-0.051	0.00014
M(1,000,000)	9.74	0.00199
constant	-0.705	0.00025

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