Routledge
Taylor & Francis Group

Edinburgh Napier University

INTERNATIONAL JOURNAL OF STRATEGIC PROPERTY MANAGEMENT
ISSN 1648-715X / eISSN 1648-9179

2015 Volume 19(1): 13–26
doi:10.3846/1648715X.2014.1000429

HOUSING MARKET DIFFERENTIATION: THE CASES OF YENIMAHALLE AND ÇANKAYA IN ANKARA

Leyla ALKAN [a,*]

[a] *Department of City and Regional Planning, Faculty of Architecture, Gazi University, Eti Mah. Yükseliş Sok. No: 5, Maltepe, Ankara, Turkey*

Received 30 March 2013; accepted 24 January 2014

ABSTRACT. This study aims to investigate housing market differentiation, drawing upon the results of case studies of the Çankaya and Yenimahalle districts that adopt a set of statistical techniques. As a first step, a cluster analysis is carried out to identify whether identifiable clusters of housing attributes exist on the basis of neighborhoods. Next, a Multiple Discriminant Analysis (MDA) is applied to investigate the differences between clusters, and to understand which housing attributes contribute most to submarket separation. Finally, a hedonic price analysis is conducted for each cluster and for the overall market to identify price differences in the housing market. The results of the study support the hypothesis that the housing market is segmented in Yenimahalle and Çankaya, and that location is the main determining factor in this segmented structure of different house values. The study also reveals that within this segmented structure, each cluster has its own dynamics, and that the price formation in each cluster is dependent on different variables.

KEYWORDS: Segmentation; Discriminant; Cluster; Hedonic; Submarkets

1. INTRODUCTION

Following Ankara's promotion to the status of capital in 1923, large-scale migration from Turkey's rural areas began increasing the population of the city. By the 1930s, Ankara had become a compact city, arranged around a single dominant core; and as the old housing stock next to the city center began to fill up, the new arrivals began setting up homes on open farmland. The rapid urban growth of the 1950s in the wake of industrialization was unexpected, and sourcing adequate housing stock to meet the housing demand of successive waves of immigration was difficult. As a result, newcomers to the city began to construct the illegal settlements that would eventually encircle the city (Uzun 2005). In 1965, the Condominium Law was enacted, easing the construction of multi-story apartment houses with only a small amount of capital. This brought individual contractors and small entrepreneurs into the construction market, and as a result, a build-and-sell system of housing production became widespread throughout the city. A high-rise residential pattern began to emerge, especially in the central neighborhoods, which witnessed an increase in density after higher buildings were permitted in the already built-up areas. The high-income groups, on the other hand, began moving out of the center, establishing new suburbs after the rapid increase in private car ownership witnessed in the 1970s (Uzun 2005; Onder 2000). Ankara has experienced a number of different but simultaneous processes since the 1980s, including suburbanization and the expansion of the city towards the west, alongside a transformation of the inner-city residential areas as a result of the increase in squatter settlements (Uzun 2005).

This historical development has resulted in a segmentary urban pattern in Ankara, supported by deficiencies in the housing finance system in Turkey that bears little resemblance to the well-functioning systems found in other countries. In Turkey, home-ownership among the different socio-economic groups is limited, and this has led low-income groups to create their own irregular mechanisms in order to become home-owners, alongside the regular methods of housing provision. As a result of this, discussions of socio-eco-

* Corresponding author. E–mail: leylaalkan@gazi.edu.tr

nomic factors affecting homeownership in Turkey differ significantly from discussions in literature related to housing tenure choice (Alkan 2011).

The main hypothesis of this study is that these various processes, in both the historical development of residential areas and in housing tenure in Ankara, have resulted in residential areas becoming segmented in terms of the structural and locational characteristics of the housing units that have emerged to meet the demands of households of different socio-economic status. This study aims to investigate this segmentation through case studies of the Çankaya and Yenimahalle districts of Ankara.

Çankaya is one of the oldest districts in Ankara, containing a spatial mix of high – and middle-income neighborhoods and squatter settlements. Most state offices and foreign embassies are located within the boundaries of this district, and while some of the older housing stock has been torn down to build apartment blocks, there remain a large number of original dwellings that are still in good condition (Erkip 2010). In summary, Çankaya has a heterogeneous character, including the oldest and most prestigious neighborhoods of the city, and also neighborhoods of newly constructed apartment blocks that emerged after the transformation of the squatter settlements. Yenimahalle also contains squatter neighborhoods that are earmarked for transformation; however, unlike the Çankaya case, the district features suburban areas of high-income groups that emerged hand-in-hand with the increase in private car ownership.

This paper utilizes a cluster analysis, a discriminant analysis and a hedonic regression analysis to characterize the housing markets in Yenimahalle and Çankaya. The cluster and discriminant analyses examine the differences between the physical characteristics of the current stock in the housing market, while the hedonic regression allows an understanding of the housing characteristics that define the price structure in each segment. It should be noted that only structural characteristics are included in the regression analysis, given the lack of information on locational and environmental characteristics of the housing units in the available data.

The following section comprises a summary of the literature review, while the third section defines the methodology and provides an explanation of the data. In the fourth section, the results of the analyses are presented. The fifth section opens the subject for discussion, and the last section concludes the study.

2. LITERATURE REVIEW

The housing market is not a uniform entity, but can rather be considered as a set of distinctive submarkets that are based on the structural and locational attributes of neighborhoods and dwelling units (Adair *et al.* 1996). Housing submarket models have focused on differential hedonic prices across housing areas (Goodman, Thibodeau 1998). The concept of submarkets that developed via a hedonic price analysis is defined in terms of house prices, and submarkets will exist in areas where the prices of dwelling units are the same within the market and differ from other parts of the market (Jones *et al.* 2004). The determinants of house prices may include the characteristics of the housing unit, the structure of the building, the characteristics of the neighborhood, the local market conditions and housing policies. In addition to these factors, accessibility to the CBD, employment opportunities, and accessibility to urban facilities may also play a defining role (Keskin 2008).

An early study of the housing market was made by Goodman (1978), who used a hedonic approach in his assessment of the formation of housing price indices when measuring variations within a metropolitan area. In forming these indices, Goodman followed the methods of Box and Cox in describing 15 submarkets. Another early study of submarkets using a hedonic pricing model was made by Goodman and Dubin (1990), who argued that housing and locational characteristics may differ across different submarkets, and so equations should be created that allow the coefficients to differ according to the submarket. Another study on the specification of housing submarkets was made by Adair *et al.* (1996), who examined existing housing market areas and the valuation process with the help of a multiple regression analysis, and argued that the house price structure could be used to identify and differentiate between housing submarkets. Bourassa *et al.* (1999) combined different statistical techniques in one comprehensive procedure in order to define the boundaries of housing submarkets in Sydney and Melbourne. They began by using a principal component analysis to extract a set of factors from the original variables, after which they calculated factor scores and used a cluster analysis to evaluate the composition of the housing submarkets. As a final step, hedonic equations were estimated for the overall market and for the submarkets defined in the cluster analysis. Goodman and Thibodeau (2003) investigated housing submarket segmentation within metropolitan areas using hedonic price models – a method that facilitated the systematic identification of submarkets, and permitted a decomposition of the effects of both price and quantity/quality. The authors used a hierarchical linear modeling technique in which dwelling characteristics, neighborhood characteristics and submarkets were seen to interact and influence house prices. Jones *et al.* (2004) focused on submarket definitions in a re-examination of the concept and the tests applied to identify submarkets, and identified the role of intra-urban migration as an underlying dynamic of submarkets. They argued that the standard hedonic statistical tests for submarkets were incomplete, and that the test procedure needed to be extended to consider the relationship between household mobility and submarkets, with a migration analysis providing additional justification for their existence. Bates (2006) examined the different factors causing segmentation in the housing market. They defined the factors through a factor analysis, after which a cluster analysis was used to reveal the quality-defined housing submarket areas. As a final stage, these statistically created submarkets were tested to determine whether the groupings of areas were acceptable for creating significantly different quality-level submarkets. Sing *et al.* (2006) examined the relevance of different factors in the price dynamics of different housing sub-markets, using a stochastic permanent breaks model in their investigation, while Bourassa *et al.* (2007) used a hedonic approach looking at the house prices in different submarkets, with the main objective being to compare the house price predictions of several alternative specifications. Another study using a hedonic approach in the estimation of housing prices was made by Ozus *et al.* (2007), who looked into the factors affecting housing prices in İstanbul according to areal units, applying a regression analysis at the metropolitan and district scale to explore the nature of housing price differentiations. The authors examined housing market prices in İstanbul according to the administrative boundaries. The results of the study revealed that housing price was dependent upon three characteristics: structure, location and environment. They discovered that the impact of the sub-market was the most important factor at the metropolitan level, while effects of the other variables changed from one district to another. At the metropolitan level, the most important factor affecting housing prices was sub-market, floor area and sea view, with the age of the building having a positive influence at the metropolitan level. This was based on the positive impact of renovated buildings in the old districts and the higher housing prices in the well-established neighborhoods than in the newly developing ones. Alkay's (2008) examination of the housing submarkets in İstanbul revealed that in a segmented housing market, the house price structure is different in each segment, and that the entire market area price structure does not reflect effectively a realistic housing price structure. Keskin (2008) examined housing market prices in İstanbul using a hedonic price model. In the study, the size of the living area, being in a low storey building, being in a secure site, the age of the building, the length of time the inhabitants had lived in İstanbul, the average income of the household, neighbor satisfaction and the earthquake risk of the area were all factors affecting house prices. Kiel and Zabel (2008) used the 3L approach to house price determination in their study, which was based on the assumption that location, location and location were the three main factors determining the price of a house. The three locations covered in the study were the Metropolitan Statistical Area (MSA), the town and the street on which the house was located. The study used a data set based on the American Housing Survey (AHS) of small "clusters" of housing units, with information on their characteristics, the resident profiles and the census tract-level attributes. The study revealed that all three levels of location were jointly significant when estimating the house price hedonic equation. Selim (2009) examined the determinants of house prices for the whole of Turkey, including both urban and rural areas, using a hedonic regression model and artificial neural netwok (ANN). The results of the hedonic model showed that the water system, access to a pool, type of house, number of rooms, house size, locational characteristics and type of building were the most significant variables affecting house prices; however, because of potential non-linearity in the hedonic functions, the author employed ANN as an alternative method in the prediction. By comparing the prediction performance between the hedonic regression and ANN models, the author argued that ANN could be a better alternative for predicting house prices in Turkey. Koramaz and Dokmeci (2012) examined the spatial determinants of housing price values in İstanbul by creating a semi-hedonic price model, generated from a multiple regression model. They investigated housing prices taking into consideration distance to the city center, transportation arteries and coasts, housing and neighborhood characteristics. The results indicated that housing prices were significantly affected by spatial determinants such as distance to the CBD, sub-centers, main transportation arteries and the coast.

This literature review has revealed that there is general consensus among researchers regarding the existence of submarkets; however, views tend to differ on how submarkets should be specified (Adair *et al.* 1996). With the emergence of hedonic price analyses and a number of different analytical methods, the identification and proper characterization of submarkets has gained critical importance (Goodman, Thibodeau 1998). This study examines house prices in Çankaya and Yenimahalle to understand the level of segmentation in the housing market. Following the methods of Keskin (2008) and Ozus *et al.* (2007), administrative boundaries are used to define each neighborhood in Çankaya and Yenimahalle; however, in order to define the boundaries of submarkets, the neighborhoods are grouped according to the set of techniques used in the study of Bourassa *et al.* (1999). As such, this study attempts to combine different statistical techniques in an analysis of the definition and construction of housing submarkets in Ankara.

3. METHODOLOGY AND DATA

The data used in the analysis was collected from one of the largest real estate websites (*Housing asked prices in Ankara* 2011), providing information about dwelling units on sale between February 2011 and October 2011 in the different neighborhoods of Çankaya and Yenimahalle. The sample comprised 1,733 dwelling units, spread across 30 neighborhoods in Çankaya and 15 in Yenimahalle. For each neighborhood, data was garnered on the asked prices and the different attributes of each dwelling unit. Table 1 presents a description of the variables in the data.

In the statistical analyses conducted here, categorical variables with more than two levels could not be entered directly into the model. To address this problem, the process of dummy coding was used to transform categorical variables with k levels into k-1 variables. The analyses were run by entering each new two-level variable into the model. For example, the Heating System, with four levels, was transformed into three dichotomous variables that contained the same information as the single categorical variable. In Table 1, Balcony, Garden, Stove, Boilers and Central ere entered into the

Table 1. Description of variables

Variable	Description					
Price	Price of the dwelling unit					
Age	Age of the building in which the unit is located					
Floor area	Floor area of the dwelling (m2)					
Rooms	Number of rooms in the dwelling unit					
Balcony	Dummy equal to 1 if there is a balcony					
Bathrooms	Number of bathrooms in the dwelling unit					
Garden	Dummy equal to 1 if there is a garden					
Story	Story on which the unit is located					
Number of stories	Total number of the stories in the apartment unit					
Stove	Dummy equal to 1 if heating system is a solid-fuel stove					
Boilers	Dummy equal to 1 if heating system is powered by a wall hung gas boiler					
Central	Dummy equal to 1 if heating system is a common heating system for the entire block					
	Descriptive statistics					
	Mean	Median	Mode	Std. Dev.	Min.	Max.
Price	178437.27	138000	125000	120478.82	20000	1350000
Age	10.11	6	2	9.76	0	51
Floor area	141.67	125	100	61.31	42	550
Rooms	3.26	3	3	1.00	1	7
Balcony	0.95	1	1	0.20	0	1
Bathrooms	1.43	1	1	0.64	1	4
Garden	0.95	1	1	0.20	0	1
Story	2.48	2	3	2.67	–2	25
Number of stories	5.11	4	4	2.96	2	28
Stove	0.01	0	0	0.11	0	1
Boilers	0.84	1	1	0.36	0	1
Central	0.14	0	0	0.35	0	1

analysis in the form of dummy variables, indicating the presence or absence of each characteristic in the dwelling unit.

Following Bourassa *et al.* (1999), this study attempts to apply a set of techniques to investigate housing submarkets in a three-stage analysis. In the first stage of the study, a cluster analysis was carried out to form homogenous groups of different neighborhoods in Çankaya and Yenimahalle, which is a multivariate method that is used to classify data into a number of different groups on the basis of a set of measured variables (Cornish 2007). The groups created in the cluster analysis are not unique, since they depend upon the variables used and how cluster membership is defined (Chan 2005b). To analyze the different types of clusters in this study, an agglomerative hierarchical method was chosen, within which are a number of different methods used to determine which clusters should be merged at each stage (Cornish 2007). This study adopts the between-groups linkage method with squared Euclidean Distance as the distance or similarity measure. In this method, the distance between two clusters is calculated as the average distance between all pairs of subjects in the two clusters (Cornish 2007). After deciding upon the most appropriate procedure and method for the analysis, the optimum number of clusters (k) in the sample needs to be defined. In this stage, a cluster analysis is applied, and the optimum number of clusters is chosen by examining the agglomeration schedule generated by the results, after which the hierarchical cluster analysis is rerun with the selected number of clusters.

In the second stage of the study, a discriminant analysis was used to determine the main characteristics of dwelling units that differed across the clusters identified in the first stage. A discriminant analysis (DA) is a statistical technique used for differentiating between groups when the independent variables are quantitative (Chan 2005a). If the independent variable has more than two groups, a Multiple Discriminant Analysis (MDA) is applied rather than a simple Discriminant Analysis. An MDA comprises three different steps: 1) The estimation of the coefficients of the variables; 2) the calculation of the discriminant score of each case; and 3) the classification of each case, taking into account the discriminant scores (Leksrisakul, Evans 2005). A discriminant function is conducted at the end of an MDA, which is similar to a regression function. The unstandardized discriminant coefficient (analogous to the "b"s in the regression function) maximizes the distance between the means of the dependent variable. That is, the discriminant function maximizes the distance between clusters. Good predictors tend to have large weights (Burns, Burns 2008).

In the third stage of the study, hedonic price models were created to estimate the housing characteristics that define the price structure in each segment and the overall data. Such methods have proven to be an important means of analyzing commodities with various characteristics (Goodman, Thibodeau 1998), and are useful tools for explaining the determinants of housing prices by taking into consideration structural, locational and environmental attributes. Hedonic models are important tools for understanding housing segmentation by focusing housing price changes (Keskin 2008). That said, owing to the lack of data on the locational and environmental attributes of the dwelling units, the regression analysis was conducted focusing only on the structural characteristics of the dwelling units.

4. RESULTS

4.1. Cluster analysis

In order to define whether identifiable clusters of housing attributes exist on the basis of neighborhoods, a cluster analysis was conducted as a first step to determine whether certain combinations of physical attributes of dwelling units are common to certain neighborhoods. There are five variables in the data that are available for the classification of neighborhoods in the cluster analysis, information on which can be found in Table 2. The cluster analysis was run for 45 neighborhoods, and at the end of the examination of the agglomeration schedule generated by the results nine different clusters were identified. Table 3 presents the

Table 2. Description of variables in cluster analysis

Variable	Description
A.Price	Average price of the dwelling units in the neighborhood
A.Age	Average age of the buildings in the neighborhood
A.Floor Area	Average floor area of the dwelling units in the neighborhood (m^2)
A.Rooms	Average number of rooms of the dwellings in the neighborhood
A.Number of Stories	Average number of the stories in the apartment units in the neighborhood

Table 3. Frequencies of clusters

	Frequency	%	Neighborhood	District
Cluster 1	5	0.29	Anıttepe	Çankaya
Cluster 2	252	14.54	Ayrancı	Çankaya
			Cevizlidere	Çankaya
			Emek	Çankaya
			Kırkkonaklar	Çankaya
			Çamlıca	Yenimahalle
Cluster 3	149	8.60	Bahçelievler	Çankaya
			Birlikmahallesi	Çankaya
			Kavaklıdere	Çankaya
			Çankaya	Çankaya
Cluster 4	438	25.27	Balgat	Çankaya
			Dikmen	Çankaya
			Keklikpınarı	Çankaya
			İlker	Çankaya
			Öveçler	Çankaya
			Çarşı	Yenimahalle
Cluster 5	514	29.66	Büyükesat	Çankaya
			Cebeci	Çankaya
			Sağlık	Çankaya
			Seyranbağları	Çankaya
			Sokullu	Çankaya
			Topraklık	Çankaya
			İncesu	Çankaya
			Demet	Yenimahalle
			Ergenekon	Yenimahalle
			Karşıyaka	Yenimahalle
			Pamuklar	Yenimahalle
			Susuz	Yenimahalle
			Yakacık	Yenimahalle
			Yunusemre	Yenimahalle
Cluster 6	37	2.14	Yıldızevler	Çankaya
			Çukurambar	Çankaya
Cluster 7	82	4.73	Gaziosmanpaşa	Çankaya
			Çayyolu	Yenimahalle
Cluster 8	50	2.89	Hilal	Çankaya
			Oran	Çankaya
			Sancak	Çankaya
			Yaşamkent	Yenimahalle
Cluster 9	206	11.89	Kızılay	Çankaya
			Küçükesat	Çankaya
			Öncebeci	Çankaya
			Gazimahallesi	Yenimahalle
			Kentkoop	Yenimahalle
			Ostim	Yenimahalle
			Ragıp Tüzün	Yenimahalle
Total	1733	100.0		

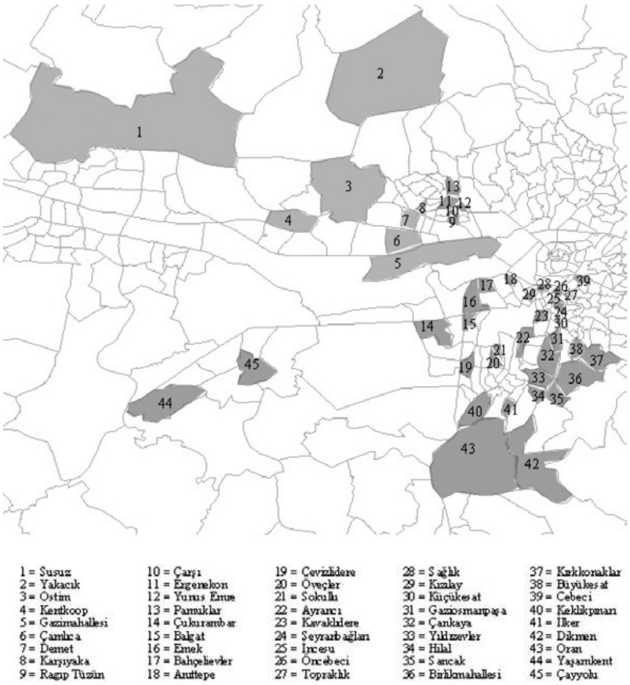

Fig. 1. Spatial distribution of neighborhoods

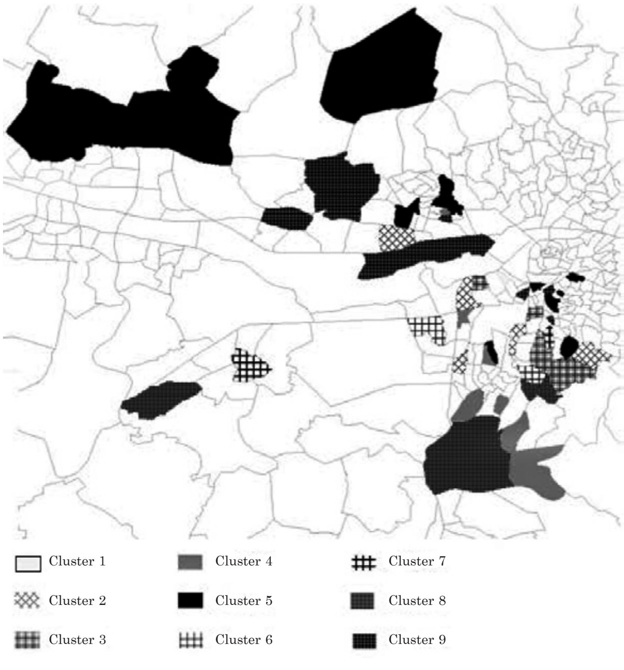

Fig. 2. Spatial distribution of clusters

names of neighborhoods in each cluster garnered from the Hierarchical Cluster Analysis. Figure 1 illustrates the spatial distribution of neighborhoods, and Figure 2 illustrates the spatial distribution of clusters.

After establishing the clusters of neighborhoods, each of the 1,733 cases in the two districts were fixed to their particular cluster in the data, and the number of cases in each cluster is also presented in Table 3. Cluster 5 contains the most number of cases, with 514; followed by Cluster 4, containing 438 neighborhoods. The least number of cases are found in Cluster 1, with Anıttepe being the only neighborhood in this cluster. Also, Cluster 3 and Cluster 6 contain no neighborhoods from the Yenimahalle district.

Table 4. Cluster statistics

Cluster		Minimum	Maximum	Mean	Std. Deviation*
1	Age	2	46	24.40	20.695
	Floor area	80	300	160.00	95.917
	Rooms	2	5	3.40	1.517
	Price (.000 TL)	115	570	317.00	210.315
	Number of stories	3	4	3.80	0.447
2	Age	1	41	12.73	12.113
	Floor area	55	420	151.30	66.856
	Rooms	1	7	3.35	1.155
	Price (.000 TL)	63	850	207.68	118.726
	Number of stories	2	28	5.10	3.728
3	Age	1	51	12.48	12.257
	Floor area	42	550	171.37	80.229
	Rooms	1	7	3.58	1.079
	Price (.000 TL)	72	700	260.89	131.014
	Number of stories	2	23	4.50	2.850
4	Age	1	41	8.56	6.792
	Floor area	60	380	143.94	59.669
	Rooms	1	7	3.34	1.036
	Price (.000 TL)	49	580	166.08	80.276
	Number of stories	2	14	4.20	1.992
5	Age	0	46	11.05	10.221
	Floor area	50	300	119.26	41.253
	Rooms	1	7	2.98	0.839
	Price (.000 TL)	20	355	108.43	42.851
	Number of stories	2	18	4.95	2.326
6	Age	1	11	2.75	2.518
	Floor area	100	420	208.70	87.364
	Rooms	2	7	3.92	1.038
	Price (.000 TL)	210	940	448.92	157.653
	Number of stories	3	14	9.08	3.324
7	Age	1	31	10.70	9.141
	Floor area	50	425	163.17	66.358
	Rooms	1	7	3.61	1.027
	Price (.000 TL)	75	1350	295.10	190.575
	Number of stories	2	15	6.28	3.938
8	Age	1	30	8.14	6.848
	Floor area	110	385	198.32	67.449
	Rooms	3	7	4.18	0.850
	Price (.000 TL)	175	850	367.42	127.796
	Number of stories	2	26	6.02	4.529
9	Age	1	46	8.39	9.223
	Floor area	50	280	124.76	36.652
	Rooms	1	6	2.96	0.699
	Price (.000 TL)	44	390	139.74	56.829
	Number of stories	3	18	6.53	2.935
Overall	Age	0	51	10.11	9.766
	Floor area	42	550	141.68	61.310
	Rooms	1	7	3.26	1.006
	Price (.000 TL)	20	1350	178.44	120.479
	Number of stories	2	28	5.12	2.965

* The reason for high standard deviation values is that the data used in cluster analysis is not normally distributed for Age, Floor area, Rooms, Price, and Number of stories.

Table 4 provides descriptive statistics for each cluster after fixing each of the 1,733 cases in the two districts to their particular cluster in the data. In Table, it can be seen that age may be a good discriminator for Cluster 1 and Cluster 6, while other clusters score relatively similar results in this category. Table 4 also illustrates that Cluster 5 and Cluster 9 have smaller floor areas, associated with lower house prices; while Cluster 6 has the most expensive average house prices and the largest floor areas. From this it can be safely assumed that floor area will constitute one of the most important variables affecting house prices. In the table, Cluster 1 has the oldest housing stock with the smallest number of stories, and Cluster 6 has the newest housing units with the highest number of stories, pointing to a significant relationship between age of the building and the number of stories. Also, the table illustrates that Cluster 6 seems to be highly differentiated from the other clusters. To test these hypotheses and examine the segmented housing market within these two districts, Multiple Discriminant and Hedonic Function analyses were conducted as the second and the third steps in the study.

4.2. Multiple discriminant analysis

A Multiple Discriminant Analysis (MDA) was used to investigate the differences between clusters, and to identify which attributes of housing contributed most to submarket separation. After excluding the variables with missing values, 1,139 cases were identified as suitable for analysis. The MDA was run using a range of key variables, including Price, Age, Floor Area, Rooms, and Number of Stories. The test of equality of the group means in Table 5 indicates that there are significant group differences in each of the independent variables (at $p < 0.000$) in the study.

Table 6 provides information on the Eigenvalues, Canonical Correlations, Wilks' Lambda and Coefficient Discriminant Functions. A total of five functions are produced in the discriminant analysis, and both the eigenvalues and canonical correlations are higher for the first function in the table. That is, the first function is statistically more significant than the others, and so the first function will be used for the estimation of the discriminant function.

Wilks' Lambda tests the statistical significance of discriminant functions, illustrating that the first three discriminant functions have significant discriminating power. In Table 6, the unstandardized coefficients are illustrated as canonical discriminant function coefficients. The table also provides information on standardized canonical function coefficients. The standardized discriminant function coefficients (b) indicate the partial contribution of each variable to the discriminate function, controlling all other variables in the equation. They can be used to assess the contribution of each variable to the discriminate function, and therefore provide information on the relative importance of each variable (Burns, Burns 2008).

The Price of the dwelling is the strongest predictor in the allocation of housing market clusters, as its "b" is the highest for the first function; this is followed by Floor Area and Number of Stories. In the second function, the strongest predictor is the Number of Stories, while Age is highly relevant for the third function. Only the first three functions are interpreted in this part, in that they explain more of the variance between groups, while Functions 4 and 5 are not significant. The results of the discriminant analysis illustrate that Price, Floor Area, and Number of Stories are more significant variables in the formation of the segmented housing structure in both Çankaya and Yenimahalle. The unstandardized coefficients in Table 6 are used to create the discriminant function as:

$$D = (0.014 \times \text{Age}) + (-0.007 \times \text{Floor Area}) + (-0.222 \times \text{Rooms}) + (0.016 \times \text{Price(,000TL)}) + (-0.128 \times \text{Number of Stories}) - 0.646$$

Table 7 presents the classification results of the discriminant analysis, in which the rows are the observed categories of the dependent and the columns are the predicted categories. When the prediction is perfect, all cases will lie on the diagonal, meaning that the percentage of cases on the

Table 5. Tests of equality of group means

	Wilks' lambda	F	df1	df2	Sig.
Age	0.942	8.713	8	1140	0.000
Floor area	0.915	13.299	8	1140	0.000
Rooms	0.944	8.429	8	1140	0.000
Price (,000 TL)	0.643	79.030	8	1140	0.000
Number of stories	0.867	21.770	8	1140	0.000

Table 6. Eigenvalues, canonical correlations, Wilks' lambda, coefficients discriminant functions

	Function				
	1	2	3	4	5
Eigenvalue	0.748	0.156	0.062	0.009	0.004
Canonical correlation	0.654	0.367	0.241	0.094	0.061
Tests of function(s)	1 thr 5	2 thr 5	3 thr 5	4 thr 5	5
Wilks' lambda	0.460	0.804	0.930	0.987	0.996
Sig.	0.000	0.000	0.000	0.152	0.366
Standardized canonical discriminant function coefficients (b)					
Age	0.131	–0.241	1.035	0.048	–0.110
Floor area	–0.406	–0.230	0.453	–0.958	1.667
Rooms	–0.218	–0.063	0.031	1.695	–0.604
Price (,000 TL)	1.443	–0.004	–0.239	–0.147	–0.510
Number of stories	–0.369	0.936	0.445	0.178	0.203
Canonical discriminant function coefficients					
Age	0.014	–0.025	0.108	0.005	–0.011
Floor area	–0.007	–0.004	0.007	–0.016	0.028
Rooms	–0.222	–0.065	0.031	1.726	–0.615
Price (,000 TL)	0.016	0.000	–0.003	–0.002	–0.006
Number of stories	–0.128	0.325	0.155	0.062	0.070
(Constant)	–0.646	–0.666	–2.642	–3.527	–1.245

Table 7. Classification results

		Clusters	Predicted group membership									Total
			1	2	3	4	5	6	7	8	9	
Original	Count	1	1	2	0	0	0	1	0	1	0	5
		2	15	31	24	65	12	11	7	13	4	182
		3	16	4	19	34	0	4	4	8	1	90
		4	1	13	43	183	63	2	7	13	29	354
		5	2	15	2	82	113	0	3	1	65	283
		6	0	0	2	0	0	18	4	2	1	27
		7	3	3	1	8	3	5	6	2	6	37
		8	3	0	6	2	0	6	2	11	1	31
		9	2	11	2	25	20	0	1	2	77	140
	%	1	20.0	40.0	0.0	0.0	0.0	20.0	0.0	20.0	0.0	100.0
		2	8.2	17.0	13.2	35.7	6.6	6.0	3.8	7.1	2.2	100.0
		3	17.8	4.4	21.1	37.8	0.0	4.4	4.4	8.9	1.1	100.0
		4	0.3	3.7	12.1	51.7	17.8	0.6	2.0	3.7	8.2	100.0
		5	0.7	5.3	0.7	29.0	39.9	0.0	1.1	0.4	23.0	100.0
		6	0.0	0.0	7.4	0.0	0.0	66.7	14.8	7.4	3.7	100.0
		7	8.1	8.1	2.7	21.6	8.1	13.5	16.2	5.4	16.2	100.0
		8	9.7	0.0	19.4	6.5	0.0	19.4	6.5	35.5	3.2	100.0
		9	1.4	7.9	1.4	17.9	14.3	0.0	0.7	1.4	55.0	100.0

39.9% of original grouped cases correctly classified.

diagonal can be considered as the percentage of correct classifications in the analysis. The overall predictive accuracy of the discriminant function is called the "hit ratio" (Burns, Burns 2008), and Table 7 thus reveals that 39.9% of the total cases are correctly classified. This hit ratio can be accepted as being satisfactorily valid, in that most researchers accept a hit ratio of greater than 25%, which may be attributed to chance (Burns, Burns 2008). In the table, Cluster 6 is classified with greater accuracy (66.7%) than the other clusters, which could be predicted from the cluster statistics in Table 4.

4.3. Hedonic regression

After the cluster and discriminant analyses, a hedonic regression analysis was performed for each of the submarkets and the overall sample. The

Table 8. Results of hedonic regression

Variables in model (significant at the 0.05 level)		ANOVA				Unstandardized coefficients		Standardized coefficients			
		F	Sig	R Square	Adjusted R square	B	Std. Error	Beta	t	Sig.	VIF
Cluster 1	–	–	–	–	–	–	–	–	–	–	
Cluster 2	Floor area	52.542	0.000	0.804	0.789	0.769	0.154	0.497	4.992	0.000	5.823
	Number of stories					12.081	2.002	0.417	6.035	0.000	2.811
Cluster 3	Age	15.983	0.000	0.738	0.692	1.569	0.752	0.185	2.087	0.042	1.525
	Floor area					0.588	0.194	0.482	3.030	0.004	4.936
	Story					16.200	5.945	0.456	2.725	0.009	5.467
Cluster 4	Floor area	58.368	0.000	0.687	0.675	0.606	0.105	0.440	5.770	0.000	4.939
	Story					6.896	1.713	0.183	4.025	0.000	1.764
	Number of stories					7.491	1.668	0.193	4.492	0.000	1.575
Cluster 5	Floor area	22.387	0.000	0.511	0.488	0.379	0.092	0.352	4.115	0.000	3.211
	Rooms					13.746	4.150	0.258	3.312	0.001	2.659
	Stove					–32.285	14.263	–0.112	–2.264	0.025	1.077
	Story					3.604	1.184	0.194	3.043	0.003	1.785
Cluster 6	Floor area	6.178	0.003	0.805	0.674	1.445	0.540	0.698	2.675	0.020	4.179
Cluster 7	Floor area	5.330	0.001	0.681	0.553	1.959	0.682	1.021	2.874	0.009	7.911
	Number of stories					25.875	9.241	0.627	2.800	0.011	3.137
Cluster 8	Central	7.647	0.001	0.805	0.699	224.649	64.840	0.821	3.465	0.004	3.735
	Bathrooms					110.295	50.079	0.403	2.202	0.046	2.228
	Story					38.114	15.913	0.850	2.395	0.032	8.373
Cluster 9	Floor area	21.798	0.000	0.651	0.621	1.587	0.201	0.914	7.889	0.000	4.044
	Rooms					–25.211	9.581	–0.269	–2.632	0.010	3.159
Overall	(Constant)	144.394	0.000	0.751	0.746	–70.923	17.987	–	–3.943	0.000	–
	Floor area					0.777	0.063	0.449	12.401	0.000	4.525
	Central					29.481	7.078	0.085	4.165	0.000	1.425
	Bathrooms					11.400	4.343	0.072	2.625	0.009	2.593
	Story					5.938	0.943	0.149	6.297	0.000	1.929
	Number of stories					4.493	0.871	0.129	5.159	0.000	2.162
	cls1					160.431	25.607	0.111	6.265	0.000	1.094
	cls2					54.322	7.410	0.175	7.331	0.000	1.976
	cls3					77.309	9.049	0.181	8.543	0.000	1.560
	cls4					32.486	6.411	0.139	5.067	0.000	2.617
	cls5					–14.037	6.435	–0.057	–2.182	0.029	2.326
	cls6					189.974	13.267	0.268	14.320	0.000	1.211
	cls7					51.056	11.548	0.084	4.421	0.000	1.255
	cls8					159.803	13.398	0.225	11.927	0.000	1.235

database for the hedonic price regression comprises information on a range of key variables, including Price, Age, Floor Area, Rooms, Balcony, Bathrooms, Garden, Story, Number of Stories, Stove, Boilers and Central. However, after examining the Variance Inflation Factors (VIF), the Boilers variable was excluded from all regression analyses because of its high collinearity. Also Rooms were dropped from the regression analyses for Clusters 7 and 8, as its VIF scores exceeded 10. The assumptions of homoscedasticity and normality of residuals were checked with the help of Q-Q-Plot of z*pred and z*presid. The plots indicated that in all multiple linear regression analyses error terms had constant variances, and they were normally distributed.

Table 8 summarizes the hedonic price functions for each submarket and the overall data by reporting the significant variables in each analysis. The regression for Cluster 1 provides no information, as the number of cases was insufficient for the analysis. In the Table, the ANOVA scores show that the adjusted squared multiple correlations are significantly different from zero for all regression analyses. That is, independent variables used together in all models as a set are significantly related to the dependent variable (Burns & Burns, 2008). The adjusted R square values range from 0.488 to 0.789; while the adjusted R square values are higher for the 2nd (0.789) and the 8th (0.699) clusters. The adjusted R square is 0.746 for the overall model. In the overall data, independent variables explain 75.1% of the price variance, which is highest for the 6th and 8th clusters, accounting for 80.5% of the total.

Aside from in Cluster 8, Floor Area is positively significant, with the prices of dwelling units increasing with floor area. This relationship can also be predicted from the descriptive analyses in Table 4. Number of Stories is a significant indicator for the 2nd, 4th and 7th clusters and for the overall sample. The price of dwelling increases with higher buildings.

In the overall sample, Age was not significant; however, it was significant for the 3rd cluster. There is a reverse relationship in the 3rd cluster, in which the price increases as the building becomes older. This result is consistent with the results of Ozus *et al.* (2007), who also highlighted a positive effect of age on the price of housing at the metropolitan level in İstanbul. In this study, all neighborhoods in the 3rd cluster are in Çankaya, and as discussed at the beginning of the study are the prestigious and old residential areas of the capital city.

The Story on which the unit is located is statistically significant in the 3rd, 4th, 5th and 8th clusters, and for the overall sample, with the price of the dwelling being positively related to the story number. The Number of Rooms is a significant variable for the 5th and 9th clusters. In Cluster 5, the price of the dwelling increases depending on the number of rooms; however, there is a negative relationship for the Cluster 9. The presence of a Stove is significant only for the Cluster 5. As expected, dwelling units using a Stove as a heating system decreases the price of the dwelling units. Having a Central Heating System and the Number of Bathrooms increases the price of the dwelling units for the 8th cluster and for the overall sample, while the presence of a Garden and Balcony are not important indicators determining the price of dwelling units.

In the hedonic regression of the overall sample, clusters were added to the model as an explanatory variable in order to test whether the prices of dwelling units were affected by the locational preferences of the households. All clusters displayed positive and significant effects on the price of dwelling units, aside from Cluster 5, which features the lowest house prices in the data. In the overall data, the standardized coefficients indicate that the most significant factor affecting house prices is the Floor Area of the unit, followed by cls6, which indicates that the dwelling units located in one of the locations in Cluster 6 (Yıldızevler or Çukurambar) have higher house prices. The next important explanatory factors are cls8 and cls3, which indicate that house prices increase if the dwelling unit is located in Hilal, Oran, Sancak, Yaşamkent, Bahçelievler, Birlikmahallesi, Kavaklıdere or Çankaya.

5. DISCUSSIONS

The results of the discriminant analysis have shown that the main determinant in the formation of clusters is the price of the dwelling units. In this segmented housing market, a hedonic price analysis illustrates that housing price structures differ from cluster to cluster as a result of variations in the demands of households. Table 9 summarizes the residential characteristics of the neighborhoods in each cluster, defining how the demand of households creates housing segments with different preferences.

Table 9 reveals that the Çankaya neighborhoods of Ayrancı and Emek contain older housing stock, while Kırkkonaklar and Cevizlidere in Cluster 2

Table 9. Residential characteristics of neighborhoods

Cluster	District	Neighborhood	Age	Floor area	Number of stories	Price
1	Çankaya	Anıttepe	24.40	160.00	3.80	317 000.00
2	Çankaya	Ayrancı	26.82	128.10	5.13	199 188.12
		Cevizlidere	4.94	171.86	4.36	211 616.28
		Emek	14.83	132.42	3.64	227 833.33
		Kırkkonaklar	6.60	184.29	3.81	210 455.88
	Yenimahalle	Çamlıca	4.50	134.42	10.89	217 263.16
3	Çankaya	Bahçeli	29.82	140.72	5.41	265 250.00
		Birlikmahallesi	6.93	188.42	4.10	264 188.17
		Çankaya	12.71	144.59	6.14	248 676.47
		Kavaklıdere	30.67	143.81	4.79	252 452.38
4	Çankaya	Balgat	9.76	142.68	3.70	177 347.83
		Dikmen	9.14	143.83	3.90	160 119.27
		İlker	9.49	139.47	4.13	151 496.09
		Keklikpınarı	4.73	149.03	4.43	167 898.57
		Öveçler	8.98	144.11	4.20	168 910.96
	Yenimahalle	Çarşı	7.56	146.17	5.03	172 159.09
5	Çankaya	Büyükesat	13.33	124.55	3.73	117 500.00
		Cebeci	14.83	108.13	3.90	114 229.17
		İncesu	2.14	105.61	4.84	108 173.91
		Sağlık	18.00	104.90	4.51	116 979.59
		Seyranbağları	11.93	112.42	4.03	114 930.23
		Sokullu	16.97	108.91	4.10	113 320.45
		Topraklık	3.50	101.67	3.25	109 666.67
	Yenimahalle	Demet	17.10	116.80	6.09	95 806.67
		Ergenekon	9.79	125.96	3.31	104 000.00
		Karşıyaka	16.35	111.86	6.71	83 071.43
		Pamuklar	3.56	145.98	6.15	119 559.52
		Susuz	5.25	135.90	9.60	99 700.00
		Yakacık	2.08	137.25	5.00	89 166.67
		Yunusemre	18.00	125.83	4.33	80 416.67
6	Çankaya	Çukurambar	5.00	196.44	8.56	432 777.78
		Yıldızevler	1.85	212.64	9.26	454 107.14
7	Çankaya	Gaziosmanpaşa	13.88	167.17	4.98	299 091.67
	Yenimahalle	Çayyolu	6.55	152.27	9.83	284 204.55
8	Çankaya	Hilal	4.47	206.27	4.21	371 409.09
		Oran	15.30	176.33	8.13	370 333.33
		Sancak	10.40	231.29	3.71	356 428.57
	Yenimahalle	Yaşamkent	2.60	185.67	9.80	358 333.33
9	Çankaya	Küçükesat	22.90	116.82	4.19	139 214.29
		Kızılay	30.50	100.00	4.29	144 714.29
		Öncebeci	4.81	107.50	4.26	130 783.33
	Yenimahalle	Gazimahallesi	12.00	107.00	3.20	136 600.00
		Kentkoop	6.01	132.17	8.25	142 765.22
		Ostim	5.33	127.20	5.90	124 800.00
		Ragıp Tüzün	8.36	136.09	3.64	145 727.27

have relatively newer housing stock, along with Çamlıca in Yenimahalle. The table further shows that there has been a strong shift towards larger dwelling units, but not increases in building heights in these neighborhoods in Çankaya; whereas increases in the heights of buildings are more remarkable in Çamlıca, although there has been no significant increase in Floor Area.

All of the neighborhoods in Cluster 3 are in Çankaya, where there has been a shift to larger housing units in new settlements like Birlikmahallesi. Again, there has been no increase in the number of stories in newer buildings, and the hedonic analysis shows a positive relationship between the age of the building and the price of the dwelling units for this cluster. The average prices in Bahçelievler and Kavaklıdere in particular are high, despite the average age of the housing stock in these locations, being the inner, older and more prestigious areas of Ankara.

There is a more homogenous pattern in Cluster 4 in terms of Age, Floor Area and Number of Stories. As discussed previously, there is a positive relationship between Price and the Number of Stories for this cluster, and Table 9 shows that Çarşı in Yenimahalle contain relatively higher apartment buildings.

In Cluster 5, there is no significant increase in Floor Area or the Number of Stories in Topraklık and İncesu, where the housing stock is newer than in other parts of Çankaya. In Yenimahalle, the newer housing stock in Pamuklar, Yakacık and Susuz features relatively larger dwelling units, and a greater Number of Stories in Susuz.

Cluster 6 contains the most expensive neighborhoods in the Çankaya district – Çukurambar and Yıldızevler. These neighborhoods have similar patterns in terms of larger floor areas and higher apartment units.

Cluster 7 comprises Çayyolu in Yenimahalle and Gaziosmanpaşa in Çankaya, which feature similar mean prices. There is no significant difference in the average floor area of the dwelling units in these two neighborhoods, although the housing stock in Çayyolu is relatively newer than that of Gaziosmanpaşa. That said, Çayyolu is a suburban residential area of Ankara that was affected by the rapid growth in high-rise apartment buildings, as discussed at the beginning of the study. It is important to note that the hedonic analysis highlights a positive relationship between Price and the Number of Stories for this cluster.

As discussed previously, the results of the hedonic analysis highlight no significant relationship between house Prices and the Number of Stories for Cluster 8. All of the neighborhoods in Çankaya in Cluster 8 feature relatively larger dwelling units; however, there has been a shift to a lower Numbers of Stories in newer settlements like Sancak and Hilal in contrast to Oran, where the housing stock is older. There has also been a growing trend of high-rise buildings in Yaşamkent (another suburban settlement in Ankara) in Yenimahalle.

Table 9 illustrates that the Öncebeci neighborhood has the newest housing stock in Çankaya in Cluster 9, although there is no significant variation in Çankaya in terms of Floor Area and the Number of Stories for this cluster. In addition, there is again a trend towards higher apartment buildings in the newer settlements of Yenimahalle in this cluster.

Table 9 highlights a shift towards larger dwelling units within most clusters, consistent with the results of the hedonic analysis; and the overall trend in floor area is upwards, both in Çankaya and Yenimahalle. In terms of number of stories within clusters, there is no immediate change in Çankaya; however, the data shows an important increase in higher apartment buildings, especially in the outer neighborhoods of Yenimahalle. That is, the demand side of the housing market indicated in the hedonic price analysis does not appear to have had an observable impact on the supply side of housing in terms of the number of stories.

6. CONCLUSIONS

This paper has investigated housing market differentiation in Ankara through a case study of the Yenimahalle and Çankaya districts by employing a cluster analysis, a discriminant analysis and a hedonic price analysis. The paper demonstrates that the housing market in Çankaya and Yenimahalle has a segmented structure, with location being the main determining factor of different house prices. The hedonic analysis revealed that analyzing the price structure in the market area as a whole prohibits the development of an understanding of the housing market, as the price structures of different clusters have their own dynamics, consistent with the results of the study by Alkay (2008).

The results of this study reveal the demand-side preferences of households in different neighborhoods. Both Çankaya and Yenimahalle have experienced a trend of larger housing units in new residential areas, although there has been no immediate change in Çankaya in terms of the Number of Stories. In contrast, the data shows a converse increase in higher apartments, especially in the suburban neighborhoods of Yenimahalle. This trend in growth areas towards higher apartment buildings is inconsistent with the housing choice of households, as the results of the hedonic analysis illustrate, highlighting an invisible mechanism that shapes the residential pattern of growth areas in Ankara. The results of the study can be seen as a useful tool for understanding the demand side of the housing market in Çankaya and Yenimahalle, and further studies may be conducted to cover all urban residential areas in Ankara in order to characterize the residential pattern for the city as a whole.

REFERENCES

Adair, A. S.; Berry, J. N.; McGreal, W. S. 1996. Hedonic modelling, housing submarkets and residential valuation, *Journal of Property Research* 13: 67–83. http://dx.doi.org/10.1080/095999196368899

Alkan, L. 2011. *Tenure choice and demand for homeownership in Ankara*: Unpublished PhD Dissertation. Department of City and Regional Planning, Middle East Technical University, Ankara.

Alkay, E. 2008. Housing submarkets in Istanbul, *International Real Estate Review* 11(1): 113–127.

Bates, L. K. 2006. Does neighborhood really matter?: Comparing historically defined neighborhood boundaries with housing submarkets, *Journal of Planning Education and Research* 26(1): 5–17. http://dx.doi.org/10.1177/0739456X05283254

Bourassa, S. C.; Hamelink, F.; Hoesli, M.; MacGregor, B. D. 1999. Defining housing submarkets, *Journal of Housing Economics* 8(2): 160–183. http://dx.doi.org/10.1006/jhec.1999.0246

Bourassa, S. C.; Cantoni, E.; Hoesli, M. 2007. Spatial dependence, housing submarkets, and house price prediction, *Journal of Real Estate Finance and Economics 3*5: 143–160. http://dx.doi.org/10.1007/s11146-007-9036-8

Burns, R.; Burns, R. 2008. *Business research methods and statistics using SPSS*. London: Sage Publications Inc.

Chan, Y. H. 2005a. Biostatistics 303. Discriminant analysis, *Singapore Medical Journal* 46(2): 54–62.

Chan, Y. H. 2005b. Biostatistics 304. Cluster analysis, *Singapore Medical Journal* 46(4): 153–160.

Cornish, R. 2007. *Statistics: 3.1 cluster analysis* [online]. Mathematics Learning Support Centre. Available at: http://www.statstutor.ac.uk/resources/uploaded/clusteranalysis.pdf

Erkip, F. 2010. Community and neighborhood relations in Ankara: an urban–suburban contrast, *Cities* 27(2): 96–102.

Goodman, A. C. 1978. Hedonic prices, price indices and housing markets*, Journal of Urban Economics* 5: 471–484. http://dx.doi.org/10.1016/0094-1190(78)90004-9

Goodman, A. C.; Dubin, R. A. 1990. Sample stratification with non-nested alternatives: theory and a hedonic example, *The Review of Economics and Statistics* 72(1): 168–173. http://dx.doi.org/10.2307/2109756

Goodman, A. C.; Thibodeau, T. G. 1998. Housing market segmentation, *Journal of Housing Economics* 7(2): 121–143. http://dx.doi.org/10.1006/jhec.1998.0229

Goodman, A. C.; Thibodeau, T. G. 2003. Housing market segmentation and hedonic prediction accuracy, *Journal of Housing Economics* 12(3): 181–201. http://dx.doi.org/10.1016/S1051-1377(03)00031-7

Housing asked prices in Ankara. 2011. [Online]. Available at: http://www.emlak.net/

Jones, C.; Leishman, C.; Watkins, C. 2004. Intra-urban migration and housing submarkets: theory and evidence, *Housing Studies* 19(2): 269–283. http://dx.doi.org/10.1080/0267303032000168630

Keskin, B. 2008. Hedonic analysis of price in the Istanbul housing market, *International Journal of Strategic Property Management* 12(2): 125–138. http://dx.doi.org/10.3846/1648-715X.2008.12.125-138

Kiel, K. A.; Zabel, J. E. 2008. Location, location, location: the 3L approach to house price determination, *Journal of Housing Economics* 17: 175–190. http://dx.doi.org/10.1016/j.jhe.2007.12.002

Koramaz, T. K.; Dokmeci, V. 2012. Spatial determinants of housing price values in Istanbul, *European Planning Studies* 20(7): 1221–1237. http://dx.doi.org/10.1080/09654313.2012.673569

Leksrisakul, P.; Evans, M. 2005. A model of corporate bankruptcy in Thailand using multiple discriminant analysis, *Journal of Economic and Social Policy* 10(1): 1–36.

Onder, Z. 2000. High inflation and returns on residential real estate: evidence from Turkey, *Applied Economics* 32(7): 917–931. http://dx.doi.org/10.1080/000368400322255

Ozus, E.; Dokmeci, V.; Kiroglu, G.; Egdemir, G. 2007. Spatial analysis of residential prices in İstanbul, *European Planning Studies* 15(5): 707–721. http://dx.doi.org/10.1080/09654310701214085

Selim, H. 2009. Determinants of house prices in Turkey: hedonic regression versus artificial neural network, *Expert Systems with Applications* 36: 2843–2852. http://dx.doi.org/10.1016/j.eswa.2008.01.044

Sing, T.-F.; Tsai, I.-C.; Chen, M.-C. 2006. Price dynamics in public and private housing markets in Singapore, *Journal of Housing Economics* 15: 305–320. http://dx.doi.org/10.1016/j.jhe.2006.09.006

Uzun, C. N. 2005. Residential transformation of squatter settlements: urban redevelopment projects in Ankara, *Journal of Housing and the Built Environment* 20: 183–199. http://dx.doi.org/10.1007/s10901-005-9002-9