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Estimating the HARA Land Use Model for Housing Planning based on Hedonic Price Analysis

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1 ABSTRACT

HARA is a land-use model that uses a search algorithm to find the optimal spatial allocation of new housing demands in an urban plan area. In the model, the plan area is represented as a grid of cells. A core element of the algorithm is a function that is used to evaluate the value of a cell for each possible land-use given its location. The value function is specified as the net value of a (housing) development given the land costs, the construction costs, and the market value of the development at a location. Specified in that way, the solution generated represents an optimum as well as a market equilibrium (maximum net value for developers). A critical prerequisite for this is, however, that the value-function is specified such that it accurately represents buyers' willingness-to-pay for dwelling and location characteristics in the housing market. In this paper, we show how the value function can be estimated using hedonic price analysis. The analysis is carried out based on a large housing transaction data set focusing on two medium-sized cities in The Netherlands combined with detailed land-use data of these areas. Although a full set of land-use types is taken into account, special attention is paid to the classification of urban green space, given the purpose to analyze scenarios for developing urban green space. The results indicate that land-use effects on housing prices differ considerably between housing types as well as city. We conclude therefore that it is important in the estimation of land-use models to take the specific local conditions of housing markets and housing segments into account.

Keywords: Land use allocation, Hedonic price method, Housing, Urban planning, decision making model

2 INTRODUCTION

Urban green space (UGS) attracts more and more attention as a means to release urban area climate problems given its variety of climate functions. Many studies have proved that UGS has great potential to deal with heat, hydrology, biodiversity and air quality problems. Also, UGS can improve the quality of the living environment for inhabitants by providing open space for relaxation, exercise and pleasant scenery. The value of UGS (e.g., as park or lake) for creating a pleasant living environment is also reflected in the value of real estate properties in the neighborhood. Purchasers of residential properties, for example, are willing to pay more for dwellings that have an attractive green neighborhood environment as shown by many studies (Engström & Gren, 2017; Huang & Yin, 2015; Jim, 2013; Kong, Yin, & Nakagoshi, 2007; Baranzini & Schaerer, 2011; Diewert, de Haan, & Hendriks, 2015). Given these advantages, urban planners generally seek proper ways to make current cities more climate adapted by using UGS as a tool. How to develop green space wisely in the city context is, however, not straight forward. Specifically, two main challenges need to be addressed. One is the costs of development and maintenance of UGS or, when retrofitted in buildings, of green vegetation on roofs or facades. Due to these costs a conflict may arise in the urban area development process between stakeholders who are seeking financial benefits and inhabitants or planners who care about living quality. The other is the scarcity of space to develop UGS especially in high-density urban area due to demands for other land-uses that must be met. The scarcity is reflected in land-prices and, therefore, also responsible for the high costs. These challenges may limit the amount and spatial flexibility of developing UGS.

Spatially, both the UGS climate (cooling effect) and (housing) property market value effects are strongly affected by their spatial allocation pattern (Li et al. 2018). Furthermore, the climate characteristics of urban green vary based on vegetation species. Spatial allocation of UGS therefore should be optimized considering their climate and land economic characteristics and effects. To support land-use decisions taking into account these objectives, in earlier work, we extended and refined the HARA[1] land-use allocation model system (Li et al. 2018). The model focuses on housing development. Using a function that determines the impact of locations on the net value of properties, the model generates allocation plans that have maximized housing

[1] HARA is an acronym for Housing-type Allocation in Residential Areas

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net value while meeting given demands for different housing types. In the process, the model considers a full range of urban and non-urban land-uses, including different green land-use types and mixing of green and built-up area (e.g., green building decorations). In Li et al. (2018) it is demonstrated how the model can be used in combination with a climate effect model to evaluate housing development strategies to release the climate pressure.

Land-use models have a long history in urban and spatial planning. A variety of modeling approaches has received attention including CA (cellular automata), regional economics (Lowry models and derivations) and optimization models. Invariably, the models use a classification of land-uses and a particular value function to evaluate the suitability of a location for a particular land-use taking into account interactions between land-uses and accessibility of locations. Obviously, for creating useful solutions the validity of the value function is of critical importance. Yet, the empirical estimation and validation of value functions have only received very little attention in land-use modeling. Usually, the models are manually calibrated based on face validity of the land-use plans generated. An exception is Ligmann-Zielinska, Church, & Jankowski (2008) who use an empirically estimated land–use allocation model to explore feasible land use possibilities. Hedonic price analysis offers a possibility to estimate the value function in a more rigorous way. A hedonic price model is able to predict the price level of a real-estate object based on characteristics of the object itself and location characteristics, and can be estimated based on transaction data.

In this paper, we consider the empirical estimation of the land value function used in the HARA model. We propose a specification of the value function that enables an empirical estimation of the parameters based on hedonic price analysis. To create a tool that is suitable for evaluating urban green scenarios, the sensitivity of the value function for urban green receives special attention. Next, we use a large transaction data set from the Netherlands to estimate the model for two cities in the Netherlands - Eindhoven and Almere. These two cities differ largely in terms of housing market and green land-use characteristics. They were chosen as cases to see whether parameter estimates show local differences between cities. Occurrence of such differences would indicate that local estimation (and application) of land-use models is needed.

The remainder of the paper is structured as follows. First, in the next section we explain the methodology used in terms of the land-use model and the hedonic price analysis. Next, in the third section, we describe the study area and data. Then, in the section that follows, we discuss the results of hedonic price analysis to estimate the value functions of the land-use allocation model. Finally, in the concluding section, we summarize the major conclusions and discuss remaining problems for future research.

3 METHODOLOGY

To provide a background for the empirical analysis that follows, in this section, we will briefly explain the HARA model, the value function that is to be estimated and hedonic price modeling as an estimation approach.

3.1 The HARA land-use model system

HARA implements an algorithm to generate optimal land-use plans, given demands for particular land-uses in a delineated plan area. The algorithm assumes that the plan area is represented as a regular grid of cells where each cell corresponds to a piece of land that has a particular land-use. Land-use allocation decisions concern decisions to develop current unbuilt-land (so-called Nature cells) for a particular urban land-use. Both the value function and allocation algorithm are focused on housing developments, so that the model can be used to generate housing development plans for a given plan area. The user specifies the size of (new) demand for each relevant housing type (e.g., stand alone, terraced houses, apartments, etc.) as well as the zones available for new housing development. Given the demands and zoning regulations, Hara determines which cells are to be developed for which housing type such that the best use for each location is realized, given the land-value function. Below we describe the function used to evaluate land developments and a method to estimate the parameters based on housing transaction data using well-known hedonic price analysis.

The value function used in Hara has the following form:

$$V_{ijk} = Vcon_{ijk} + Vnbh_{ijk} + Vacc_{ijk} \quad (1)$$

where V_{ijk} is the (market) value of housing of type k in cell ij, *Vcon* is a constant, *Vnbh* is a value component related to the direct neighborhood of the cell and *Vacc* is a value component related to accessibility of particular other land-uses from the cell. The neighborhood component is specified as:

$$Vnbh_{ijk} = \sum\nolimits_{h \in H} \alpha_{kh} \cdot N_{ij0h} \quad (2)$$

where H is the set of all land-uses (nature, the housing land-uses and other land-uses), N_{ij0h} is the number of cells with land-use h in the neighborhood of cell ij and α_{kh} are parameters representing the marginal value of h-cells in the neighborhood for a housing land-use k. The neighborhood of a cell consists of the 8 adjacent cells. The accesibility component is specified as:

$$Vacc_{ijk} = \sum\nolimits_{h \in H} \sum\nolimits_{m} \beta_{khm} \cdot I_m(D_{ijh}^{min}) + \sum\nolimits_{h \in H} \sum\nolimits_{q} \gamma_{khq} \cdot N_{ijqh} \quad (3)$$

where H is defined as above, D_{ijh}^{min} is the distance to the nearest cell with land-use h from cell ij, I_m is a binary variable indicating whether the distance falls in the m-th distance band (= 1, if it does and 0 if it does not), β_{khm} is the value of having land-use h within distance band m for land-use k, N_{ijqh} is the number of h-cells within distance D_q from cell ij and γ_{khq} is a parameter representing the value of the accessibility of h-cells within that distance for a housing land-use k. Thus, accessibility is measured in two ways - availability of land-uses in distance ranges from the cell and distance to nearest cells with particular land-uses. Which of these two methods is most appropriate may depend on the land-use under concern.

The constants and coefficients $Vcon_{ijk}$, α_{kh}, β_{khm} and γ_{khq} are parameters that need to be estimated. We propose to use hedonic price analysis to estimate the parameters. The impact of urban green on value of residential property comes to expression in the alpha parameters (green land-uses in the direct neighborhood) and possibly also in beta and gamma parameters (accessibility to recreational green). As the subscripts indicate the values of all parameters are housing type (k) specific.

3.2 Hedonic price analysis

Hedonic price analysis uses multiple regression analysis to estimate the contributions of housing attributes on the total value (or price) of a dwelling (Rosen, 1974). When demand and supply of dwellings are in equilibrium, the estimated marginal values represent willingness-to-pay values of buyers for the specific attributes (Maslianskaïa-Pautrel & Baumont, 2016). Since the analysis of urban green scenarios is a special aim of the land-use model (HARA), the impact of UGS on housing values is of special interest in the hedonic price model we develop here. Therefore, in this section, we briefly review existing studies that have aimed to model UGS and measure its impact on housing values through hedonic price analysis.

Melichar & Kaprová (2013) investigate the distance ranges in which UGS have positive effects on housing prices. Tyrväinen & Miettinen (2000) finds that buyers have to pay more to obtain a dwelling with a green space view, which depends on the natural environment quality and amount. Conway, Li, Wolch, Kahle, & Jerrett (2010) show that each additional percentage of greenery coverage significantly increases the housing price. GIS has been used as a tool to determine a wide range of spatial factors in a hedonic pricing model to explore the urban green spatial configuration impacts on residential building prices (Asmawi, Norzailawati, & Tuminah, 2016). Diversity of urban green vegetation types and spatial landscape has also been shown to have added value on dwelling price (Panduro & Veie, 2013; Franco & Macdonald, 2016) . However, existing research has mostly focused on one single type of urban green (e.g., a park). In the present study, we extend existing literature by considering a broader range of urban green types that can be taken into account in land-use models. Furthermore, in our analysis, we make a comparison between two regions, in order to see whether local land-use configurations and housing market conditions have an influence on price relationships.

3.3 Estimation approach

A complication for hedonic price analysis is that structural, neighborhood and accessibility variables relate to different levels of scale - the plot and building, the direct neighborhood and the wider area of the dwelling, respectively. A robust and well-known way of estimating the parameters in such a multi-level case is to estimate fixed effects for locations in a first step regression analysis which are then used as dependent

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variable to estimate the effects of the location factors in a second-step regression (Helbich, Brunauer, Vaz, & Nijkamp, 2014). Formally, the regression models for the two steps are specified as follows. For the first-step regression analysis, the model is specified as:

$$\ln Y_{ij} = \beta_{01} + \beta_1 H_j + \beta_2 L_i + S_i + \varepsilon_{ij1} \quad (4)$$

where Y_{ij} is the transaction price of a dwelling j at location i, β_{01} is an intercept, H_j is a vector of value-relevant dwelling characteristics (volume, lot size, construction year, maintenance condition, etc.) and β_1 is a vector of related coefficients, L_i is a vector of neighborhood characteristics (urban green and other land-use types) and β_2 is vector of related coefficients, S_i represents the *fixed* effect of location i, and ε_{ij1} is random error term. By using the natural log of price as dependent variable, which is a commonly used approach, the coefficients represent effects as a percentage price increase. In this model, S_i captures the price effect of the location after having taken into account the dwelling and neighborhood characteristics.

In the second step, the fixed effects are regressed on accessibility factors to identify the marginal effects of location characteristics. The regression equation for the second step can be written as:

$$S_i = \beta_{02} + \beta_3 D_i + \varepsilon_{i2} \quad (5)$$

where β_{02} is an intercept, D_i a vector of location accessibility characteristcs, β_3 is a vector of related coefficients and ε_{i2} is a a random error term.

This two-step hedonic price model allows us to estimate the parameters of the HARA value function: the *Vcon* term (Eq. 1) corresponds to $\beta_{01} + \beta_1 H_j + \beta_{02}$, the alpha parameters (Eq. 2) to β_1 and the beta parameters (Eq. 3) to β_3 with proper handling of the log transformation of price. Since all parameters in the HARA model have housing type specific values, the regression models (Eqs 4 and 5) must be estimated housing type specific. Given limited space, we will only consider the first-step regression analysis in the application described in the next section.

4 STUDY AREA AND DATA

Figure 1 shows the location of the Eindhoven and Almere cities in the Netherlands. Almere is a planned city with 208,000 citizens (2019) in the province of Flevoland, Netherlands. Eindhoven is the fifth-largest city of the Netherlands with 231,000 citizens (2019) and located in the south of the country. Eindhoven is an industrial city in the center of a region that houses a lot of high-tech companies.

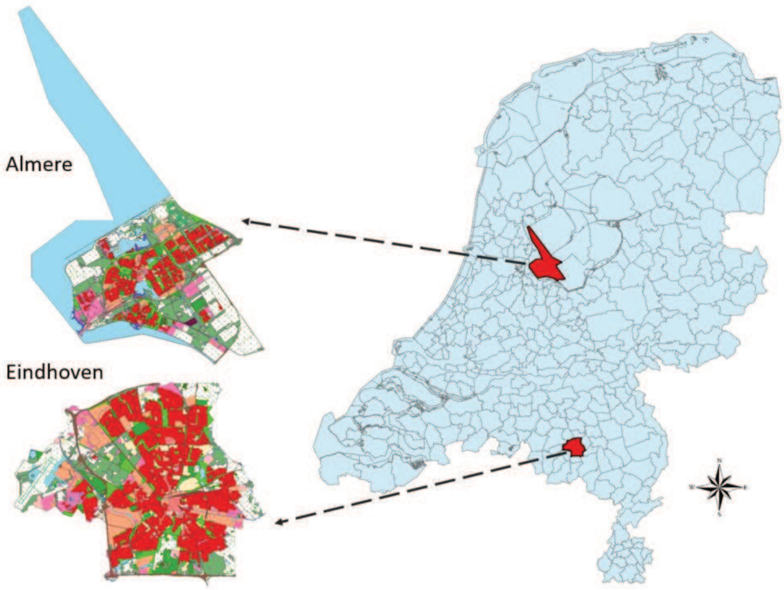

Figure 1: Research areas location (the cities Almere and Eindhoven)

The spatial land-use data used for the analysis are provided by the CBS (Central Bureau of Statistics) in the Netherlands. The transaction data used are provided by the NVM, the largest real estate market agency, in the Netherlands. For the present study NVM-data of transactions that took place in Eindhoven and Almere from 2014 to 2018 were used. The data-set consists of 18813 geocoded housing transactions. Table 1 shows the dwelling characteristic variables Hj and neighborhood land use variables Li that entered the hedonic regression model. Of interest here is the estimation of location effects on housing price on the level of the neighborhood land-use variables. The land-use data include all land-use categories that are potentially relevant for housing value and land-use planning. The classification of UGS is extensive compared to earlier studies. This allows us to estimate housing value effects of UGS in a more detailed way than have been done so far. Also on the level of other land-uses, we are not aware of other hedonic price analysis studies that have modeled neighborhoods in this level of detail. The dwelling characteristics are included as control variables.

Dwelling characteristics			
Variable	Description	Measure	Expected sign
Log of transaction price		Number	DV[a]
Area		Number	+
Number of rooms		Number	+
Volume of the dwelling		Number	+
Construction year	Old to new (0-9)	Categorical	-
Lift	House has a lift (0/1)	Binary	+
Heating system	No; simple; advanced (0/1/2)	Categorical	+
Parking space	House has a parking space (0/1)	Binary	+
Facing direction	Good to normal (0-4)	Categorical	+
Maintenance inside	Excellent to bad (1-9)	Categorical	+
Neighborhood land use variables			
Variable	Description	Measure	Expected sign
Shopping area	Retail; restaurant; shopping mall, etc	%	+
Industry and office	Industry area; business offices	%	-
Public buildings	Museum; city hall; school; hospital	%	+
Road traffic area	Road traffic area	%	-
Park and sports field	Parks, sports field	%	+
Day recreational area	Day recreational area	%	+
Agricultural	Agricultural land use	%	+
Forest	Forest	%	+
Open wet natural terrain	Open wet natural land use	%	+
River and lake	River and lake	%	+
Other water body	Other inland water	%	+

[a] Dependent variable

Table 1: Definitions and descriptive of variables entering the hedonic model

The land-use variables related to each transacted dwelling are determined based on the HARA land use modeling framework. Each spatial observation is located by its postcode on a six-digit level and overlayed by a 100 by 100 meter cells grid. After this, the land-use characteristics of each cell's direct neighborhood (eight cells) are calculated as the percentage of cells covered by the land-use (Figure 2). The 4-digit postcode to which each transaction belongs are entered as dummies in the regression equations to estimate the fixed effects, Si. Eindhoven counts 47 4-digit postcode areas and Almere 52.

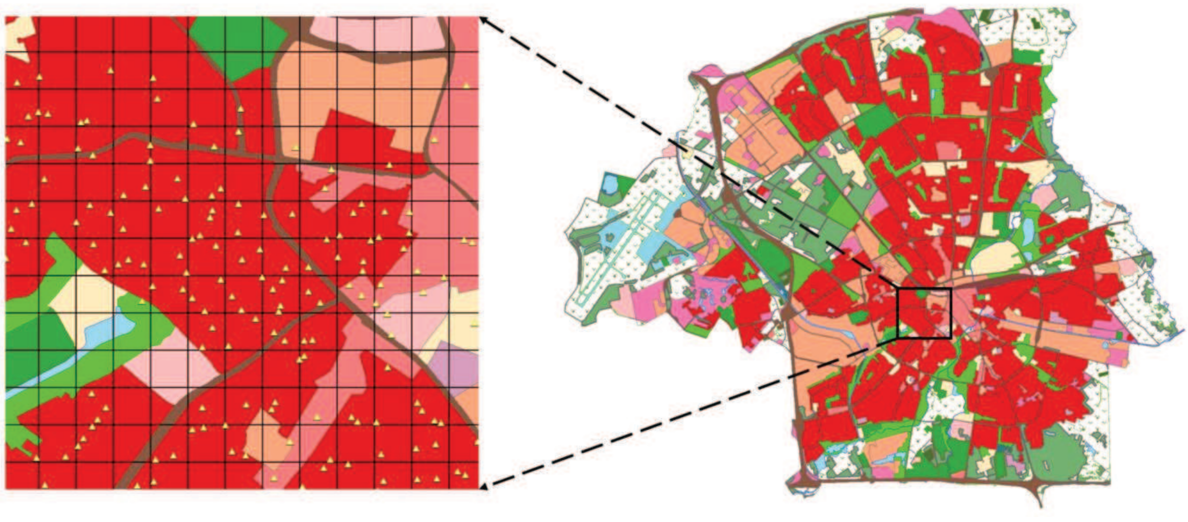

Figure 2: Transaction cases plotted on the grid map in Eindhoven

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5 RESULTS AND DISCUSSION

Housing types are classified into four categories: apartments, row house, semi-detached and detached. The hedonic regression model is estimated separately for the four major housing types and the two study areas Eindhoven and Almere. The Enter method was used and non-significant variables were removed to obtain a final model specification in each estimation using 5% alpha level. Table 2 shows summary statistics of the eight models.

Model	City	Adjusted R Square	N
All	Almere	.735	8115
Apartment	Almere	.582	1738
Row	Almere	.462	4804
Semi-detached	Almere	.583	1036
Detached	Almere	.603	491
All	Eindhoven	.784	10698
Apartment	Eindhoven	.718	3894
Row	Eindhoven	.638	4944
Semi-detached	Eindhoven	.718	1211
Detached	Eindhoven	.820	559

Table 2: Summary statistics of the eight models

Given the purpose of the present study, we will focus on the estimation results on the level of the land-use variables. For these variables, Table 3 shows the estimation results for Almere, and Table 4 for Eindhoven.

	Variable	Mean	Std. Deviation	Unstandardized Coefficients B	Standardized coefficients Beta	sig
All	Shopping area	2.523	11.322	.001	.040	.000
	Industry and office	2.188	7.162	.001	.020	.002
	Road traffic area	1.984	3.224	.002	.019	.002
	Park and sports field	11.129	12.572	.001	.035	.000
	Day recreational area	.218	2.373	.004	.026	.001
	Agricultural	.333	2.764	.003	.024	.000
	Forest	1.015	4.815	.001	.021	.001
	Open wet natural terrain	.0162	.730	.007	.016	.007
	River and lake	.226	2.440	.007	.049	.000
	Other water body	4.277	7.752	.003	.078	.000
Apart-ment	Shopping area	9.855	22.245	.003	.211	.000
	Industry and office	3.002	8.906	.005	.167	.000
	Park and sports field	11.586	15.121	.002	.105	.000
	Agricultural	.713	4.181	.003	.037	.037
	River and lake	.834	4.306	.009	.139	.000
	Other water body	8.020	12.840	.005	.203	.000
Row	Shopping area	.549	3.231	.003	.040	.000
	Industry and office	1.887	6.163	-.001	-.025	.029
	Road traffic area	1.780	3.049	.003	.044	.000
	Day recreational area	.096	1.737	.006	.050	.000
Semi-det.	Other water body	5.116	7.954	.003	.114	.000
Det.	Industry and office	1.605	7.525	-.003	-.105	.004
	Open wet natural terrain	.088	.685	.035	.102	.003

Table 3: Hedonic price regression results for the land-use variables in Almere

	Variable	Mean	Std. Deviation	Unstandardized Coefficients B	Standardized coefficients Beta	sig
All	Shopping area	4.647	12.371	.001	.029	.000
	Public buildings	3.771	9.617	-.002	-.043	.000
	Park and sports field	4.235	8.502	.001	.013	.008
	Day recreational area	.0258	.539	.007	.009	.047
	Other water body	.220	1.243	.005	.014	.004
Apart-ment	Shopping area	9.633	17.709	.002	.068	.000
	Industry and office	4.563	9.486	.001	.032	.002
	Public buildings	7.023	13.472	-.002	-.084	.000
	Road traffic area	8.009	7.122	.002	.040	.000
Row	Public buildings	2.004	6.026	.001	.029	.002
	Agricultural	.523	3.507	.002	.026	.006
	Forest	.572	3.264	-.003	-.029	.001
Semi-det.	Shopping area	1.708	6.855	.002	.053	.003
	Road traffic area	4.335	5.501	-.002	-.040	.017
	Park and sports field	4.244	8.628	.001	.039	.017
	Forest	1.241	4.895	-.004	-.060	.000
	Other water body	.223	1.467	.009	.042	.012
Det.	Park and sports field	6.305	10.442	.002	.056	.006

Table 4. Hedonic price regression results for the land-use variables in Eindhoven

We will discuss the results of Tables 3 and 4 with regard to the question whether there are differences between the two cities and within cities between housing types regarding the neighborhood land-use effects. First, for the question whether differences exist between cities, we consider the estimation results for all housing types together. In both cities, shopping area, park and sports field, day recreation area and water all have significant positive effects on housing price. For the other land-uses, however, there is no correspondence between the cities indicating that land-use neighborhood effects are dependent on the existing local landscape and housing pattern.

Second, regarding the question whether there are differences in the valuation of neighborhood land-uses between housing types we will consider Eindhoven as case. We consider the different land-uses in turn.

Shopping area has positive effects on housing price for apartments and semi-detached housing and no significant effect for row houses and detached houses. Since the pattern is different in Almere (shopping area only positive for apartment and row), the specific local pattern of housing facilities probably plays a role so that it is hard to generalize the finding.

Similarly, Park and sports field has positive effects on semi-detached housing and detached housing. There is no significant influence on the apartments and row houses. From the overall regression result, the park and sports field land use have positive effects. The possible explanation is that the low-density expensive housing buyers (high-income or family with children segment) are more concerned about the open urban green space for sports recreation compared to the market segment living in apartments and row houses.

Other water body has a low standard deviation in Eindhoven, reflecting the fact that relatively few transaction cases concern dwellings that possess water land-use in the direct neighborhood. In segments where the standard deviation is higher the effect is positive. Therefore, it is plausible that overall water land-use has positive impacts on the housing price. The same holds for day recreational area.

Public buildings have a positive effect on the price of row houses, but a negative effect on the price of apartments in Eindhoven. Since there is no common finding for both two cities, we didn’t find significant effect of public buildings. This may be because the public buildings land use type includes so many different types, such as city hall, hospitals, museums, schools and so on. And we didn’t specify the type of public facilites. Therefore, since mutiple funtional facilities may affects housing value differently, it is difficult to find a common effect regarding public buildings as a single land use type.

Industry and office has a positive effect on the price of apartments. This land-use mainly refers to business and commercial land-use, including creative business offices and small-scale industry, which are typically located near the city center. Given the nature of this industry negative externalities such as noise and pollution is not in play. That may explain the positive influence on the housing price. The positive influence does not have significant influence on other housing types (based on the overall results in Eindhoven). So the explanation could be that for owners of apartments on average the creative business activities add to the quality of the environment in or around the city center locations.

Road traffic land use has a positive impact on apartment prices and a negative impact on price of semi-detached houses in Eindhoven. In Almere, road traffic has a positive effect on price of row houses. Based on the results of both cities, we can conclude that, to some extent, from row house to semi-detached house, there is a negative effect. This indicates that the balance between convenience and quietness may differ between housing types.

Agricultural and forest are mostly located at the edge of a city. Only the neighborhoods located near the border of the city have agriculture and forest land-use in the direct neighborhood. Agricultural land-use has a positive effect on the price of row houses. This may be an edge-of-the-city effect. Unexpectedly, forest has a negative effect on row and semidetached housing types. However in Almere, all the natural environment land use, including open wet natural terrain, agricultural and forest all have a positive effect. In Almere the allocation pattern of these nature elements is much more evenly distributed compared to Eindhoven. Hence, the negative effect of forest in Eindhoven may not be a generalizable effect.

In conclusion, shopping area and park and sports field are two types of land-use environment that have a positive impact on house purchasers’ preferences. Housing buyers’ evaluations of industry and office, public buildings, and traffic land use depend on housing type, which may be related to differences in family situations between housing types. Apartment owners prefer industry and office and road traffic area in the

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neighborhood possibly due to convenience and a city like atmosphere, while house owners of lower density housing assign more value to public buildings in the neighborhood such as schools and hospitals. Agriculture and forest are located at the edge of the city and may reflect how isolated the housing locations are.

6 CONCLUSIONS

In this paper we have proposed and illustrated the use of hedonic price modeling to estimate parameters of a land-use allocation model. The model focuses on housing. Although all land-uses are taken into account, UGS receives special attention given the intended use of the model to analyze urban green scenarios. We showed how a hedonic price model can be specified to fit the framework of the land-use model. A large housing transaction dataset was used and the analysis was conducted for two medium-sized cities in the Netherlands. Hedonic price models were estimated separately for different housing types and a full range of land-uses was taken into account.

The results indicate that UGS indeed has a positive influence on residential real estate prices to some extent. Different UGS types have different impacts on dwelling prices. Comparing the two cities - Eindhoven and Almere - the results indicate that local differences exist that are related to specific characteristics of the spatial land-use arrangement in the two areas. Especially, some UGS types do not occur in both municipalities. We also found structural differences in the way land-use affects housing prices between different housing types that may be related to differences in socio-demographic and socio-economic characteristics. Therefore, the findings indicate that land-use models should be estimated locally and housing market segment specific. The parameter estimates can be transferred to the HARA model system. In a follow-up we plan to develop an application of the estimated model to analyze UGS scenarios to support the development of urban greening strategies.

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