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Housing appraisal under model uncertainty: Bayesian model averaging method

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ABSTRACT

This study aims to examine which variables have a higher impact on the determination of market values of houses than the others through the Bayesian Model Average method. Therefore, variables, compiled from appraisal reports prepared with 742 housings from different districts in the city center, were used in the study. The 12 different independent variables at different measurement levels as continuous and categorical, thought to affect the housing prices were used in the study. The study results were presented by comparing the traditional statistical application and Bayesian Model Average methods. Both methods concluded that the variables such as the floor area (m2), number of rooms, and year of construction have a very strong effect on housing prices. The results of the remaining nine explanatory variables revealed that there were qualitative differences between the two methods. Setting the factors that determine the values of the houses and developing reliable statistical models are critical in real estate appraisal studies.

1. INTRODUCTION

Real estate appraisal, in its simplest form, is the determination of the value of a property to be traded on a certain date. On the other hand, the value of a real estate is also required in public procedures such as expropriation, taxation, or registration, and in private sector applications such as bank loans, insurance transactions (Açlar and Çağdaş, 2002). Therefore, for a suitable and fair transaction, it is essential to determine the regional appraisal parameters and to do the appraisals correctly by standardizing them with factor analysis (Erdem, 2016).

Several parameters affect the market value of real estate. These parameters, which are independent, also interact with each other. The important components of these parameters are summarized below:

Physical parameters: Location, size, form, view, transportation, infrastructure, etc.

Economic and financial parameters: Unemployment, inflation, household income, cost and availability of mortgage, consumer trends, real estate supply, etc.

Legal and administrative parameters: Government Policies, planning, land use regulations, tax policies, etc.

Social and demographic parameters: Social behaviors and preferences, migration trends, crime rates, population density, population growth rate, market value trends, etc.

Looking at the real estate appraisal system of Turkey, it can be seen that there is a contradiction in terms of this issue, and there are uncertainties in the unit and number of parameters. This leads to some problems such as

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getting very different results in appraisals made by different institutions and organizations for the same real estate. Therefore, to provide consistent results in the appraisal practices carried out for taxation and other purposes in Turkey, there is a need for regulation of the relevant legislation, determining the regional technical parameters to be used, and setting the standards integrated with factor analysis (Erdem, 2016).

The lack of a well-functioning technical structure in the real estate appraisal system in Turkey is undeniable. The appraisal practices are not standardized. Therefore, within the scope of the study, firstly, an in-depth analysis was conducted for the parameters used in the real estate appraisal system of Turkey. Then, the basic parameters that should be used for housing appraisal in the city center of Osmaniye were determined. The answers to the following questions were sought according to the results of the application:

- What are the real estate properties needed in appraisal?
- What are the necessary parameters for mass/individual housing appraisal?
- How can the number of parameters be reduced for housing appraisal by optimization?

The lack of standard parameters in the scope of housing appraisal causes negativities such as the following:

- Failure to collect the appropriate property taxes and title deed fees,
- Failure to carry out state-operated expropriation transactions at fair market values,
- The appraisals carried out by different institutions and organizations at uncoordinated rates for the same housing,
- Prolongation of transactions due to differences in housing appraisal and lack of necessary infrastructure in private sector applications such as mortgage lending and insurance.

In addition, the lack of reliable data on the housing industry makes the market open to speculation. Such negativities directly affect property owners. For example, some of the owners living in the same city and receiving the same service pay property tax at market value, while others pay lower; Imbalances arise between the fees paid for the transfers of housing, and the owners whose housing is being expropriated can be aggrieved with price offers far below the market value.

Furthermore, as there are many laws and regulations in the legislation regarding the parameters used in the applications of real estate appraisal in Turkey, some differences occurred in the use of these parameters in general. In this context, the study aims to examine the parameters that can be used in appraisal practices throughout the country and the issue of creating the appraisal standards for residential real estate in Osmaniye Province. In this sense, the main purpose of the study is to organize and standardize all the parameters required for housing appraisal in the city center of Osmaniye in a way that will form a basis for collective and individual real estate appraisal. In determining the standard parameters, graduate theses, legal foundations, international appraisal standards, the Capital Market Boards of Turkey (SPK) appraisal principles, and application guidelines were taken as the basis. Also, the parameters affecting the value were determined by conducting surveys with real estate agents, contractors, appraisers, expropriation commission members, and legal experts working in the courts operating in the city center of Osmaniye. With these studies, it is aimed to arrange and standardize the parameters so as to form a basis for collective real estate appraisal, and to make the necessary pilot application to determine the most suitable parameter for housing in Turkey, based on regional standard parameters.

With this study, an applied proposal will be developed for the solution of the lack of standard parameters, one of the first and most important steps of the appraisal activities, and the problems this causes.

2. LITERATURE REVIEW

There are many parameters that affect the value of real estate. The number and effects of these parameters differ depending on the location, type (parcel, land, building, housing, workplace, office, etc.), and properties. Apart from these tangible technical data, sociological factors also have an effect on the value. The point where the supply and demand for real estate are balanced (Figure 1) is the point where the value can be estimated (Yalpır and Ünel, 2016). Similarly, in housing appraisal, which is the subject of the study, the parameters such as location, housing floor, structure layout, frontage, floor area, number of rooms, workmanship, and quality of the building material, etc. will be the primary determinants.

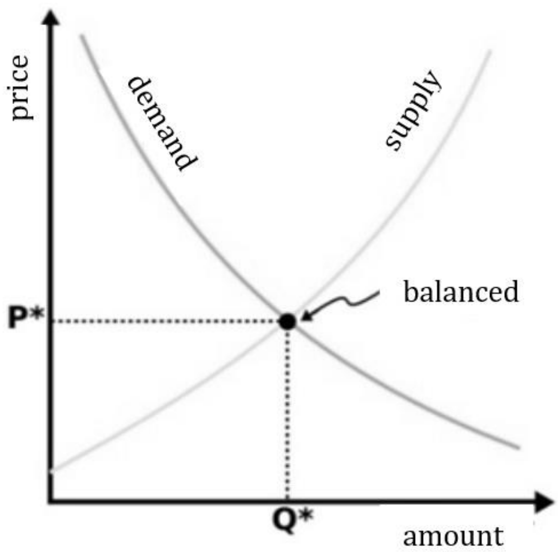

Figure 1. The balance point of supply and demand (Yalpır and Ünel, 2016).

The main expectations in the appraisal methods carried out for all types of real estates are the accuracy of the results, the speed, and the lowest possible number of parameters used (Yalpır and Ünel, 2016). Therefore, parameter reduction is of great importance for the housing appraisal, which is the subject of the study. Additionally, fast and reliable real estate appraisal transactions would provide important benefits for the country's economy.

In recent years, there have been many methods used in real estate appraisal. Statistical methods are among the most commonly used applications in appraisal. In line with the developments in technology, the use of statistical methods is also increasing (Özkan et al., 2007; Zurada et al., 2011; Yalpır and Tezel, 2013; Yalpır and Ünel, 2013).

In mass appraisal, methods such as Artificial Neural Networks, Spatial Analysis, Fuzzy Logic are also used (Heine, 2001; Yomralıoğlu, 1993).

When scientific studies in Turkey are examined, it can be seen that the subject of real estate appraisal attracted the attention of many disciplines and it has been intensively studied. It is noteworthy that the number of studies on method development is more than others. Among method applications, mainly, conventional methods (Nuhoğlu, 2007), hedonic approach and regression methods, nominal appraisal method, and artificial intelligence (Yalpır, 2007) draws attention. Fuzzy logic, on the other hand, is one of the recently developed methodologies for real estate appraisal (Heine, 2001; González, 2008; Mert and Yılmaz, 2009; Kuşan et al., 2010; Yaşar et al.,2013; Krol et al., 2007; Yalpır and Özkan, 2008). Since the objective meaning of the concept of value in the mind of individuals is not clear, inference with fuzzy logic in real estate appraisal would be helpful in reaching the correct result. It was found to be used in the office-space appraisal (Karimov, 2010) and housing appraisal studies in the literature in Turkey. Also, there are studies of Yalpır (2007) on both housing and land appraisal.

Following the pioneering studies of Raftery (1996), the Bayesian Model Averaging method, developed as an alternative approach to model uncertainty, was frequently preferred by different disciplines such as economics (Geweke, 1999; Błażejowski et al. 2016), ecology (Banner and Higgs, 2017), surveying engineering (Stadelmann, 2010; Magnus et al., 2011; Kholodilin and Ulbricht, 2015; Bianchi et al., 2017; Çepni et al., 2020), hydrology engineering (Liang et al., 2013), constructional engineering, systems engineering, and political science (Montgomery and Nyhan, 2010), and was in several studies.

Inconsistent model results can be obtained due to the randomness of the observations, as the selection of a single model ignores the uncertainty in model selection. Hence, a simple consideration to include model uncertainty in decisions as to average a number of competing models is useful (Ando, 2010).

During the literature review, no studies using the Bayesian Model Averaging method were found among the articles and dissertation studies carried out in Turkey. In this sense, this study is the first to use the mentioned method in housing appraisal studies.

3. METHOD

Multiple regression analysis is used to examine the relationship between a dependent variable and one or more independent variables.

A general form of the linear regression model is as follows:

$$y = f(x_1, x_2, \dots, x_K) + \varepsilon$$
$$= x_1\beta_1 + x_2\beta_2 + \cdots + x_K\beta_K + \varepsilon,$$

whereas y refers to the dependent or explained variable and $x_1, x_{2,\dots,}x_K$ refer to the independent or explanatory variables (Greene, 2012).

It is quite common for multiple models to provide adequate descriptions of the distributions producing the observed data. In such cases, it is a standard statistical practice to select a better model based on some criteria such as the model, predictive abilities, or knowledge criteria, suitable for the observed dataset. After the model selection, all inferences and conclusions are made assuming that the model selected is the real model. However, this approach has some disadvantages. Since the selection of a particular model ignores the existing model uncertainty in favor of very specific distributions and assumptions on the preferred model, it can lead to overly reliable inferences and risky decision-making. Therefore, modeling this source of uncertainty to select or combine more than one model is encouraged. The Bayesian Model Averaging (BMA) models both parameter uncertainty through the prior distribution and model uncertainty through the posterior parameters. It, therefore, enables direct model selection, composite estimate, and forecasting (Fragoso and Neto, 2015).

Therefore, appealing the notation of Ando (2010), the aforementioned BMA approach can be formulated as follows:

Consider a model universe consisting of r number of models M_1, M_2, ..., M_r. Each M_k model is assumed to be characterized the following:

Probability density is $f_k((x|\theta_k)$. Where $\theta_k(\in \Theta_k \subset R^{p_k})$ is a vector of unknown parameters with p_k dimensions. $\pi_k(\theta_k)$ is a prior distribution for the parameter vector θ_k under the M_k model.

The posterior probability of M_k model is as follows for a given data set $\boldsymbol{X}_n = \{x_1, x_2, \dots, x_n\}$;

$$P(M_k|\boldsymbol{X}_n) = \frac{P(M_k)\int f_k(X_n|\theta_k)\pi_k(\theta_k)d\theta_k}{\sum_{j=1}^{r} P(M_\alpha)\int f_j\big(X_n\big|\theta_j\big)\pi_j(\theta_j)d\theta_j},$$

Where, $f_k(X_n|\theta_k)\pi_k$ and $P(M_k)$ are probability function and prior probability for M_k model, respectively. Marginal probabilities can be estimated by asymptotic or simulation approaches. The prior probabilities of $P(M_k)$ and $\pi_k(\theta_k|M_k)$ for M_k model determine the first appearance of the model uncertainty. After observing the $\boldsymbol{X}_n$ information, the posterior $P(M_k|\boldsymbol{X}_n)$ model probability is based on and the appearance of the model uncertainty is updated. In principle, the Bayesian approach in the selection of a model is the choice of the model with the greatest posterior probability among a range of candidate models. Therefore, posterior model probability $P(M_1|\boldsymbol{X}_n)$,..., $P(M_r|\boldsymbol{X}_n)$ is the main area of interest for model selection. Within the Bayesian model averaging, the predictive distribution $f(\boldsymbol{z}|\boldsymbol{X}_n)$ for a future **z**-observation is defined as follows:

$$f(\boldsymbol{z}|\boldsymbol{X}_n) = \sum_{j=1}^{r} P\big(M_j\big|\boldsymbol{X}_n\big)f_j(\boldsymbol{z}|\boldsymbol{X}_n),$$

and

$$f_j(\boldsymbol{z}|\boldsymbol{X}_n) = \int f_j\big(\boldsymbol{z}\big|\boldsymbol{\theta}_j\big)\pi_j\big(\boldsymbol{\theta}_j\big|\boldsymbol{X}_n\big)d\boldsymbol{\theta}_j, \quad j = 1, \dots, r.$$

The predictive distribution of this weighted $f(\boldsymbol{z}|\boldsymbol{X}_n)$ according to the posterior model probabilities is the average of the predictor distributions under each model considered. When Δ becomes the size examined, similar to the estimation of the predictive distribution, the model averaging estimation of the sizes examined, for example, the average is calculated as follows:

$$E[\Delta|\boldsymbol{X}_n] = \sum_{j=1}^{r} P(M_j|\boldsymbol{X}_n)\Delta_j,$$

and

$$\Delta_j = E[\Delta_j|\boldsymbol{X}_n, M_j], \quad j = 1, \ldots, r.$$

Although BMO seems like an appealing option in theory, two practical difficulties must be resolved before it can be implemented.

First, the results of BMA largely depend on the model space and it is necessary to choose a suitable candidate model set. The most obvious approach is to include all possible models. However, when the number of possible models is large, the process of the BMA method becomes quite time-consuming. Currently, one way to solve this problem is the Occam's Window Method. It is possible to define this method as eliminating models that make weaker estimates than others. The second challenge with the BMA approach is the fact that the marginal model likelihood without a closed-form integral cannot be analytically calculated, easily (Gibbons et al., 2008; Zou et al., 2012). Learning the parameters for all candidate models and then combining the predictions according to the posterior probabilities of the relevant models is known as the Bayesian Model Average (BMA) (Wintle et al., 2003; Golam et al., 2016; Xiujie et al., 2019; Hinne et al., 2020).

4. FINDINGS

4.1. Data

Osmaniye province, where the data was collected, was established in the eastern part of the Ceyhan River on the east side of Çukurova in the east of the Mediterranean Region. With its geographical area of 3222 km^2, Osmaniye is the 67th largest province of Turkey. Osmaniye is located between 35°52'–36°42' East and 36°57'–37°45' North (Figure 2). In 1933, Osmaniye was made the district governorate of Adana province, which continued till 1996, and in 1996, Osmaniye became the 80th province of Turkey (OİKTM, 2017). Osmaniye has become a domestic migration-receiving city thanks to being a gate of transportation from the Southeast to the Mediterranean and suitable climate conditions. While the population of the city center was 13.000 according to the census of 1950, this figure reached to 122.400 in 1990 and 229.000 in 2016 (Koç, 2008).

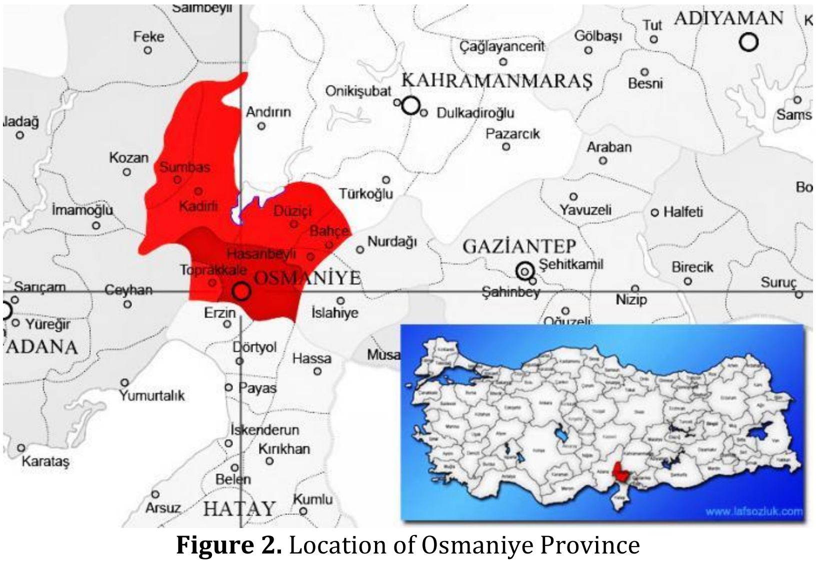

Figure 2. Location of Osmaniye Province

In the study, variables compiled from 742 housing appraisal reports from different districts in the city center of Osmaniye within the scope of the Scientific Research Projects (SRP) numbered OKÜBAP-2019-PT2-001 and titled "*Determination of Housing Appraisal Parameters at City Scale: Pilot Project Application of Osmaniye Province*" were used. Housing prices calculated based on 2019 were taken as the dependent variable. 12 different independent variables at different measurement levels, continuous and categorical, were used, which were thought to affect the housing prices. Table 1 presents these variables and their conditions and Table 2 presents the descriptive statistics of these variables.

Table 1. Variables Used in Housing Appraisal and Their Conditions

Variables	Description	Measurement Type	Conditions
Price ($\boldsymbol{Y}$)	Housing price (tl)	Continuous	
Floor area (X_1)	Net (gross) floor area of housing (m^2)	Continuous	
Building_floors (X_2)	Number of floors in the building	Discrete	
Which_floor (X_3)	Housing floor	Discrete	
Street_frontage (X_4)	Does it have a frontage to the street?	Discrete	**0.** No **1.** Yes
Frontage (X_5)	Frontage direction	Discrete	**1.** North-East **2.** North-West **3.** South-East …**30.** North-East-West-South
Workmnshp_qlty (X_6)	Workmanship quality of housing	Discrete	**1.**Very poor **2.**Poor **3.**Average **4.**Good **5.**Very good
District (X_7)	District where the residence is located	Discrete	**1.** Central and developed neighborhood **2.** Districts out-of-center and where squattering is at high levels
Mtrl_qlty (X_8)	Material quality of the house	Discrete	**1.**Very poor **2.**Poor **3.**Average **4.**Good **5.**Very good
Room (X_9)	Number of rooms	Discrete	
Parking space (X_{10})	Does it have a parking space?	Discrete	**0.** No **1.** Yes
Site (X_{11})	Is the housing in a gated community?	Discrete	**0.** No **1.** Yes
Construction_year(X_{12})	Age of housing ($days$)	Continuous	

Table 2. Descriptive Statistics of the Variables Used in Housing Appraisal ($N = 742$)

Variables	Mean	SD	Min	Max	Range
Price ($\boldsymbol{Y}$)	255204.907	94005.508	35000.000	686027.000	651027.000
Floor area (X_1)	140.146	37.806	32.000	384.000	352.000
Building_floors (X_2)	5.311	1.477	1.000	8.000	7.000
Which_floor (X_3)	2.271	1.713	0.000	8.000	8.000
Street_frontage(X_4)	0.872	0.802	0.000	2.000	2.000
Frontage (X_5)	6.489	7.086	1.000	30.000	29.000
Workmnshp_qlty (X_6)	3.895	0.665	0.000	6.000	6.000
District (X_7)	1.542	0.499	1.000	2.000	1.000
Mtrl_qlty (X_8)	3.902	0.564	2.000	6.000	4.000
Room (X_9)	3.364	0.868	1.000	8.000	7.000
Parking space (X_{10})	0.477	0.500	0.000	1.000	1.000
Site (X_{11})	0.422	0.494	0.000	1.000	1.000
Construction_year (X_{12})	1949.770	1232.980	451.000	11546.000	11095.000

4.2. Analysis

In this section, modeling results for multiple linear regression equations were explained using the Bayesian Model Averaging approach. In the study, EViews-10 (BMA package) software was used for Bayesian Model Averaging calculations and SPSS-20 software for classical regression analysis. The variables defined for house pricing modeling are presented in Table 1. These 12 explanatory variables are at different measurement levels as continuous and categorical. The number of different models likely to be set up with this number of explanatory variables is $2^{12} = 4096$. After the models with low estimation performance among all different models are eliminated via Occam's window method, models with high estimation performance are determined. These models are presented in Table 3.

As presented in Table 3, ten alternative models were selected according to Occam's window method. Model 1, with the highest probability of posterior model, accounted for about 39% of the total posterior probability. The total posterior probability values for Model 2 and Model 3 were about 25% and 13% respectively. These values were below 7% for the remaining models. These results indicate that there was a high rate of model uncertainty in housing appraisal modeling, even if Model 1 with the highest total posterior probability were selected. The statistics for BMA in Table 4 were obtained from the models 1-10 in Table 3. Table 4 is calculated as follows:

For the variable X_1: Posterior Average is the weighted average of the posterior averages of the respective variable statistics under each model in Table 3; P! = 0 (%) value indicates that the relevant variable is also included in 10 models in Table 3. It expresses the sum of the posterior probabilities of the models including the relevant variable in Table 3 as a percentage. For detailed calculations, see Raftery (1995).

Compared to other models, Model 1 is in a dominant position with a high posterior probability value and takes into account five explanatory variables (X_1, X_7, X_8, X_9 *and* X_{12}). Model 2 with the second highest total posterior probability takes into account five explanatory variables (X_1, X_6, X_7, X_9 *and* X_{12}), while Model 3 with the third highest posterior probability takes into account four explanatory variables (X_1, X_8, X_9 *and* X_{12}). In Table 3, it was observed that there was covariance (X_1, X_9 *and* X_{12}) included in all models, however, there was also covariance (X_3 *and* X_{10}) not included in all models.

Table 3. Parameter Estimations of Alternative Models

Dependent variable: price

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Floor area (X_1)	1288.266 (88.74574)	1298.509 (89.12417)	1320.521 (88.54748)	1331.642 (88.95620)	1290.509 (88.71560)	1287.194 (88.70604)	1298.089 (89.03039)	1295.222 (88.97644)	1285.245 (88.78466)	1297.555 (89.06915)
Building_floors (X_2)	-	-	-	-	1897.464 (1427.61042)	-	-	-	-	-
Which_floor (X_3)	-	-	-	-	-	-	-	-	-	-
Street_frontage (X_4)	-	-	-	-	-	-	-	-2841.251 (2662.45243)	-	-
Frontage (X_5)	-	-	-	-	-	-390.2653 (297.45983)	-	-	-	-415.6328 (297.42041)
Workmnshp_qlty (X_6)	-	14739.53 (3237.88305)	-	15355.67 (3249.71987)	-	-	7313.375 (5658.89356)	-	-	14637.24 (3236.61684)
District (X_7)	-12652.69 (4255.48281)	-12972.02 (4253.63472)	-	-	-12468.92 (4255.51528)	-12456.32 (4256.03184)	-12662.25 (4253.55299)	-12582.08 (4255.59598)	-12265.51 (4270.87370)	-12752.53 (4253.78444)
Mtrl_qlty (X_8)	17890.32 (3846.33076)	-	18772.91 (3855.20302)	-	17619.41 (3849.72885)	17684.33 (3847.65177)	10757.33 (6726.33424)	17959.84 (3846.51976)	17782.85 (3847.36640)	-
Room (X_9)	30184.23 (3974.75262)	29828.22 (3986.84260)	29184.32 (3981.51046)	28802.66 (3994.94192)	30253.14 (3973.02270)	30088.13 (3973.48152)	29825.47 (3982.63065)	29965.12 (3979.67792)	30412.24 (3980.28248)	29718.40 (3985.03924)
Parking space (X_{10})	-	-	-	-	-	-	-	-	-	-
Site (X_{11})	-	-	-	-	-	-	-	-	4519.109 (4274.57418)	-
Construction_year (X_{12})	4053.524 (674.07149)	3884.693 (667.49839)	4182.474 (676.24338)	4003.696 (670.09860)	3990.506 (675.38705)	4007.461 (674.65558)	4040.182 (673.84389)	3950.517 (680.88450)	4042.299 (674.10123)	3840.653 (667.81070)
C	-98822.85 (20003.3336)	-85274.06 (17915.5593)	-123619.6 (18278.2996)	-109503.1 (16147.7377)	-108336.7 (21235.6754)	-95069.81 (20197.1375)	-99561.19 (20002.3927)	-96413.00 (20128.5205)	-101190.4 (20126.7073)	-81778.52 (18077.8611)
Number of Variables	6	6	5	5	7	7	7	7	7	7
R^2	0.632720	0.632280	0.628310	0.627630	0.633600	0.633580	0.633560	0.633290	0.633280	0.633260
BIC	-710.1633	-709.2749	-707.9164	-706.5601	-705.3339	-705.2934	-705.2529	-704.7064	-704.6861	-704.6457
Posterior Probability	0.386439	0.247840	0.125652	0.063777	0.034546	0.033853	0.033174	0.025242	0.024988	0.024488

Number indicating the maximum rate to exclude models in Occam's Window: 20

BIC: Bayesian Information Criterion

Table 4 presents the characteristics of the model obtained by the BMO method and the estimation, standard error and probability values for the coefficients obtained using the traditional statistical technique and assuming a complete model. Table 4 also presents the characteristic outputs of the BMA approach for each variable (posterior mean, posterior standard deviation, and posterior effect probability value). The posterior effect probability calculated in the BMA approach reveals the total value of the posterior model probabilities of the models containing the variable in question.

Since the corresponding posterior effect probabilities for variables (X_1, X_9 *and* X_{12}) were equal to 100% and p-values were 0.0000, it can be stated that the variables mentioned have a very strong effect on housing prices. The results for the nine other explanatory variables show that there were qualitative differences between the two methods. The posterior effect probability for the (X_7) variable specifically shows that the 81.1% effect on housing prices is positive but not very strong. It shows that the effect of this on the housing prices with the $p-value = 0.0057$, which in the classical regression model is statistically significant. Hoeting et al. (1999) explain this as the p-value overstating the evidence for an effect. The posterior effect probability variable for (X_8) shows that the impact on housing prices by 66.4% was positive but not strong, while the $p-value = 0.0555$ and the effect on housing prices were statistically insignificant ($\alpha = 0.05$ significane level). On the other hand, it can be concluded that the p-values for $X_2, X_3, X_4, X_5, X_6,$ *and* X_{10} variables are not statistically significant (if 0.05 is chosen as the level of significance) and the posterior effect probabilities are weak or ineffective.

Table 4. Comparison of the Results

		Bayesian Model Averaging			Classical Regression Analysis		
Variable Number	Variables	Posterior Mean	Posterior SD	P!=0(%)	Coefficient	Std. Error	p
(X_1)	**Size**	**1298.319**	**89.87197**	**100.00**	**1302.730**	**89.43391**	**0.0000**
(X_2)	**Building_floor**	65.54901	436.4477	3.5000	1707.817	1462.130	0.2432
(X_3)	**Which_floor**	-	-	0.0000	-644.9935	1277.818	0.6139
(X_4)	**Street_frontage**	-71.71967	614.4621	2.5000	-2325.061	2692.335	0.3881
(X_5)	**Frontage**	-23.38957	118.3250	5.8000	-395.5161	298.1962	0.1851
(X_6)	**Workmnshp_qlty**	5233.442	7287.341	36.900	4560.247	5852.081	0.4361
(X_7)	**District**	-10313.35	6289.880	81.100	-11850.48	**4270.283**	**0.0057**
(X_8)	**Mtrl_qlty**	11734.29	9072.516	66.400	13180.56	6870.953	0.0555
(X_9)	**Room**	**29858.23**	**4003.743**	**100.00**	**29758.87**	**3993.134**	**0.0000**
(X_{10})	**Parking space**	-	-	0.0000	-14045.78	8251.503	0.0891
(X_{11})	**Site**	112.9244	976.8060	2.5000	16094.68	8404.223	0.0559
(X_{12})	**Construction_year**	**4012.433**	**679.3675**	**100.00**	**3785.648**	**685.4729**	**0.0000**
	C	**-99068.89**	**22467.58**	**100.00**	-101711.1	**21762.03**	**0.0000**

P!=0 (%): Posterior probability

5. DISCUSSION

The main results obtained in the study show that house prices are primarily determined by the floor area (m^2), the number of rooms, and the construction year. While the neighborhood, the quality of the construction materials, and the quality of workmanship clearly determine the house prices, the direction of the house, the number of floors in the apartment building, whether it is facing a street and whether the house is within a gated community were determined as variables with relatively low posterior probabilities in affecting the house prices. In addition to these, it seems that the apartment floor and whether the house has a parking space are unimportant in determining the house prices. When the Bayesian Model Average and the classical regression model results are compared, it can be seen that there are qualitative differences between the two methods, although there are common points.

6. CONCLUSION

Statistical methods, one of the methods of real estate appraisal frequently used in the literature, are mostly based on classical multiple regression analysis. Accordingly, an explanation of the price dependent variable in the real estate appraisal includes uncertainty due to the presence of a large number of explanatory variables that are likely to be included in the constructed model. In the multiple regression models, excluding one or more related variables from the model in a large number of potential variables creates the problem called omitted-variable bias (Kim and Frees, 2006) in the statistics. The estimation results of the housing appraisal models obtained without taking this problem into account are quite likely to be biased.

In this study, 12 different independent variables at different appraisal levels as continuous and categorical, which are thought to be effective in determining the market values of the residences in Osmaniye Province, were used. The results obtained in the study are presented by comparing traditional statistical applications and Bayesian Model Averaging methods. Both methods concluded that the floor area (m^2), the number of rooms, and the year of construction had a very strong effect on housing prices. The results for the remaining nine explanatory variables show that there are qualitative differences between the two methods.

In the study, first, with the inclusion of the 12 different independent variables, it was revealed that the number of different models likely to be set up can be $2^{12} = 4096$. Then, it was mentioned that the standard practice in this type of situation is to select a model that qualifies as the best according to some of the criteria and that the results were obtained by assuming that this "best" model is the real model. It was emphasized that since it ignored the existing model uncertainty, it could lead to overly reliable inferences and risky decision-making. On the other hand, it was underlined that the Bayesian Model Averaging method, which was put forward as a solution, took into account the source of uncertainty by selecting more than one model appropriately and that the approach was achieving results by using this selected model set while making inferences. Moreover, the results for both methods were analyzed by comparison.

Through this paper on housing appraisal, it was aimed to contribute to the literature in two aspects. The first is to apply the Bayesian Model Averaging method in the field of housing appraisal for the first time in Turkey. Thanks to this methodology, it was possible to discuss and analyze a large number of potential variables likely to affect the housing price in the literature. In modeling, aimed at real estate appraisal in general and housing appraisal in particular, considering that many influencing factors can be included in the model in regression-based statistical methods, the Bayesian Model Average approach stands as an alternative solution when model uncertainty is suspected. The second contribution of the study, departing from the fact that in classical regression models, the *p-value*, which shows the statistical significance of each variable, may overestimate the evidence in the statistical decision-making process, is that the information to be obtained from the results of modeling studies that have been subjected to an alternative comparison will be more guiding to housing pricing experts and appraisers.

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