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The Impact of External, Environmental, and Neighbourhood Factors on Housing Prices in Stavanger

- A hedonic price model study

Photo: Øystein Andersen

By

Synne Lærdal

&

Joachim Vorkinn

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The Impact of External, Environmental, and Neighbourhood Factors on Housing Prices in Stavanger

A hedonic price model study

AUTHOR(S)		SUPERVISOR: Yuko Onozaka
Candidate number:	Name:	
1059 ………………	Synne Lærdal ………………………………….	
1081 …………………	Joachim Vorkinn …………………………………….	

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Abstract

A dwelling is made up of a bundle of attributes, all of which may affect its value. Hedonic pricing models are usually used in to estimate the value of these individual attributes. Few hedonic price studies however, have focused on the Norwegian housing market.

The aim of this thesis is to study factors that may affect housing prices in Stavanger. The hedonic price model was used to analyse these factors. The thesis focuses on external, environmental and neighbourhood attributes. These factors have previously been neglected in Norwegian hedonic house price models.

In order to do this, micro-level data were collected from Eiendomsverdi.no and Finn.no. The databases include information sold dwellings and its respective characteristics. The data obtained resulted in a carefully collected and original dataset.

The result from the estimated regression model was that external and environmental characteristics affect housing prices to a lesser degree. Neighbourhood characteristics appears to have a greater impact on the housing prices in Stavanger.

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1. Introduction

“To seek perfect specification for quantitative analysis of human behaviour is to seek the stars. Earthbound creatures must be content with approximately correct specification” (Taylor & Wilson, 1964).

The housing sector is associated with economic heath and wealth of a nation. Due to this, research into the variables that impact property prices are essential (Chau & Chin, 2003). Economists therefore, devote considerable effort towards understanding the structure of demand for housing and equilibria in these markets (Sheppard, 1999).

In many economies, a dwelling represents the single most valuable asset owned by individuals (Sheppard, 1999). Deciding to buy a dwelling is therefore an important decision. In Norway, it is common to own a home. It is normal to take up a mortgage to be able to afford one. Thus, buying a home also represent a large financial undertaking. Consequently, homebuyers’ decision to purchase a home is not random. It is usually a well-planned and thought through purchase.

A house can be defined as a bundle of attributes such as number of rooms, age and location. Each house has its own unique set of features that affect price. However, each homebuyer has a unique utility function, causing them to value attributes differently. For example, one buyer might place a greater value on a balcony than another buyer. Consequently, buyers value a certain house with a given set of characteristics differently. The fact that each house has a different bundle of attributes make valuation difficult. Combined with the fact that buyers might value individual attributes differently, makes the valuation even more complicated. Nevertheless, a large amount of research is dedicated to explaining the value of a house by valuing its individual attributes. The most common method used is the hedonic price model. This model allows total expenditure to be broken into the price of the individual attributes. However, previous research results are limited to a specific geographic location. Not being able to generalize findings, is a caveat of hedonic pricing models (Sirmans, Macpherson, & Zietz, 2005).

In Norway, only a limited number of hedonic price model studies focuses on house prices. Those few studies who do, only include internal attributes such as size, age and location in their hedonic price models. The purpose of this thesis is to research if other types of attributes affect housing prices, and to contribute to hedonic house price research in Norway. In order to make this objective feasible, the thesis will focus on the Norwegian submarket, Stavanger. The research question for the thesis is as follows:

Do external, environmental, and neighbourhood attributes affect the housing prices in Stavanger?

This thesis is structured the following way: Chapter 2 provides background for the housing market in Stavanger. A literature review is also included in this chapter. Chapter 3 describes the theory behind the research in this thesis, and provides a description for how the data is gathered. The categorization of variables are addressed in this chapter. Chapter 4 presents data is applied in this thesis, and a description of each variable. Chapter 5 consists of the results from the regression model. In chapter 6, a discussion of the results is provided. Limitations and implications for future work are included in this chapter. Finally, a conclusion is presented in chapter 7.

2. Background

This thesis studies housing prices in Stavanger. Stavanger is a city and municipality in Rogaland, Norway. It has a total resident population of 132 644 as of 2016 (Stavanger kommune, 2017), and the city is the fourth largest municipality in Norway (Statistisk Sentralbyrå, 2016). The municipality shares borders with Randaberg and Rennesøy to the North, Sandnes to the South and Sola to the West. Stavanger is also the centre of administration in Rogaland.

2.1 Housing market in Stavanger

The registered number of dwellings in Stavanger as of 2016, were 60 956 (Stavanger kommune, 2017). Housing prices in Stavanger has suffered a downward sloping trend in the last years. While Oslo has experienced a large growth in housing prices in recent years, Stavanger has been faced with negative growth. At the time of writing the housing market in Stavanger seems to have stabilised, and realtors in Stavanger began to see positive signs already during 2016 (Havnes, 2016). The industry in Stavanger is highly influenced by the oil sector and its fluctuations. Due to this, Stavanger is often described as the “oil capitol” in Norway.

The development in housing prices compared to other Norwegian cities is presented in Figure 1 below. The statistics are developed Eiendom Norge, with support from Finn.no. The table shows annual price change in percent, relative to the year before from 2009 until 2016. Oslo has experienced the highest growth in prices the last years, while Bergen and Trondheim have both experienced growth in their housing markets but to a lesser extent. Stavanger is the only city mentioned in the table with negative growth in recent years. Much due to the negative development in the oil sector and following ripple effects.

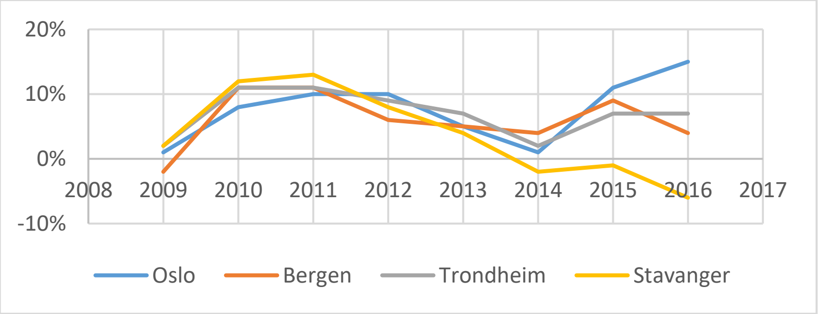

Figure 1: Historic change in housing price (Eiendom Norge, 2017)

2.2 Districts in Stavanger

Stavanger is divided into seven districts (Kart over bydelene i Stavanger, 2017). Figure 2, shows a map for Stavanger, and how the city is divided. The districts are Eiganes/Våland, Madla, Tasta, Hinna, Hillevåg, Hundvåg and Storhaug. Eiganes/Våland are considered as one ditstrict. This study will use the same district borders as presented in Figure 2. These are the official districts according to Stavanger municipality.

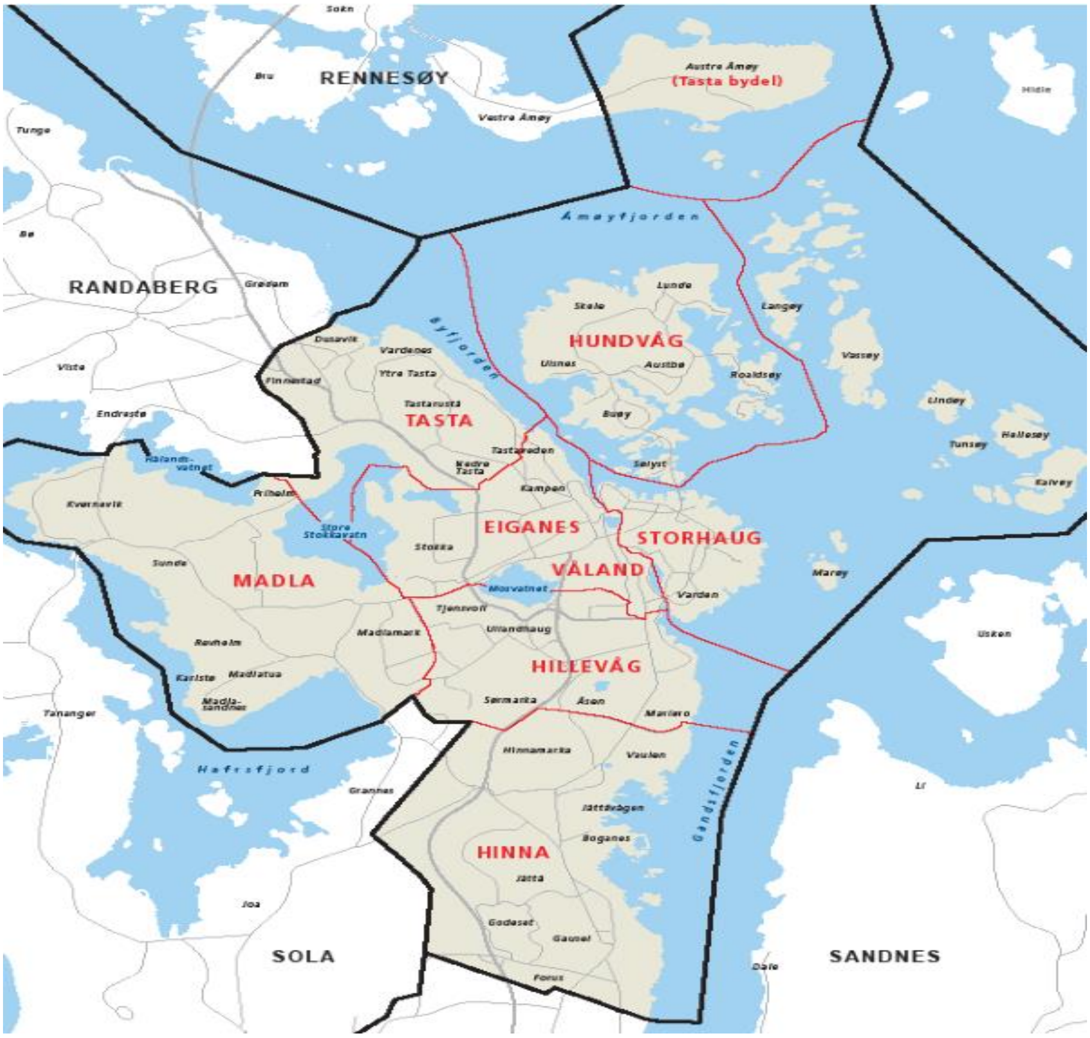

Figure 2: Map for districts in Stavanger (Kart over bydelene i Stavanger, 2017)

Figure 3 consist of each district with its respective population. Eiganes/Våland is the most populated district, while Hundvåg has the smallest population.

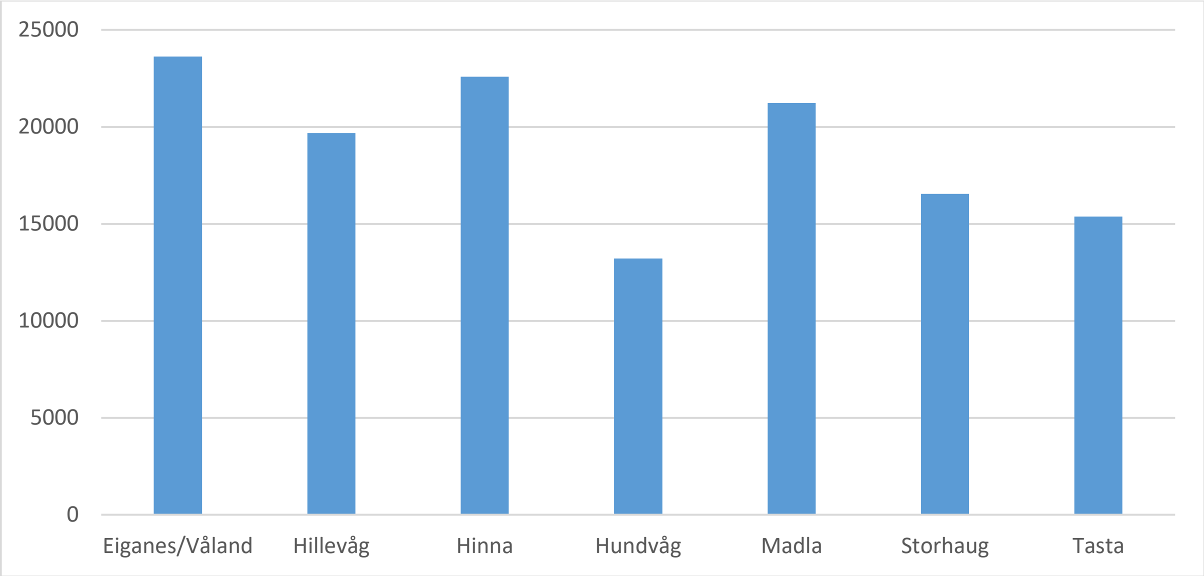

Figure 3: Population in Stavanger 2016 (Stavanger-Statistikken, 2017)

2.3 Literature review

The housing price itself is undoubtedly one of the determining factors when a person decides to purchase a dwelling. There are however, certain attributes that in turn determine the housing price. What these attributes are and how they influence price is an interesting and popular research topic. The hedonic price model has been used vigorously and often by researchers who try to determine what characteristics effect housing prices.

The identity of the founding father of the hedonic pricing model is not easy to determine. Still, most researchers cite Andrew Court as the pioneer. He was the first to formally coin the term “hedonic” in his article in 1939. In the article, Court recognized that a single variable could not explain automobile demand. He therefore developed a hedonic price index for automobiles using three variables: dry weight, wheelbase, and horsepower. His model is to date considered modern in the way he used a semi-log form, accounted for cars that actually sold and estimated models over different periods. (Sirmans, Macpherson, & Zietz, 2005; Goodman, 1998; Malpezzi, 2003). The model was later popularized by Zvi Griliches in the early 1960’s. Griliches continued the path of Andrew Court using the hedonic model to analyse the automobile market. The regression produced by Griliches was reported in more modern terms such as standard errors of the coefficients and R^2. Even though Griliches analysis did not appear in a conventional economics publication, it received considerable response. From this point on, the hedonic pricing model moved quickly into the micro-econometric tool kit (Goodman, 1998).

Two approaches contributed heavily towards the theoretical framework on hedonic pricing today. The first approach was developed by Kelvin J. Lancaster in 1966. His paper, "A New Approach on Consumer Theory" provided a microeconomic foundation for estimating the value of utility-generating characteristics (Lancaster, 1966; Chau & Chin, 2003). The second approach comes from the model Sherwin Rosen developed in his paper in 1974. In the paper, Rosen demonstrates how buyers and sellers of a good with different utility-bearing characteristics in a perfect competitive market will reach a market equilibrium. The location of the equilibrium will depend on the implicit prices of the good's characteristics (Rosen, 1974; Jensen, Panduro, & Lundhede, 2014). Rosen's approach focused on characteristics with less emphasis on utility and more on price determination. His work provided the foundation for nonlinear hedonic pricing models (Sirmans, Macpherson, & Zietz, 2005).

Previous empirical studies have concluded that housing prices are influenced by physical house attributes such as structure, number of bedrooms and balcony, as well as environmental and neighbourhood characteristics (Grether & Mieszkowski, 1974; Sirmans, Macpherson, & Zietz, 2005). It is important that the hedonic model include a wide set of house characteristics in order to avoid omitted variable bias (Atkinson & Crocker, 1987). According to Nguyen-Hoang & Yinger (2011), researchers are dependent on the accessibility of data in terms of house characteristics. For this reason, the number of characteristics used in the hedonic price model differs from one study to another.

Given the fact that buying a dwelling is usually a long-term investment and that dwellings are immobile, it is important to carefully consider environmental and neighbourhood characteristics. A study conducted by Jim & Chen (2009) found that a good harbour view increased the value of an apartment 3% in Hong Kong. In their study, they also found that a street view would decrease the value of an apartment with almost 4%. The location of the dwelling usually determines the associated school district. Nguyen-Hoang & Yinger (2011) found that an increase by one-standard deviation in a school's student test scores, would lead to a rise in housing values with 1-4%. In another study, they found that proximity to open spaces such as public parks, natural areas and golf courses had a positive influence on housing prices (Bolitzer & Netusil, 2000). Many hedonic price studies focus only on one or few neighbourhood attributes (Benefield, 2009). These studies risk having omitted variable bias and their result might be overstated as a result. There are however, few studies that take a wide set of neighbourhood characteristic into consideration (Tse, 2002).

There are also different social factors that may affect a neighbourhood and its respective housing prices. Buonanno, Montolio, & Raya-Vilchez (2013) concluded that crime has a negative impact on housing prices in Barcelona. In their study, they found that houses located in a less safe neighbourhoods were valued on average 1,27% less. In a study conducted by Holly & Jones (1997), they found that real income was one of the central driving forces behind real housing prices. In their study, they used a dataset from 1939 to 1994 in order to research housing prices behaviour in the United Kingdom. Their results showed that from 1939 real income had increased by 312%, while real house prices had risen by 278%. In a different study by Li & Brown (1980), they estimated three models. In the first model, they found that median income had a positive impact on housing prices. However, after adding micro-neighbourhood characteristics (i.e. distance to non-residential activities) in the second and third model, median income became statistically insignificant. Another social characteristic that has been researched is racial composition of neighbourhoods and if it has an effect on housing prices. Harris (1999) found that neighbourhoods that consists of 10% or more black people had 16% lower housing values in the United States. His study showed however, that the value reduction was not primarily caused by an aversion to black people. It was mainly caused by a preference to have affluent and well-educated neighbours, which is more prevalent among whites than among blacks.

Distance to important amenities can also affect the price of a dwelling. The basic assumption is that when the accessibility to amenities (i.e. schools, public transport, and job opportunities) increase, the value of a dwelling will also increase. Previous research supports this assumption. A study found that short distances between dwellings and schools had a positive impact on housing prices in Greenville, South Carolina. On the other hand, the authors also found that an above average distance between dwellings and schools would be negative for housing values (Owusu-Edusei, Espey, & Lin, 2007). Another study concluded that travel time to a central business district (CBD) is negatively correlated with housing prices in Hong Kong. Longer travel time to i.e. work, would decrease housing values (Hui, Chau, Pun, & Law, 2007). According to a study by Agostini & Palmucci (2008), housing units with close proximity to public transport had higher housing values than units with poorer access. In the study, they explain the difference is caused by lower cost of transportation to central business areas and shopping areas in town. Being located close to certain amenities may also have a negative impact on housing prices. A Swedish study by Wilhemson (2000) found that noise pollution had a negative effect on single-family houses. His research showed that if a single-family house was located near a road known for noise pollution, the value of this home would be reduced by approximately 30%. Another study found that proximity to wind turbines had a significant negative impact on neighbouring residential properties (Jensen, Panduro, & Lundhede, 2014).

Hedonic modelling can be (and has been) useful in addressing several issues in housing valuation. It allows total housing expenditure to be broken into individual components and estimate its respective value. Hedonic price models have been used in valuing the more obvious components such as square meter, bedrooms, and bathrooms. It has however, been useful when estimating the effect off less obvious components such as crime, school quality and proximity to wind turbines (Sirmans, Macpherson, & Zietz, 2005). One disadvantage of the hedonic model is that it requires micro-level data about the relevant product characteristics that likely will affect its value. This type of dataset is not always available or easy to get (de Haan & Diewert, 2013). A second disadvantage is that researchers have different opinions about selection and specification of variables and functional forms. For example, one study measures bedrooms simply as the number of bedrooms, whereas a different study uses dummy variables for each additional bedroom. The different empirical specifications lead to complicated and limited comparability of previous hedonic pricing studies. (Sirmans, Macpherson, & Zietz, 2005). Another risk related to the hedonic price model is the existence of multicollinearity between characteristics and instability of estimates (So & Tse, 1997). The results from a hedonic pricing model is often location specific. It is therefore hard to generalize results across different markets. Consequently, the hedonic price model is generally used to gain insight in the mechanisms in a particular market (Sirmans, Macpherson, & Zietz, 2005).

3. Theory and model

The elements from Rosen's paper (1974) can be implemented for the housing market. The basic assumptions is that a buyer wants to maximize one's utility by bidding as little as possible for the house. On the other hand, the seller wants to maximize its capital rent by offering the house for the highest price possible. The equilibrium price for the house will be where the buyer's bid function and the seller's offer function meet. A house can be described as a bundle with different utility bearing characteristics (Jensen, Panduro, & Lundhede, 2014). There is no market for these attributes, since they cannot be sold separately. This implies that the attributes cannot be independently observed. The demand and supply for the dwelling implicitly determines the characteristics' marginal contribution to the price of the dwelling. Hedonic regression models can be used to estimate those marginal contributions or shadow prices (de Haan & Diewert, 2013).

There are different approaches to hedonic modelling. The method used in this thesis is called simple hedonic approach. This straightforward method assumes that the coefficients of the estimated hedonic regression are sufficient to reveal the preference structure. More precisely put, the marginal willingness to pay for a specific characteristic is interpreted as the derivative of the hedonic regression with respect to the characteristic. The marginal price derived from the hedonic function does not estimate what a particular household is willing to pay for additional units of a housing characteristic. Rather, it is the valuation of the demand and supply interactions of the entire market (Follain & Jimenez, 1985).

In accordance Sirmans, Macpherson, & Zietz (2005) study, it is possible to categorize the attributes that affect housing price in the following manner; internal, external, environmental and neighbourhood attributes.

The general hedonic regression model can therefore be written as:

$$Price = f(I, Ex, En, N)$$

Where I represent internal characteristics, Ex signifies external characteristics, En denote environmental characteristics and N represent neighbourhood characteristics in the model.

3.1 Dependent variable

There is no handbook in hedonic modelling that states which variables to use in the regression. Even Lancaster (1966) and Rosen (1974) papers did not say much about what characteristics to use or how exactly they relate to price. The first step is usually to choose which dependent variable to look at. The term “housing price” is often used loosely. This could either mean rent or value of the housing unit. Studies that focus on rents must deal with problems related to the fact that different dwellings have different lease terms and contracts conditions. One notable example of this is the exclusion, or inclusion of utility payment in rent. There are also issues when estimating a hedonic regression using values instead of rent. A number of studies use owner estimates to the value the housing unit (Malpezzi, 2003). There is reason to be concerned that occupant estimates might not be accurate (Follain & Malpezzi, 1981). In Goodman & Ittner’s paper (1992) they researched if home owner’s estimates where precise. They conclude that home owners slightly overvalued their properties, but for most research purposes, this bias was not a major problem. It is also possible to use recent sales prices. Sales price has some obvious advantages as dependent variables. Recent transactions data may give less potential bias, and greater potential precision, than home owners’ self-assessment. However, recent sales are not necessarily a random pick from the total stock. Which in turn may lead to possible selection bias in the sample (Malpezzi, 2003).

3.2 Independent variables

Malpezzi (2003) gives a review for selection of independent variables used in hedonic price models for housing. There are hundreds of potential hosing characteristics that could be included on the right-hand side of the model. Previous studies suggest that a full dataset should include following features:

- Rooms (bedroom, bathroom, etc.)
- Floor area of the unit
- Structure type (single family house, detached, semi-detached, and apartment)
- Type of heating and cooling systems
- Age of the unit
- Structural features such as basement, attic, garages, etc.
- Categories of structural materials and quality of finish
- Neighbourhood variables
- Distance variables
- Characteristics of the tenant that affect prices (i.e. length of tenure and whether utilities are included in rent)
- Date of data collection (if the data are collected over a period of months or years)

However, there are no complete list of variables. Malpezzi (2003) punctuates that this only gives a general overview for the independent variables. Amemiya (1980) compares several criteria for selection of variables, and concludes that the choosing should be based on one's intuition and knowledge of the underlying econometric theory.

3.3 Model

The dataset used in this study was generated with access to Eiendomsverdi.no. Eiendomsverdi AS is a Norwegian company that registers and monitors all the activity in the Norwegian housing market. They collect data from realtors, official records and Finn.no. There are however, several ways to obtain data about the housing market. In an article by Keskin (2008), he used surveys to obtain the information needed in Istanbul in Turkey. Buonanno, Montolio & Raya-Vilchez (2013) gathered the data from a real estate agency in Barcelona, whilst data concerning crime in the city were obtained from a survey. In Norway, the article by Larsen & Anundsen (2015) used the same approach as this study, by using

Eiendomsverdi.no and Finn.no. The availability of data differs from country to country, which often lead to different approaches in regard to hedonic price studies.

The applied categories and the classification of the collected variables in the dataset, is based on a study by Sirmans, Machpherson & Zietz (2005). In their study, they reviewed approximately 125 hedonic model studies and classified all the variables into groups. In the present study, the data collected were organized into the following categories; internal-, external-, environmental- and neighbourhood attributes.

3.3.1 Internal attributes

The internal features are defined as the physical variables inside the dwelling, and are used as control variables for the external, environmental and neighbourhood attributes. The different internal attributes are selected due their availability and importance to the housing value. The most common internal attributes used are square meter, number of bedrooms, number of bathrooms, age, etc.

3.3.2 External attributes

External features are defined as physical attributes located outside the four walls of a dwelling. Examples of external variables is garage, garden, balcony and pool. External attributes are also physical attributes, which makes it easier to collect and quantify. Previous studies indicate that external features have positive impacts. Garage have a positive impact on the housing price (Do & Sirmans, 1994). This may however, vary across geographical location (Sirmans, MacDonald, Macpherson & Zietz, 2005). Earlier research suggests that balcony could also have a positive effect on housing value (Chau, Wong & Yiu, 2004). Luttik (2000) examined the presence of gardens in hedonic pricing model, conditioned that the garden was facing water. The author concluded an increase in housing value on average when dwelling had garden facing water. The hedonic pricing model for Istanbul (Keskin, 2008) included garden as a dummy variable, founding that garden had a negative effect on price. This is a contradiction to the overview Sirmans, Macpherson & Zietz (2005) presents, where garden has a clear positive effect on price.

3.3.3 Environmental attributes

Environmental attributes have been defined as attributes provided by nature. For example, ocean view, evening sun and "good view". There are no environmental characteristics included in the table containing the twenty most appearing characteristics in hedonic price models (Sirmans, Machpherson & Zietz, 2005). No environmental attributes were included in similar hedonic price study in Norway (Røed Larsen & Anundsen, 2015). The possible reason for this, is that environmental characteristics are not quantified and registered in a database in the same manner as some internal attributes. For example, ocean view may just be mentioned by relators in ads. Gathering information about these types of attributes are therefore a time-consuming task. A study by Benson, Hansen, Schwartz & Smersh (1998) examine the value of views in USA. In their study, they did field research in order to determine if a dwelling had a view. They conclude that view has a large impact on the market price. For example, an otherwise comparable dwelling with an ocean view could increase the value by 60%. Another study (Do & Sirmans, 1994) focused only on distinguishing between view or no view. According to previous research, a view adds a scenic aspect to the dwelling, and should therefore add value according to previous studies.

3.3.4 Neighbourhood attributes

Neighbourhood attributes include location, crime, distance, golf course, school district, etc. Location is often measured as a neighbourhood identifier and can be found by using the dwelling's zip code. Distance variables typically used is distance to city centre (Sirmans, Machpherson & Zietz 2005). In an article by McMillen (2002), the model used distance to city centre as the only distance variable. While the general relationship between house prices and location has been examined in previous studies (Muth, 1970; Ridker & Henning, 1967). Tse (2002) suggests that if a dwelling is located far from an employment centre, it would lower its respective value, due to the cost of commuting. He also implies that units of high standard could reflect the quality of the district. Thus, the relation between house prices and neighbourhood are complex, making the measuring of housing value a challenging task.

3.4 Econometric specification

The econometric theory lay few restraints on selection of form concerning hedonic pricing models. Forms that are commonly used are linear, quadratic, semi-log and log-log etc. (Hui, Chau, Pun & Law, 2007). Using a linear regression model can however, be problematic since the values are not likely to be the same for houses in different price ranges. For example, the value added of an additional bedroom might be greater for a four million kroner home than for a two million kroner home. To avoid this complication, the hedonic pricing model is often estimated in semi-log form with the natural log of price used as the dependent variable. In semi-log form, the coefficients estimate the percentage change in price for a one-unit change in the given independent variable. Another advantage the semi-logarithmic form has over linear, is that is helps minimize the problem of heteroscedasticity (Sirmans, Macpherson, & Zietz, 2005). So far, no strong theoretical evidence suggests which functional form one should choose (Malpezzi, 2003). In the present study, the semi-logarithmic form is used for the hedonic regression model.

Regarding the functional form of the independent variables previous studies have used both dummy and continuous variable (Malpezzi, 2003). The interpretation of the dummy variable in regard to the semi-logarithmic functional form have been discussed in previous papers. The conventional interpretation is that the dummy variable has a percentage effect on the explanatory variable. In a paper by Halvorsen & Palmquist (1980) they argued that this interpretation was not precise. This result was however, disputed in a paper by Kennedy (1981). Regardless, both dummy variables and continuous has been used in most hedonic price models concerning the housing market to date.

Following the categorization of the housing characteristics in this study, the regression model can be mathematically represented by:

$$\text{Ln } P = \beta_{\circ} + \delta(\text{Internal}) + \gamma(\text{External}) + \theta(\text{Environmental}) + \lambda(\text{Neighbourhood}) + \mathcal{E}$$

Where δ are the internal coefficient vector. γ are the external coefficient vector, θ are the coefficient vector for environmental factors and λ are the coefficient vector for neighbourhood factors. $\mathcal{E}$ is the stochastic disturbance vector.

4. Data

The dataset used in this thesis consists of sold houses and apartments during the last quarter of 2016 (01.10.2016-31.12.2016) in Stavanger municipality. The sample includes 577 sold dwellings. The dwellings can be categorized into; single-family, detached, semi-detached and apartments. Figure 4, shows the scattering of the homes sold in Stavanger in the sample. The colours of the dots describe type of dwelling sold:

- Red dot = Apartment
- Green dot = Single-family
- Dark blue dot = Detached
- Light blue dot = Semi-detached

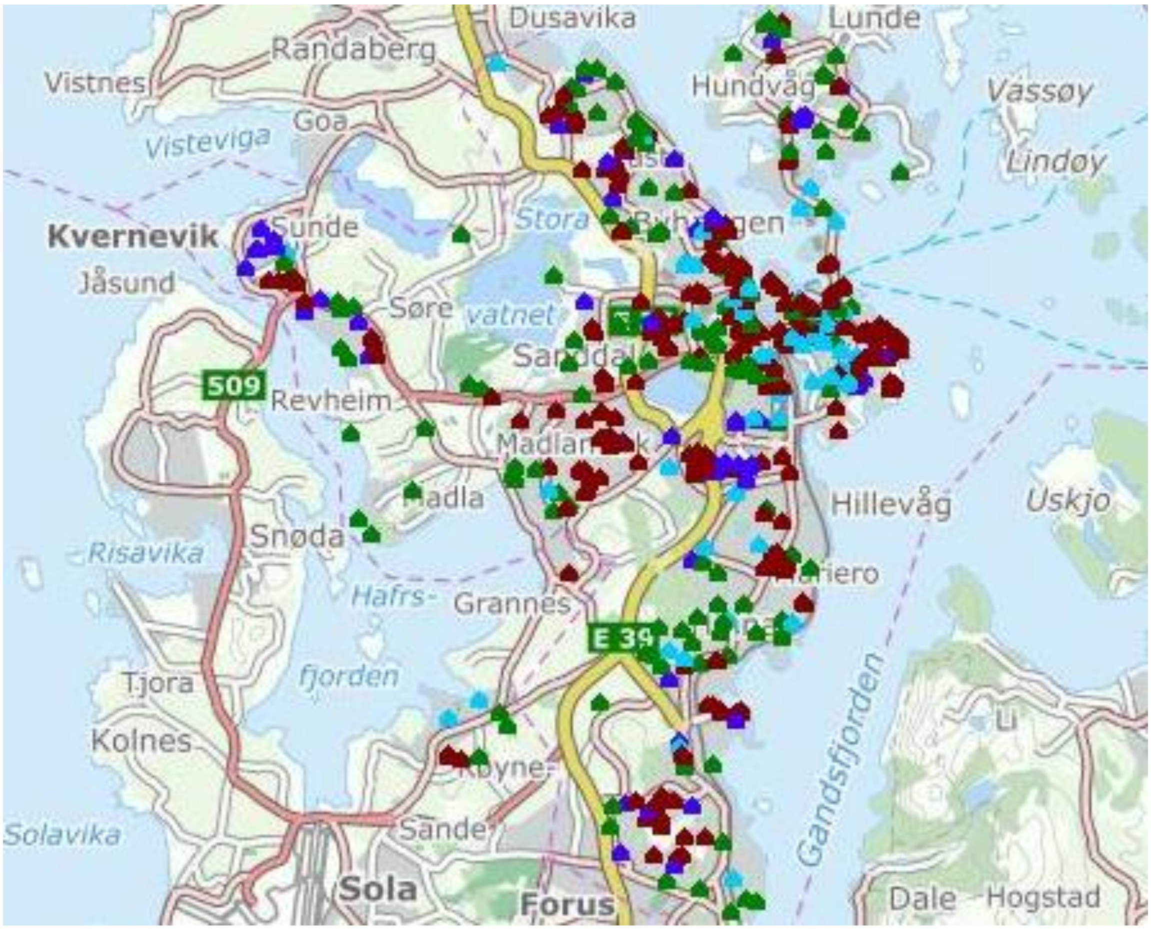

Figure 4: Sold dwellings in Stavanger (Eiendomsverdi, 2017)

Apartments contribute to the majority of the dwellings sold in the sample period. A total of 313 apartments were sold the sample period in Stavanger, followed by single family with 138 sold units. Detached dwellings sold 66 and semi-detached dwellings sold 60. This is graphically illustrated in Figure 5.

In Figure 6 below, shows the historic composition of sold dwellings in Stavanger over the last five years (01.10.2011-01.10.2016). In this period, a total of 16457 dwellings were sold. By comparing the sample (Figure 5) with sold dwellings over the last five years (Figure 6), it is possible to see that they are relatively similar. Over the last five year there have been sold slightly more single-family dwellings and fewer semi-detached dwellings compared to the sample. Nonetheless, the difference in composition is small. The sample is therefore likely representative for sold dwellings in Stavanger and should provide suitable estimates.

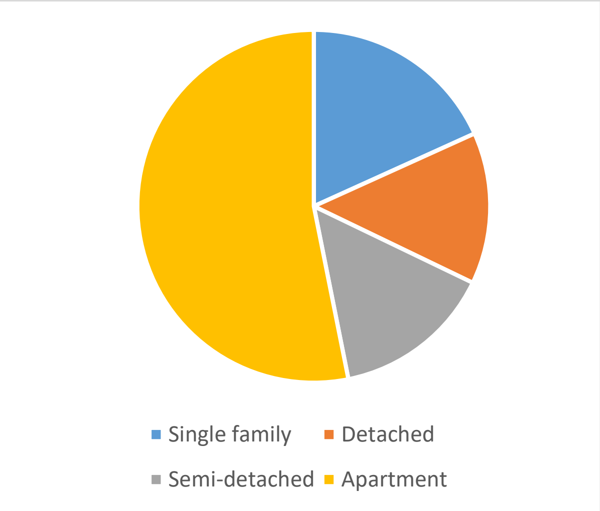

Figure 5: Sold dwellings in sample period (Eiendomsverdi, 2017

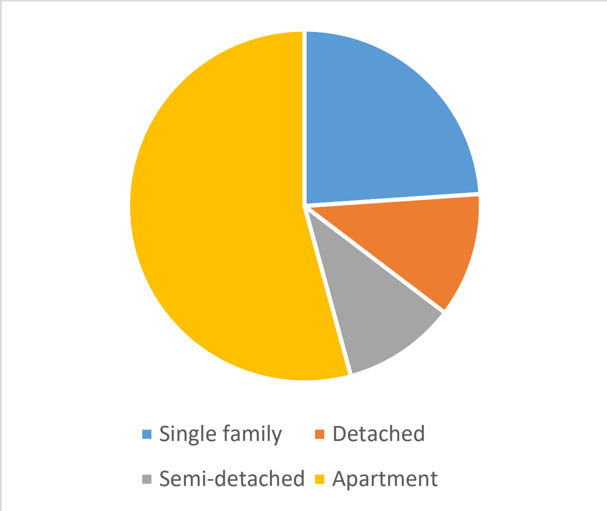

Figure 6: Sold dwellings in a five year period (Eiendomsverdi, 2017)

4.1 Trimming of dataset

In order to ensure that the dataset provided good estimates, it was trimmed. The original dataset contained 577 observations. However, several observations from Eiendomsverdi's database were missing sales ads from Finn.no. It is suspected that these dwellings were sold privately and had no need for an ad. Due to the missing sales ad, it was not possible to gather information about external, environmental and neighbourhood attributes. They were therefore excluded from the dataset. The postal code containing houses in Vassøy was also removed from the dataset. Vassøy had registered two sold dwellings in the sample period. Vassøy is an island with no mainland attachment. Due to this, distance variables like distance to bus stop were abnormally large since there are no bus stops on Vassøy.

There were also a few prestigious dwellings that were sold for a considerable higher amount than the rest of the sample. For example, one house in the Hinna district were sold for 17 500 000 NOK. This is approximately 6 million more than the next house. Give the extreme value, the house was dismissed from the dataset. After having dismissed dwellings for either containing insufficient information or extreme values, the dataset was reduced to 462 observations.

There were also made an alteration in the variable sales price. The dataset includes both freehold and housing cooperative (co-op) dwellings. It is normal for co-op dwellings to have joint debt. Joint debt in this context is defined as shared debt within housing cooperative. The joint debt is part of the actual price of a co-op dwelling. The buyer is equally liable for this amount as he or she is for the bid submitted. However, it is not included in the registered sales price in Eiendomsverdi.no. In order to be able to compare freehold and co-op dwellings, the joint debt was incorporated as part of the sales price. The basis for this alteration is taken from a study by Larsen & Anundsen (2015). In their study, they altered the sales price variable in the same manner as in this study.

4.2 Variables

Comparing the variables used in the regression model to the twenty characteristics appearing most often in hedonic studies, nine of the variables are applied in this thesis (Sirmans, Macpherson, & Zietz, 2005). P-room (square feet), age, bedrooms, baths, fireplace, basement, garage, balcony (deck) and distance are included. In Table 1 below presents an overview of the variables used in this study.

Internal features	**External features**	**Environmental**	**Neighbourhood**
P-room	Garden	View	Distance to grocery store
Freehold	Garage		Distance to bus stop
Floor	Balcony		Distance to city center
House			Distance to airport
Age			Distance to gym
Bedrooms			Eiganes/Våland
Baths			Hillevåg
Basement			Hinna
Attic			Hundvåg
Parquet			Madla
Cable-TV			Storhaug
Heath pump			Tasta
Fireplace			
High standard			

Table 1: Variable overview

Following is a detailed description of each variable included in the trimmed dataset, which contributes to the final regression model.

Sales price:

Sales price is the price registered in Eiendomsverdi.no. The variable consists of the sales price plus joint debt if any. The currency used for sales price is Norwegian kroner (NOK).

P-room:

P-room is the primary room, which is the area primarily used inside the walls of the home. This area includes the living room, kitchen, bath and bedrooms according to Norsk Standard NS 3940 (Finansnorge, 2017). Rooms like storage rooms and common stairwells are excluded. P-room is measured in square meter, which is the commonly used measurement for size in Norwegian dwellings. The variable is continuous.

Freehold:

Freehold identifies if the observation is a freehold dwelling or not. A dummy variable is used, where 1 represent freehold and 0 otherwise. OBOS, a Nordic cooperative building association, describes the two ownerships as "both gives you exclusive user rights to use your dwelling, but when buying a freehold dwelling you buy a share of the whole property to the condominium. For example, 1/30 of the entire property. When buying a co-op you buy a share in the condominium, but the condominium owns the property" (OBOS, 2017). Co-ops are often attached with joint debt, and are more expensive then what the asking price implies. In this study, joint debt is added to the sales price, giving a more correct interpretation.

House:

The variable is constructed as a dummy variable in order to separate different housing structures. The observation is denoted as 1 if house, and 0 if apartment. Under the term "house", single-family, detached houses, and semi-detached houses and are included.

Floor:

The variable specifies which floor the dwelling is located. Houses are usually located on the first floor. Apartments has wider variations in regard to floor location. This variable is continuous.

Age:

Age explains the year of construction for the dwelling. It is a continuous variable. Clapp & Giaccotto (1998) concluded that empirical work concerning age in hedonic studies should be estimated as series of dummy coefficients, but previous studies before 1998 were arguing against this conclusion. In the present thesis, the age variable contains year of construction.

Bedroom:

Almost every house in the sample have at least one bedroom. The few exceptions are small studio apartments that includes kitchen, living room and bedroom in one room. The number of bedrooms are categorized in the dataset by using dummies:

- bed1 = 1 if the observation contains 1 bedroom or less, 0 if not. This is applied as the base.
- bed2 = 1 if the observation contains 2 bedrooms, 0 if not.
- bed3 = 1 if the observation contains 3 bedrooms, 0 if not.
- bed4 = 1 if the observation contains 4 bedrooms or more, 0 if not.

Bath:

All dwellings in the dataset include at least one bathroom. The same method used in the bedroom variable is applied for bathrooms. In the dataset, there are seven dwellings with more than three baths. The rest either contain one, two, or three bathrooms. Considering this, following partition were applied using dummies variables:

- bath1 = 1 if the observation contains 1 bath, 0 if not. This is applied as the base.
- bath2 = 1 if the observation contains 2 baths, 0 if not.
- bath3 = 1 if the observation contains 3 or more baths, 0 if not.

Basement:

Basement is applied as a dummy variable, receiving 1 if the observation contains a basement and 0 otherwise. If an apartment is listed with a basement in the advertisement, and simultaneously not listed as primary room (p-room) due to below standard height and lighting conditions but as a storeroom, then this is not defined as a basement in this thesis.

Attic:

Attic is applied as a dummy, receiving 1 if the observation contains an attic and 0 otherwise. If the observation is listed with an attic in the advertisement, and simultaneously not listed as primary room (P-room) it is denoted as 1. If the observation is listed with an attic and this attic counts as primary room it is denoted as 0.

Parquet:

The parquet variable considers if the observation contains a parquet/hardwood floor or not, and are implemented as a dummy. The observation receives 1 if it contains parquet and 0 otherwise. Parquet is often the preferred choice when it comes to floor material, and it has been used in previous hedonic price models (Sirmans, Machpherson & Zietz 2005).

Cable-TV:

Cable-TV variable is constructed as a dummy variable. It is denoted 1 if the observation contains cable-TV and 0 otherwise. For an observation to be denoted as 1, the advertisement had to specify that cable-TV is present.

Heath pump:

The variable heath pump is constructed as a dummy, receiving 1 if the observation has a heath pump installed and 0 otherwise. It does not consider if the observation has several heath pumps installed or not. Heath pump are known to be environmental and to reduce the energy costs, but it is also the most expensive heating alternative to acquire (Naturvern Forbundet, 2017). Buying a dwelling already including a heath pump means not having to pay a large sum to acquire one, which should make the dwelling more attractive.

Fireplace:

The variable fireplace has been constructed as a dummy, where 1 is equal to having a fireplace and 0 if not. Hence, the variable does not account for multiple fireplace.

High standard:

High standard is constructed as a dummy variable, receiving 1 if the quality of the observation is good and does not require renovation and 0 if not. Whether a dwelling is renovated or not will most likely have a significant effect on the selling price. Special attention has been given to kitchen and bathrooms in evaluation of high standard, as they often are the most expensive rooms to renovate. While generating the dataset a clear assumption was made to separate the high standard from those who are not. A "low" standard dwelling is where there are immediate renovation needs. For example, if bathroom, kitchen, or both requires renovation, the high standard variable was denoted as 0 in the dataset. If no renovation is necessary, and you could move in without making necessary changes it was denoted as 1.

Garden:

Garden variable is constructed as a dummy, denoted 1 if the observation includes a garden and 0 otherwise. Observation with garden where identified by looking for the description in the advertisement and confirmation in the pictures. The size or scenic view from the garden are not taken into consideration in evaluating the attribute in this thesis.

Garage:

Garage is constructed as a dummy variable, receiving 1 if the observation contains a garage and 0 otherwise. This study defines the garage variable as 1 if the observation contains parking space. Either a garage or a parking lot. Apartments in the city centre does not always include parking. Usually parking space is scarce in the city centre and can therefore be quite expensive to rent. This makes parking lots attractive for buyers.

Balcony:

Balcony is constructed as dummy variable, denoted 1 if the observation contains a balcony and 0 otherwise. In this study balcony is defined as either terrace or balcony, meaning observations including either is denoted as 1.

View:

View is constructed as dummy variable, denoted 1 if the view is present and 0 if not. The definition of view is when dwelling has a clear and open line of sight. A no view is when the line of sight is short and have been disrupted with other buildings or trees.

Distance to grocery store:

Distance to grocery store is computed as the distance from the observation to the nearest grocery store in kilometres. Every Finn.no ad used had distance parameters for nearest grocery store included from nabolag.no which made it possible to register this.

Distance to bus stop:

Distance to bus stop are plotted in kilometres, where the number are distance from the observation to the nearest bus stop. Every Finn.no ad used had distance parameters for nearest bus stop included from nabolag.no which made it possible to register this.

Distance to city centre:

Distance to city centre are plotted in kilometres, where the number are distance from the observation to Stavanger city centre in meters. Every Finn.no ad used had distance parameters for proximity to city centre listed, which made it possible to register this.

Distance to airport:

Distance to airport are plotted in kilometres, where the number are distance from the observation to Sola airport in meters. Every Finn.no ad used had distance parameters for the proximity to Sola Airport included, which made it possible to register this.

Distance to gym:

Distance to gym are plotted in kilometres, where the number are distance from the observation to the nearest gym in meters. Every Finn.no ad used had distance parameters for the nearest gym included from nabolag.no, which made it possible to register this.

Districts:

The districts are divided into seven dummy variables, where 1 means the observation is located in that district and 0 otherwise. The district dummies are Eigane/Våland, Hillevåg, Hundvåg, Hinna, Madla, Tasta, and Storhaug.

5. Results

Table 2 presents the summarized statistics for the dataset used in this thesis.

Variables	Mean	Standard error	Minimum	Maximum
Totalsalesprice	3608369	1663625	900000	11650000
bed2	.3484	.4770	0	1
bed3	.2446	.4303	0	1
bed4	.1797	.3843	0	1
bath2	.3398	.4742	0	1
bath3	.1342	.3412	0	1
Freehold	.7056	.4562	0	1
PRoom	104.1515	56.4140	19	354
Floor	2.0216	1.9213	1	16
Age	1968.184	40.9376	1831	2016
Basement	.2381	.4264	0	1
Attic	.1710	.3770	0	1
Parquet	.6320	.4827	0	1
CabelTV	.5736	.4951	0	1
Heathpump	.1104	.3137	0	1
Fireplace	.3875	.4877	0	1
Garage	.8030	.3981	0	1
Garden	.4329	.4960	0	1
Balcony	.9675	.1774	0	1
View	.3095	.4628	0	1
Highstandard	.7944	.4046	0	1
Distancetogrocerystore	479.1126	360.7083	0	3,3
Distancetobustop	256.3853	186.9011	0	1
Distancetocitycenter	3974.026	2879.467	0,2	11,9
Distancetoairport	14515.15	7170.84	1,4	15,8
Distancetogym	1216.667	1026.447	0	5,6
EiganesVåland	.2186	.4138	0	1
Hillevåg	.0931	.2909	0	1
Hinna	.1818	.3861	0	1
Hundvåg	.0693	.2542	0	1
Madla	.1147	.3190	0	1
Storhaug	.2229	.4167	0	1
Tasta	.0996	.2997	0	1
N	462			

Table 2: Descriptive statistics from dataset

Table 2 presents the summarized statistics for dwellings in Stavanger for last quarter of 2016. The average transaction price is 3 608 369 NOK, ranging from 900 000 NOK to 11 650 000 NOK. 70% of the observations are freehold units. The year of construction varies from 1831 to 2016, with the mean of 1968. This means that the average age for houses is 49 years old.

The average square meter primary room (p-room) is 104 m^2, with a minimum of 19m^2 to a maximum of 354m^2. External physical attributes like garage are included in 80% of the observations, garden is included in 43% of the observations and 96% has balcony. When it comes to quality of the dwellings, 79% is with a high standard categorization, which means that most of the dwellings in the dataset does not require renovation. Dwellings with view consist of 30% of the total observations.
Distance to grocery store, bus stop and gym has a minimum distance of zero kilometres, which usually means they are located in the same building. The average distance to grocery store is 0,5 kilometres, to bus stop it is 0,2 kilometres and to gym it is 1,2 kilometres. The average distance to city centre is 3,9 kilometres, the minimum is 0,2 kilometres and the maximum is 12 kilometres. Distance to airport has an average of 15 kilometres.

Concerning the descriptive statistics on districts, Storhaug is the one most frequently appearing in the dataset. Of the 462 observations, Storhaug counts for 22% of this. Hundvåg represents 7% of the total observations and are therefore the district with fewest dwellings in the sample. Following Storhaug, Eiganes/Våland is represented just below 22% of the observations. Hillevåg and Tasta figures in 9% of the observations, while Hinna and Madla appear in 18% and 11% of the total observations, respectively.

5.1 House vs apartments

The data collected in the dataset includes information from both houses and apartments. Some theory suggests that these should be evaluated separately. The characteristics that are relevant for a detached dwelling units may differ from those that are relevant for high rise apartments. For example, the floor which an apartment is located on may be an important price determining variable, but might not be for houses (de Haan & Diewert, 2013). To test if there is structural difference between houses and apartments in the dataset, a Chow test need to be executed. A Chow test will reveal if there is structural change between different groups (Wooldridge, 2013). Here, it will reveal if the dataset should be divided into two separate datasets, one for houses and one for apartments.

The hypothesis is the following:

$$H_0\colon\ \alpha_0 = \beta_0$$
$$\alpha_1 = \beta_1$$
$$\vdots$$
$$\alpha_k = \beta_k$$
$$H_1\colon Not\ H_0$$

The null hypothesis states that there is no structural difference between houses (α) and apartments (β). If the null hypothesis is rejected, there is reason to believe that there is structural change.

Chow test:

$$F = \frac{[SSR_p - (SRR_1 + SSR_2)]}{SSR_1 + SSR_2} \times \frac{[n - 2(k+1)]}{k+1}$$

SSR_p = Sum of squared residuals of total dataset

SRR_1= Sum of squared residuals of only houses

SSR_2 = Sum of squared residuals of only apartments

n = Number of observations

k = Number of predictors

The numbers used in the Chow test is gathered from the STATA output of the regressions preformed in this thesis.

$$F = \frac{[16{,}87 - (7{,}91 + 6{,}57)]}{7{,}91 + 6{,}57} \times \frac{[462 - 2(16 + 1)]}{16 + 1} = 4{,}16$$

The resulting Chow test value is 4,16. The critical value is found in the F-distribution table with α=0,05 significance. The critical value (16, 445) is 2,01. The Chow test value is larger than the critical value (4,16 > 2,01). The null hypothesis is therefore rejected. This indicates that there is structural change between houses and apartments and that they should be analysed separately. From here on, the dataset will be divided according to structure (house or apartment) for further analysis.

5.2 Hedonic regression model

The results of the hedonic regression models are presented in Table 3 and Table 4. Following the Chow Test, houses and apartments are analysed in separate models. Both regressions contain the same variables. To test the effect of the different types of variables in the two regressions, the variables are divided into four models. The first model only includes the internal features for a dwelling. External variables were added in the second model. In the third model, environmental variables were included. In the last and fourth model, neighbourhood and location variables was added. This method is applied to see the added influence of external, environmental and neighbourhood factors, and to see how the adjusted R^2 is changes as a result of the added variables. For a variable to be considered as significant in the model, a significance level of 5% is required.

Variables	Model 1	Model 2	Model 3	Model 4
bed2	0.138 (0.134)	0.180 (0.134)	0.174 (0.133)	0.0541 (0.125)
bed3	0.101 (0.130)	0.133 (0.130)	0.119 (0.129)	0.0669 (0.121)
bed4	0.167 (0.134)	0.213 (0.135)	0.200 (0.134)	0.124 (0.125)
bath2	0.0889^{*} (0.0428)	0.0918^{*} (0.0427)	0.0912^{*} (0.0424)	0.0440 (0.0397)
bath3	0.0590 (0.0588)	0.0658 (0.0586)	0.0645 (0.0581)	0.0308 (0.0547)
Freehold	-0.0481 (0.0800)	-0.0564 (0.0796)	-0.0645 (0.0791)	-0.0903 (0.0767)
P-Room	0.0039^{***} (0.0005)	0.0037^{***} (0.0005)	0.00362^{***} (0.0005)	0.0035^{***} (0.0005)
Floor	-0.0649 (0.0706)	-0.0570 (0.0716)	-0.0512 (0.0711)	-0.0744 (0.0666)
Age	0.00005 (0.0004)	-0.0005 (0.0005)	-0.0005 (0.0005)	0.0003 (0.0005)
Basement	-0.0029 (0.0336)	-0.0077 (0.0337)	0.0030 (0.0340)	-0.0018 (0.0361)
Attic	-0.0325 (0.0349)	-0.0414 (0.0349)	-0.0426 (0.0346)	-0.0516 (0.0335)
Parquet	0.0523 (0.0323)	0.0602 (0.0324)	0.0566 (0.0322)	0.0506 (0.0308)
CabelTV	-0.0803^{*} (0.0365)	-0.0795^{*} (0.0363)	-0.0713 (0.0362)	-0.0337 (0.0346)
Heathpump	0.0200 (0.0394)	0.0119 (0.0395)	0.0200 (0.0395)	0.0072 (0.0372)
Fireplace	0.0744^{*} (0.0350)	0.0574 (0.0358)	0.0594 (0.0355)	0.0408 (0.0346)
Highstandard	0.174^{***} (0.0359)	0.180^{***} (0.0360)	0.175^{***} (0.0358)	0.151^{***} (0.0338)
Garage		0.0672 (0.0557)	0.0629 (0.0554)	0.0727 (0.0517)
Garden		0.0676 (0.0433)	0.0566 (0.0433)	0.0427 (0.0408)
Balcony		0.0360 (0.132)	0.0342 (0.131)	-0.0057 (0.120)
View			0.0706 (0.0371)	0.0741^{*} (0.0352)
Distancetogrocerystore				0.0156 (0.0428)
Distancetobustop				0.312^{***} (0.0794)
Distancetocitycenter				-0.0211 (0.0115)
Distancetoairport				-0.0007 (0.0014)
Distancetogym				-0.0489^{*} (0.0209)
Hillevåg				-0.259^{***} (0.0754)
Hinna				-0.0551 (0.0828)
Hundvåg				-0.0926 (0.0842)
Madla				0.0581 (0.0797)
Storhaug				-0.146^{**} (0.0519)
Tasta				-0.153^{*} (0.0600)
Constant	14.36^{***}	15.27^{***}	15.38^{***}	14.15^{***}
	(0.812)	(0.971)	(0.966)	(1.007)
Observations	196	196	196	196
R^2	0.642	0.652	0.659	0.737
Adjusted R^2	0.610	0.615	0.620	0.687

Table 3: Regression results for houses

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Variables	Model 1	Model 2	Model 3	Model 4
bed2	0.0735** (0.0283)	0.0697* (0.0283)	0.0679* (0.0274)	0.0871*** (0.0235)
bed3	0.0937* (0.0452)	0.0953* (0.0452)	0.111* (0.0439)	0.159*** (0.0388)
bed4	-0.220 (0.120)	-0.212 (0.120)	-0.197 (0.116)	-0.134 (0.101)
bath2	-0.0195 (0.0288)	-0.0211 (0.0291)	-0.0172 (0.028)	0.0254 (0.0247)
bath3	-0.109 (0.0818)	-0.109 (0.0816)	-0.108 (0.0790)	-0.0936 (0.0679)
Freehold	0.110*** (0.0219)	0.117*** (0.0221)	0.117*** (0.0213)	0.0711*** (0.0211)
P-Room	0.0094*** (0.0007)	0.0092*** (0.0007)	0.0089*** (0.0007)	0.0082*** (0.0006)
Floor	0.0192*** (0.0047)	0.0199*** (0.0048)	0.0105* (0.0051)	0.00270 (0.00459)
Age	0.0010*** (0.0003)	0.0010** (0.0003)	0.0010** (0.0003)	0.0013*** (0.0003)
Basement	-0.0901 (0.0485)	-0.0939 (0.0491)	-0.104* (0.0476)	-0.101* (0.0410)
Attic	-0.0357 (0.0403)	-0.0373 (0.0408)	-0.0358 (0.0395)	-0.0519 (0.0340)
Parquet	0.0351 (0.0243)	0.0252 (0.0248)	0.0267 (0.0240)	0.0233 (0.0206)
CabelTV	-0.0156 (0.0154)	-0.0148 (0.0154)	-0.0137 (0.0149)	-0.0065 (0.0129)
Heathpump	-0.0342 (0.0565)	-0.0360 (0.0571)	-0.0273 (0.0553)	-0.0328 (0.0475)
Fireplace	-0.0218 (0.0292)	-0.0264 (0.0294)	-0.0123 (0.0286)	0.0132 (0.0254)
Highstandard	0.168*** (0.0302)	0.173*** (0.0302)	0.177*** (0.0293)	0.148*** (0.0254)
Garage		0.0057 (0.030)	0.0157 (0.0286)	0.0238 (0.0251)
Garden		0.0074 (0.0309)	0.0175 (0.0300)	0.0087 (0.0260)
Balcony		0.111* (0.0524)	0.0681 (0.0517)	0.062 (0.0444)
View			0.102*** (0.0241)	0.107*** (0.0211)
Distancetogrocerystore				0.0263 (0.0325)
Distancetobustop				0.2320*** (0.0550)
Distancetocitycenter				-0.0191* (0.0076)
Distancetoairport				-0.0034 (0.0090)
Distancetogym				-0.0338* (0.0155)
Hillevåg				-0.127** (0.0403)
Hinna				-0.026 (0.0563)
Hundvåg				-0.222*** (0.0628)
Madla				-0.033 (0.0462)
Storhaug				-0.069* (0.0276)
Tasta				-0.074 (0.0551)
Constant	11.80***	11.82***	11.79***	11.55***
	(0.581)	(0.643)	(0.622)	(0.566)
Observations	266	266	266	266
R^2	0.753	0.758	0.774	0.846
Adjusted R^2	0.737	0.739	0.756	0.826

Table 4: Regression results for apartments

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The regression results are presented in Table 3 for houses and Table 4 for apartments. Model 1 includes internal house attributes, which involves 16 attributes. The results show that the adjusted R^2 is 61% for houses and adjusted R^2 is 73% for apartments in Model 1. In the regression model for houses, shows that the internal attributes, p-room, and high standard are robust variables. For apartments, the internal attributes that were robust in model was freehold, p-room, age, and high standard.

Model 2 includes the same variables as Model 1, but is extended by adding external attributes. The added external variables are garden, garage, and balcony. The adjusted R^2 rises by 0,5% for houses and 0,2% for apartments. This is close to an insignificant improvement. None of the added external attributes is significant for houses. When the external variables were added to the apartment regression, balcony was the only significant variable. The sales price increases by 11% on average when an apartment has a balcony.

In the next model, environmental attributes are added. However, the only collectable variable in this category, was view. View is almost significant with the p-value at 0,059 for houses, but due to the 5% significance level requirement, it is dismissed. In Model 3, the adjusted R^2 increases to 62% for houses. A 0,5% rise in respect to Model 2. For apartments, the adjusted R^2 increases to 76% after adding view. This is almost a 2% increase from Model 2. The view is highly significant for apartments. Model 3, estimates a 10% increase in apartment prices on average. After the variable view is added to Model 3, the variable balcony becomes insignificant for apartments.

In the fourth and final model, the neighbourhood variables are added. The adjusted R^2 increases to 69% for houses and to 83% for apartments. This is a 7% with respect to Model 3. This is the largest rise in goodness of fit for houses and apartments. The environmental variable, view becomes significant in Model 4 for houses. The estimated coefficient explains that view adds 7% to the house value at average. View is still significant and robust in Model 4 for apartments. The coefficient is approximately the same as in Model 3. The distance variables included in the model show significant results for distance to bus stop and gym. Distance to bus has a positive coefficient for both houses and apartments. This means that a house located one additional kilometre away from bus stop, experience a 31% increase in value. For apartments, it is 23%. Distance to gym has a negative coefficient. If the house or apartments is located one additional kilometre away from the gym the value of the dwelling goes down with 5% and 3% respectively. Distance to city centre was only significant for apartments. This coefficient is negative. For apartments, each additional kilometre away from city centre results in a 2% decrease in value. Regarding the added district variables, several of them are significant. Eiganes/Våland is used as the base in the model, which means that the coefficients must be interpreted with respect to Eiganes/Våland. In the regression model for houses, Hillevåg, Shorhaug and Tasta have negative coefficients. The houses located on Hillevåg is estimated to be worth 26% less than houses located on Eiganes/Våland. The districts, Storhaug and Tasta is valued 15% less. For apartments, the regression estimated that apartments located on Hillevåg, Storhaug, and Hundvåg are respectively priced 13%, 7% and 22% less than apartments located on Eiganes/Våland on average.

6. Discussion

The hedonic price model indicates that housing prices in Stavanger is influenced by external, environmental and neighbourhood attributes. The Chow test imply that there is a structural change between houses and apartments, which has been considered in this thesis.

When internal characteristics are accounted for, external variables have a small impact on both house and apartments. Balcony was the only variable with statistical significance for apartments. Model 2 suggests that the price for apartments would increase by 11% on average when balcony is present. Other studies have implied that balcony has a positive effect on housing prices (Sirmans, Macpherson, & Zietz, 2005; Chau, Wong, & Yiu, 2004). Balcony could add a better view and an outdoor area to use without leaving the apartment. A 11% increase in price might be reasonable, assuming most people appreciate having a balcony. A disadvantage with this assumption is that the model does not consider the size or scenic aspect from balcony, which would influence the value of the variable. Nonetheless, the model indicates that balcony has a positive impact on apartments in Stavanger.

However, balcony appear statistically insignificant in Model 3 and 4, when view is added to the model. It is possible that balcony explained view in Model 2. As previously discussed, balcony could extend the view from an apartment. Model 3 and 4 suggests that view increases price for apartments with 10% on average, with the variable being statistically significant in both Model 3 and 4. This indicates that view is robust and has a significant impact on price for apartments. View is close to being significant in Model 3 for houses, but when neighbourhood characteristics are accounted for, view show statistically significant result for house. The coefficient implies that price for house increase by 7% on average when view is present.

The differentiation between the results for apartments and houses concerning view, could be explained by the number of stories each type normally includes. Apartments are located from first floor to sixteenth floor, while houses is normally limited to the third floor. This could contribute to a higher impact for view on apartments. The adjusted R^2 show a slight increase when adding the external and environmental variables, whereas the increase are 1,9% for apartments and 1% for houses.

In the fourth and final model, neighbourhood variables are added. By adding these variables, the adjusted R^2 increased by 7% in both models for houses and apartments. Among the location variables, distance to gym and distance to bus stop influence housing prices regardless of structural type. Distance to gym variable is negative and indicates that for every additional kilometre from the gym the housing price goes does down. For houses, an additional kilometre away from the gym indicated a 5% drop in price. For apartments, the impact was 3%, slightly lower than houses. Although, it is reasonable to believe that distance to a gym is not a decisive factor when buying an apartment, the negative sign still reveals a preference to be close to one. Due to its relative high coefficient for not being a decisive factor, distance to gym variable may be overstated. This might be caused by omitted variable bias. It is possible that distance to gym indicates a central location within a district in Stavanger.

Distance to bus stop is on the other hand, positive. This variable indicates that for every additional kilometre away from the bus stop the price goes up by 31% for houses and 23% for apartments. One possible explanation to the positive coefficient is that bus stops are often located on trafficked streets. Noise has in earlier studies showed having a negative impact on price (Li & Brown, 1980; Sirmans, Macpherson, & Zietz, 2005). Hence, being further away from a bus stop may be positive for housing prices. However, the coefficients are noticeably large. It is also worth mentioning that according to the summary statistics (Table 2) from the total sample, no dwelling was more than one kilometre away from a bus stop. Being located more than one kilometre away from a bus stop would be considered out of the norm. Nevertheless, there is reason to that distance to bus stop variable is overstated. A possible reason for this is omitted variable bias.

Distance to city centre is only significant for apartments. The variable is negative and indicates that for each additional kilometre the apartment is located away from city centre, the price goes down 2%. This result is as expected. The result also corresponds with the findings from Ottensmann, Payton & Man`s study (2008). The city centre in Stavanger can be described as a central business district (CBD), and proximity to a CBD should add value to a housing unit.

Model 4 also indicates different prices for different districts in Stavanger, when internal, external, and environmental attributes are accounted for. According to the model, a house located on Hillevåg would be valued 26% less, than a house located on Eiganes/Våland. If the house was located on Storhaug or Tasta it would be valued 15% less. An apartment located on Hillevåg, Storhaug, Hundvåg would respectively be priced 13%, 7%, 22% lower, than if it was located on Eiganes/Våland. In the model, Hillevåg and Storhaug have both negative impact on housing price regardless of structure type. Eiganes/Våland is commonly known as more prestigious districts. However, there is reason to believe that prestige is not the only factor that contributes to the price difference. Other social factors that may be explained in the district variable is differences in income, crime, and school quality. It is possible that there has been a build-up of people with poorer living conditions in Hillevåg and Storhaug. This may cause the public to see the districts as less attractive. According to a living conditions study done by Stavanger municipality (2017) there is no clear difference in living conditions between districts. However, of the fourteen neighbourhoods that were deemed with the biggest living conditions challenges, five of them were located on Storhaug and three in

Hillevåg. In recent years Stavanger municipality have initiated a "living condition lift" for Storhaug district in an attempt to equalize the differences between districts. Their study showed that Storhaug have experienced a positive development after the implementation (Stavanger Kommune, 2017). It is possible that this is the reason why there is not a larger price difference between Storhaug og Eiganes/Våland in the model. The adjusted R^2 in the final model is 83% for apartments compared to 69% for houses. The difference implies that the model is a better fit for apartments than for houses.

6.1 Limitations

This study, like many other hedonic price studies, has some limitations. One of these limitations are data availability and accessibility. The database used in similar Norwegian hedonic price studies is Eiendomsverdi.no. This database is limited to record sales price, location and a few internal attributes. In the more recent sales transactions, it is possible to locate the connected sales ad from Eiendomsverdi.no. The other attributes used in this thesis, were found by examining each dwelling's individual sales ad. This made data collection both time-consuming and demanding. There are also some social factors (i.e. income, crime, school quality) that arguably could affect housing prices that were not included in the dataset due to lack of quantifiable data. Studies that were able to include these factors were most likely conducted in countries with different legislation regarding freedom of information. For example, in the United States it is possible to find information about the buyer's race, income, the purchased property price, and mortgage due to the Home Mortgage Disclosure Act of 1975 (Bishop & Timmins, 2001). Similar database is not available to the public in Norway. Not being able to include attributes that possibly affect housing prices in the regression could lead to omitted variable bias. A limitation of this study is therefore, that the effect of some variables may have been overestimated or underestimated, due to omitted variable bias.

Regarding the scope of the study, the composition of the sample is representative according to Figure 5 and Figure 6 in chapter 4. It is however, reasonable to assume that the hedonic regression model, would benefit from more observation collected over an extended period. Hence, it is a limitation of this study.

6.2 Implications for future work

The hedonic regression estimates obtained in this study provide an insight in the mechanisms' behind housing prices in Stavanger at a micro-level. However, due to the limitations of this study, further research is necessary in order to fully understand the impact of housing attributes.

The development of the hedonic price model for the housing market in Stavanger is dependent on data availability and accessibility. Previous hedonic price studies conducted in other countries have found that income, school quality, and crime may affect housing prices. In order to avoid omitted variable bias these factors should be controlled for in the hedonic price model in Stavanger as well. Gathering and quantifying data regarding these factors is therefore essential in order to implement them properly in the hedonic price model.

While many variables are included in this thesis, there is a possible to classify some of them in a greater extent. As previously stated, view is classified as either present or not in this study. It is however, possible to distinguish between ocean view, mountain view and other views. Investigating in more detail, in regard to the impact of view, could provide valuable insight.

One of the limitation of this study was in respect to sample size and length of estimation period. Further research should also focus on expanding both sample size and estimation period.

7. Conclusion

The purpose of this thesis was to study if external, environmental and neighbourhood attributes had effects on housing prices in Stavanger. In order to research this, the hedonic price model was used as the analytical tool. Extensive microlevel data from all the dwellings sold in the last quarter of 2016 was carefully collected and transformed to an original dataset. The characteristics in focus were based on both previous hedonic house price model studies and what data were accessible.

During the development of the estimation model, it was found most useful to the analysis to divide the model into four blocks. By sequentially adding external, environmental and neighbourhood attributes to the model, it was possible to observe each respective impact on the housing market. Internal attributes were used as control variables. A Chow test uncovered structural differences between houses and apartments. They were therefore analysed in separate hedonic regressions.

The results from the hedonic price model showed that external and environmental attributes had no clear impact on price. After adding these attributes to the model, the adjusted R^2 only rose by a little. In the fourth model, view was the only significant variable among external and environmental attributes. The presence of view indicated an increase in value for house and apartments.

After adding neighbourhood characteristics to the model, the adjusted R^2 rose by 7% for both houses and apartments. Several distance characteristics were significant, but its relative importance as opposed to internal and neighbourhood characteristics is questioned. High coefficients connected to some of the distance characteristics raise suspicion regarding possible omitted variable bias. The model also indicated a price difference between districts in Stavanger. Dwellings, regardless of structure, located on Hillevåg and Storhaug had on average lower prices than dwellings located on Eiganes/Våland. The overall fit of the fourth and final model was better for apartments than for houses, due to a higher adjusted R^2.

This study presents a hedonic price model that includes previously neglected attributes by former Norwegian hedonic studies. The results suggest that external and environmental attributes affect housing prices in Stavanger to a lesser degree. Neighbourhood attributes appears to have a greater impact. The estimates obtained provide valuable insight in regard to housing prices in Stavanger. However, further research needs to be conducted.

8. References

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