Assessing the explanatory power of dwelling condition in automated valuation models*

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Abstract

This study investigates the role of dwelling-condition attributes in automated valuation models (AVMs) by utilizing detailed dwelling-condition assessment reports in Norway. A hedonic linear regression model, a gradient boosted decision tree, and a support vector machine were trained and evaluated to predict the sale price of dwellings in three urban regions. The study aims to evaluate the explanatory power of condition attributes in AVMs through a comparison of predictive performance with and without these attributes. The results indicate that the inclusion of condition attributes significantly improves the accuracy of all models across all regions. Furthermore, the models show consistent results regarding which condition attributes are important and their relationship to the price. The study finds that the condition of the bathroom has a high impact on the price, while the condition of doors, roof and exterior extensions have a low impact. The study concludes that dwelling condition holds explanatory power in both linear and non-linear AVMs, which can benefit researchers, practitioners, and homeowners looking to renovate. The findings highlight the importance of including detailed dwelling-condition attributes in AVMs and

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provide insights into the valuation of different aspects of a dwelling.

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1 Introduction

Real estate is an important class of assets that constitute a large part of any country's economy, and involves a wide range of stakeholders. Whether to be used in a purchasing decision to determine the appropriate size of a mortgage, or to estimate taxable wealth, accurate valuations of real estate properties are of interest to individuals, banks and governments alike. Historically, real estate valuation methods involve single-property valuations, which rely to a great extent on the appraiser's subjective experience and judgements. Due to their objective and systematic valuations, automated valuation models (AVMs) have gained popularity in recent years, in addition to their ability to perform mass appraisals in a time- and cost-efficient manner. AVMs have obtained a central role in the growing Proptech industry, among these iBuy companies where renovaton plays an important role (Anderson et al., 2023; Harrison et al., 2023; Helgaker et al., 2022; Seiler and Yang, 2023). AVMs typically rely on regression models trained on historical sales data, which attempt to capture the relationship between a property's characteristics and its price. Commonly considered property characteristics include location, structural information, such as size or the number of rooms, and neighborhood factors, such as air pollution and crime rate. However, little research has been dedicated to assessing the explanatory power of a dwelling's condition.

This study aims to bridge this gap in the literature and assess the explanatory power of a dwelling's condition in AVMs. To achieve this, a hedonic linear regression model, a gradient boosted decision tree and a support vector machine (SVM) are trained using the sales data of dwellings in Oslo and its surroundings, Bergen and Trondheim, three urban regions in Norway. To the best of the authors' knowledge, this is the first study that aims to assess the explanatory power of condition attributes in both linear and non-linear AVMs. Furthermore, the data used is unique, both in terms of the granularity of the condition assessments and their close proximity to the time of sale. Knowledge about the impact of dwelling condition on the sale price can be of value for two reasons. Firstly, it can help researchers and practitioners increase the accuracy of AVMs. Secondly, it may aid homeowners in assessing the profitability of renovations of various aspects of the dwelling.

This study uses data provided by the Norwegian Proptech startup Vendu AI. The data contains assessments of the condition of dwellings in the form of reports written by assessors in connection with the dwellings being put up for sale. This study utilizes data sets covering three regions in Norway: 6,651 dwellings in Oslo and its surroundings, 2,975 dwellings in Bergen and 1,677 dwellings in Trondheim. Attributes describing the size, location, build year, selling year and building type are included, in addition to attributes describing the condition of a range of checkpoints within the dwelling, such as the kitchen, bathroom and building structure.

To assess the explanatory power of dwelling condition in AVMs, the models are trained with and without condition attributes, and their predictive performance is recorded and compared. The data is split into a training and a test set, so that the out-of-sample predictive performance can be accurately assessed. The root mean squared error (RMSE), mean percentage error (MPE), mean absolute percentage error (MAPE) and percentage of prices predicted within 10% and 50% of the actual selling price are used to assess the performance. Finally, the models are interpreted in order to analyze the determined relationship between condition and price.

The inclusion of dwelling condition resulted in accuracy improvements in all three regression models. All models benefited similarly in magnitude, and the accuracy gain was consistent across the three regions. The models were also consistent in terms of which condition attributes ranked high in terms of importance, and what the relationship was between these attributes and the price. The combination of increased predictive accuracy and the consistency in model interpretations leads us to conclude that dwelling condition provides explanatory power in AVMs. However, this explanatory power varies between condition categories. Across all models and regions, the condition of the bathroom is consistently reported to have a high impact on the price, while the condition of the doors, roof and exterior extensions are consistently reported to have a low impact.

This paper is structured as follows: Chapter 2 reviews related literature within real estate valuation, covering traditional and modern machine learning approaches and previous work done exploring the relationship between dwelling condition and sale price; Chapter 3 provides relevant background knowledge of the housing markets in the three regions, as well as an introduction to the structure of the condition reports utilized in the study; Chapter 4 presents a statistical description of the data; Chapter 5 describes the methodology, including a theoretical introduction to the models used; Chapter 6 presents and discusses the results; Chapter 7 concludes the study, summarizing the most important findings.

2 Related literature review

2.1 AVM approaches

A wide variety of techniques have been applied in the task of the automatic prediction of dwelling prices, but the oldest and most prominent is the linear regression model. Linear regression models in AVMs are based on the theory of the hedonic price function, as outlined by Rosen (1974). By breaking down the property into its characteristics, the estimated coefficients of the linear regression function represent the implicit marginal price of each characteristic, and provide an economic interpretation of their value. The predictive accuracy of linear regression models in AVMs has been thoroughly examined, and researchers frequently use them as a baseline for comparisons to other models (Antipov and Pokryshevskaya, 2012; Do and Grudnitski, 1992; Kok et al., 2017; Lam et al., 2009; Lin and Mohan, 2011; Marjan et al., 2018; Mimis et al., 2013; Nghiep and Al, 2001).

The support vector machine (SVM) (Cortes and Vapnik, 1995) is a machine learning approach that has been found to outperform the linear regression model in terms of its predictive accuracy on multiple occasions. The superior performance is accredited to the SVM's ability to efficiently capture non-linear relationships, the relative ease of finding optimal values for its hyperparameters and the guarantee of a globally optimal model (J.-H. Chen et al., 2017; Kontrimas and Verikas, 2011; Lam et al., 2009).

Another class of machine learning approaches that has seen more recent use in AVMs are ensemble methods, in which multiple models are trained and an aggregated output used as the prediction. Ensemble methods that have been found to show promising results in terms of predictive accuracy when predicting dwelling prices include random forests (Antipov and Pokryshevskaya, 2012; Dimopoulos et al., 2018; Marjan et al., 2018), boosting methods (Ho et al., 2021; Kok et al., 2017; Mayer et al., 2019) and stacking methods (Graczyk et al., 2010; Kontrimas and Verikas, 2011).

2.2 Dwelling condition

Most studies within real estate research focus on methods of enhancing the predictive accuracy of AVMs, and few conclusions have been drawn regarding the explanatory power of dwelling condition. Recent examples of studies considering dwelling condition to a limited extent include Doumpos et al. (2020), Renigier-Biłozor et al. (2019) and Helbich and Griffith (2016), but the dwelling attributes considered are general and few, with no explicit conclusions drawn regarding their explanatory power.

Kain and Quigley (1970) is one of the first studies to attempt to establish the economic value of dwelling condition. The study uses five categories to describe the condition of a dwelling. The categories are determined by factor analysis of 39 initial variables, which are partly derived from surveys asking homeowners to assess the quality of various aspects of their property, and partly from city building inspectors assessing neighborhood factors. When regressed against the sale price, three of the five categories were deemed significant, and indicated that homeowners were willing to pay for higher quality.

Instead of relying on a homeowner's subjective assessments of dwelling condition, Ooi et al. (2014) attempt to use a standardized metric assessed by professionals. The Construction Quality Assessment System (CONQUAS) is used in Singapore to assess three categories describing a property's condition. When regressed against price, a better CONQUAS score was found to command a higher price. More recently, Mathur (2019) considers dwelling condition described by the construction quality and level of maintenance, measured by standardized scales defined by the local tax assessor. Also in this case, both factors were found to significantly and positively affect the price.

Overall, the studies agree that dwelling condition has a statistically significant relationship with the dwelling price, and that dwellings in better condition typically command a higher price. However, they are lacking in some regards. Firstly, the level of detail in the attributes describing the condition is low. Secondly, there is often a large gap between the time of the condition assessment and the time of sale. Thirdly, the studies only employ linear regression models, and make no conclusions regarding the explanatory power of condition attributes in the task of predicting dwelling prices. This study extends the literature by examining the impact of dwelling condition, using both linear and non-linear models in the framework of AVMs.

3 | Real estate market in Norway

The explanatory power of dwelling condition in AVMs is examined using dwellings from three data sets covering urban regions in Norway. This section presents information regarding the housing markets in these regions. Maps of the regions are provided in appendix B. A more detailed description is provided for the housing market in Oslo and its surroundings, which is the main area of focus in this study. An explanation of the property transaction process and the condition reports utilized in the study is also provided.

3.1 The property market in Oslo and surroundings

The data set covering Oslo and its surroundings includes dwellings located in the city of Oslo, and in the five surrounding municipalities of Bærum, Drammen, Asker, Lillestrøm, and Lørenskog. This area will simply be referred to as Oslo for the remainder of the study. The decision to include additional municipalities was primarily motivated by data availability. Additionally, the surrounding municipalities are densely populated urban areas that are included in the Oslo Region Alliance, a cooperation between municipalities that considers the capital as their natural center.[1] The city of Oslo is the capital of Norway, and had a total population of 693,494 per 01.01.2020 (SSB, 2021). The combined population of Bærum, Drammen, Asker, Lillestrøm and Lørenskog was 446,964 per 01.01.2019 (Mæhlum, 2020).

The average square meter price in the city of Oslo was NOK 77,342 in 2019 (OsloMunicipality, 2021). The square meter prices were somewhat lower in the surrounding municipalities, with NOK 40,457 in Drammen, NOK 49,659 in Lillestrøm, NOK 64,062 in Bærum, NOK 45,128 in Asker and NOK 51,970 in Lørenskog (Krogsveen, 2021). All locations in the Oslo data set had a substantial price increase over the last decade. The city of Oslo had an increase of 85% between 2010 and 2020, while the five municipalities in Viken had an increase of between 68%-81% within the same period (Krogsveen, 2021).

3.2 The property market in Bergen and Trondheim

The other regions covered in the study are the municipalities of Bergen and Trondheim, the second and third largest cities in Norway. Bergen lies in Vestland County, and has a population of 283,929 (Bergen municipality, 2020). Trondheim lies in Trøndelag County, and has a population of 207,595 (Trondheim municipality, 2020). The square meter prices in both regions ranged from approximately NOK 30,000 to approximately NOK 50,000 in 2020 (Krogsveen, 2021), indicating a generally lower price level than in Oslo. It is also

[1]Description of membership requirements in Norwegian: https://www.osloregionen.no/dokumenter/vedtekter/

worth noting that Bergen and Trondheim have significantly fewer administrative districts compared to Oslo.

3.3 Property transaction procedure and condition report

The property sale process in Norway is characterized as an English auction, in which the price is determined in a near-perfect bidding context (Olaussen et al., 2017). This, coupled with the fact that non-professional buyers and sellers dominate the Norwegian housing market, makes it highly suitable for studies on property pricing in general (Oust et al., 2020). The sales process in Norway typically goes as follows:

1. The seller hires a real estate agent and an assessor.
2. The assessor evaluates the technical condition of the property, and hands in a report outlining the condition of the dwelling.
3. The real estate agent collects all available information, including the condition report, creates a sales report for potential buyers and sets an asking price.
4. Potential buyers are given the opportunity to visit the property and assess it, typically through an announced public open house.
5. The real estate agent arranges an English auction. Bids are binding, and any bid accepted by the seller is a binding contract.

The condition report assesses the condition of various aspects of the home. It is a technical report covering everything from the condition of the floors to the quality of air circulation. It typically focuses on aspects of the dwelling that are difficult to assess by a buyer during the showing, and which often lead to conflicts between the seller and the buyer. The buyer is responsible for any deficiencies in the dwelling as long as it has been reported before the bidding process. However, if it is not reported, the seller is often responsible.

Standards NS 3424 Standard (2012) and NS 3600 Standard (2015) exist to ensure consistency between condition reports. The standards describe what must be assessed, and outline four levels describing the condition.

This paper utilizes a inverted version of the scale originally used by the appraises due to issues with data quality and to improve the interpretability of the results[2]:

- 1: Major faults: Reparations are required immediately.
- 2: Significant faults: There is a need of reparations soon.
- 3: Small or moderate faults: No reparations are necessary, but there may be minor discrepancies.

Details on the background of this modification is provided in section 4.

The dwelling conditions have been set by the appraisers as part of previous sales in line with the standards and independent of this research paper. Potetial home buyers were aware of these dwelling conditions at the time of sale.

[2]In the original scale, TG 1 is Small or moderate faults, while TG 3 is Major faults.

4 Data

This study uses data provided by Vendu AI, a Norwegian prop-tech start-up. Vendu AI has access to data collected from two providers: Ambita and Norsk takst. Ambita is responsible for registering all property and land transactions in Norway, and provides general sales data. Norsk takst is an industry organization for appraisers that provides condition reports. This section introduces the process of merging and cleaning the two data sets, and provides a descriptive analysis of the final data. The final data set is comprised of dwellings in Oslo, Bergen and Trondheim sold between 2016 and 2020.

4.1 Data description

The format of the condition reports provided by Norsk takst requires pre-processing. The reports consist of a number score between zero and three, in addition to an accompanying descriptive text for checkpoints in the dwelling. These checkpoints are identified by a room number and a checkpoint number. Because not every checkpoint is relevant for every dwelling, there are differences in the number of checkpoints with scores in each report. Consequently, the checkpoints cannot be used as attributes representing dwelling condition in the AVM. Furthermore, it was discovered through a visual inspection of checkpoint descriptions that multiple checkpoints with a score of zero represented no score given. For this reason, all checkpoints with a score of zero were deemed corrupt and discarded.

A simple heuristic method was used to solve the problem of a varying number of checkpoints. Checkpoints were merged into categories, with the average score of the checkpoints used to represent the condition of that category. Categories were defined by subjective judgments, of which checkpoints can be naturally grouped to represent the condition of a given aspect of the dwelling. Reports with more than two scores still missing after merging and averaging were discarded. For reports with missing scores for two or fewer categories, the missing values were replaced by the average of the remaining categories. Finally, the scores were flipped so that a score of 1 corresponds to the lowest quality (TG3) and a score of 3 corresponds to the highest (TG1). This was done to make the results more intuitive. Table 4.1 provides an overview of the final condition attributes with their underlying checkpoints specified, as well as the non-condition attributes employed in the study.

Attribute	Type	Description
Building framework	Numeric	Condition of foundation, wall construction and exterior facades
Plot	Numeric	Condition of plot drainage, retaining walls, driveways, gardens and porch stairs
Windows	Numeric	Condition of all windows
Doors	Numeric	Condition of all doors
Roof	Numeric	Condition of roof construction and roofing
Exterior extensions	Numeric	Condition of balconies, railings, and terraces
Interior surfaces	Numeric	Condition of interior ceilings, walls, floors, stairs and surfaces
Bathroom	Numeric	Condition of sanitary equipment, furnishings, air treatment systems, floors, ceilings, walls, wiring harnesses, plumbing, drains, membranes, and ceilings of bathrooms and wet rooms
Kitchen	Numeric	Condition of kitchen floors, walls, ceilings, equipment, furnishings, plumbing, sanitation and air treatment
HVAC, sanitary	Numeric	Condition of heating systems, hot water systems, ventilation systems, air conditioning and sanitation
Large plot	Binary	Indicates whether plot size is above 500 square meters
Build year	Numeric	Build year of dwelling
Size	Numeric	Size of primary living space
Building type	Categorical	Either apartment (A), townhouse (TH), detached house (DH), or semi-detached house (SDH)
Region	Categorical	Administrative district of dwelling
Sale year	Numeric	Sale year of dwelling
Sale month	Numeric	Sale month of dwelling
UTM coordinates	Numeric	UTM x- and y-coordinates for exact location of dwelling

Table 4.1: Overview of all attributes employed in the study

4.1.1 Data merging and cleaning

The condition reports from Norsk takst and the general sales data from Ambita were merged by matching address information. The majority of apartments had insufficient address details to confidently match the correct condition report to the correct apartment unit, and are mostly left out of the study. The data was cleaned by discarding any of the following dwellings:

- Dwellings with likely erroneous entries for price or size. Dwellings with an abnormally high or low square meter price were discarded.
- Dwellings with multiple matching condition assessments for the same date. This was done to ensure the correct condition is matched with the correct price for all dwellings.

- Dwellings sold more than once within three months for more than double the first sale price.
- Dwellings lacking UTM coordinates.

Table 4.2 illustrates the process, and shows the exact number of entries removed for each check.

	Oslo	Bergen	Trondheim
Original size	7104	3308	1748
Abnormal size or price	47	18	12
Duplicated	400	315	59
Sold more than once	1	0	0
Missing location data	5	0	0
Final size	6651	2975	1677

Table 4.2: Number of dwellings removed at every step in the data cleaning process

The ten dwelling conditions were not chosen by us for this paper, but the selection was implicitly given by the data since these ten building elements were the ones for which we were able to extract the conditions for all the homes.

4.2 Data exploration

This section presents an exploratory data analysis for the Oslo data set. For brevity, exploration is only presented for Oslo since this is the largest data set and the main focus of the study.

Table 4.3 shows the sale year distribution of dwellings in Oslo, Bergen and Trondheim. We note that the majority of dwellings were sold in 2018 and that only a small fraction were sold in 2020.

Sale year	Oslo	Bergen	Trondheim
2016	598 (8.99%)	534 (17.95%)	344 (20.51%)
2017	1,906 (28.65%)	860 (28.91%)	454 (27.07%)
2018	2,283 (34.33%)	896 (30.12%)	521 (31.07%)
2019	1,825 (27.44%)	668 (22.45%)	346 (20.63%)
2020	39 (0.59%)	17 (0.57%)	12 (0.72%)

Table 4.3: Sale year distribution of dwellings in Oslo, Bergen and Trondheim

Figure 4.1 shows the distribution of the square meter price in NOK of dwellings in Oslo. Most dwellings are priced between NOK 20,000 and NOK 100,000 per square meter. We note that there are outliers, and that the distribution is approximately log-normal.

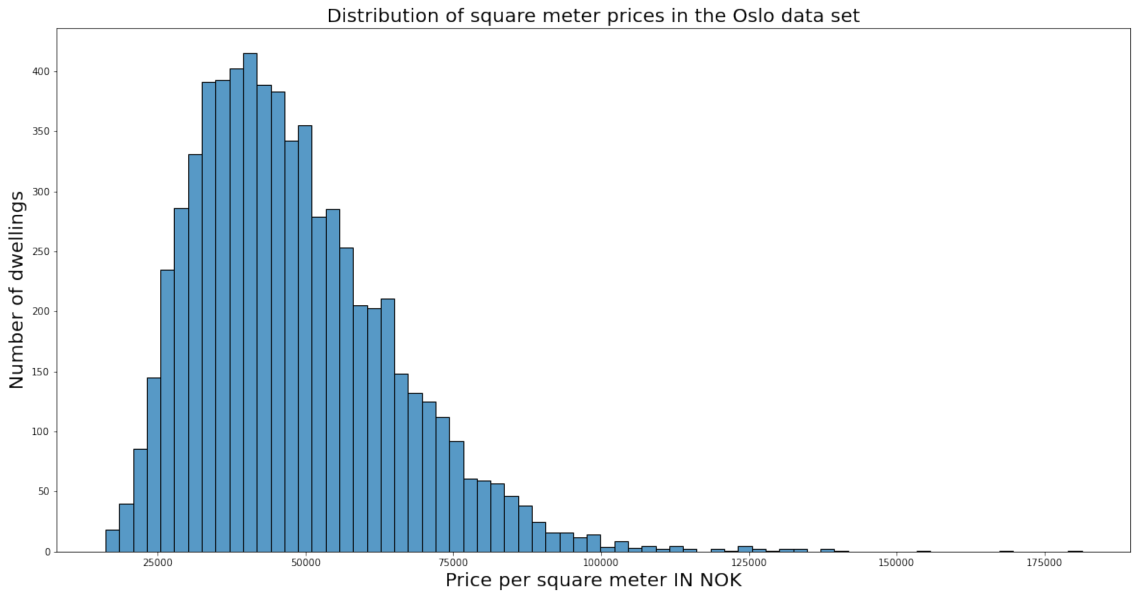


Figure 4.1: Square meter price distribution for dwellings in Oslo

Table 4.4 provides descriptive statistics for the numeric attributes of dwellings in Oslo. Similar tables for Bergen and Trondheim are available in appendix A. On average, dwellings in the data set are 49 years of age, and approximately 167 square meters in size. In terms of condition, the average dwelling scores approximately 2.5 and the 75th percentile is close to 3.0. This indicates that the condition attributes have distributions that are skewed toward better condition. An example of this can be seen in figure 4.2, which shows the distribution of scores for the condition of the bathroom. We observe that the frequency of the average dwelling conditions attributed to bathrooms has a skewed distribution. There are few homes with the lowest dwelling conditions for their bathrooms. Most homes have a dwelling condition above 2, with a peak at 3.

Attribute	Mean	Std	Min	25%	Median	75%	Max
Size	167.4	59.9	51.0	126.0	158.0	199.5	763.0
Build year	1969	29	1745	1955	1971	1986	2018
Building Framework	2.549	0.410	1.000	2.200	2.600	3.000	3.000
Plot	2.352	0.517	1.000	2.000	2.333	2.996	3.000
Windows	2.363	0.527	1.000	2.000	2.000	3.000	3.000
Doors	2.565	0.420	1.000	2.102	2.506	3.000	3.000
Roof	2.561	0.457	1.000	2.000	2.500	3.000	3.000
Exterior Extensions	2.559	0.528	1.000	2.000	3.000	3.000	3.000
Interior Surfaces	2.664	0.384	1.000	2.500	2.750	3.000	3.000
Bathroom	2.457	0.438	1.000	2.167	2.500	2.800	3.000
Kitchen	2.669	0.478	1.000	2.000	3.000	3.000	3.000
HVAC, Sanitary	2.481	0.454	1.000	2.000	2.500	3.000	3.000

Table 4.4: Descriptive statistics for numeric attributes in Oslo

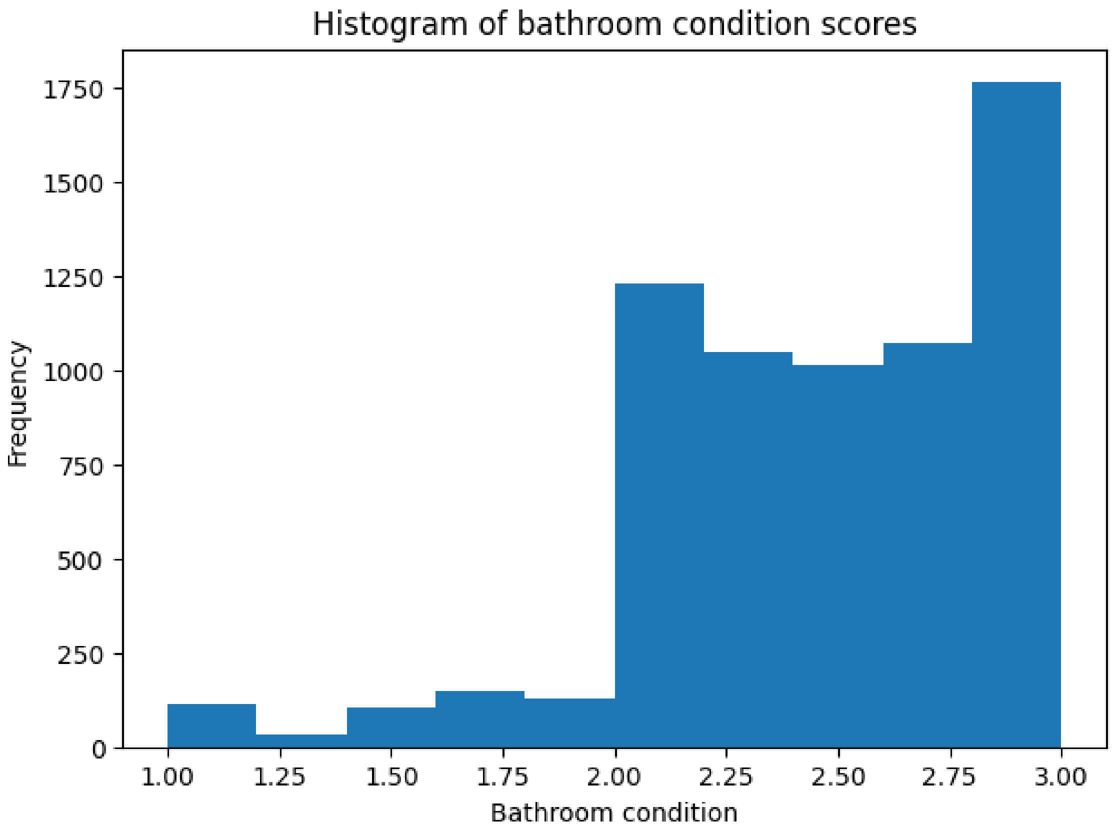


Figure 4.2: Distribution of bathroom condition scores in Oslo

Condition attributes correlation

Figure 4.3 shows the correlation among condition attributes and selected non-condition attributes, including the target variable.

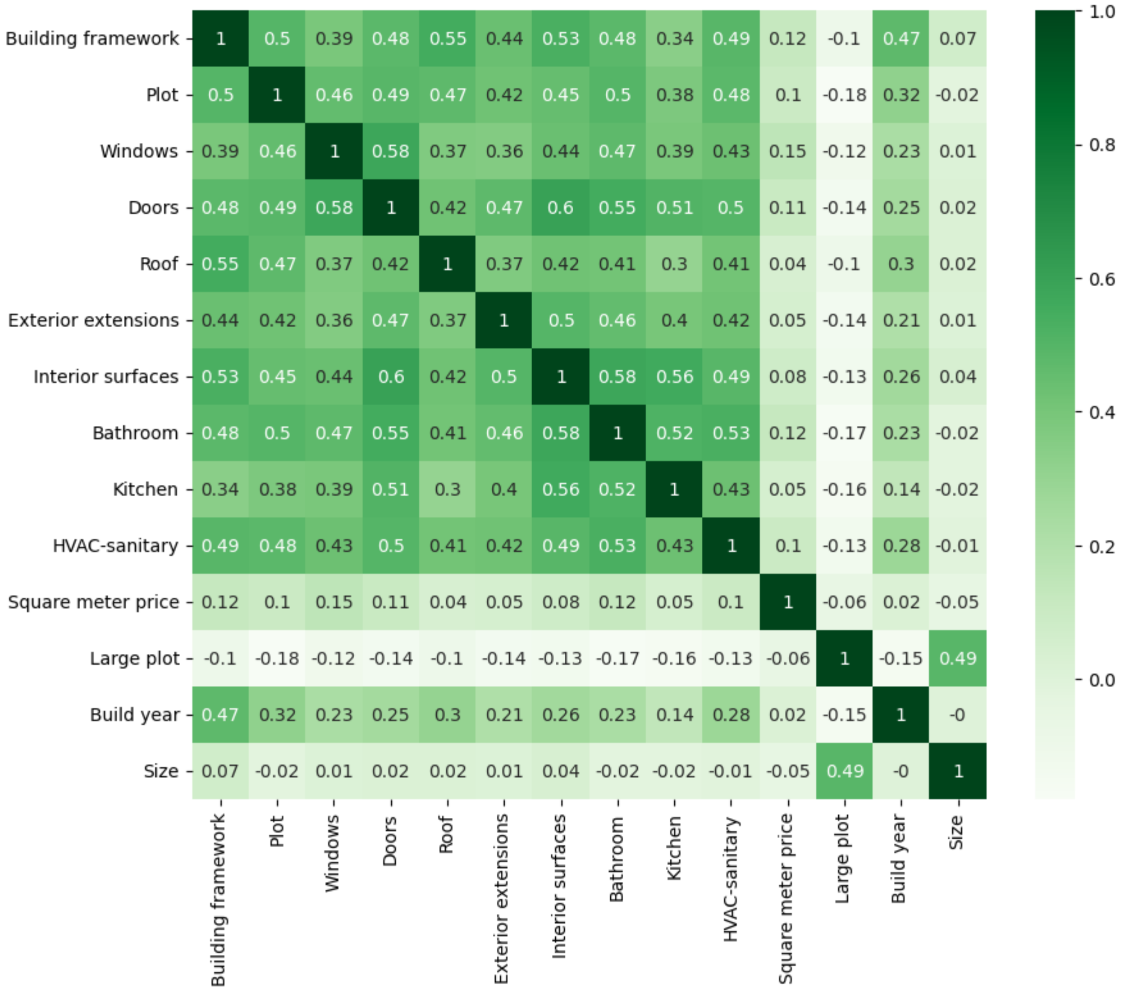


Figure 4.3: Heatmap displaying correlation between condition attributes and selected non-condition attributes, including the target variable. A number close to 1, or a dark green color, indicates high positive correlation, and a number close to -1, or a light color, indicates high negative correlation.

As seen from Figure 4.3, all condition attributes are positively correlated. This is reasonable, as one should not expect the condition of one attribute to improve as another deteriorates. We also note that all condition scores are positively correlated to the square meter prices. Additionally, there is no correlation between the size of dwellings and the condition attributes.

5 | Methodology

In order to assess the explanatory power of dwelling condition in AVMs, three models are used: a hedonic linear regression model, a gradient boosted decision tree known as XGBoost (short for eXtreme Gradient Boosting) and a support vector machine (SVM). This selection provides a variety of distinctly different modeling approaches, both in terms of linearity and non-linearity, as well as the underlying mathematical assumptions.

The models are first trained with and then without condition attributes. The experiment is first run for dwellings in Oslo, then separately for dwellings in Bergen and Trondheim. Bergen and Trondheim are included in the study as a basis of comparison between different urban areas in Norway, which can help to either increase confidence in the results or uncover discrepancies.

Before running the experiment, the data was randomly split into a training and test set. The test set was held out during training, and was only used to estimate out-of-sample performance. A 75%/25%-split was chosen based on the recommendation of Hastie et al. (2009).[3]

In order to isolate temporal effects in market prices, dummy variables for year and month of sale are included. Moreover, intercept district dummy variables are used to represent the location of dwellings. The district dummy variables are based on statistical districts defined by clustering dwellings on their UTM coordinates using the K-means clustering algorithm (Lloyd, 1982).

Dummy variables are also generated for the building type and district indicators, and any data transformations necessary in the model are performed. All models utilize the logarithm of the square meter price as the target variable, a transformation that is motivated by the distribution seen in Figure 4.1. The model is then trained using the training set, and evaluated using the test set. The root-mean-square error (RMSE), mean percentage error (MPE), mean absolute percentage error (MAPE), percentage of dwellings within 50% of the actual sale price and the percentage of dwellings within 10% of the actual sale price are noted.

Optimal hyperparameters are found empirically using k-fold cross-validation in conjunction with grid search for XGBoost and random search for the SVM. To analyze the explanatory power of dwelling condition in the machine learning models, a framework known as SHAP is utilized. Below are descriptions of the methods and techniques used in the study. The full mathematical derivations are complex, and the reader is encouraged to refer to the referenced papers for further details.

[3]Measuring the true predictive power of AVMs is often done with out of time predictions. As our primary focus is on the relative gains, we apply a cross validation approach.

5.1 Hedonic linear regression

Hedonic linear regression relies on the hedonic pricing theory outlined by Rosen (1974). The regression equation for dwelling i is given by:

$$ln(P_i) = \beta_0 + \sum \beta_k X_{ki} + \epsilon_i, \qquad \varepsilon \Rightarrow i.i.d. \tag{5.1}$$

where k is the number of attributes, X_{ki} is attribute k for dwelling i, β_k is the regression coefficient for attribute k, β_0 is the bias term and ϵ_i is the residual. Where the attributes consist of the ten dwelling conditions, size, a dummy variable for a large plot, size, dummy variables describing location, dummy variables for housing type, time-related dummies (sales year and sales month), dummy variables for the year of construction, and size-related dummy variables to account for non-linear relationships.

This study uses least absolute deviation (LAD) robust regression (Koenker and Bassett Jr, 1978) to estimate equation 5.1 based on the findings of Janssen et al. (2001) and Yoo (2001). LAD estimates the optimal regression coefficients in equation 5.1 by solving:

$$\arg\min_{\beta} \sum_{i=1}^{n} |P_i - \beta X_i| \tag{5.2}$$

where β is the coefficient vector, P_i is the true price, and X_i is the vector of characteristics for dwelling i. Dummy variables are introduced to the model where necessary.

5.2 Support vector machine

The SVM was introduced in 1995 and extended to regression in 1996 (Drucker et al., 1997). This study employs the Scikit-learn implementation for Python (Pedregosa et al., 2011).

The SVM finds a regression line by solving the primal optimization problem given by:

$$\min_{w,b,\zeta,\zeta^*} \frac{1}{2} w^T w + C \sum_{i=1}^{n} (\zeta_i + \zeta_i^*) \tag{5.3}$$

$$\text{subject to } y_i - w^T \phi(x_i) - b \leq \epsilon + \zeta_i, \tag{5.4}$$

$$w^T \phi(x_i) + b - y_i \leq \epsilon + \zeta_i^* \tag{5.5}$$

$$\zeta_i, \zeta_i^* \geq 0, i = 1, ..., n \tag{5.6}$$

where w is a vector of weights, ζ_i and ζ_i^* are slack variables, y_i is the target variable, $\phi(x_i)$ is a mapping of the input vector x to a feature space, b is the bias term, ϵ is the error tolerance threshold, n is the number of training examples and C is a free parameter controlling the strength of the penalization of erroneous prediction.

The primal problem can be rewritten in its corresponding dual form given by:

$$\min_{\alpha,\alpha^*} \frac{1}{2} (\alpha - \alpha^*)^T (\alpha - \alpha^*) K(x_i, x_j) + \epsilon \sum_{i=1}^{n} (\alpha_i + \alpha_i^*) + \sum_{i=1}^{n} y_i (\alpha_i - \alpha_i^*) \tag{5.7}$$

$$\text{subject to } \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) = 0, \tag{5.8}$$

$$\alpha_i \geq 0, \alpha_i^* \leq C, i = 1, ..., n \tag{5.9}$$

where $K(x_i, x_j)$ is a kernel function and α, α^* are the vectors of dual coefficients. After solving the dual problem, the final regression function can be expressed by:

$$f(x) = \sum_{i \in SV} (\alpha_i - \alpha_i^*) K(x_i, x_j) + b \tag{5.10}$$

where b can be calculated according to

$$b = y_i - \sum_{i=1}^{n} \alpha_i^* K(x_i, x_j) - \epsilon, \forall i \text{ such that } 0 < \alpha_i^* < C \tag{5.11}$$

The SVM is sensitive to differences in magnitude of the input data. As a result, the input attributes were scaled to the range of $[0, 1]$, as described by J.-H. Chen et al. (2017).

5.3 XGBoost

XGBoost (short for eXtreme Gradient Boosting) is a highly efficient and optimized implementation of gradient boosted decision trees (T. Chen and Guestrin, 2016). In this study, the native Python implementation of XGBoost[4] was used.

XGBoost builds an ensemble of regression trees. The predicted output for a given training example ($x_i \in \mathbb{R}^m$, $y_i \in \mathbb{R}$) is the sum of the leaf weights for all trees in the example. This is described mathematically as:

$$\hat{y}_i = \phi(x_i) = \sum_{k=1}^{K} f_k(x_i), f_k \in \mathcal{F} \tag{5.12}$$

where $\mathcal{F} = \{f(x) = w_{q(x)}\}(q : \mathbb{R}^m \to T, w \in \mathbb{R}^T)$ is the space of regression trees. q refers to a specific tree structure that maps an example to one of T leaf nodes. w refers to the weights of the leaf nodes in the tree. Each f_k thus corresponds to the weight of the leaf node that is reached when traversing the independent tree structure q for the given example x.

To build an optimal regressor, XGBoost minimizes the objective function:

$$L^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y}^{(t-1)} + f_{(t)}(x_i)) + \Omega(f_t) \tag{5.13}$$

$$\text{where } \Omega(f_t) = \gamma T + \frac{1}{2}\lambda \|w\|^2 \tag{5.14}$$

where $L^{(t)}$ represents the objective value at the t-th iteration, l is a convex differentiable loss function, y_i is the true output, $y_i^{(t-1)}$ is the prediction of the $(t-1)$-th decision tree and $f_{(t)}(x_i)$ is the output of the t-th decision tree. $\Omega(f_t)$ is a regularization term, in which T is the number of leaves in the tree, γ is a pruning factor, λ is the regularization factor and w are the output values of the tree.

To reduce mathematical complexity, the loss function is approximated by a second-order Taylor expansion. To minimize, the loss function is differentiated and set equal to zero. The resulting optimal output value of a leaf j is:

$$w_j^* = -\frac{\sum_{i \in I_j} g_i}{\sum_{i \in I_j} h_i + \lambda} \tag{5.15}$$

[4] https://xgboost.readthedocs.io/

where I_j is the set of training instances in leaf j, and g_i and h_i are the first and second order gradients of the loss function, respectively.

The measure used to find the optimal splitting feature for a tree is called similarity and is given by the formula:

$$\mathcal{L}_{split} = \frac{1}{2}[\frac{(\sum_{i \in I_L} g_i)^2}{\sum_{i \in I_L} h_i + \lambda} + \frac{(\sum_{i \in I_R} g_i)^2}{\sum_{i \in I_R} h_i + \lambda} - \frac{(\sum_{i \in I} g_i)^2}{\sum_{i \in I} h_i + \lambda}] - \gamma \tag{5.16}$$

where L and R represent the left and right node after splitting, respectively.

5.4 SHAP

SHAP (SHapley Additive exPlanations) is a game-theoretic approach that can be used to explain the output of any machine learning model. SHAP uses the concept of Shapley values (Shapley, 1953) to calculate the importance of an input feature according to:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!}[f_{S \cup \{i\}}(X_{S \cup \{i\}}) - f_S(X_S)] \tag{5.17}$$

where ϕ_i is the Shapley value of feature i, F is the set of all features, S is any subset of F not containing feature i, $f_{S \cup \{i\}}(X_{S \cup \{i\}})$ is the regression prediction using both feature i and the subset S and $f_S(X_S)$ is the regression prediction using only feature subset S.

This study utilizes the SHAP Python package (Lundberg and Lee, 2017) to calculate feature importance. The package calculates global feature importance according to:

$$I_i = \frac{\sum_{j=1}^{n} |\phi_i^j|}{n} \tag{5.18}$$

where I_i is the global importance of attribute i, ϕ_i^j is the SHAP value of attribute i in training example j and n is the total number of training examples.

Although SHAP values provide a unified method of explaining any machine learning model, it is important to keep in mind that such explanations only show that a feature provides explanatory power to the model, and does not necessarily say anything about causality. Causal effects are complex and machine learning models are likely to suffer from correlations between included features and unobserved, true causal effects.

Additionally, regularized models, such as XGBoost and the SVM, will often rely on as few features as possible to avoid overfitting during training. In the case of correlated features, the model may end up identifying a feature as an important predictor because it summarizes multiple other correlated features. For this reason, SHAP values are only used in this paper to examine explanatory power, not causality.

6 | Results and Discussion

This chapter presents and discusses the results of the study. The difference in predictive performance with and without condition attributes is analyzed, followed by an analysis of model interpretations. The primary focus is on the results for dwellings in the Oslo data set, and results for Bergen and Trondheim are commented on for robustness.

6.1 Model performance

Model	Location	Condition	RMSE	MPE	MAPE	50%	10%
LR	Oslo	☐	**9368.90**	1.470	12.83	98.44%	50.99%
		☑	9402.84	**1.205**	**12.26**	**98.50%**	**52.50%**
	Bergen	☐	6372.40	1.855	13.83	97.98%	**49.06%**
		☑	**6052.45**	**1.644**	**13.19**	**98.39%**	48.39%
	Trondheim	☐	6352.88	2.165	13.43	97.86%	48.57%
		☑	**6204.51**	**1.439**	**12.56**	**98.57%**	**54.29%**
SVM	Oslo	☐	**9516.47**	1.693	13.18	**98.62%**	50.45%
		☑	9586.79	**1.313**	**12.59**	98.32%	**51.59%**
	Bergen	☐	6487.40	1.590	13.97	97.98%	47.58%
		☑	**6136.81**	**1.329**	**13.41**	**98.39%**	**48.79%**
	Trondheim	☐	6587.25	1.849	13.85	97.62%	50.48%
		☑	**6335.93**	**1.474**	**13.04**	**98.33%**	**50.71%**
XGBoost	Oslo	☐	9304.98	**2.899**	12.99	98.44%	50.81%
		☑	**9192.79**	3.057	**12.55**	**98.56%**	**52.14%**
	Bergen	☐	6368.57	3.454	14.32	97.98%	47.85%
		☑	**6078.28**	**3.444**	**13.72**	**98.52%**	**49.19%**
	Trondheim	☐	6509.02	3.886	13.71	97.14%	51.19%
		☑	**6363.82**	**3.223**	**13.04**	**97.62%**	**54.05%**

Table 6.1: Test set performance for the linear regression (LR), XGBoost and SVM models with and without condition for dwellings in Oslo, Bergen and Trondheim. The best result for each city is highlighted in bold.

Table 6.1[5] presents the out-of-sample performance results for all models with and without condition attributes in all cities. All models have a small but observable decrease of similar magnitude in MAPE, ranging from a decrease of 3.39% for XGBoost in Oslo to 6.48% for the linear regression model in Trondheim. The remaining metrics are also mostly improved by the inclusion of condition attributes, with the exceptions of the RMSE for the linear regression and SVM models, the MPE of the XGBoost model, the number of dwellings predicted within 50% of actual sale price for the SVM and the number of dwellings predicted within 10% of actual sale price for the linear regression model in Oslo. This can likely be attributed to the fact that the metrics are sensitive to outliers, which are more

[5] The reason why the SVM and XGBoost do not systematically do better than the LR is that we have imposed the same limitation to the SVM and the XGBoost as the Linear regression. Especially related to time and location, this gives lower explanatory power. We made these choice to make the results more comparable and thus more interpretable.

prominent in the Oslo data set.

It is evident that all models benefited in terms of predictive accuracy from the inclusion of condition attributes. The small but observable improvement in several metrics in all three regions suggests that dwelling condition contributes additional explanatory power not already present in conventionally considered attributes such as age, location and size. The results also indicate that linear and non-linear models may benefit on a similar magnitude in terms of predictive accuracy from the inclusion of condition attributes. The size of the improvement was in line with our expectations.

6.2 Model interpretations

The degree to which dwelling condition provides additional explanatory power can be further explored by examining the coefficients of the linear regression model and the feature importance of the XGBoost and SVM models.

Attribute	Coefficient		
	Oslo	Bergen	Trondheim
Building framework	0.0322 ***	0.0117	0.0883 ***
Plot	0.0198 ***	0.0147	0.0415 ***
Windows	0.0134 **	0.0069	0.0338 ***
Doors	0.0067	-0.0002	-0.0146
Roof	-0.0085	0.0172	0.0046
Exterior extensions	0.0007	-0.0077	0.0145
Interior surfaces	0.0338 ***	0.0441 ***	-0.0024
Bathroom	0.0382 ***	0.0337 ***	0.0565 ***
Kitchen	0.0203 ***	0.0186 **	0.0063
HVAC, sanitary	0.0030	0.0586 ***	0.0394 ***
Dwelling attributes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Location FE	Yes	Yes	Yes

Table 6.2: Linear regression coefficients for condition attributes in Oslo, Bergen, and Trondheim. *** indicates significance at 1% and ** indicates significance at 5%.The model performance is already described in Table 6.1.Dwelling attributes (Size, large plot, dwelling type built year), Time FE (sold year, sold month), Location FE (location). The full regression results for Oslo is presented in Appendix Table C.0.1

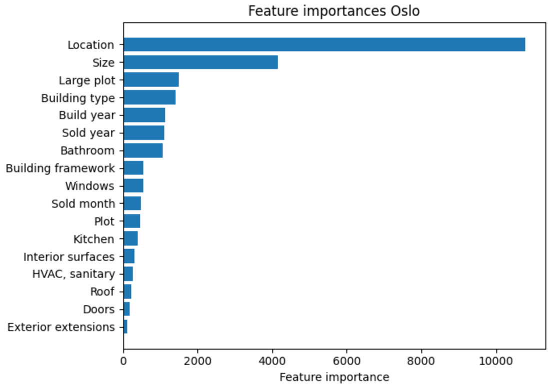
Table 6.2 shows the regression coefficients for the condition attributes in the linear regression model for dwellings in Oslo, Bergen and Trondheim. Regression coefficients for all variables in the model are provided in table C.0.1. For dwellings in Oslo, six out of the ten condition attributes are deemed statistically significant at 5%, and all significant attributes have positive coefficients. Positive coefficients implys that better condition gives a higher price. In terms of magnitude, the bathroom condition is deemed the most important, while the condition of the doors, roof, HVAC and sanitary equipment, and exterior extensions are all deemed to be statistically insignificant. Bergen and Trondheim have four and five out of the ten condition attributes statistically significant at 5%, respectively. The condition of the bathroom also has one of the largest coefficients of the condition attributes in both data sets.Some of the non-significant coefficients are negative, but this is not uncommon in a simple linear model with such a high correlation between the dwelling condition. This is a significant reason why we proceed to apply non-linear models.

Similar patterns in the importance of condition attributes and their relationship with the price were observed in XGBoost and the SVM. Figure 6.1 shows the feature importances and beeswarm plots for XGBoost in Bergen and Oslo and the SVM in Oslo. The importance of an attribute is determined by its mean absolute SHAP value for all training examples. A higher importance means that the attribute provides more information when making a prediction, and the size of the bar gives an indication of that attribute's relative importance. In the beeswarm plots, the SHAP value of every condition attribute in each training sample is plotted along the x-axis. The color of the dot indicates the value of the condition attribute in that training sample. In this case, blue dots indicate a worse condition, whereas red dots indicate a better condition.

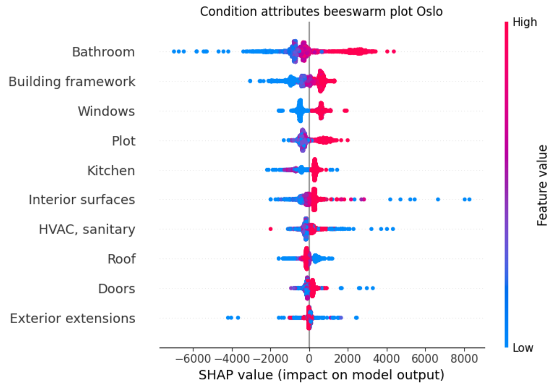
Figures 6.1a, 6.1c and 6.1e show, as one would expect, that location and size dominate in terms of importance. The condition of the bathroom has an impact of a magnitude similar to that of the remaining non-condition attributes, while the impact of the other condition attributes are the next tier down. Altogether, the ten dwelling condition significantly contribute to the price prediction in the various models.

The condition of the bathroom is reported to have an impact similar to that of the remaining non-condition attributes, and the other condition attributes are next tier down in terms of impact. Additionally, the impact of the condition of the roof, doors and exterior extensions are consistently reported to be low. It's worth noting that the interpretation of SHAP values for feature importance may encounter difficulties in assigning true importance when there is a high correlation between the features. This can, for example, manifest as inconsistencies between the values reported for different models. Tree-based models like Boosting, which we have included, are more resilient to correlated features. We also observe significant consistency in the results between the two nonlinear models, further supporting model interpretation.

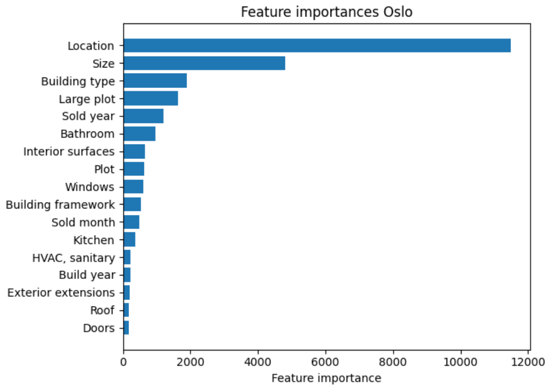
In the terms of the determined relationship with the price, figures 6.1b, 6.1d and 6.1f show that both models have determined a clear relationship, in which a better condition results in a higher price for the condition attributes with the highest importance. This can be seen from the clustering of blue dots to the left and red dots to the right for these attributes. For the less important condition attributes, the dots are more dispersed, and the relationship is less clear. Figures 6.1e and 6.1f also illustrate that there are variations in the ranking of feature importances across cities. The full set of model interpretations for Bergen and Trondheim are omitted for brevity, but they follow the same pattern.



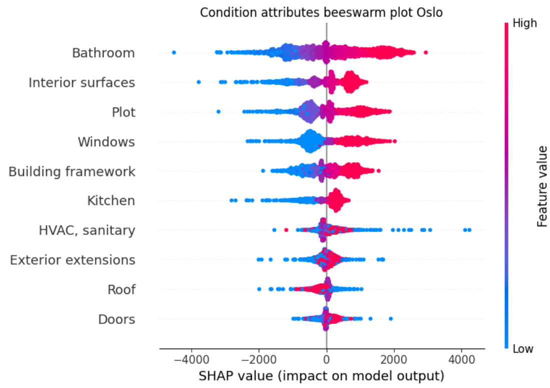
(a) XGBoost mean absolute SHAP value for all condition attributes in Oslo



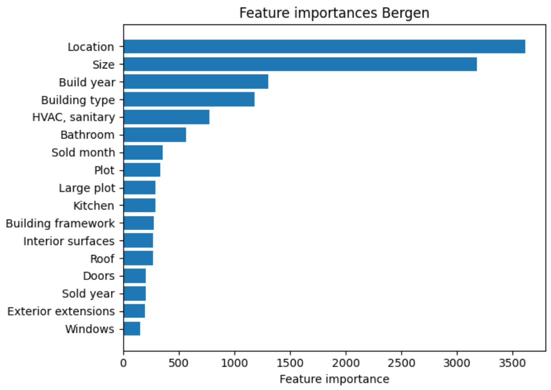
(b) XGBoost beeswarm plot for condition attributes in Oslo.



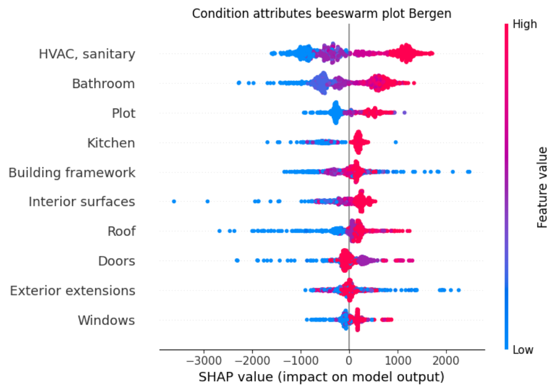
(c) SVM mean absolute SHAP value for all attributes in Oslo



(d) SVM beeswarm plot for condition attributes in Oslo



(e) XGBoost mean absolute SHAP value for all condition attributes in Bergen



(f) XGBoost beeswarm plot for condition attributes in Bergen.

Figure 6.1: XGBoost and SVM model interpretation plots in Oslo. Figures 6.1a and 6.1c illustrates the relative importance of the attributes, with larger bars indicating higher importance. Figures 6.1b and 6.1d illustrates the identified relationship between price and the condition attributes. The SHAP value represents the estimated impact on the square meter price in NOK. For each attribute, the dots represent a dwelling in the data set. The color of the dot indicates the condition of that attribute, with more blue dots indicating worse condition. Clustering of blue dots to the left and red dots to the right indicate a positive relationship, i.e., a better condition results in a higher price.

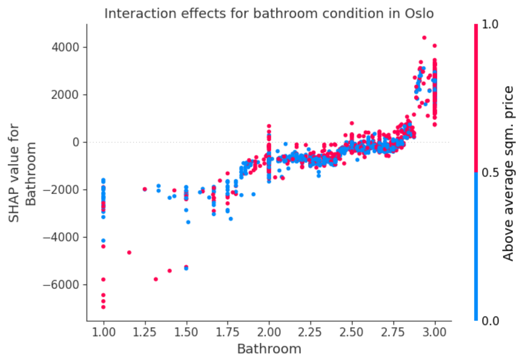
For Oslo, we see this relationship quite clearly for Bathroom, Building framework, Windows, plot, and Kitchen in both XGBoost and SVM. For Interior surfaces, we observe clear clustering in SVM, while in XGBoost, we have some blue points far to the right. One explanation could be that these are renovation projects. For HVAC, sanitary, Roof, Doors, and Exterior extensions, the color relationships appear less clear. When combined with the low weight attributed to dwelling conditions of these building elements according to feature importance, they are given little weight and have an unclear explanation in price prediction. For Bergen, HVAC and sanitary, on the other hand, have high feature importance and show fine clustering. This may indicate that this variable is used differently by appraisers in Bergen compared to Oslo. For example, there might be a clearer correlation with the condition of the bathroom in Bergen. Once again, there are clear similarities to the linear models. The results strongly suggest that homebuyers assign little importance to Roof, Doors, and Exterior extensions when bidding on and buying a home.

There are three important takeaways from the analysis of the model interpretations across the three cities. Firstly, there is consistency between the linear and non-linear models regarding which condition attributes are ranked high in terms of feature importance, and what the relationship is between these attributes and the price. Secondly, this consistency between models is observed in each region. Thirdly, the identified relationship between condition attributes and price is consistent with the findings of Kain and Quigley (1970), Ooi et al. (2014) and Mathur (2019). These takeaways are further evidence that the performance gain observed when condition attributes were included is not by chance, and that dwelling condition provides additional explanatory power to linear and non-linear AVMs.

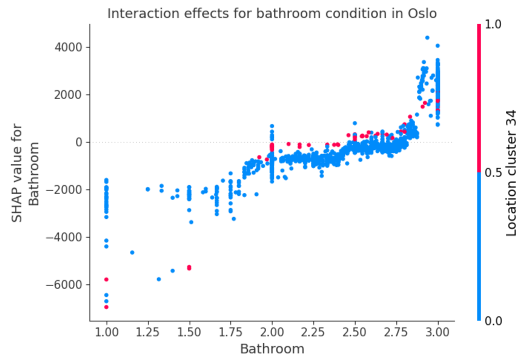
It appears that homebuyers pay the most attention to the condition rating of the housing elements that are visually easy to assess when walking around the property. Homebuyers seem to consider the technical descriptions in the sales documents to a lesser extent, even though these elements can be just as, and often more expensive to deal with.

SHAP also allows for a deeper analysis of the condition attributes and price. Figure 6.2 shows the relationship between the condition of the bathroom and building framework, the two condition attributes with the highest feature importance, and the price for dwellings in Oslo, as determined by the XGBoost model. Each dot corresponds to a dwelling in the data set. The dwellings are plotted according to the condition score on the x-axis, and the determined impact that condition score has on the predicted price on the y-axis. The dwellings are also colored according to a second attribute to illustrate interaction effects. Figures 6.2a and 6.2c colors dots red if the dwelling is above the average square meter price in Oslo, and blue if below. Figures 6.2b and 6.2d colors dots red if the dwelling is located within a given statistically generated cluster, and blue if not.

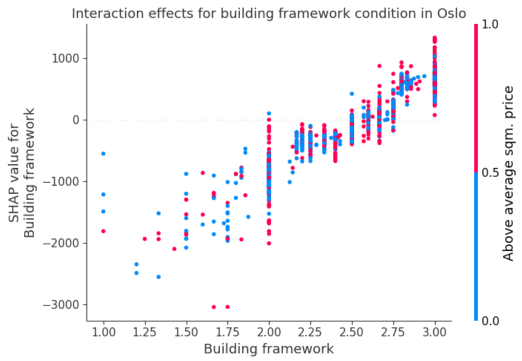
There are some further insights to be gained from examining the figures. Firstly, they are further evidence that XGBoost has determined a clear relationship, in which a better condition results in a higher price for both attributes. This is illustrated by the distinctive, upward sloping shape of the clustering of dots as the condition improves. Secondly, they illustrate that the relationship is not equal for both attributes. While the relationship between the price and the condition of the building framework seen in figures 6.2c and 6.2d seems to be fairly linear, the relationship between the price and the condition of the bathroom is more complex. The trend in figures 6.2a and 6.2b indicates that there is a markedly sharp drop in price when the bathroom condition is slightly degraded from close to 3.0 to 2.75, as can be seen from the sharp "dip" in the general trend in this range. The price does not seem to be impacted as much in the range of 2.75 to 2.0, in which the dots tend to follow a flat, linear shape. Finally, the trend indicates that the price seems to again fall at a steeper rate when the condition moves beyond 2.0 towards 1.0, in which there is again a sharp "dip".



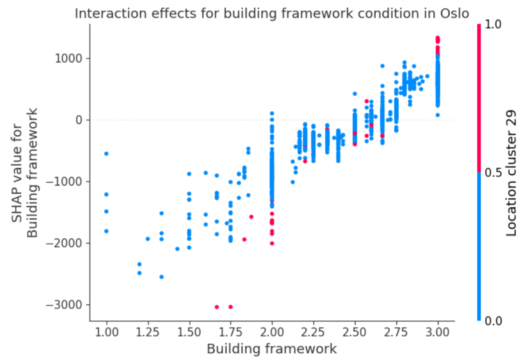
(a) Bathroom condition and square meter price interaction. The dots are colored red if the corresponding dwelling has a square meter price above the average of 48,000 NOK, and blue otherwise



(b) Interaction between bathroom condition and one of the statistically generated district clusters. The dots are colored red if the corresponding dwelling is present in the district, and blue otherwise



(c) Building framework condition and square meter price interaction. The dots are colored red if the corresponding dwelling has a square meter price above the average of 48,000 NOK, and blue otherwise



(d) Interaction between building framework condition and one of the statistically generated district clusters. The dots are colored red if the corresponding dwelling is present in the district, and blue otherwise

Figure 6.2: Relationship between the price and the bathroom and building framework condition attributes. Each dot represents a training example. The x-axis holds the value of the condition attribute for that training example, with worse condition to the left. The y-axis holds the SHAP value, which is the estimated impact on the square meter price in NOK. The dots are colored according to binary variables to illustrate interaction effects.

Thirdly, the figures allow for an examination of interaction effects with other variables. Figures 6.2b and 6.2d highlights the interaction effects between the condition attributes and location. The statistically defined cluster with the strongest interaction for the attribute is used as an example. Figure 6.2b indicates that dwellings located in location cluster 34 commands a higher price for a given bathroom condition in the range of 2.0-2.75. This can be seen from the red dots being higher on the y-axis in this range. Similarly, figure 6.2d indicates that dwellings located in location cluster 29 commands a lower price for a given building framework condition in the range of 1.5-2.75, as can be seen by the red dots being lower on the y-axis in this range. Figures 6.2a and 6.2c indicates that the price impact of the condition is not dependent on the general price level, as can be seen from the dispersion of red dots along the y-axis in both figures.

Lastly, the greater dispersion of the dots for the grades between 2.0 and 1.0 indicates that the model is less accurate for samples with condition scores in this interval. This is hypothesized to be a consequence of the skewed distribution of condition scores towards higher values, thereby making it harder for the model to determine the relationship between condition scores in this range and price. Overall, these plots illustrate that the relationship between dwelling condition and price is likely complex; therefore, further investigation on the subject may lead to additional insights.

7 | Conclusion

Real estate is a crucial asset class with significant implications for individuals, institutions, and governments alike. Accurately valuing properties is important for a variety of reasons, from aiding prospective buyers and mortgage lenders to informing tax assessments. The value of a home is influenced by a multitude of characteristics, making it a complex task to determine its true worth. These characteristics include factors such as the home's location, size, age, and condition, as well as any unique features or amenities it may possess. Properly accounting for these factors is essential for achieving accurate valuations.

In recent years, computer-assisted automated valuations have emerged as a popular and practical tool for valuing properties. These models rely on sophisticated algorithms that consider a range of variables to predict a property's value. To achieve high levels of accuracy, it is important to identify variables with significant explanatory power. Using machine learning techniques to develop automated valuation models (AVMs) can also provide valuable insights into the relationship between variables. Explanatory AI tools such as SHAP can help to further elucidate these connections, enabling a deeper understanding of the factors that drive property values. This information can be valuable for both buyers and sellers, as well as appraisers and researchers seeking to better understand the real estate market.

This study fills a gap in the literature by exploring the explanatory power and price importance of dwelling-condition attributes in AVMs. To accomplish this, the study utilizes detailed dwelling-condition assessment reports and trains and evaluates three AVM models – a hedonic linear regression model, a gradient-boosted decision tree, and a support-vector machine – to predict the sale price of properties in three regions in Norway. These models are widely used in AVM literature and provide different approaches to modeling, both in terms of linearity and non-linearity, as well as the underlying mathematical assumptions. The study analyzes the performance gains and model interpretations resulting from the inclusion of condition attributes to assess the importance of these attributes for price determination.

The inclusion of dwelling-condition attributes led to performance gains across all models and regions on several metrics, with similar magnitude improvements observed across all models. Moreover, there was consistency among all models in terms of the impact of condition attributes on predictions, with better condition leading to higher prices. This consistency, coupled with the consistent performance gains, supports the conclusion that dwelling condition has explanatory power in AVMs.

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A Descriptive statistics for numerical attributes in Bergen and Trondheim

A.1 Descriptive statistics for numerical attributes in Bergen

Attribute	Mean	Std	Min	25%	Median	75%	Max
Size	146.3	55.60	51.00	110.0	139.0	177.0	520.0
Build year	1967	37	1685	1954	1971	1993	2017
Building Framework	2.642	0.371	1.000	2.375	2.750	3.000	3.000
Plot	2.337	0.514	1.000	2.000	2.000	3.000	3.000
Windows	2.437	0.539	1.000	2.000	2.500	3.000	3.000
Doors	2.703	0.387	1.000	2.500	3.000	3.000	3.000
Roof	2.540	0.446	1.000	2.000	2.500	3.000	3.000
Exterior Extensions	2.609	0.491	1.000	2.000	3.000	3.000	3.000
Interior Surfaces	2.707	0.366	1.000	2.500	2.769	3.000	3.000
Bathroom	2.361	0.473	1.000	2.000	2.333	2.778	3.000
Kitchen	2.726	0.458	1.000	2.500	3.000	3.000	3.000
HVAC, Sanitary	2.495	0.415	1.000	2.000	2.500	3.000	3.000

Table A.1.1: Descriptive statistics for numeric attributes in Bergen

A.2 Descriptive statistics for numerical attributes in Trondheim

Attribute	Mean	Std	Min	25%	Median	75%	Max
Size	162.3	54.59	52.00	124.0	151.0	190.0	444.0
Build year	1973	24	1842	1961	1973	1988	2018
Building Framework	2.702	0.339	1.250	2.400	2.800	3.000	3.000
Plot	2.606	0.373	1.000	2.333	2.667	3.000	3.000
Windows	2.530	0.481	1.000	2.000	2.712	3.000	3.000
Doors	2.690	0.412	1.000	2.500	3.000	3.000	3.000
Roof	2.707	0.395	1.000	2.500	3.000	3.000	3.000
Exterior Extensions	2.705	0.445	1.000	2.407	3.000	3.000	3.000
Interior Surfaces	2.708	0.430	1.000	2.333	3.000	3.000	3.000
Bathroom	2.454	0.409	1.000	2.000	2.500	2.750	3.000
Kitchen	2.780	0.385	1.000	2.667	3.000	3.000	3.000
HVAC, Sanitary	2.664	0.425	1.000	2.331	3.000	3.000	3.000

Table A.2.2: Descriptive statistics for numeric attributes in Trondheim

B | Maps of areas used in the study

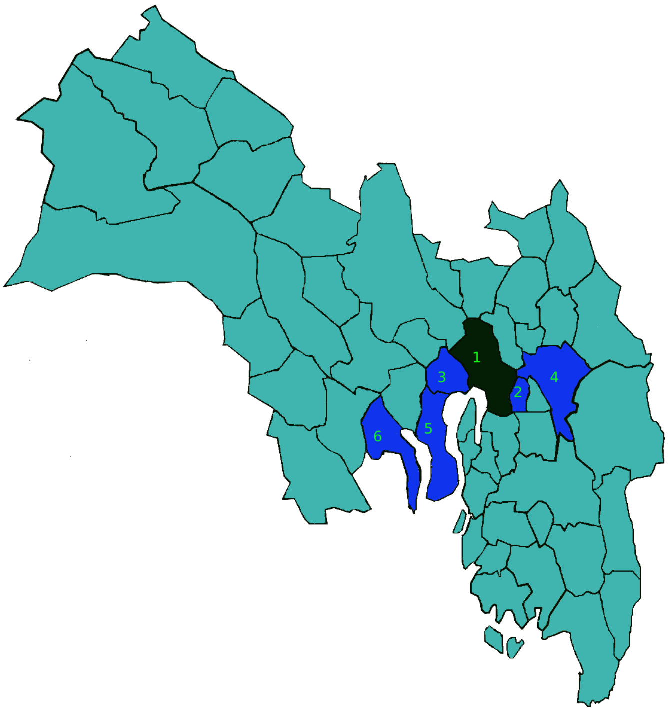

Figure B.0.1: Oslo and Viken county, with the main focus area of study highlighted. The city of Oslo is marked in black. The numbering of the municipalities is as follows: 1. Oslo, 2. Lørenskog, 3. Bærum, 4. Lillestrøm, 5. Asker, 6. Drammen

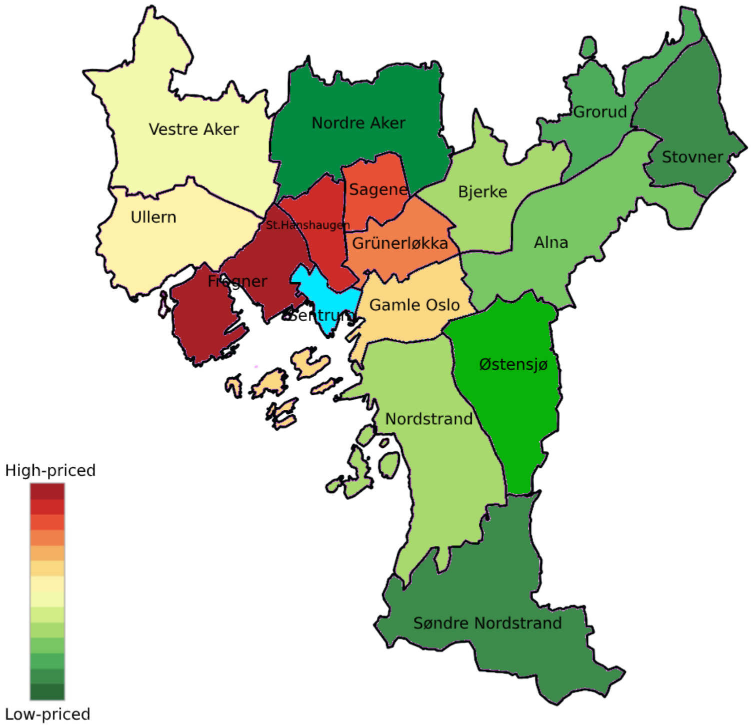

Figure B.0.2: Map of boroughs in Oslo, color coded according to average dwelling square meter price. Square meter prices are retrieved from Oslo municipality fact database (OsloMunicipality, 2021). There was no price information provided for the centre of Oslo, colored in blue. Red color indicates higher prices, green color indicates lower prices. The prices range from around NOK 43,000 to NOK 90,000.

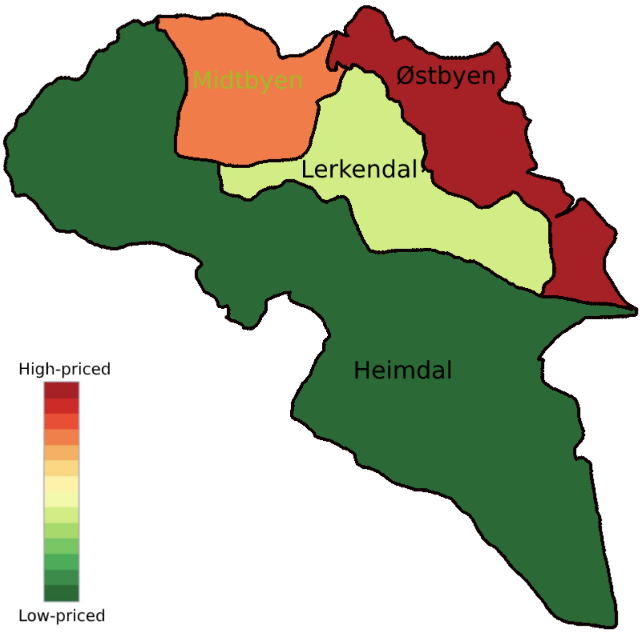

Figure B.0.3: Map of boroughs in Trondheim, color coded according to average dwelling square meter price. Prices range from around 34,000 NOK to around 51,000 NOK and are for last quarter of 2020. Prices are retrieved from Krogsveen (2021)

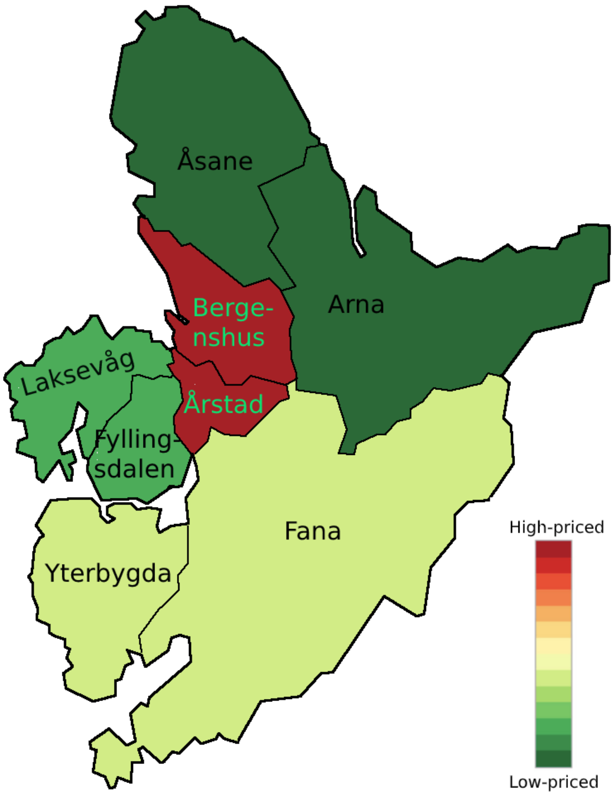

Figure B.0.4: Map of boroughs in Bergen, color coded according to average dwelling square meter price. Prices range from around NOK 30,000 to around NOK 50,000 and are for 2020. Prices are retrieved from Marschhäuser (2021).

C | Regression results

Table C.0.1: Full regression results for Oslo

	coef	std err	P> |z|
const	10.6523	0.038	0.000
Building fwk.	0.0322	0.008	0.000
Plot	0.0198	0.006	0.000
Windows	0.0134	0.005	0.014
Doors	0.0067	0.008	0.375
Roof	-0.0085	0.006	0.154
Exterior ext.	0.0007	0.005	0.883
Interior surf.	0.0338	0.008	0.000
Bathroom	0.0382	0.007	0.000
Kitchen	0.0203	0.006	0.001
HVAC	0.0030	0.006	0.628
size	-0.0017	0.000	0.000
large plot	0.0755	0.006	0.000
location 0	-0.2045	0.019	0.000
location 10	0.2108	0.021	0.000
location 11	0.4482	0.019	0.000
location 12	-0.1235	0.023	0.000
location 13	-0.4448	0.018	0.000
location 14	0.1430	0.019	0.000
location 15	-0.1195	0.019	0.000
location 16	0.2151	0.020	0.000
location 17	0.1128	0.019	0.000
location 18	-0.2310	0.023	0.000
location 19	0.2947	0.019	0.000
location 2	-0.4052	0.018	0.000
location 20	-0.2643	0.019	0.000
location 21	-0.0948	0.025	0.000
location 22	0.0132	0.020	0.504
location 23	-0.4757	0.019	0.000

	coef	std err	P> |z|
location 24	-0.0922	0.024	0.000
location 25	-0.0774	0.021	0.000
location 26	0.5689	0.030	0.000
location 27	-0.2398	0.022	0.000
location 28	0.3271	0.021	0.000
location 29	0.4572	0.020	0.000
location 3	0.2460	0.021	0.000
location 30	0.2106	0.019	0.000
location 31	0.0509	0.020	0.012
location 32	0.3408	0.020	0.000
location 33	-0.0961	0.021	0.000
location 34	0.4700	0.018	0.000
location 35	-0.2471	0.021	0.000
location 36	-0.3310	0.034	0.000
location 37	0.2976	0.019	0.000
location 38	0.0022	0.023	0.925
location 39	-0.1175	0.022	0.000
location 4	0.2967	0.019	0.000
location 5	0.3196	0.020	0.000
location 6	-0.0509	0.020	0.010
location 7	-0.0306	0.019	0.110
location 8	-0.5271	0.020	0.000
location 9	-0.2330	0.021	0.000
apartment block	-0.0357	0.027	0.181
detached house	0.1082	0.007	0.000
semi-detached house	0.0408	0.007	0.000
sold year 2017	0.0778	0.009	0.000
sold year 2018	0.0814	0.008	0.000
sold year 2019	0.1304	0.009	0.000

	coef	std err	P> |z|
sold year 2020	0.1041	0.032	0.001
sold month 10	0.0267	0.011	0.015
sold month 11	0.0286	0.011	0.009
sold month 12	0.0358	0.011	0.001
sold month 2	-0.0182	0.011	0.109
sold month 3	0.0083	0.012	0.484
sold month 4	-0.0067	0.012	0.563
sold month 5	0.0119	0.012	0.308
sold month 6	0.0295	0.011	0.005
sold month 7	0.0247	0.010	0.018
sold month 8	0.0281	0.010	0.007
sold month 9	0.0326	0.011	0.003
built 1950-1970	-0.1449	0.011	0.000
built 1970-1990	-0.1299	0.011	0.000
built 1990-2000	-0.0964	0.013	0.000
built 2000-2010	-0.0416	0.012	0.001
built <1950	-0.0983	0.012	0.000
size 110-130	-0.1191	0.022	0.000
size 130-150	-0.1480	0.025	0.000
size 150-170	-0.1663	0.028	0.000
size 170-190	-0.1849	0.031	0.000
size 190-210	-0.1966	0.035	0.000
size 210-250	-0.2103	0.040	0.000
size 250-300	-0.2276	0.049	0.000
size 300-350	-0.1588	0.061	0.009
size 350-400	-0.0338	0.074	0.649
size 70-90	-0.0300	0.021	0.150
size 90-110	-0.0872	0.020	0.000
size >400	0.2524	0.102	0.013