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MODELING HOUSEHOLDS AND LOCATION CHOICES IN METRO MANILA USING SPATIAL MICROSIMULATION APPROACH

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Abstract: The development of urban models has been prompted by the need for informed policy recommendations from urban planners and informed decisions by policymakers. While continuous development and application has been pursued extensively in advanced countries, there have been little efforts in the developing regions of the world. This is mainly due to serious data limitations and the complexity of modeling issues. However, the imperative to develop integrated urban models for developing countries is growing with the need to estimate impacts of various urban policies. This paper focuses on the development of a location choice model for households in Metro Manila under a spatial microsimulation framework. This study is part of a research initiative to develop an integrated urban model for Metro Manila.

Key Words: urban model, location choice, spatial microsimulation, developing countries

1. INTRODUCTION

The development of urban models has been prompted by the need for informed policy recommendations from urban planners and informed decisions by policymakers. While continuous development and application have been pursued extensively in advanced countries, there has been little effort in developing countries. This is partly due to the serious limitations in data availability that severely constrain the kind of modeling work that can be pursued for cities in developing countries. If available, existing data sets do not possess the desired spatial and temporal coverage to allow detailed and sophisticated analyses of urban phenomenon. Secondly, the lag in urban modeling work in developing countries is brought about by serious difficulties in capturing the complex inter-relationships among factors in the urban system. Needless to say, direct transfer of models from advanced countries to developing ones is no longer acceptable.

However, the imperative to develop practical urban policy tools for planners and policy-makers in large metropolitan areas in developing countries is growing. This is brought about by an increasing awareness among decision-makers to evaluate the effectiveness of current urban policies, as well as, the need to forecast the probable impacts of proposed policy measures.

This paper first discusses the issues in urban modeling and its imperatives for Metro Manila. It then tackles the problem of data availability by pursuing the development of a 'synthetic household microdata' for Metro Manila using a spatial microsimulation model. The model system provides detailed household microdata by integrating available but disparate survey and census-based data. The resulting household microdata possesses more detailed attributes and spatial detail that will allow for more sophisticated subsequent analyses. Finally, the paper reviews existing theories of location choice that can be adopted and tested in order to develop a model of location choice for Metro Manila.

2. MODELING URBAN SYSTEMS IN DEVELOPING COUNTRIES

The intricacies of the structure of the social organizations and individual behavior, as well as, the presence of many market imperfections, has prompted urban analysts and researchers to express caution on to the issues that need to be dealt with in making models work for developing counties.

McGee (1971) has tried to unravel the urbanization process in developing countries by comparing western theories and third world realities. He notes that while the process of urbanization in developing countries show some similar trend with its western counterparts, urbanization in the third world is happening at a compressed time-scale, greater magnitude and complex socio-economic conditions. McGee further exposed that urbanization studies in the third world should be undertaken in the broader investigation of the 'forces influencing the society and country as a whole'.

Lakshmanan (1981) has reviewed the policy applications of urban development models in the United States and the implications on developing countries. He argues that the key to the development of urban models lie in the structures that promote modeler-policy maker interactions. The modeler must be in touch with the policy maker and the policy maker should understand the attributes of the models. Lakshmanan points out that it would be a mistake to make *isomorphic transfers* of urban development models from developed cities to the developing world.

Finally, Mohan (1979) stresses the need to account for the larger public sectors and market structures in developing countries. If a model is to be useful, it is important that attention should be given to the particular institutional structure of the country concerned. Furthermore, he points out that urban models should be seen as a process rather than as products. Mohan suggests that clear and reliable information is required in areas such as transport, housing, and the informal sector in developing countries.

Tiglao and Tsutsumi (2001) highlighted key modeling issues that need to be tackled in the development of urban models for developing countries citing the particular experience of Metro Manila in the Philippines. Firstly, there has been explosive population growth among cities in developing countries. The rapid growth in population is also coupled by the presence of severe economic inequality among individuals and households. The large gap between the rich and the poor is very much evident in the housing and labor sectors of the urban economy. From the viewpoint of modeling, there is a need to effectively distinguish the various income and social groups. The current modeling practice of defining 'representative households' needs to be refined in order to capture the household structure in developing countries at a disaggregated level.

A second very vital issue is the presence of large informal sector. Until recently, urban analysts have largely dismissed the existence of low-income or the so-called marginal settlements or the informal sector in the analysis of the urban system. More seriously, policy-makers and planers have failed to recognize at an early stage the evolution of an ever-growing informal sector in cities in developing countries. The analysis of the informal sector is severely limited by the lack of reliable data, as well as, non-existence of formal methods of measurement. The definition of the informal sector varies, however, it is generally considered to be that portion of the economy which are operating outside the formal, or established system of laws and urban structure. The previous two issues are compounded by urban primacy and high in-city migration. In developing countries, a lot of people are moving to capital cities in which there are no jobs reserved for them. The surge in population drives further urban sprawl, unemployment and the expansion of the urban informal sector. The complex interplay of regional and international migration leads to a very dynamic population base.

3. MICROSIMULATION MODELING OF HOUSEHOLD CHARACTERISTICS

3.1 Microsimulation and Urban Modeling

There has been renewed interest in the integrated models of urban land use and transport in the light of environmental debate. Sustainability issues, together with new technological developments and new planning policies, also present new challenges to urban modelling. Existing urban models are too aggregate to respond to modeling challenges. Typical models distinguish only few socio-economic groups and dwelling categories, too fee to take account of new production and distribution technologies and emerging lifestyles and work patterns. Moreover, most urban models get their spatial dimension through a zonal system in which it is assumed that all attributes are uniformly distributed throughout a zone. These considerations suggest a fundamentally new organization of urban models based on a microscopic view of urban change. The method for this new type of model is Monte Carlo microsimulation (Wegener 2002).

Figure 1 illustrates how microsimulation can be employed for the creation of a micro-level population with the population characteristics: age, sex, marital status and household tenure. Supposing that age, sex, and marital status of the household head is available from the census, it is then possible to estimate probabilities of household tenure. The first synthetic household has the following characteristics: male household head, aged 27, married. The estimated probability that a household of this type would be owner-occupied is 70. The next step in the procedure is to generate a random number to see if the synthetic household gets allocated to the owner-occupier category. The random number in this example is 0.542 which falls within the 0.001 to 0.700 range needed to quality as owner-occupied. The same procedure is then carried out sequentially for the tenure allocation of all synthetic households. It should be noted that that difficult task in microsimulation is to specify which variables are independent upon others and to determine the ordering of probabilities.

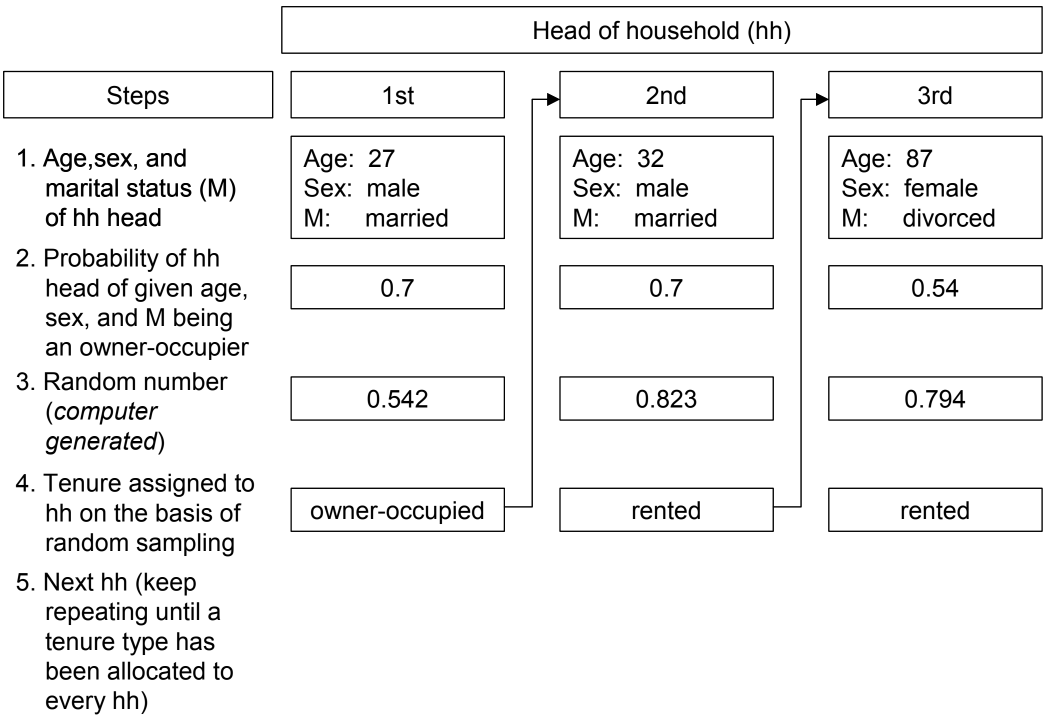

Figure 1. Example of spatial microsimulation process (Clarke, 1996)

Clarke and Holm (1987) provides a through presentation on how microsimulation methods can be applied in regional science and planning analysis. Clarke (1996) points out that there are two major works involved in applying microsimulation methods in spatial analysis. The first involves the creation of a microdata set using conditional probabilities and contingency tables. A method called iterative proportional fitting is also used to create probabilities using data sets which have different spatial scale. The next step involves the creation of a sample of individuals or households based on the set of probabilities. Microsimulation methods has not received wide application in regional science due to the lack of microdata sets to calibrate or test results of simulation. This situation is changing as survey data are becoming more readily available, even for developing countries.

There are several early applications of microsimulation to urban modeling in literature. Wegener (1985) used Monte Carlo simulation approach to model housing market of Dortmund taking into account the choice behavior of households and landlords. On the demand side, considerable effort was devoted to modeling the life cycle of households and their concurrently changing decision situations and preferences. On the supply side, the housing stock is changed through aging, public housing programs, or private construction by housing investors or owner-occupants.

Up to now, a large number of microsimulation models are inherently aspatial. This means that existing microsimulation models does not incorporate sufficient geographic detail so as to allow richer analysis at fine spatial levels. Microsimulation models would potentially find relevant applications to policy simulations at neighborhood levels, and even voting and school districts. An on-going development of state-of-the-art application of microsimulation to landuse-transport modeling is the UrbanSim at the University of Washington. The model system is implemented as a set of interacting model components that represent the major actors and choices in the urban system, including household moving and residential location, business choices of employment location, and developer choices of locations and types of real estate development, all subject to the influence of governmental transportation and land use policy scenarios. The model design is unusual in the degree of disaggregation of space, time, and agents, and in the adoption of a dynamic disequilibrium approach.

This study argues that spatial microsimulation approach provides a very powerful framework in overcoming the data and modeling problems in the development of integrated urban models for developing countries. One main advantage of the spatial microsimulation approach is that it is capable of building reliable disaggregate data sets at the household level and provide it at an appropriately fine geographic scale for detailed analysis. It is able to utilize existing disparate data sets and it is flexible enough to incorporate new available information. Finally, since household micro data can be developed, appropriate models can be calibrated and tested using the rich database.

3.2 Spatial Microsimulation of Informal Households in Metro Manila

InformalSim is the first application of spatial microsimulation approach for modeling the characteristics of households, particularly those in the informal sector. Presently, InformalSim covers the City of Manila. However, the model can be easily extended to cover other cities and municipalities in Metro Manila. The City of Manila consists of 54 traffic analysis zones, 900 barangays and around 1.65 million persons in 1990. The model system consists of several modules that provide spatially-disaggregate household microdata that enables the distinction between the formal and informal households. In InformalSim, the *informal household* is characterized using two dimensions, namely, urban poverty and housing tenure. It is noted that the term *informal settler* which only refers to the tenure condition is more commonly used. Table 1 shows the data sets used in developing the spatial microsimulation model.

Each data set is available under a specified zoning system and sampling scheme. Each data were undertaken with specific purposes in mind. Since, data are very costly to obtain, there is great benefit in utilizing existing data. The challenge therefore is how to integrate disparate data and produce a richer data set that would allow the identification of informal households.

The main source of household income and expenditure data is the Family Income and Expenditure Survey (FIES). The FIES has been conducted every three years since 1988. It contains very detailed information of sources of household income and expenditure, however, only for a very limited sample. The subset of the data for Metro Manila consists of about 4,030 samples. Through the FIES data, household income profiles are officially published at the city and/or municipality level. The next source of household income data is the 1996 Metro Manila Urban Transportation Integration Study (MMUTIS). The primary source of detailed socio-demographic data used in the study is the 1990 Census of Housing and Population (CPH). The CPH does not contain income-related variables. The study also utilized GIS data sets from MMUTIS. A recent spatial data set used is the building footprint for Metro Manila. The data set contains the plan projection of roof of individual dwelling units and buildings.

Table 1. Available data sets

Zone level	Data set	Description
City/ Municipality	1997 Family Income and Expenditure Survey (FIES)	Household demographics, some housing variables, Detailed household incomes and expenditures, 4,030 samples for Metro Manila
Traffic Zone	1996 Metro Manila Urban Transportation Integration Study (MMUTIS)	Selected household demographics, Member and household income, 50,000 samples for Metro Manila
Barangay	1990 Census of Population and Housing (CPH)	Detailed household and housing characteristics, No income/employment variable, Non-response on housing variables, All households in 1990 (1,567,665 households)
GIS	1996 Land Use/ Building Footprint Data	Urban land use zoning map for entire Metro Manila, building footprints for most cities

Each data set is available under differing zoning system and sampling scheme. As such, each data were undertaken with specific purposes in mind. However, data are very costly to obtain and there is great benefit in utilizing existing data. The challenge therefore is how to integrate disparate data and produce a richer data. Figure 1 shows the various levels of zoning. The *barangay* is the smallest administrative unit in the Philippines.

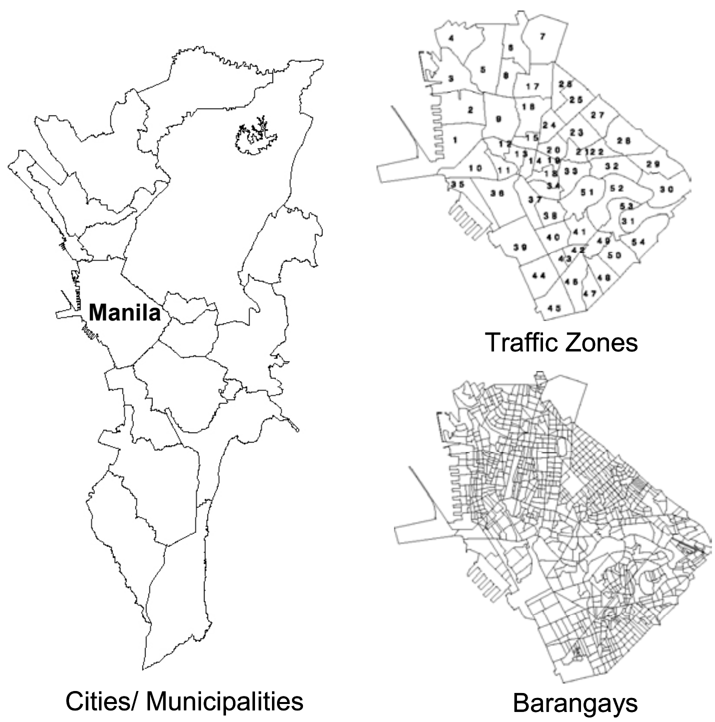

Figure 2. Levels of zoning

Figure 3 shows the simulation process of InformalSim. The object of the microsimulation is to estimate characteristics of households in the microdata that would allow identification of informal households. First, a baseline population consisting of all households in the 1990 CPH is initialized. Then, the economic activity of household head is estimated using conditional probabilities from the 1996 MMUTIS data. The MMUTIS, or Metro Manila Urban Transportation Integration Study, is a transportation planning project undertaken from 1996 to 1999 which had assembled detailed household and member characteristics for 2.5 of the total number of households in Metro Manila. The characteristics include household income and employment information of the household head. Assignments of economic activity are done using Monte Carlo sampling based on the characteristics of the household head, namely, sex, age, and location. Next, occupation and employment sector probabilities are computed and assignments are done using Monte Carlo sampling. The occupation and employment sector probabilities are estimated using multinomial logit models which are calibrated using the 1997 FIES data set. The FIES, or Family Income and Expenditure Survey, is undertaken every 3 years for a small number of households nationwide. In 1997, the sample size is 40,000 households which are taken to be representative only at the city or municipality level.

The next stage involves the estimation of household incomes based on the characteristics of the household head. To achieve this, the employment status of the household head is first determined. The employment status of the household is estimated using a probit model, that is, a binary choice model of being a wage earner (i.e. formal sector) or self-employed (i.e. informal sector). Then, conditional on employment status, the household income is computed using a regression model with correction for selectivity in the lines of Lee (1978). Then, the permanent income of the household is estimated. Permanent income is needed to estimate the imputed housing value. Housing values are estimated using in two steps. First, housing tenure choice is estimated using a probit model of whether the household is under formal or informal housing. Formal housing consists of owner-occupiers and renters. On the other hand, informal housing are attributed to households who own the house but rents (with or without consent of owner) the land. Then, housing value is computed using a regression model conditional on the tenure status with the appropriate correction for selectivity bias in the lines of Lee and Trost (1978). Simulated values can then be visualized using GIS and the output can be analyzed in a ‘complete-data’ setting.

Figure 4 presents the object representation of household microdata. Object-oriented programming offers a very flexible platform for estimation and handling of very large data sets. InformalSim is implemented in *Java*. There are two major objects in InformalSim, namely, the member object and the household object. These two objects contain variables and methods. Variables correspond to the actual characteristics of the respective objects. Variables are of two types-baseline (i.e. observed) and unobserved. Methods contain computational codes or models that operate on the variables. Each household object contains a vector (or collection) of member objects as would be true in the physical sense. This representation is completely convenient as the characteristics of the household are entirely dependent on the members that comprise it. Moreover, the approach allows limitless flexibility as future implementations may be conveniently incorporated into the structure.

3.3 Calibration of Spatial Microsimulation Model

The current implementation of InformalSim consists of 10 modules. Each of the modules are calibrated econometric models, either in the form of Ordinary Least Squares (OLS) regressions models or Limited-Dependent models that incorporate sample selection. The modules are as follows:

1) Economic Activity Module

Economic activity rates are computed as conditional probability of an individual being economically active given age, sex and location using the 1996 MMUTIS data. MMUTIS contains employment data of household heads with a 2.5 percent sampling for each of the traffic analysis zone. The estimated rates for each zone are applied to all households in the barangays that are located with each particular zone. The assignment of whether a particular household head or member is economically active or not is determined using Monte Carlo sampling. The process involves drawings of random numbers and comparing it with the conditional probabilities.

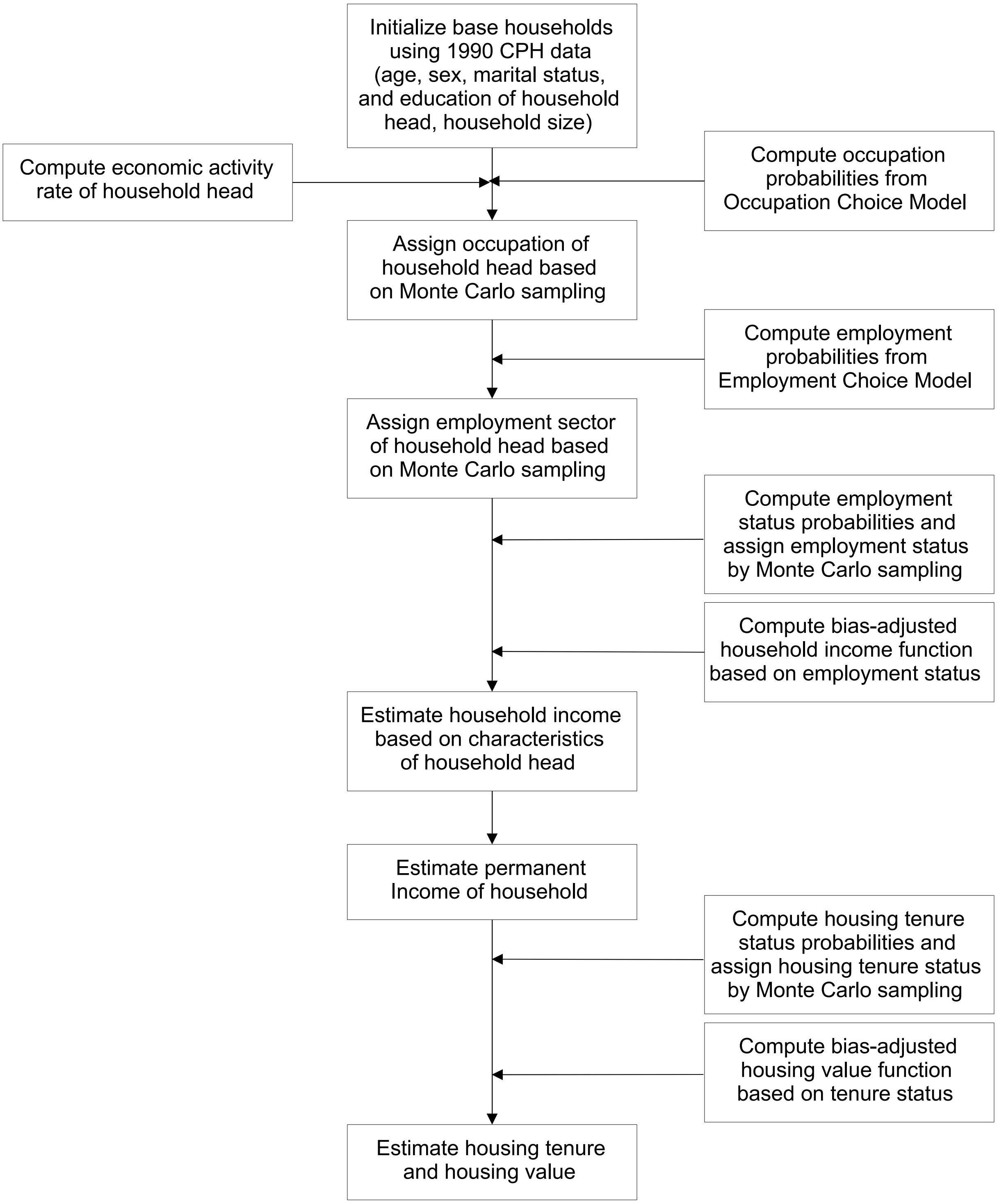

Figure 3. Spatial microsimulation of informal households

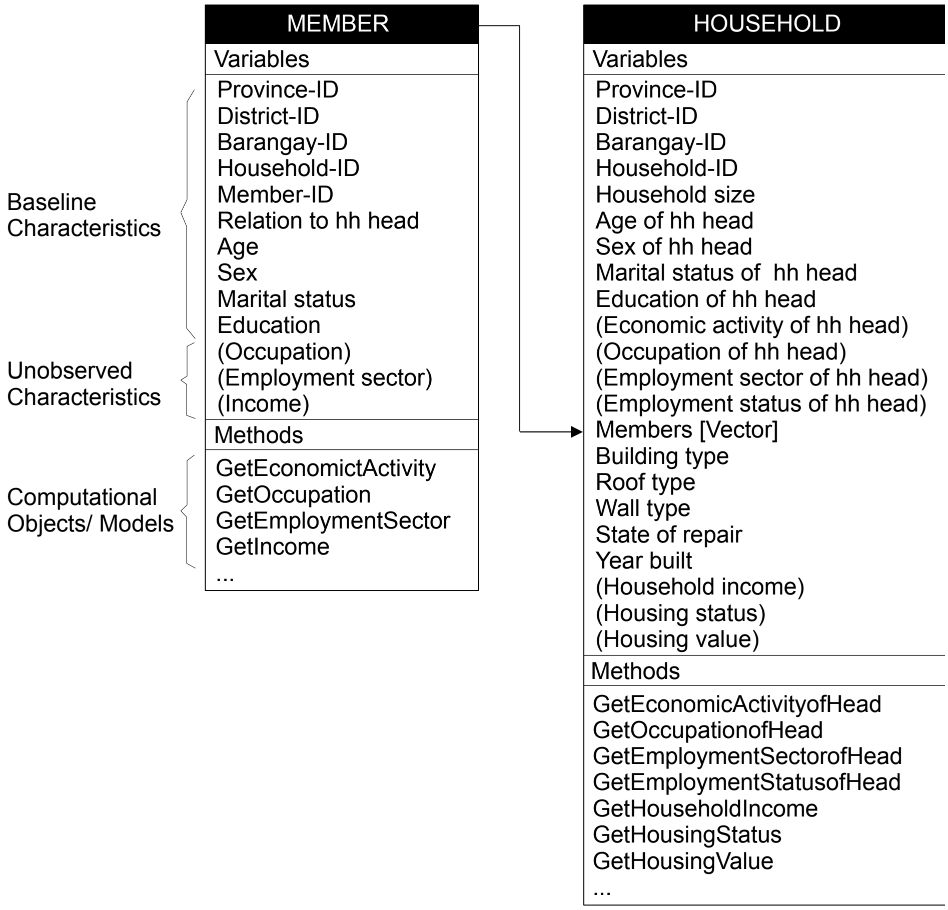

Figure 4. Object representation of household microdata

2) Occupational Choice Module

The occupational choice is formulated as a multinomial logit model with the actual occupation type as observed choices of the household head. The model includes education level and age (proxy for experience) as explanatory variables. Separate models are estimated for male and female household heads. There are seven occupation groups, namely: Professional, Administrative, Clerical, Sales, Services, Agriculture, and Production.

3) Employment Sector Choice Module

The employment sector choice is also formulated as a multinomial logit model. It includes education level and age as explanatory variables for observed employment sector. Similarly, separate models are estimated for male and female household heads. There are six employment sectors, namely: Agriculture, Manufacturing, Wholesale & Retail, Transportation, Financing, and Community Services.

4) Employment Status Module

The employment status sub-model determines whether the household head works in the formal or informal sector. The household head works in the formal sector when he/she is employed by a firm, whether government or in the private sector. On the other hand, a household head who is self-employed or works for another household is considered to be in the informal sector. Employment status is formulated as a probit model with the following explanatory variables: sex, age, age squared, marital status, education level, household size, occupation type, and employment sector. This model provides a reduced-form probit equation in a three-stage model of household income with selectivity on employment status.

5) Household Income Module

The household income sub-model estimates the household income for a household head and taking into account the employment status of that particular head. Rather than simply calibrating regression models by ordinary least squares (OLS), the household income models incorporate bias corrections for selectivity. Separate household income functions were estimated for the formal and informal sector. Moreover, correction terms were found to be statistically different from zero.

6) Permanent Income Module

The permanent income sub-model estimates the permanent income of the household given human and non-human wealth characteristics of the household. The explanatory variables include age, age squared, education level, education level squared, household type, and household income.

7) Housing Tenure Module

The housing tenure sub-model determines whether the household belongs to the formal or informal housing. Formal tenure consists of owners, renters, and those who own land while informal tenure refers to those who may own house but does not own the land. Housing tenure status is formulated as a probit model with the following explanatory variables: education level of household head, household size, and permanent income. This model provides a reduced-form probit equation in a three-stage model of housing value with selectivity on housing tenure status.

8) Housing Value Module

The housing value sub-model estimates the imputed value of housing for each household which incorporates bias corrections for selectivity on housing tenure status. Separate housing value functions were estimated for the formal and informal housing tenures. Correction terms were found to be statistically different from zero.

9) Inequality Measures Module

The module takes the full array of incomes in the household microdata and generates three measures of inequality, namely: Gini coefficient, Theil index, and Coefficient of Variation (CV). It is possible to incorporate other measures on inequality based on human capital.

10) Mapping and Visualization Module

The mapping and visualization module provides the graphical interface for the internal data in the modeling system.

3.4 Simulation Results and Validation

Figure 5 shows the mean household incomes per zone and Figure 6 shows the percentage of informal employment per zone. Figure 7 shows the percentage of households with informal housing tenure. Figure 8 shows the mean housing values for each of the traffic analysis zone.

Validation was conducted in order to gain confidence on the simulated values. The validation process generally involves the establishment of reliable estimates of parameters of interest using small area estimation techniques. These reliable estimates provide benchmark values at that can be used to compare with simulated values. In this particular case, the average household income of each traffic analysis zone was used as the parameter for the validation work. Small area estimation provides more reliable estimates since it incorporates the use of auxiliary variables to estimate mean incomes for each traffic zone. The validation process is depicted in Figure 9. There is generally good agreement between simulated and benchmark values as show in Figure 10.

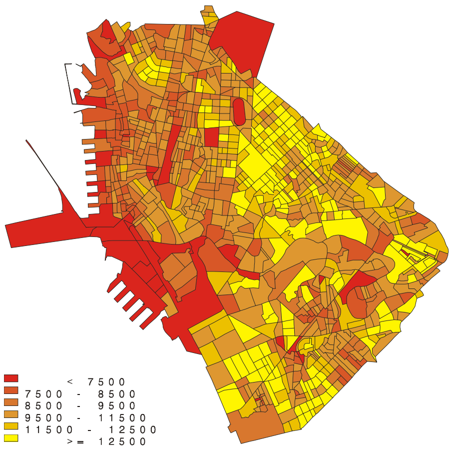

Figure 5. Mean household incomes

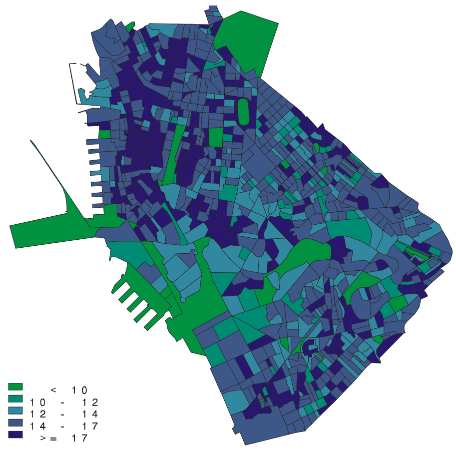

Figure 6. Informal employment (% hh)

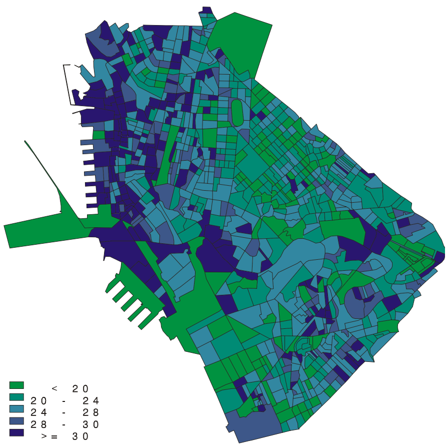

Figure 7. Informal housing tenure (% hh)

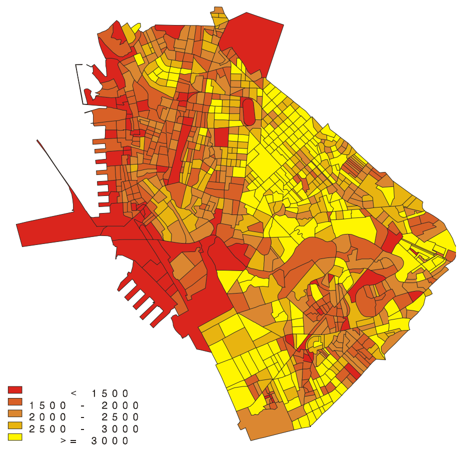

Figure 8. Mean housing values

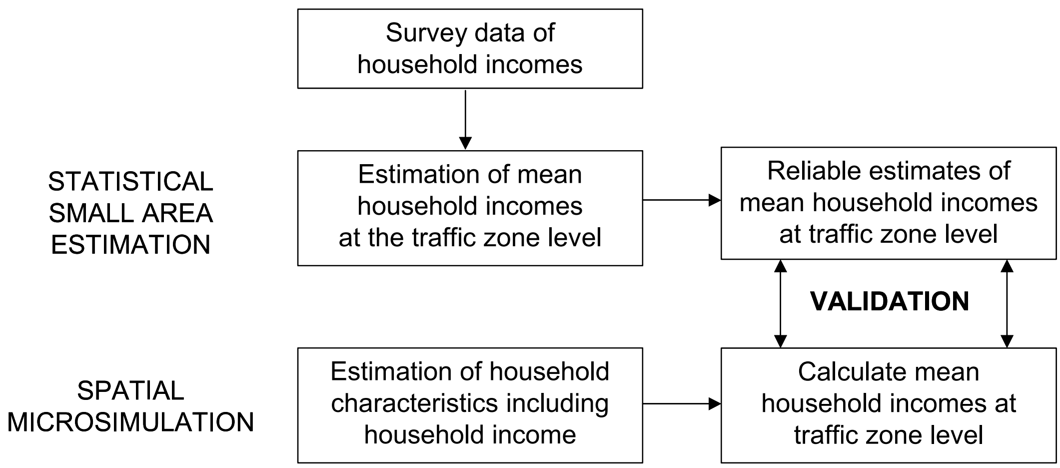

Figure 9. Validation of spatial microsimulation output

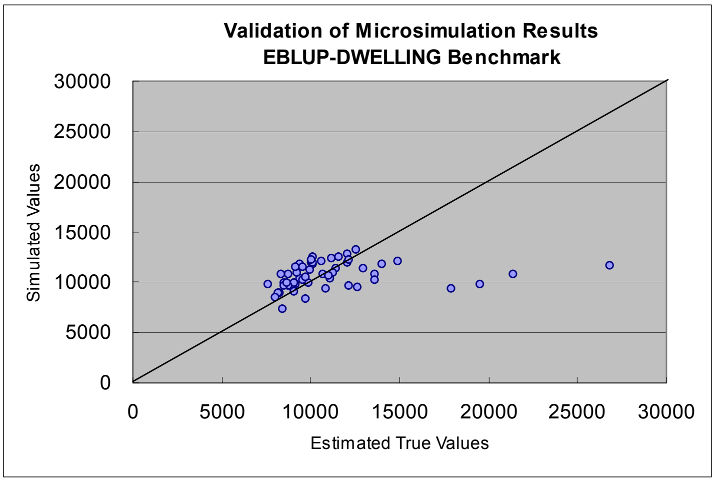

Figure 10. Comparison of simulated and true values

4. RESIDENTIAL LOCATION CHOICE THEORY

Reviews of literature in urban land use modeling are ample. As pointed out by Anas (1982), the concept of 'bid rent' forms the basis of modern urban economic analysis and provides the foundation for most microeconomic models of urban spatial structure. The concept originated form Von Thünen's 1826 work on agricultural land use, and became the centerpiece of Alonso's (1964) models of residential location and urban housing markets. This bidding approach, in the microeconomic tradition, assumes perfectly informed and efficient consumers make bids on all properties. Property owners, also fully informed, auction the property to the highest bidder, with steady state long-run equilibrium reached when this bid-auctioning process succeeds in allocating each property to the highest bidder. All consumers are expected to costlessly and instantaneously change residence when any change in condition occurs that temporarily disrupts equilibrium, by repeating this bid-auction process. The monocentric model and its extensions by Alonso (1964) to Muth (1969) adopted the constraint that all employment was location in the central business district, and focused on the problem of predicting residential location as a function of transportation and housing costs, or the so-called 'cost-accessibility trade-off'.

There are three streams of research activity dealing on residential location. The first one involves the prediction of housing prices and the willingness to pay of consumers for the underlying attributes of housing. This body of work, which draws on Lancaster's (1966) theory of consumer behavior, views housing as a bundle of services, and households as utility maximizing consumers based on some function of these underlying attributes of housing, including locational characteristics. Rosen (1974) developed the hedonic theory of housing markets, in which households choose housing so as to maximize a utility function subject to a budget constraint. There have been several extensions of this body of theory and empirical estimation, particularly in the estimation of housing demand. The second stream of research on residential location focuses not on prices but on household residential location choice. The work of McFadden (1978), among others, on the use of random utility theory to develop multinomial logit models of residential location opened a significant direction for research in this area. This body of work was applied to assess and highlight the importance of accessibility and travel mode on residential location.

Some research has emerged that crosses the two streams, notably by Ellickson (1981) that develops a logit model of the property auction process using the bid rent function rather than the utility function. Essentially, this approach focused on the landowner's problem of selling to the highest bidder, which is the consumer making the highest bid. It differs from the majority of logit models of residential choice, which focus on the consumer's problem of choosing among properties based on maximizing their utility function. Essentially this approach represent the two sides of the auction: the buyer's perspective and the seller. Martinez (1992) extended Ellickson's work by developing a 'bid-choice' model that dealt with both sides of the auction simultaneously, through a nested logit formulation in which the higher level of the model represented the consumer's choice among properties, and the lower level represented the landowner's choice among bidders. Under equilibrium assumptions, Martinez showed the consistency of these approaches.

At the core of the model developed by Martinez is a formulation based on consumer surplus, defined as the willingness to pay for an alternative less the market price of that alternative. It has a simple and intuitive interpretation: a consumer is happiest with an alternative that maximizes the difference between what they are willing to pay and what they must pay based on the market price.

Martinez (1992) derives a multinomial logit model predicting the probability that a consumer h will choose lot i:

$$P_{i|h} = \frac{e^{\mu(\Theta_{hi} - p_i)}}{\sum_j e^{\mu(\Theta_{hj} - p_j)}} \tag{1}$$

where

Θ_{hi} is the willingness of consumer h to pay for lot i

p_i is the market price of lot i

The probability of choosing alternative i then is a function of the relative consumer surplus of the alternative:

$$CS_{hi} = \Theta_{hi} - p_i \tag{2}$$

Martinez (1992) adopts an equilibrium formulation in which the market price is endogenous and determined by the highest bidder for each site among all consumers. This interpretation is founded on the view of land as a quasi-unique commodity in fixed supply, so that demand dictates price. It does not, apparently, represent buildings as part of the supply, with either short or long-term adjustment in supply interacting with demand to influence prices.

A third relevant line of research in residential location, originating in geography and sociology, is on residential mobility. These models include work that focuses on the household characteristics and on dissatisfaction, or push factors, including mobility. Research in this vein includes that of modeling decisions to move and decisions to search. Economists formalized these models as disequilibrium models of housing expenditure. More recent work has linked mobility and location choice approaches.

Waddell (1998) provides an approach to deal with aggregation of alternatives to the zone since the model does not explicitly deal with elemental housing or lots as the level of choice. This is done by including the size of the choice set represented by each of the aggregate choices. Substituting equation 2 into 1 and incorporating a size term yields

$$P_{i|h} = \frac{e^{\mu(CS_{hi} - \ln S_i)}}{\sum_j e^{\mu(CS_{hj} - \ln S_j)}} \tag{3}$$

5. MODELING HOUSEHOLD LOCATION CHOICES

5.1 Specification of Location Choice Model

The first step in the development of the location choice model is the estimation of the bid functions. The bid functions we estimate follow the approach pursued by Waddell (1998), that is, bid prices are considered to be the successful bids that households make that match the market price for the alternative. The structure of the bid functions takes the following generic form:

$$BP_{hi} = \beta_0 + \sum \beta_j X_j + \sum \beta_k Z_k \tag{4}$$

where:

BP_{hi} is the bid price of household h on dwelling unit i
X_j are dwelling attributes
Z_k are zone or neighborhood attributes
β are parameters to be estimated

At the outset, it is expected that bid prices will vary across socio-economic classes and that bid prices are assumed to be different depending on whether households are living in formal or informal means. A formal type of tenure refers to dwelling units which occupy house or land with the consent of the owner while the informal type are those which occupy without owner's consent.

We estimate bid functions for households stratified by income level, by the number of household members, and by housing tenure. Table 2 shows the categories of households. The data produce 16 household types. In order to estimate the bid function under each household class, the microsimulated housing value was used. Once the bid functions have been estimated, the bid equations are used to generate bid for each of the alternatives in the choice set, in order to estimate the consumer surplus for each alternative, and finally to predict the location choice probability.

Table 2. Household classification categories

Income	Household Size	Tenure
Under ₱ 9,000	Less than 5	Formal
₱ 9,000 – ₱ 14,999	5 or more	Informal
₱ 15,000 – ₱ 29,999		
₱ 30,000 or more		

5.2 Bid Functions

Table 3 shows the explanatory variables used in the estimated of the bid price functions. The estimates for the dummy variables for occupation type of the household heads are significant in all bid functions which suggest a logical grouping of household bids according to occupation classes. The relative bids suggest that households with heads having 'white collar' jobs bid higher. This is true for both households with formal and informal tenure.

Table 3. Household bid price variables

Variable	Definitions
Occpd1, Occpd2, Occpd3, Occpd4, Occpd5, Occpd6	Dummy variable for occupation type of the household head: Professional (Occpd1=0), Administrative (Occpd1=1), Clerical (Occpd2=1), Sales (Occpd3=1), Services (Occpd4=0), Agriculture (Occpd5=0), Production (Occpd6=1),
Flrarea29, Flrarea30, Flrarea50	Percent of dwelling units with area less than or equal to 29 sq. m, 30 sq. m to less than 50 sq. m and 50 sq. m or more, respectively
Yrbuilt80, Yrbuilt81, Yrbuilt86	Percent of dwelling units that are built in 1980 and earlier, between 1981 and 1985, and after 1986, respectively
Rooftype	Percent of dwelling units with durable roof quality
Walltype	Percent of dwelling units with durable wall quality
Repair	Percent of dwelling units not needing repair
Lowinc, Midinc, Highinc	Percent of households with low income (less than ₱9,000), middle income (between ₱9,000 and 14,999), and high income (more than ₱15,000)
Formal	Percent of households with formal tenure
Single, Duplex, Multi	Percent of dwelling units under single, duplex and multi-unit types, respectively

Landval	Average land value
Access, Distmkti, Timemkti	Accessibility measure, Distance and travel time to the Makati CBD area
Density	Population density of the zone
Res, Educ, Ind, Comm	Percent of land classified as residential, educational, industrial, and commercial, respectively

5.3 Logit Estimation of Residential Location Choice

The study pursued a sampling-of-alternatives approach in estimating a logit model of residential location choice. A total of 5,000 samples were randomly selected from the household microdata with formal and informal tenure, respectively. Then, the bid functions were used to generate estimates of the consumer surplus of each alternative. A total of 10 alternative residential zones, including the observed choice, were sampled. Table 4 shows the estimation results.

Table 4. Residential location choice model estimation results

Variable	Formal Households	Informal Household
Consumer Surplus	0.31685	0.56290
	(1.690)	(2.024)
Nunits	-0.31719	-0.30316
	(-1.383)	(-1.343)
Log-Likelihood	-8956.3508	-11510.0356

The model estimates yielded significant parameter estimates and expected signs for the consumer surplus term. It implies that the greater the consumer surplus, the more likely the household will choose that option. The estimates for Nunits yields consistently negative signs which implies that the larger the number of alternatives, the less likely the household will choose the zone, holding constant the consumer surplus of the alternatives.

5.4 Modeling Employment Location Choice

The employment location choice model may be specified as a multinomial logit model that includes the accessibility variables (e.g. access to population areas, distance or travel time to the CBD), agglomeration variables in the sense that similar employment tend to cluster in a zone (e.g. percent of employment or occupation type), and land use characteristics.

In order to estimate the model, a new microsimulation module needs to be developed. The aim of the module is to assign the workplace zone for each of the household heads in the microdata. Once the workplace zones for each household head has been assigned, a sampling-of-alternatives approach can be done in order to generate a set of alternatives for which the employment location choice model can be estimated. The process will be as follows:

(1) Generate conditional probability of a household head in each zone having a particular workplace zone given its age, sex, marital status, education level, economic activity rate, occupation type, employment type, and employment status (whether formal or informal);
(2) Assign the workplace zone for each household head using monte carlo sampling;
(3) Stratify the household heads according to employment status (formal and informal);
(4) Generate alternative workplace zoning by random sampling; and
(5) Estimate the employment location choice model for household heads in the formal and informal sector, respectively.

6. Concluding Remarks

InformalSim is a spatial microsimulation model for Metro Manila. It provides household microdata by integrating available survey and census-based data. The resulting household microdata possesses more detailed attribute and spatial detail. The estimation of household incomes and housing tenure characteristics enable analysts to distinguish between formal and informal households. The resulting household microdata has been put to practical use with the development of residential and employment location choice models. Still, further work should be pursued in order to improve the models and estimate models at finer geographic levels, specifically, at the barangay and parcel levels.

A more sophisticated understanding of the location choice pattern and behavior of households in Metro Manila presents practical implications for spatial planning. First of all, the identification of households 'on the ground' provides a high-resolution image of how households are located in space. The exploration of choice models allow policy makers and analysts to discern how location decisions are made and how such decision will change as a result of policy changes.

Spatial microsimulation provides a powerful platform in overcoming data problems in developing countries. With the flexibility of object-oriented approach, additional modules and extensions to the model system can be explored in the future. It is envisioned that spatial microsimulation will become an indispensable tool in policy analysis and urban modeling for cities in developing countries.

REFERENCES

a) Books and Book Chapters

Alonso, W. (1964) **Location and Land Use**, Harvard University, Cambridge, MA.

Anas, A. (1982) **Residential Location Markets and Urban Transportation: Economic Theory, Econometrics and Policy Analysis with Discrete Choice Models**, Academic Press, New York.

Clarke, G. (1996) **Microsimulation for Urban and Regional Policy Analysis**, Pion Ltd., London.

Lakshmanan, T. R. (1981) Urban development modeling and policy analysis: Review and prospects, **Cities in Transition: Problems and Policies**, Sijthoff & Noordhoff International Publishers, The Netherlands, 193-215.

McGee, T.G. (1971) **The Urbanization Process in the Third World: Explorations in Search of a Theory**, G. Bell and Sons Ltd, London.

McFadden, D. (1978) Modeling the choice of residential location in spatial interaction theory and planning models, in A. Karlqvist, L. Lundqvist, F. Snickars and J.W. Weibull (eds.), **Spatial Interaction Theory and Planning Model**, North Holland, Amsterdam, 75-96.

Mohan, R. (1979) **Urban Economic and Planning Models**, The John Hopkins University Press, The International Bank for Reconstruction and Development/ The World Bank.

Muth, R. (1968) **Cities and Housing**, Chicago, University of Chicago Press.

Wegener, M. (1985) The Dortmund Housing Market Model: A Monte Carlo Simulation of a Regional Housing Market, in **Microeconomic Models of Housing Markets**, Konrad Stahl, ed., Springer-Verlag.

b) Journal Papers

Clarke, G. and E. Holm (1987) Microsimulation methods in spatial analysis and planning, **Geografiska Annaler B 69(2)**, 145-164.

Ellickson, B. (1981) An alternative test of the hedonic theory of housing markets, **Journal of Urban Economics**, 9, 56-79.

Lancaster, K. J. (1966) A new approach to consumer theory, **Journal of Political Economy 74**, 132-157.

Lee, L. F.(1978) Unionism and wage rates: a simultaneous equations model with qualitative and limited dependent variables, **International Economic Review**, 19(2), 415-433.

Lee, L. F. and R. P. Trost (1978) Estimation of some limited dependent variable models with application to housing demand, **Journal of Econometrics**, 8, 357-383.

Martinez, F. (1992) The bid-choice land use model: an integrated economic framework, **Environment and Planning A 24**, 871-885.

Merz, J. (1991) Microsimulation – a survey of principles, developments and applications, **International Journal of Forecasting 7**, 77-104.

Rosen, S. (1974) Hedonic prices and implicit markets: product differentiation in pure competition, **Journal of Political Economy 82**, 34-55.

Waddell, P. (1993) Exogenous workplace choice in residential location models: Is the assumption valid?, **Geographical Analysis**, **Vol. 25**, **No. 1**, 65-82.

Wheaton, W. C. (1977) A bid rent approach to housing demand, **Journal of Urban Economics 4(2)**, 200-217.

c) Papers presented to conferences

Moeckel, R., C. Schürmann and M. Wegener (2002) Microsimulation of land use, **Proceedings of the 42nd European Congress of the Regional Science Association**, Dortmund, 27-31 August 2002.

Tiglao, N. C. and M. Tsutsumi (2001) Towards the development of empirical urban development models for large metropolitan regions in developing countries, **Proceedings of the 9th World Conference on Transport Research (WCTR)**, Seoul, Korea, 22-27 July 2001.

Tiglao, N. C., M. Tsutsumi and E. Shimizu (2003) Towards integrated urban models for developing countries: modeling households and location choices using spatial microsimulation approach, **Proceedings of the Eastern Asia Society for Transportation Studies (EASTS) Conference**, Fukuoka, Japan, 29 Oct - 1 Nov 2003.

Waddell, P. (1998) An urban simulation model for integrated policy analysis and planning: residential location and housing market components of UrbanSim, **Proceedings of the 8th World Conference on Transport Research (WCTR)**, Antwerp, Belgium, 12-17 July 1998.

d) Other documents

Tiglao, N. C. (2002) **Small Area Estimation and Spatial Microsimulation of Household Characteristics in Developing Counties with Focus on Informal Settlements in Metro Manila**, Unpublished Ph.D. Dissertation, University of Tokyo.