Economic Systems Research
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/cesr20

THE EXTENDED ECONOMETRIC INPUT-OUTPUT MODEL WITH HETEROGENEOUS HOUSEHOLD DEMAND SYSTEM

Kijin Kim[a], Kurt Kratena[ab] & Geoffrey J.D. Hewings[a]
[a] Regional Economics Applications Laboratory, University of Illinois, Urbana, USA
[b] Austrian Institute of Economics Research (WIFO), Wien, Austria
Published online: 24 Dec 2014.

To cite this article: Kijin Kim, Kurt Kratena & Geoffrey J.D. Hewings (2014): THE EXTENDED ECONOMETRIC INPUT-OUTPUT MODEL WITH HETEROGENEOUS HOUSEHOLD DEMAND SYSTEM, Economic Systems Research, DOI: 10.1080/09535314.2014.991778

To link to this article: http://dx.doi.org/10.1080/09535314.2014.991778

Economic Systems Research, 2014
http://dx.doi.org/10.1080/09535314.2014.991778

Routledge
Taylor & Francis Group

THE EXTENDED ECONOMETRIC INPUT–OUTPUT MODEL WITH HETEROGENEOUS HOUSEHOLD DEMAND SYSTEM

KIJIN KIM[a*], KURT KRATENA[a,b] and GEOFFREY J.D. HEWINGS[a]

[a]*Regional Economics Applications Laboratory, University of Illinois, Urbana, USA;* [b]*Austrian Institute of Economics Research (WIFO), Wien, Austria*

(*Received 22 November 2013; accepted 21 November 2014*)

This paper proposes an extension to the regional econometric input–output model (REIM) [Conway, R.S. (1990) The Washington Projection and Simulation Model: A Regional Interindustry Econometric Model. *International Regional Science Review*, 13, 141–165; Israilevich, P.R., G.J.D. Hewings, M. Sonis and G.R. Schindler (1997) Forecasting Structural Change with a Regional Econometric Input–Output Model. *Journal of Regional Science*, 37, 565–590]. We integrate a demand system with age and income parameters into the REIM. The extended model thus addresses concerns about the effects of household heterogeneity. The initial testing is conducted with a model for the Chicago metropolitan area. First, using aggregate expenditure data by income and age groups, the almost ideal demand system with group fixed effects is constructed. Next, the estimated demand system is linked to the REIM to reflect long-term changes in the age and income distribution of households. The long-range simulation from the extended model takes into account structural changes in expenditure type stemming from changing demographic composition. The extended model further broadens the scope of impact analysis under various scenarios associated with age and income changes.

Keywords: Econometric input–output model; Demand systems; Long-run disaggregated models; Almost ideal demand system (AIDS); Seemingly unrelated regression (SUR)

1. INTRODUCTION

Personal consumer expenditures account for approximately 70% of gross domestic product in the USA. Yet most economic models persist in aggregating all the household heterogeneity into one ‘representative’ household sector while, in contrast, industries are often represented by 50–500 different sectors. As limitations of representative-agent-based models have long been recognized, heterogeneity in national macroeconomic models has been drawing modelers’ attention. Stoker (1993) and Blundell and Stoker (2005) extensively discussed *aggregation problems* arising from the perspective of empirical modeling.[1] With an aging population, increasing mobility and widening income inequality becoming critical issues in advanced economies, analysis that highlights their implications for consumer demand is now regarded as a major priority. One interesting aspect of demographic heterogeneity has been age distribution due to increasing awareness of an aging population.

*Corresponding author. E-mail: kkim96@illinois.edu

[1] According to the description by Stoker (1993) on the modeling approaches, our paper can be placed under the *micro–macro* model, in between the representative agent model and the micro-simulation model.

Fair and Dominguez (1991) tested the effects of the US age distribution on consumption by adding age variables and showed that the models with age structure offer superior explanatory power. Dowd et al. (1998) used an inter-industry input–output macro model to simulate the long-term impacts of changes in age composition on the US economy.[2] Similarly, parameter estimates of age structure were shown to play a significant role in consumer demand studies for other countries (Denton et al. (1999) for Canadian provinces; Bardazzi and Barnabani (2001) for Italy; Lührmann (2008) for the UK; and Erlandsen and Nymoen (2008) for Norway).

The regional econometric input–output model (REIM; see Conway, 1990; Israilevich et al., 1997) is one of the several alternative economic models that provide a way to extensively examine the long-term effects of socio-demographics changes at the regional level. The REIM has its roots in an empirical macro-econometric model with an integrated input–output component for subnational economies. The combination of dynamic econometric and static input–output approaches offers better forecasting accuracy than the traditional structural econometric models and it also allows inter-industry impact studies with dynamics (Rey, 2000). Based on Conway's methodology (1990), Israilevich et al. (1997) further developed the REIM for the Chicago metropolitan area to evaluate the economic impacts with inter-industry spillover reflected through the structure of the input–output table and also provided an endogenous procedure for updating the input–output structure. One of the caveats in the REIM is that household consumption is limited to a representative consumer mainly due to the absence of detailed consumer expenditures data at the regional level. Thus, the economic effects of changes in household characteristics such as age and income distributions have not been captured so far in the current structure of the REIM.

This paper proposes an extended econometric input–output model for the Chicago region in which an aggregate demand system with parameterized household characteristics is augmented. The integration procedure is as follows: first, using aggregate consumption data from the 1987–2011 Consumer Expenditure Survey (CES) and the Consumer Price Index (CPI), we estimate the almost ideal demand system (AIDS) with age- or income-group fixed effects. Income and price elasticities for goods or services are allowed to vary by age or income groups. Next, an integration procedure is proposed by which the demand system is linked to the REIM. In the extended model, distinct spending patterns by cohort are major forces that drive differentiated changes in output, employment, and income.[3] Simulations reveal that a demographic change (e.g. an aging population) results in compositional changes in consumption in the long run, consequently influencing other endogenous variables as well.

Our paper accounts for heterogeneity in terms of income as well as age in the consumer demand at the regional level in contrast to the previous models that captured national-level impacts of consumption heterogeneity. To the best of our knowledge, this is the first attempt to *fully integrate* the REIM and a demand system that allows heterogeneity in household consumption. Mongelli et al. (2010) discussed the integration of the AIDS model within the static input–output framework. Yoon and Hewings (2006) attempted to incorporate

[2] The long-term inter-industry forecasting tool developed by Inter-industry Forecasting project at the University of Maryland (INFORUM).

[3] A cohort generally means a group of individuals with *time-invariant* characteristics (e.g. birth cohort; woman born in 1970). However, this study defines a cohort as a group of households with *common* characteristic and 'a group' is used interchangeably.

the results separately obtained from the REIM and a demand system. This paper produces superior results in that: (1) a generalized approach to endogenizing a demand system within the REIM framework is proposed; (2) the demand systems are constructed so that they are not only consistent with *aggregate* demand theory, but also parsimonious for empirical estimation.

This paper proceeds as follows. Section 2 describes the structure of the REIM. Section 3 contains a brief introduction to the micro-level AIDS model and the derivation of aggregate demand model. Section 4 presents the data. Section 5 discusses the estimation method and results. Section 6 describes the procedure of integrating the demand system into the REIM. Section 7 includes the simulation results and Section 8 concludes the paper.

2. THE REGIONAL ECONOMETRIC INPUT–OUTPUT MODEL

Since its introduction by Israilevich et al. (1997), the REIM for the Chicago metropolitan area (CREIM) has been continually maintained and updated by the Regional Economics Application Laboratory. Focusing on subnational regions, the methodology in the REIM is based on a macro-econometric modeling framework in which a static input–output model and dynamic econometric models are integrated. The CREIM has adopted *the coupling strategy* as a way of integration that "reflect[s] the greatest degree of model closure and extent of interaction between the EC [econometric] and IO [input–output] modules" and this approach "results in the most comprehensive representation of regional system" compared to the alternative methods such as the *embedding* and *linking* strategies (Rey, 1998, pp. 6 and 10). The integration offers improved forecasting accuracy and inter-industry analysis with dynamics. Characteristics of the REIM are described in greater detail in West (1995) and Rey (2000).

An overview of the REIM is presented in Figure 1. Exogenous exports and endogenous final demand lead to changes in output. Constant-price *actual* output (a vector of sectoral output, o_i's; $\mathbf{o}$) is expressed as a function of constant-price *expected* output ($\mathbf{z}$) that contains the deterministic structure of the base-year input–output table:

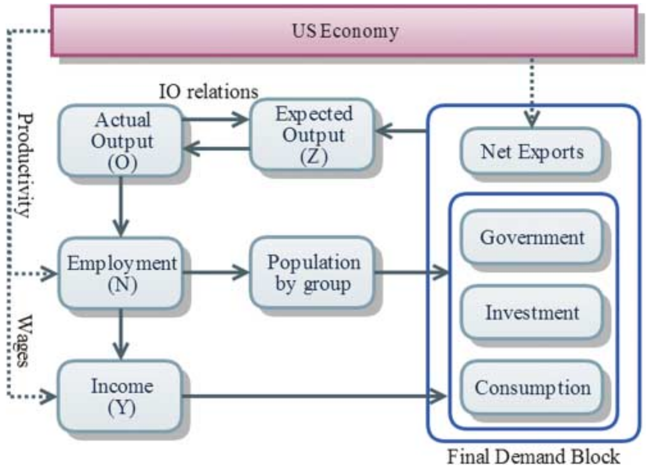
$$\mathbf{z} = \mathbf{Ao} + \mathbf{BF},$$

$$\log\left(\frac{o_i}{z_i}\right) = f_i(\cdot) + \varepsilon_i \quad \text{or} \quad \log(o_i) = f_i'(\log(z_i), \cdot) + \varepsilon_i',$$

where $\mathbf{A}$ is a matrix of technical coefficients; $\mathbf{B}$ is a coefficient matrix normalized so that each column of final demand component adds up to one; $\mathbf{F}$ is a matrix of final demand including personal consumption expenditure (PCE), investment, government expenditures, exports and imports; ε_i and ε_i' are the random disturbances.[4] The functions f_i and f_i' for industry i generally contain lagged-dependent variables and time dummy variables. The

[4] Since personal consumption expenditure data for the Chicago region are not available, it is assumed that for four expenditure types, that is, auto and parts, other durables, nondurables and services, consumption equations for Chicago and the USA have identical functional forms. Consumption expenditures on a per-capita basis for the USA are first estimated using personal income as one of the explanatory variables. Then, consumption expenditures for Chicago are generated by inserting local personal income into the estimated equations for the USA.

FIGURE 1. Overview of the REIM.



elements in the matrices **A** and **B** are constant since they are based on the base-year input–output table. The stochastic relationship between actual and expected output is one of the various ways to overcome the often-criticized constancy of technical coefficients in the input–output approach:[5] the movement of differences between o_i and z_i represents overall changes in technical coefficients over time while they are identical in the base year by construction. Labor productivity defined by output per worker is estimated in the following form:

$$\log\left(\frac{o_i}{n_i}\right) = g_i(\cdot) + u_i,$$

where the function g_i usually includes the lagged-dependent variable, the national counterpart and time dummy variables; u_i is the random error. Similarly, per-capita real income is estimated as

$$\log\left(\frac{y_i}{n_i}\right) = h_i(\cdot) + v_i,$$

where h_i has a functional form similar to g_i and v_i is the random error.

In the CREIM, total population is determined by endogenous labor demand and exogenous national population, accounting for net-migration induced by job opportunities. Then, five age sub-groups are assumed to follow the national trend of the corresponding groups and the remaining group (aged 25–44) is determined as the residual. Population and income (Y) determine final demand in turn, completing the feedback loop starting from final demand to output, employment, population, income, and again to final demand. To generate forecasts, all of estimated equations are numerically solved for endogenous variables using the Gauss–Seidel algorithm.[6] Long-term forecasts of exogenous variables (i.e. national variables) were provided by the IHS Global Insight.

[5] See Klein et al. (1999, pp. 35–39) for other ways to estimate changes in the IO coefficients over time.
[6] See Klein et al. (1999, Chapter 5) for the Gauss–Seidel algorithms for nonlinear equations.

3. THE MODEL

The AIDS of Deaton and Muellbauer (1980a) has been widely used for empirical studies of consumer demand due to its functional form that allows flexibility in income elasticity as well as substitutability and complementarity among goods. The AIDS specification is an extension to the Working–Leser model (Working, 1943; Leser, 1963) which accounts for the relationships between the share value and log of total expenditure. In the remainder of this section, starting from the micro-level AIDS model, we show the derivation of aggregate demand equations containing the parameters of cohort heterogeneity, which is useful in empirical estimation when only macro-level data are available.

At the *household* level, the AIDS model defines the budget share for commodity i in household h ($h = 1, \dots, H$) as follows:

$$w_{ih} = \alpha_i + \sum_j \gamma_{ij} \log p_j + \beta_i \log\left(\frac{x_h/k_h}{P}\right), \tag{1}$$

where p_j is the price of commodity j and x_h is total expenditure for household h; k_h is the characteristics of household h; P is a price index defined by

$$\log P = \alpha_0 + \sum_k \alpha_k \log p_k + \frac{1}{2}\sum_k \sum_j \gamma_{kj} \log p_k \log p_j.$$

If the price index P is proportional to a known price index such as Stone's (1953) price index P^*, that is, $P^* \equiv \prod_k p_k^{w_k} \approx \lambda P$ for a constant λ, Equation 1 can be written linearly in parameters, which facilitates simpler econometric estimation. The AIDS model satisfies properties of demand functions (Deaton and Muellbauer, 1980b) providing:

$$\begin{aligned} \text{Adding up}: &\quad \sum_i \alpha_i = 1, \quad \sum_i \gamma_{ij} = 0, \quad \sum_i \beta_i = 0, \\ \text{Homogeneity}: &\quad \sum_j \gamma_{ij} = 0, \\ \text{Symmetry}: &\quad \gamma_{ij} = \gamma_{ji}. \end{aligned} \tag{2}$$

The parameter k_h represents a measure of effective household size such as the number of family members and demographic characteristics of family. With the presence of k_h, it is possible to take into account total expenditure adjusted for per-capita level. Equation 1 can be rewritten as follows:

$$w_{ih} = \alpha_i + \sum_j \gamma_{ij} \log p_j + \beta_i \left[\log\left(\frac{x_h/k_h}{\bar{x}^c}\right) + \log\left(\frac{\bar{x}^c}{P}\right)\right], \tag{3}$$

where $\bar{x}^c$ is the average total expenditure for cohort c.[7] Denote the budget share for good i in cohort c by

$$W_i^c \equiv \frac{\sum_{h\in c} p_i q_{ih}}{\sum_{h\in c} x_h} = \frac{\sum_{h\in c} x_h w_{ih}}{\sum_{h\in c} x_h} = \frac{\sum_{h\in c} x_h w_{ih}}{X^c},$$

[7] Some examples of a cohort include households where their heads are in their 30s and households whose income levels are in the lowest 20%.

where $c = 1, \ldots, C(\ll H)$; X^c is the total expenditure for all households in cohort c; q_i is the quantity of commodity i. Taking average of Equation 3 over households in the same cohort weighted by household-specific total expenditure yield aggregate demand share for cohort c:

$$W_i^c = \alpha_i + \sum_j \gamma_{ij} \log p_j + \beta_i \log\left(\frac{\bar{x}^c}{P}\right) + \theta_i^c, \tag{4}$$

where

$$\theta_i^c = \beta_i \left[\sum_{h\in c} \frac{x_h}{X^c} \log\left(\frac{x_h}{\bar{x}^c}\right) - \log\left\{\left(\prod_{h\in c} k_h^{x_h}\right)^{1/X^c}\right\}\right].$$

The aggregation factor θ_i^c in Equation 4 contains not only an income inequality measure, but also average household characteristics of cohort c. The first term inside the square bracket in θ_i^c represents Theil's income inequality measure for cohort c, which has a value of zero in the case of perfect income equality. The second term is the logarithm of the weighted geometric mean of family size in cohort c. Since average family size is likely to be positively correlated with aggregate total expenditure, estimation of Equation 4 omitting θ_i^c produces biased and inconsistent estimates.

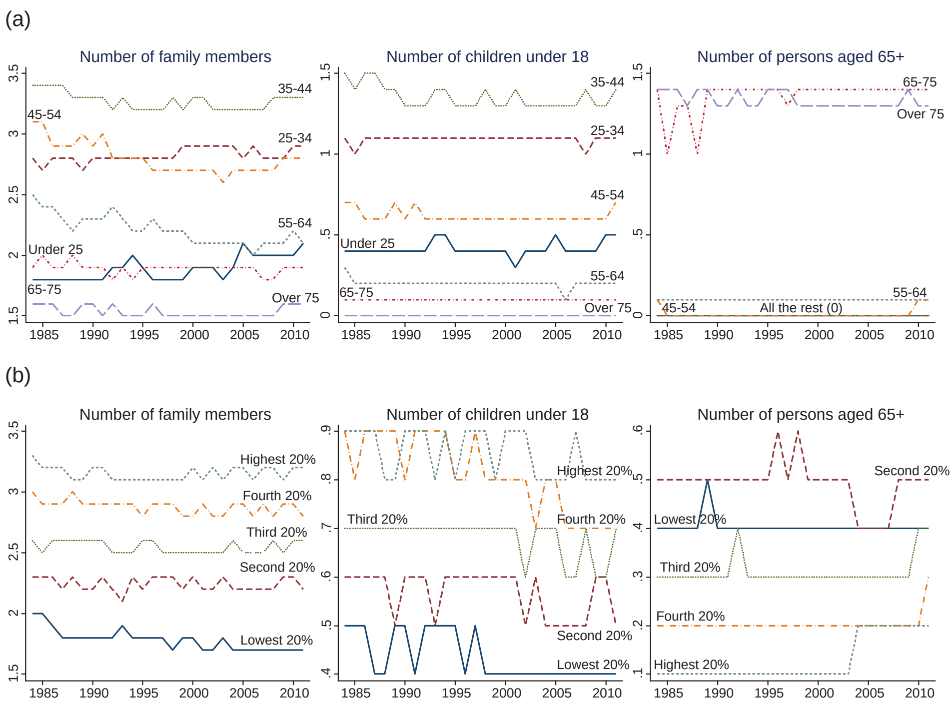
The aggregate AIDS model estimated using macro-data is subject to aggregation errors unless certain restrictions are imposed on income distribution and household characteristics while the two parameters can be directly estimated using cross-sectional micro-data (Denton and Mountain, 2011). For econometric estimation using aggregate time-series data, two assumptions are required to account for the cohort effects on expenditure type i, θ_i^c. First, we assume that cohort effects do not change over time. This assumption is a variant of partial distributional restrictions on demographic characteristics used together with the exact aggregation form (Equation 4) (Blundell and Stoker, 2005). The most significant changes in cohort characteristics will stem from family size. Figure 2 shows the trends of household characteristics by age of household head and by family income in the CES for the USA.[8] Average family size varies among groups and also features a slight variation or very slowly changing trends for the last two and a half decades. This strongly supports the assumption of time-invariant cohort effects related to family composition. Thus, prices and total expenditure being held constant, the second term in θ_i^c represents average spending patterns of good i unique to the cohort in the long run.[9] Next, it is assumed that the income inequality measure for each cohort shares a common linear time trend, but has its own intercept.[10] It turns out that adding the time trend also captures the effects of average

[8] Family characteristics for the Chicago region are not available in the CES. Thus, we assume that the national family characteristics are good approximates for city-level characteristics.

[9] Noticeable differences of long-term average consumption patterns among age or income groups can be also observed in Figure 3. With a limited number of observations (only one observation for each period is available for each cohort), it was not possible to estimate time-varying group effects. Instead, we experimented the following alternatives: (1) a model with cohort effects and time fixed effects and (2) a model with simplified time-specific cohort effects, in which each period is assigned one if expansion or zero if recession. None of the models showed improvement in the Bayesian information criterion than the model with constant cohort effects.

[10] Gini coefficient for the USA compiled by the Census Bureau shows a rising trend since the mid-1960s. We calculated the Theil index for each cohort using the micro-data for the USA. Estimation results from the model with the Theil index did not show much difference compared to the model with common trends.

FIGURE 2. Household characteristics in the CES for the USA. (a) Age groups: by age of household head. (b) Income groups: by family income.



household characteristics that show a rising (or declining) trend such as the percentage of household heads with college degrees and the percentage of female household heads. As Denton et al. (1999) points out, the inclusion of the trend variable is suggested in the demand analysis because it captures long-run shifts like taste changes as well. Hence, the final system of demand equations contains additional variables for the time trend and the cohort fixed effects with the stochastic error terms:[11]

$$W_{it}^c = \alpha_i + \delta_i t + \sum_j \gamma_{ij} \log p_{jt} + \beta_i \log\left(\frac{x_t^c}{P_t}\right) + \varphi_i^c + \varepsilon_{it}^c, \tag{5}$$

where $i = 1, \ldots, I$; $c = 1, \ldots, C$; $t = 1, \ldots, T$; φ_i^c is a fixed effect for cohort c's expenditure on good i; $\sum_i \delta_i = \sum_i \varphi_i^c = 0$ for adding up in addition to the constraints in Equation 2.

[11] Bar notation on total expenditure is dropped for convenience. In reality, each cohort might face different aggregate prices due to weighting: for example, the young consumes more meat (or less vegetable) than the old does, which leads to differences in aggregate prices (say foods) that each group faces. In this case, p_{jt} and P_t in Equation 5 can be replaced with p_{jt}^c and P_t^c.

4. THE DATA

4.1. The Consumer Expenditure Survey

Aggregate household expenditures in the Chicago region are obtained from the 1987–2011 CES by the Bureau of Labor Statistics (BLS).[12] The CES defines consumer units as households representing the US civilian non-institutional population. Nearly 80% of 7,000 households remain in the sample for 5 successive quarters and then are replaced with new households after the fifth interview (i.e. a rotating panel). Each household is randomly drawn to represent 10,000 households in the USA. The resulting expenditure data are used to compute the weights in the CPI.

Seven broadly defined categories are used for the demand analysis: (1) food and beverages, (2) nondurables and services for housing, (3) durables for housing, (4) durables for transportation, (5) nondurables and services for transportation, (6) health care, and (7) miscellaneous goods and services. A detailed list of goods and services covered in the CES is provided in Table 1. The national CES contains average annual expenditures by income and age groups: quintiles of income (from the lowest 20% to the highest 20%) and 7 age groups (under 25, 25–34, 35–44, 45–54, 55–64, 65–74, and over 75). The BLS releases only average expenditure of all consumer units in the Chicago region, thus expenditures by age or income groups require estimation on the basis of available national data: first, by assuming that the shape of the joint distributions for age (or income) and total expenditure in the USA and Chicago are identical, it is possible to generate total expenditures for each income and age cohort in Chicago. Next, it is assumed that consumption patterns (i.e. budget shares) in the USA and Chicago within the same age (income) cohort are identical.

Since expenditure data in the CES exist only in dollar amounts (i.e. quantity times unit price), additional price measures are necessary for the demand analysis. Price data are obtained from annual CPI for all urban consumers (CPI-U) in the Chicago-Gary-Kenosha area. As given in Table 1, the categories in the CPI are matched as closely as possible with the CES at the most detailed level of classification, and then are aggregated to higher levels using annual expenditures amounts as weights. For the items where the CPIs for the Chicago area are not available, the corresponding indices for the USA are used instead. The CPIs for education and recreation are available since 1992 and the CPI for vehicle purchases is available since 1998 while the PCE prices in the US national accounts for these items are available since 1987. We estimated an autoregressive integrated moving average (ARIMA) model for each CPI with the corresponding PCE price as an explanatory variable and used the model to back-calculate earlier prices.

Figure 3 shows the age- and income-specific spending patterns in the USA over 1987–2011 with the dollar amount of total expenditures in 2011 on the far right-hand side of the graphs. Families with older heads tend to allocate more budget relatively to health care and other goods and services, less to apparel, transportation, and entertainment. Low-income families tend to spend relatively more on housing (mostly rent) and foods. Budget allocation to entertainment and personal insurance and pension rise as family income

[12] The Chicago region in the CES covers 14 counties: Cook, DeKalb, Du Page, Grundy, Kane, Kankakee, Kendall, Lake, McHenry, Will (IL); Lake, Porter, Newton (IN); and Kenosha (WI). Meanwhile, the CREIM defines the Chicago region as 7 counties in Illinois: Cook, Du Page, Kane, Kendall, Lake, McHenry, and Will.

TABLE 1. Classifications in the CES and CPI.

Consumer expenditure survey			Consumer price index	
New category (7)	2011 share (%)	Description (share, %)	Description	Geo-coverage
Food and beverages	13.2	Food (94.2)	Food	Chicago
		Alcoholic beverages (5.8)	Alcoholic beverages	Chicago
Housing (ND + S)	33.1	Shelter (68.6)	Shelter	Chicago
		Utilities, fuels, and public services (20.9)	Fuels and utilities	Chicago
		Household operations (7.0)	Housing	Chicago
		Housekeeping supplies (3.5)		
Housing (D)	2.6	Household furnishings and equipment (100)	Household furnishings and operations	Chicago
Transportation (D)	4.6	Vehicle purchases (100)	New and used motor vehicles	US city avg.
Transportation (ND + S)	9.9	Gasoline and motor oil (42.8)	Motor fuel	Chicago
		Other vehicle expenses (42.2)	Transportation	Chicago
		Public transportation (15.1)	Public transportation	US city avg.
Health care	7.1	Health care (100)	Medical care	Chicago
Miscellaneous	29.6	Apparel (12.1)	Apparel	Chicago
		Entertainment (18.2)	Recreation	Chicago
		Reading (0.7)		
		Education (10.4)	Education	US city avg.
		Personal insurance and pension (38.8)	All items	Chicago
		Personal care (4.3)	Personal care	US city avg.
		Tobacco products (1.5)	Tobacco and smoking products	US city avg.
		Miscellaneous (4.7)	Miscellaneous personal services	US city avg.
		Cash contribution (9.4)	All items	Chicago

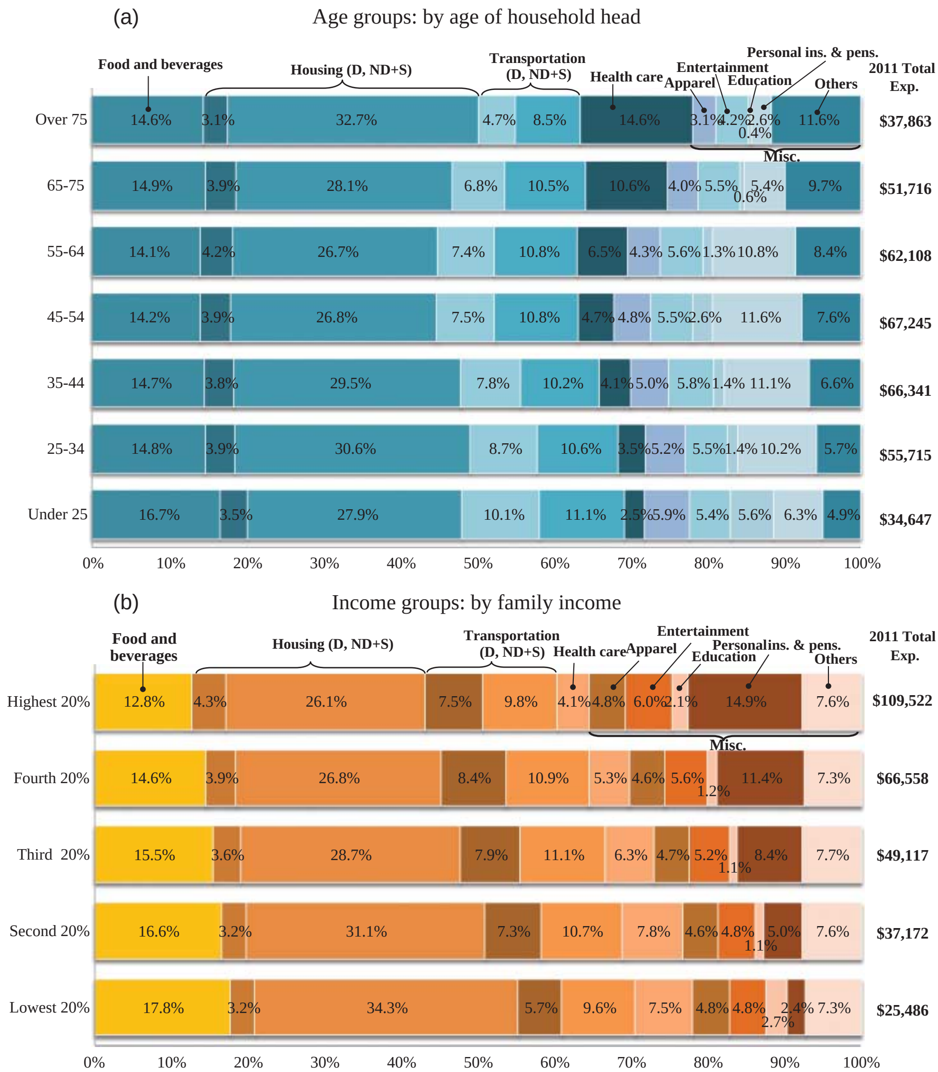
Note: D, ND and S stand for durables, nondurables and services, respectively.

increases. Total expenditures in 2011 across age group show a hump-shaped curve to peak at the 45–54 age group. Obviously, total expenditure increases as income increases, but with a large jump between the highest and the second highest income groups. These findings suggest that it is essential for consumption analysis to take into account heterogeneity of households in each group.

4.2. Classification Match Between the CES and the CREIM

Private consumption in the CREIM is classified into 47 aggregate types of products as given in Table 2. Its classification is based on the categories of the 2009 input–output table for the Chicago region. The 2009 input–output table for the Chicago region was

FIGURE 3. Spending patterns of households in the USA: average budget shares by item. D, ND and S stand for durables, nondurables and services, respectively.



Source: The 1987–2011 CES.

provided from IMPLAN Group (formerly MIG Inc.). The original input–output table is based on the six-digit North American Industry Classification System (NAICS).[13] On the contrary, the reclassified CES for the demand system has 7 types of consumer expenditure goods and services aggregated from 21 categories. Since the estimated demand system using the CES data is to be integrated to the CREIM, the integration requires a bridge matrix linking the classifications between the CES and the CREIM. Before considering

[13] See MIG, Inc. (2002) for more details on the construction of IO tables by IMPLAN.

TABLE 2. Classifications in the CREIM.

No.	Type of product	2009 Consumption ($Mil)
1	Livestock and other agricultural products	74
2	Agriculture, forestry and fisheries	27
3	Mining	162
4	Utilities	4,042
5	Construction	–
6	Food and kindred products	5,323
7	Tobacco product manufacturing	2,203
8	Apparel and textile products	199
9	Leather and leather products	9
10	Lumber and wood products	44
11	Paper and allied products	168
12	Printing and publishing	1,234
13	Petroleum and coal products	3,254
14	Chemicals and allied products	4,083
15	Rubber and misc. plastics products	220
16	Stone, clay, and glass products	51
17	Primary metals industries	4
18	Fabricated metal products	58
19	Industrial machinery and equipment	33
20	Computer and other electric product, component manuf.	343
21	Transportation equipment manufacturing	253
22	Furniture and related product manufacturing	206
23	Miscellaneous manufacturing	452
24	Wholesale trade	10,970
25	Retail trade	25,355
26	Air transportation	1,803
27	Railroad transportation and transportation services	666
28	Water transportation	285
29	Truck transportation and warehousing	2,131
30	Transit and ground passenger transportation	888
31	Pipeline transportation	30
32	Information (except 33 sector)	3,873
33	Motion picture and sound recording industries	813
34	Finance and insurance	25,663
35	Real estate	49,216
36	Professional and management services and other support serv.	7,284
37	Educational services	9,298
38	Health care	45,867
39	Social assistance	4,189
40	Arts, entertainment, and recreation	3,955
41	Accommodation services	163
42	Food services	14,512
43	Repair and maintenance	2,538
44	Personal and laundry services	4,339
45	Membership organizations and private households	7,005
46	Federal government	46
47	State and local governments	2,950
	Total	246,285

direct conversion between the two systems, it is worth noting the fact that the PCE in the National Income and Product Accounts (NIPA) are compiled separately by two standards: by type of products (NIPA table 2.4.5) and by function (NIPA table 2.5.5). If a bridge matrix connecting the two criteria is available, it would be possible to relate consumer expenditures in purchasers' prices (by function) to production in producers' prices (by type of products). For example, consumers' new car purchases are translated by the bridge matrix into car manufacturing, wholesale and retail trade (trade margin), truck, air or rail transportation (transportation margin). Note that expenditures in the CES are recorded from a consumer perspective while those in the CREIM are from a supplier perspective. Hence, the PCE bridge matrix can be used as an intermediate link between the classifications in the CES and the CREIM. The 110 × 83 US PCE bridge matrix for 2010, which relates 110 products to 83 consumption types, was provided by the INFORUM.

Matching between the CREIM and the CES proceeds as follows. First, the PCE by function is matched with the CES category. Similarly, the PCE by type of products is matched with the CREIM classification. Next, the 110 × 83 PCE bridge matrix is reduced to 47 × 7 to be used for linking the classifications between the CREIM and the CES. Finally, a coefficient matrix is generated by dividing each element by its column sum so that the (i, j)th element represents the fraction of a dollar demanded for the production of good i in the CREIM when one dollar is spent on good j in the CES.[14] By assuming the constancy of the coefficient matrix, one can convert 7 expenditure types in the CES to 47 sectors in the CREIM during the whole sample period and the forecast period.

5. ESTIMATION OF DEMAND SYSTEM

5.1. Seemingly Unrelated Regression with Fixed Effects

In matrix notation where time series for all cohorts given good i are stacked vertically, Equation 5 can be written as

$$\underset{\mathrm{CT}\times 1}{\mathbf{w_i}} = \underset{\mathrm{CT}\times(\mathrm{I}+3)}{\mathbf{X}} \underset{(\mathrm{I}+3)\times 1}{\mathbf{\Pi_i}} + \underset{\mathrm{CT}\times(\mathrm{C}-1)}{\mathbf{D}} \underset{(\mathrm{C}-1)\times 1}{\mathbf{\Phi_i}} + \underset{\mathrm{CT}\times 1}{\boldsymbol{\varepsilon}_{\mathrm{i}}}$$

$$\begin{bmatrix} \mathbf{w}_\mathbf{i}^1 \\ \mathbf{w}_\mathbf{i}^2 \\ \vdots \\ \mathbf{w}_\mathbf{i}^\mathbf{C} \end{bmatrix} = \begin{bmatrix} \mathbf{X}^1 \\ \mathbf{X}^2 \\ \vdots \\ \mathbf{X}^\mathbf{C} \end{bmatrix} \begin{bmatrix} \alpha_i \\ \delta_i \\ \gamma_{i1} \\ \vdots \\ \gamma_{iI} \\ \beta_i \end{bmatrix} + \begin{bmatrix} 1_\mathbf{T} & 0 & \cdots & 0 \\ 0 & 1_\mathbf{T} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1_\mathbf{T} \end{bmatrix} \begin{bmatrix} \varphi_i^2 \\ \varphi_i^3 \\ \vdots \\ \varphi_i^C \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon}_\mathbf{i}^1 \\ \boldsymbol{\varepsilon}_\mathbf{i}^2 \\ \vdots \\ \boldsymbol{\varepsilon}_\mathbf{i}^\mathbf{C} \end{bmatrix},$$

where $i = 1, \ldots, I$; $1_\mathbf{T}$ is a T × 1 vector of ones; $\mathbf{D}$ is a matrix of dummy variables where the first cohort is the base; $\mathbf{w}_\mathbf{i}^\mathbf{c}$ is a T × 1 vector of good i's budget shares for cohort c; $\mathbf{X}^\mathbf{c}$ is a T × (I + 3) matrix of column vectors for ones, time, prices, and deflated total expenditures for cohort c; $\varepsilon_\mathbf{i}^\mathbf{c}$ is a T × 1 vector of random errors for cohort c. For the disturbances

[14] Since we focus on a smaller region than a country, the following rows and columns in the PCE bridge matrix are discarded: (row) non-comparable imports/scrap, used and secondhand/rest of the world adjustment to final uses; (column) Americans' travel abroad/foreigners' spending in the US/final consumption expenditures of nonprofits.

contemporaneously correlated across commodities given cohort (i.e. $E[\varepsilon_{it}^{c}\varepsilon_{js}^{c}] = \sigma_{ij}$ if $t = s$ and 0 otherwise), the seemingly unrelated regression (SUR; Zellner, 1962) is the standard method of estimation for a set of demand equations. In the SUR, it is straightforward to impose cross-restrictions such as symmetry. A system of demand equations for all goods and services is written as

$$\mathbf{W} = (\mathbf{I_I} \otimes \mathbf{X})\boldsymbol{\Pi} + (\mathbf{I_I} \otimes \mathbf{D})\boldsymbol{\Phi} + \boldsymbol{\varepsilon},$$

$$\begin{bmatrix} \mathbf{w}_1 \\ \mathbf{w}_2 \\ \vdots \\ \mathbf{w_I} \end{bmatrix} = \begin{bmatrix} \mathbf{X} & 0 & \cdots & 0 \\ 0 & \mathbf{X} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathbf{X} \end{bmatrix} \begin{bmatrix} \boldsymbol{\Pi}_1 \\ \boldsymbol{\Pi}_2 \\ \vdots \\ \boldsymbol{\Pi}_\mathbf{I} \end{bmatrix} + \begin{bmatrix} \mathbf{D} & 0 & \cdots & 0 \\ 0 & \mathbf{D} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathbf{D} \end{bmatrix} \begin{bmatrix} \boldsymbol{\Phi}_1 \\ \boldsymbol{\Phi}_2 \\ \vdots \\ \boldsymbol{\Phi}_\mathbf{I} \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon}_1 \\ \boldsymbol{\varepsilon}_2 \\ \vdots \\ \boldsymbol{\varepsilon}_\mathbf{I} \end{bmatrix}, \quad (6)$$

where $\mathbf{I_I}$ is an identity matrix of order of I; $E(\boldsymbol{\varepsilon}) = 0$. The vector of errors in Equation 6 is assumed to have the following variance–covariance matrix:

$$E(\boldsymbol{\varepsilon}\boldsymbol{\varepsilon}') = \boldsymbol{\Omega} = \begin{bmatrix} \sigma_{11}\mathbf{I_{CT}} & \sigma_{12}\mathbf{I_{CT}} & \cdots & \sigma_{1I}\mathbf{I_{CT}} \\ \sigma_{21}\mathbf{I_{CT}} & \sigma_{22}\mathbf{I_{CT}} & \cdots & \sigma_{2I}\mathbf{I_{CT}} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{I1}\mathbf{I}_{\mathrm{CT}} & \sigma_{I2}\mathbf{I}_{\mathrm{CT}} & \cdots & \sigma_{II}\mathbf{I}_{\mathrm{CT}} \end{bmatrix}$$

$$= \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1I} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2I} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{I1} & \sigma_{I2} & \cdots & \sigma_{II} \end{bmatrix} \otimes \mathbf{I_{CT}} = \boldsymbol{\Sigma}_\mathbf{I} \otimes \mathbf{I_{CT}}.$$

When $\boldsymbol{\Omega}$ is unknown, the feasible generalized least-squares (FGLS) estimator is given by

$$\boldsymbol{\eta}^{\mathbf{FGLS}} = (\mathbf{M}'\hat{\boldsymbol{\Omega}}^{-1}\mathbf{M})^{-1}\mathbf{M}'\hat{\boldsymbol{\Omega}}^{-1}\mathbf{W},$$

where $\boldsymbol{\eta} = [\boldsymbol{\Pi}\vdots\boldsymbol{\theta}]'$; $\mathbf{M} = [\mathbf{I_I} \otimes \mathbf{X}\vdots\mathbf{I_I} \otimes \mathbf{D}]$; $\hat{\boldsymbol{\Omega}}$ is a consistent estimator of the variance–covariance matrix.

When identical explanatory variables are present in each equation, the FGLS estimation of the full system is identical to the equation-by-equation OLS estimation (Zellner, 1962). For the AIDS model, one of the equations must be dropped for estimation because the additivity implies the sum of errors across equations to be zero, which creates the singularity problem of covariance matrix of errors.[15] Parameters in the omitted equation are estimated by using the linear relationship among parameters across equations accounting for imposed additivity and homogeneity. Iterated FGLS, which is equivalent to the maximum likelihood estimation under the normal errors (Oberhofer and Kmenta, 1974), was used because the resulting estimates are invariant to the choice of the omitted equation.[16]

[15] By construction, ε_i's are linearly dependent since $\sum_i \varepsilon_i = 0$ or $\varepsilon' 1 = 0$. Singularity of the covariance matrix follows from the fact that $E(\varepsilon\varepsilon' 1) = \Omega 1 = 0$ (Greene, 2003, Chapter 14).
[16] The command NLSUR in STATA was used for estimation.

5.2. Estimation Results

The AIDS estimates for age and income groups with homogeneity and symmetry constraints are reported in Table 3. A priori value was assigned to α_0 following Deaton and Muellbauer (1980a).[17] Dummy variables for groups are included in each equation. Group fixed effects are shown to be highly significant (not reported due to limited space) suggesting that heterogeneity among groups are modeled properly through dummy variables. With a few exceptions, signs, and magnitudes of the coefficients for age and income groups show similar patterns. Similarity in parameters between age and income groups is in line with our expectations because the same sampling units are grouped by either age or income. Furthermore, these results support the assumption that the parameters on prices and total expenditure are assumed to be identical across individual households. Trends measuring income inequality in aggregate demand are significant in food, housing, and transportation. For health care in the age-group AIDS model, none of the explanatory variables but cohort fixed effects seems to influence the budget share.

Figure 4 illustrates the estimates of (a) own-price elasticities and (b) total expenditure elasticities. Calculations of the elasticities are based on the formula in Green and Alston (1990). Elasticity estimates are in line with our expectations: all of the own-price elasticities show negative signs and total expenditure elasticities are distributed just below or above one. In the age-group model, food, housing, and transportation are classified as necessities (i.e. total expenditure elasticities are less than one) while housing and transportation are classified as necessities in the income-group model. Food is shown to be the most price-inelastic item in the age-group model and this finding is consistent with the results in Taylor and Houthakker (2010, Chapter 7) where the AIDS models were estimated using the 1996 CES micro-data for the USA. Note that except for the group-specific fixed effects, consumption behaviors, that is, the responsiveness to prices and total expenditure, are assumed to be the same across groups, and thus the intra-group differences in the estimated elasticities are attributed to the variations in the budget shares among cohorts.

It is worth noting one of the important issues associated with the empirical application of the AIDS model, especially in the long-run analysis with a large number of expenditure types. In the AIDS model, additivity in the shares equations, that is, $\sum_i \beta_i = 0$, eventually results in negative β's in one or more equations. Thus, if real income continues to rise, the predicted shares in the equations with negative β's will at some point start to deviate from the [0,1] interval. This *regularity problem* is more likely to occur in a long-term simulation where real income exhibits upward trend. Items accounting for very small shares (i.e. close to 0) of total expenditure and those with very large shares (i.e. close to 1) will suffer from this problem sooner than those with medium shares. For that reason, a number of empirical studies on demand systems have adopted alternative demand systems that circumvent the regularity problem by directly deriving a conformable functional form of demand equations, or that have improved regularity by modifying preferences on which the derivation of demand is based. Bardazzi and Barnabani (2001), for example, addressed the regularity problem by employing the perhaps adequate demand system of Almon (1996), an extension to his earlier work (1979). Other competing models that improved regularity

[17] α_0 is the minimum cost of living when prices are unitary at the base year. It was determined in prior to be a number just below the lowest value of log of total expenditures for all groups in 2009, which is 10.

TABLE 3. Estimated AIDS models: Equation 5.[a]

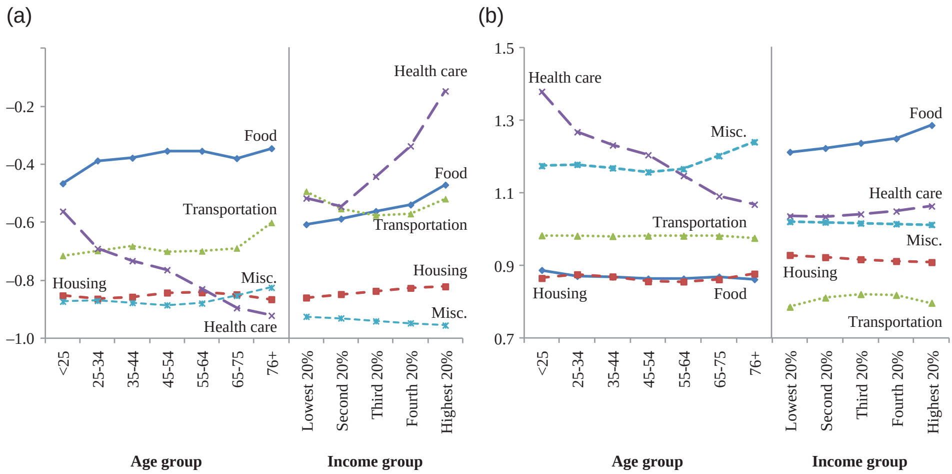
	Food	Housing	Transportation	Health care	Misc.
			(Age group)		
Price of food	0.099**	– 0.016	– 0.004	– 0.020	– 0.059*
	(0.031)	(0.017)	(0.006)	(0.019)	(0.028)
Price of housing	– 0.016	0.034*	– 0.005	– 0.009	– 0.005
	(0.017)	(0.017)	(0.006)	(0.013)	(0.020)
Price of trans.	– 0.004	– 0.005	0.036**	– 0.008	– 0.020*
	(0.006)	(0.006)	(0.005)	(0.005)	(0.009)
Price of health.	– 0.020	– 0.009	– 0.008	0.013	0.024
	(0.019)	(0.013)	(0.005)	(0.023)	(0.029)
Price of misc.	– 0.059*	– 0.005	– 0.020*	0.024	0.061
	(0.028)	(0.020)	(0.009)	(0.029)	(0.048)
Real tot. exp.	– 0.022**	– 0.044**	– 0.002	0.011	0.057**
	(0.007)	(0.010)	(0.005)	(0.007)	(0.012)
Constant	0.216**	0.306**	0.132**	0.023	0.323**
	(0.012)	(0.009)	(0.004)	(0.014)	(0.020)
Trend	– 0.001*	0.002**	0.000	0.000	– 0.001
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
			(Income group)		
Price of food	0.085**	– 0.040*	– 0.017**	– 0.060**	0.032
	(0.032)	(0.018)	(0.006)	(0.020)	(0.030)
Price of housing	– 0.040*	0.043*	0.017*	0.008	– 0.028
	(0.018)	(0.022)	(0.007)	(0.015)	(0.023)
Price of trans.	– 0.017**	0.017*	0.051**	– 0.008	– 0.044**
	(0.006)	(0.007)	(0.004)	(0.005)	(0.008)
Price of health.	– 0.060**	0.008	– 0.008	0.040	0.020
	(0.020)	(0.015)	(0.005)	(0.025)	(0.032)
Price of misc.	0.032	– 0.028	– 0.044**	0.020	0.020
	(0.030)	(0.023)	(0.008)	(0.032)	(0.050)
Real tot. exp.	0.042**	– 0.027	– 0.023**	0.003	0.005
	(0.012)	(0.017)	(0.008)	(0.011)	(0.017)
Constant	0.183**	0.360**	0.111**	0.089**	0.256**
	(0.013)	(0.010)	(0.004)	(0.016)	(0.022)
Trend	0.000	0.002**	0.000*	0.000	– 0.001
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)

Notes: Standard errors are in parentheses; prices and real total expenditures are in logarithms; cohort fixed effects are not shown here; sample sizes are 175 for the age-group model and 125 for the income-group model.
[a]Homogeneity and symmetry are imposed.
*$p < 0.05$.
**$p < 0.01$.

include the modified AIDS (MAIDS) of Cooper and McLaren (1992), the implicitly additive demand system of Rimmer and Powell (1996) and the dynamic MAIDS of Kratena et al. (2004).

Taking into account these results from the literature and being aware that the regularity may not be satisfied under different settings in our model, we carefully examined the AIDS model used in this paper and found that it does not show signs of the regularity problem during the simulation periods (2012–2040) for the following reasons: for example, among

FIGURE 4. Estimated elasticities: (a) own-price elasticities (uncompensated) and (b) total expenditure elasticities. Calculations of the elasticities are based on the formula in Green and Alston (1990).



the items with negative coefficients on real income in the age-group model, housing and food account for shares large enough not to stray outside the [0,1] interval even in the long-term simulation. For transportation, the marginal negative effect of real income increase is near zero. Furthermore, the price variables (nondurables and services) for these items, whose coefficients on the own-prices are significantly positive, are forecast to rise nearly as fast as real income does or at faster rates so that the negative effects of a real income increase are canceled out or even dominated by the positive effects of a price rise.

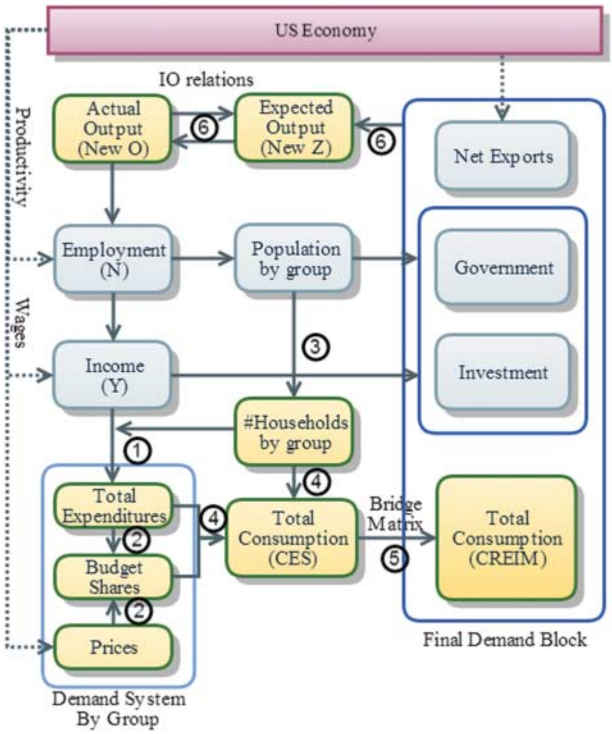
6. INTEGRATING THE DEMAND SYSTEM INTO THE REIM

Integrating the demand system into the CREIM requires additional linkages and blocks. The proposed procedure is intended to make full use of the results from the CREIM without altering its main structure. Figure 5 shows a schematic diagram of the extended model where additional features can be found in the lower area.

A combination of personal income endogenously determined in the CREIM, prices established in the national market, and the cohort fixed effects generates average budget shares for households in each cohort via the separately estimated demand system for the five nondurable goods and services.[18] Since the levels of consumption in the demand system are on a per-household basis, the equations for the number of cohort must be available in order to derive total consumption. The numbers of households by age or income groups are estimated using the relationship between population (determined in the CREIM) and the number of households during the sample period. Then, group-specific

[18] Personal income comprises total earnings by place of work, dividends, interest, and rent, adjustment for residence, personal current transfer receipt less contribution for government social insurance.

FIGURE 5. A schematic representation of the extended REIM. Details on the circled numbers are described in text.



total consumption is calculated simply by multiplying the group-specific average consumption level by the total number of households in the group. As the resulting consumption estimates follow the CES classification, it is necessary to convert them to the CREIM classification. The bridge matrix comes into play for the conversion, resulting in 47 products. The new consumption estimates by the CREIM sector entail re-estimation of actual output (**o**) equations as well as re-calculation of expected output (**z**). Further details are described below using the circled numbers as references between the diagram and the explanations.

6.1. Linkage Between Personal Income and Total Expenditure

For each cohort, a linear Engel curve is estimated on a *per-household* basis: it expresses the real total expenditure for a cohort as a function of real personal income, which is determined in the CREIM and thus is common for all cohorts, and a lagged-dependent variable:

$$\log\left(\frac{x_t^c}{P_t}\right) = \xi_0^c + \xi_1^c \log\left(\frac{y_t}{H_t}\right) + \xi_2^c \log\left(\frac{x_{t-1}^c}{P_{t-1}}\right) + e_{1t}^c,$$

TABLE 4. Estimated equations for real total expenditures by group[a].

Group	Income[b]	First-order lag	Constant	Adj. R^2	LM F-stat[c]
			(Age group)		
Under 25	0.274** (0.10)	0.587** (0.14)	– 3.043* (1.08)	0.698	0.003
25–34	0.207** (0.07)	0.566** (0.13)	– 2.050** (0.72)	0.737	0.062
35–44	0.139 (0.07)	0.712** (0.13)	– 1.315 (0.75)	0.644	0.236
45–54	0.086 (0.06)	0.604** (0.16)	– 0.587 (0.68)	0.410	0.156
55–64	0.204** (0.07)	0.669** (0.11)	– 2.058** (0.73)	0.815	1.224
65–75	0.231* (0.09)	0.731** (0.11)	– 2.490* (0.95)	0.854	0.038
Over 75	0.216* (0.10)	0.666** (0.12)	– 2.368* (1.09)	0.796	0.222
			(Income group)		
Lowest 20%	0.135* (0.06)	0.417* (0.17)	– 1.538* (0.72)	0.401	6.347*
Second 20%	0.172* (0.07)	0.376* (0.18)	– 1.742* (0.75)	0.474	0.609
Third 20%	0.143* (0.06)	0.492** (0.16)	– 1.300 (0.63)	0.519	0.416
Fourth 20%	0.119* (0.05)	0.538** (0.16)	– 0.918 (0.56)	0.536	3.741
Highest 20%	0.173** (0.06)	0.543** (0.14)	– 1.312* (0.56)	0.714	0.060

Notes: Standard errors in parentheses; sample periods: 1987–2011.
[a]Log(total expenditure/price index).
[b]Log(total personal income/total number of households).
[c]Breusch–Godfrey's LM test for H_0: no first-order autocorrelation.
*$p < 0.05$.
**$p < 0.01$.

where x_t^c is an average total expenditure for cohort c in current dollars; P_t is the translog price index in the AIDS model; y_t is the total personal income in constant dollars determined in the CREIM; H_t is the total number of households in cohort c; e_{1t}^c is the error term. ξ_1^c and ξ_2^c can be interpreted as propensity to consume and habit formation in consumption, respectively, by cohort in a rather loose sense because average income is based on all groups of households, not on a specific group. Estimated equations for total expenditure by age and income groups are presented in Table 4. Personal income and a lagged-dependent variable seem to explain total expenditure by group relatively well in that the coefficients of determination range 0.41–0.85 for age cohorts and 0.40–0.71 for income cohorts. Lagrange multiplier (LM) tests show that the estimated equations for all groups but the lowest 20% income group are free of the first-order autocorrelation in the residuals.

6.2. Demand System Block

Given the prices and the real total expenditure determined in the Engel curve above, the estimated AIDS model for *nondurables and services* (provided in Table 3) determines the budget share of expenditure type i for cohort c as

$$W_{it}^c = \alpha_i + \delta_i t + \sum_j \gamma_{ij} \log p_{jt} + \beta_i \log\left(\frac{x_t^c}{P_t}\right) + \varphi_i^c.$$

For simulation purposes, p_{jt}'s outside the sample period are forecast by a simple ARIMA model using national price forecasts for total expenditure, durables, nondurables, services, or gasoline as explanatory variables.

6.3. Linkage Between Population and the Number of Households

For age cohorts, the CREIM has four groups of population (18–24, 25–44, 45–64, and over 65) that can be matched with the seven groups of households (under 25, 25–34, 35–44, 45–54, 55–64, 65–75, and over 75) in the demand estimation (one-to-many matching). We expect the ratios of population to the number of households to be stationary, moving within the range of two to five. A log-ratio equation for a cohort is estimated as follows:

$$\log\left(\frac{\mathrm{POP}_t^{c'}}{H_t^c}\right) = \pi_0^c + \pi_1^c \log\left(\frac{\mathrm{POP}_{t-1}^{c'}}{H_{t-1}^c}\right) + e_{2t}^c,$$

where $\mathrm{POP}_t^{c'}$ is the population for cohort c'; H_t^c is the number of households for cohort c; e_{2t}^c is the error term. The estimated equation is rearranged to isolate the current number of households on the left-hand side.

For income cohorts, the demand equation represents consumption patterns of households within an income quintile. Thus, once an equation for total number of households is established, each income cohort simply has one-fifth of the total number of households. We employ an identical functional form just for the log-ratio of total population and total number of households. Table 5 presents the estimation results for the log-ratios of population to the number of households. Equations by age group are presented in columns (1)–(7) and the ratio of totals is given in column (8). Adjusted R^2 of 0.34–0.80 imply that the proposed AR(1) form adequately captures the short-term movements of the ratios.

6.4. Determination of Consumption in the CES

Real consumption of a good i is obtained by summing over cohort deflated expenditure on type i for all households in cohort c:

$$C_{it}^{\mathrm{CES}} = \sum_c \left(\frac{C_{it}^c}{p_{it}}\right) H_t^c\ ,$$

TABLE 5. Estimated equations for log-ratios of population to the number of households.

Population	(1) 18–24	(2) 25–44	(3) 25–44	(4) 45–64	(5) 45–64	(6) > 65	(7) > 65	(8) Total [a]
#HHs	< 25	25–34	35–44	45–54	55–64	65–75	> 75	Total
First-order lag	0.825**	0.834**	0.741**	0.858**	0.794**	0.863**	0.577**	0.744**
	(0.14)	(0.09)	(0.14)	(0.10)	(0.11)	(0.09)	(0.17)	(0.12)
Constant	0.217	0.249	0.343	0.151	0.286	0.135	0.462*	0.233*
	(0.16)	(0.13)	(0.18)	(0.11)	(0.14)	(0.09)	(0.19)	(0.11)
Adj. R^2	0.613	0.785	0.552	0.755	0.711	0.795	0.342	0.701
LM F-stat [b]	0.713	1.364	2.810	4.586*	5.765*	0.883	4.272	4.076

Notes: Standard errors in parentheses; sample periods: 1987–2011.
[a]Year dummy variables for 2000 and 2006 are included in the equation.
[b]Breusch–Godfrey's LM test for H_0: no first-order autocorrelation.
*$p < 0.05$.
**$p < 0.01$.

where $i = 1, \ldots, 5$; $C_{it}^{c} = x_t^c\ W_{it}^{c}$. Similarly, summation over expenditure type yields real consumption by all households in cohort c.

6.5. Bridge Matrix: Conversion to Consumption in the REIM

Note that all consumption expenditures so far include only nondurables goods and services in the CES. The existing CREIM estimates of nondurables and services are replaced with the estimates from the demand system based on the CES while the estimates of durables goods in the CREIM are preserved. Conversion to real consumption of sector i in the CREIM is accomplished via the bridge matrix:

$$C_{it}^{\text{CREIM}} = (b_{i1}C_{1t}^{\text{CES}} + \cdots + b_{i5}C_{5t}^{\text{CES}}) + (b_{i6}D_t^1 + b_{i7}D_t^2),$$

where $i = 1,\ \ldots,\ 47$; b_{ij} is the (i, j)th element of the 47×7 coefficient matrix described in Section 4.2; D_t^1 and D_t^2 are auto and parts and other durables determined in the CREIM.

6.6. Re-estimation of Actual and Expected Outputs

Expected output, a linear combination of actual output and final demand components, needs to be updated due to newly generated estimates of consumption by sector. Accordingly, the existing equations relating actual output to expected output are re-estimated.

7. SIMULATIONS

7.1. Baseline

The long-range forecasts for the next 30 years or so, 2012–2040, are generated by numerically solving the system of nonlinear equations. The data are based on the observations over 1987–2011 in the CES in addition to the 1969–2011 observations for final demand, output, income, employment, and population in the CREIM. The baseline solutions for select variables in the age-group model are presented in Table 6. Outlook for household expenditure shares by age group is plotted in Figure 6(a)–(e). Except for consumption shares by income, the baselines solutions from the income-group model are not provided in Table 6 since the long-term forecasts in the income-group model do not differ much from those in the age-group model.

Real income is forecast to grow at an annual rate of 2% over the next 30 years. Consumption of nondurables and services show a similar growth path during the same periods because personal income is a major determinant of spending in the consumer demand. Note, however, that the speed of consumption growth is forecast to slow over time with a growing aging population. In the extended CREIM, structural changes in consumption patterns stem mainly from changing demographic composition. Figure 6(f) depicts the outlook for the number of household by age of family heads in the Chicago region. As baby boomers age, the number of households with family heads aged 65 and above is expected to grow more rapidly than any other age groups. Elderly households (aged 65 and over) are forecast to reach 1.5 million households, comprising approximately 30% of total households by 2040, up from 20% in 2011. As a result, their contribution to consumption growth is expected to continue to rise as well: the consumption share of elderly families is expected

TABLE 6. Baseline solutions for select endogenous variables in the extended CREIM (unit: \$2009 billion, 1,000 persons, %).

	Observed		Forecast		
Variables	1990–1999	2000–2011	2012–2019	2020–2029	2030–2040
Output	684.9	907.2	1,163.3	1,594.3	2,263.5
	(2.3)	(2.6)	(3.2)	(3.2)	(3.2)
Income	240.7	266.8	315.7	386.0	480.3
	(2.3)	(0.9)	(2.1)	(2.0)	(2.0)
Employment	4,690	4,773	5,456	6,385	7,592
	(1.5)	(0.2)	(1.7)	(1.6)	(1.6)
Gross regional domestic product	384.0	425.3	532.4	695.3	872.5
	(2.5)	(0.9)	(2.8)	(2.7)	(2.0)
Consumption	166.5	235.5	286.1	369.0	474.3
	(0.1)	(3.2)	(2.5)	(2.6)	(2.3)
Nondur. and serv.	130.5	172.7	204.1	249.7	299.2
	(– 0.7)	(2.6)	(2.1)	(2.0)	(1.6)
By item; share (%)					
Food	16.5	15.6	14.2	12.7	11.2
Housing	33.7	34.8	36.3	37.7	39.0
Transportation	12.3	9.8	8.9	8.8	8.4
Health care	7.2	7.1	6.3	5.9	5.3
Misc.	30.2	32.7	34.3	34.9	36.1
By age; share (%)					
Under 25	4.2	3.7	3.9	4.2	4.5
25–34	17.1	16.0	15.3	15.3	15.5
35–44	26.0	20.4	22.4	22.8	23.1
45–54	24.3	23.9	24.4	21.9	20.5
55–64	13.4	19.1	15.8	14.2	13.7
65–75	8.7	10.4	11.0	13.2	14.0
Over 75	6.3	6.5	7.2	8.5	8.7
By income; share (%)					
Lowest 20%	9.0	9.0	8.7	8.6	8.5
Second 20%	12.8	13.0	12.5	12.4	12.3
Third 20%	17.0	17.0	16.9	16.7	16.5
Fourth 20%	23.3	22.9	22.9	22.8	22.7
Highest 20%	38.0	38.0	39.0	39.5	40.0

Notes: Figures in parentheses are average growth rates during the periods. Levels and shares are for the last year of the periods. All numbers but shares by income are obtained from the age-group model. The results from the income-group model are not presented since the long-term forecasts for aggregate variables in the income-group model do not differ much from those in the age-group model.

to rise to 23% by 2040 from 17% in 2011. In contrast, the consumption share of the 45–64 age group is forecast to decline to 34% by 2040 from 43% in 2011.

Historically, households with elderly heads have been likely to allocate more budget to housing and health care than other age groups, as shown in Figure 3. If this is the case in the future, total expenditures on housing and health care are expected to increasingly take up larger portion of total consumption as the group aged 65 and over is expected to be the fastest-growing segment of the population. The long-term forecast shows that the consumption of housing rises to 39% by 2040 from 35% in 2011. However, it is not

FIGURE 6. Outlook for expenditure shares by age group and the number of households. Since the results for income groups show similar trends to those for age groups, they are not presented here.

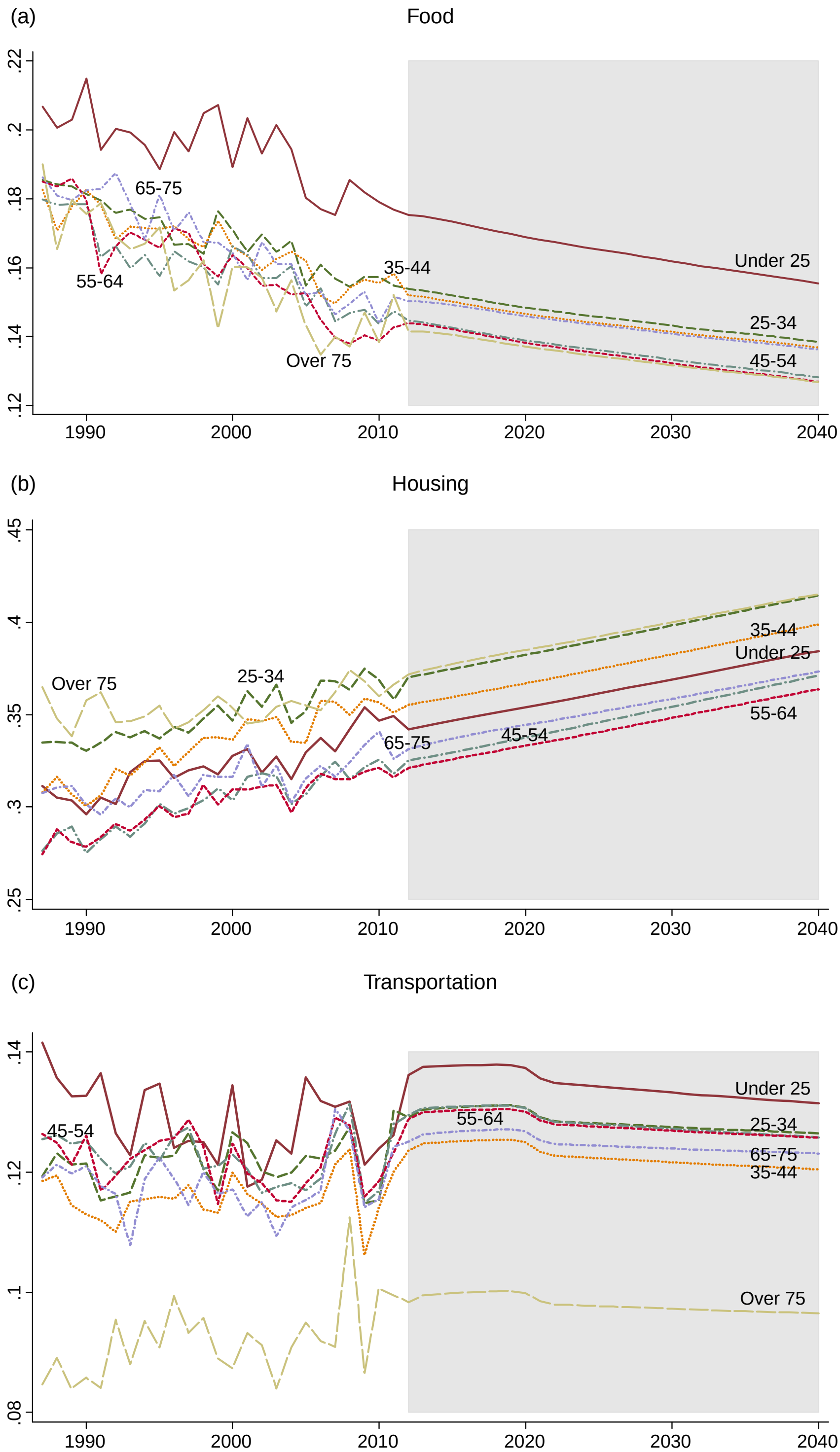


FIGURE 6. Continued.

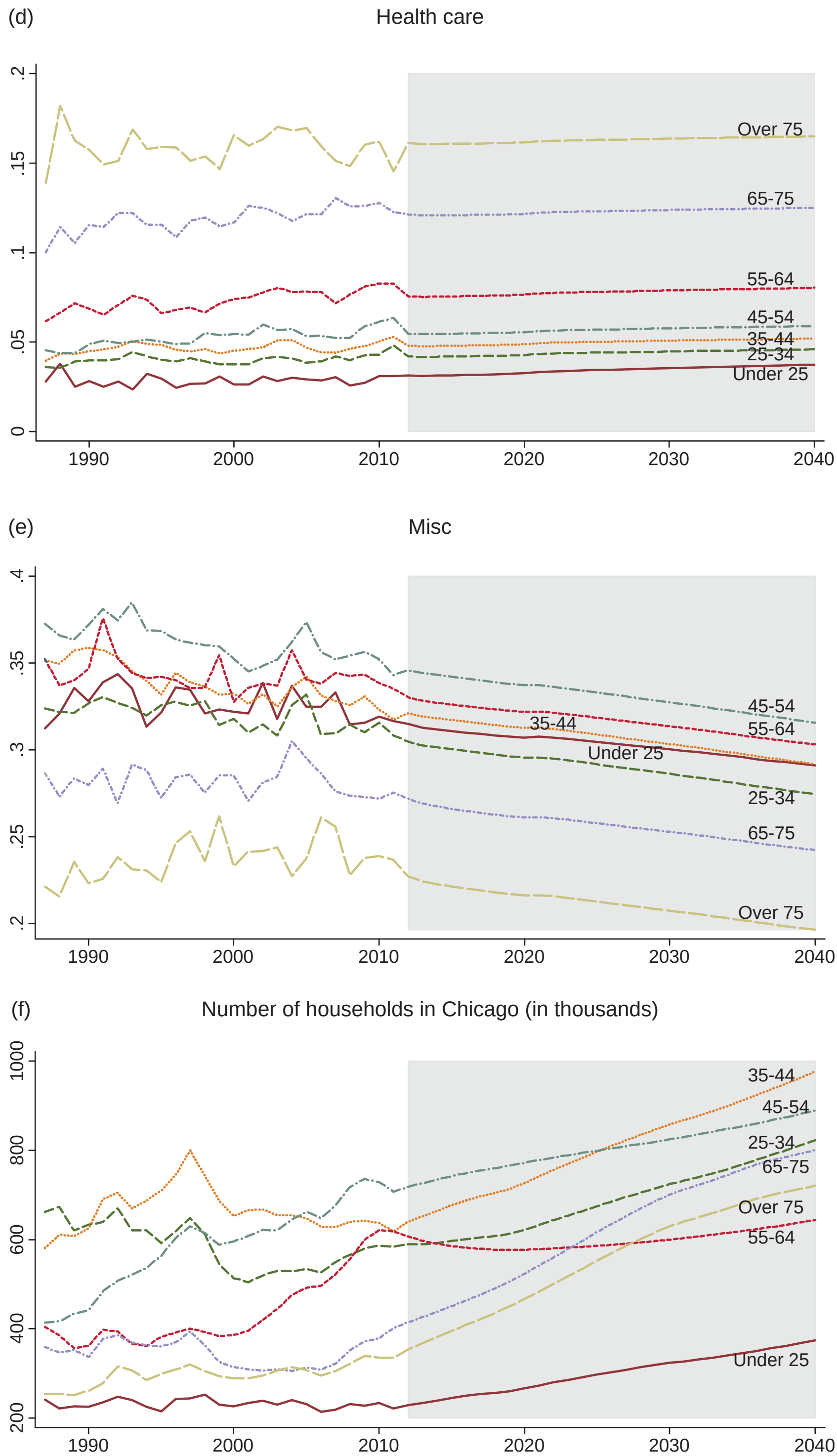
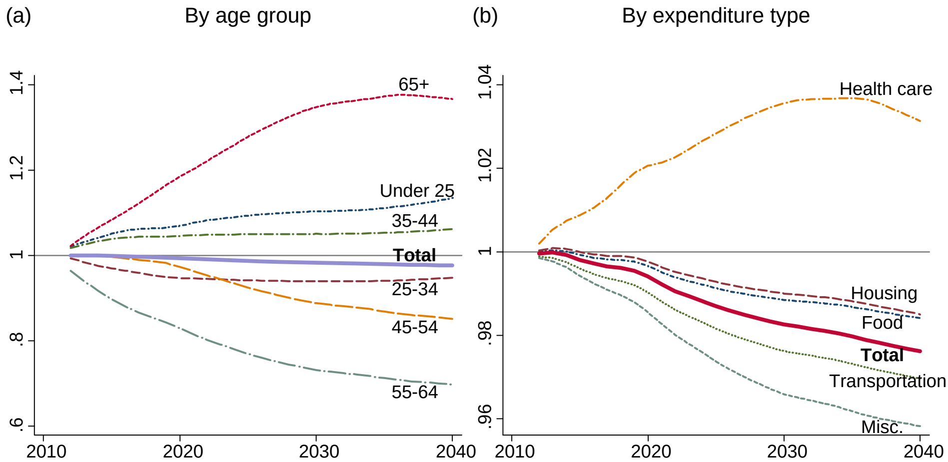


FIGURE 7. The effects of heterogeneous household: the ratio of consumption in the age–group model against consumption in the fixed-age structure model during the simulation periods (2012–2040). In the fixed-age structure model, age distribution is held fixed at the 2011 structure.



in line with our expectations that the consumption share of health care shows a declining trend. It is because real expenditure on housing increases more rapidly than that on health care even if real consumption of heath care in level does increase. Additionally, the price of services used to deflate health care spending during the forecasting periods are assumed to rise at a faster rate than the deflators for other expenditure types. Unlike age cohorts, income groups show only the slightest variation over time in consumption shares since each group represents exactly 20% of total households at any point in time. Though baseline solutions from the income-group model do not provide many insights, it proves to be more useful in the next section where the effects of migration are analyzed.

Additionally, as an attempt to evaluate the effects of introducing heterogeneous households in the simulation, we compare the new baseline with the baseline in a model where the age distribution does not change from the last observed year 2011 on. Figure 7 presents the trends during the simulation periods in the ratios of consumption in the age-group model against consumption in the fixed-age structure model by age group and by expenditure type. Although the total consumption differences between the two models do not appear to be very large (the range of the ratio is between 0.976 and 1), a clear distinction can be made in the distributional differences in consumption by age group and by expenditure type. Also note that the magnitude of differences becomes increasingly noticeable over time. The growing elderly population, reflected only in the age-group model, accounts for the upward trends of the ratios especially when it comes to health-care expenditures as well as total consumption by those aged 65 and over. Accordingly, it can be argued that the model with a constant age structure underestimates the effects of population aging, particularly in health care, and the size of bias is growing over time.

7.2. Scenario Analysis: The Effects of Inmigration

The Chicago region includes the most populous counties in Illinois, accounting for approximately 70% of total population in the state, and shows highly active migration flows. According to the 2006–2010 five-year American Community Survey, the Chicago region had a net annual out-migration of 100,546 residents on average during 2006–2010: 175,170 in-migrants and 275,716 out-migrants. The total number of people who moved in or out of the Chicago region in a single year accounts for more than 5% of total population in the region. In the extended CREIM, various scenarios can be simulated by altering the distributions of age or incomes groups, which was not possible in the existing CREIM due to the assumption of homogeneous households. The extended model provides a useful analytical tool to evaluate the effects of migration of households whose main characteristics differ by age or income.

Inflows of households initially stimulate local consumption. Then, output rises, and increases in employment and income follow. The positive income shock induces additional consumption. Total impacts of inmigration on local economy encompasses direct (immediate changes due to the population inflow), indirect (supplier-induced), and induced (income-induced) impacts. Table 7 presents the impacts in the hypothetical cases where 1,000 households under the same age or income group move in to the Chicago region in 2015. Note that economic impacts are initiated by consumption and thus the changes in labor supply and labor income directly associated with the inflows are not taken into account in the extended model. For example, the inflow of the 45–55 age group increased by 1,000 households induces $83 million of consumption, $113 million of output, $27 million of income, and 587 jobs in the Chicago region. The inflow of the youngest households (under 25) by the same amount makes an impact less than half the size of the total impacts generated by the 45–55 age group. As for income group, suppose an inmigration of 1,000 households whose income level income corresponds to the highest 20% in the income distribution of Chicago residents. The inflow generates $139 million of consumption, $192 million of output, $47 million of income, and 1,007 jobs. The total impacts of inflows of the lowest income group are less than one-fourth of the total impacts generated by the wealthiest group.

Since each cohort shows a unique spending pattern, inflows of households in different cohorts generate compositional differences in expenditure types. For age-group impacts, there is no significant difference in *total* impacts of inflows between the youngest group ($35.8 million) and the eldest group ($38.2 million), but each group shows noticeable difference in impacts on each expenditure categories. Consequently, there would be different outcomes on production and labor demand sector by sector. Especially, the contrast of spending on health care and food is worth noting: health-care spending increases by $1.2 million (3% of total impact on consumption) due to the youngest inmigrants as opposed to $5.3 million (14%) due to the eldest inmigrants. The inflow of under-25 group leads to an increase in local food consumption by $6.2 million (17%), while the inflow of the over-75 group results in additional spending of $5.5 million (14%). For income groups, if the lowest income group moves in to Chicago, 41% of the total impact on consumption is concentrated on housing, compared to 34% for the highest income group. Inflow of the highest income group stimulates spending on miscellaneous goods and services, accounting for 39% of the total impact on consumption, compared to 25% for the lowest income group.

TABLE 7. Economic impacts of inmigration by group (unit: $2009 million, person).

	Age group							Income group				
(2015)	Under 25	25–34	35–44	45–54	55–64	65–75	Over 75	Lowest 20%	Second 20%	Third 20%	Fourth 20%	Highest 20%
Output	53.8	87.2	108.8	112.6	95.7	75.3	53.9	42.6	61	83.3	113.2	191.8
Income	12.8	20.6	25.9	27.2	23.1	18.1	12.8	9.9	14.4	19.8	27.2	46.5
Employment	281	449	563	587	499	390	273	218	314	433	593	1,007
Consumption	38.9	64.3	80.0	82.6	70.6	56.2	41.2	31.2	44.7	60.7	82.2	139.2
ND&S	35.8	59.3	73.8	76.1	65.0	51.9	38.2	28.8	41.2	55.9	75.6	128.0
Food	6.2	9.1	11.1	11.0	9.4	7.8	5.5	4.9	6.6	8.5	10.9	16.3
Housing	13.0	22.9	27.3	26.2	22.2	18.2	14.7	11.9	16.1	20.7	26.8	43.9
Trans.	3.5	5.5	6.6	7.1	6.1	4.8	2.9	2.5	4.0	5.6	7.5	11.6
Health.	1.2	2.5	3.5	4.0	4.5	5.5	5.3	2.2	3.3	3.8	4.5	6.3
Misc.	12.0	19.3	25.3	27.7	22.8	15.6	9.8	7.2	11.2	17.4	26.0	49.9
Share (%)												
ND&S	100	100	100	100	100	100	100	100	100	100	100	100
Food	17.2	15.3	15.1	14.5	14.5	15.1	14.3	16.9	16.1	15.1	14.4	12.7
Housing	36.3	38.6	37.0	34.5	34.1	35.1	38.5	41.4	39.0	37.0	35.4	34.3
Trans.	9.6	9.3	8.9	9.4	9.4	9.2	7.7	8.8	9.6	10.0	9.9	9.1
Health.	3.4	4.2	4.7	5.2	6.9	10.6	13.8	7.7	8.1	6.8	5.9	4.9
Misc.	33.4	32.6	34.3	36.4	35.1	30.0	25.7	25.1	27.2	31.1	34.4	39.0

Notes: Each column represents the impact results of a scenario where 1,000 households in the group inmigrates to Chicago. ND and S stand for nondurables and services, respectively.

8. CONCLUSIONS

Since its initial applications to a number of regions including the state of Washington (Conway, 1990) and the Chicago region (Israilevich et al., 1997), the REIM has proven its usefulness for forecasting and impact study. Due to lack of regional data, however, the representative-household restriction has limited the scope of consumption analysis in the REIM. This paper proposes an extended REIM for the Chicago region that integrates the existing REIM and the demand system that allows household heterogeneity by utilizing actual household expenditure survey information. The integration requires the estimation of a demand system and a bridge matrix converting the estimated consumption demand to the classification in the existing REIM. The proposed approach will benefit regional modelers in that integration procedure can be applied without difficulty to any regional econometric model with a similar structure. Furthermore, with the modeled structure of inter-regional spillovers, it is possible to extend its application to multi-regional models.

The long-range simulation in the extended model suggests that structural changes in expenditure type stem from demographic composition changes. As population ages, the contribution to consumption growth by elderly households is expected to continue to grow. As a result, the goods and services consumed by the elderly group increase their market size. With the aid of an augmented demand system, the extended REIM enables us to evaluate economic impacts of various scenarios associated with demographic changes. For example, experiments on inmigration of households in each cohort show that the affected sectors vary by cohort characteristics even though the total impacts might not be so different. These types of simulation exercises can help regional policy-makers analyze the long-term consequences of regional policies regarding economic development, migration, and income inequality.

Limitations of this study include the imperfect classification match between the CES and the CREIM. There does not exist a bridge matrix that directly links the household expenditure survey and the NAICS due to their underlying methodological differences. This paper attempts to address the classification mismatch issue by using the PCE bridge matrix as the intermediate link between the two different kinds of classifications. One of the limitations is associated with the highly aggregated data (only 5 items) in the demand system relative to 47 sectors in the REIM. The AIDS model in this study requires explanatory variables per equation for prices of all items and real income along with dummy variables for group fixed effects. Therefore, the number of items in the demand system might be increased by imposing additional restrictions on the structure of complementarity and substitutability to secure more degrees of freedom (though how to justify the structure would still remain an issue).

One of the issues left for future research is to model demand for durables goods. Intertemporal choice plays a more important role for durables than for nondurables and services since the presence of stocks in the previous period affects present consumption of durables. Next, although net migration in the CREIM is treated simply as a residual, that is, population change less net births, it will require more attention when the model is extended to multiple regions, especially for regions with active inter-regional migration flows like states or counties in the USA.

Acknowledgements

We acknowledge the support of the EU center, University of Illinois at Urbana-Champaign in the form of a Graduate Student Research Travel Grant. The PCE bridge matrix for 2010 was kindly provided by Dr Douglas Meade from the Inter-industry Forecasting project at the University of Maryland (INFORUM).

References

Almon, C. (1979) A System of Consumption Functions and Its Estimation for Belgium. *Southern Economic Journal*, 46, 85–106.

Almon, C. (1996) *A Perhaps Adequate Demand System*. INFORUM Working Paper, Series 97(7), University of Maryland.

Bardazzi, R. and M. Barnabani (2001) A Long-Run Disaggregated Cross-Section and Time-Series Demand System: An Application to Italy. *Economic Systems Research*, 13, 365–389.

Blundell, R. and T.M. Stoker (2005) Heterogeneity and Aggregation. *Journal of Economic Literature*, 43, 347–391.

Conway, R.S. (1990) The Washington Projection and Simulation Model: A Regional Interindustry Econometric Model. *International Regional Science Review*, 13, 141–165.

Cooper, R.J. and K.R. McLaren (1992) An Empirically Oriented Demand System with Improved Regularity Properties. *Canadian Journal of Economics*, 25, 652–667.

Deaton, A. and J. Muellbauer (1980a) An Almost Ideal Demand System. *The American Economic Review*, 70, 312–326.

Deaton, A. and J. Muellbauer (1980b) *Economics and Consumer Behavior*. New York, Cambridge University Press.

Denton, F.T. and D.C. Mountain (2011) Exploring the Effects of Aggregation Error in the Estimation of Consumer Demand Elasticities. *Economic Modelling*, 28, 1747–1755.

Denton, F.T., D.C. Mountain and B.G. Spencer (1999) Age, Trend, and Cohort Effects in a Macro Model of Canadian Expenditure Patterns. *Journal of Business & Economic Statistics*, 17, 430–443.

Dowd, T.A., R.M. Monaco and J.J. Janoska (1998) Effects of Future Demographic Changes on the US Economy: Evidence from a Long-term Simulation Model. *Economic Systems Research*, 10, 239–262.

Erlandsen, S. and R. Nymoen (2008) Consumption and Population Age Structure. *Journal of Population Economics*, 21, 505–520.

Fair, R. and K.M. Dominguez (1991) Effects of Changing U.S. Age Distribution on Macroeconomics Equations. *The American Economic Review*, 81, 1276–1294.

Green, R. and J.M. Alston (1990) Elasticities in AIDS Models. *American Journal of Agricultural Economics*, 72, 442–445.

Greene, W.H. (2003) *Econometric Analysis*. 5th ed. Upper Saddle River, NJ: Prentice Hall.

Israilevich, P.R., G.J.D. Hewings, M. Sonis and G.R. Schindler (1997) Forecasting Structural Change with a Regional Econometric Input–Output Model. *Journal of Regional Science*, 37, 565–590.

Klein, L.R., A. Welfe and W. Welfe (1999) *Principles of Macroeconometric Modeling*. Amsterdam: Elsevier.

Kratena, K., M. Wüger and G. Zakarias (2004) *Regularity and Long-run Dynamics in Consumer Demand Systems*. WIFO Working Paper 217.

Leser, C.E.V. (1963) Forms of Engel Functions. *Econometrica*, 31, 694–703.

Lührmann, M. (2008) *Effects of Population Ageing on Aggregated UK Consumer Demand*. London, IFS and CEMMAP, February 1.

MIG, Inc. (2002) *Elements of the Social Accounting Matrix*. MIG IMPLAN Technical Report TR-98002.

Mongelli, I., F. Neuwahl and J.M. Reuda-Cantuche (2010) Integrating a Household Demand System in the Input–output Framework. Methodological Aspects and Modelling Implications. *Economic Systems Research*, 22, 201–222.

Oberhofer, W. and J. Kmenta (1974) A General Procedure for Obtaining Maximum Likelihood Estimates in Generalized Regression Models. *Econometrica*, 42, 579–590.

Rey, S.J. (1998) The Performance of Alternative Integration Strategies for Combining Regional Econometric and Input–Output Models. *International Regional Science Review*, 21, 1–35.

Rey, S.J. (2000) Integrated Regional Econometric + Input–output Modeling: Issues and Opportunities. *Papers in Regional Science*, 79, 271–292.

Rimmer, M.T. and A.A. Powell (1996) An Implicitly Additive Demand System. *Applied Economics*, 28, 1613–1622.

Stoker, T.M. (1993) Empirical Approaches to the Problem of Aggregation Over Individuals. *Journal of Economic Literature*, 31, 1827–1874.

Stone, R. (1953) *The Measurement of Consumers' Expenditure and Behaviour in the United Kingdom, 1920–1938*, Vol. 1. Cambridge: CUP Archive.

Taylor, L.D. and H.S. Houthakker (2010) *Consumer Demand in the United States: Prices, Income, and Consumption Behavior*. 3rd ed. New York: Springer.

West, G.R. (1995) Comparison of Input–output, Input–output + Econometric and Computable General Equilibrium Impact Models at the Regional Level. *Economic Systems Research*, 7, 209–227.

Working, H. (1943) Statistical Laws of Family Expenditure. *Journal of the American Statistical Association*, 38, 43–56.

Yoon, S.G. and G. Hewings (2006) *Impacts of Demographic Changes in the Chicago Region*. REAL Discussion Paper 06-T-7.

Zellner, A. (1962) An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias. *Journal of the American Statistical Association*, 57, 348–368.