Modeling and Forecasting Household Workers by Occupation in Metropolitan Areas- A Mesoscopic Framework

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Abstract

The need for activity based models to provide micro, disaggregate simulations of travel patterns have become increasingly important to understand the complexity involved with travel behavior. Traveler occupation is one of the factors that are determinative of a trip end. To fully model how travel behavior will be influenced in the future, it is imperative to be able to estimate future occupation. The current literature does not provide suitable methods to model and forecast occupation. Two methods have primarily been used in the past to model occupation; the cohort-component method or a population synthesizing approach. The cohort-component method requires a significant amount of detailed birth, aging, death and migration information and the results obtained are at an aggregate geographic level. Such data at larger geographies (macro level) may not be suitable for advanced travel demand modeling purposes. Occupation synthesizers are used to obtain individual information at any geographic level (micro-level), but suffer from a limitation of evolution of occupation over time while considering other depend variables such as employment, and other household characteristics.

In this paper, the authors propose a mesoscopic approach where occupation by employment type evolves over a time period using a logistic regression technique. Five types of occupation: management, sales, service, other and unemployed is modeled. The methodology is presented in three steps: coefficient estimation, forecast and validation. First, the occupation evolution trend from 1990 to 2000 is analyzed. The estimation result is applied to forecast 2010 and 2030 occupation composition. This evolutionary model is applied to the Baltimore Metropolitan Council (BMC) region based on 1990 and 2000 Census data then validated with 2010 Census data. The results show that the proposed model produces a forecast that reliable and accurate. The important insights gained from this study are: (1) this model provides a good estimation and forecast for management, sales and unemployment; (2) service and other occupation prove less predictable as evolution trends among these groups are not consistent over time. The proposed tool can be adapted for use by small and large scale planning agencies to prepare detailed socio-economic and demographic profiles for input data into a population synthesizer or activity based model.

Key words: occupation, cohort component method, population synthesizer, logistic regression, mesoscopic approach

Introduction

Activity Based Models (ABM) have increasingly been developed and applied by a number of agencies including state Departments of Transportation (DOTs), and Metropolitan Planning Organizations (MPOs). ABMs recognize individual trips are not a series of unlinked excursions, but are a chain of connected events motivated by the desire to pursue activities distributed in space and time. ABMs need a significant amount of socio-economic disaggregate data such age, gender, occupation and employment along with other supply (car ownership, housing characteristics, land use characteristics) and demand data (activity opportunities, networks of spatial and non-spatial activities). While significant research has been done on forecasting data related to many needed model inputs, there is a substantial gap in in the ability to forecast occupation.

The Bureau of Labor Statistics (BLS) provides occupation and a variety of related employment information. Occupation projections developed by BLS are used to estimate long-term employment patterns within the US economy. In general, these projections encompass the future size and composition of the labor force, aggregate economic growth and provide detailed estimates of industry production and occupational employment. The resulting data serve a variety of users who need information about expected patterns of economic growth and the effects these patterns could have on employment. In addition, policymakers and community planners who need information for long-term policy planning purposes make use of BLS employment projections. The data is also used by states in preparing state and local area projections. The Bureau of Economic Analysis (BEA) also provides information on occupation by industry with greater detail on occupations not covered by BLS figures and more source data to capture self-employed workers. For travel demand forecasting, occupation is an important factor associated with income level, commute activities, working destination, and flexibility of employment hours, etc. Therefore, it is critical to include occupation as a parameter in travel demand and planning models.

Occupation projections from sources like BLS or BEA while providing important information on past employment tends, does not provide a source of data that can be readily used in ABMs. There are several reasons for this limitation. First, procedures have centered on projections of an inter-industry, or input–output, models that determine job requirements associated with production needs at the state or county level, but ignore detailed information at a much more local level. Second, occupation data at a larger geography (macro level) are not suitable for advanced travel demand modeling purposes. Third, if procedures such as Iterative Proportional Fitting (IPF), are used to disaggregate occupation data from national sources to a micro level the evolution of various input data such as population age and land use change will not be captured. To address the limitations of macro and micro level occupation forecasts and the need for detailed occupation data for travel demand modeling purposes, we propose a meso-level modeling framework which can be used (1) to obtain control variables at the travel analysis zone level which is suitable for a population synthesis, and (2) to capture historical evolution of socio-economic and demographic characteristics and incorporate these trends into an employment projections.

The paper is organized as follows. In the following section we discuss literature related to occupation synthesis, evolution and occupation projection. The methodology section discusses steps for coefficient estimation, forecasting and validation followed but a discussion of data used in this study related to past and current occupation composition. The results section provides details on the model outcomes and performance. Finally, summary and conclusions of the paper are discussed.

Past Research on Forecasting Occupation

The vast majority of transportation demand models rely on the traditional four-step method. There are a number of benefits associated with the use of these models, not the least of which is the very aggregate level socio-economic data needed to drive the model. Typically these models rely on an activity system at the transportation analysis zone (TAZ) level that provides a static forecast of total employment, sometimes by a few sectors *(1)*. However the ease of data collection that comes with the four-step model also represents a trade-off of accuracy and model output detail. A newer generation of disaggregate models has emerged to address the issues that take a much finer grain detailed approach to the activity system. These models focus on individuals in the study area rather than a zonal structure *(2)*. This transition to disaggregate models requires a much more intensive data collection; but has significant benefits for travel forecasting.

An important component of the detailed data needed for these disaggregate models is worker occupation. Employment plays a large role in generation the amount and location of travel demand *(3)*. Along with household location, employment location choice (and type of occupation) heavily influence the amount of type of transportation individuals choose *(4)*. Many scholars have found that employment tends to have a significant influence on both mode choice *(5)* as well as the amount of miles drivers travel *(6)*.

Other population updating methods have been developed in the travel demand forecasting community with varying levels of detail and sophistication, including Micro-analytic Integrated Demographic Accounting System (MIDAS) proposed by Goulias and Kitamura (1996) and the Micro-Analytical Simulation of Transport Employment and Residences (MASTER) recommended by Mackett (1990). Certain aspects of the population evolution processes, such as residential relocations and automobile ownership are focused on land-use transportation modeling systems, including TRANUS (Barra, 1989), MEPLAN (Hunt, 1993), URBANSIM (Waddell, 2002), STEP2 (Caliper Corporation, 2003), ILUTE (Miller et al., 2004), PECAS (Hunt et al., 2011), and PopGen (Pendyala et al., 2011).

Rather than simply projecting future zonal population and employment, a simulation method, that mirrors the natural evolution of population by age cohort is employed to predict future population at the individual level *(7, 8)*. Most of these simulation methods and many others focus almost entirely on simulating future population *(9–11)* or households *(12)*. An important component missing from simulation based modeling structures used to develop inputs to ABM models is tools to forecast future occupation. Employment and more specifically, the type of occupation a household member engaged in is a critical component of the activity system. Occupation plays a significant role in determining how an individual conducts their daily activities *(13)*.

Methods that produce micro-simulations of population and households are limited but growing; tools to simulation occupation are much more esoteric but none-the-less important.

Attempts at simulating the labor market and occupations of have been made in the past, but they rely on vast amounts of data have produce aggregate results *(14)*. In other cases, the data requirement has been reduced but use an Iterative Proportional Fitting (IPF) method which ignores the temporal or evolutionary aspect of the changing labor market *(15)*. In this paper we propose a logistic regression model that synthesizes the evolution of occupations in the study area over multiple periods of time.

Methodology

The modeling framework in this research is shown in Figure 1. The methodology in this study consists of three steps: estimation, forecast and validation.

Coefficient Estimation

The first step is coefficient estimation using variables corresponding to historical occupation and other secondary variables, such as household size, income, workers, and zone characteristics for further support. The methodology in this process is the multinomial logistic regression model. To predict the future occupation distribution by various socio-economic and demographic characteristics in each TAZ, the distribution data for two lag years, 1990 and 2000, in these zones is required. The impact of historic occupation (1990) on future occupation (2000) is examined and the evolutionary trend is captured, simplifying the forecasting process by allowing for the omission of detailed birth, death and migration. The probability of each occupation in the base year 2000 (π_{j_00}) is dependent on population occupation in the lag year 1990 following the formulation below.

$$\frac{\pi_{j\_00}}{\pi_{5\_00}} = exp\left(X\beta_j\right),\ j = 1, 2, \dots, 5. \tag{1}$$

where $j = 1$ for *manufacturing;* $j = 2$ for *sales;* $j = 3$ for *service;* $j = 4$ for *other;* $j = 5$ for *unemployed*.

Forecast

The second step uses the estimation result $\widehat{\beta_j}, j = 1, 2, \dots, 6, 5$ from step 1 as the growth trend and 2000 census data as the base year input X_{00} to forecast the occupation in 2030. This step assumes that the future evolution trend from 2000 to 2030 is consistent with the trend from 1990 to 2000. The forecast is conducted as the following process by each decade. First, probability of 2010 occupation in each age group π_{j_10} will be calculated using 2000 as the base year.

$$\pi_{j\_10} = \frac{\exp\left(X_{00}\widehat{\beta_j}\right)}{1+\sum_i exp\left(X_{00}\widehat{\beta_i}\right)},\ \ i, j = 1\ 2, \dots, 5$$

$$\pi_{7\_10} = \frac{1}{1+\sum_i exp\left(X_{00}\widehat{\beta_i}\right)},\ \ i = 1\ 2, \dots, 5 \tag{2}$$

Then the population by each group is calculated based on the total population Pop_{10} in each TAZ in 2010 by the formulation $Age_{10} = Pop_{10} \times\ \Pi_{10}$, where

$\Pi_{10} = [\pi_{1\ 10}, \pi_{2\ 10}, \ldots, \pi_{5\_10}]$. Π_{10} can serve as a major component of X_{10} which also includes other secondary variables as well. Similar to the previous step, we can calculate the probability of occupation by each age group in 2020 π_{j_20} using X_{10} as input.

$$\pi_{j\_20} = \frac{exp(X_{10}\widehat{\beta_j})}{1+\sum_i exp(X_{10}\widehat{\beta_i})}, \quad i, j = 1\ 2, \ldots,\ 5$$
$$\pi_{7\_20} = \frac{1}{1+\sum_i exp(X_{10}\widehat{\beta_i})}, \quad i = 1\ 2, \ldots,\ 5 \qquad (3)$$

Iteratively, $\pi_{j\_30}, j = 1\ 2, \ldots, 8$ can be calculated and the target population by each age group X_{30} can be achieved.

Validation

We compare the fitted value and observation for 2000 at the TAZ level to examine the accuracy of the estimation. Mean Absolute Percentage Error (MAPE) and Median Absolute Percentage Error (MedAPE) are the two indicators in the validation.

$$\mathrm{MAPE} = \mathrm{mean}(\left|\frac{\mathrm{estimation} - \mathrm{observation}}{\mathrm{observation}} \times 100\%\right|) \qquad (4)$$

$$\mathrm{MedAPE} = \mathrm{median}(\left|\frac{\mathrm{estimation} - \mathrm{observation}}{\mathrm{observation}} \times 100\%\right|) \qquad (5)$$

If the validation at this step is acceptable, we can continue the forecasting for 2010. If the validation result indicates a significant deviation between the predicted and observed values, we need to improve the model with more suitable independent variables until a better fit is achieved. The second steps is validation with 2010 County level Census, and the third steps is quality control with 2030 projection provided by the Maryland Department of Planning (MDP).

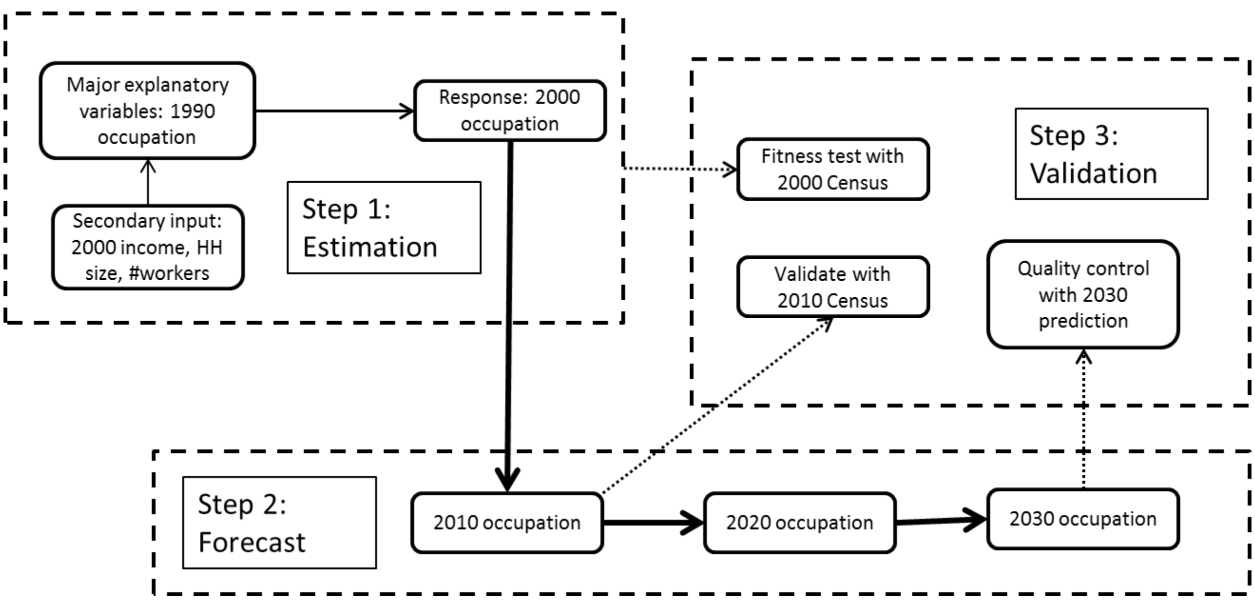


FIGURE 1 Flowchart of the Framework

Data

In this paper, we apply the framework to forecast occupation in Baltimore Maryland within a boundary called the Baltimore Metropolitan Council (BMC) area occupation group. The study area covers five counties, including Anne Arundel, Baltimore County, Carroll, Harford, and Howard, for a total of 814 TAZs. The study area is shown in Figure 2. The percentage of each occupation group and unemployment in 2000 are presented in Figure 3. Unemployed and Management employees are the main residents in this area. The other occupation categories such as sales, service and other employment types are generally less than 20% of total employment in the study area. Employees engaged in management are more concentrated in Howard County and south of Baltimore County. A description of explanatory variables is also presented in Table 1. In 1990, the dominant type of employment for residents was service, followed by majority of those that were unemployed. This indicates a trend of occupation evolution from service to management between 1990 and 2000. The pattern of the evolutionary trend is estimated and discussed in the following section.

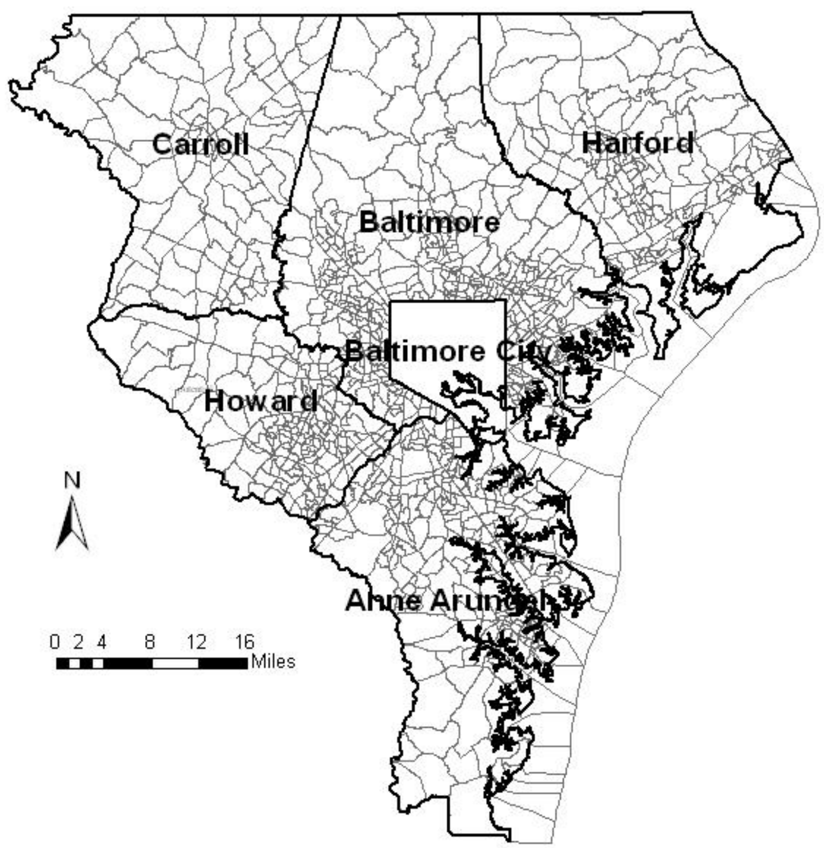


FIGURE 2 TAZ and County Boundary of the Study Area

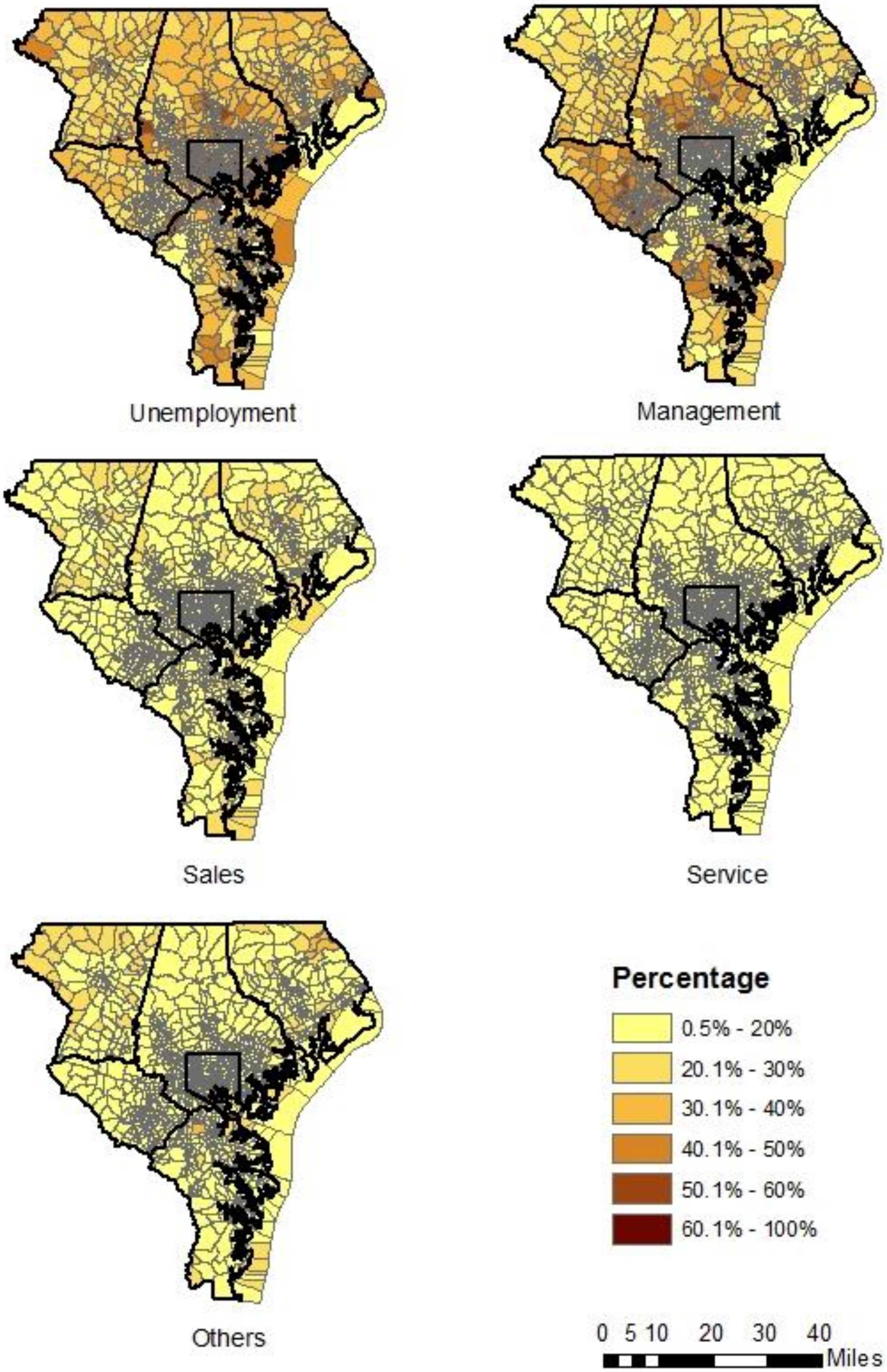


FIGURE 3 Percentage of population by each occupation in 2000

TABLE 1 Description of explanatory variables in the occupation sample

Variables	Label	mean	min	max	Std-deviation
P_MAN_90	Percentage of management/ profession/ administration in 1990	9.46%	5.06%	19.76%	2.81%
P_SAL_90	Percentage of sales in 1990	14.02%	2.67%	33.86%	3.58%
P_SER_90	Percentage of service in 1990	28.05%	10.46%	48.17%	7.35%
P_OTH_90	Percentage of other (Farming, fishing, and forestry; Construction, extraction, and maintenance; Production, transportation, and materials) in 1990	18.41%	6.07%	29.96%	5.02%
P_UEMP_90	Percentage of unemployed in 1990	30.05%	11.56%	64.70%	8.48%
Medinc (10K)	2000 Median income in TAZ (in unit 10,000)	6.23	1.15	13.55	2.19
HHDEN00	2000 Household density in TAZ (per acre)	2.29	.01	21.94	3.09
EMPDEN00	2000 Employment density (per acre)	2.79	.00	26.33	3.36

Estimation and Forecasting Result

In this section, we present an example problem using household workers. The sample size in the estimation after data cleaning is 763 TAZs, with the dependent variable classified by 5 occupation groups. We also examined variables, such as distribution of household size, income and number of workers. However, these variables do not appear to be highly correlated with age distribution in the estimation process. For occupation estimation purposes we use population of 16 and over. The occupation group is categorized as 1) Management, business and financial, Profession, Administration; 2) Sales and office; 3) Service; 4) Other (Farming, fishing, and forestry; Construction, extraction, and maintenance; Production, transportation, and materials) and 5) Unemployed/not in labor force. The sample size used in estimation is 804 TAZs. The data description is presented in

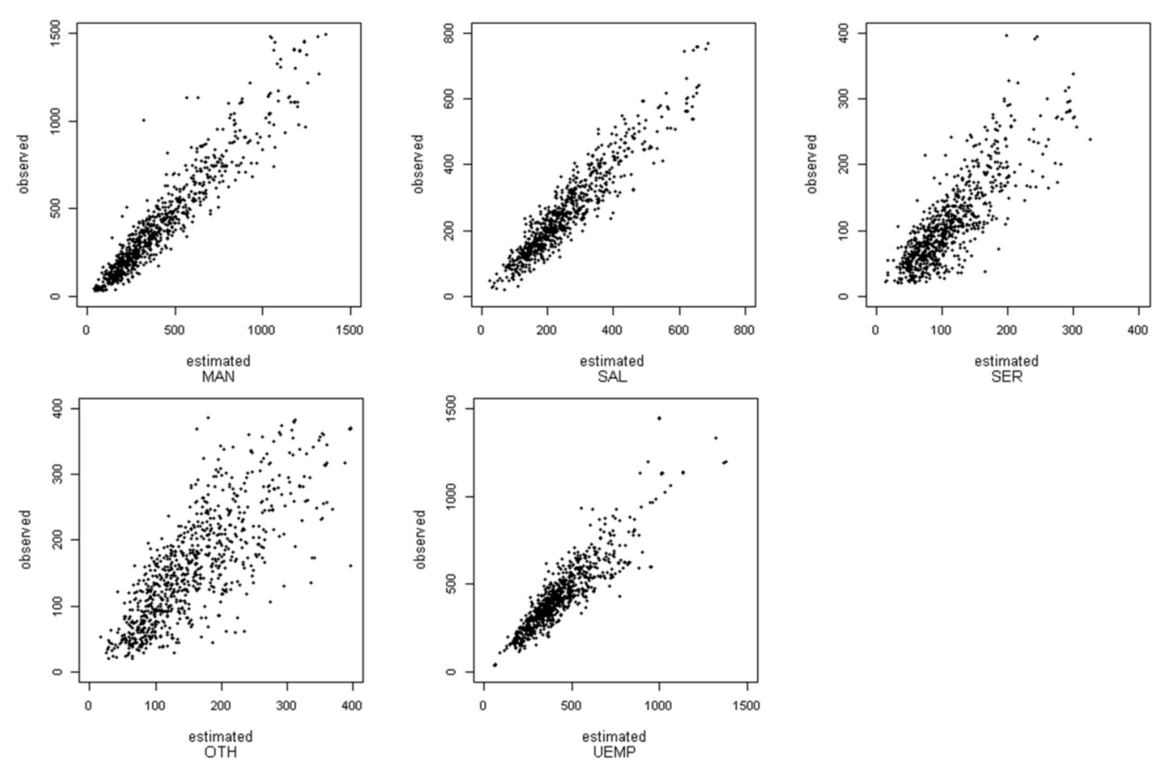
2.

From the estimation result, there are more management employees living in the zone that used to have more management and service employees. There will be more service employees in 2000 if the zone has more sales employees in 1990. The zones with higher median income in 2000 represent the higher proportion of management employees and less service and other employees. Household density in the TAZ has negative effect for all the four type of employments, comparing with the unemployed population. Therefore, the unemployed people are more likely to live in the zone with higher household density, such as apartments, high rising, rather than single family home. Employment density is opposite to the household density. The population of all kinds of employments increases rather than the unemployed in the zones with higher employment density. Comparatively, management employees are less likely to live in the zones with higher working opportunities than other employees. This may be explained as employed people are tending to live close to jobs, but also prefer less noisy/crowded location when it is affordable.

TABLE 2 Estimation results for occupation group

	MAN00	SALES00	SER00	OTH00
constant	-2.993	-2.188	-2.587	-1.788
P_MAN_90	3.880	1.785	0.428	-1.441
P_SAL_90	2.267	2.575	2.931	2.110
P_SER_90	3.707	2.066	2.138	0.144
P_OTH_90	1.808	2.657	2.902	5.295
Medinc (10K)	0.115	-0.003	-0.070	-0.075
HHDEN00	-0.132	-0.216	-0.207	-0.241
EMPDEN00	0.138	0.192	0.193	0.203

The estimation accuracy for the year 2000 shows a MAPE of 24.3% and MedAPE of 15.4%, by comparing fitted and actual value of TAZ level population for each occupation (Figure 3). From **Error! Reference source not found.**4, we observe the estimation for management and sales has a better performance in terms of model fitness. There is heterogeneity for the rest of the occupations, especially the category of “Other occupation”.



(Note: MAPE = 24.3% and MedAPE = 15.2%, sample size=804)

FIGURE 4 Validation plot of observed and model workers occupation in 2000

The prediction procedure for 2010 is applied to 1,374 TAZs and is shown in Table 3. The average error of MAPE at county level is 11.9% and MedAPE is 9.9% (Table 3). The error terms are reasonable demonstrating an acceptable fit. From Table 3, we observe a better match of observed and predicted data for manufacturing, sales, and unemployment categories. It is largely underestimation error for service employments. For other category it is a mix of under and over estimation of predicted results when compared to the observed data. Generally, we observed that the proposed model has an underestimation for service and an overestimation for sales category when comparing with the projection data.

Table 3 Estimated County Level Occupation and Percentage Error in 2010

County	MAN	SAL	SER	Other	UEMP
Anne Arundel	130,726	76,214	27,395	37,295	155,112
	10.4%	3.6%	-28.1%	-9.9%	-0.1%
Baltimore County	170,886	117,027	47,857	63,968	250,299
	-2.8%	13.5%	-25.3%	7.3%	1.1%
Carroll	36,048	24,410	9,195	14,353	47,340
	-9.2%	21.7%	-37.4%	1.3%	10.8%
Hartford	53,281	35,214	13,481	19,407	70,415
	2.4%	7.4%	-15.9%	-10.7%	1.8%
Howard	93,513	36,702	10,686	10,131	70,917
	1.3%	15.3%	-35.4%	-21.7%	3.8%

(MAPE = 11.9%; MedAPE=9.9%)

We also display the error by occupation group in Figure 5 for five counties. Each circle represents one of the five counties. Predictions for MAN are matched with observation quite well, with the points along the diagonal line. The percentage error for Carroll -9% for MAN, but all other counties fall closer to the diagonal line. SALE category is always over predicted and SER is under predicted. Bothe these categories have larger deviations in the year 2010. Other occupation also matches well with the observed data except Howard County. UEMP matches well with the observed data for all counties.

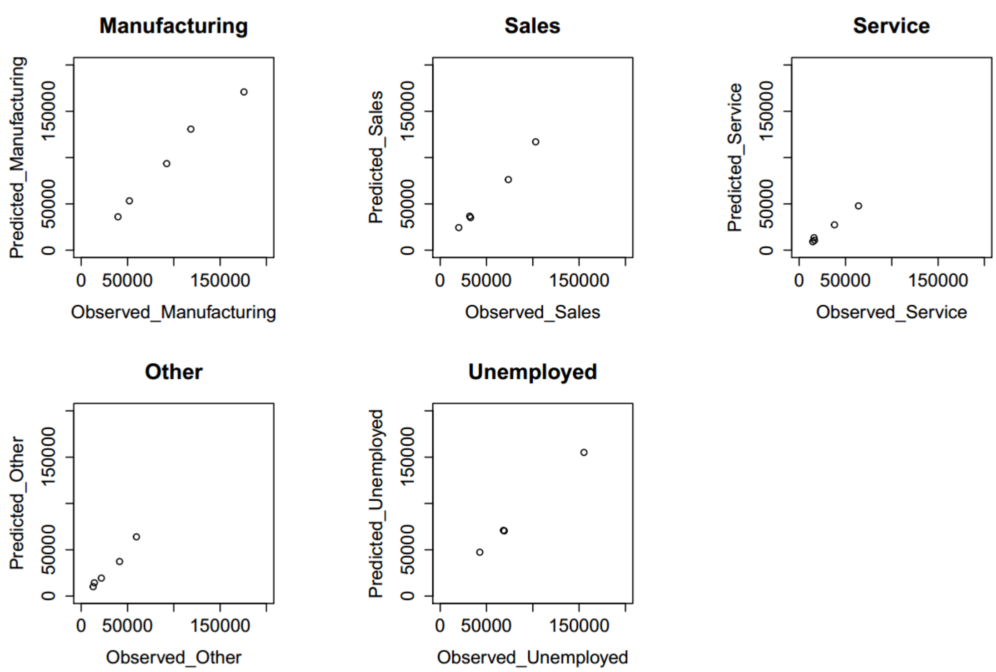


FIGURE 5: Validation plot of predicted and observed occupation for 5 counties

Next, we present forecasting result for occupation in 2030 at aggregated county level for each category (Table 4). The approximate total occupation for each TAZ in 2030 is provided by BMC. The management and sales category matches well with the 2030 observed data, as the percentage error for all counties are less than five percent. Large discrepancies are found for the service and other employment. The percentage error is a comparison of prediction with demographic projection provided by MDP. The MAPE is 5.3% and MedAPE is 3.1%, representing a close prediction result with MDP.

TABLE 4 Estimated County level population by occupation and percentage error in 2030

County	MAN	SAL	SER	Other	UEMP
Anna Arundel	127,600	74,841	26,953	36,872	153,612
	4.10%	*1.30%*	*12.00%*	*-5.60%*	*-4.20%*
Baltimore County	172,914	118,175	48,244	64,437	252,950
	3.10%	*2.70%*	*13.80%*	*-1.60%*	*-4.90%*
Carroll	36,858	25,113	9,491	14,912	48,721
	0.50%	*1.60%*	*13.90%*	*0.50%*	*-3.60%*
Harford	52,996	35,175	13,448	19,563	70,205
	1.10%	*1.40%*	*13.60%*	*-2.10%*	*-3.10%*
Howard	89,893	35,799	10,546	10,446	70,520
	2.60%	*0.40%*	*23.40%*	*-7.20%*	*-4.90%*

(MAPE is 5.3% and MedAPE is 3.1%)

To observe the evolution pattern in each TAZ, the occupation distribution from 2010 to 2030 by decades is presented in Figure 6. Two categories (management and unemployment) are presented to demonstrate the pattern at TAZ level, and all other graphs are omitted for brevity. The unemployment rate is observed to overspread in the whole area, especially the north part. The zones with high unemployment rate diminish after years. The unemployment category seems higher in the outskirts TAZs because of residential TAZs does not have any employment. However, the urban and suburban areas appear to have lesser unemployment. In Howard County, the management category employment is high in the base year, also attract more people living in this county in the next 20 years. Baltimore county gains management employment in the future.

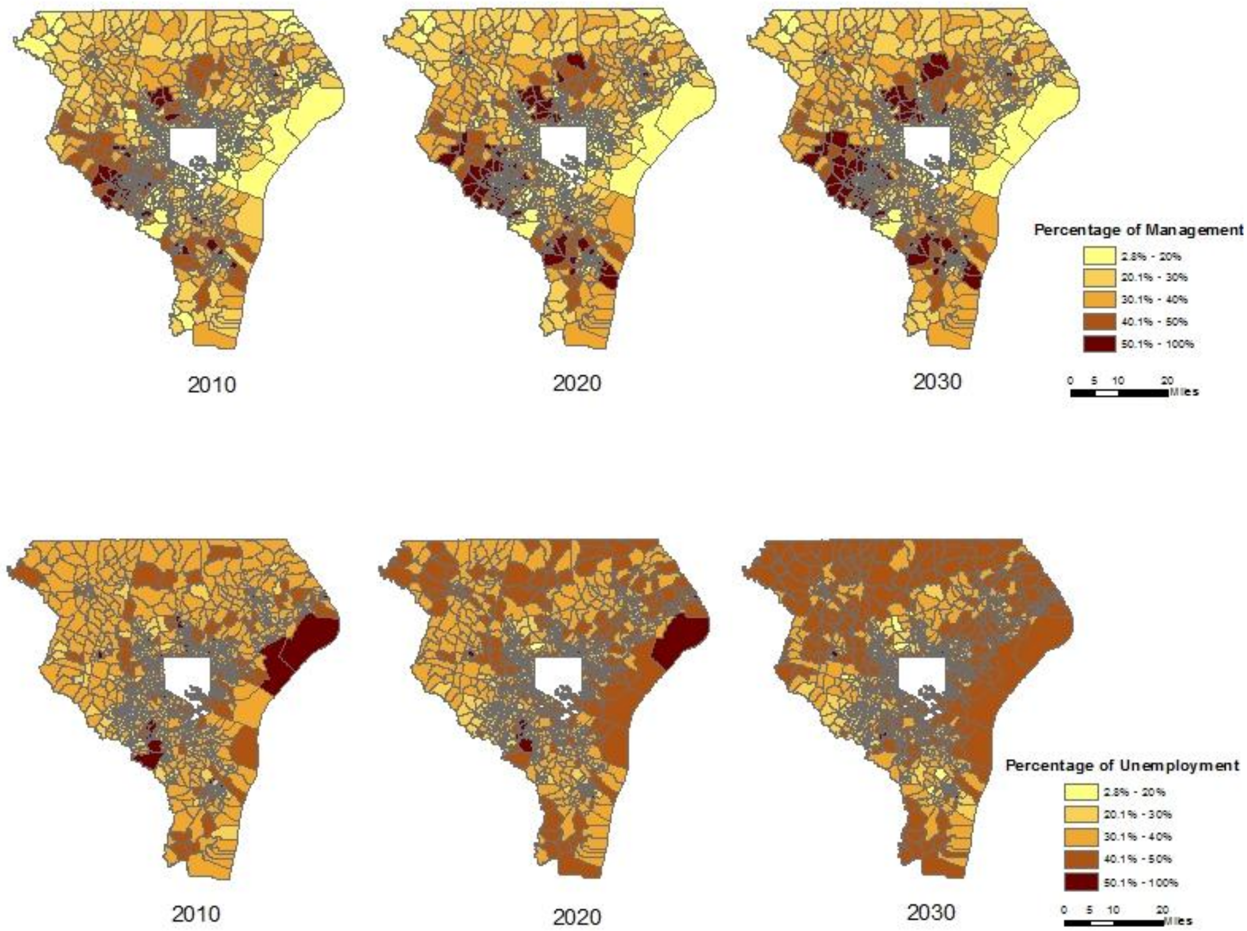


FIGURE 6 Comparison between percentages of occupation in 2000 and 2030 for each TAZ (Management and Unemployment)

Conclusion and Discussions

A focus on occupation trends and models that incorporate employment evolution, could significantly aid agencies interested in urban economy and community development. One of the tasks for urban agencies such as MPOs, is to assess occupation of various industry categories to inform travel demand models for transportation related decision making. Key occupation categories foster economic development, which in turn nurtures key industries. Occupations are not confined to one category of a socio-economic group such as highly educated professionals but may encompass a variety of groups including immigrants among others. Modeling and forecasting occupation is a challenging task for two primary reasons. First, because of global economic integration and new technologies, substantial changes are taking place that bear heavily on regional and community economic development; exploring factors on which occupation is dependent is a difficult task. Second, capturing evolution of occupation over a period of time is often ignored. Either growth factor models or IPF techniques are used to forecast or disaggregate occupation, both approaches ignore occupation evolution.

In this paper, we propose a novel approach to synthesize occupation, as it is a critical input to many travel demand models. A number of factors considered are including residential location, work location and activity patterns. The methodology can also be used to predict the occupation change over time with consideration towards evolution of specific employment categories over many years. Because of the necessity of detailed data at the micro level, and common aggregation errors found at the macro level, we propose a meso-level approach to model and forecast occupation. A multinomial logistic regression approach is used to model five categories of occupation: management, sales, service, other and unemployed. Median income, household and employment density are used as other explanatory variables. A six county area in the Baltimore Metropolitan region is used as the case study.

Results of the study indicate that management employed population is increasing to the north of Baltimore City. The population is observed to have an evolutionary pattern from sales, to service and then to management; while most of the residential location by each type of occupation remains stable over the study period (people receive a promotion in their careers and also change their residential location). The occupation composition in each TAZ is highly dependent on the historical population occupation composition and the current median income, housing density and employment density in the area. The results are compared to observed and forecasted data from empirical sources for the base and future years respectively. The results show reasonable accuracy at the MPO geographic level for planning purposes. The major caveat of this paper is the unavailability of other data sources that could be related to occupation. With more data sources such as type of business and employment by category in the study area and surrounding areas, the results can be improved to better model urban economy and occupation. However, the proposed approach takes a significant step towards bridging the gap in avoiding the use of static growth factors or proportional fitting approaches to model and forecast occupation.

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