Developing a Multiregional Social Account Matrix (MSAM) for Projecting Household Income Distribution in SCAG region

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JiYoung Park, Ph.D.
Assistant Professor
Department of Urban and Regional Planning
University at Buffalo, The State University of New York
(T) 716-829-3485 x209, (F) 716-829-3256
jp292@buffalo.edu

Simon Choi, Ph.D., AICP
Chief Demographer
Lead of Data/GIS, Forecasting
Southern California Association of Governments
818 West 7th Street, 12th Floor
Los Angeles, CA 90017
(T) 213-236-1849, (F) 213-236-1963
choi@scag.ca.gov

Frank Wen, Ph.D.
Manager,
Model/Tool Development, GIS/Data, and Forecasting
Planning Method, Assessment and Compliance Department (PMAC)
Southern California Association of Governments (SCAG)
(T) 213-236-1854, (F) 213-236-1963
wen@scag.ca.gov

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Abstract

This research is to develop an extended model for economic-demographic projection. To do the work, this research is to intend developing a multiregional SAM (MSAM) model for the SCAG region. Constructing a new MSAM model for the SCAG region requires developing several technical procedures and methodologies. Steps to construct MSAM for SCAG are composed as

1. Industry sectors in different data sets are matched to the industry sectors scheme of DIIM.
2. Once data have a consistent sectors scheme, then county-to-county trade flows for each industry are estimated.
3. The industrial trade flows matrices are combined with migration flow matrices of household income levels.
4. The SAM data sets of each county available via IMPLAN program are prepared.
5. The final step produces a multiregional SAM (MSAM) based on the constructed flows matrices and IMPLAN's SAMs. A MSAM involving 6 counties of SCAG region are produced, which named Southern California Inter-county Social Account Matrix (SCI-SAM).

Applying the inverse SCI-SAM, income distribution changes resulted from government investments or trade changes can be simulated. The simulation provides economic impact analysis of the SCAG's planning proposals for various local issues in the SCAG region.

Key words: Economic-demographic Projection Modeling, Multiregional Social Account Matrix, County-to-County Trade Flows, Demographic-Industry-Income Matrix,

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I. Introduction

This research is to develop an extended model for economic-demographic projection. Projecting future demands on a region's socio-economic situation such as housing, transportation, energy, land use, and other local planning issues, usually depends on the status changes of persons, households and employees. Therefore, to project the variables related to population and employment is important for diagnosing possible local problems in future.

To connect economic and demographic situations of a region, the approach linking those households and employees status to income distribution is widely used. This is because income distribution of a region can capture the economic situation of the region, including economic development, tax issues, education-related issues, etc. (Reed et al., 1996), and hence policy-related issues for future of the local region's economy can be addressed via the projected income distribution.

This research targets on the Southern California Association of Government (SCAG) for constructing a model linking households, employees, and income distribution. This is because SCAG involves 6 counties of Los Angeles, Orange, San Bernardino, Riverside, Ventura, and

Imperial and 189 cities in those counties. Because SCAG, the largest council of governments, covers over 18 million residents and over 38,000 square miles, most urbanization issues appear foremost in the SCAG region. Further, involving Los Angeles, the fastest growing city in the U.S., the SCAG region is getting the most number of immigrants, leading very rapid changes in demographic characteristics of the region.

Diverse projecting methods for examining income distribution linking economic-demographic variables have been suggested. Traditional approaches to income distribution are to find income distribution functions using mathematic distribution functions. The benefit using the mathematic income distribution functions is to calculate inequality of income status with ease. For example, Lorenz curve is widely used to show income distribution graphically and Gini coefficient is easily calculated once Lorenz curve is fixed (Samuelson and Nordhaus, 1995). However, mathematic approaches only show the base-year's income distribution and do not project reflecting the effects changed from various socio-economic characteristics for a target-period.

The dynamic issue for projecting income distribution in the mathematic approaches is partially resolved by introducing some demographic variables. Static income distribution model suggested by the Office of State Planning (OSP) includes age and race groups of the households' heads (NJOSP, 1992) for a base-year. The inclusion of demographic variables is important because income distribution is affected by various demographic characteristics (Bianchi et al., 1980). According to the changes of age and race cohorts in a future, the constant ratios between the base year and target year determine the future income distribution. Issues are raised about the assumption that income distribution is affected only by demographic variables.

Extension for the assumption in demographic approach is to combine the economic situation with demographic variables. One is to introduce directly industry sectors to the demographic variables. In the case, the employee variable is a key component connecting demographic variables and economic variables. Recent development of Southern California Income Distribution Model (SCIDM) utilizes this approach (Choi, 2007). Another is to use Social Account Matrix (SAM). SAM model already includes Input-Output transaction flows and transferring flows of non-market sectors, among industry sectors and institutions of households, private company, and federal and local governments (Pyatt and Round, 1985) as seen in Figure 1.

While SCIDM more depends on demographic changes, including the changes of the number of births, deaths, in- and out-migrants for the target year's projection of income distribution by industry, the SAM approach well reflects economic relationship in a region but somewhat neglects involving the changes in demographic characteristics. That is, the SCIDM and one region SAM approaches to projecting population distribution contain their own limitations. A possible extension for future projection of income distribution, therefore, would develop multiregional SAM to adopt regional movements of people.

	Industry	Intermediate Inputs	Intermediate Outputs	Total Outputs
Industry	I-O Transaction Flows		Final Demand	
Intermediate Inputs	Value Added			
Intermediate Outputs	Sales	Institutional Transfer	Institutional Transfer	
Total Inputs				

Note: 1. 'Intermediate Inputs' usually include payments to employees, land, capital and imports.
2. 'Intermediate Outputs' usually include final demands of consumers (households), governments, private companies, and exports.
3. White blocks are not measured.

Figure 1. Social Account Matrix (SAM) Framework for a Region

This research, therefore, is to intend developing a multiregional SAM (MSAM) model for the SCAG region. The MSAM consists of 6 counties. To combine the MSAM with 2000 based Demographic-Industry-Income matrix (DIIM) available in the SCAG, number of industries are matched to DIIM. Detail data and modeling issues for constructing MSAM and combination processes with DIIM are followed in the next section.

II. MODELING ISSUES

Constructing a new MSAM model for the SCAG region requires resolving several problems, including data and methodology issues. Because trade flow data among counties by industry sector are not available for the 6 counties of SCAG region, one major issue is how to estimate the trade flows. The U.S. Commodity Transportation Survey data on interregional trade flows have been available since 1977, but reporting was discontinued for some years. For the years since 1993, this data deficit can be met to some extent with the recent Commodity Flow Survey (CFS) data from the Bureau of Transportation Statistics (BTS). Since 1993, CFS data have been widely used, but the data have several inherent problems (Erlbaum and Holguin-Veras, 2005). The most serious one among them is that the CFS data do not include trade flows below the state level but also that they are not complete even between the states. Since Polenske (1980) and Faucett Associates (1983), there has been no comprehensive inventory of flows for probably these reasons.

Furthermore, even though the commodity flow data between the states of the U.S. are published every five years, there is no inventory of trade flows for services. Recent approaches to estimating state-by-state trade flows of U.S. based on 1997 CFS, therefore, have included too little attention paid to the problems of estimating the trade flows among service sectors and maintained strong assumptions of no or small trades in these sectors (Park et al., 2008). However, in the modern information economy, this is a serious omission. So far, only Park (2006) seems to report the way to estimate service sector flows among regions.

The third major issue is in estimating migration flows among regions. Because the SAM includes several household vectors classified with income levels, the migration flows among 6 counties for each household's income level should be constructed for regionally disaggregating each household income level. After that, the constructed migration flows will be transformed to row sum based migration coefficients matrix.

The final issue is to connect MSAM with DIIM. Because DIIM includes various demographic variables, interlocking MSAM with DIIM extends the usefulness of MSAM model. To do so, it requires matching industrial sectors of MSAM to those of DIIM. Once the sector scheme is established, both models can be benefited from each other.

Therefore, this research requires developing several technical procedures and methodologies. The data and methodological issues and model development progress introduced in this research are described in the next section.

III. DATA, METHODS, and MODELING PROCEDURE

III-1. Modeling Procedure

MSAM for SCAG region includes several steps of data preparation. Figure 2 shows the progress of constructing MSAM model.

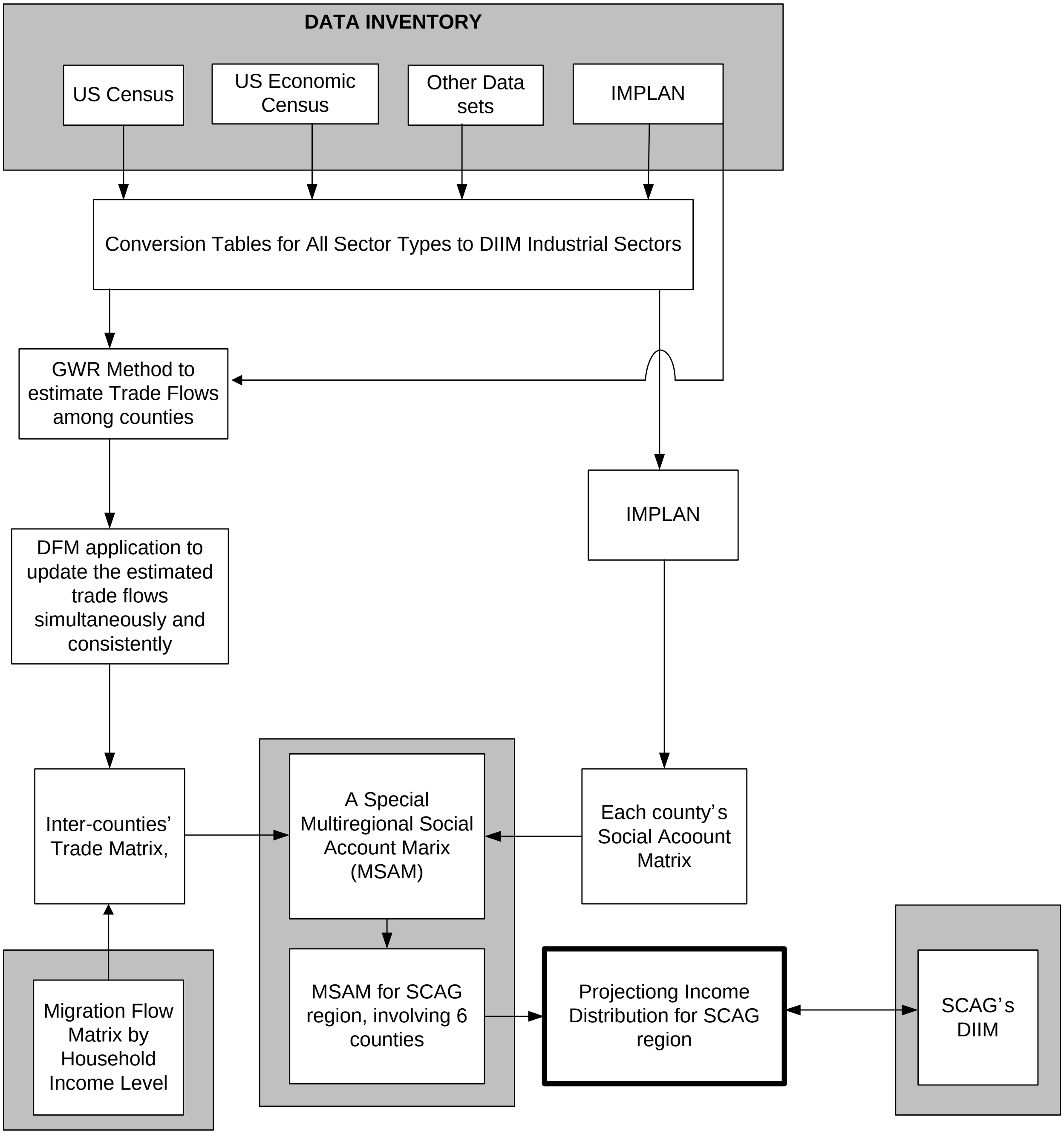


Figure 2. Constructing Procedure of MSAM model for SCAG region.

According to the Figure 2, steps are composed as

6. Industry sectors in different data sets are matched to the industry sectors scheme of DIIM.
7. Once data have a consistent sectors scheme, then county-to-county trade flows for each industry are estimated.
8. The estimated trade flows are tuned using Doubled-constrained Fratar Model (DFM).
9. The final industrial trade flows matrices are combined with migration flow matrices of household income levels.
10. Also, SAM data sets of each county available via IMPLAN program are prepared.
11. The final step produces a multiregional SAM (MSAM) based on the constructed flows matrices and IMPLAN's SAMs. A MSAM involving 6 counties of SCAG region will be produced. Income distribution for the SCAG region is projected, interlocking with SCAG's DIIM data.

Following are descriptions of two key methodologies for constructing the MSAM for SCAG region.

III-2. Geographically Weighted Regression (GWR)

Because there is no comprehensive inventory of interindustrial trade flows at the county level, Park's (2006) approach will be applied for estimating county-to-county trade flows for each commodity and service sectors. Although Park (2006) proposed the new approaches to estimating interstate trade flows for the service sectors, the basic principle in the method suggests to examine the economic relationships between sub-state-level areas, as well as to forecast future trade flows.

A key method in the approach is to use Geographically Weighted Regressions (GWR) econometric analysis. The GWR model can be rewritten according to LeSage (1999, p.205~206) as applying Weighted Least Squares (WLS). If ε_i has heteroscadasticity according to spatial (i) characteristics, a new variance matrix of error term ε_i can be specified as follows.

$$\sigma_\varepsilon^2 = \begin{bmatrix} \sigma_1^2 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_n^2 \end{bmatrix} \tag{1}$$

Therefore, net domestic import of each sector vector y_i can be weighted by σ_ε^2 letting error term ε_i follow normal distributions.

$$y_i = \sum_{k=1}^{K} \beta_k x_i + \varepsilon_i \tag{2}$$

$$\frac{y_i}{\sigma_i} = \frac{1}{\sigma_i}\sum_{k=1}^{K}\beta_k x_i + \frac{\varepsilon_i}{\sigma_i} \qquad \frac{\varepsilon_i}{\sigma_i} \sim N(0, I) \tag{3}$$

If W_i is a similar weight to adjust a regional heteroscadasticity, then equation (3) can be shown as,

$$\sqrt{W_i}\, y = \sqrt{W_i}\, X\beta_i + \sqrt{W_i}\,\varepsilon_i \tag{4}$$

where, an i is spatial observation (e.g. state, county, etc.) and β_i is K x 1 parameter column vector related to region i . W_i represents n x n diagonal matrix including distance-based weights for i and hence reflects the distance between i and all other regions, d_i .

Here, distance-based weights can be suggested via three types. While Brunsdon et al. (1996) introduced “bandwidth” decay parameter θ using exponential decay function or McMillen (1996) used a tri-cube function, Gaussian standard normal density function in equation (5) is a better approach for estimating trade flows because the “bandwidth” decay parameter θ adjusting the distance-effects are affected by various independent variables (Park, 2006).

$$W_i^G = \phi(d_i / \sigma\theta) \tag{5}$$

where σ indicates the standard deviation of the distance vector d_i

The "bandwidth" decay parameter θ relies on cross-validation value that uses a score function shown in equation (6). Hence, to estimate the optimal decay parameter θ, new iteration approach was used as,

$$\sum_{i=1}^{n}(y_i - y^*_{\neq i}(\theta))^2 \qquad (6)$$

where, $y^*_{\neq i}$ is the optimally fitted value of y_i omitting region i.

The equation (6), therefore, shows that the θ is selected when sum of residual is minimized using the similar weighted least squares in equation (4) via iterations. In other words, the most optimally estimated $y^*_{\neq i}$ reflects all effects of the independent variables and invisible spatial relations given at a fixed distance. Therefore, the weights W_i^G are not fixed as other spatial autoregressive models are, but flexibly changed, depending on the independent variables.

Because the optimal "bandwidth", $\hat{\theta}$, is selected from the equation (6) omitting regressed region i itself, the trade matrix T is separated into two types. One is the diagonal matrix of intra-state trade movement by each state, denoted as $\hat{T}$. Another is non-diagonal trade flow ($\tilde{T}$) empty in the main diagonal. The existing data set includes only total domestic imports without the non-diagonal state-by-state trade flows $\tilde{T}$. Therefore, given $\hat{T}$, the $\tilde{T}$ is estimated using the GWR.

Based on the prediction vector y_i^h for each service sector after being estimated optimally based on the $\hat{\theta}$ from the equation (4), the estimated trade flows $\tilde{T}^*$ of $\tilde{T}$ is calibrated,

$$\tilde{T}^*{}_s = (W_i^* {}^{R\Sigma}\hat{W}_i^{-1} \hat{y}_i^h)_s \qquad (7)$$

where, W_i^* is the fitted weighted matrix, ${}^{R\Sigma}\hat{W}_i^{-1}$ is inverse matrix of ${}^{R\Sigma}\hat{W}_i$ where ${}^{R\Sigma}\hat{W}_i$ is diagonal matrix of row sum of W_i^*, $\hat{y}_i^h$ is diagonal matrix of y_i^h, and s indicates industrial sectors.

Finally, the estimated trade flows are obtained from the equation (8).

$$T_s^* = \tilde{T}_s^* + \hat{T}_s \qquad (8)$$

To adjust the initial estimates from the GWR due to its net domestic import based application, I will also apply the Doubly-constrained Fratar Model (DFM). Detail method can be found in Park et al. (2008) and brief introduction is followed. Fratar models are useful for estimating updated trade flows. The starting matrices include numerous estimated values for missing entries in the trade flows data. However, the traditional Fratar model calibrates only off-diagonal interregional cells. In this application, new diagonal values accounting for intra-regional trade flows also have to be estimated. For this, I apply the Doubly-Constrained Fratar model (DFM), a new formulation that updates the diagonal values in the trade flows matrix, along with the traditional Fratar model to estimate the off-diagonal values. The DFM iteratively estimates all the estimated trade flows simultaneously and consistently. The estimated values for each industry sector are the starting values for the next iterative step of the DFM.

III-3. Multiregional SAM (MSAM) construction

According to the procedure that Park et al. (2008) constructed an operational MRIO model at U.S. State level along with the formulation that Chenery (1953) and Moses (1955) had suggested, construction of multiregional SAM (MSAM) was made. The requirements to fulfill the MSAM are *flows* and *SAM* matrices for given regions and sectors (of industries and household income levels). Once those are prepared, then multiplication of the two matrices which are shown in Figures 3-5, allows constructing MSAM.

$$\mathbf{MSAM} = \mathbf{C^{O}A}_0 \qquad (9)$$

where, $\mathbf{C}$ = an $nm \times nm$ diagonal block matrix of interregional trade flows and migration flows

$\mathbf{C^{O}} = \mathbf{C}(\hat{\mathbf{C}}_{\mathbf{j}}^{\mathbf{m}})^{-1}$ and $\hat{\mathbf{C}}_{\mathbf{j}}^{\mathbf{m}}$ is an $nm \times nm$ diagonal matrix of $1 \times nm$ row vector

$\mathbf{C}_{\mathbf{j}}^{\mathbf{m}} = \sum_i c_{ij}^m$, that is, the off-diagonals for a specific region block should be

zero and c_{ij}^m is an element of matrix $\mathbf{C}$ for region i to j trade flow of industry

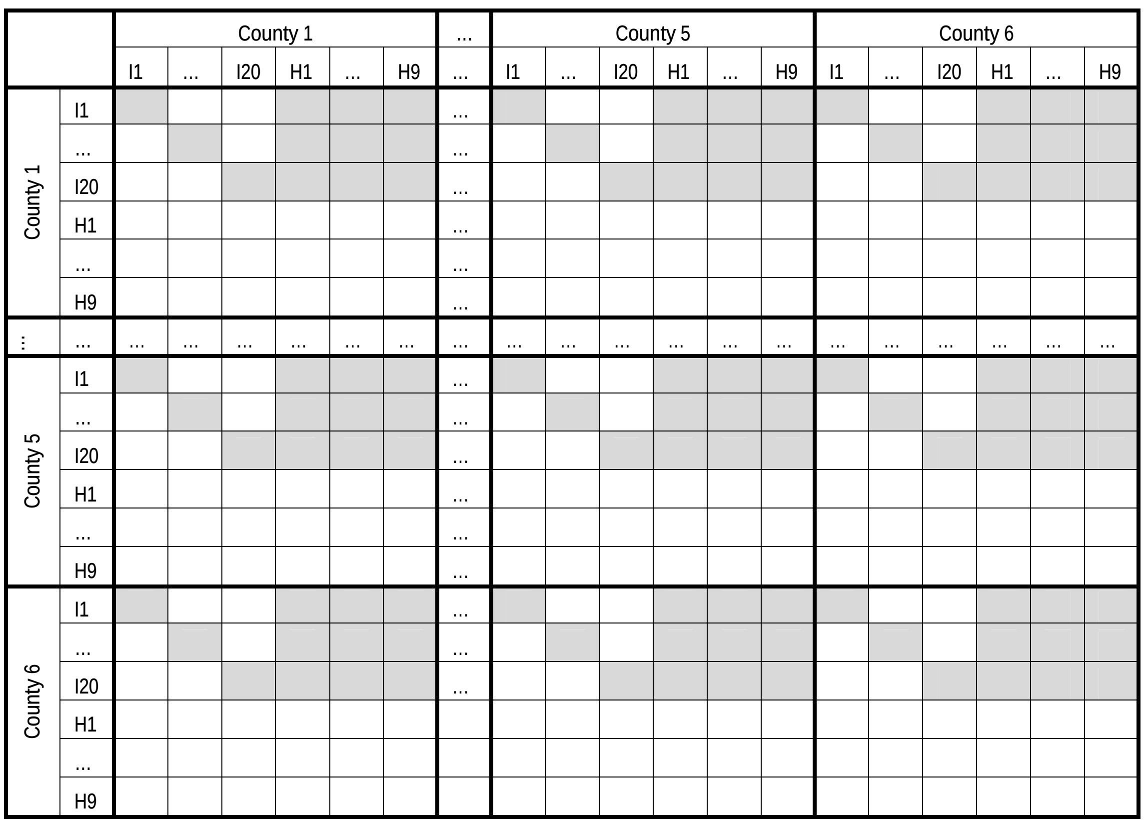
sector and household income level m ,

$\mathbf{A}_0 = \mathbf{SAM}(\hat{\mathbf{X}}^{\mathbf{I}})^{-1}$ and $\hat{\mathbf{X}}^{\mathbf{I}}$ is an $nm \times nm$ block diagonal matrix of vector $\mathbf{X}^{\mathbf{I}}$,

and hence the elements in all blocks off the regional diagonal would be zero,

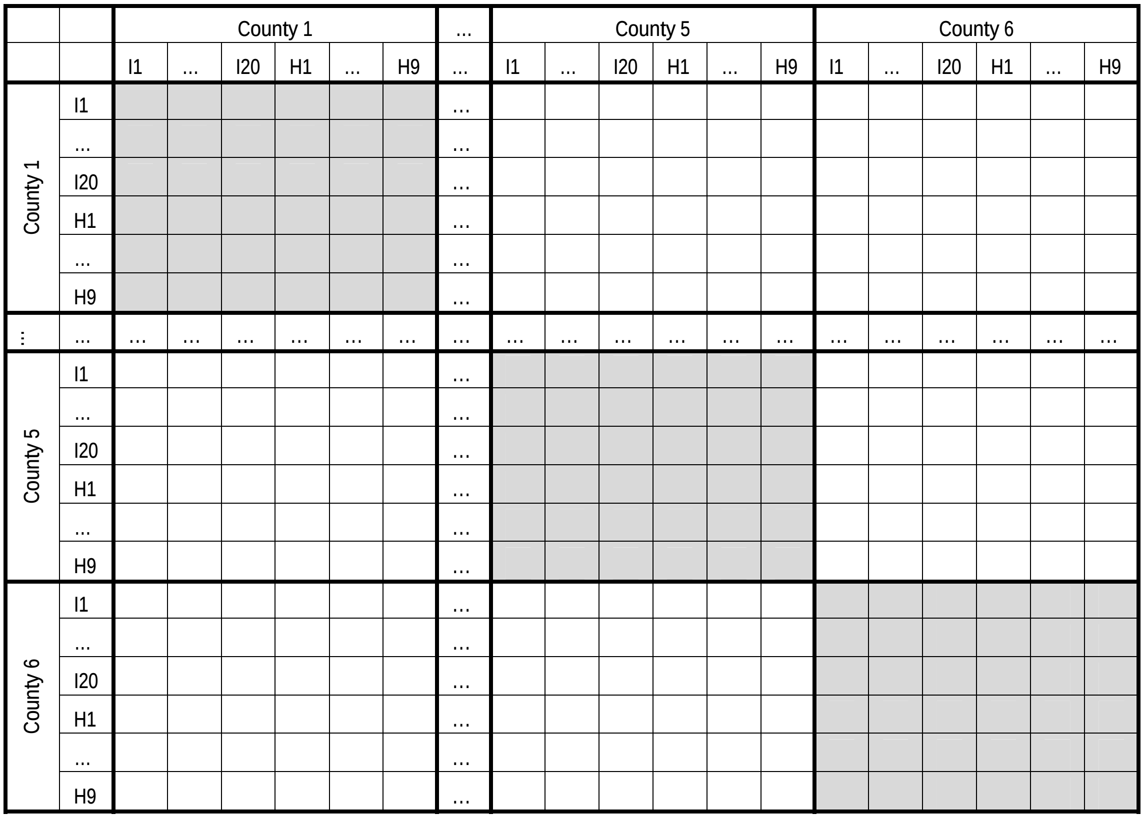
$\mathbf{X^I}$ = the total input row vector for the various industry sectors and household income level m and regions n,

SAM = an $nm \times nm$ block diagonal matrix of direct technical flows between industries and institutional transaction flows between household income levels within a region.



Note: 1. White cells identify zero values

Figure 3. Interregional coefficients of trade and migration flows



Note 1. White cells identify zero values

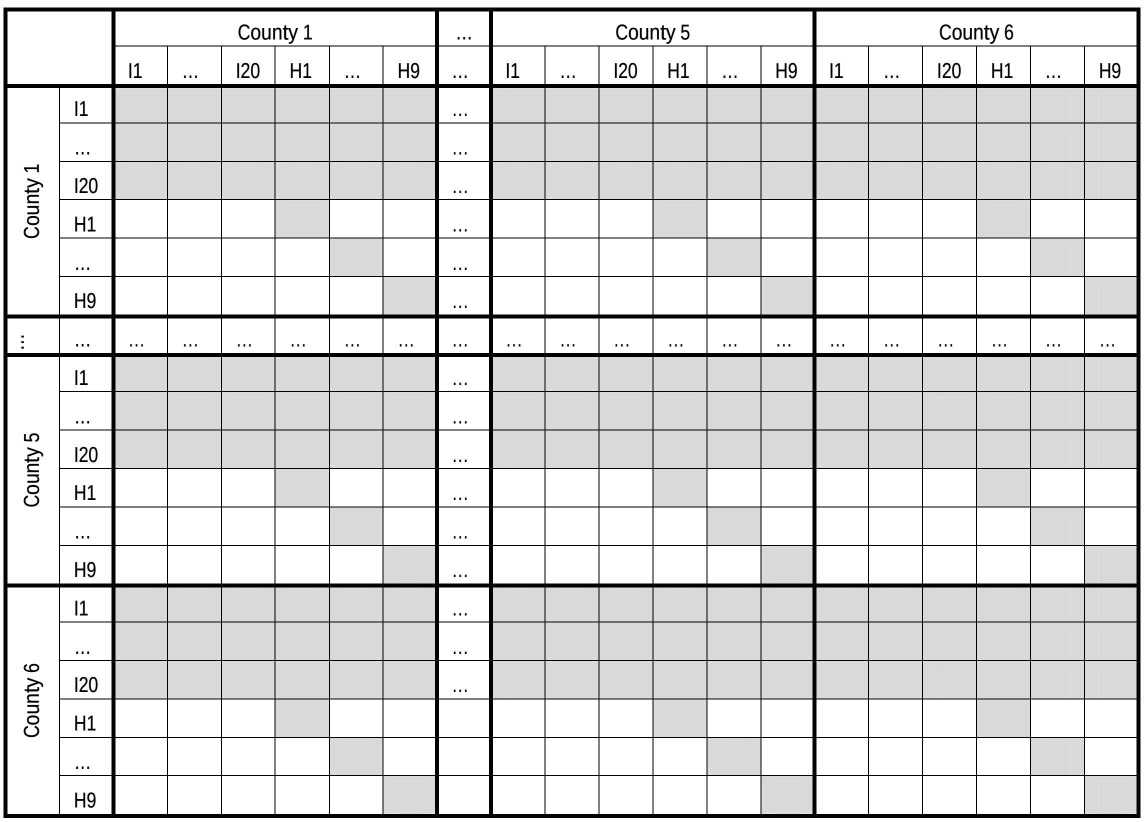
Figure 4. Inter-industrial and inter-institutional SAM coefficients of 6 counties

The MSAM in equation (9) can be directly applied to the change of household income distribution resulted from demographic changes in ages, races, or both variables. However, for projecting income distribution based on the MSAM resulted from exogenous changes, e.g. government investment or trade changes, this MSAM should be converted to equation (10).

$$\mathbf{(I - MSAM)^{-1} Y} \quad (10)$$

where, $\mathbf{Y}$ is a column vector of regional specific government expenditures or trade changes.

The results from equation (10) produce new income distributions for target period when government intends to invest publically for specific or mixed sectors. The new income distributions can be transferred to employment changes by income distribution, and hence may affect to the population components via DIIM matrix.



1. White cells identify zero values

Figure 5. Inversed Multiregional Social Account Coefficients Matrix (MSAM)

IV. RESULTS

Several technical works constructing multiregional social account matrix (MSAM) conducted, named Southern California Inter-county Social Account Matrix (SCI-SAM), based on two central data sets of 2004 IMPLAN and 2000 Census. The SCI-SAM is classified with 2 digit level North American Industry Classification System (NAICS) industry code system and has 20 industry sectors matching to the current SCAG's industry sector scheme previously developed (Refer to Table 1 for the detail information).

Table 1. SCI-SAM's industry and income sector system

SCI-SAM sectors	2 DIGIT Code System Used in Modeling	Explanation
SCI-IND 1	11	Total Farm
SCI-IND 2	21	Natural Resources and Mining
SCI-IND 3	22	Utilities
SCI-IND 4	23	Construction
SCI-IND 5	31	Manufacturing
SCI-IND 6	42	Wholesale Trade
SCI-IND 7	44	Retail Trade
SCI-IND 8	48	Transportation and Warehousing
SCI-IND 9	51	Information
SCI-IND 10	52	Finance and Insurance
SCI-IND 11	53	Real Estate and Rental and Leasing
SCI-IND 12	54	Professional, Scientific and Technical Services
SCI-IND 13	55	Management of Companies and Enterprises
SCI-IND 14	56	Administrative and Support and Waste Services
SCI-IND 15	61	Educational Services
SCI-IND 16	62	Health Care and Social Assistance
SCI-IND 17	71	Arts, Entertainment, and Recreation
SCI-IND 18	72	Accommodation and Food Service
SCI-IND 19	81	Other Services
SCI-IND 20	92	Public Administration
SCI-INC 1	510	Personal Income than $9,999
SCI-INC 2	511	$10,000=<Personal Income <$15,000

SCI-INC 3	512	$15,000=<Personal Income <$25,000
SCI-INC 4	513	$25,000=<Personal Income <$35,000
SCI-INC 5	514	$35,000=<Personal Income <$50,000
SCI-INC 6	515	$50,000=<Personal Income <$75,000
SCI-INC 7	516	$75,000=<Personal Income <$100,000
SCI-INC 8	517	$100,000=<Personal Income <$150,000
SCI-INC 9	518	$150,000=<Personal Income

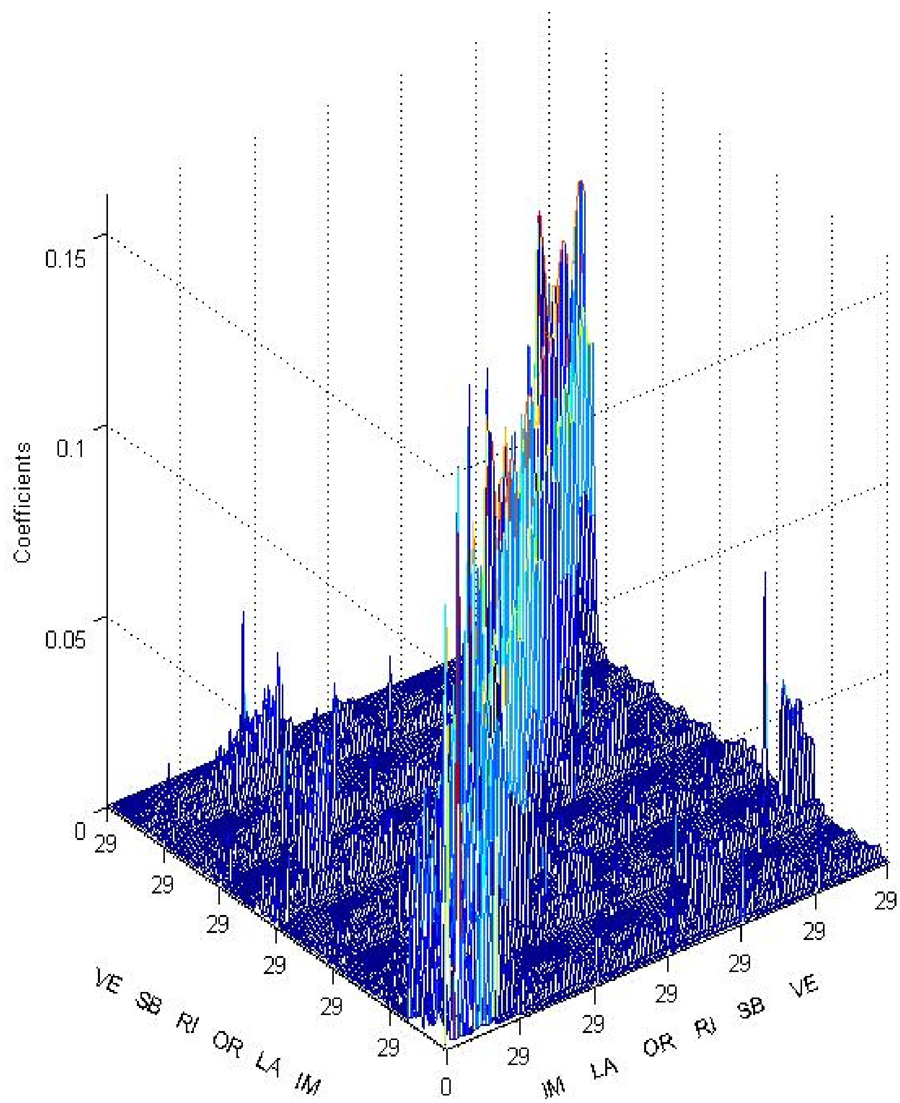
Developing the SCI-SAM involved several sub-model constructions of;

- estimating county-to-county trade flows for each industry,
- creating county-to-county personal commuting travelers by industry, and
- each county's SAM (20industries+9 household income level) structure.

County-to-county trade flows were estimated applying Geographically Weighted Regression (GWR) method. After estimating the trade flows, trade coefficients table were calculated from the transaction values divided by the row sum of the trade flows. Statistical results for the estimated coefficients applying Ordinary Least Squares (OLS) and GWR approach by SCAG industry sector can be found in the Appendix.

County-to-county commuting table includes number of commuting travelers and the coefficients from one county to another county by NAICS 2-digit industry code by personal income level. The final products of them are available from the final technical report and delivery.

Those ‘county-to-county trade flows’ and ‘county-to-county commuting table’ data sets create a main input data set for SCI-SAM model via some modification in the format. The SCI-SAM table and inverse matrix of SCI-SAM are available from the final delivery. The inverse matrix of SCI-SAM provides impact analysis on the investments of government and private institutions. The detail process to construct can be referred in the equations (9) and (10) of this report. Figure 6 shows the structure of SCI-SAM in a graphic format.



Note: IM=IMPERIAL; LA=LOS ANGELES; OR=ORANGE; RI=RIVERSIDE; SB=SAN BERNARDINO; VE=VENTURA

Figure 6. SCI-SAM Technical Coefficients by County and by Industry and Personal Income Level

V. CONCLUDING REMARKS

Compared to the dominant studies of income distributions linking population, industries, and migration, all other studies except this research seem not to involve regionally disaggregated connections. The suggested MSAM approach for updating income distribution contains the regional interaction, and hence provides county based income distribution changes. Especially, using inverse MSAM, income distribution changes resulted from government investments or trade changes can be simulated. The simulation can justify the SCAG's planning proposals for various local issues in SCAG region.

Although the suggested MSAM is an extension of current methods projecting income distribution, other advanced methods e.g. suggested by Gordon et al. (2009) can improve the MSAM approach and make it endogenous to update income distribution periodically. The flexible updated approach can predict the long-term change of SCAG region's SAM structure as well as the long term economic impacts reflecting resilient effects from a government investment or a disaster. Also, regional expansion of the SCAG's MSAM, for example, including San Diego County, would play a key role of balancing the SCAG's policy issue conflicting with counties out of SCAG. Further, the localization of MSAM to the city level may improve the utility of the model significantly.

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