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Household disaggregation and forecasting in a regional econometric input–output model

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Abstract The overwhelming attention to disaggregation of the interindustry components of the regional economy has neglected the problems generated by the adoption of the representative household in the modeling of economic impacts and forecasting in many regional economic models. Drawing on a recently modified regional econometric input–output model (REIM) for the Chicago metropolitan region in which households were disaggregated by age (Kim et al., Econ Syst Res. doi:10.1080/09535314.2014.991778, 2014), this paper provides an assessment of the differences generated by consumption of a representative and disaggregated households using data at the corresponding level of aggregation. The results reveal that the total effects of disaggregation that can be ascribed to population ageing vary by a much smaller extent than those generated by model specification and data. The disaggregate REIM with heterogeneous households by age yields smaller RMSEs than the aggregate REIM with a representative household, but a statistical testing suggests that forecasting gains from disaggregation are modest compared to the aggregate model.

Keywords Econometric input–output model · Almost ideal demand system · Heterogeneity · Forecasting accuracy

JEL Classification C53 · D12 · R15

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1 Introduction

Many economic models persist in using a representative household formulation thereby ignoring potential problems presented by the heterogeneity of households. In particular, consumer demand is one of the areas where heterogeneity and aggregation of economic agents matter considerably and thus its implications have been extensively researched theoretically (Blundell and Stoker 2005). With limited data and theoretically generalized solutions at hand, addressing the aggregation problem eventually focuses on empirical choices, for example, model specification and the level of aggregation facilitated by available data. Many attempts have been made to investigate the significance of disaggregation, particularly by age, due to increasing attention to population ageing occurring in most of developing and advanced economies. A number of consumer demand studies have demonstrated the significant role of demographic heterogeneity in empirical models. (See, for example, Fair and Dominguez 1991; Denton et al. 1999; Bardazzi and Barnabani 2001; Erlandsen and Nymoen 2008). Notwithstanding the common belief in its impact on particular sectors such as health care, there is no general consensus on the magnitude of economy-wide effects of changes in age structure and, equally critically the importance of the underlying assumptions governing the demographic-economic interactions.[1] It is worth noting that especially for large scale (regional) macro econometric models with smaller demand models inside, the modeling procedures in most of the studies have usually ended up constructing models without further investigation of the effects of disaggregation on the entire model. Instead the models' superiority has been commonly argued due to the presence of statistical significance on parameter estimates representing heterogeneity.

The objective of this paper is to explore the differences in simulation and prediction accuracy arising from household disaggregation by age within the framework of a regional econometric input–output model (REIM).[2] Recent work by Kim et al. (2014), building on earlier explorations by Yoon and Hewings (2006), investigated the long-term economic impact of socio-demographic changes in Chicago by incorporating a consumer demand system by households of different age and income into the REIM. Based on the extended REIM by Kim et al. (2014), this study evaluates the effects of household disaggregation by age in terms of their impact on forecasts of the regional economy.

Differences resulting from forecasts generated by a model with and without disaggregated households have not been the focus of much attention in studies of the heterogeneity of consumer demand despite a few studies using simulation exercises (Dowd et al. 1998; Lührmann 2008). Furthermore, prediction accuracy of the REIMs has been analyzed mostly in the context of integration strategy for interindustry

[1] Some health economics literature even found that a rise in health expenditure is not explained largely by population ageing alone, but rather by a combination of elderly population, income and technological progress (Matteo 2005; Martín et al. 2011).

[2] The econometric input–output model or so-called Leontief–Keynes system is one of the dominant regional modeling systems centered on macroeconometric models that derived their original inspiration from the work of Lawrence R. Klein. As heterogeneity deepens, regional models are more likely to suffer from aggregation problem due to data availability, which was pointed out by Klein back in (1969), but still holds even today.

spillovers (see, for example, Fawson and Criddle 1994; LeSage and Rey 2002; Motti 2005; Motti and Blevins 2007). The present paper is associated with a strand of literature on the choice between aggregating forecasts made with one or more components that have been disaggregated and forecasting with more aggregated components; in the current case, the two options are (1) summing age-specific consumption estimates and (2) estimating aggregate consumption. For vector ARMA models, Lütkepohl (1984) showed that forecasting gains from contemporaneously summing disaggregate models are not generally guaranteed except for the rare case where the underlying data generating processes are known.[3]

The next section of the paper provides a brief overview of the extended REIM model of Kim et al. (2014). Section 3 describes the measures used to evaluate prediction accuracy and the methodology of decomposing the differences between two sets of forecasts, one using a representative household and the other using disaggregated households specified by age. The results are discussed in Sect. 4 and a final section provides some summary commentary.

2 Overview of the extended regional econometric input–output model

As an extension to the REIM, Kim et al. (2014) proposed a strategy for the integration of an heterogeneous household demand system into an existing REIM where homogeneous households would be assumed in most cases.[4] The original REIM was the model for the Chicago region (CREIM) which Israilevich et al. (1997) further developed based on Conway's (1990) Washington model. Schematic representations of the CREIM and the extended model are presented in Fig. 1.

In the CREIM, it is assumed that economic variables at the national level, including prices, are exogenous to the Chicago economy. Due to the absence of regional consumption data, four types of consumption expenditure are estimated using the Kendrick and Jaycox (1965) method in which regional consumption is constructed based on a consumption function for the nation that contains explanatory variables for which there exists a localized version. *Actual* output is estimated as a function of *expected* output that is a linear combination of intermediate and final demands using the input–output relations.[5] Employment is derived from the estimated equation for labor productivity defined by output per worker while labor income is derived from the estimated equation for average annual wage per worker. Population is endogenously determined by employment, accounting for net migration induced by job opportunities. Final demand per capita is estimated as a function of total income, population and national-level variables. Finally, the demand-driven production completes the feedback structure in the system. A system of non-linear equations is numerically solved for all endogenous variables.

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3 An extensive theoretical discussion on temporal aggregation as well as contemporaneous aggregation can be found in Lütkepohl (2006).

4 See Rey (2000) for the characteristics of the REIM.

5 This is one of the techniques to overcome the problem of constant input–output coefficients (Klein et al. 1999).

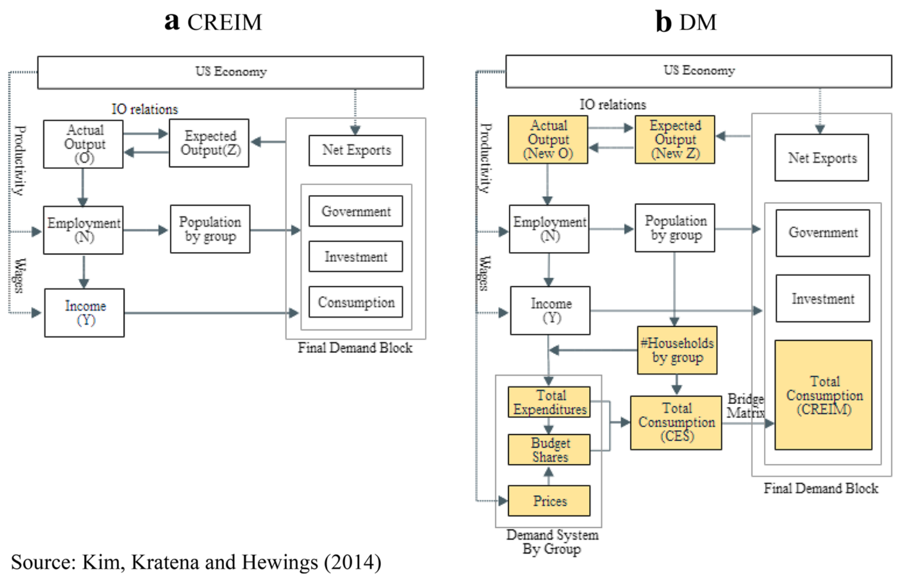

Fig. 1 Schematic representations of the Chicago Regional Econometric Input–output Model (*CREIM*) and an extension to the CREIM with disaggregated households (*DM*; Kim et al. 2014). **a** CREIM, **b** DM. Source: Kim et al. (2014)

While maintaining the structure of the CREIM, Kim et al. (2014) first estimated the almost ideal demand system (AIDS; Deaton and Muellbauer 1980a) with cohort fixed effects using the Consumer Expenditure Survey (CES) data, and then linked the estimated demand system to the CREIM in such a way to allow the two models to interact each other.[6] More specifically, the total expenditure in the demand system is linked to the total income determined by the CREIM. Since the CES is a household-based survey, it was also required to link the number of households and population. Differences in the sector classifications between the CES and the CREIM were addressed by introducing a bridge matrix.

3 The methodology

3.1 Aggregate vs. disaggregate demand systems

Two AIDS models are estimated here under different hypothetical circumstances depending on data availability as well as heterogeneity assumptions: (a) all households are homogeneous and only aggregate consumption expenditure data are available and (b) the age of household heads is recognized and the expenditure data by age group are available. Then, the estimated AIDS models are integrated to the CREIM employing the integration strategy described in Sect. 2.

[6] The integration strategy for combining the demand system and the CREIM in Kim et al. (2014) bears resemblance to *linking*, which is one of the three integration approaches to combine econometric and input–output models, together with *embedding* and *coupling* (Rey 1998).

In the aggregate AIDS model under the assumption (a), the budget share for good i at time t is given by:

$$W_{it} = a_i + \sum\nolimits_j c_{ij} \log p_{jt} + b_i \log\left(\frac{x_t}{P_t}\right) \tag{1}$$

where a_i, b_i, and c_{ij} are parameters to be estimated; p_j is the price of good j; x is the mean of total expenditure for *all* households; P is the translog price index defined in Deaton and Muellbauer (1980a). For the heterogeneous demand model under the assumption (b), aggregating individual demand over households in the same cohort, Kim et al. (2014) derive an AIDS model with two extra parameters as follows:

$$W_{it}^c = \alpha_i + \delta_i t + \sum\nolimits_j \gamma_{ij} \log p_{jt} + \beta_i \log\left(\frac{x_t^c}{P_t}\right) + \varphi_i^c \tag{2}$$

where α_i, β_i, γ_{ij}, δ_i, and φ_i^c are parameters; x^c is average total expenditure for all households in cohort c. Under the assumptions of constant cohort characteristics (e.g. stable family composition over time) and a common linear trend of income inequality measure for all age groups, δ_i represents the income inequality trend common to all cohorts and the fixed-effect term φ_i^c reflects the time-invariant spending patterns for the expenditure type i unique to cohort c.

Prior to estimation, homogeneity and symmetry (Deaton and Muellbauer 1980b) are imposed as maintained hypotheses in the demand systems. With one of the equations in the system omitted due to the singularity of the covariance matrix of the error terms, the seemingly unrelated regression (SUR) are estimated using the iterated feasible generalized least square (IFGLS) method to ensure that the estimates are not dependent upon the choice of the omitted equation.[7] Estimation results for the two AIDS models are presented in Table 1. The lower panel in the table shows the estimates for Eq. (1) and the figures in the upper panel are the estimates for Eq. (2). Except for a few coefficients that represent own-price and total expenditure elasticities, signs and magnitude of the estimates in general show different patterns across the models. In particular, the off-diagonal coefficients are quite different in terms of signs and statistical significance, implying that the estimates for substitutability and complementarity between goods in the disaggregate model are different from those in the aggregate model. Empirical models of consumer demand often produce different estimates depending on the type of data and the functional forms used for estimation (Taylor and Houthakker 2010). It is, however, worth emphasizing that the aggregate AIDS model estimates are potentially subject to aggregation errors caused by omitted variable bias since aggregation factors are missing in contrast to the disaggregate AIDS model.[8]

The difference in private consumption of good i between the two models is computed as:

[7] The iterated FGLS and the maximum likelihood method are equivalent under normally distributed errors. See Greene (2003; chapter 14) for more details on the iterated FGLS.

[8] See Denton and Mountain (2011) for empirical exploration of aggregation errors in the AIDS model.

Table 1 Estimated AIDS models

	Food	Housing	Transportation	Health care	Misc.
(a) Age-group model					
Food price	0.099** (0.031)	−0.016 (0.017)	−0.004 (0.006)	−0.020 (0.019)	−0.059* (0.028)
Housing price	−0.016 (0.017)	0.034* (0.017)	−0.005 (0.006)	−0.009 (0.013)	−0.005 (0.020)
Trans. price	−0.004 (0.006)	−0.005 (0.006)	0.036** (0.005)	−0.008 (0.005)	−0.020* (0.009)
Health. price	−0.020 (0.019)	−0.009 (0.013)	−0.008 (0.005)	0.013 (0.023)	0.024 (0.029)
Misc. price	−0.059* (0.028)	−0.005 (0.020)	−0.020* (0.009)	0.024 (0.029)	0.061 (0.048)
Real tot. exp.	−0.022** (0.007)	−0.044** (0.010)	−0.002 (0.005)	0.011 (0.007)	0.057** (0.012)
Constant	0.216** (0.012)	0.306** (0.009)	0.132** (0.004)	0.023 (0.014)	0.323** (0.020)
Trend	−0.001* (0.001)	0.002** (0.000)	0.000 (0.000)	0.000 (0.001)	−0.001 (0.001)
(b) Representative-agent model					
Food price	−0.087 (0.080)	0.069 (0.044)	0.016 (0.016)	−0.075** (0.014)	0.077* (0.034)
Housing price	0.070 (0.044)	0.032 (0.036)	−0.045** (0.013)	0.070** (0.013)	−0.127** (0.023)
Trans. price	0.016 (0.016)	−0.045** (0.013)	0.022 (0.012)	−0.009 (0.007)	0.016 (0.012)
Health. price	−0.075** (0.014)	0.070** (0.013)	−0.009 (0.007)	0.037** (0.009)	−0.023* (0.012)
Misc. price	0.077* (0.034)	−0.127** (0.023)	0.016 (0.012)	−0.023* (0.012)	0.056* (0.023)
Real tot. exp.	−0.031 (0.029)	−0.070* (0.029)	0.015 (0.019)	−0.072** (0.021)	0.159** (0.038)
Constant	0.166** (0.023)	0.425** (0.024)	0.093** (0.016)	0.124** (0.017)	0.192** (0.031)
Budget share	0.162	0.343	0.108	0.057	0.330

Standard errors are in parentheses
Prices and real total expenditures are in logarithms
Age-group model includes age-group fixed effects, which are not presented here because of space limitations
Sample periods: 1987–2011
* $p < 0.05$; ** $p < 0.01$

$$DIF_i = \sum_c C_i^c H^c - C_i \sum_c H^c$$
$$= f(\text{difference in model specification and data,}$$
$$\text{difference in population composition}) \quad (3)$$

where the time script is omitted for exposition; H^c is the number of households in cohort c; C_i and C_i^c is the real consumption of good i for a representative household and a household in cohort c, respectively, defined by $C_i = xW_i/p_i$ and $C_i^c = x^c W_i^c/p_i$. In the integrated models for the two cases, total expenditures (x_t^c and x_t) are linked to the income that is endogenously determined in the REIM. *DIF* reflects the effects of disaggregation due to the differences in model specification, data and population composition between the disaggregate REIM with heterogeneous demand system (DM) and the aggregate REIM with homogeneous demand system (AM). The difference between C_i and C_i^c is attributed to the dissimilarities of (1) model specifications (i.e., the presence of fixed effects and the time trend) between the disaggregate and aggregate AIDS models and to (2) difference between disaggregate and aggregate data used in each model (x^c's vs. x). In addition, a part of *DIF* can be also explained by (3) difference in the age distribution (H^c's) between the DM and the AM.

3.2 Prediction accuracy measures

In this section, we discuss within-sample forecasting accuracy between the two models using (1) one of the conventional *deterministic* measures, the root mean squared errors (RMSEs), and (2) the approach proposed by Fair and Shiller (1990). Fair and Shiller (1990) is designed particularly for *statistical* comparison of forecasts from a pair of econometric models differing in size, structure and data.[9]

First, the s-period-ahead sample RMSE is defined by:

$$\text{RMSE}_s = \sqrt{T^{-1} \sum_t \left(\hat{y}_{t+s|t} - y_{t+s}\right)^2}$$

where $\hat{y}_{t+s|s}$ is the log of s-period-ahead forecast of y_{t+s} using the observations available at time t (i.e., static forecast for $s = 1$; dynamic forecast for $s \geq 2$); T is the size of the samples available for comparison. Notice that the difference between the logarithms of actual and predicted values is scale-independent.

Next, we use the method by Fair and Shiller (1990), a variant of encompassing tests (Davidson and MacKinnon 1981) for non-nested models.[10] This approach proves simple yet useful when the difference in deterministic measures of prediction accuracy

[9] See Hyndman and Koehler (2006) for review of various forecasting accuracy measures.

[10] In the following section, we implement Fair and Shiller (1990) to two pairs of models: (1) CREIM vs. the extend model with aggregate AIDS model (AM) and (2) CREIM vs. the extended model with disaggregated AIDS model (DM). Two models compared in each pair are non-nested with regard to model structure and data; the consumption blocks in the extended models adopt AIDS models using actual survey data for estimation, whereas the consumption block in the CREIM is based on the Kendricks–Jaycox technique.

between models is small. The procedure starts with a regression of actual values on predicted values from two competing models (say, M_1 and M_2)[11]:

$$y_{t+s} - y_t = \alpha + \beta \left(\hat{y}^{M_1}_{t+s|t} - y_t \right) + \gamma \left(\hat{y}^{M_2}_{t+s|t} - y_t \right) + u_t \tag{4}$$

where α, β and γ are parameters; u_t is an random error. The procedure essentially regresses actual growth rates on predicted growth rates by using the differences of the logs. Non-zero estimates for β and γ imply that both models produce two forecast values that play independent roles in explaining the actual value. Zero coefficients for β and γ suggest that neither of the models contains any information relevant to forecasting. For $\beta \neq 0$ and $\gamma = 0$, M_1 covers a broader range of information useful for forecasting than M_2 does, and vice versa. The regression equation is estimated using the generalized methods of moments (GMM; Hansen 1982) with heteroskedasticity and autocorrelation consistent (HAC) covariance matrix (Newey and West 1987) in which the selection of optimal lag for autocorrelation is based on the Bartlett kernel (Newey and West 1994).[12]

4 The results: the effects of disaggregation

4.1 Decomposition and simulations

For the period 2012–2040, simulation results from (a) the disaggregate model (DM) and (b) the aggregate model (AM)[13] are presented in Table 2. The effects of age distribution change are simulated in (c) the DM with age composition fixed at the 2011 distribution and these results are provided in the last three columns of Table 2. In the DM, the number of elderly household aged 65 and over steadily increases to 1.5 million by 2040, accounting for approximately 30 percent of total households, from 0.74 million (21 percent) in 2011. Although the differences in aggregate output, income and employment between the models seem small, the DM consistently generates smaller estimates for total consumption of nondurables and services than the other models do and the gap between the models could be expected to widen over time. This supports the common belief that, *ceteris paribus*, population ageing could affect the economy negatively, even if the effect is not so large, due to the smaller purchasing power of elderly households.

[11] To compare a macroeconometric model (Fair model) with VAR models, Fair and Shiller (1990) removed exogenous variables in the Fair model by replacing them with AR equations because exogenous variables do not exist in the VAR models. For the coefficient-estimate problem, they implemented rolling estimation. However, such adjustments were not made in this paper since significant parts of the models are overlapped, resulting in small differences in the degrees of exogeneity and parsimony.

[12] The estimation method in Fair and Shiller (1990) was based on the GMM with asymptotic covariance matrix (Hansen 1982; Cumby et al. 1983; White and Domowitz 1984) which is not necessarily positive semi-definite.

[13] We also attempted to add the time trend, which approximates income inequality measure, in the aggregate AIDS model that was then integrated to the REIM. Although a few sectors showed significant time trend, any large differences in the total consumption were not detected.

Table 2 Baselines

Variable ($2009 Bil.; 1000 persons; %)	Observed		Simulations								
			(a) DM			(b) AM			(c) DM with fixed age structure		
	1990–1999	2000–2011	2012–2019	2020–2029	2030–2040	2012–2019	2020–2029	2030–40	2012–2019	2020–2029	2030–2040
Output	685	907	1163	1594	2263	1157	1591	2260	1165	1602	2279
	(2.3)	(2.4)	(3.2)	(3.2)	(3.2)	(3.1)	(3.2)	(3.2)	(3.2)	(3.2)	(3.3)
Income	241	267	316	386	480	315	387	483	316	388	483
	(2.3)	(0.9)	(2.1)	(2.0)	(2.0)	(2.1)	(2.1)	(2.0)	(2.1)	(2.1)	(2.0)
Employment	4690	4773	5456	6385	7592	5436	6394	7627	5466	6421	7647
	(1.5)	(0.1)	(1.7)	(1.6)	(1.6)	(1.6)	(1.6)	(1.6)	(1.7)	(1.6)	(1.6)
Consump. of ND&S	130	173	204	250	299	206	265	336	205	254	306
	(−0.7)	(2.4)	(2.1)	(2.0)	(1.7)	(2.0)	(2.5)	(2.2)	(2.2)	(2.2)	(1.7)
Food (share, %)	16.5	15.6	14.2	12.7	11.2	12.2	9.1	6.3	14.2	12.6	11.2
Housing (%)	33.7	34.8	36.3	37.7	39.0	37.5	38.8	39.6	36.2	37.4	38.7
Trans. (%)	12.3	9.8	8.9	8.8	8.4	7.8	7.7	7.3	8.9	8.8	8.4
Health. (%)	7.2	7.1	6.3	5.9	5.3	5.5	4.6	3.9	6.2	5.6	5.0
Misc. (%)	30.2	32.7	34.3	34.9	36.1	37.0	39.7	42.9	34.5	35.5	36.7
#HH 65+[a] (%)	20.3	21.2	24.6	28.3	29.1	–	–	–	21.2	21.2	21.2

Levels and shares are for the last period of the periods
Figures in parentheses are average growth rates during the periods
ND and S stand for nondurables and services respectively
DM represents the disaggregate REIM with heterogeneous demand system using disaggregate data and AM represents the aggregate REIM with homogeneous demand system using aggregate data
[a] Age of household head

Table 3 Deviation from the DM: decomposition of sources of differences

	The effects of disaggregation attributable to								
	Model specification, data and population ageing			Population ageing			Model specification and data		
	(A) AM			(B) DM with fixed age structure			(C) = (A)−(B)		
	2019	2029	2040	2019	2029	2040	2019	2029	2040
ND & S ($2009 Bil.)	2.25	15.63	36.66	0.93	4.24	7.32	1.32	11.39	29.34
(In levels, %)	1.1	6.3	12.3	0.5	1.7	2.5	0.7	4.6	9.8
Food	−13.2	−23.8	−37.0	0.2	1.1	1.6	−13.5	−24.9	−38.6
Housing	4.5	9.4	14.0	0.1	1.0	1.5	4.3	8.5	12.5
Trans.	−11.7	−6.4	−2.6	0.8	2.3	3.1	−12.5	−8.8	−5.7
Health.	−11.9	−16.3	−17.2	−1.9	−3.3	−3.0	−10.1	−13.0	−14.1
Misc.	9.2	20.7	33.5	1.2	3.4	4.4	8.0	17.4	29.2
(In shares, %p)									
Food	−2.02	−3.59	−4.93	−0.03	−0.07	−0.09	−1.99	−3.51	−4.84
Housing	1.21	1.12	0.60	−0.12	−0.27	−0.35	1.33	1.40	0.95
Trans.	−1.12	−1.05	−1.11	0.03	0.06	0.06	−1.15	−1.10	−1.16
Health.	−0.81	−1.25	−1.39	−0.14	−0.29	−0.28	−0.67	−0.96	−1.11
Misc.	2.74	4.76	6.83	0.26	0.58	0.67	2.47	4.18	6.16

In (A), negative (−) means that the results from the one-household model are smaller than those from the disaggregate model
In (B), negative (−) means that the results from the disaggregate model with fixed age structure are smaller than those from the disaggregate model
DM disaggregate model, *AM* aggregate model

Compositional differences in consumer spending show dissimilar patterns depending on the model being compared with the DM. Deviation from the DM in the AM and the fixed-age-structure model is calculated in Table 3. Specifically, the AM yields much smaller food consumption while it generates larger consumption of miscellaneous nondurable goods and services[14] by roughly the same amount as the decline in food consumption. The elderly population growing at a faster rate than the rest of the population, reflected only in the DM, explains the smaller consumption expenditure on health care in the AM. In the fixed-age-structure model, a similar phenomenon also occurs with regard to heath care spending and it is the only sector showing a decline in level. Therefore, it can be argued that heath care is one of the sectors where the effects of population ageing are underestimated and the size of the bias is growing over time in the AM and the DM with a fixed age structure.

It is important to understand the sources of the deviation from the DM. Between the AM and the DM, the simulation results vary due to three factors, as shown in

[14] Miscellaneous nondurable goods and services include apparel, entertainment, education, personal insurance and pensions and other goods and services.

Eq. (3) in Sect. 3.1: (1) model specification (aggregate vs. disaggregate AIDS models), (2) data (total households vs. households by age), and (3) age composition in population (fixed vs. varying age structure). The difference in the simulation results between the DM and the fixed-age-structure model is attributed only to the changing age distribution in the former. Although analytic decomposition of the sources does not appear to be straightforward, an attempt has been made to decompose the effects of disaggregation (panel A in Table 3) into contributions from population ageing (panel B) and methodology (panel C), implying model specification and data in this case, by calculating the differences in differences. The computed effects of population ageing is intuitive, particularly for heath care, but modest (0–4 percent in levels; less than 1 percentage point in shares) due to the fact that age structure changes gradually and the other age groups as well as the elderly consume heath care goods and services. However, the contribution to disaggregation effects from methodological differences is found to be much larger than those from the age assumption. In health care, for example, the impact of methodology (fixing the age structure at 2011 levels) is four to five times as large as that of age structure. Such large methodological differences are found across all of the other sectors.

However, it is worth emphasizing that the marginal effect of an increase in the size of an age group could be influential across sectors holding other groups unchanged even if the overall effects of population ageing are modest. Simulation results are provided in Table 4 for each case where the number of age-group-specific households increases by 1000 in the DM. We apply the same scenario to the AM and the results are compared with average impact from the DM in the last two columns of Table 4. While average marginal effects weighted by the number of households in the DM resembles the marginal impacts in the AM, there exist clear distinctions across age groups within the DM: the DM forms an inverted U-shaped curve in the age-impact plane for aggregate variables such as output, income, employment and consumption, accounting for the largest influence of the middle age group (35–54). The impacts on spending patterns in shares, however, reveals quite a different picture across age groups given an expenditure type, for instance, the rising health care share with age at an increasing rate.

4.2 Prediction accuracy

Four models are targeted for a comparison of prediction accuracy: the original model (CREIM), the AM, the DM with fixed age distribution (DMf) and the DM.[15] Among the 240 endogenous variables common in the three models, we select output, income and employment in 45 sectors, based on the relative importance of variables (see Appendix for the CREIM sectors).

First, the RMSEs are calculated based on one- to four-step-ahead predicted values for the 1990–2011 periods. Figure 2 shows the distributions of the selected variables'

[15] For the disaggregate model with fixed age distribution, we assume that age structure has not changed since the last year of the observed periods used in the model to generate forecasts.

Table 4 Marginal effect of an increase in age group: holding the other groups unchanged

(Unit: $2009 Mil., person) (2015)	DM								AM
	Under 25	25–34	35–44	45–54	55–64	65–75	Over 75	Avg.[a]	
Output	53.8	87.2	108.8	112.6	95.7	75.3	53.9	91.0	91.2
Income	12.8	20.6	25.9	27.2	23.1	18.1	12.8	21.8	22.1
Employment	281	449	563	587	499	390	273	471	479
Consumption	38.9	64.3	80.0	82.6	70.6	56.2	41.2	67.2	70.4
ND&S	35.8	59.3	73.8	76.1	65.0	51.9	38.2	61.9	65.1
Food	6.2	9.1	11.1	11.0	9.4	7.8	5.5	9.2	8.7
Housing	13.0	22.9	27.3	26.2	22.2	18.2	14.7	22.3	24.2
Trans.	3.5	5.5	6.6	7.1	6.1	4.8	2.9	5.7	5.2
Health.	1.2	2.5	3.5	4.0	4.5	5.5	5.3	3.8	3.8
Misc.	12.0	19.3	25.3	27.7	22.8	15.6	9.8	20.9	23.1
Share (%)									
ND&S	100	100	100	100	100	100	100	100	100
Food	17.2	15.3	15.1	14.5	14.5	15.1	14.3	14.9	13.3
Housing	36.3	38.6	37.0	34.5	34.1	35.1	38.5	36.0	37.2
Trans.	9.6	9.3	8.9	9.4	9.4	9.2	7.7	9.2	8.0
Health.	3.4	4.2	4.7	5.2	6.9	10.6	13.8	6.2	5.9
Misc.	33.4	32.6	34.3	36.4	35.1	30.0	25.7	33.7	35.5

Each column represents the impact results of a scenario where the number of households in the group increases by 1000
ND and S stand for nondurables and services respectively
DM disaggregate model, *AM* aggregate model
[a] Weighted by the number of households

RMSEs by model and also by the forecasting horizon.[16] Medians of each distribution are specified at the bottom of each box plot. The RMSEs in all models increase with the forecasting horizon and four-step-ahead forecasting errors are approximately twice as large as one-step-ahead forecasting errors. The output block shows the best forecasting performance in that the medians and variability of RMSEs are the smallest among all blocks. The DM generally shows the smallest RMSEs and the CREIM shows the largest RMSEs in terms of the median. Moreover, the differences in the RMSEs between the DM and the CREIM increase as the forecasting period extends, which indicates that the disaggregate model increasingly outperforms the CREIM for longer term predictions. The finding that differences among the AM, DMf and DM are indiscernible implies that disaggregation in data and model specification does not necessarily enhance prediction. Comparison between the DM and the CREIM, however, leads to the conclusion that regional consumption data in the DM (no matter how disaggregate the data are), that used to be unavailable in the CREIM, significantly improve the forecasting accuracy.

As an alternative measure for prediction accuracy, Eq. (4) is estimated for the four models using Fair and Shiller (1990)'s method. Since the method is designed for comparison between two models, we compare the CREIM with the remaining models one by one. In particular, high collinearity in the prediction errors among AM, DMf and DM precludes proceeding with the estimation, leading to indirect comparison via the original model. Unlike the RMSE, this approach statistically determines whether a model encompasses a competing model in terms of information relevant to prediction. For one- to four-step-ahead forecasts, Table 5 provides the number of variables in each block that contain information explained by (1) the AM, DMf or DM exclusively, (2) the CREIM exclusively, (3) both independently, and (4) none of the models. The ratios of (1) to (2) in the italicized cells of Table 5 capture the degree to which a model performs better relative to the CREIM.

One-step-ahead forecast comparison between the CREIM and the DM shows that the predicted values for 46 of 135 variables in the DM contains more information than those in the CREIM while for 24 variables the CREIM explains the actual values more than the DM does. As the forecasting horizon increases, the number of variables explained exclusively by either of the models decreases while more variables are increasingly explained by both models. Similar to the RMSE results, it is the output block among all blocks that shows the largest numbers of the variables explained by the DM, followed by the income block and then the employment block. Outperformance in the output block is due to the fact that the consumption in the DM is enriched with data relevant to actual consumption in the Chicago region and that output is constructed as a direct function of consumption. The same applies to the AM and the DMf, which indicates that both models also cover a wider range of forecast-relevant information than the CREIM does, maintaining similar patterns shown in the CREIM vs. the DM comparison. All these findings strengthen the evidence presented earlier using the RMSEs in that there exist forecasting gains in the AM, DMf and DM against the CREIM (i.e. majority of the ratios are greater than one) by incorporating the demand

[16] We also calculated the mean absolute percentage errors (MAPEs) to examine the effect of choice of forecasting accuracy measure, but it did not alter the main findings based on the RMSEs.

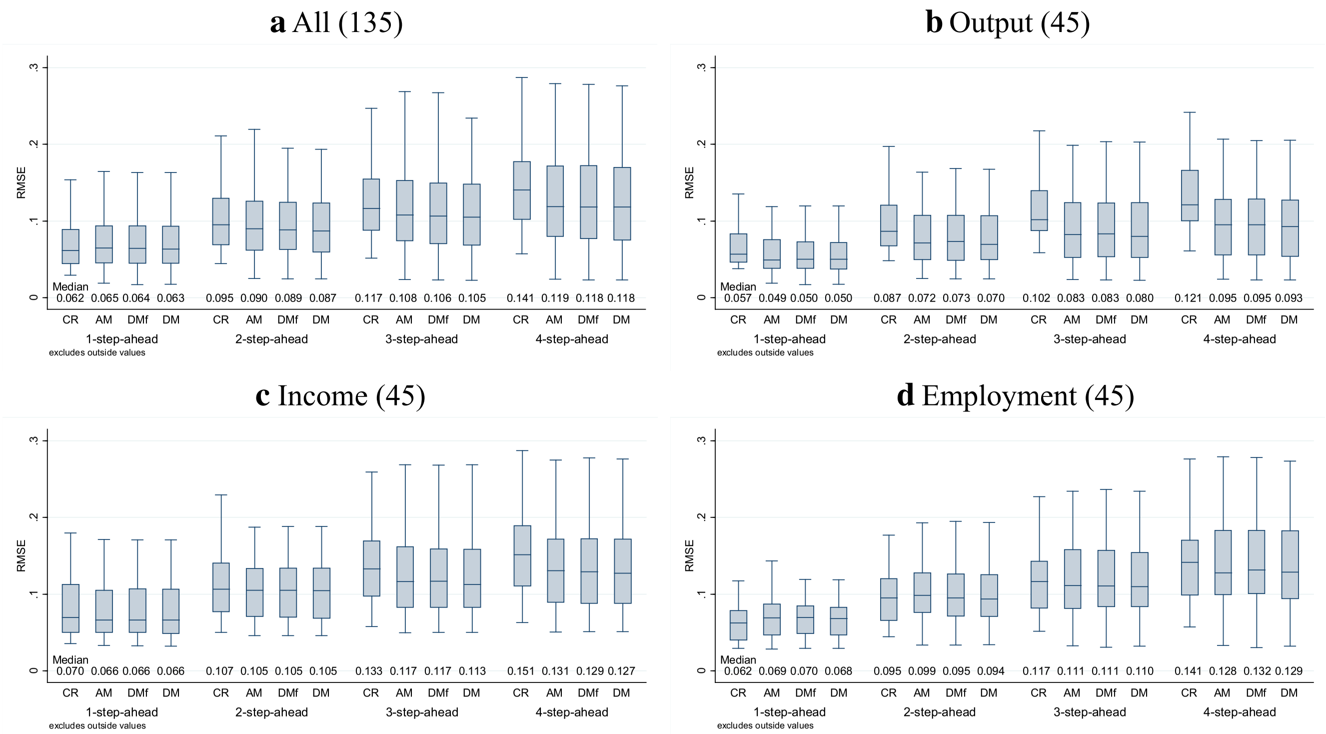

Fig. 2 Prediction accuracy measure I: RMSEs. **a** All (135). **b** Output (45). **c** Income (45). **d** Employment (45). (1) Figures in the *parentheses* represent the number of equations in the block; (2) in-sample forecasting periods are 1990–2011; (3) *CR* CREIM, *AM* aggregate model, *DMf* disaggregate model with fixed age distribution, *DM* disaggregate model

Table 5 Prediction accuracy measure II: Fair and Shiller's (1990) approach, number of equations that contain more information relevant to actual values

Block (#eq.)	Step Ahead	CREIM vs. AM					CREIM vs. DMf					CREIM vs.DM				
		No. of variables explained by:					No. of variables explained by:					No. of variables explained by:				
		AM (a)	CR (b)	Both	None	$(a)/(b)$	DMf (c)	CR (d)	Both	None	$(c)/(d)$	DM (e)	CR (f)	Both	None	$(e)/(f)$
Total (135)	1	44	22	41	28	*2.0*	40	25	39	31	*1.6*	46	24	36	29	*1.9*
	2	42	23	48	22	*1.8*	40	23	47	25	*1.7*	44	24	41	26	*1.8*
	3	36	22	55	22	*1.6*	36	18	53	28	*2.0*	41	19	50	25	*2.2*
	4	36	20	62	17	*1.8*	38	16	61	20	*2.4*	37	15	60	23	*2.5*
Output (45)	1	22	5	14	4	*4.4*	22	6	13	4	*3.7*	26	6	10	3	*4.3*
	2	19	8	17	1	*2.4*	18	9	17	1	*2.0*	22	9	13	1	*2.4*
	3	16	6	22	1	*2.7*	14	5	23	3	*2.8*	18	4	19	4	*4.5*
	4	15	5	25	0	*3.0*	14	3	25	3	*4.7*	15	4	24	2	*3.8*
Income (45)	1	12	9	11	13	*1.3*	10	10	11	14	*1.0*	12	9	11	13	*1.3*
	2	13	6	13	13	*2.2*	13	6	13	13	*2.2*	13	6	12	14	*2.2*
	3	10	7	18	10	*1.4*	12	5	15	13	*2.4*	11	7	16	11	*1.6*
	4	10	6	20	9	*1.7*	13	5	19	8	*2.6*	11	4	19	11	*2.8*
Emp (45)	1	10	8	16	11	*1.3*	8	9	15	13	*0.9*	8	9	15	13	*0.9*
	2	10	9	18	8	*1.1*	9	8	17	11	*1.1*	9	9	16	11	*1.0*
	3	10	9	15	11	*1.1*	10	8	15	12	*1.3*	12	8	15	10	*1.5*
	4	11	9	17	8	*1.2*	11	8	17	9	*1.4*	11	7	17	10	*1.6*

In-sample forecasting periods are 1990–2011

CR CREIM, *AM* aggregate model, *DMf* disaggregate model with fixed age distribution, *DM* disaggregate model system into the REIM using additional data. When compared to the AM and DMf, however, the DM does not show much greater forecasting gains. In totals, for instance, the DM explains only one to five (one to six) extra variables relative to the AM (the DMf).

5 Summary and conclusion

The overwhelming attention to industry disaggregation of the regional economy has failed to address heterogeneity of households in the modeling of economic impacts and forecasting in a number of regional economic models. To evaluate the effects of household disaggregation, this paper carries out long-term simulations and examines prediction accuracy for a regional econometric input–output model to which a demand system is integrated under various assumptions. More specifically, two demand systems are integrated into the Chicago model (CREIM): (1) a fixed-effects AIDS model using age-specific disaggregate data and (2) an aggregate AIDS model using aggregate data. Then, the effects of household disaggregation are decomposed into contributions from changes in age structure and methodology. Forecasting accuracy is also compared among the disaggregate model (DM), the aggregate model (AM) and the original model (CREIM). Major findings include the followings:

- The DM is capable of capturing marginal impacts of a change in age structure unlike the AM and the CREIM.
- The DM projects smaller total consumption than the AM does and compositional differences in consumption between the two models occur in the long run.
- The effects of population ageing are most noticeable in health care and miscellaneous expenditure categories, but total effects of household disaggregation are largely attributable to changes in model specification and data.
- Generally, the DM shows the smallest RMSEs and the original model (CREIM) shows the largest RMSEs. This is more conspicuous in longer-term forecasts.
- According to the Fair and Shiller's (1990) method, forecasting gains do exist in the DM as well as the AM compared to the CREIM. However, the DM's forecasting gains are negligible compared to the AM.

The effects of population ageing found in this paper are consistent with main findings in Dowd et al. (1998) and Lührmann (2008) in that the sectoral impact is concentrated in health-related sectors even though the size of its total impact could vary widely by model. Despite the relatively large impact of disaggregation in total, the effects of demographic change are found to be modest, as Lührmann (2008) similarly found when it was assumed that "population ageing took place without any accompanying changes of the socioeconomic environment of households".

Prediction outperformance of the DM and the AM over the CREIM suggests that a model's explanatory power in general could be enhanced by incorporating submodels using additional information. The baseline solutions are, however, shown to be sensitive to model specification and aggregation level of the data and this is more likely to be apparent in a large-scale model where even a single misspecified equation could have influential feedback on the whole system. These results can be interpreted in the same context of what Barker and Pesaran (1990) discuss in their extensive investigation on aggregation problems in econometric models from various perspectives: despite information gain from micro models, the level of aggregation must be carefully chosen depending on the objective of the study, specification errors involved, data available, and the degree to which parsimony is allowed.

The analysis presented here has offered one form of household disaggregation based on age; with increasing attention being paid to issues of income distribution and changes in the sources and returns to different types of income (e.g., wages and salaries as opposed to capital), a similar analysis could be performed with the income disaggregation presented in Kim et al. (2014). However, this disaggregation only provides information on wage and salary (factor) income; estimating returns to capital income presents enormous difficulties of tracing the geography of payments but the arguments advanced by Pyatt (2001) and more recently by Piketty (2013) suggest that this is a challenge that needs to be embraced.

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6 Appendix

Sectors in the CREIM

1 Livestock & other agri. prod.	16 Stone, clay, & glass prod.	31 Pipeline trans.
2 Agriculture, forestry & fisheries	17 Primary metals prod.	32 Information
3 Mining	18 Fabricated metal prod.	33 Motion picture & sound recording
4 Utilities	19 Industrial machinery & equip.	34 Finance & insurance
5 Construction	20 Computer & other electric prod.	35 Real estate
6 Food & kindred prod.	21 Trans. equip. manuf.	36 Professional & management serv.
7 Tobacco prod.	22 Furniture & related product	37 Educational serv.
8 Apparel & textile prod.	23 Misc. manuf.	38 Health care
9 Leather & leather prod.	24 Wholesale trade	39 Social assistance
10 Lumber & wood prod.	25 Retail trade	40 Arts, entertainment, & recreation
11 Paper & allied prod.	26 Air trans.	41 Accommodation serv.
12 Printing & publishing	27 Railroad trans. & trans. serv.	42 Food serv.
13 Petroleum & coal prod.	28 Water trans.	43 Repair & maintenance
14 Chemicals & allied prod.	29 Truck trans. & warehousing	44 Personal & laundry serv.
15 Rubber & misc. plastics prod.	30 Transit & ground passenger trans.	45 Membership org. & households serv.

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