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USING SPATIAL MICROSIMULATION FOR INTEGRATED LAND USE AND TRANSPORT MODELING IN METRO MANILA: IMPROVING TRANSPORT STATISTICS FOR POLICY ANALYSIS

by

Noriel Christopher C. Tiglao and Mark Angelo Y. Tacderas

For additional information, please contact:

Author's name	Noriel Christopher C. Tiglao
Designation	Associate Professor
Author's name	Mark Angelo Y. Tacderas
Designation	University Researcher I
Affiliation	National College of Public Administration and Governance
Address	Raul P. de Guzman St., University of the Philippines Diliman, 1101 Quezon City
Tel. no.	928-3861
E-mail	nctiglao@up.edu.ph, mytacderas@up.edu.ph

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ABSTRACT

The development of integrated land use and transport model is prompted by the need to enhance rational decision-making processes in controlling and directing urban change in the light of sustainability issues. Modelling efforts for cities in developing countries like Metro Manila have been hampered by serious limitations in data availability. If available, existing data sets do not possess the desired spatial and temporal coverage to allow detailed and more sophisticated analyses of complex urban phenomenon. This study presents a spatial microsimulation approach in providing overcoming the data and modeling problems in the development of integrated urban models. The spatial microsimulation approach is that it is capable of building reliable disaggregate data sets at the household or individual level and provide it at an appropriately fine geographic scale for detailed analysis by utilizing disparate data sets and developing a complete microdata set using conditional probabilities, contingency tables and iterative proportional fitting techniques. InformalSim is a static spatial microsimulation model for estimating characteristics of informal households for Metro Manila. This paper presents the development of modules that provide transport-related characteristics such as residential and employment location choice, as well as, car ownership that can provide policy and decision support.

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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 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 policymakers in large metropolitan areas in developing countries is growing. This is brought about by an increasing awareness among decisionmakers to evaluate the effectiveness of current urban and transport policies, as well as, the need to forecast the probable impacts of proposed policy measures.

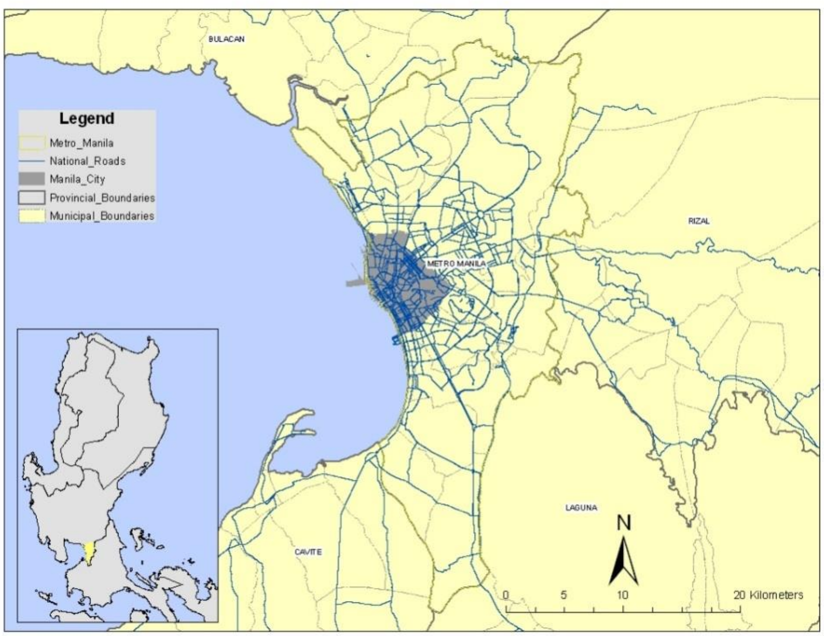
This paper discusses the issues involved in the development of urban models and its imperatives for Metro Manila. It tackles the problem of data availability by pursuing the development of a ‘synthetic household microdata’ for Metro Manila using spatial microsimulation model. The model system provides 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. The paper presents the initial development of location choice models for Metro Manila. Finally, it discusses the potential pursued modeling framework in the development of spatial planning and decision support tool for developing countries.

2. Key Urban Issues in Metro Manila

2.1 Rapid Population Growth

Figure 1 shows the map of Metro Manila and its vicinity. Metro Manila area consists of 17 cities and municipalities. This administrative region is collectively referred to as the National Capital Region, or NCR. The old urban core area is located in the City of Manila. The metropolitan area has been experiencing rapid population growth and high levels of urbanization and migration along with the other mega-cities in developing world. The high population growth and urbanization rate in Metro Manila has been brought about by the both natural increase in population and migration. Table 1 shows the population growth rates for the Philippines and Metro Manila. While the country grew at an average rate of 2.7 percent annually during the period from 1970 to 1990, Metro Manila experienced explosive population growth at an average of almost 4 percent annually. In 1990, Metro Manila comprised 13 percent of the entire national population. As such, Metro Manila dominates the economy accounting for 43.5 percent of the country's GDP in 2000.

Figure 1. Metro Manila and its vicinity



The effect of rapid urbanization of Metro Manila spilled over the adjoining municipalities. People from areas adjoining Metro Manila and depressed rural areas have been moving to the capital city to look for better economic opportunities. Rural to urban migration as a factor influencing urbanization has been very evident in the Philippines. With continued rapid population growth and diminishing agricultural frontiers after the colonial years, rural-urban migration accelerated in the 1970s and picked up further in the 1980s. By 1990, the level of urbanization had risen to nearly 50%, the highest in Southeast Asia and next only to South Korea.

Table 1.Population of the Philippines and Metro Manila

Census Year	Philippine Population (000)	Growth Rate (%)	Metro Manila Population (000)	Growth Rate (%)	Percent of National Population
1960	27,088	na	2,462	na	9.09%
1970	36,684	3.08	3,967	4.89	10.81%
1980	48,098	2.75	5,926	4.1	12.32%
1990	60,703	2.35	7,928	2.95	13.06%
2000	76,504	2.34	9,932	2.28	12.98%

Source: NSO

Similar to other developing countries, one pervading and serious issue is that wealth and economic power have been concentrated to a certain few and has resulted in severe economic inequality across socio-economic cases and geographic regions (Boyce, 1993). The problem of inequality is clearly evident in the labor and housing sectors. In the Philippines, the proliferation of informal settlements in the metropolis has prompted that Government to implement various housing programs aimed at promoting home-ownership among the urban poor and low-income households since the early 1990's. However, these programs have not been successful in reaching their intended beneficiaries (Llanto and Orbeta, 2001) because of weak targeting mechanisms. More so, the impacts of the various housing programs were never clearly measured or evaluated.

2.2 Urban Primacy

Urban primacy refers to the phenomenon wherein economic development and urban prosperity is mainly concentrated in the capital city, or a major urban area while other cities lag. Reasons for this are the centralization of power in the capital, the high ratio of foreign capital in domestic economy, and the discrepancy of income levels between the metropolis and other regions of the country. Primacy is a phenomenon that does not come about by itself. It has been closely intertwined with industrialization and economic development that is acutely concentrated in the metropolis. Historically, urban and industrial development in the metropolis seems to have started by virtue of its natural strategic advantages and/or resource endowments.Table 2 shows the primary and four-city index for the Philippines. The primary index is defined as the ratio of Metro Manila relative to the population of the second largest city[1], while the four-city index shows the ratio of the population of Metro Manila relative to the combined populations of the next three largest cities[2]. It shows that Metro Manila's dominance has only slightly dipped through the years. The 2000 census data shows that DavaoCity is quickly catching up with Metro Manila as exhibited by the drop in the primacy index compared to the 1990 figure. However, in terms of the four-city index, Metro Manila still continues to dominate.

Table 2. Primacy and four-city index

Census Year	Primacy Index	Four-city Index
1960	9.81	3.24
1970	10.12	3.45
1980	9.71	3.47
1990	9.33	3.50
2000	8.66	4.02

Source: NSO

[1]The second largest city based on the 2000 census year is DavaoCity.

[2]The next three largest cities after Metro Manila in 1990 are: DavaoCity, CebuCity and ZamboangaCity.

2.2 Urban Housing Problem

The urban housing problem in Metro Manila is complex. Rebullida et al. (1999) highlights the various interdependent dimensions of the urban housing problem. These include urban squatting, housing backlog and housing need, lack of access to housing finance, insecurity of tenure, and lack of comprehensive policy and institutional framework for tackling the housing problem. The problem if housing in Metro Manila has been viewed in terms of the illegal occupancy of land or of housing space, and the subsequent formation of squatter communities. Squatting which is legally defined as the unlawful occupancy of land rightfully owned by others, became widespread in the ensuing years after the Second World War.Studies of squatting usually explain the spread of such practice working under the social network consisting of friends, relatives or town-mates, who facilitate the illegal occupancy of government-owned or private land. In some cases, the settler pays some rent to a "caretaker". Dwelling units in these areas are usually made from scrap materials. In later years, the term squatter also came to refer to anyone who could afford to buy a house and lot, but continue to live in an illegal settlement in order to avoid paying rent or mortgage. Moreover, there are the so called "professional squatter" or squatter syndicates referring to those occupying vacant land owned by others in order to sell the right for its use to others. Makeshift housing also became a measure of inadequate housing, with the lack of facilities and the conditions of poverty of its dwellers as additional indicators (Endriga et al., 1996). Makeshift housing refers to the use of salvaged or improvised construction materials for the roofs or walls used with other construction materials.

There have been various estimates of the number of squatters and urban poor in Metro Manila, but the different criteria and methods of measurement used renders the estimates incomparable against each other and misleading (Rebullida et al., 1999). While there are differences in actual magnitude of informal settlements in Metro Manila, there is a consensus that the number has been growing through the years. Table 2 shows the estimated magnitude of informal households. In 1998, the magnitude of informal settlers was estimated to consist around 10 percent of the total number of households. However, in 2000, this number is estimated to comprise one-third of the total households with 726,908 households classified as informal settlers.

Table 3.Magnitude of informal settlers in Metro Manila

Year	Number of informal households	% of total households
1988	150,721	10.5
1991	192,394	11.7
1994	245,425	13.9
2000	726,908	34.2

Source: Urban Sector Profile, ADB (1999)
National Housing Authority (2000)

The UN Commission on Sustainable Development (UNCSD) proposed two formal definitions for informal settlements, as follows:

1) Residential areas where a group of housing units has been constructed on land to which the occupant have no legal claim, or which they occupy illegally; and
2) Unplanned settlements and areas where housing is not in compliance with current planning and building regulations (unauthorized housing).

However, there is still a serious lack of operational definition in the Philippines due to inherent issues. Firstly, the legal framework for settlements as embodied in the first definitions poses a vague criterion as laws varies from place to place and across time. A case in point is that while squatters in the Philippines used to be totally illegal several decades ago, they now enjoy a certain level of leverage or protection under the present set of housing and urban development laws.Another issue concerns the serious lack of available data, that is, informal housing is not captured in the existing official statistics. Finally, research studies to date have provided only limited quality and have heavily relied on proxy variables that are very restrictive, oftentimes confusing and are very weak in providing insights into the current state of the housing problem. The urban structure of Metro Manila as with other cities in developing countries is indeed complex. In order to understand the structure, there is a need to understand the complex interplay of problems and issues (Tiglao and Tsutsumi, 2003).

2.3 Urban Poverty

Poverty measures in the Philippines are:

1) the food threshold (FT) or subsistence threshold; and
2) the poverty threshold (PT) or poverty line

Both measures were officially adopted by the National Statistics Coordination Board in 1992. The food threshold (FT) is measured in terms of a basket which satisfies all (100 percent) of the Recommended Daily Allowance (RDA) for protein, and 80 percent of the RDA for vitamins and other nutrients. The RDAs are prescribed by the Food and Nutrition Research Institute (FNRI). Low-cost menus are prepared for each region in a particular year based on average prices of goods. Families with incomes below the established FT constitute the core poor or subsistence families. The proportion of the core poor to the total number of families is the subsistence incidence or food poverty incidence. The poverty threshold (PT) or poverty line is computed as the ratio between the food threshold (FT) with the expenditure.Expenditure ratio is the ratio of the food expenditure to the total basic expenditure. Basic expenditures include those for clothing, footwear, light, fuel, water, housing (i.e. maintenance, minor repair, and rental of the occupied dwelling units, among others), medical care, education, transportation and communication, nondurable furnishings, household operation and personal care and effects. Poverty incidence is the proportion of families with incomes below the poverty threshold to the total number of families.

An alternative method of identifying the poor is presented by Tabunda and de Jesus (1996). They classified all households in Metro Manila according to the socioeconomic classification rule used by market research agencies, using data from the 1990 Census of Population and Housing (CPH). The classification rule uses the following variables: educational attainment of household head, construction material of roof of dwelling unit. construction material of outer walls, floor area of dwelling unit, presence of household conveniences, status of repair, tenure status of housing unit and tenure status of lot.Based on the rule, approximately 31 percent of households in Metro Manila belonged to E, the lowest socioeconomic class in the scale. While Tabunda and de Jesus (1996) demonstrated how the proposed method can be used to identify the poorest segment, it has yet to be validated and refined. Moreover, poverty measures based on the proposed classification rule are still not generally available for use.

Balisacan (2001) evaluates the current poverty monitoring system in the Philippines. He concludes that existing poverty measures are not robust because it does not provide consistent evaluation of regions because poverty norms are not fixed in terms of a given living standard. The two official measures of poverty, namely, food threshold and poverty threshold, necessitates the availability of income data. However, it is worthwhile to note that official income estimates are only provided at the city or municipal level. On the other hand, the methodology proposed by Tabunda and de Jesus (1996) relies heavily on the socio-economic and housing-related variables contained in the CPH data. However, the census suffers from severe non-response in housing-related variables which restricts the use of such variables.

3. SPATIAL ANALYSIS OF HOUSEHOLDS

3.1 Urban Modeling Issues

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 (2003) 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, policymakers 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.

3.2 Spatial Analysis Framework

Figure 2 shows the proposed spatial analysis framework adopted in this study. The main focus of the framework is the household decision. It is recognized that spatial decisions of households are strongly influenced by the existing housing and labor market structures. This is consistent with the activity approach rather than the trip approach to travel demand analysis.The housing market is characterized by the distribution of housing units across space including the land where such housing units are built. The distribution of housing spaces includes potential areas for informal settlements. On the other hand, the labor market is characterized by the distribution of jobs across space, both formal and informal. The housing and labor markets are influenced by land use and transport policies. Figure 3 depicts the collective spatial decisions of households.

Figure 2. Spatial analysis framework

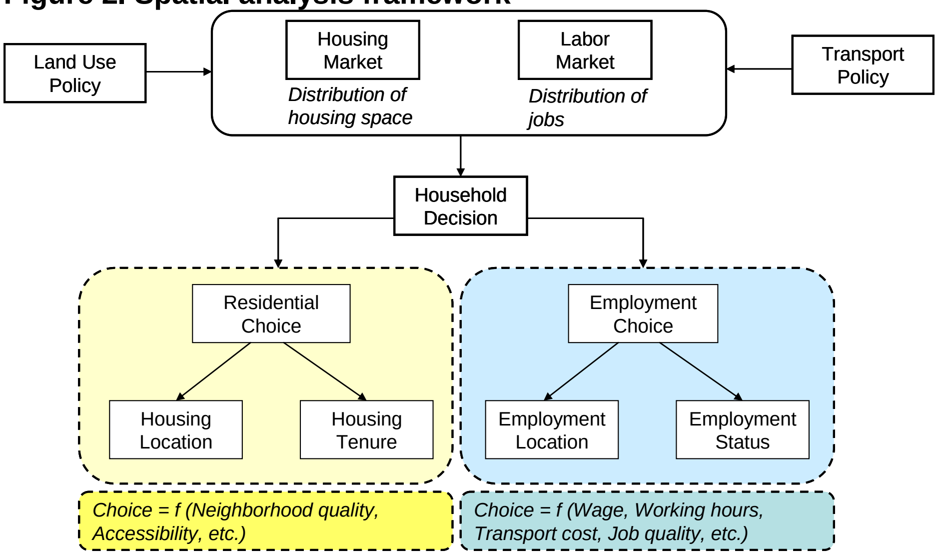
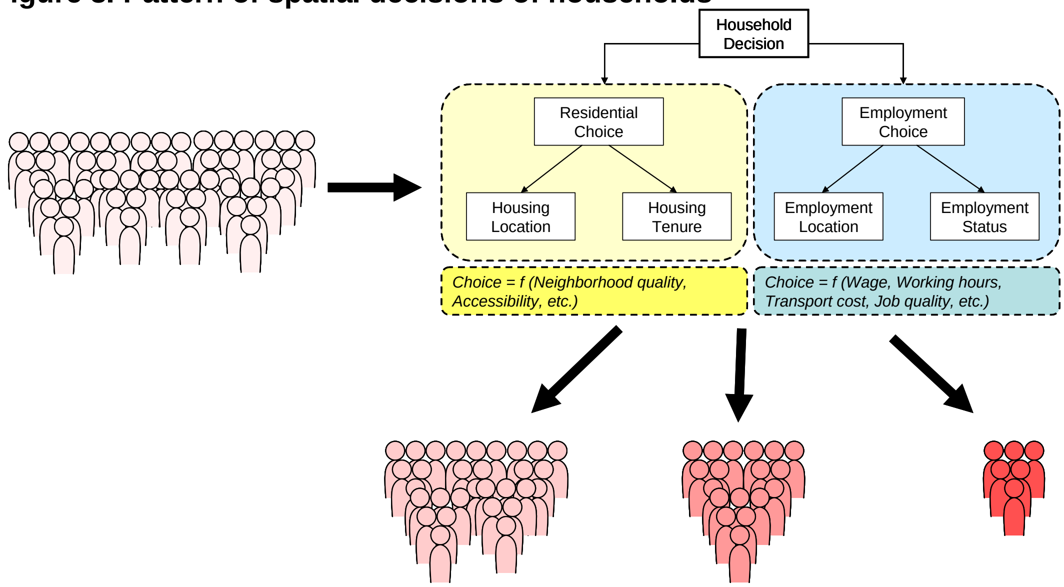


Figure 3. Pattern of spatial decisions of households



The household decision structure consists of two major choice processes, that is, residential choice and employment choice. The residential choice process can be structured as a joint decision on housing location and housing tenure type (whether formal or informal). On the other hand, the employment choice process can be structured as a joint decision on employment location and employment status (whether formal or informal). Consequently, the residential choice and employment choice processes can be specified as discrete choice models (McFadden, 1978).

Once the choice models are specified and estimated from a representative sample of households then theoretically, it would be possible to simulate the emerging spatial patterns brought about the cumulative decisions of all households in the population. This perspective would lend itself to a detailed treatment of household microdata. This approach which is now referred to as microsimulation is borne out of an observation that “current models of socio-economic systems only predict aggregrates and fail to predict distributions of individuals, households, or firms in single or multi-variate classifications.” (Orcutt, 1957). Thus, under a microsimulation framework, it is feasible to analyze distribution of households in a more disaggregate level. Figure 3 depicts an analysis that would be capable to deriving patterns of spatial decisions.

3.3 Identification of Informal Households

An inherent and basic problem underscoring the design of effective urban policies and programs is the appropriate identification of program beneficiaries, specifically, the households in the informal sector. However, up until now, the identification of such households has not been satisfactorily achieved due to serious constraints in data availability and reliability. Survey data are difficult and very costly to obtain considering the wide range of socio-economic classes and poverty levels. As such, the number of samples is constrained such that the scale of the sampling domain is kept at a fairly aggregated level. For example, the National Statistics Office (NSO) does not provide household income estimates for domains below the city and/or municipality level. In addition, some data are omitted from the census questionnaire due to it sensitive nature as such is the case for household incomes and housing tenure.

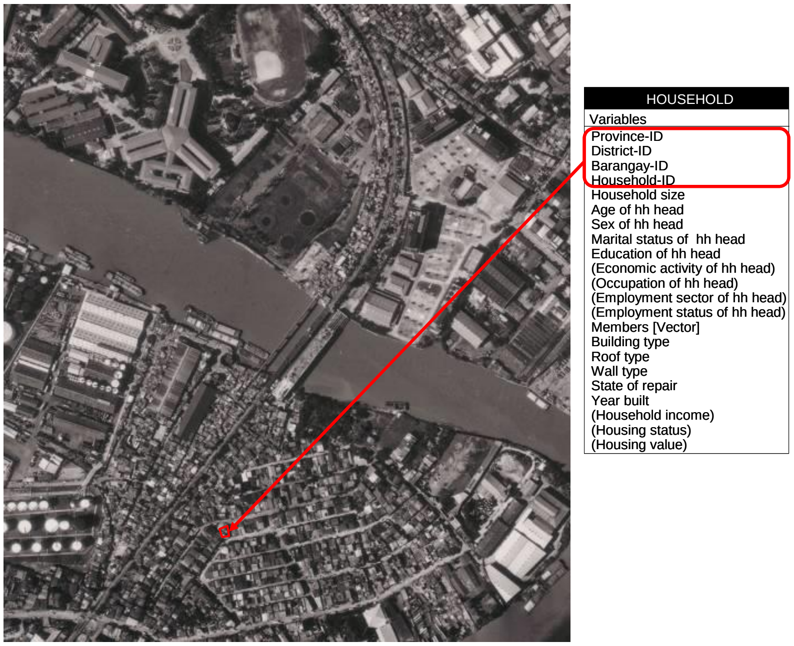
There is great scope in identifying the urban poor ‘on the ground’. First, it is vital in providing effective targeting mechanisms for housing and social policies and is essential in formulating new policies. Secondly, proper identification of households supports the need for a more robust poverty monitoring system. Identifying the proper beneficiaries of socialized housing constitutes a major problem and an essential requirement to effective and responsive policy formulation and program implementation. Limited government resources should be channeled to rightful beneficiaries. However, data sources have been found to be inadequate. The various estimates of the size and scope of urbanization have used different criteria and have produced incomparable results. (Rebullida, et al. 1999). It should be pointed out that a clear identification of Metro Manila’s urban poor is but a prerequisite to more realistic data collection. This, in turn, should lead to better policy formulation and program implementation. Distinguishing the urban poor from and identifying their spatial distribution vis-à-vis non-poor should also lead to finer distinction between and among groups comprising the urban poor sector for purposes of ascertaining differences in their housing and other basic needs. (Rebullida, et al. 1999, p.33)

3.4 Use of Spatial Information

Several studies point to the beneficial use of spatial information technology in the management of informal settlements (Mason et. al, 1998; Abbott, 2001 and 2003; Sliuzas, 2003). Most of the applications to date have been limited to a few African cities and has revolved around the use of aerial imagery (mainly for shack identification) in management of slum upgrading activities. The infusion of participatory approaches in spatial data provision in recent years is quite notable (Sliuzas, 2003). On the other, the provision of spatial information for other policy areas like poverty alleviation is a new field (Tiglao, 2006).Informal households can be identified using a multi-dimensional indicator that takes into account both household and housing characteristics. These variables are only partially measured in the Census of Population and Housing (CPH) due to non-response. The proposed indicators of informal households incorporate measures along two dimensions, namely urban poverty and housing need (Tiglao, 2002). Urban poverty is characterized by household income while housing need is characterized by housing tenure. In order to identify informal households, the two indicators, namely household income and housing tenure, should be made available at fine geographic details. More specifically, the barangay is considered the most ideal reference zone as it is the basic unit of administration.

The National Statistics Office (NSO) does not provide household income estimates for domains below the city and/or municipality level. Household incomes are also not incorporated in the Census because of cost limitations and the likelihood of non-response. This study proposes simulation to obtain household income distributions. Elsewhere in the world, the estimation of household incomes constitutes a major research area (Bramley and Smart,1996; Bramley et al, 2000). As previously mentioned, housing tenure variables suffer from non-response in the Census. However, there is a need to establish estimates at the barangay level or even at the household level. Again, since primary surveys are costly to undertake, simulation provide a cost-effective alternative to derive estimates. Figure 4 shows an image of a proper identification of informal households using a prescribed set of useful variables that will allow for better analysis of urban policies.

Figure 4. Identification of informal households



4. SPATIAL MICROSIMULATION APPROACH

Microanalytic simulation or microsimulation models have been increasingly applied in the quantitative analyses of economic and social policy problems in recent years. Merz (1991) provides a comprehensive review of the principles, development and application of microsimulation found in economics. Clarke and Holm (1987) provides a thorough presentation on how microsimulation methods can be applied in regional science and planning analysis. Microsimulation models are directly concerned with microunits, or the individual units such as persons, households or firms. It is considered a forecasting instrument because policy effects can be tested and estimated within a microsimulation model system. The microunits are identified by characteristics such as age of an individual, number of children in a family, income and transfers of a household, employment structure of a firm, etc. The characteristics of the individual units are then modified depending on their individual behavior and the institutional relationship in which they operate. The individual impact of economic and social policies can thus be analyzed in a differentiated manner on the microunits concerned.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. On the other hand, microsimulation models would potentially find relevant applications to policy analysis if the spatial dimensions are incorporated. 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.

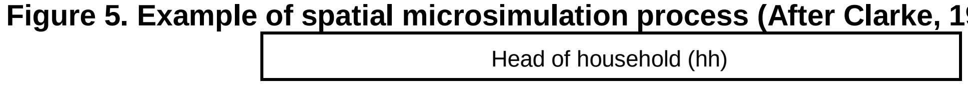
4.1 Spatial Microsimulation Process

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).

Clarke (1996) points out that there are two major works involved in applying microsimulation methods in spatial analysis. The first involves the construction of a microdata set. This procedure usually involves the use of contingency tables or conditional probability analysis to estimate chain conditional probabilities. In particular, conditional probabilities are calculated from available known data and then they are used to reconstruct detailed micro-level populations. The use of conditional probabilities allows the incorporation of the widest range of available known data. As most small-area population data are provided as predetermined tabulations, converting them into probabilities conditional on the attributes from another table allows separate tables to be linked together.There are a number of ways to generate probability relationships, such as linear programming models, discrete choice models, balancing factor methods in spatial interaction models and iterative proportional fitting (IPF) techniques (Williamson, 1998). There are also other approaches to microdata generation such as reweighing of a parent sample of microdata, which are available at a different spatial scale. The next step involves the creation of a sample of individuals or households based on the set of probabilities. Computational constraints in the past are quickly being overcome by computer technologies in both hardware and software that now offers considerable opportunities and flexibility for large-scale simulations. Moreover, the lack of microdata sets to calibrate or test results of simulations are quickly being addressed as more and better data sets are becoming available.

Figure 5 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 5. Example of spatial microsimulation process (After Clarke, 1996)



Steps	1st	2nd	3rd
1. Age,sex, and marital status (M) of hh head	Age: 27 Sex: male M: married	Age: 32 Sex: male M: married	Age: 87 Sex: female M: divorced
2. Probability of hh head of given age, sex, and M being an owner-occupier	0.7	0.7	0.54
3. Random number (*computer generated*)	0.542	0.823	0.794
4. Tenure assigned to hh on the basis of random sampling	owner-occupied	rented	rented

4.2 Modeling Characteristics of Households in Manila

Tiglao (2002) presents the first application of spatial microsimulation approach to model missing characteristics of households in the City of Manila. The city makes up one of the 17 cities and municipalities in Metro Manila. Figure 6 shows the zoning systems for ManilaCity. The city consists of 54 traffic analysis zones and around 900 barangays (the smallest administrative unit in the Philippines). According to the 1990 census, Manila City had a total population of around 1.65 million persons.

Table 4 shows the different data sets used in model. 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 next major source of household income data is the 1996 Metro Manila Urban Transportation Integration Study (MMUTIS). Aside from containing information about the household and member characteristics and very detailed data about their trip characteristics, the Household Interview Survey (HIS) data from MMUTIS provides information about the income range of respondent households. The samples which consists of 2.5% of the total number of households in 1996 are referenced based on Traffic Analysis Zones (TAZs). The size of the TAZ differs with higher levels of aggregation at the other areas of the study area. The primary source of detailed socio-demographic data used in the development of the model is the 1990 Census of Housing and Population (CPH). This data set provides the basic household microdata as the census conducts survey on all households. Building footprint data for Metro Manila was utilized in the validation of the model.

Figure 6. Zoning systems of Manila City

Cities/ Municipalities

Traffic Zones

Barangays

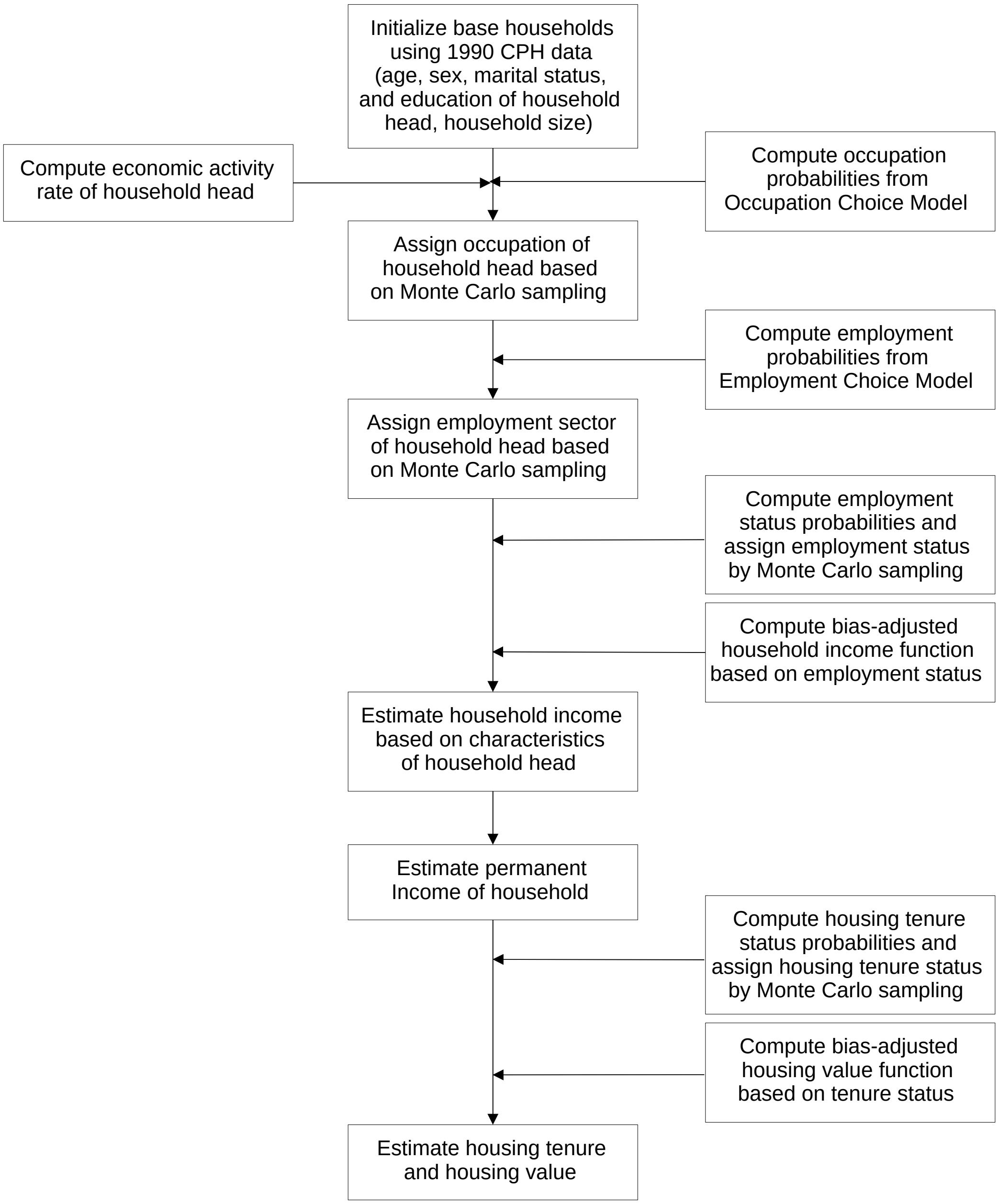
Table 4.Data sets used in the model

Scale	Data Set	Description / Coverage of the Data Set
City/ Municipality	• 1997 Family Income and Expenditure Survey (FIES)	• Household demographic data • Detailed household incomes and expenditures • 4,030 samples for Metro Manila
Traffic Zone	• 1996 Metro Manila Urban Transportation Integration Study (MMUTIS)	• Selected household demographic data • Member and household income • 50,000 samples for Metro Manila
Barangay	• 1990 Census of Population and Housing (CPH)	• Detailed household and housing characteristics • All households in 1990 • Non-response in the tenure question • No income question
Building	• 1996 Land Use/ Building Footprint Data	• Urban land use zoning map • Building footprint data

4.3 Spatial Microsimulation of Informal Households

Figure 7 shows the spatial microsimulation process for estimating missing household characteristics. The model initializes a baseline population consisting of all households in the 1990 CPH data. The design of the CPH survey allows the identification of each household unit on a reference system referred to as enumeration area (EA). However, the information about EAs are highly confidential and are not provided to the public. Nevertheless, this spatial reference will be quite useful for succeeding model development efforts. After the initialization of the baseline microdata, the economic activity participation, as well as occupation and employment sector of the household head is estimated using Monte Carlo sampling using conditional probabilities derived from the 1996 MMUTIS data.

Figure 7. Spatial microsimulation of informal households


Initialize base households using 1990 CPH data (age, sex, marital status, and education of household head, household size)
Compute economic activity rate of household head
Compute occupation probabilities from Occupation Choice Model
Assign occupation of household head based on Monte Carlo sampling
Compute employment probabilities from Employment Choice Model
Assign employment sector of household head based on Monte Carlo sampling
Compute employment status probabilities and assign employment status by Monte Carlo sampling
Compute bias-adjusted household income function based on employment status
Estimate household income based on characteristics of household head
Estimate permanent Income of household
Compute housing tenure status probabilities and assign housing tenure status by Monte Carlo sampling
Compute bias-adjusted housing value function based on tenure status
Estimate housing tenure and housing value

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 using a probit model, specifically, 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. The next step involves the estimation of permanent income of the household. Permanent income is needed to estimate the value. Housing values is 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).

Figure 8 presents the object representation of the household microdata. The object-oriented approach to spatial microsimulation modeling was proposed by Ballas et al. (1999). 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, thar is, 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.

Figure 8. Object representation of household microdata

	MEMBER	HOUSEHOLD
	Variables	Variables
	Province-ID	Province-ID
	District-ID	District-ID
	Barangay-ID	Barangay-ID
	Household-ID	Household-ID
Baseline	Member-ID	Household size
Characteristics	Relation to hh head	Age of hh head
	Age	Sex of hh head
	Sex	Marital status of hh head
	Marital status	Education of hh head
	Education	(Economic activity of hh head)
	(Occupation)	(Occupation of hh head)
Unobserved	(Employment sector)	(Employment sector of hh head)
Characteristics	(Income)	(Employment status of hh head)
	Methods	Members [Vector]
	GetEconomicActivity	Building type
Computational	GetOccupation	Roof type
Objects/ Models	GetEmploymentSector	Wall type
	GetIncome	State of repair
	…	Year built
		(Household income)
		(Housing status)
		(Housing value)
		Methods
		GetEconomicActivityofHead
		GetOccupationofHead
		GetEmploymentSectorofHead
		GetEmploymentStatusofHead
		GetHouseholdIncome
		GetHousingStatus
		GetHousingValue

4.3 Spatial Microsimulation Modules

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, discrete 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. 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.
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 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 also 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 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 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 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.

4. MODELING LOCATION CHOICE

4.1 Residential Location Choice Theory

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 these 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 represents 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.

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. 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:

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

where:

Θ_{hi} is the willingness of consumer h to pay for lot i; and
$p_i$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:

$$CS_{hi} = \Theta_{hi} - p_i \qquad (2)$$

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.

Waddell (2003) 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

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

4.2 Specification of the 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:

$$BP_{hi} = \beta_0 + \sum \beta_j X_j + \sum \beta_k Z_k \qquad (4)$$

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
$\beta$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.

Tiglao and Tsutsumi (2005) estimated bid functions for households stratified by income level, by the number of household members, and by housing tenure. Table 5 shows the categories of households. The data produced 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 5. Household classification categories

Household income	Household size	Tenure
Under P9,000	Less than 5	Formal
P9,000 – P14,999	5 or more	Informal
P15,000 – P29,999		
P30,000 or more		

4.3 Bid Function

Table 6 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 6. Household bid price variables

Variable	Definition
Occpd1, Occpd2, Occpd3, Occpd4, Occpd5, Occpd5	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 P9,000), middle income (betweenP9,000 and P14,999), and high income (more thanP15,000)
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

4.4 Logit Estimation of Residential Location Choice

Tiglao and Tsutsumi (2005) 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 7 shows the estimation results.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.

Table 7. Residential location choice model estimation results

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

4.5 Modeling Employment Location Choice

The employment location choice model may be specified as a multinomial logit model thatincludes the accessibility variables (e.g. access to population areas, distance or travel time tothe CBD), agglomeration variables in the sense that similar employment tend to cluster in azone (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. Theaim of the module is to assign the workplace zone for each of the household heads in themicrodata. Once the workplace zones for each household head has been assigned, asampling-of-alternatives approach can be done in order to generate a set of alternatives forwhich the employment location choice model can be estimated. The process will be asfollows:

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
6) and informal sector, respectively.

5. MODELING CAR OWNERSHIP

5.1 Discrete Choice Theory

A discrete choice model describes a particular choice situation, which is, for this study, to own or not to own a car. It is based on a theoretical framework called the random utility theory. The models are based on observed choices made by individual termed as the decision-maker. The use of this framework will enable more realistic models when compared to other estimation methods such as least squares method. In general, discrete choice models postulate that 'the probability of individuals choosing a given option is a function of their socioeconomic characteristics and the relative attractiveness of the option'. The model is specified by different explanatory variables (listed above), known as the attributes of the decision-maker. The decision-maker, for this research, is the household.

There are many factors affecting car ownership, namely

1. Household characteristics (e.g. income, number of members, age, etc.)
2. Relative location of the household
3. Cost and Service level (e.g. purchase price, repairs, fuel costs, etc.)

The second type of factor, relative location of the household, pertains to locational factors that affect car ownership. There is a relatively higher percentage of car-owning households in most urban areas as opposed to rural areas. Level of car ownership as well as car use is likewise linked to the supply of public transport services. The third type of factor pertains to costs and prices related to car ownership as well as car usage. Factors such as fuel prices, public transport fares, maintenance and spare parts costs, purchase price and other fixed cost are but a few issues that can be regarded.

5.2 Car Ownership Model

Rubite and Tiglao (2003) presents a model for predicting the probability of the household's choice of owning a car or not as a function of the household's and house head's characteristics (e.g. income, household size, number of working adults, sex, age, occupation type, etc.). The result is a binary choice of whether to own 0 cars, or 1+ (one or more) cars. The decision unit or decision maker will be the household given a binary choice set of owning 0 or owning 1+ cars. The modeling process consists of an iterative process of forcing into the model, one by one, in combination, or both, the different variables in order to come up with the best model. Car ownership was defined as a binary choice of owning or not owning a car. Households with more than one car were ”lumped” together in order to define the binary choices or response values of 0 or 1+ cars owned. The response value for non-car-owning households will take the value of ’0’, while those that own at least one car takes the value of ’1’. Therefore, this results into a binary choice of either ’0’ or ’1’.

The explanatory variables used were household income (HHinc) and the number of working adults (Nwork) in the household significantly explains car-ownership behavior in Metro Manila. Table 8 presents parameters estimates of the car ownership model. Undoubtedly, household income still plays a major role in determining the probability of a household owning at least one car. As household income level increases, so is its probability of owning a car as shown in its positive parameter estimate. It is also interesting to note the negative correlation between household income and the number of working adults which means that increase in the number of workers in a household does not correspond to an increase in income level of the household.

Table 8. Car ownership model parameters

Variable	Parameter Estimate	Standard Error	*t*-statistic	Prob>X^2
Constant	-2.617	0.1095	-12.494	0.000
HHinc	0.1366	0.0409	3.268	0.000
Nwork	0.3876	0.717	5.331	0.000
EDSA-in	-0.2827	0.1458	-1.823	0.034

Thus, using the above parameter estimates, the probability of a household to own a car can be expressed as:

$$\boldsymbol{Prob(own)} = \frac{\boldsymbol{e^{logit(P)}}}{\boldsymbol{1 + e^{logit(P)}}}$$

where:

$\boldsymbol{logit(P)}$ = −2.617 + 0.1366·HHinc + 0.3876·Nwork− (0.2827·EDSA-in)

6. CONCLUDING REMARKS

InformalSim is a spatial microsimulation model specifically developed 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.

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