Orava AVM
External audit of the model

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1.1 Purpose and Scope of the audit

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Purpose

The purpose of the external audit is to independently verify that the automated valuation model developed, maintained and used by Orava Funds (Orava Rahastot Oyj) to estimate the fair value of Orava Residential REIT (Orava Asuntorahasto Oyj) residential assets (further referred as "Orava's model" or "the model") fulfils the following criteria:

- Both the general methodology used as well as the specific model parameters have a solid theoretical foundation and are plausible in the given context.
- The data feeded to the model is adequate in terms of recency, representativeness, quality and amount
- The data preparation includes only reasonable, non-biased correction procedures
- The modelling pipeline has no obvious flaws and the whole modelling process is performed with care
- The accuracy of the model results are on acceptable levels

Scope & Auditing process overview

The scope of this audit is restricted to cover only the objectiveness and fair use of the statistical modelling and the related data preparation processes. The scope does not include e.g. relevance of the modelling practice from the business perspective or reporting of the values. In detail, the audit addresses the five sections detailed under the "Purpose" section on the left, which in practice covers the standard statistical modelling pipeline from data preparation to modelling and result accuracy assessment. All five sections are validated based on the model documentation and modelling related toolsets (excel- and code-files) provided by Orava, as well as by interviewing the person responsible for the technical model development from the Orava. The results are also validated by partially reproducing the modelling with different software by the auditing person.

The auditing covers the model and data used for the 2017:12 valuation.

The responsibility and liability of Jones Lang LaSalle Finland Oy is limited to the amount of the auditing fee and as agreed with the Client.

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1.2 Materials and methods used in the audit

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Materials

The auditor has received the following material from the Orava for the auditing purposes:

- Documentation of the modelling process, including flow-chart with technical specification relating to model.
- Excel toolset used for data cleaning and imputing missing data
- Code files used to run the statistical model
- Data files used for model
- Excel toolset used for calculating the final valuations and the modelled variables for dwellings included in the Orava's own portfolio
- Excel toolset used for calculating the bargaining-range
- Final modelled values for 12/2017

As the JLL performed the external valuation of the Orava's residential portfolio in 2017 Q4, we have also used that valuation as benchmark for the Orava's modelled values for accuracy calculation purposes, with the permission from the Orava.

Methods

The auditing is performed via the following methods:

- Reviewing the documentation and code files provided.
- Interviewing the person responsible for the technical model development and monthly control valuation modeling in Orava (Mikael Postila).
- Partially re-building the statistical models with different software
- Evaluating the accuracy of the results using the independent valuation as benchmark.

2 Audit of the model

2.1 General methodology & Model parameters

General methodology

Orava's automated valuation model consist of one main statistical modelling method (ordinary least squares linear regression). The main method, linear regression with multiple explanatory variables, is both well known and widely spread, has solid scientific support and long history as one of the most used frameworks for statistical predictive models.

In the context of automated valuation models for residential dwellings the linear regression has generally been among the most used methods. With the increase in computing power in the recent years also more sophisticated methods (e.g. neural networks) have seen progression into the domain, but the overall usability of linear regression has not diminished.

Being strictly a parametric method, the linear regression has tendency to work well with smaller amounts of data, not to overfit the data easily and therefore to generalize well. In addition it is also easily interpretable, which makes it suitable for not only predicting, but validating the model and the results based on expert knowledge on the subject. On the other hand, it presumes exact model specification (as opposed to non-parametric methods, where the parameters are extracted from data) and fulfilment of certain criterions of the data (most importantly normally distributed data and linear relationships between explanatory and response variables).

As it stands, the linear regression needs deep expert knowledge from the modeller, as he / she needs to decide beforehand, what variables to include / exclude in the model and what variable transformations to use. Due to the general inflexible nature of the method, the predictive power is often slightly inferior to that of more complex methods when larger datasets are available (e.g. Nguyen & Cripps 2001, Zurada & all 2011), but with smaller datasets it often might offer a more robust and reliable estimates.

Model parameters

As outlined in the previous section, the success of the whole model is highly dependent of the decisions made by the modeller. One of the most important of those decisions is the reasonable choice of variables included in the model, together with the variable transformations applied. The variables and their transformations included in the Orava's model are displayed in the table on the following page.

2.1 General methodology & Model parameters (cont.)

Variable	Unit	Transformation	Note
Value	Numeric; € / sq. m.	Natural logarithm	Response variable
Floor area	Numeric; Sq. m.	3rd order polynomial	
Age	Numeric; Years	3rd order polynomial	
Floor	Numeric	3rd order polynomial	Variable omitted if the n_f in model too small**.
Apartment condition	Ordered class	-	Spesific condition correction / calculation procedure for Orava's own assets, please refer to section 2.4 ”The modelling pipeline”.
Sauna	Binary class	-	
Plot ownership	Binary class		Variable omitted if the n_a in model too small**.
[Same] Time	Ordered class; quarters	-	
[Same] Zip code	Binary class; zip code areas	-	Is the predictor observation from the same zip code as the target
[Same] 1 or 4 sq. km	Binary class	-	Is the predictor observation within the same 1 or 4 sq. km. area as the target. Variable selection ($1km^2$ or $4km^2$) based on n_a**.
[Same] Building	Binary class	-	Is the predictor observation from the same building as the target.
[Same] Apartment	Binary class	-	Is the predictor observation from the same apartment as the target.
[Same] Building type	Nominal class	-	Is the predictor observation from the same building type as the target. Variable omitted if the n_a in model too small**.

** The models are chosen using n_a (number of physically separate assets having that spesific criterion in the dataset used for modeling) < 15 and n_f (number of observations having that spesific criterion in the dataset used for modeling) < 750 as a stopping criterion. If the inclusion / restriction of certain variable would reduce the n_a or n_f under the spesified limit, then the more general model without the mentioned variable is used. For example, if there are less than 15 assets with the same plot ownership than for the asset in question, then model without the plot ownership variable is used.

2.1 General methodology & Model parameters (cont.)

Model parameters (cont.)

All of the variables included have a sound theoretical backing in the literature, and the variable transformations applied seem reasonable. The inclusion of multiple spatial levels / granularity in the prediction process (municipality, zip code, square km, building, apartment) is well in line with the idea of different processes operating at different scales in geography.

Addressing the issue from real estate perspective, the inclusion of the building and apartment level binary indicators add asset specific information, while the zip code and square kilometre level assess the meso- and microlocational effects. Confining the prediction process to single municipality at time, using only data from that municipality, has the positive effect of homogenizing the dataset while adversely reducing the n. This in turn favours the use of robust statistical model for small n, such as the linear regression.

2.2 Data quality, representativeness and amount

Data sources

The data used in the Orava's model comes from single main source (the Oikotie-database) and is further enhanced by manually searching and adding observations from multiple other sources. The manually searched observations are added if

a) The found observations are from asset / apartment that is included in Orava's own portfolio, but the observation is not Orava's own advertisement.
b) When n in the municipality containing Orava's asset is too small (under 150).

The Oikotie-data

Oikotie.fi, being major channel for transactions of residential properties in Finland, has provided the access to their marketing-database to Orava. This data represents the significant share of marketed residential units in Finland, and offers a wide coverage of the market, with both geographic coverage, as well as in terms of other variables (e.g. size, age or type of asset etc.). Therefore the representativeness of the data is deemed to be on good level.

The data submitted to the Oikotie.fi is subject to errors made by the individual brokers. In practice the effect is thought to be small, as the channel is really popular and under constant scrutiny, forcing the brokers / adds to be fair, honest and transparent to gain positive attention. Also the sheer size of the database is reducing the potential error, as it most likely consist of few abnormal outliers and normally distributed random errors. For these reasons we believe the data should not have any systematic bias to any direction.

The amount of data was over 6,000 observations for December 2017, which is roughly in line with the database of The Central Federation of Finnish Real Estate Agencies. The total dataset used for the modeling covers 24 months, and at the 2017:12 modeling the size was over 161,000 records, which more than exceeds the needed size for total dataset.

Potential data-related problems

As the Orava's modeling pipeline splits the datasets by municipality and further reduces the data by using only applicable subset (e.g. only block-of-flat records for modeling values for block-of-flats) the effect of single outliers / individual biased observations might pose a problem for single asset values. Also when such single influential observation suddenly appears as a new ad or is removed from the dataset (older than 24 months), the sudden disruptive change in the predicted value might appear.

Another major flaw is the data including mainly asking prices and not the actual selling prices (with the exception of Orava's own ads, that do have the selling price information). To mitigate this, Orava has implemented a bargaining range estimation process, where average bargaining range is calculated for 2-year moving window for each zip code separately, based on the average selling prices (from Statistics Finland) and asking prices per zip-code. The bargaining range is restricted to the range of -10% to +10%, and is used in the modeling as aggregated to the city level. The estimation process seems reasonable, even slightly conservative, as only city level values are used to correct the asking prices to selling prices.

2.3 Data pre-processing

Pre-processing pipeline

The freshest raw data covering the latest month from Oikotie.fi is fetched from the server, and then run through the following procedures:

- Deletion of clearly erroneous observations: includes deletion of observations with e.g. missing price information, floor area or location.
- Deletion of special cases, i.e. the observations from the dwellings with city-supported plots in Helsinki (HITAS) and bargain-sales which do not represent the market standard of arms-length transactions.
- Outlier deletion: observations defined as outliers (e.g. floor area outside of range 15 - 150 sq. m., total selling price under 5,000€, buildings age outside of range -2.5 – 150 years) are omitted from the data
- Missing data imputation: The variables building year, building type, lot ownership, location coordinates and apartment condition are imputed based on the information gained from last 24 months of data from Oikotie.fi, which are then validated manually. If a match from the 24 month data is not found, then imputing is tried with internet search.

The newest month of data is then merged with the old 24 months dataset, dropping the oldest month simultaneously.

The observations from the assets that are in the Orava's portfolio are thoroughly scanned and imputed with all possible data sources. The observations from the same asset / apartment are kept in the data longer than the standard 24months, using the prolonging-factor (i.e. interpolating the value to the oldest quarter present in the current data using the price index from Statistics Finland).

The data pre-processing is then internally validated in two phases, first with person responsible for the valuation modelling and finally with the management of alternative investment fund manager.

Considerations relating to the data pre-processing

As stated in the section 2.2, the Orava's model splits the data to small subsets and the small number of observations might pose a problem if influential / biased observation is present in the data. Therefore the data pre-processing, particularly the removal of the erroneous observations, special cases or outliers, plays an important role. Orava has addressed this issue with two-fold validation process as defined above, and also in the model results validation: if the modelled value has changed over c. 75,000€ (per asset) or markedly in relative terms (as compared to previous month), then the dataset is reviewed with extra care. If outliers are found in this second revision, they are removed and the model is then rerun.

Overall the data pre-processing practices and related decision criteria seem reasonable and fair, with no obvious flaws in the process.

2.4 The modelling pipeline

Linear regression fitting and prediction

After the pre-processing and data validation the regression is performed for each asset separately, resulting in multiple models per asset. The final model is then chosen with specific criteria and exported to excel-toolset for predicting the final values. The regression and data restriction are performed with Gretl-software (version used in 2017:12 was 2017c), and the actual predictions are performed with dedicated excel toolset:

- Data is first restricted to include only observations from the same municipality as that of the asset in question
- Based on the type of the asset, four (or eight) linear regression models are calculated, with all the possible combinations of choosing from the following variables (data has the first two of the following variables dummy-coded):
  - 1km^2 neighbourhood vs. 4km^2 neighbourhood
  - Rented lot vs. owned lot
  - Number of floors included in model vs. excluded
- After the regression the models outputs are saved and final model is chosen with defined criteria (e.g. if asset is of type block-of-flats, the model with observations from only block-of-flats is used etc.). There are also restrictions that the if data has less than 15 assets with similar variable value than the asset in question, the variable is not included in the model and a more general model is used instead.
- The model parameters / coefficients from the chosen model are then exported to excel-toolset used for actual prediction of the dwelling's values.
- Orava's own dwelling / asset specific properties are defined / updated in the excel-toolset (e.g. apartments condition is based on the average of estimates given by facility manager and inhabitants, bargaining range is updated if new data is available, asset condition is re-estimated / downgraded if the asset consist of mainly rental apartments).
- All the model parameters / regression coefficients are validated, both in relation to the previous modelling and in absolute terms; if anomalies are found, the dataset used will be further inspected to derive the potential outliers or to find the cause for the anomaly.
- The valuations are also validated in relation to that of the previous month.

Auditing tests performed

Ten assets were randomly chosen and the corresponding statistical models were re-created for them by the auditor. Software used for testing was R (v. 3.4.3). Based on the random tests the linear regression coefficients obtained for the assets were identical to those of used in the Orava's model. The datasets and formulas used for calculation of the final valuation on the assets were then checked within the excel-toolset provided by Orava and no problems, errors or flaws were found.

2.4 The modelling pipeline (cont.)

Considerations of the modelling pipeline

The overall modelling pipeline is well defined with the model fitting and prediction phases separated and performed with different software. Assumptions and criterion used seem plausible and theoretically sound. As noted in sections 2.2 and 2.3, the small number of observations creates possibility that single influential observation might greatly affect the end result. While this risk is mitigated with data pre-processing practices currently in use (e.g. screening for outliers) as well as the validation of both the model coefficients and the resulting value, there is still room for further improvement. As is the case in the context of residential mass appraisal models, the multicollinearity of the explanatory variables often makes the comparison of the regression coefficients infeasible and inefficient way of finding problems in this regard. This leaves only comparison of value to previous valuation, which provides no direct reason for abrupt changes in values, and is also infeasible if in case of first time valuations. Potentially better way this could be implemented would be e.g. via cross validation or bootstrapping when building the models: These methodologies could be used to gain understanding of influential observations as well as general robustness of the predictions.

Another potential development path could be transferring the model selection and prediction-phases also to the same software as the model fitting. This would reduce the need for manual work performed currently in the excel-toolset and therefore further reduce the risk of manual errors.

2.5 Accuracy and reliability of the model results

Internal validation process

The data and related pre-processing, model and it's coefficients and the actual predicted values are all internally validated by Orava for each month's valuation. The overall validation process employs the practice of performing the key parts of the whole process separately by different persons and often with different toolsets / methodologies. At the intermediate stages the results are compared against each other and no differences are allowed before advancing to the next stage of the process. In addition, the specific validation criteria apply to certain phases (e.g. bargaining ranges are not allowed to extend beyond the limits of ±10% etc.).

Based on the information received, the internal validation practices are on good level, and adequate precautions are taken to prevent and mitigate any human made errors both in the data collection part (outside of Orava's direct influence) as well as in pre-processing and modelling part performed within the Orava.

Reliability of the results

Reliability in this respect is understood as un-biasedness and general representativeness of the modelled values. Reliable results are obtained when all parts (data amount, quality, representativeness; modelling method & specification; general fair use of the statistical methods and plausible assumptions) are deemed to be on good level and adequately performed. Based on the audit of the model (sections 2.1 – 2.4) the above mentioned criteria is fulfilled in the Orava's model.

Accuracy

Two most commonly used accuracy measures in the context of real estate mass appraisals are the mean absolute prediction error (MAPE) and percentage of units within certain range from the observed (e.g. within ±10% from observed) (e.g. Rossini & Kershaw 2008, Matysiak 2017). Using the independent external valuation performed by JLL for the 2017:12 valuation of Orava's portfolio as a benchmark, the following table gives overview of the accuracy of the Orava's model.

Measure	Minimum requirement*	Reasonable level*	Orava's model
Mean absolute prediction error	< 13 %	< 10 %	8.9 %
Within ± 5%	-	-	35.6 %
Within ± 10%	> 50 %	> 65 %	66.0 %
Within ± 20%	> 80 %	> 90 %	91.0 %

* As suggested in the the work of Rossini & Kershaw (2008)

3 Discussion and Summary

3.1 Observed potential issues in the model

During the audit no fatal problems that would undermine the credibility of the modelling results were observed. The issues outlined below are minor in nature and in the effect they pose in the total reliability of the results. These issues are also relative to the larger context of the operating environment, and while addressed here from only technical perspective, also subject to restrictions imposed by the operating environment. In Orava's case this means that while accuracy of the results is main factor, also continuity and consistency of the results over time must be guaranteed. Balancing these factors is context specific, and therefore no strict guidelines / limits can not be applied or suggested. During the audit the following three smaller potential issues were covered:

- Overall the whole modelling workflow had some un-needed complexity (e.g. different parts of the modelling were performed with different software, with partially extensive amount of manual work). While the chosen approach is valid and understandable taking into account both the ease-of-continuity –perspective as well as the internal validation process with double-checking the results at intermediate stages, there is increased risk for human errors when the system is dispersed among many platforms.

- While in general the estimating of the actual sales prices with bargaining-range –estimates provides completely reasonable results, it may hide some finer detail of variation. As the bargaining ranges are used per city basis (single constant per city), they do not reflect smaller geographic variation or any asset specific attributes. Aggregating the bargaining ranges by city basis therefore has the positive effects of providing more robust results over time and reducing the potential effects of outliers, but it might lose some information in the process. However, there is no clearly defined limit how one should decide on the balancing the robustness / information gain issue, and therefore this note is mainly speculative.

- The limiting / restricting of the data both geographically and variable-wise used by the Orava's model is both the culprit and the greatest advantage of the model. As noted in multiple sections (2.2 – 2.4) the problem lies with the potential influence by single observations, which grows with every restriction imposed on the data. This is particularly problematic when single influential observation enters or leaves the dataset used for model building between different valuations in time, potentially creating strong and disruptive change in the estimated value for consecutive valuations.

3.2 Suggested modelling considerations

Suggested considerations

Along the lines of the findings in section 3.1 “Observed potential issues in model”) three main suggestions for further consideration are outlined here:

- The complexity of the whole process could be reduced with transferring the analyses to one single software and rewriting / refactoring the code base, which would both reduce the risk for human-induced error and increase the efficiency.
- Overcoming the limitations of the bargaining range estimation has two options: First option is to use more flexible approach for calculating the bargaining range with smaller geographic areas / timeframes. This would need a one-time separate simulation / validation process, where optimal configuration of the granularity vs. robustness would be defined. The second option is to gain more comprehensive data where sales prices would be directly available: This has already been under negotiation with The Central Federation of Finnish Real Estate Agencies (KVKL, Kiinteistönvälitysalan Keskusliitto ry).
- Relating to the finding and reducing the effect of single influential observations, the use of either cross-validation or bootstrapping is recommended. This would not need any major changes to current workflow, and would produce information on how robust the results for single dwelling are while modelled with subsamples of the dataset.

Potential speculative development paths

In addition to the aforementioned considerations more speculative thoughts for further development of the model are listed below:

- The modelling of the non-spatial and spatial features could be separated to two different modelling steps. Then some more flexible, non-parametric method for the spatial modelling (e.g. kriging) could be used instead of the 1km^2 or 4km^2 areal dummy variable. The kriging framework could also be used to derive information about the effect of the single observation, although only in relation to the spatial properties.
- Using a clearly defined framework for testing and developing the model further. This would include criteria / measure for evaluating the model performance, and the potential development paths could be tested against this framework.
- Testing if the inclusion of interaction terms in the model improve the accuracy: In the context of appraisal of residential real estate the interactions of the different variables are evident, which is also present in the multicollinearity of the different features. Based on the development work performed on the JLL’s AVM, the interactions were one important topic to address. The effect might be lesser in models, like the Orava’s model, which restrict the data before modelling, but still worth investigating.

3.3 Summary of the audit

JLL

Scope & Purpose

The purpose of this report is to independently verify the true and fair treatment of the data and use of statistical methods in the automated valuation model used by Orava, finally assessing the reliability and credibility of the resulting modelled values. The scope of the audit is restricted to include only the statistical foundation of the model, the data and related preparation procedures used, the actual modelling pipeline and the accuracy of the modelling results.

Methods used in the audit

Audit was performed by first reviewing the documentation obtained from the Orava and interviewing the person responsible for the technical model development and control valuations in Orava (Mikael Postila). The technical modelling was then validated by reviewing the code- and excel files and formulas used in the modelling. Results were validated by partially replicating the statistical models within different software by the auditor. The accuracy of the Orava's modelled values was assessed with benchmarking them to external valuation of the Orava's residential portfolio.

Results

The results obtained show that both the model and it's parameters were theoretically sound along with the data used being adequate and representative. The pre-processing and related decisions applied to the data were deemed plausible. The actual modelling pipeline was implemented in two phases, performed in different software; both parts were validated to perform as intended, producing credible results. The accuracy of the Orava's modelled values against a benchmark of external valuation showed that the accuracy figures obtained exceeded both the minimum and 'reasonable level' criterion found in the literature.

Reliability of the model

Overall, the implementation of the whole modelling process from data collecting to actual modelling showed good practice of the internal validation in use. No systematic flaws or biases in the data, pre-processing or in the modelling pipeline were found. The test replicating the statistical models and their results were all passed. The accuracy figures exceeded those recommended in the literature. Based on the audit, we deem the model and it's results generally both reliable and un-biased.

3.4 Tiivistelmä

Raportin laajuus ja tarkoitus

Auditoinnin tarkoituksena oli validoida Orava asuntorahasto Oyj:n käyttämän automaattisen arvonmääritysmallin, siihen liittyvien aineistojen ja näiden yhteistoiminnan luotettavuus sekä soveltuvuus käyttötarkoitukseensa. Tarkastelun laajuuteen rajattiin kuuluvaksi mallin teoreettinen tausta, käytetty aineisto ja sen esiprosessointi, varsinainen mallinnus sekä tuloksien tarkkuus.

Käytetyt auditointimenetelmät

Auditointi perustuu Oravalta saatuun kirjalliseen materiaaliin sekä Oravalla mallin teknisestä kehityksestä ja kontrollilaskennasta vastaavan henkilön (Mikael Postila) haastatteluihin. Mallinnuksen teknistä toteutusta on arviotu Oravalta saatujen malliin liittyvien koodi- ja excel tiedostojen avulla, sekä tekemällä satunnaisia pistokokeita. Pistokokeissa tilastolliset mallit on toisinnettu auditoijan toimesta eri ohjelmistolla. Oravan mallin tuottamien tulosten tarkkuutta ja luotettavuutta on arvioitu vertaamalla niitä ulkopuolisen arvioitsijan tekemään arvonmääritykseen Oravan asuntoportfoliosta.

Tulokset

Saatujen tulosten perusteella mallin yleinen rakenne sekä mallispesifit valinnat ja parametrit vaikuttavat teoreettisesti perustelluilta. Käytetty aineisto on edustavaa ja riittävän suuri; aineistoon liittyvä esi-prosessointi ja siinä käytetyt kriteerit ovat järkeviä ja aineiston käsittely on toteutettu huolellisesti. Varsinainen mallinnus on toteutettu kahdessa eri osassa (kahdessa eri ohjelmistossa), ja dokumentoinnin, teknisen materiaalin sekä pistokokeiden osalta molempien osien on todettu toimivan tarkoituksenmukaisesti. Oravan mallintamien arvostuksien ja ulkopuolisen arvioitsijan suorittaman arvonmäärityksen vertailussa mallinnuksen tarkkuus ylitti kirjallisuudessa esitetyt minimi- ja keskimääräiset kriteerit tarkkuudelle.

Mallin tulosten luotettavuus

Koko mallinnusprosessin toteutuksessa, datan keruusta tilastolliseen mallinnukseen saakka, on käytetty Oravan sisäistä validointimenettelyä virheettömyyden varmistamiseksi. Aineistoon, sen käsittelyyn tai itse mallinnukseen liittyen ei löytynyt merkittäviä ongelmia tai systemaattista vääristyneisyyttä, ja suoritettujen pistokokeiden osalta saadut tulokset olivat identtisiä Oravan tulosten kanssa. Mallin tarkkuus ylitti kirjallisuudessa esitetyt minimi- ja keskimääräiset tasot. Auditoinnin perusteella Orava asuntorahasto Oyj:n käyttämän mallin tuloksia voidaan pitää yleisesti ottaen luotettavina ja harhattomina.

3.5 Sources

Sources

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