X. Modeling urban activities spatial distribution and dwellings price interactions

by Agostino Nuzzolo[*] and Pierluigi Coppola[*]

1. Introduction

Differentiated changes of accessibility among the zones of a metropolitan area can have relevant impacts on the land use pattern, particularly on the spatial distribution of the population and of the economic activities: typically, the bigger the accessibility of a zone, the bigger, *ceteris paribus*, the bigger the number of activities located in that zone (i.e. the bigger the "location utility"). Moreover, changes in accessibility may induce changes on the local firms productivity as well as on the dwellings market, i.e. the dwellings stock and the dwellings prices. Particularly, the latter effects arises when the changes in the accessibility do attract new demand for houses which cannot be satisfied by the current stock. In such cases, it could be observed either an increase of the dwellings stock if there is room for new development or, more often, an increase of the dwellings prices as the result of the equilibrium between dwellings demand and supply.

A number of factors does contribute to the complexity of such equilibrium: on the one hand, the land development regulation and the decision-making processes of the land developers, which shape the dwellings supply and, in turn, affect the prices; on the other hand, the location choice behavior of the households and of the firms which gives rise to the spatial distribution of the socioeconomic activities over the study area.

Microeconomic theory tested using disaggregate spatial data offers behavioral foundations and a better understanding of such decisions. Using a random utility maximization and equilibrium theory, this paper presents an activities location choice model which simulates the behavior of multiple agents of the urban system (i.e. the workers distinguished by income, the firms by economic sector) to estimate the spatial distribution of socioeco-

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nomic activities within the study area as well as the impacts on the dwellings price. The paper is organized as follows. In section 2 we review the literature of the Land-Use Transport Interaction (LUTI) models which have included (exogenously or endogenously) the simulation of the dwellings price market. In Section 3 we presents the proposed LUTI modeling framework which has been developed both with endogenous and exogenous dwellings price formulation. A comparison of the results of the application to the metropolitan area of Napoli (South Italy), of these the above two different modeling approaches is presented in section 4. Finally, conclusions are drawn in section 5.

2. The state of the art

Microeconomic theories of land use and transport interactions can be traced back to the early 19th century. Von Thunen's (1826) first attempted to incorporate transport cost in the location decisions (as reported in De la Barra, 1989). Under the assumptions of a closed system, homogenous land and zero cost of entering/leaving the agricultural market, the commodity having the highest ratio of the cost of transport (of one unit of commodity per unit of distance) to the amount of land required to produce one unit of commodity (i. e. the slope for its surplus/rent profile), takes the locations closest to the single market. Using Von Thunen's ideas, Alonso (1964) explained the urban cases, where equilibrium patterns emerge around a single employment center. These models treat land as homogenous and continuous and recognize only one employment center (located in the centre of an imaginary study area).

Herbert and Stevens' model (1960) determined residential prices by maximizing aggregate rents subject to constraints on (total) land availability and the number of households to be accommodated. Such model treats spatial elements in an aggregate manner, using an exhaustive zone-based subdivision of the region. Other simulation models rely on artificial intelligence methods, like neural networks, genetic algorithms and cellular automata (e.g. Clarke et al. 1997). These models may mimic many aspects of the dynamic and complex land use system, but they generally lack behavioral foundations to explain the process.

More advanced models (e.g. Anas and Xu 1999, Change and Mackett 2005) predict the households distribution via a general equilibrium and land use-transportation interactions approach. However, their complexity has greatly limited their application.

More recently, the "UrbanSim" model (Waddell, 2002, Waddell et al.

2003) simulates the land-market interactions with the location choices of households, firms, developers and public actors, in a micro-simulation framework. Following such approach, Zhou and Kockelman (2007) examines microscopic equilibrium of the single-family residential land development based on the bid-rent theory. Finally, de Palma et al. (2005) coupled Urbansim with the dynamic traffic assignment model “Metropolis”, developing a modeling framework which explicitly allows for two types of endogeneity in residential location choices: the interdependency of residential location with dwellings prices, and the interdependency of residential location with the travel times for work trips.

Basically, the above modeling frameworks can be cast into two classes of models according to the way in which the interactions between accessibility/travel costs and dwellings prices are simulated: the class of exogenous dwellings prices models and the endogenous ones (Fig. 1).

The exogenous dwellings prices models are based on linear multivariate regression: the average price of the houses in a zone is a linear function of zonal attributes, such as the accessibility to services, the presence of green spaces, etc. (i.e. “hedonic price” approach).

The endogenous dwellings prices models estimate the dwellings prices jointly to the location of the socio-economic activities. The dwellings price in a given zone results from the interaction among demand and supply in that zone, where the demand for dwellings depends on the location utility of that given zone and, therefore, on the transports system.

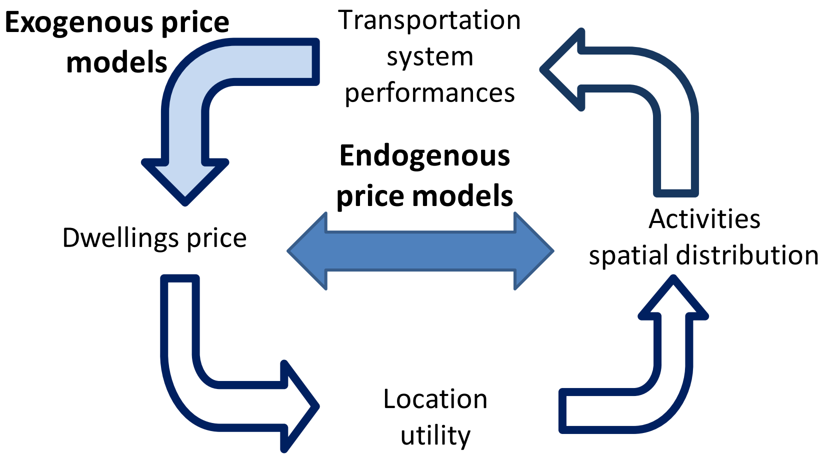

Figure 1 – Exogenous vs. endogenous dwellings price LUTI models.

3. The proposed modeling framework

The aim of the proposed modelling system is to predict the spatial distribution within a given area of the urban activities (e.g. residents, services and commercial activities) due to changes in the performances of the transportation systems, the latter affecting the zone accessibility and the generalized travel costs between zones.

We assume that the distribution of the spatial activities derives from the location choices of several urban decision makers (i.e. in the remaining of the paper called "agents"). For instance, the distribution of the population derives from where the households choose to live; the distribution of the services derives from where the firms decide to locate their offices.

The adopted behavioural paradigm, underlying such decision processes, is that of the Random Utility Maximization (RUM). In facts, it is assumed that the urban agents choose to locate their activities (e.g. the choice of residing in a given zone, or the choice of locating an office or a shop in a given zone) in the zones which do maximize their utility (i.e. the location utility). The latter depends, in turn, on several attributes related to the characteristics of the zone itself (e.g. the dwelling price per square meters, the availability of floor space, the accessibility, etc.), and peculiar to the specific agent (e.g. the income, the willingness-to-pay for rent, and so on).

Consistently with the RUM principles we assume the utility is a random variable consisting of two terms: the systematic utility and the random residuals. Then, if the random residuals are assumed to be independently and identically Gumble distributed, the probability for the agent "i" of locating its activity in zone "o", $P^i(o)$ is given by the well-known Logit formulation:

$$P^i(o) = \frac{\exp\left[V^i(o)\right]}{\sum_{o'} \exp\left[V^i(o')\right]}$$

where $V^i(o)$ is the systematic location utility of zone "o", relative to the agent "i".

For the generic firm, the systematic utility of locating the activity in a zone is given by the linear combination of the attributes, $X_k(o)$, depending both on the zone, "o", and on the agent, "i", weighted by the parameters β^i:

$$V^i(o) = \sum_k \beta^i_k X^i_k(o)$$

Given the total number of agents belonging to class "I", A^i, the number of firms locating in the zone "o", $A^i(o)$, follows as:

$$A^i(o) = P^i(o) \cdot A^i$$

On the other hand, for the generic worker, the systematic utility of locating the residence in a zone is given by the linear combination of the attributes, X_k,, depending not only on the zone, “o”, and on the agent, “i”, but also on the workplace zone “d”. In facts, the number of workers in a given zone *o*, is given by:

$$A^i(o) = \sum_d P^i_{\text{res-cond}}(o \mid d) \cdot J^i_{tot}(d)$$

where $P^i_{\text{res-cond}}(o|d)$ is the probability of choosing to live in zone “o” conditional to working in zone “d” and $J^i_{tot}(d)$ represents the total number of jobs in the zone “d” available for workers of class “i”.

Some of the attributes $X_k(o)$ may depend, directly or indirectly, on the number of agents locating in the zone “o”:

$$X(o) = x\left[\ldots, A^i(o), A^j(o), \ldots\right]$$

For example, the number of jobs (e.g. in services or commerce) in a zone may be affected by the number of households in that zone. The latter may, in turn, depends on the number of services located in that zone, e. g. the presence of schools or shops. Therefore, there is a circular dependency among agents and the attributes of the location utility which gives rise to an equilibrium problem. This can be treated as a fixed-point problem, whose solution is represented by the vectors $A^{\mathbf{i}*}$ and X_k*:

$$\begin{cases} A^i*(o) = P^i\left[\mathbf{X}(o)\right] \cdot A^i & \forall i \\ X_k*(o) = x\left[\sum_i A^i*(o)\right] & k \in K \end{cases}$$

being K the set of attributes which depend on the number of agents locating in a given zone.

The existence and the uniqueness of the equilibrium solution can be proved under certain condition of the probability functions P[·] and of the function *x*[·] following the conditions imposed by the Brouwers’ theorem (Cascetta, 2009). The uniqueness of the solution can be proved when the function *x*[·] is strictly monotone and the location choice probabilistic model is additive (as for e.g. the Logit model).

3.1 Exogenous vs. Endogenous dwelling price models

In the above modelling architecture, the dwelling price can be treated either as a variable exogenous with respect to the decision process of the agents of the study area, or as an endogenous variable. In the one case, it is an attribute of the zones not depending on the locating choices of the agentsbut only on exogenous factor such as the accessibility of the zone, the built environment, the parking facilities of the zone, the presence of green, etc. In the other case (endogenous price), the dwelling price is affected by the location choice of the agents and results from the equilibrium among the demand and the supply of floor space available in that zone (supply).

Let “j” denote the typology of the floor space available in the study area, (e.g. detached dwellings, semidetached, apartments, shops, sheds,…), and let $X_j(o)$ be the average price of the floor space of typology “j” in the zone “o”. An exogenous price model can be formulated as follows:

$$X_j(o) = \sum_n \gamma_n \cdot X_{nj}(o) + \varepsilon$$

where the $X_{nj}(o)$ are the attributes of the zone (e.g. the accessibility, the presence of green spaces and amenities, etc.), the γ's are parameters to be estimated and the ε is the error term.

Let $S_j(o)$ be the floor space of the dwelling of typology j available in the zone “o” and be δ_{ij} an index equal to 1 if agent “i” can be interested in the dwelling of type j (or, equivalently, if the dwelling of type “j” belongs to the choice set of the agent “i”), 0 otherwise. An endogenous price model can be formulated as follows:

$$X_j(o) = \gamma_0 \cdot X_{0,j}(o) + \gamma_1 \cdot \left(\frac{\sum_i \delta_{ij} A^i(o)}{\sum_j \delta_{ij} S_j(o)} \right)^{\gamma_2} + \varepsilon \qquad (9)$$

where

- $X_{0,j}(o)$ is the hedonic price of the dwellings of typology “j” in zone “o”, depending on the characteristic of the zone such as the quality of the built environment, the presence of green, etc,

- the second term represents the ratio between the demand and the supply of dwellings of typology “j” in zone “o”;

– γ_0, γ_1 e γ_2 are parameters to be estimated;

- ε is the error term.

From the above model specifications it can be seen that in the exogenous price models, the average price of dwellings in a generic zone is given by a multiple regression of several attributes which are not influenced by the location decision process of the agents of the study area. On the other hand, in the endogenous price models, the dwelling price depends on the number of agents which chose to locate their activity in the given zone (demand) and on the available floor space in that zone (supply). In other words, they result from the interactions between the agents involved in location decision process in the study area.

4. Model specification for the metropolitan area of Napoli

4.1 The Study area

The Study area for the application of the models system presented in the previous section is the metropolitan area of Napoli (South-Italy). It includes 88 municipalities, with a total population of 2,4 millions of residents and about 680.000 jobs. The zoning system adopted consists of 133 zones, most of which represent a single municipality, only the most dense and widespread urbanized areas have been split into different zones. For instance, the city of Napoli has been split into 27 zone, Torre Annunziata into 3 zones, and so on. Moreover, the zones have been grouped into territorial "basins", i.e. macro-areas which includes municipalities with a high level of interaction due to administrative, political and historical reasons, e.g. the municipalities belong to the same health district, or to the same justice court, or to the same industrial district, and so on (Tab. 1).

We have here considered 6 basins (Fig. 2): "Napoli", including the city of Napoli and its hinterland; "Aversa" and "San Giuseppe" two agglomerations of municipalities respectively staying North and West of Napoli; "Torre Annunziata", "Castellammare" and "Peninsula Sorrentina" at the southern end of the Gulf of Napoli. For each basin we have identified an "attractor", i.e. the municipality which has the main number of residents and economic activities and/or which has a leadership role among the other municipalities of the basin (e.g. due to the presence of a justice court, an hospital, etc.).

Table 1 –Population and employment in the basins of the study area.

Basin	number of zones	number of municipalities	Popolation	Total Employment (n. of jobs)	Emploment Services (n. of jobs)	Employment commerce (n. of jobs)
Aversa	18	18	174.234	37.046	11.448	6.150
Castellammare	9	8	102.950	26.519	6.652	4.729
Napoli	84	42	1.809.151	545.375	163.807	88.687
Pen. Sorrentina	6	6	76.053	17.756	7.579	3.293
San. Giuseppe	8	8	123.107	28.598	5.656	8.201
Torre A.	8	6	129.157	28.116	6.831	5.455
	133	88	2.414.653	683.410	201.973	116.515

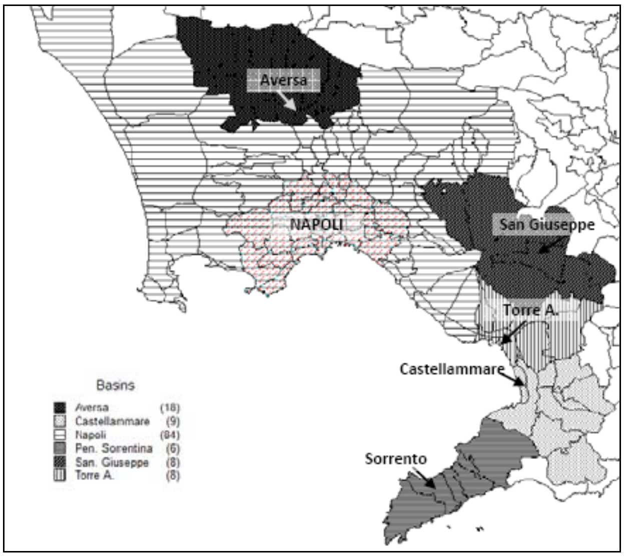

Figure 2 – Basins and relative "attractor" of the study area

The population is concentrated in the city of Napoli and along the coast of the Gulf of Napoli. Here we have zones with a population density over 10.000 Residents per squared Kilometer with peaks of 17.000 pop/sq-km. The economic activities present the same spatial distribution as the population (Fig. 3): an strong concentration of activities in the city center of Napoli can be observed, with peaks of density of 10.000 jobs/sq-km.

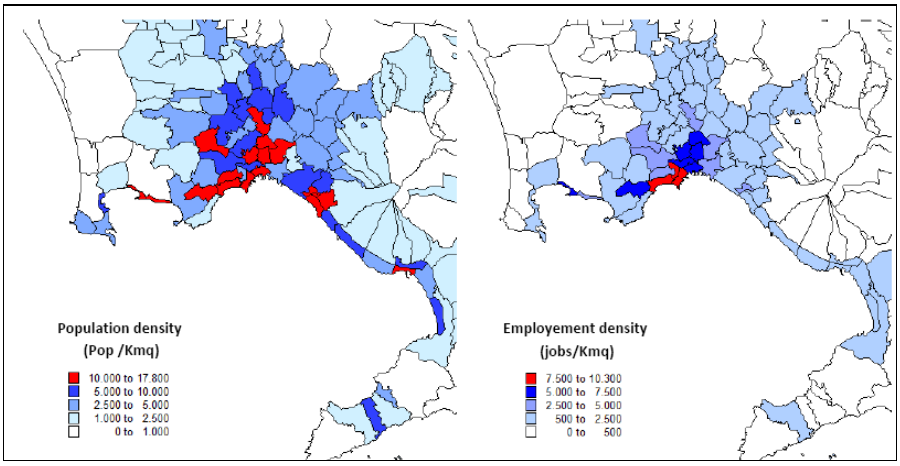

Figure 3 – Population and Employment density.

4.2 The activities spatial distribution sub-model

The activity location sub-model has been specified and calibrated for 4 urban-agent classes: the workers of the study area distinguished by income (i.e. the "High" and the "Medium-Low" income workers) and the firms involved in private services and commerce.

The location utility function for the generic agent *i*, includes the following attributes:

- the commuting generalized travel cost (expressed in hours) between the zone of residence and the workplace zone (note that, as it can be drawn from Table 2, this attribute is included in the location utility of only the classes of workers);
- the passive accessibility with respect to the population of the study area (note that, as it can be drawn from Table 2, this attribute is included in the location utility of only the classes of firms);
- the active accessibility of the households to services (e.g. schools, banks, hospitals, …);
- the dwelling stock, distinguished by typologies: a) apartments, detached and semi-detached houses available for all the workers and for the firms involved in services; b) front-street and flat stores available for services firms (e.g. banks) and commercial firms;
- the dwelling price, expressed in thousands of Euro per square meter (sqm);
- the number of shopping mall in the zone (note that this attribute is included in the location utility of only the classes of firms)
- the number of hospitals in the zones;
- a dummy variables equal to 1 if the zone belongs to the municipality of Napoli, 0 otherwise;
- a dummy variables equal to 1 if the zone belongs to a touristic area, 0 otherwise;
- a dummy variables equal to 1 if the zone belongs to an industrial district, 0 otherwise;
- a dummy variables equal to 1 if the zone is the "attractor" of the basin, 0 otherwise;
- a dummy variable equal to 1 if the zone belongs to a dense urbanized area;
- and finally, six basin specific constants.

The parameters β's of the systematic location utility function (1) have been estimated, starting from an existing model specification (Nuzzolo and

Coppola, 2007) through the fine-tuning of the parameters, in order to match the model predictions in the reference scenario with the census data.

Table 2 –Coefficients of the location utility function.

attribute	Workers (high-income)	Workers (med-low income)	firms (service sector)	firms (commerce)
Commmuting cost [h]	-0,800	-1,100	-	-
Passive accessibility w.r.t .to population	-	-	0,025	0,015
Active accessibility w.r.t .to services	0,002	0,003	-	-
Population [10^3]	-	-	0,350	0,500
jobs in public sectors	-	-	0,005	0,020
dwelling price [10^3Euro/sqm]	-0,105	-0,520	-0,055	
dwelling stock [10^3]	1,100	2,600	-	0,002
n. of shopping mall	-	-	0,450	0,650
n. of hospitals	-	-	-0,050	-0,100
dummy_Tribunal	-	-	0,300	0,400
dummy Turistic area	-	-	0,400	0,200
dummy_industrial district	-	-	0,350	0,350
dummy_urban area	0,200	0,200	-	-
dummy_attractor of the basin	-	-	0,500	0,450
Municipality of Naples	0,225	0,200	0,950	0,450
Basin_Naples	-0,300	-0,500	0,550	0,400
Basin_Aversa	-0,400	-0,300	0,200	-0,200
Basin_Torre A.	-0,300	-0,200	0,050	0,100
Basin_Castellammare	-0,050	0,300	0,050	-0,050
Basin_San Giuseppe	-0,200	-0,050	-0,050	0,400
Basin_Pen. Sorrentina	0,600	0,700	0,550	0,050

From the values reported in Table 2, it can be noted that the dwelling price parameter in the choice of the location, is more relevant for “medium/low-income” class than for “high income” one and for firms in “services”. Moreover, for the “services” the accessibility plays a greater role than for the commercial activities, whose locations, on the other hand, is more affected by the spatial distribution of the population.

From the relative weights of the parameters the trade-off between the attributes can be estimated. For instance it can be drawn that 1 hour less of commuting times, for the class of “medium-low income workers”, is equivalent to 2,1 (= -1,1 /-0,52) 10^3euro per square-meter in the dwelling price, i.e. a mid-low income worker willingness-to-pay for buying a house closer of 30 minutes to the workplace is about 1.050 Euro/sqm. Moreover, it can also be observed that such willingness-to-pay is about one quarter (i.e 0,28) of the willingness-to-pay for buying an house of the “high-income workers”.

4.3 The accessibility functions

The accessibilities have been expressed either as the potential of a given zone to be reached by other agents (Passive accessibility) or as the potential to reach the other agents (Active accessibility) from a given zone. For instance, the active accessibility of households to services, has been calculated as:

$$\mathrm{Acc\_active(o)} = \sum_{d} \mathrm{W(d)}^{\alpha_1} \cdot \exp\left(\alpha_2 \cdot \mathrm{C(o,d)}\right)$$

where

- W(d) is the number of services (expressed in thousands) in the zone “d”;
- C(o,d) is the generalised travel cost between zones “o” and “d”;
- α_1 α_2 are estimated parameters respectively equal to 0.85 and 1.25 (Nuzzolo and Coppola, 2007).

Moreover, the passive accessibility of the firms to the population, has been calculated as:

$$\mathrm{Acc\_passive(o)} = \sum_{o} \mathrm{HH(o)}^{\alpha_3} \cdot \exp\left(\alpha_4 \cdot \mathrm{C(o,d)}\right)$$

where

- HH(o) is the number of households (expressed in thousands) in the zone “o”;
- C(o,d) is the generalised travel cost between zones “o” and “d”;
- α_3 α_4 are two estimated parameters, respectively equal to 0.72 and 1.14 (Nuzzolo and Coppola, 2007).

4.4 The dwelling price functions

Based on a survey carried out through the real-estate agencies in the study area, the average prices of the dwellings in the zones of the study area, available either for residential use by the households or for services activities by the firms (i.e. the above defined typology “*a*” consisting of the apartments, the detached and semi-detached houses) have been estimated (Fig. 4).

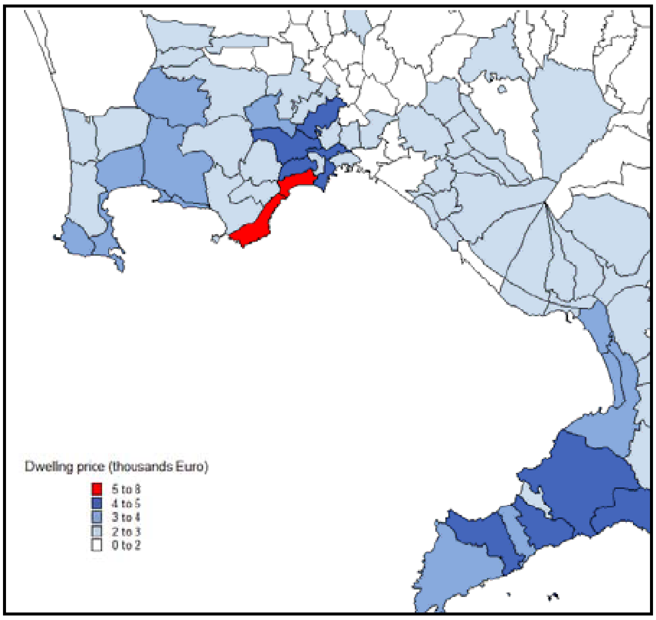

Figure 4 – Average dwelling prices in the zone of the study area.

Based on such observations, two different dwelling price functions have been estimated. The exogenous price location function is specified as follows:

$$X(o) = \gamma_0 \cdot X_0(o) + \gamma_1 \cdot Acc\_passive(o)$$

where:

- the X(o) is the average dwelling price (in thousands of euro) in zone “o”;

- the X_0(o) is the dwellings hedonic price in zone “o”, depending on the characteristic of the zone such as the quality of the built environment, the presence of green, etc;

-Acc_passive(o) is the passive accessibility of the zone “o”;

– γ_0 and γ_1 are parameters respectively equal to 0,857 and to 0,0032.

The endogenous price location function is specified as follows:

$$X(o) = \gamma_0 \cdot X_0(o) + \gamma_1 \cdot \left(\frac{HH(o) + SF(o)}{Stock_a(o)} \right)^{\gamma_2}$$

where:

- X(o) and X_0(o) are the average dwellings prices above defined;

- HH (o) is the number of households in zone “o”;

- SF(o) is the number of firms involved in services in the zone “o”;

- $Stock_a$(o) the number of dwellings of typology *a* (above defined) in the generic zone “o”;

– γ_0 γ_1 and γ_2 the estimated parameters equal to 0.717, 4.1 and 1.8.

4.4 Model Validation

To validate the model, we have made a simulation of the reference scenario (i.e. year 2001) and analysed the differences between the model predictions and the “observed” census data. Such differences in percentage, at the level of single basin, has resulted to be less than 8% (Tab. 3).

Table 3 – Reference scenario (year 2001) model prediction vs. census data.

	Service [jobs]				**Commerce [jobs]**			
Basin	Census	Model	Diff.	% Diff.	Census	Model	Diff.	% Diff.
Aversa	11.448	11.444	-4	0,0%	6.150	6.252	102	1,7%
Castellammare	6.652	6.231	-421	-6,3%	4.729	4.496	-233	-4,9%
Napoli	163.807	165.381	1574	1,0%	88.687	89.823	1136	1,3%
Peninsola sorrentina	7.579	7.265	-314	-4,1%	3.293	3.284	-9	-0,3%
San Giuseppe	5.656	5.714	58	1,0%	8.201	7.900	-301	-3,7%
Torre Annunziata	6.831	6.340	-491	-7,2%	5.455	5.196	-259	-4,7%
	201.973	202.375	402	0,2%	116.515	116.951	436	0,4%

	Medium-Low income [workers]				**High income [workers]**			
Basin	Census	Model	Diff.	% Diff.	Census	Model	Diff.	% Diff.
Aversa	46.084	49.018	2.934	6,4%	3.197	3.262	65	2,0%
Castellammare	29.806	31.367	1.561	5,2%	2.088	2.165	77	3,7%
Napoli	517.353	516.436	9.083	1,8%	44.454	45.084	630	1,4%
Peninsola sorrentina	26.513	25.364	- 1.149	-4,3%	2.428	2.445	17	0,7%
San Giuseppe	36.918	39.772	2.854	7,7%	2.691	2.765	74	2,7%
Torre Annunziata	37.238	39.828	2.590	7,0%	2.447	2.592	145	5,9%
	693.912	701.785	7.873	1,1%	57.305	58.313	1.008	1,8%

At the level of the single zone, an overall good matching between model predictions and census data can be observed, However, in some zones it can be observed a peak in percentage differences (model vs. census) over 50% (Fig. 5).

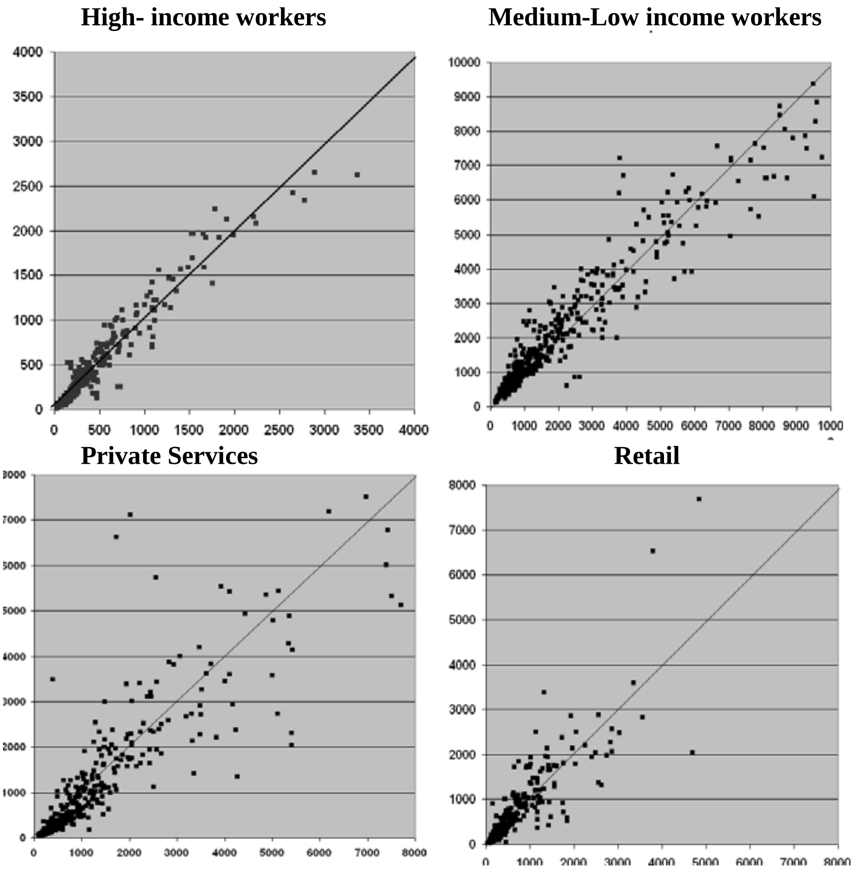

Figure 5 – Reference scenario (year 2001) models predictions (y-axis) vs. census data (x-axis).

To overcome such problems, despite limited to few cases, in the application of the model to future scenarios, to predict the number of agents of class “i” in the zone “o”, $A^i(o)$, we have adopted the “pivot-point” technique (Manheim, 1979):

$$A^i(o) = \frac{A^i_{future}}{A^i_{ref}} \cdot A^i_{census\_ref}$$

where:

- A^i_{future} is the number of agents of class “i” in the zone “o”, predicted by the model in the future scenario;

- A^i_{ref} is the number of agents of class “i” in the zone “o”, predicted by the model in the reference scenario (i.e. year 2001);

- $A^{i}_{census\_ref}$ is the number of agents of class “i” in the zone “o”, observed by the Census in the reference scenario.

4.5 Model forecasting

To test the forecasting capability of the model we have done an application of the models system to the 2001 scenario, using as reference a transportation scenario dated back to year 1981 (i.e. “back-casting” analysis). In other terms, we have applied the model as if we were in year 1981 and wanted to predict the spatial distribution of the activities in the study area on a 20-years long time horizon (i.e. year 2001). Then, we have compared the forecasting results in year 2001 with the available Census data of this year.

In building up the “forecasting” scenario (2001), it came out that the main changes to the transportation system took place on the road network between the years 1985 and 1990. This can be explained by the fact that in year 1980 a big earthquake devastated the whole Region, particularly the area around Napoli and Avellino. Consequently a wide reconstruction plan allowed the renovation and partly the reconstruction of the regional road network, particularly the one in area North of Napoli (see Fig. 6).

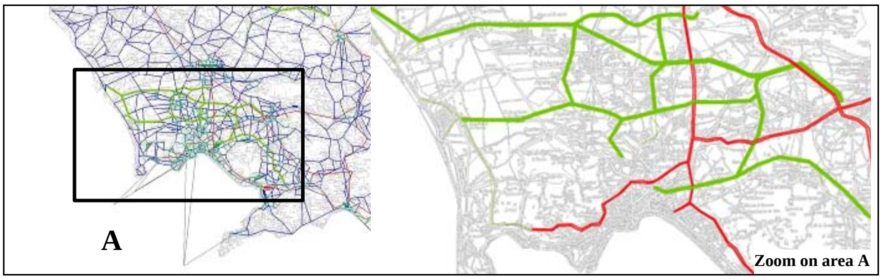

Figure 6 – The modified road network (depicted in green) in the “forecasting” scenario (in red the existing highways).

In such applications of the models system, two different dwelling price models have been tested: exogenous vs. endogenous dwelling price models. The results we obtained show significant difference in the forecast population pattern. In facts, using the exogenous price model, we observed, on the one hand, an overall increase of population in the zones with the greater increase of accessibility, i.e. the area North of Napoli, some zone of Napoli and the zones along the northern coast of the Gulf; on the other hand, we observed a decrease of population in the zones of the Peninsula Sorrentina, which are the zones less affected by the changes of accessibility due to the new roads.

The endogenous price model yield a different population pattern with a significant decrease of population in the zones of Napoli and an increase in the zones North of the study area (Fig. 7). Such difference can be explained by the fact that the increase of accessibility in Napoli does attract more urban agents which in turn induces an increase of the dwelling prices, due to limited availability of dwelling stock. The competition of different agents for acquiring the floor space available in such zones has resulted in a replacement of households with firms, the former having a lower willingness-to-pay than the latter. This resulted in the migration of the population in the area of new development located in the North of the study area.

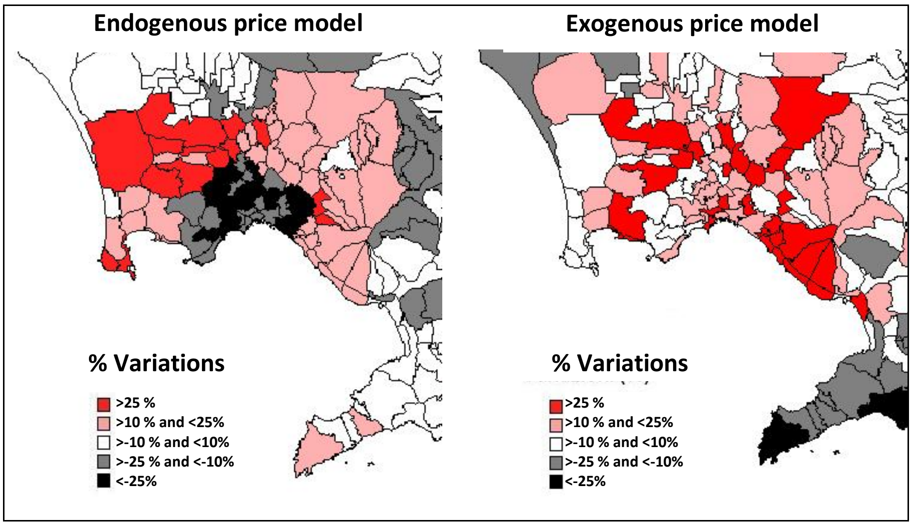

Figure 7 – Population variations predicted by endogenous and exogenous dwelling price models.

If we compare the results of the simulation using the two different models with the observed trends of population by the Census (Fig. 8), we can conclude that the endogenous dwelling price model performs better than the exogenous one in forecasting the population pattern. This is due to the fact that the former does explicitly simulate the interactions among the different urban agents.

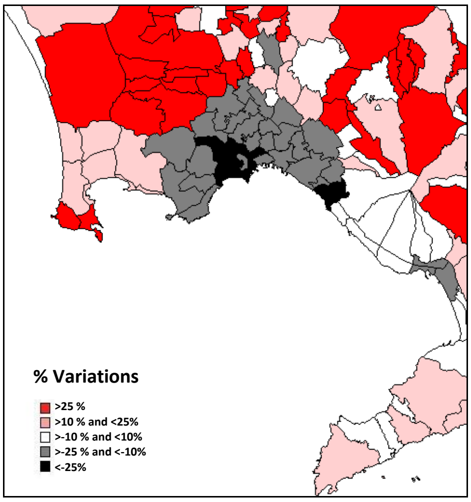

Figure 8 – Population variations between 2001 and 1981 in the study area, by Census data.

5. Conclusions

In this paper we have presented a modeling framework to forecast the evolution of the spatial distribution pattern of the activities in a metropolitan area, based on the simulation of the location choices of multiple agents of the urban system (i.e. the workers distinguished by income, the firms by economic sector). The parameters of the overall models system has been calibrated for the metropolitan area of Napoli by fine-tuning of the parameters of an existing models specification.

The calibrated models system reproduces, with a good level of approximation, the spatial distribution of the population and of the firms within the study area.

Two different approaches to simulate the interactions among the location choice of the agents and the dwelling prices have been tested: the “exogenous price” approach and the “endogenous price” approach.

A “back-casting” application of the models system using the above two approaches, has shown that the endogenous dwelling price model outperforms the exogenous one. Therefore, we can conclude that in dense urbanised area, where dwelling market is saturated, it is necessary to take explicitly into consideration, the interactions among the different urban agents, and the effects of such interaction on the dwelling prices, in order to correctly forecast the evolution of the land use pattern.

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Abstract

In this paper we present an activities location choice model with endogenous price which simulate, based Random Utility Theory principles, the behavior of different agents of the urban system (i.e. the workers distinguished by income, the firms by economic sector) to estimate the spatial distribution of socioeconomic activities within the study area as well as the impact of differentiated changing accessibility on the dwellings price. The study area for this research is the metropolitan area of Napoli (South-Italy), for which we show the results of the model estimation and the results of a “backcasting” application to future transportation scenarios.