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The International Practice of Statistical Property Valuation Methods and the Possibilities of Introducing Automated Valuation Models in Hungary*

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In the wake of regulatory, information technology and methodological changes, statistical property valuation has gained traction in Hungary. This paper looks at the available methods of appraisal based on the literature. We provide an overview of the advantages and drawbacks of the currently known methods. Based on these, automated valuation models (AVMs) can be readily introduced alongside the estimated median value based methods used so far. For real estate industry-specific reasons, the introduction of parametric hedonic estimates supplemented with spatial correlations can be expected for the time being. The better performance of statistical models would need improved quality of duties office data.

Journal of Economic Literature (JEL) codes: C15, C45, G21

Keywords: mortgage, collateral valuation, automated valuation model, statistical valuation

1. Introduction: The new regulation of statistical valuation

The Minister of Finance Decree on real property valuation[1] was amended in the summer of 2016, introducing statistical valuation alongside the three previous methods as a means of determining the market value of a property. For one, this change was a reaction to the prevailing practice in Hungary where the majority of financial organisations had already been using statistical evaluation based on the analysis of comparative data. In addition, the change was also in line with

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[1] Decree 25/1997 (VIII. 1.) of the Minister of Finance on the methodological principles for determining the mortgage lending value of property not qualifying as arable land

the international trend characterised by the spread of approaches referred to as automated valuation models.

This paper presents the background, methods and possibilities of statistical valuation. The second section presents the main concepts used in statistical valuation, based on the literature. The third section summarises the methodological approaches related to statistical valuation. The fourth presents why it is difficult to make general statements about the performance of various methods. We then present the possibilities in Hungary, in light of the data sources available to modellers. The last section presents the conclusions.

2. Definitions and sources of information

The European Mortgage Federation (EMF) and the European AVM Alliance (EAA) classify valuation methods into the groups shown in Figure 1 (*EMF – EEA 2016*). The group of statistical valuations are presented separately from individual expert appraisal. The difference between the two methods is that statistical valuation uses far more data for appraisal and generates the property's value from the data in a reproducible manner. There are also methods that are situated between statistical and individual expert appraisal, referred to under the umbrella term of hybrid valuation.[2]

Within statistical valuation, Automated Valuation Models (AVMs), which are used increasingly in recent years, are specified as a sub-group of statistical valuation models. No historical price information is needed for AVMs, in contrast to the methods based on indexation that estimate changes in value. They are able to appraise property based on a large quantity of data without an individual human decision, and are more complex than the estimates using average unit prices or average prices, meaning that they build strongly on managing the impacts of value-modifying factors.

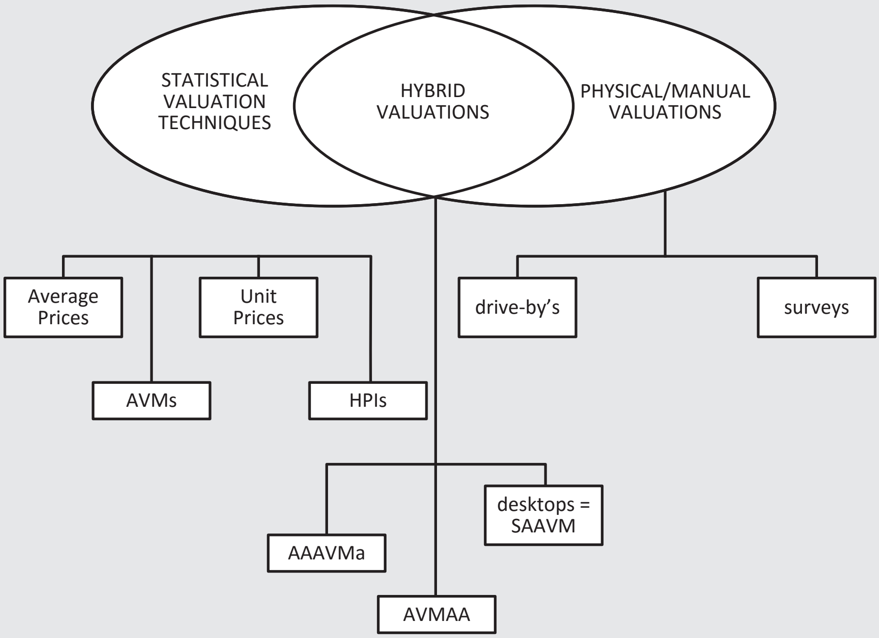
So far, the average unit price and indexation methods have been adopted by financial entities in Hungary. The development in methods can be seen as a kind of evolution, as at the time being only the aforementioned, less complex techniques are used in Hungary. There are several reasons why the more complex methods have not spread so far: in part, the FHB Index was a pioneer in indexation, the first to

[2] We only mention hybrid valuation methods in this paper as part of a list. The EMF and the EAA distinguish three categories:
- Analyst Assisted AVM (AAAVM): Relies on the experience and judgment of a professional, but not necessarily a qualified surveyor, to validate and supplement the output of an AVM.
- Surveyor Assisted AVM (SAAVM): Relies on the experience and judgment of a qualified surveyor, to validate and supplement the output of an AVM.
- AVM Assisted Appraisal (AVMAA): Relies on the experience and judgment of a qualified surveyor, to translate the output of an AVM into a legally compliant valuation, obtained without conducting a physical inspection of the subject property (*EMF – EEA 2016*).

calculate sub-indexes derived from national indexes. In addition, the spread of more complex methods is hindered by data limitations, as financial entities can only use the National Tax and Customs Administration's duties office transaction database, which does not contain detailed property attributes and thus cannot be used for more sophisticated methodologies. Third, the financial supervisory body has so far accepted the use of average unit prices and indexation for statistical revaluation, so agents were not compelled to develop their own methods.

Meanwhile, Hungarian financial market agents have recently contemplated whether more complex methods can yield more than the ones currently used. In Western Europe, several tools are used for statistical evaluation, including the techniques that have been adopted in Hungary, so these are not obsolete. At the same time, these may well become obsolete in the wake of possible methodological development in the future. The Hungarian subsidiaries of banks in foreign ownership have considered the possibility of adopting more complex methods in Hungary. This paper therefore focuses on AVMs, which are expected to appear as a novelty in Hungary. As the above definition suggests, the unit value and average price level based valuation can be seen as a special, simple form of AVM.

Figure 1
Types of property valuation



Source: EMF-EEA (2016:5).

Various patents filed in the United States define the general principles of automated valuation methods. These patents do not provide detailed guidance on valuation methodology, but merely a description of the processes used, without specific model specifications. However, they disclose the reasons for developing automated valuation methods and the requirements that must be met in terms of reliability. Most patents provide assistance for processing loans using the automated valuation of property (*US5361201, US6115694, US20040153330*).[3] The exception is *Rossbach and Conway's* (*2003*) patent which calculates the warranty of the value generated by the AVM, protecting the parties from the consequences of a potentially inaccurate appraisal (*US20030149658*). *Sennot's* (*2004*) patent tests a property pending appraisal in several stages to determine whether the available data quantity is sufficient for applying an AVM (*US20040019517*). *Graboske et al*. (2005) developed a decision-making mechanism that selects the most suitable AVM to maximise AVM utilisation compared to standard valuation methods depending on the guidance of the financial entity providing the mortgage and the specified accuracy (*US20050288942*).

To better understand the chances for the local adoption of statistical valuation procedures using more advanced methods and their adopted forms, it is worth looking at the international methodological practice along with the principles and processes involved. However, when assessing this, the firms typically offering and using the service as private entities do not share any details. Even the aforementioned EAA members do not share any relevant information on their websites. Besides general references, they only emphasise the use of automated evaluation based on large quantities of data. Even less information is available from clients, as financial institutions and asset managers do not publish the valuation methods that they use. The reason for this observed lack of information is that AVMs are almost always unique and tailored to the client. The more closely adjusted to the user's needs and opportunities, the better these methods work. Different parametrisation and systems will be optimal for a bank aiming to define the mortgage lending value of a collateral portfolio or for a mutual fund managing a portfolio of new homes. This paper therefore presents, based on the literature, the methodological foundations that can allow the adoption of systems suited to the applicants operating in the circumstances prevailing in Hungary.

3. Statistical valuation methods

In this section, we review the theoretical background of the known statistical valuations. We provide details on the methods that are not part of the economic academic curriculum, so we will not cover the indexation method taught in statistical

[3] The table summarising patents is included in *Annex 1.*

courses. According to *Pagourtzi et al*. (*2003*) automated valuations can be classified into four groups. First, they mention traditional *hedonic regressions*, according to which the value of the property can be defined by pricing its various attributes. *Spatial analysis*, is an approach that treats the dependence of the price of a given property on the characteristics of neighbouring units. The authors differentiate *models based on artificial neural networks,* belonging to the nonparametric family, where the model is developed with the help of learning algorithm sequentially applied to the available data. Finally, the authors define *models based on fuzzy logic as* the fourth group, where every observation belongs to one specific group and the extent of similarity is defined by a membership function taking on a value between 0 and 1.

We follow this classification in our paper.

3.1. Hedonic pricing

The hedonic pricing model used for property appraisal is the most frequently applied technique for pricing heterogeneous goods. Its core principle is the statistical valuation of the correlation between the price and the characteristics of the good. This method has been used since the 1960s for statistical analyses, and has become the most widespread analytical tool of empirical pricing problems since *Rosen's* (*1974*) development of the theoretical foundation of the method. Since there are no two properties that are identical, the hedonic method became a canonical property pricing technique. The application of the hedonic regression method for residential properties started from the pioneering work of *Ridker and Henning* (*1967*) *and Nourse* (*1963*). The first more widely known hedonic analysis conducted on a database of individual properties is the seminal paper of *Kain and Quigley* (*1970*). *Coulson* (*2008*) summarised the hedonic methods in his monography. The model can be described as follows in a multiplicative form:

$$\ln(p)=\beta_0+\beta_1\ln(x_1)+\beta_2\ln(x_2)+\cdots+v \qquad (1),$$

where *p* is the price of the property, *x* are the various attributes of the property and *v* is the error term.

The advantage of this method is that the results immediately show the marginal impact of the various value influencing factors which eases the comparison of the property appraisal by the model with professional appraisers' valuation. A great number of papers address these value modifying factors, starting from the impact of green areas through landmark protection all the way to the value related to the existence of an elevator. According to this research, information available on the property increases the accuracy of the model, but one factor stands out; the most important value modifying factor, as generally viewed in the industry, is the location of the property. In line with early research, the basic models form disjoint spatial units for the location. Due to the availability of the data, this often meant and still means a public administration grouping (e.g. according to postal code). In this case, the location of the property will be entered into the model as a category variable. In such cases, for example, the associated coefficient in the hedonic model shows how much more expensive a property located in the 6th district of Budapest is compared with ones located in another district used as the reference group, for properties that are otherwise identical. Handling spatial categories in such a way often corresponds with the knowledge held by the real estate profession, e.g. a housing project represents a completely different unit than the set of condominium buildings located on the other side of the road; however, spatial correlations are often more complicated than this. This is one the reasons why research has mainly developed in that direction, as we explain in the next sub-section.

3.2. Spatial econometrics

According to the early definition of the spatial econometrics (*Anselin 1988*), this discipline addresses the spatial attributes of the data, due to which the canonical[4] econometric methods cannot be applied. According to *Anselin* (*1988*), spatial impacts can be of two types: spatial dependence and spatial heterogeneity. Spatial dependence is a spatial cross-sectional correlation, where the correlation structure of the various spatial units cannot be handled by standard econometric tools. Spatial heterogeneity is such an observed or non-observed heterogeneity, where the spatial structure may carry information, but in terms of methodology, it does not necessarily require spatial analysis tools. The two impacts often cannot be differentiated from one another when using cross-sectional data; namely, in this case, the clusters and the patterns may be identified, but the processes causing them might not (*Anselin 1988*). In the short description of the models that form part of spatial analysis, we follow the summary of *Anselin* (*2010*) *and Elhorst* (*2010*) and we rely on the text books by *LeSage and Pace* (*2008*) and *Fotheringham and Rogerson* (*2009*).

According to *Anselin* (*2010*), the main criterion of spatial econometrics is the application of *spatial lag variables*. These are basically the weighted averages of observations that are the ‘’neighbours’’ of the given variable. As to what we exactly mean by neighbour, is a key component of the definition, which is provided by the spatial weights matrix. A spatial lag may be included in the dependent variable (these are the spatial lag models), in the explanatory variable (spatial cross-regressive model), or in the error term (spatial error models) or possibly in all of them (*Anselin 2010*).

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[4] As we mentioned earlier, we regard the current master level university curriculum to be canonical and publicly known.

Spatial heterogeneity may be discrete or continuous; in the first case, the parameters of the model are different for the preliminary indicated units differing from one another (these are the spatial regime models, see e.g. *Anselin 1990*), while in a continuous case, it is part of the model specification as to how the parameters change in space. This can be described by a pre-defined function (*Cassetti 1997:* spatial expansion method) or by a function estimated locally from the data (Fotheringham et al. 2002 geographically weighted regression (GWR). According to another approach, the spatial heterogeneity is a spatial case of the random coefficient variation (*Gelfand et al. 2003*).

Elhorst (*2010*) briefly reviews the topics addressed in the textbook of *LeSage and Pace*, along with extensions, and describes the preferred model specification process illustrated by *Figure 2*. *Elhorst* (*2010*) regards the most general specification known as the Manski model to be his starting point. *Manski* (*1993*) mentions three interactions due to which an observation made at a given location may depend on observations made at other locations:

1) endogenous interaction effect which specifies how the behaviour of one spatial unit depends on that of other units,

2) exogenous interaction effect, whereby the behaviour of the spatial unit depends on independent variable(s) explaining the behaviour of another spatial unit, and

3) correlated effect where similar non-observed attributes result in similar behaviour.

The Manski model is given by two equations:

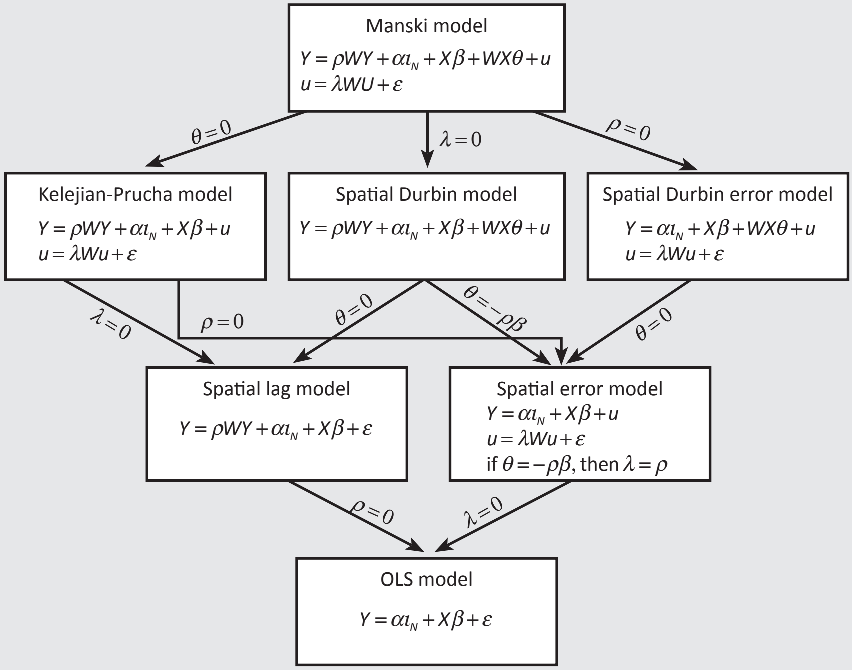
$$Y = \rho WY + \alpha\iota_N + X\beta + WX\theta + u \quad (2)$$

$$u = \lambda Wu + \varepsilon \quad (3)$$

where Y is a vector of Nx1 components, which contains an observation for every unit in the sample ι_N is an Nx1 unit vector, X is an NxK dimension matrix of the explanatory variables, u is an Nx1 vector of the error terms, $\varepsilon=(\varepsilon_1,\varepsilon_2,\ldots,\varepsilon_N)$, which is a variable with IID distribution, with mean 0 and σ^2 variance. *WY* denotes the endogenous interaction among the dependent variables of the various spatial units, *WX* is the exogenous interaction among the independent variables, and *Wu* is the interaction among the error terms. ρ denotes the spatial auto-regression coefficient, λ the spatial auto-correlation coefficient while β and θ are the fixed, but unknown parameters. The following technical conditions must be fulfilled for the *W* matrix: its components are non-negative known constants with zeros in the main diagonal, and the $I_N - \rho W$, and $I_N - \lambda W$ matrixes should be invertible. In addition to this, at least one of the K+2 interaction impacts should be excluded so that the parameters can be identified (*Manski 1993*). Making various parameter restrictions, from the

Manski model one can arrive at other spatial models, and then finally at the simple linear regression as shown in *Figure 2*.

Figure 2
Spatial models



Source: Elhorst (2010:13).

Although it can be estimated, the Manski model is difficult to use because the endogenous and exogenous interaction effects cannot be disentangled, and therefore the estimated parameters cannot be interpreted (*Manski 1993*). Therefore, instead of the Manski model, *Elhorst* (*2010*) recommends the spatial Durbin model for two reasons. First, not taking into consideration the spatial dependence of the error terms only decreases the precision of the estimation, while ignoring the spatial dependence of the dependent or independent variables leads to endogeneity problems. Second, however, the Durbin model correctly estimates the standard errors of the parameters if the real data generating process is a spatial lag or a spatial error model, as these are special cases of the Durbin model, therefore, the Durbin model's covariance matrix properly takes into account the spatial dependence of the error term.

The weakness of spatial econometrics models is that the W spatial weights matrix is given on an ad-hoc basis. Because there are no generally accepted rules for the specification of W, econometricians rely on robustness checks carried out by Monte Carlo simulations. The valuation of this gives room for the non-parametric methods as well.

We next briefly review another important branch of the relevant econometric research, semi-parametric and non-parametric methods. In this, we rely on chapter 14 of the textbook by *Fotheringham and Rogerson* (*2009*). Semi-parametric methods are a compromise between fully parametric specification and the non-parametric approach, where the data fully define the parameters alongside a minimal prior structure. One instance of the application of non-parametric methods is necessitated by the weakening of the assumptions regarding the spatial weight matrix in the spatial lag model. *Pinkse, Slade and Brett* (*2002*) use the following model:

$$y_i = \sum_{j \neq i} g\left(d_{ij}\right) y_j + x_i \beta + \varepsilon_i \qquad (4)$$

Instead of the weight matrix, dependent variables of the neighbouring units are weighted by a coefficient depending on the distance of two units, where they approach the appropriate function with a polynomial series.

In *Gress's* (*2004*) approach, the spatial weight matrix is as in the spatial lag model, but the dependence from the other variables in modelled in a nonparametric way:

$$y = \rho W y + g\left(X\right) + \varepsilon \qquad (5)$$

Henderson and Ullah (*2005*) use a semi-parametric spatial error term model as a special application of the local linear weighted least squares (local WLS) method. Finally, *Gibbons and Machin* (*2003*) use a spatial filtering approach which consists of performing a non-parametric modelling of spatial spillover effects, referred to as the smooth spatial effects (SSE) model:

$$y_i = x_i \beta + g\left(c_i\right) + \varepsilon_i \qquad (6)$$

The SSE estimating function is essentially an OLS applied to a transformed equation, where the transformation replaces the dependent variable and explanatory variables with the deviation from their conditional expected value.However, advances in information technology now enable non-parametric approaches as well, one of which is addressed in the following section.

3.3. Neural networks

Nowadays, quantitative, multiple-variable regression-based methodology are considered the orthodox procedural technique of AVMs. The past decades have seen the development of novel procedures, which differ from the most widespread methods of mass automated valuation on a theoretical basis. The use of model-free estimation methods such as neural networks or fuzzy logic in property appraisal calculations provide flexibility without sacrificing mathematical rigor, thus creating a more powerful method compared to “inflexible” regression (*Kauko – d’Amato 2008b*).

Increasing computation capacity has also paved the way for the application of non-parametric models on the housing market. The book edited by *Kauko and d’Amato* (*2008a*) provides a thorough presentation of the possibilities that these models offer. This section highlights the key basic assumptions based on two papers that compare artificial neural network (ANN) based models with more traditional linear hedonic regression and the spatial lag model.

Mimis et al. (*2013*) compare a spatial autocorrelation (SAR) and the ANN model on a database containing the observation-based attributes (including geographic location) and price of 3,150 properties located in Athens. The ANN model is made up of neurons (or nodes) linked by synapses. The assigned weight refers to the strength of a synaptic connection. The neurons are structured in layers, which are either input layers, hidden layers, or output layers. The data enter through the input layer and are then transmitted to the neurons of the hidden layer through the synapses. Here, the data is exposed to weighted summarising functions and the transformation function, and the result then exits the network through the output layer. *Mimis et al.* (*2013*) use the multilayer perceptron (MLP), a feedforward supervised ANN, which means that the network structure is a controlled, fully interconnected graph that is taught using a supervised backpropagation algorithm.[5] The explanatory variables used describe property structure, the neighbourhood’s characteristics (within a 1 km radius) and access to the property (in this case: distance from the subway). The database was randomly broken down in a ratio of 60–20–20 per cent into training, validation and test data. *Mimis et al.* (*2013*) used numerous metrics to compare the models: the forecasting error and its deviation, mean absolute error (MAE), mean absolute percentage error (MAPE), root mean squared error (RMSE), actual and estimated value correlation and R^2 for the model fit. With the exception of the mean error, the MLP exhibited better values than SAR in every case. The authors interpret this result as meaning that the ANN is better suited for describing the nonlinear relationship between price and explanatory variables.

Peterson and Flanagan (*2009*) applied an ANN and a linear hedonic regression to a residential property sales database containing 46,467 pieces of observation-based data for Wake County (North Carolina, USA) for the period 1999–2005. The authors used 10–90, 25–75, 50–50, and 75–25 per cent of the data for the model’s

[5] During the backpropagation learning algorithm, the ANN calculates output for specific inputs using weights. It then compares this to actual values, adjust the weights by minimising squared errors until the estimation precision reaches a desired threshold.

estimation and testing for each year, and then drew a 100-element random sample of observations for each year. The OLS and ANN were estimated using the training sample, then the absolute errors calculated per observation were summarised for the partial samples; this yields the average absolute pricing error differential. According to the null hypothesis, there is no significant difference between the OLS and the ANN. *Peterson and Flanagan* (*2009*) also provide the RMSE and MAPE values for the two models alongside t-statistics. All three statistics favoured the ANN; the authors also stress that the errors increased over time (property price volatility increased in Wake County during the period under consideration), and a larger training database brought about larger errors. The weaker performance of the OLS might have resulted from neglected nonlinearity, which *Peterson and Flanagan* (*2009*) tested for using the RESET misspecification test. According to this, the null hypothesis which states that there is no ignored nonlinearity, can be rejected so the ANN provides a better fit.

3.4. Fuzzy logic

Fuzzy logic essentially differs from probability in that it addresses the inaccuracy prevailing in the present, while probability pertains to future uncertainty. Fuzzy logic allows for the truth values of a statement to be any real number between 0 and 1, as opposed to Boolean logic, where a statement is either true (taking a truth value of 1) or false (truth value of 0). According to the theory of fuzzy logic, the relation between a set and its elements can be described using what is referred to as a membership function, which allows for various degrees of membership compared to the usual 0 and 1 (*d'Amato – Siniak 2008*). These degrees can also be used for property appraisal. According to *Lee et al.* (*2003*), the fuzzy quantification theory help manage the subjectivity stemming from appraisal and also allows for the more accurate calibration of the factors shaping value. *Sui* (*1992*) highlights that standard regression methods – characterised by sharp sets – lead to loss of information in the presence of equivocality or inaccuracy.

Actual data may be inaccurate for various reasons, which impede the creation of mass revaluation models. Amongst other things, errors arising from flawed model specification may increase, as well as simultaneous correlations between explanatory variable and murky transitions among submarkets. A prime example of the latter is the difficulty in classifying municipalities in the case of consecutive market regions (e.g. where does an agglomeration end?). The segmentation of data or the grouping of the database into subsamples renders modelling quite complicated. Alongside traditional methods, more flexible and complex models such as fuzzy systems have emerged. However, these systems are unable to learn market attributes independently, so they are generally developed in combination with other methods such as artificial neural networks or genetic algorithms. The hybrid systems thus created are capable of addressing the uncertainties of the housing market (*González 2008*).

Lughofer et al. (*2011*) examined the relative performance of linear regression, ANN, SVM and fuzzy logic-based models (SparseFIS and FLEXFIS) using the data of 50,000 housing properties sold between 1998 and 2008. The authors found that fuzzy models offer the best forecasting performance based on average squared and average absolute error and cross validation error.

4. Assessment of the performance of statistical valuation

In the previous section of this paper, we presented several different models used for statistical valuation. This diversity stems from the varying needs of users. Accordingly, the rating criteria of models are also varied. The models are generally used to support the work of experts, but they are also used in the context of labour- and cost-effective mass appraisal. In the former case, it is important that the models yield the most accurate result possible, thereby supporting the work of experts, while apparent errors can be easily identified and overwritten based on real estate industry experience. This requirement has induced users to rely on hedonic models. In the course of mass appraisal, avoiding major errors may be an even more important criterion, i.e. keeping substantial misappraisals to a minimum even when working with large data sets of thousands of properties. This places emphasis on model fits tested according to statistical criteria, even to the detriment of the interpretability of partial impacts. For this reason, the models can only be qualified as better or worse very conditionally. Of course, as a general result of the nature of statistical indicators, the results of investigations on different databases or different sources of information cannot be compared. As a result, in every case, the statistical valuation model must be tailored to the user’s objectives and opportunities. The following section therefore provides an overview of studies that offer valuable insight into the use of valuation criteria and testing.

Bourassa et al. (*2003*) use data on the residential properties sold in 1996 in Auckland (New Zealand) to estimate hedonic regressions by comparing local appraisers’ market segmentation with a statistics-based segmentation[6]. *Bourassa et al.* (*2003*) test the models’ forecasting performance by retaining 20 per cent of the data for testing. The authors measure forecasting performance of different specifications using the absolute value of the forecast error: the forecasting error is less than 10

[6] The authors selected the orthogonal factors from among the property’s physical attributes, distance from the business district and the neighbourhood’s demographic and socioeconomic attributes using main component analysis, and then rotated them using the VARIMAX method to obtain uncorrelated factors and the associated factor scores. They then defined homogenous submarkets using cluster analysis (which are not necessarily related in spatial terms, but are used by surveyors). Using *MacQueen’s* (*1967*) method, the authors obtain 14–18 submarkets depending on the sample (all properties; only single-family houses; single-family houses for which an appraisal is available).

per cent of the price for 40–50 per cent of estimated values. Their findings imply that the model using submarket definition based on statistical methods performed worse than the one that used the local appraisers' submarket definition. The authors conclude that using sophisticated statistical tools to define submarkets is not worthwhile. However, incorporating spatial analysis into any of the models allows for a slight improvement in forecasting accuracy.

Goodman and Thibodeau (*2003*) use data for approximately 30,000 single-family home transactions for the submarkets of Dallas County defined using four different methods to examine the accuracy of hedonic estimates: with no spatial segmentation, based on postal codes, based on census districts, and taking into account the hierarchical structure of the submarkets (certain areas are located in school districts, administrative districts and city districts). The authors tested a total of eight models: a narrower (with three explanatory variables) and a broader (with all available explanatory variables) hedonic regression alongside the four submarket definitions. Submarket validity was examined using three tests: the structure associated with the smallest squared error was retained, an F-test performed (this, however, only works for embedded alternatives) and a Davidson – MacKinnon F-test.[7] The authors retained 10 per cent of the data to test the model in terms of its forecasting performance which was measured using various statistics of forecasting error value, its absolute value and the proportionate value (error/price). According to the F-tests and J-tests, neither model predominates in terms of forecasting accuracy. The most accurate results were obtained by combined estimates (that have the lowest average squared forecasting error). The authors conclude that the estimate should be performed for smaller markets, as any model based on submarkets provided a more accurate forecast than those run on county-level data, and that the combined estimate stood out in precision.

Clapp and O'Connor (*2008*) conduct an experiment where they applied three models created by academics specialising in the field of property economics and a simple OLS, alongside six expert-created models to the same database, retaining a portion of the data, and subsequently evaluating the models based on the precision of out-of-sample forecasting. The authors used a database containing over 50,000 observations of property sales in Fairfax County, Virginia between 1967 Q1 in 1991 Q4, supplemented by the properties' longitude and latitude coordinates. Only the models featuring an average absolute forecasting error of less than 20 per cent were retained for further comparison. The best performing models were the OLS, a multiplicative specification where the trend variable depended on the census district and a hedonic regression that included a residual of the closest neighbours. The authors defined two conditions for well-performing models: geographic location must be modelled using at least neighbourhood dummies and closest neighbour

[7] *Davidson – MacKinnon* (*1981*)

residuals; and the models must be specified ensuring that the defined districts are not too small.

Rossini and Kershaw (*2005*) apply various AVMs to on a data set of 2,000 observations on properties sold in Adelaide (Australia) for the period 1998–1999. The authors estimated linear, log-linear (multiplicative) and hybrid models, using the geographic location of the properties (longitude and latitude coordinates). Finally, they estimated six models modelling geographic location effect in two different ways. The spatial effects are captured in one case by a location variable estimated based on location value response surface calculated from the basic models residuals and coordinates, which describes the main location attributes, but ignores local neighbourhood effects, while in the other case, the authors calculated smoothed residuals from the response surface using kriging[8] subsequently defining a variable that incorporates neighbourhood effects. The authors used absolute percentage forecasting error (average and under 10 per cent) and the statistics describing estimated value/actual selling price (average, deviation) to evaluate the models. Based on this, hybrid models performed the best for residential properties: 60 per cent of the predicted values featured an absolute percentage error of less than 10 per cent.

While respecting the considerations outlined at the beginning of this section, prudent conclusions may be drawn from these results. No matter what goal the user has in the course of modelling, it is important to examine the results of alternative models using several indicators. An important and general lesson is that the data used for the estimation (calibration) and testing of the models should be distinguished (in other words, a portion of the data set should be retained for testing) to prevent the model from being excessively sample-specific.

In terms of model specification, spatial analysis in parametric form is useful regarding estimation results, for example by addressing neighbourhood effects. The other interesting point is that it is difficult to do better than models with market segmentation defined by experts using statistical methods; in other words, models relying on the definition of urban areas defined based on real estate expert experience cannot be outperformed by automated methods.

5. Possibilities in Hungary

Based on a summary of the well-known methods at present, this section addresses the possibilities of application in Hungary. Currently, Hungarian financial institutions use statistical property valuation methods, but these are indexation and the average

[8] Kriging is an interpolation technique where the interpolated values are described by an earlier (associated with the previous steps) covariance-led normal distribution process. If the conditions defined for prior covariances are met, the best undistorted linear estimate is achieved.

value methods that differ from AVMs. In order to see a rise in the use of AVM models, more complete data sets are needed in addition to user incentives. Data on property sales with the broadest current coverage can be obtained from the National Tax and Customs Administration. This data set is based on actual property sales transactions and county duties offices record transactions entered into the unified National Tax and Customs Administration system. All records must contain the following property data:

- Property address
- Ownership share sold
- Time of contract signed
- Selling price specified in the contract[9]
- Property area
- Property type: single-family house or semi-detached house, condominium, housing project

Two significant uncertainties arise regarding the contents of the database. One of them is varying content of the variable “area”. In most cases, the total area of the property itself is listed in the NAV records, but in case of single-family housesit is the area of the plot that is often listed. The two types of areas cannot be clearly distinguished from the recorded data, and as a result, the total area of the house is not even present in the database. The other uncertainty is the property type classification. In many cases, properties registered as apartments often appear in exclusively single-family detached home neighbourhoods, and housing project dwellings are often not identified as such. Exacerbating the issues with the database, access to it also limits the opportunities of using the data for statistical purposes. Referring to data protection policies, only 50–60 per cent of total data can be accessed by third parties, and among the variables addresses are truncated to the street level and dates are only available with quarterly accuracy. Based on user experience, due to these shortcomings, using the database for statistical purposes requires intense filtering and backcasting procedures. *Békés et al.* (*2016*) show that only an R^2 of roughly 50 per cent can be achieved by using this database for national-level estimates.

This fit can be increased by incorporating additional property attributes. The HCSO (Hungarian Central Statistical Office) housing survey analysis, based on own samples and property appraisal contains a regression using 30 explanatory variables. These variables (which include several category variables) yield an R^2 of 84 per cent of explanatory power of housing prices, illustrating the role of detailed information

[9] The basis of the duty paid is the purchased property’s current value rather than the selling price negotiated by the parties. Therefore, if the National Tax and Customs Administration deems that the selling price falls short of the current value, it will determine the property’s current value in the context of an on-site inspection. In these cases, the value determined by the tax authority is available as the property price.

on properties. Financial and real estate sector players could benefit from this opportunity by accessing a more detailed, publicly available land registry. Another solution would be to combine the results of several databases, such as the NAV's observations supplemented by estimates on advertising data.

Relying on the data available in Hungary, a better fit could be achieved using AVM methods. This objective could be approached by using spatial analysis methods. Still, without knowing the detailed attributes of properties, the estimation error will be substantial in the case of properties with unique attributes, which may result in a high frequency of large estimation errors. As long as users wish to apply more precise statistical models, the NAV database should be improved and access to it expanded in addition to methodological developments. Once this is achieved, the approaches presented in this paper could also be examined based on quantified criteria.

6. Summary

In the wake of regulatory, IT and methodological changes, statistical property valuation has gained traction in Hungary. In our paper, we looked at the what methods could possibly be applied to achieve this goal based on the literature. The fit of estimates based on classic hedonic models could be improved by using spatial analysis tools more intensively; however, nonparametric methods, such as neural networks, are able to yield an even better fit (smaller error). Nonetheless, regression methods are most suitable to contrast with real estate industry views, since experts, in line with the relevant legislation, present the partial effect of value-influencing factors on prices as part of the appraisal process.

Our review of methods that could possibly be applied shows that in Hungary everything is available to introduce automated valuation models (AVMs) besides the estimated mean-value based methods used so far. According to the results of related estimations performed in Hungary, statistical methods are able to provide useful information even outside the municipal boundaries defined by the current regulations. None of the statistical methods are able to approach individual expert knowledge for the time being, partly due to the size of the set of information that is difficult to quantify, and because of the degree of experience-based processing. However, statistical valuations, which are far less costly, will not crowd out but rather support the work of appraisers. For the aforementioned real estate industry specific reasons, in an effort to combine the benefits of automated and expert estimation, the introduction of parametric hedonic estimates augmented with spatial dependence can be expected.

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Annex 1

Patent number	Year	Authors	Note
US5361201	1994	Jost–Nelson–Gopinathan–Smith	An AVM using neural networks that calculates property value based on learned relationships first between individual property characteristics, followed by property and surface area characteristics.
US6115694	2000	Cheetham–Bonissone	A computer-implemented method for validating specified prices on real property.
US6609109	2003	Bradley–Gordon–McManus	An AVM combining the results of predictive models.
US6609118	2003	Khedkar–Bonissone–Golibersuch	Calculates property value by combining three processes: the first is based on location and living area, the second is based on a fuzzy neural network model, and the third uses a case based reasoning process.
US20010039506	2001	Robbins	An AVM that uses a comparative sales method.
US20030149658	2003	Rossbach–Conway	This system defines property value and its warranty for appraisal, protecting the party from the consequences of an inaccurate AVM appraisal.
US20040019517	2004	Sennott	The method determines whether there is sufficient information about a property to run an AVM.
US20040153330	2004	Miller–Hansen–Sennott–Sklarz	A process for evaluating default and foreclosure loss risk, which uses an AVM estimate as one of the first steps.
US20050288942	2005	Graboske–Walker–Helbert	Chooses the most accurate AVM calculation among those available to maximize AVM utilisation.
US20060085234	2006	Cagan	Calculates the deviation of AVM appraisals.