Linking the Regional Demographic Processes and the Small Area Housing Growth: Implications for the Small Area Demographic Projections

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Abstract

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The population and demographic change of small areas is mostly driven by both the regional economic-demographic influence and small area demographic processes in a spatio-temporal context. The popular cohort-component method is not easily applicable to population projections of small area(e.g.,city or censustracts) for a couple of reasons: (1) the historical and current trends in vital statistics and migration of the small areas are not easily available; (2) it is difficult to independently develop reasonable migration assumptions of small areas. An alternative approach is to derive population projections of local communities through the enhanced link age of small area housing growth and regional demographic processes. This study presents a modeling approach toward developing the long term projection of total population and the key demographic characteristics(e.g.,age,race / ethnicity) at the transportation analysis zone level. A proposed small area modeling approach is as follows: (1) project the regional employment, population, and household growth using the employment, demographic, and household projections models; (2) allocate the regional housing and employment growth into the small area; (3) convert the small area housing growth into population growth using the housing unit method; (4) disaggregate the small area population into their demographic characteristics. This study focuses on the fourth stage of projecting the small area demographic characteristics and presents the multi-nomial logit regression method to project the small area demographic characteristics utilizing the past trend of those demographic components of population at the small area. The study finds the proposed method as reasonable, and suggests that the topic requires the further research.

Keywords: demographic projections, small area, envisioning, growth scenarios, spatial distribution of age and racial/ethnicity.

I. Introduction

The small area population projections are important in understanding the diverse community service needs of the future (Klosterman, 1990). Although the population size of the small area might be a useful indicator for measuring the community needs, the detailed demographic projections, if available, would be able to more accurately estimate the community service needs. This study presents a coherent modeling framework for projecting the population size and demographic characteristics of the small area within the metropolitan planning context.

The population and demographic change of small areas is mostly driven by both the regional economic-demographic influence and small area demographic processes (births, deaths, and migration) in a spatio-temporal context. The small area demographic process, in particular, small area migration, is volatile along the national and regional economic cycles and hard to forecast as a major component of small area population projections. The expected small area migration would be easily absorbed into small area population projections with the expected small area demographic processes assuming that the timely housing supply is available for the projected in-migrants. If the timely housing supply is not readily available and the small area migration projection remains unchanged, local communities would experience a lot of changes in a small area population-housing relationship (e.g., higher household size) and a lower housing quality (e.g., household overcrowding). It is important for the small area demographic projections to consider both the demographic process at the large area level and the availability of housing at the small area level as part of a small area demographic modeling framework.

In fact, the previous study emphasized the importance of population or housing at the different levels of geography (Field and MacGregor, 1987). The study indicated that housing become a key measure for smaller levels of geography, while population for a larger levels of geography. The reason might be related to lack of necessary data and reliable assumptions. For example, the popular cohort-component method is not easily applicable to population projections of small area (e.g., city or census tracts) for a couple of reasons: (1) the historical and current trends in vital statistics and migration of the small areas are not easily available; (2) it is difficult to independently develop reasonable migration assumptions of small areas. An alternative approach is to derive population projections of local communities through the enhanced linkage of small area housing growth and regional demographic processes.

Small area housing growth can be easily used to determine migration and population projections of local communities from the local planning perspective. Local planners cannot easily access the small area demographic data due to its limited availability, but are familiar with housing development permits and process, the existing local general plan, zoning codes, and other land use regulations. They, at local jurisdictions, are monitoring the land use changes and housing development on a daily basis. They are charged with envisioning the future housing growth of the community. If there is opportunity, they tend to translate the future housing development into population and demographic projections, instead of vice versa.

This study presents a modeling approach toward developing the long term projection of total population and the key demographic characteristics (e.g., age, race/ethnicity) at the transportation analysis zone level. A proposed small area modeling approach is as follows: (1) project the regional employment, population, and household growth; (2) allocate the regional housing growth into the small area;(3) convert the small area housing growth into population growth using; (4) disaggregate the small area population into their demographic characteristics. This study focuses on the fourth stage of projecting the small area demographic characteristics and presents the multi-nomial logit regression method to project the small area demographic characteristics utilizing the past trend of those demographic components of population at the small area.

Ⅱ. Overview

The cohort-component model is a widely used population projection model in the world due to its capability to produce key demographic characteristics including age, gender, and race/ethnicity (Smith et al, 2001). US Census Bureau has used the cohort-component method to produce the national population projections. The forecasting accuracy was relatively high. The cohort-component focused on age and gender at the early period of application, later added one more dimension of race/ethnicity with its increasing importance. There is a recent effort of adding more detailed demographic characteristics of immigrant residents (Myers & Pitkin, 2011). The additional characteristics include the birth place, length of stay in the US, of the US immigrants.

While the cohort-component model produces useful information of demographic characteristics of the projected population, it tends to target the larger levels of geography. The minimum level of geography is usually county in the United States due to the availability of the necessary information of births, deaths, and migration. In particular, migration data is not readily available and might not track the gross migration (e.g., inflows and outflows of migration) in many cases. There is a wide range of studies of how to develop migration assumptions (Plane and Rogerson, 1994). The studies try to figure out the major determinants of migration at both the large area (usually county or state) level or above. The most popular determinant of migration would be job growth. Lowry used the job to population linkage to develop metropolitan growth model (Lowry, 1964).The job-population (or migration) linkage is still a dominant modeling framework in the urban and land use modeling field.

There is a growing demand of more detailed demographic characteristics at the very small area level in the field of business demography and transportation demand modeling and business demography. The private vendors in the economic and demographic field tend to produce short and long term population and demographic projections for clients of public and private sectors. These projections tend to reflect the business and public facility demand due to inclusion of population related variables, and are used to identify the optimal business and public facility location. The methodology and assumptions underlying the small area demographic projections are not well known to the general public due to its nature of business (Smith et al, 2001). The demographic characteristics of projected population at the small area level are directly related to diverse human behavior including travel (trip generation, trip distribution, trip assignment, and mode choice), household formation, homeownership, health care, retirement, etc. With the reasonable estimates of the demographic characteristics, we might easily derive the implication for housing, travel, health care, retirement, etc. Because of the strong linkage of demographic characteristics to the diverse human behavioral activities, a regional planning organization tend to use that linkage to understand the future community needs and to derive policy options to accommodate the future service needs.

In contrast to the large area employment-population (migration) dynamics, the small area's demographic characteristics might not be easily figured out without knowing the overall population and housing growth of the small areas. A good example is a housing unit method. The housing unit method is a conceptually clear and theoretically sound population estimation method in the U.S.(Smith and Lewis, 1982). Since there is no officially mandated population registration system in the U.S., the population estimate is oftentimes derived using the housing growth. Housing estimate is relatively easy to collect through the local government. According to the housing unit method, the housing growth is translated to population through the necessary conversion process. There is a risk of the volatile conversion factors, such as housing occupancy rate, household size, or the share of group quarter population to total population, but the housing unit method is widely used due to the easiness of the data accessibility and method application.

The housing unit method is sometimes further extended to project the small area population in the metropolitan planning process (Southern California Association of Governments, 2008). As part of the baseline population projection development for the city level or below, the trend extrapolated housing growth is translated into population through the conversion process. A few conversion factors might not be stable during the projection period, and they are subject to major review. The housing unit method is well taken by local planners. Local planners cannot easily access the small area demographic data due to its limited availability, but are familiar with housing development permits and process, the existing local general plan, zoning codes, and other land use regulations. They, at local jurisdictions, are monitoring the land use changes and housing development on a daily basis. They are even charged with envisioning the future housing growth of the community. If there is opportunity, they tend to translate the future housing development into population and demographic projections, instead of vice versa.

The demographic characteristics of the small area may be projected using three different approaches. The first approach is the iterative proportional fitting (IPF) approach, and might be one of the most popular approaches currently used in the world. The IPF technique was first introduced by Deming and Stephan in 1940 and proved by the rigorous research of Fienberg (1970). IPF approach is preferred due to its computational speed, numerical stability and algebraic simplicity (http://en.wikipedia.org/wiki/Iterative_proportional_fitting). The IPF approach is also well recognized in the field of small area demography (Kanaroglou et al, 2009; Rees et al, 2004; Simpson and Tranmer, 2005). For example, the demographic characteristics of the small area could be determined using the reference region's population and demographic projections, and the small area's population projections. The only missing element is the detailed demographic characteristics, probably age and racial/ethnic composition of the projections populations at the small area. The IPF uses the base year's age and racial/ethnic composition of the small area population as reference for the future age and racial/ethnic composition of the small area population. The IPF approach would be every effective in developing the relatively short term projections of the demographic characteristics due to the temporal continuity of the demographic characteristics of the "mature" small area, while it might be limited in projecting the long term projections for the "emerging" small area.

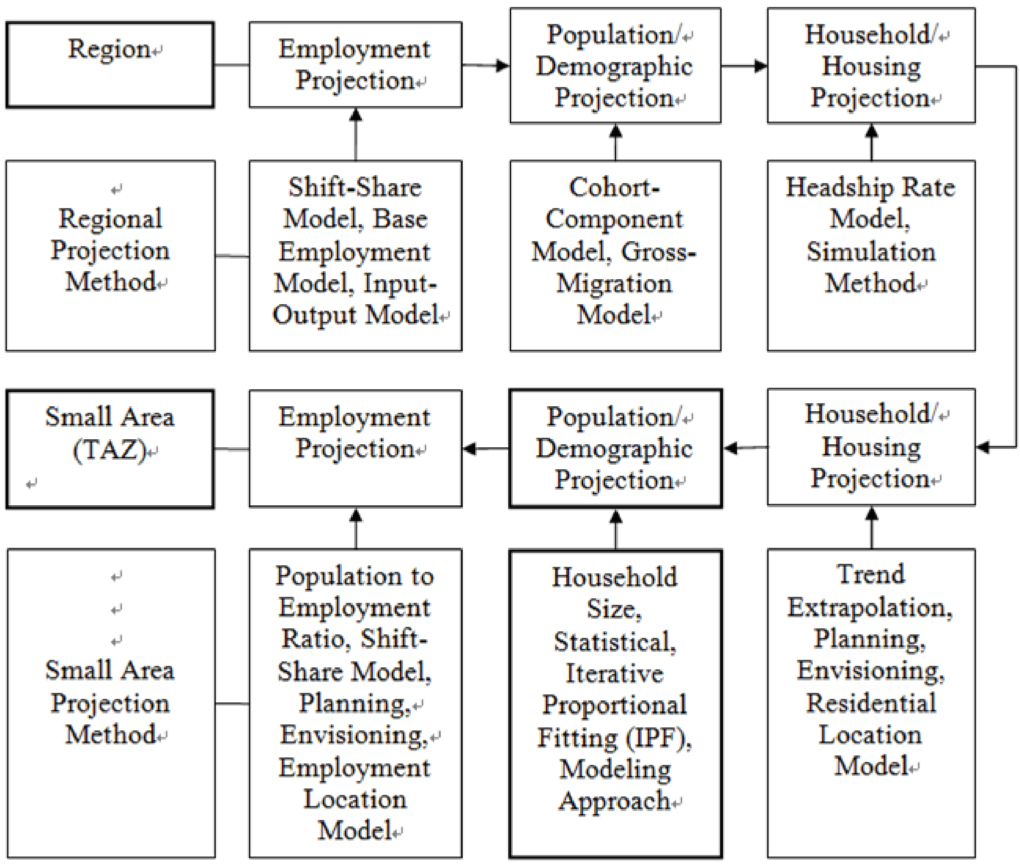
The second approach is a modeling approach. The modeling approach is often observed from the typical land use modeling process. The land use model tends to assign specified households with selected demographic characteristics (e.g., household income) to the small areas using residential location models (Pagliara, Preston, and Simmonds (eds), 2010; Brail and Klosterman (eds), 2001). There are good examples. The DRAM-EMPAL was developed by Putman in 1971, and was widely applied to the metropolitan land use modeling in 1980s and 1990s (Putman, 2010).The households by different income category are allocated to small areas using the small area zone's attractiveness and transportation accessibility. Through this kind of modeling practice, households of different income category are projected as a result of land use and/or transportation investment policy options. The modeling tradition has been carried over to the newly available land use modeling practice (e.g., PECAS, UrbanSim, DELTA, MUSSA II,). The new modeling approach tends to assign households with more demographic characteristics to small area zones according to policy alternatives. For example, Urbansim produces the small area population size and the demographic characteristics of households by income, age of head, household size, presence of children, and housing type. PECAS also produces key demographic characteristics of households, including household income, household size, status of households as senior households (whether the household are composed of population of 65 years old or more). The modeling approach does not produce a comprehensive dataset, but a limited number of key demographic characteristics related to households. In order to produce additional demographic variables of population, the statistical approach would be needed.

The third approach is a statistical approach (Cho, 2006; Kanaroglou et al, 2009;Eluru et al, 2008). The typical modeling process is to allocate the projected large area (e.g., county or metropolitan area) population into the small area (e.g., census tract, or census block group). The commonly applicable method of developing the demographic components of the small area population in the top-down statistical approach is the multi-nomial logit regression method. The regression coefficients might be derived using the individual data set (Eluru et al, 2008) or aggregate zonal database (Cho, 2006; Kanaroglou et al, 2009). The historical databases are used to extrapolate the historical trend of the small area demographic characteristics (Cho, 2006). As a result of the top-down approach, the small area database becomes consistent with the large area's demographic pattern, and the small area population size, and also the historical pattern of the demographic characteristics. Although this top-down approach presents major strength in producing the consistent small area dataset, it would not reflect the comparable demographic characteristics of a certain area to be developed. For example, a transit-oriented development around the transportation station might result in the new residential and commercial development, and gentrification of replacing existing low income or ethnically minority residents with new middle income and professional job residents. The locally unique development related demographic changes are not properly reflected in the database. The alternative method in the top-down statistical approach is the locally weighted regression (LOESS), or LOWESS (locally weighted scatterplot smoothing). LOESS, originally proposed by Cleveland (1979) and further developed by Cleveland and Devlin

(1988). LOESS combines much of the simplicity of linear least squares regression with the flexibility of nonlinear regression. It does this by fitting simple models to localized subsets of the data to build up a function that describes the deterministic part of the variation in the data, point by point.
(http://www.itl.nist.gov/div898/handbook/pmd/section1/pmd144.htm)
Park (2009) produced the reasonable small area demographic characteristics (e.g., age and racial/ethnic composition) using LOESS. The model showed a high level of the goodness of fit by showing a high R-square, and the model results were successfully validated against the actual dataset. The initial application of this technique provides a potential for the future use and requires a further research.

Ⅲ. Modeling Framework

The following is a proposed modeling approach toward developing the long term projection of the key demographic characteristics (e.g., age, race/ethnicity) at the transportation analysis zone level (Figure 1). First, project the regional employment, population, and household growth using the employment, demographic, and household projections models. Second, allocate the regional housing and employment growth into the small area through the simple trend extrapolation, residential location model, or the envisioning process. For example, the envisioning process considers urban growth scenarios (e.g., urban concentrated, suburban sprawl) and/or alternative smart growth techniques (e.g., transit-oriented development, mixed use development, employment center development, etc). Third, convert the small area housing growth into population growth using the housing unit method. The conversion factors including the occupancy rate, household size, and the share of the group quarters population need to be fully analyzed. Fourth, disaggregate the small area population into their demographic characteristics using the multi-nomial logit regression method utilizing the past trend of those demographic components of population at the small area. The historical change in the pattern of age or ethnic compositions at the TAZ level plays a key role in determining the future patterns of TAZs. The preliminary model results are controlled to the region wide projection. At the end, we would be able to assess the spatial pattern of age and ethnic composition of the small area population using the dependency ratio or diversity index. We can use the projected age and racial/ethnic distribution for the environmental justice analysis as required by the regional transportation planning process. This study focuses on the fourth stage of projecting the small area demographic characteristics.



<Fig 1> A Modeling Framework for the Regional and Small Area Demographic Projections

This study presents a modeling process for the age and racial/ethnic composition of projected population at the transportation analysis. The more hierarchical zones would be a better option for developing more refined dataset due to increased possibility of incorporating the locally unique situation. A small area modeling approach in this study is based on two hierarchical zones (region and transportation analysis zone). This study focuses on how to disaggregate the small area population into their demographic characteristics. The proposed small area secondary variables allocation model (SASVAM) designed to produce secondary variables at TAZ contains four major feature.: (1) reflect the historical pattern of the target demographic characteristics, (2) control to TAZ population and County demographic characteristics, (3) maintain consistency among the projected demographic characteristics, (4) maintain the monotonous pattern of projected demographic characteristics. The key feature of the proposed small area forecasting model is to utilize the historical pattern of the target demographic characteristics of the populations, while controlling for the county pattern of demographic characteristics of population (Cho, 2006). The changed historical pattern of the target demographic characteristics is determined by aggregated individuals as probabilistic choice. For example, a small area with a rapid population aging in the past, then it tends to continue according to the projected county level aging pattern. This approach is similar to the synthetic technique in the demographic field, but has strength in reflecting the historical pattern of the small area as part of the modeling framework.

1. Data and Methods

The study area covers the whole Southern California Association of Governments(SCAG) region, comprised of six counties: Imperial, Los Angeles, Orange, Riverside, San Bernardino, and Ventura. The SCAG region encompasses 191 cities, nearly 39,000 square miles, and over 18 million people. SCAG is the largest of nearly 750 councils of governments (COG) in the United States in terms of land area and population, functioning as the Metropolitan Planning Organization (MPO) for Southern California. SCAG is mandated by the federal and state governments to develop regional plans for transportation, growth management, housing development, air quality and other issues of regional significance. The spatial unit of analysis in this study is primarily census tract (CT) for the statistical modeling and the transportation analysis zone (TAZ) for the model application. The current TAZ is developed using the 2000 Census Tract. Except for the outlying areas where the size of census tract is so large that it should be split into two or more TAZs. The size of TAZs is equivalent to that of census tracts. These TAZs are aggregated to 55 Regional Statistical Areas (RSAs) and 6

Counties.

A multi-nomial logistic regression model is used to estimate the changing composition of the age and racial/ethnic groups at the census tract level in Southern California six counties between 1990 and 2000. A multi-nomial logistic regression describes the relationship between a categorical multi-nomial response variables and a set of predictor variables (Menard, 2002; Pampel, 2000; Liao, 1994). The model estimates the distribution probability of a certain age group or racial/ethnic group in 2000 as a function of age, racial/ethnic group, and other socioeconomic factors in 1990. The probability is transformed to a logit form so that there is a linear relationship between independent variables and the dependent variable. The logits of the unknown multi-nomial probabilities (i.e., the logarithms of the odds) are presented in the following form.

$$\Pr ob(y=j) = \frac{e^{\sum_{k=1}^{k} \beta_{jk} x_k}}{1 + \sum_{j=1}^{J-1} e^{e^{\sum_{k=1}^{k} \beta_{jk} x_k}}}$$

Where

j= 1,2,3,⋯,j-1,

Prob (y=j) = distribution probability of a certain age group or racial/ethnic group in 2000,

χ_k = independent variables,

β_{jk} = estimated coefficients,

This study uses the 1990 and 2000 census data, Summary File 3 (SF3) and Census Transportation Planning Package (CTPP), which are collected for the census tract, taken from the sample, long-form questionnaires. 1990 census tract data was converted to 2000 census tract equivalent data using the land area method. First, the age composition of population in 2000 is determined by 1990 age composition of population and other related variables (see tables 1 and 2). The age group of population in 1990 and 2000 is categorized into seven (0-4, 5-15, 16, 17, 18-24, 25-64, 65+) as required by the transportation modeling process. The age groups of population in 1990 are processed as independent variables, while the age groups of population in 2000 are processed as dependent variables. The population of age 65+ in 2000 is treated as a reference dependent variable. Additional variables including 1990 Hispanic population, 1990 median household income, 1990 employment, 1990 population density per square mile are also added as independent variables due to its potentially significant influence on age composition of population in 2000. Second, the racial/ethnic composition of population in 2000 is determined by 1990 racial/ethnic composition of population in 1990 and other related variables (Table 1). The race/ethnicity of population in 1990 and 2000 is categorized into six (Hispanic, non-Hispanic White, non-Hispanic Black, non-Hispanic American Indian, non-Hispanic Asian, non-Hispanic Others), while treating non-Hispanic Other population in 2000 as a reference dependent variable. Additional variables including 1990 population of age 25-64, 1990 median household income, 1990 employment, 1990 population density per square mile are also added as independent variables due to its potentially significant influence on the racial/ethnic composition of population in 2000.

<Table 1> Description of Independent and Dependent Variables

Variable		Description
Dependent Variable		
1. seven age groups in 2000(a reference variable is an age group of 65 years or older 2. Six racial/ethnic groups in 2000 (a reference variable is a Non-Hispanic Others category)		Probability of a person to belong to one of seven age groups or one of six racial/ethnic groups in 2000
Independent Variable		
Age in 1990	Age0-4	Population of Age0-4
	Age5-15	Population of Age 5-15
	Age 16	Population of Age 16
	Age 17	Population of Age 17
	Age 18-24	Population of Age 18-24
	Age 25-64	Population of Age 25-64
	Age 65+	Population of Age 65+
Racial/ethnicity in 1990	Hispanic	Hispanic population
	Non-Hispanic White	Non-Hispanic White Population
	Non-Hispanic Black	Non-Hispanic Black Population
	Non-Hispanic American Indian	Non-Hispanic American Indian Population
	Non-Hispanic Asian	Non-Hispanic Asian Population

	Non-Hispanic Others	Non-Hispanic Other Population
Income in 1990	Median Household Income	Median Household Income
Employment in 1990	Employment	Number of jobs by place of work
Population density in 1990	Population density	Population per square mile

Source: US Census Bureau, 1990 and 2000 Census Summary File 3 and 1990 CTPP.

Ⅳ. Model Interpretation

1. Model Results

A multinomial logistic regression model of population by age group indicates that distribution probability of each age group in 2000 can be determined by the age distribution and other additional factors (Hispanic population, median household income, employment, population density) in 1990 (Table 2). The pseudo R-square of the estimated model is 0.283. The coefficients of most independent variables are significant for the estimation model for each age group. A multinomial logistic regression model of population by racial/ethnic group indicates that distribution probability of each racial/ethnic group in 2000 can be determined by the racial/ethnic distribution and other additional factors (population of age25-64, median household income, employment, population density) in 1990 (Table 3). The pseudo R-square of the estimated model is 0.44, higher than the age model. The coefficients of most independent variables are significant for the estimation model for each age group.

<Table 2> Results of a Multinomial Logistic Regression Model of Population by Age Group in 2000

Parameter	Age0_4		Age5_15		Age16		Age17		Age18_24		Age25_64	
	Coeff	S	Coeff	S	Coeff	S	Coeff	S	Coeff	S	Coeff	S
Intercept	-0.1216	***	0.6731	***	-1.9143	***	-1.8823	***	0.3568	***	1.5995	***
age0_4_90	0.0023	***	0.0018	***	0.0011	***	0.0011	***	0.0006	***	0.0008	***
age5_15_90	-0.0002	***	0.0003	***	0.0005	***	0.0004	***	0.0002	***	-0.0002	***
age16_90	-0.0006	***	-0.0001	***	0.0013	***	0.0012	***	0.0000	NS	-0.0006	***
age17_90	-0.0006	***	0.0000	NS	0.0011	***	0.0016	***	-0.0007	***	-0.0010	***
age18_24_90	0.0002	***	0.0001	***	0.0001	***	0.0002	***	0.0009	***	0.0003	***
age25_64_90	-0.0001	***	-0.0002	***	-0.0002	***	-0.0002	***	-0.0001	***	0.0001	***
age65_over_90	-0.0012	***	-0.0011	***	-0.0011	***	-0.0011	***	-0.0013	***	-0.0011	***
pop_his_90	0.0000	***	0.0000	***	0.0000	***	0.0000	***	0.0000	***	0.0000	**
median_ho_income_90	0.0000	***	0.0000	***	0.0000	***	0.0000	***	0.0000	***	0.0000	***
employment_90	0.0000	***	0.0000	***	0.0000	***	0.0000	NS	0.0000	***	0.0000	NS
density_p_90	0.0000	***	0.0000	***	0.0000	***	0.0000	***	0.0000	***	0.0000	***
-2 Log Likelihood Chi-S	628288.50											
DF	20000											
Pseudo R-Square	0.283											
Observations	3402											

Note: Coeff = Coefficient(βk: log-odds), S=Symbol, *** p<0.01, ** p<0.05, * p<0.01, NS = not significant

<Table 3> Results of a Multinomial Logistic Regression Model of Population by Race/Ethnicity in 2000

Parameter	Hispanic		NH White		NH Black		NH Indian		NH Asian	
	Coeff	S	Coeff	S	Coeff	S	Coeff	S	Coeff	S
Intercept	3.1999	***	2.6717	***	1.7284	***	-0.8733	***	0.8758	***
pop_his_90	0.0007	***	0.0000	***	0.0001	***	0.0003	***	0.0002	***
pop_white_nh_90	-0.0001	***	0.0002	***	-0.0002	***	0.0001	***	-0.0001	***
pop_black_nh_90	0.0000	***	-0.0005	***	0.0007	***	0.0001	***	-0.0004	***
pop_indian_nh_90	-0.0002	***	-0.0003	***	0.0000	NS	0.0037	***	-0.0025	***
pop_asian_nh_90	-0.0002	***	-0.0006	***	-0.0003	***	-0.0005	***	0.0010	***
pop_other_nh_90	-0.0004	***	-0.0006	***	0.0022	***	-0.0013	***	0.0001	NS
age25_64_90	-0.0003	***	-0.0002	***	0.0000	NS	-0.0002	***	-0.0002	***
median_ho_income_90	0.0000	***	0.0000	***	0.0000	***	0.0000	***	0.0000	***
employment_90	0.0000	***	0.0000	***	0.0000	***	0.0000	***	0.0000	***
density_p_90	0.0000	***	0.0000	***	0.0000	***	0.0000	***	0.0000	**
-2 Log Likelihood Chi-Sc	2291666.00									
DF	20000									
Pseudo R-Square	0.4407									
Observations	3402									

Note: Coeff = Coefficient(βk: log-odds), S=Symbol, *** p<0.01, ** p<0.05, * p<0.01, NS = not significant

2. Model Application

The study uses a draft regional growth forecast for analysis purpose. A draft regional growth forecast was prepared for policy and planning analysis in February 2010. The draft regional growth forecast is a future snapshot of the most likely population and employment distribution without regional policy input. It reflects historical trends, based on reasonable key technical assumptions and existing and newly approved local or regional projects. According to the draft regional growth forecast (Table 4), the region will add 4.4 million people to reach nearly 23 million people by 2035. Supporting this population in 2035 will be a total of 9.8 million jobs in 2035 with 2 million new jobs. This level of population and job growth is expected to yield 1.5 million additional households in the region at an average of three persons per household.

<Table 4> The Draft Regional Growth Forecast, 2008-2035

(Unit: Thousands)

	2008	2035	Change	% Change, 2008-2035
Population	18,622	23,005	4,383	24%
Households	5,865	7,346	1,481	25%
Employment	7,740	9,754	2,014	26%

Source: SCAG, Draft Growth Forecast, February 2010.

Two growth scenarios are developed to allocate the regional growth into TAZs. The first scenario is a local input scenario, which represents the most likely growth and growth distribution of the region in the absence of the explicit regional policies. The existing local policies including zoning and general plan are reflected in growth d Source: SCAG, Draft Growth Forecast, February 2010.
istribution. The most up-to-date local input forms the foundation of the local input scenario. The second scenario is a preferred plan scenario, which reflects a combination of the following TOD and Centers strategy increasing in housing capacity. The TOD strategy resulted from assigning greater capacity to areas around transit stations. The Center strategy resulted from assigning greater capacity to areas in and around regionally significant employment centers.

The local input scenario and the preferred plan scenario produce a different set of growth distributions, while maintaining the regional control. The TAZ distribution of 2035 population and households of two growth scenarios was analyzed using the mean absolute percentage error (MAPE) (Table 5). The overall discrepancy of the region-wide population and household distributions between two growth scenarios is 65% and 74%, respectively. There is a significant change in population and household distribution among TAZs in the SCAG Region. TAZs in the Ventura County show the most discrepancy, while TAZs in the Los Angeles County shows the smallest discrepancy, in the SCAG region.

A similar approach was applied to age variables. 2035 TAZ population by age group was derived using the coefficients of the previous multi-nomial logit regression model. The total population of each age group was transformed into the relative percentage of each age group of population within TAZ for a fair comparison of two growth scenarios. The percent distribution of 2035 age groups of two growth scenarios at TAZ level was analyzed using the mean absolute percentage error (MAPE) (Table 5). The overall discrepancy of the region-wide age group distributions between two growth scenarios is low, ranging from 1.5% for age25-64 to 4.7% for age16. TAZs in the Riverside County generally show the most discrepancy, while TAZs in the Orange County shows the smallest discrepancy in the SCAG region.

<Table 5> Comparison of Model Results of Two Growth Scenarios Using the Mean Absolute Percentage Error (MAPE)

Country	Imperial	Los Angeles	Orange	Riverside	San Bernardino	Ventura	SCAG
Observations	110	2,244	666	478	402	210	4,110
Households	81.3%	25.9%	54.0%	79.1%	251.2%	301.5%	74.3%
Population	85.0%	26.2%	48.2%	75.6%	190.7%	259.7%	65.1%
age0_4	18.0%	2.8%	2.6%	5.8%	4.8%	3.7%	3.8%
age5_15	7.9%	2.8%	1.6%	5.9%	4.0%	2.8%	3.2%
age16	8.7%	4.9%	3.3%	10.5%	5.6%	4.1%	5.4%
age17	8.0%	4.7%	2.6%	10.5%	5.7%	4.5%	5.2%
age18_24	5.1%	2.6%	2.3%	6.0%	4.4%	2.8%	3.2%
age25_64	1.4%	0.9%	0.5%	5.0%	2.4%	1.5%	1.5%
age65_over	6.3%	2.6%	2.7%	13.9%	7.9%	4.7%	4.7%
pop_his	3.6%	3.8%	3.7%	7.4%	5.6%	3.8%	4.4%
pop_white_nh	14.2%	8.9%	6.0%	12.9%	13.9%	5.8%	9.4%

pop_black_nh	29.1%	13.7%	17.1%	15.1%	11.1%	20.7%	14.9%
pop_indian_nh	16.7%	26.3%	9.7%	26.3%	17.0%	13.9%	21.8%
pop_asian_nh	37.9%	9.8%	13.9%	20.6%	20.7%	12.2%	13.6%
pop_other_nh	20.7%	18.0%	26.4%	18.0%	12.8%	10.5%	18.5%

Note: * externally developed

The analysis of age distribution can be extended by using the dependency ratio, which requires only three different age groups for calculation. We use three age groups of 0-15, 16-64, 65+ for the analysis. There are three dependency ratios: the general dependency ratio (sum of age 0-15 and 65+ divided by age 16-64, then multiplied by 100), the youth dependency ratio (age 0-15 divided by age 16-64, then multiplied by 100), and the elderly dependency ratio (age 65+ divided by age 16-64, then multiplied by 100). When we aggregate the TAZ based dependency ratios to RSA level, we generally had a larger difference in three dependency ratios between the local input scenario and the preferred plan scenario than the RSA based difference (Table 6). The margin of absolute percentage error (MAPE) of the general, youth, and elderly dependency ratios for the RSA level (aggregated from TAZ MAPEs) range from 0% to 19.6% (median: 2.7%), 0.4% to 17% (median 3.5%), 0.7% to 32.6% (median 5.2%), respectively. The elderly dependency ratio shows much bigger variation than that of the youth dependency ratio. The bigger variation occurs in some RSAs (e.g., RSAs 33, 48, 50, 52, 53, 54, 55, 56) of Riverside and San Bernardino Counties.

Like age variables analysis, the total population of each racial/ethnic group was transformed into the relative percentage of each racial/ethnic group of population within TAZ for a fair comparison of two growth scenarios. The percent distribution of 2035 racial/ethnic groups of two growth scenarios at TAZ level was analyzed using the mean absolute percentage error (MAPE) (Table 6). The overall discrepancy of the region-wide racial/ethnic group distributions between two growth scenarios is higher than that of age variables, ranging from 4.4% for Hispanic population to 21.8% for Non-Hispanic Indian population. Although there is no clear general tendency, TAZs in the Imperial County show the most discrepancy in the racial/ethnic categories, while TAZs in the Ventura County show the smallest discrepancy in the SCAG region.

The analysis of racial/ethnic distribution can be conducted by using the entropy index, which measures the diversity of race/ethnic groups. We use four racial/ethnic groups of Non-Hispanic White, Non-Hispanic Black, Non-Hispanic Asian & Others and Hispanic groups The entropy index (unnormalized & normalized) can be computed using the following formula (Plane & Rogerson, 1994, p.302):

The unnormalized entropy index:

$$H = -\sum_{k=1}^{n}[(P_k / P)\ln(P_k / P)]$$

Where

n=number of racial/ethnic groups,

P_k =populationofthekthracial/ethnicgroup,

P= total population

The normalized entropy index shows the range of all values from 0 to 1. The formula is

$$H^* = H / \ln n$$

When we aggregate the TAZ based dependency ratios to RSA level, we generally had a larger difference in three dependency ratios between the local input scenario and the preferred plan scenario than the RSA based difference (Table 7). The margin of absolute percentage error (MAPE) of the unnormalzied entropy index and the normalized entropy index for the RSA level (aggregated from TAZ MAPEs) range from 0.8% to 17.4% (median: 2.9%) and 0.8% to 20.3% (median 3.1%), respectively. Two RSAs (6 in Ventura County and 53 in Riverside County) show higher MAPEs of the entropy index.

In summary, age variables maintain a relatively low variation in the difference of the age distribution between two growth scenarios. They still tend to show a noticeable gap in the difference of the age distribution between two growth scenarios among six counties in the SCAG region. Race/ethnicity variables tend to show a relatively high variation in the difference of the racial/ethnic distribution between two growth scenarios. They also show a noticeable gap in the difference of the racial/ethnic distribution between two growth scenarios among six counties in the SCAG region. It should be noted that the more refined analysis might be needed due to availability of many TAZs with small population and household figures. The presence of many such TAZs might skew the summary error statistics.

V. Conclusions

The small area population projections are important in understanding the diverse community service needs of the future. Although the population size of the small area might be a useful indicator for measuring the community needs, the detailed demographic projections, if available, would be able to more accurately estimate the community service needs. This study presents a coherent modeling framework and a statistical approach for projecting the population size and demographic characteristics of the small area within the metropolitan planning context.

First, the popular cohort-component method is not easily applicable to population projections of small area (e.g., census tract or transportation analysis zone) for a couple of reasons: (1) the historical and current trends in vital statistics and migration of the small areas are not easily available; (2) it is difficult to independently develop reasonable migration assumptions of small areas. However, housing development and assumptions are easily available from the building permit pattern and land use assumptions from the local general plan or the alternative scenarios. A reasonable approach is to derive population projections of local communities through the enhanced linkage of small area housing growth and regional demographic processes. If this framework is accepted, then the small area population and demographic projections can be derived using both the demographic process at the large area level and the availability of housing at the small area level.

Second, this study proposes a statistical multi-nomial logit regression method to develop more detailed demographic characteristics of projected population at the TAZ level. The presented regression approach showed several advantages in terms of maintaining a consistency with the large area's demographic pattern, and the small area population size, and also the historical pattern of the demographic characteristics of the large area. Through the comparison analysis of mean absolute percentage error of age and racial/ethnic distribution for two different growth scenarios, the presented regression

<Table 6> Comparison of Age Distribution of Two Growth Scenarios Using the Dependency Ratio

county	rsa	taz(n)	Dependency Ratio			Youth Dependency Ratio			Elderly Dependency Ratio		
			local	preferred	mape	local	preferred	mape	local	preferred	mape
Imperial	55	110	52.4	53.5	6.8	28.1	28.2	11.1	24.3	25.3	8.4
Los Angeles	0	1	59.5	59.5	0.0	36.1	35.9	0.4	23.5	23.6	0.7
Los Angeles	7	12	59.4	58.3	2.2	30.4	31.2	3.0	29.0	27.1	8.6
Los Angeles	8	56	56.1	57.4	4.8	35.6	35.8	17.0	20.6	21.5	7.2
Los Angeles	9	67	73.9	75.1	5.7	37.1	37.6	7.5	36.8	37.5	8.2
Los Angeles	10	45	65.0	65.8	4.0	41.9	42.5	6.0	23.1	23.3	4.8
Los Angeles	11	4	70.1	63.9	11.8	29.9	29.0	10.7	40.3	34.8	13.3
Los Angeles	12	173	59.3	59.6	0.8	31.1	31.2	1.3	28.2	28.3	2.0
Los Angeles	13	75	54.7	54.7	0.6	28.9	29.0	0.7	25.8	25.8	1.5
Los Angeles	14	83	60.9	61.1	0.4	35.6	35.5	0.4	25.3	25.5	1.3
Los Angeles	15	6	53.0	48.2	11.5	23.4	20.4	15.7	29.7	27.8	9.2
Los Angeles	16	89	50.9	51.4	1.5	19.6	19.8	3.9	31.4	31.6	1.8
Los Angeles	17	279	56.7	56.1	1.9	28.5	28.9	3.0	28.1	27.3	3.1
Los Angeles	18	135	56.2	56.1	1.0	32.4	32.5	1.9	23.8	23.6	3.3
Los Angeles	19	112	66.1	66.2	0.6	32.6	32.5	0.8	33.4	33.7	1.8
Los Angeles	20	124	62.2	62.2	1.2	35.3	35.3	12.8	26.9	26.9	2.6
Los Angeles	21	263	66.0	66.1	1.2	47.5	47.3	1.4	18.5	18.8	3.4
Los Angeles	22	148	64.0	64.3	0.7	37.2	37.2	0.7	26.8	27.1	1.5
Los Angeles	23	48	57.5	55.3	4.8	31.7	32.3	4.8	25.8	22.9	10.2
Los Angeles	24	121	59.1	59.2	0.6	31.1	31.1	0.7	28.0	28.1	1.4
Los Angeles	25	180	64.6	64.4	1.0	30.8	30.7	1.2	33.8	33.7	2.0
Los Angeles	26	152	62.5	62.2	2.1	35.7	35.7	1.5	26.8	26.5	3.5
Los Angeles	27	45	63.9	63.5	2.7	36.9	36.1	3.7	27.0	27.4	3.5
Orange	35	37	66.1	66.2	0.5	34.7	34.4	1.1	31.4	31.8	1.9
Orange	36	54	69.9	69.9	1.0	35.1	34.8	1.4	34.7	35.1	2.4
Orange	37	90	65.4	65.5	1.0	39.5	39.4	2.3	25.8	26.1	2.9
Orange	38	85	96.1	96.9	0.8	28.4	28.0	2.1	67.7	68.9	2.6
Orange	39	65	59.4	59.5	1.2	26.2	25.7	2.6	33.2	33.8	2.4
Orange	40	65	110.1	109.4	1.2	29.9	29.6	1.8	80.2	79.9	2.4
Orange	41	53	59.8	60.0	1.9	34.9	34.7	1.5	24.9	25.2	5.2
Orange	42	106	64.4	64.6	0.9	40.9	40.7	1.4	23.5	24.0	3.0
Orange	43	58	65.4	64.9	1.2	38.0	37.5	1.6	27.4	27.4	2.8
Orange	44	40	66.9	65.5	2.9	36.2	37.1	6.3	30.7	28.4	6.9
Riverside	45	26	54.4	59.2	8.9	35.5	37.3	5.3	18.8	21.9	16.7
Riverside	46	152	51.7	56.0	9.4	34.1	35.6	6.3	17.7	20.4	20.1
Riverside	47	50	83.6	87.8	8.8	33.3	35.1	8.4	50.3	52.6	13.9
Riverside	48	38	110.0	113.5	13.4	32.0	33.7	5.6	78.0	79.8	19.3
Riverside	49	57	58.8	63.0	7.9	34.7	36.1	4.9	24.1	26.9	14.5
Riverside	50	22	94.0	88.1	12.0	31.1	32.4	5.2	62.9	55.7	17.7
Riverside	51	4	61.0	66.7	9.1	27.0	28.4	5.2	34.0	38.3	12.7
Riverside	52	73	82.9	92.2	13.6	26.0	26.8	6.4	56.9	65.4	19.9
Riverside	53	37	72.9	71.6	12.5	41.6	41.0	9.0	31.4	30.6	17.1
Riverside	54	11	49.7	51.3	16.4	29.6	28.9	12.9	20.1	22.4	21.1
Riverside	56	2	59.5	69.2	16.3	30.3	31.5	3.9	29.2	37.7	29.3
San Bernardino	28	139	56.2	57.1	4.4	37.1	37.1	4.4	19.1	20.0	10.9
San Bernardino	29	116	64.5	63.8	2.9	39.8	39.1	3.3	24.7	24.7	6.9
San Bernardino	30	21	59.7	59.6	1.7	30.5	30.2	2.2	29.2	29.3	3.9
San Bernardino	31	9	48.3	48.8	4.4	35.1	34.2	4.6	13.2	14.6	17.9
San Bernardino	32	90	69.3	69.6	3.0	37.3	37.2	3.5	32.0	32.5	5.8
San Bernardino	33	17	79.0	97.7	19.6	32.0	29.7	9.9	47.0	68.1	32.6
San Bernardino	34	5	74.0	77.3	5.4	27.5	26.7	3.6	46.5	50.6	10.3
Ventura	1	1	70.6	71.1	0.6	30.3	28.9	4.5	40.3	42.1	4.4
Ventura	2	51	77.8	78.4	3.8	33.2	33.3	6.6	44.7	45.0	3.5
Ventura	3	69	74.1	76.2	5.2	36.7	37.5	3.3	37.4	38.7	8.3
Ventura	4	41	57.9	58.6	2.2	34.9	34.7	1.4	23.0	23.9	6.2
Ventura	5	38	63.7	63.6	2.0	29.7	29.7	2.4	34.0	33.9	3.1
Ventura	6	8	83.7	84.0	3.2	47.0	47.1	1.6	36.7	36.9	7.7
Imperial	25	110	52.4	53.5	6.8	28.1	28.2	11.1	24.3	25.3	8.4
Los Angeles	37	2218	61.1	61.1	1.6	34.0	34.1	3.0	27.1	27.0	3.0
Orange	59	653	73.2	73.2	1.1	34.7	34.4	2.1	38.5	38.8	3.1
Riverside	65	472	69.4	73.5	10.7	33.0	34.2	6.5	36.4	39.2	18.1
San Bernardino	71	397	62.8	63.8	4.1	37.2	36.8	4.0	25.6	26.9	9.2
Ventura	111	208	70.0	71.0	3.6	34.5	34.8	3.5	35.5	36.2	5.7
SCAG Region		4058	64.4	65.0	3.1	34.2	34.3	3.6	30.2	30.7	5.7

<Table 7> Comparison of Racial/Ethnic Distribution of Two Growth Scenarios Using the Entropy Index

county	rsa	taz (n)	Entropy Index (unnormalized)			Entropy Index (normalized)		
			local	preferred	mape	local	preferred	mape
Imperial	55	103	0.708	0.705	8.5	0.511	0.508	10.8
Los Angeles	0	1	0.871	0.857	1.6	0.628	0.618	1.7
Los Angeles	7	12	0.797	0.842	6.0	0.575	0.607	5.2
Los Angeles	8	55	1.030	1.019	2.5	0.743	0.735	2.6
Los Angeles	9	62	1.118	1.100	2.7	0.806	0.794	2.9
Los Angeles	10	44	1.014	0.993	3.7	0.731	0.716	3.8
Los Angeles	11	4	1.065	1.025	3.9	0.768	0.739	4.1
Los Angeles	12	173	0.944	0.937	1.8	0.681	0.676	1.8
Los Angeles	13	75	0.896	0.888	1.8	0.646	0.640	1.8
Los Angeles	14	83	0.756	0.747	2.4	0.546	0.539	2.5
Los Angeles	15	6	0.835	0.907	8.7	0.602	0.654	7.7
Los Angeles	16	89	1.001	0.993	1.2	0.722	0.716	1.2
Los Angeles	17	276	0.857	0.857	3.0	0.618	0.618	3.0
Los Angeles	18	135	0.916	0.903	2.9	0.661	0.651	3.1
Los Angeles	19	111	0.916	0.906	2.2	0.661	0.654	2.4
Los Angeles	20	122	1.038	1.030	1.6	0.749	0.743	1.6
Los Angeles	21	260	0.373	0.363	6.5	0.269	0.262	7.2
Los Angeles	22	148	0.763	0.747	2.9	0.551	0.539	3.1
Los Angeles	23	48	0.672	0.667	5.2	0.485	0.481	5.7
Los Angeles	24	121	0.843	0.839	2.2	0.608	0.605	2.2
Los Angeles	25	178	0.909	0.902	2.1	0.655	0.651	2.1
Los Angeles	26	148	0.828	0.807	3.9	0.597	0.582	4.3
Los Angeles	27	45	0.872	0.853	4.2	0.629	0.615	5.0
Orange	35	37	1.046	1.040	1.6	0.754	0.750	1.6
Orange	36	53	0.872	0.864	2.2	0.629	0.623	2.2
Orange	37	89	0.820	0.807	3.4	0.592	0.582	3.4
Orange	38	84	1.019	1.025	1.5	0.735	0.739	1.4
Orange	39	63	0.927	0.922	2.4	0.669	0.665	2.7
Orange	40	64	0.965	0.965	1.9	0.696	0.696	1.9
Orange	41	52	1.041	1.025	2.2	0.751	0.739	3.5
Orange	42	104	0.666	0.651	4.1	0.481	0.470	5.0
Orange	43	57	1.041	1.039	0.8	0.751	0.749	0.8
Orange	44	35	1.006	1.002	3.7	0.726	0.723	3.6
Riverside	45	26	0.963	0.973	2.7	0.694	0.702	2.7
Riverside	46	150	1.048	1.064	5.4	0.756	0.768	4.7
Riverside	47	50	1.023	1.037	5.3	0.738	0.748	5.2
Riverside	48	38	1.002	1.022	4.1	0.723	0.737	3.9
Riverside	49	57	1.078	1.074	2.7	0.777	0.775	2.7
Riverside	50	22	1.075	1.100	4.9	0.775	0.793	4.7
Riverside	51	4	1.043	1.066	2.2	0.753	0.769	2.2
Riverside	52	73	0.924	0.939	6.5	0.667	0.677	6.1
Riverside	53	37	0.625	0.630	17.4	0.451	0.454	20.3
Riverside	54	11	1.034	1.021	5.2	0.746	0.736	6.1
Riverside	56	2	1.031	1.093	6.1	0.744	0.788	5.7
San Bernardino	28	137	0.969	0.974	4.2	0.699	0.702	4.0
San Bernardino	29	115	0.990	0.988	4.4	0.714	0.713	4.4
San Bernardino	30	21	1.083	1.090	2.0	0.782	0.786	2.0
San Bernardino	31	9	1.265	1.273	0.9	0.912	0.918	0.8
San Bernardino	32	89	1.096	1.091	3.8	0.791	0.787	4.0
San Bernardino	33	16	1.103	1.117	2.8	0.796	0.806	2.8
San Bernardino	34	5	1.068	1.041	2.6	0.771	0.751	2.8
Ventura	1	1	0.927	0.968	4.5	0.668	0.698	4.3
Ventura	2	46	0.815	0.824	4.2	0.588	0.594	4.3
Ventura	3	65	0.750	0.751	2.9	0.541	0.542	3.0
Ventura	4	40	0.942	0.931	2.0	0.680	0.671	2.1
Ventura	5	38	0.825	0.822	2.1	0.595	0.593	2.1
Ventura	6	7	0.564	0.601	14.5	0.407	0.433	12.9
Imperial	25	103	0.708	0.705	8.5	0.511	0.508	10.8
Los Angeles	37	2196	0.833	0.824	3.1	0.601	0.594	3.3
Orange	59	638	0.912	0.905	2.5	0.658	0.653	2.8
Riverside	65	470	0.989	1.001	5.9	0.713	0.722	5.8
San Bernardino	71	392	1.023	1.024	3.9	0.738	0.739	3.9
Ventura	111	197	0.813	0.814	3.3	0.586	0.587	3.3
SCAG Region		3996	0.878	0.874	3.5	0.633	0.630	3.7

method is found to produce the low variation in the age distribution and the moderate variation in the racial/ethnic distribution. Overall the study finds the proposed method as reasonable, and suggests that the approach might need to be further enhanced to minimize the variation in the age and racial/ethnic distribution

Finally, the presented approach basically assumes that the community tends to maintain the community's existing nature during the projection period. Therefore, the presented regress approach may not properly reflect the newly emerging demographic attributes of projected local population as a result of urban development. The presented approach may not model the implication of urban infill development: gentrification, and the related demographic change from low-middle income to middle-high income. Probably the specially designed modeling approach might be needed to identify the emerging demographic changes of projected population associated with the specific development activity (e.g., TOD).

<References>

Brail, Richard K., R.E. Klosterman (eds). (2001). *Planning Support Systems.* Redlands, California: ESRI.

Eluru, Naveen, A. Pinjari, J. Guo, I. Sener, S. Srinivasan, R. Copperman, C. Bhat. (2008). Population Updating System Structures and Models Embedded in the Comprehensive Econometric Microsimulator for Urban Systems. *Transportation Research Record.* 2076: 171-182.

Field, Brian., B. MacGregor, (1987). *Forecasting Techniques for Urban and Regional Planning*. London: UCL Press

Hopkins, Lewis D., M.A. Zapata. (eds.). (2007). *Engaging the Future - Forecasts, Scenarios, Plans, and Projects.* Cambridge, Massachusetts: Lincoln Institute of Land Policy.

Kanaroglou, P.S., H.F.Maoh, B. Newbold, D.M. Scott, A. Paez. (2009). A Demographic Model for Small Area Population Projections: an Application to the Census Metropolitan Area of Hamilton in Ontario, Canada. *Environment and Planning A,* 41, 964-979.

Klosterman, Richard E. (1990). *Community and Analysis Planning Techniques.* Rowmand and Littlefield Publishers, Inc. Savage, Maryland. See chapter 4-8.

Liao, Tim Futing. (1994). *Interpreting Probability Models: Logit, Probit, and*

Other Genralized Linear Models. (Sage University Paper Series on Quantitative Applications in the Socia lSciences, Series no. 07-101). Thousand Oaks, CA: Sage.

Lowry, Ira S. (1964). A Model of Metropolis RAND Memorandum 4025-RC.

Menard, Scott. (2002). *Applied Logistic Regression Analysis. Second Edition.* (Sage University Paper Series on Quantitative Applications in the Social Sciences, Series no. 07-106). Thousand Oaks, CA: Sage.

Park, Heonsoo. (2009). Advanced Programming Support for Developing Traffic Analysis Zone (TAZ)/Grid Cell Socio-economic Data and Assessing Selected Small Area Al-location Models for Southern California Association of Governments (unpublished).

Pampel, Fred. C. (2000). *Logistic Regression: A Primer.* (Sage University Paper Series on Quantitative Applications in the Social Sciences, Series no. 07-106). Thousand Oaks, CA: Sage.

Pitkin, John and D. Myers. (2011). A Period Summary Measure of Immigrant Advancement, *Demographic Research.* 24: 257-92.
(http://www.demographic-research.org/volumes/vol24/12/)

Pagliara, Francesca, J. Preston, and D. Simmonds (eds). (2010) *Residential Location Choice: Models and Applications.* Heidelberg: Springer.

Plane, David., P.A. Rogerson. (1994). *The Geographical Analysis of Population: With Applications to Planning and Business.* New York: John Wiley & Sons

Putman, Stephen H. (2010). *DRAM Residential Location and Land Use Model: 40 Years of Development and Application, in Residential Location Choice: Models and Applications, Pagliara, Francesca, J. Preston, and D. Simmonds (eds).* Heidelberg: Springer.

Rees, P., P. Norman, D. Brown. (2004). A framework for progressively improving small area population estimates, *Journal of Royal Statistical Society A.* 167(1): 5-36

Simpson, L., M. Tranmer. (2005). Combining sample and census data in small area estimates: iterative proportional fitting with standard software, *The Professional Geographer.* 57: 222- 234.

Smith, Stanley K., B.B. Lewis. (1983). Some New Techniques for Applying the Housing Unit Method of Local Population Estimation: Further Evidence, *Demography.* Vol. 20 No. 3: 407-413.
(http://www.bebr.ufl.edu/files/1983%20Demog%20 (Further%20Evidence).pdf)

Smith, Stanley K., J. Tayman, D. A. Swanson. (2001). *State and Local Population Projections: Methodology and Analysis.* New York: Kluwer Academic/Plenum Publishers.

Southern California Association of Governments (SCAG). (2008). *2008 Regional Transportation Plan: Making the Connection,* Growth Forecast Report. (http://www.scag.ca.gov/rtp2008/pdfs/finalrtp/reports/fGrowthForecast.pdf).

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