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Valuating residential properties nearby social housing

What is the influence of social housing on neighbourhood attractiveness?

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Abstract

The aim of this research was to analyse the effect of social houses on the neighbourhood attractiveness. Neighbourhood attractiveness is reflected by residential property prices because homebuyers will bid up for the most desirable places. The literature review describes the impact of multiple characteristics on the valuation of residential properties. The characteristics are: *Structural, Locational, Neighbourhood and Environmental.* An explanation of their influence on the valuation of residential properties is given for each category. Thereafter, the measurement techniques are described. Subsequently, the impact of social houses is explained. Social houses seem to have a negative impact on the valuation of residential properties. Tenants of social houses have more problems, and a high concentration of social houses is seen as problematic.

The data of social houses is obtained from the municipality of Rotterdam and Maaskoepel (umbrella organisation for housing associations in Rotterdam) and geographical information software made it possible to link the data to residential property prices. An OLS panel regression with Entity and Time fixed effects is used to analyse theses effects. It resulted in a negative effect of the amount of social houses in the immediate vicinity on the valuation of residential properties. This effect decreases over distance. The effect of the share of social houses in a neighbourhood on the valuation of residential properties is unsure. The outcomes of different models are not in line with each other.

Preface

It was not easy to finish this thesis. Therefore, I would like to thank my supervisor Erik Braun for guiding me through the process. The subject of my thesis changed a lot of times and you always helped me with your feedback and the search for data. Many thanks to Henk Rehorst for helping me with geocoding the data. Without your help I would not be able to analyse my questions on a micro-level. Special thanks to Andromeda Jones commenting on grammar and formulation issues. Furthermore, I would like to thank my parents for supporting me during the year. It kept me motivated to finish this thesis in the best possible way.

Introduction

The national government of the Netherlands and housing corporations invested almost 1 billion euros in problem neighbourhoods during the last 10 years (Julen, 2018). In general have disadvantaged neighbourhoods a large share of social housing. Urban regeneration and revitalization programs are common ways used to improve the quality of urban neighbourhoods. The programs aim to improve the social well-being of residents and the structural quality of the urban neighbourhoods (Kleinhans, Priemus & Engbersen, 2007). Resources (money, personnel and policies) are needed to solve problems with livability in these neighbourhoods (Lelieveldt, 2004). The national government and municipalities develop different programs on varying scales to achieve these goals. Glaeser, Kolko and Saiz (2001) endorse the improvement of the quality of urban neighbourhoods in the fact that consumption in cities becomes more important. A rich variety of services and consumer goods, the quality of the services and the accessibility of them will have a positive impact on the whole neighbourhood. These characteristics of the neighbourhood are also important factors in residential location decision choices. Residents define the attractiveness of the neighbourhood and will influence the settlement patterns of residents (Chhetri, Stimson & Western, 2006). The effects of the programs are mainly investigated by comparing the outcome with a control neighbourhood. According to Galster, Tatian and Accordino (2006), these outcomes can be misleading. Citywide factors and trends might be overlooked. This research will therefore focus on social houses that influence residential property prices on the neighbourhood level. In a competitive housing market, homebuyers will bid up for the most attractive places.

Houses are built up from multiple characteristics, which will all have their own value on residential property prices. Every house is different and can therefore be assumed to be heterogeneous (Sirmans et al, 2005). The presence of social housing and the associated urban regeneration and revitalization programs can be counted as neighbourhood factor. GIS (Geographical Information Systems) software enables the opportunity to measure the impact to a specific residential property. Therefore, this research will be focussed mainly on the question:

What is the effect of social houses on neighbourhood attractiveness reflected by residential property prices?

The city of Rotterdam will be taken as the case study for this research. Rotterdam has a large share of social houses, 56.05% of the housing stock is socially rented (Provincie Zuid Holland, 2018). The municipality of Rotterdam has an active role in redesigning different parts of the neighbourhoods during the years. Some parts of the city are regenerated while the municipality also invests in projects that residents came up with to improve the liveability. Data of the 'Nederlandse Vereniging van Makelaars en Taxeurs' (NVM) about characteristics and sale prices of residential houses can be combined with neighbourhood characteristics and information about the social housing. A hedonic regression analysis attempts to estimate the contribution on the residential house price. Multiple panel regressions will be used to investigate the effect of social housing.

This research is structured in the following way. The next sext section is the literature review which is constructed based on the following questions:

- What types of environmental effects will influence residential property prices?
- Which methods can be used to measure the influence of neighbourhood effects on residential property prices?
- How will social housing influence the neighbourhood attractiveness?

The knowledge of the literature review will be used to form hypotheses in Section 3. Section 4 will elaborate on the data that is applied in this research and section 5 will describe the methodology used. The results will be presented in section 6 and the conclusion, methodological limitations and possible improvements will be discussed in section 7.

Literature Review

Environmental effects

As mentioned by Sirmans et al., (2005), houses can be assumed as heterogeneous products. Every house is built up from multiple characteristics. In general, these will characteristics be divided in *locational* and *physical* factors. Different bundles of characteristics result in different valuations. Xiao (2017) extended this division in 4 different categories which will have their influence on residential housing prices. *Structural* or internal attributes form the physical features of a house. *Locational* attributes give the distance of a house from major places of amenities, employment and transportation modes. *Neighbourhood* characteristics will determine the quality of the neighbourhood in terms of economic and social status. *Environmental* attributes will influence the quality of living determined by pollution, noise and aesthetic views. Most of these categories are influenced by the neighbourhood the residential property is located in. Therefore, each of these categories will be further analysed to get insight in the most influential factors.

Structural characteristics

The defined characteristics explain what can be expected from the property. The structural characteristics of a property describe the physical attributes of the property itself. They are an important determinant for the valuation of property. Compared to other characteristics, the structural characteristics are easier to obtain.

The top twenty characteristics that have been used to specify hedonic pricing regressions are summarized by Sirmans et al. (2005). Most of the investigated characteristics are structural. Most often used is the age of the property, which has, most of the time, a negative effect on the price of the property. Increased maintenance costs and decreased up to modern standards represent this decline in the value of the property (Clapp & Giaccotto, 1998). However, in some cases the age of the property can positively influence the valuation of the price of the property. After some point, and especially in historical parts of cities, properties can become designated as historical which will positively affect its price (Lazrak, Nijkamp, Rietveld & Rouwendal, 2014). Other structural characteristics are lot size, number of bedrooms and number of bathrooms. These characteristics are expected to have, on average, a positive correlation with house prices. Due to economies of scales in the construction process, the effects might be nonlinear. Zietz, Zietz and Sirmans (2008) found that the different valuation of these variables depends on the selling prices of properties. Purchasers of higher-priced properties value characteristics differently than purchasers of lower-priced properties. There is also an interaction effect between the lot size and number of rooms. Li and Brown (1980) suggest that there is an incentive to construct small houses on small lots and large houses on large lots. Due to the fact that there will be an increase in the price of the property with more rooms on a lot size.

Kain and Quigley (1970) found that the housing quality have as much an effect on the housing price as the lot size, the number of rooms and the number of bathrooms. They used as measures: the condition of exterior structure, walls, condition of floors, drives and walks, windows and levels of housekeeping.

The significant impact of other structural characteristics will change over time and between countries (Kohlhase, 1991). These characteristics are influenced by the climate or the tradition of building style. Monuments are also not valued the same over time. Lazrak et al (2014) mention that in the Netherlands, just after the Second World War, many older buildings were demolished in favour of newly-built buildings. Those buildings are valued today highly for their cultural significance. People value monuments more highly over time in their neighbourhood.

Locational attributes

The valuation of locational attributes can be seen as a premium that will be paid on the price of a property on a specific location compared to the same property on a less attractive location (Smith, 1978). The most important locational characteristics are the distance to major places of employment, the distance to amenities and accessibility (Xiao, 2017).

Von Thunen (1842) was one of the first who related location to the valuation of property. His classical land use theorem describes the relationship between agricultural land use and the distance to the marketplace. Productivity and transportation costs depend on who will be located close to the marketplace and will pay more for this location. This theory is developed and connected to an urban context by Alonso (1964), Muth (1969) and Mills (1972) into a trade-off between transportation costs and land rents. One of the key assumptions in the model is the supposition of a monocentric city, where there is a centralized workspace. This idea can be linked to a Central Business District (CBD) what will be the major determinant of the location specific land values and the land rents. So, more centrally located properties will be valued higher than properties which are located further away.

As mentioned by Boarnet (1994), the validity of the monocentric model is criticized during the years. At first it can be pointed out that employment is not concentrated in a CBD. Employment sub-centres and decentralization of households and firms are changing the structure of cities (Fujita & Ogawa, 1982; McDonald, 1987; Giuliano & Small, 1991). Heikkila et al (1989) emphasize a polycentric approach to discuss metropolitan areas. The CBD has become relatively less important for employment and therefore households are not willing to pay a premium for good accessibility to the CBD compared to other places. Secondly, it is questioned whether the distribution of jobs and residence is the primary determinant of the journey to work. Hamilton and Röell (1982) and White (1988) argue that the amount of 'wasteful commuting' could be eliminated by redistributing workers to different houses or jobs. The effect of location on the cost of commuting seems to be limited, even if employees want to minimize their costs of commuting (Hamilton, 1989). There also seems to be other factors (e.g. second-earner, female participation) that influence residential location (Frost, Lineker & Spence, 1998; Small & Song, 1992).

The Accessibility of a location is another factor in the valuation of properties. According to Fejarang (1994), investments in transport infrastructure will lead to benefits for properties around these locations. Reduction in transport time and cost saving, as result of the investment, will reduce the demand friction for residential properties around the CBD. Fast transportation and accessibility can be seen as a substitute for distance to the CBD, and each mode of transport will improve the accessibility of a region independently (Debrezion, Pels & Rietveld, 2007). It should be Noted that there are different effects in proximity and accessibility for transportation infrastructure. The amenity effect of transportation infrastructure and services leads, in general, to an increase in valuation of properties, while proximity to some forms of infrastructure can be valued as disamenity (Mathur, 2008). Forms of this disamenities could be noise (Debrezion, Pels & Rietveld, 2010), pollution (Langley, 1976) and attraction of criminality (Bowes & Ihlanfeldt, 2001).

The distance to major amenities is another important locational attribute in the valuation of properties. Glaeser et al. (2001) mention that cities have been becoming more and more a place for consumption. Cities with a high level of amenities are growing faster and the rent in these cities raise faster compared to the urban wages. Amenities are valued higher by residents when they are nearby. Therefore, the accessibility to amenities will have a positive impact on the valuation of residential properties. Types of amenities that have a positive influence are: schools (Kane, Reigg & Staiger, 2006), grocery shops (Addae-Dapaah & Lan, 2010), department stores (Des Rosiers, Lagana, Thériault & Beaudoin, 1996), hospitality sector (Garretsen & Marlet, 2011) and cinemas and theatres (De Groot, Marlet, Teulings & Vermeulen, 2010).

Neighbourhood Attributes

Neighbourhood Attributes are characteristics that determine the quality of the economic and social status within the neighbourhood (Xiao, 2017). In General, higher income neighbourhoods are assumed to have a higher quality of liveability. So, higher income neighbourhoods will be preferred by all households. Gans (1963) countered this with the idea that it is preferred to live in neighbourhoods dominated by households similar to themselves. Therefore, social and economic status variables, controlling for neighbourhood and amenity quality, are useful to emphasize these effects in hedonic models for residential property values.

Socioeconomic status refers to someone's position on the social ladder. This status is multifaceted and only the most significant factors will be discussed. These factors are: the number of inhabitants, reputation of the neighbourhood, income, age and race.

A common method to measure the effect of number of inhabitants on residential property valuation is by the number of inhabitants per square kilometre. This variable has a two-sided effect. If the number of inhabitants per square kilometre is high, the demand for residential properties in those regions will be high which will drive up the price. On the other hand, the expected residential property size will be smaller which will thereby lower the price.

The reputation of the neighbourhood is an important valuation indicator as well. According to Permentier, Bolt and Van Ham (2011), the reputation of a neighbourhood influenced is by its ethnic composition, socio-economic status, crime level and location. The levels of permanent and temporary income are positively related to residential property valuations (Fontenla & Gonzalez, 2009; Hou, 2010). The crime rate of a neighbourhood will also determine its reputation. Lynch and Rasmussen (2001) found in their study that neighbourhoods with a high reported crime rate have a relatively low residential property valuation. Another important factor is the accuracy of the information about a neighbourhood's reputation. Property-seekers can be unaware of improvements in quality in the neighbourhoods. The improvements do not automatically lead to an increase in the valuation of properties due to the reputation of the neighbourhood (Koopman, 2012).

The relationship between age of the population and residential property valuation is argued to be positive by Anas and Eum (1984). Older people earn, in general, higher salary and they can therefore afford higher valued residential properties. However, retired people often move to smaller, and thereby lower valued, residential properties. This relationship can turn negative after a certain age is reached and will have a upside-down U-shaped form.

Visser, Van Dam & Hooimeijer (2008) found that the lower the social status and the higher the proportion of Non-Western immigrants in a neighbourhood will lower the price of residential properties per square meter. Other studies (e.g. Clotfelter, 1975) found that the racial composition of schools have a negative impact on the valuation of residential properties in the neighbourhood. When controlled for school quality, the racial composition of a school turned to have a little effect (Jud & Watts, 1981).

So, the quality of amenities can also be helpful to determine neighbourhood attributes that influence the valuation of residential properties. Tiebout (1956) was one of the first who highlighted the importance of the quality of facilities and services for residential location decisions and the demand for residential properties in a neighbourhood. The quality of schools is one of the major investigated neighbourhood attributes that influence the neighbourhood attractiveness. Pupil-teacher ratio and standardized test scores are often used to control for school quality in valuation of residential properties (Brasington, 1999). The school quality systematically affects the valuation of residential properties (Black, 1999). Hefner (1998) investigated the relationship between quality of schooling and the valuation of residential properties and hereby used two measures for quality: student-to-teacher ratio and participation in talented programs. The price of surrounding properties can increase as a result of administrative and leadership choices made by the school and parents. Dubin and Goodman (1982) investigated the influence of school characteristics and crime rates on the valuation of residential properties. The different school characteristics were strongly correlated and it was hard to obtain the contribution in the valuation.

Environmental attributes

Another indicator in the determination of residential property valuation are environmental externalities. The environmental indicators can be distinguished in two categories; environmental quality and environmental amenities (Xiao, 2017).

The environmental quality can be measured by the quality of air, quality of water and the amount of traffic that moves through a neighbourhood. The quality of air has a negative impact on the valuation of residential properties. Chay and Greenstone (2005) found that a reduction in particulate matters improves the average valuation of residential properties. Kain and Quigley (1970) argue one of the reasons why high income households live further away from the CBD is better air quality. The same effects can be observed with quality of water. Water quality, measured by visibility, clarity and Ph value, seems to be positively related with the valuation of residential properties (Boyle & Kiel, 2001).

Another unwelcome effect that influences the environmental quality in a neighbourhood is noise pollution. When noise levels are equal to each other, noise from airplanes is perceived as most annoying, followed by car noise and noise from passing trains (Miedema & Oudshoorn, 2001). Research of Theebe (2004) found that traffic noise pollution has a negative impact on the valuation of residential properties after 65 decibels. In addition, there is weak evidence found that properties high-income neighbourhoods are more affected by traffic noise pollution than properties in low-income neighbourhoods.

Undesirable land uses could also have its negative impact on the environmental quality in a neighbourhood. Land near residential properties can be used as a location for a power plant or as a dump. Residents are not willing to live near such places and it will therefore have a negative impact on the valuation of residential properties (Boyle & Kiel, 2001). According to Farber (1998), the employment opportunities of such facilities cannot compensate for the negative health and amenity risks associated with environmental hazards.

Environmental amenities can be defined as an environmental dimension of accessibility that adds value to residential properties. The view from a residential property can be seen as one of these attributes.

Luttik (2000) stated that a view on water makes a residential property, on average, 8-10% more valuable. When a residential property overlooks some sort of open space, the valuation of the property will be valued, on average, 6-12% higher. The same effects were observed by Tyrväinen and Miettinen (2000) with respect to a view of forests. View is therefore positively correlated with the valuation of residential properties. Gillard (1981) argues: "even when a park may not be used for recreation because of crime problems, it may still be valued for aesthetic reasons by residents with a view of the park."

Another attribute that impacts the environmental amenities in a neighbourhood is the accessibility to green spaces. Morancho (2003) concluded that there is an inverse relationship between the valuation of a residential property and the distance to green spaces. Every distance of 100 meter between a green space and a residential property will decrease the valuation with approximately 1,800 euro. Similar relationships were found for golf courses (Lutzenhiser & Netusil, 2001) and forests (Tyrväinen and Miettinen, 2000). The impact on the presence of street trees is investigated by Donovan and Butry (2010) with a study in Portland, Oregon. They concluded that street trees improve the valuation of surrounded residential properties by 8,870 dollars and reduce the time-on-market by an average of 1.7 days.

Measurement methods

As already mentioned earlier in this report, residential property valuation is based on a bundle of characteristics. Some of these characteristics are relatively easy to obtain and assign value to. The valuation of, for example a bathroom, is based on a price given by the market. Assigning value to neighbourhood factors is harder to obtain, because there is a lack of a market to price them. Therefore, other methods need to be used to assign their value.

Hedonic Pricing model

The most common method to measure the assigned value of these characteristics is with a hedonic pricing model. Rosen (1974) developed the model to argue that a product can be valued by its characteristics. The price of a product is based on the sum of the price of each characteristic. The model is based on utility functions of consumers and producers. These utility functions can be used to trace back the willingness-to-pay of consumers for a product and the profit for producers. A hedonic price function is needed to reach the equilibrium in this market because multiple heterogeneous consumers will be served by one type of producer.

The demand for the different characteristics is based on the households' income and their preferences. Comparing the budgetlines of the consumers and hedonic price functions will present the choices of the consumers. All these choices combined give the hedonic demand for the characteristic. This model takes all of these factors as parameters in the consumption function of the consumer

The hedonic pricing model is more specified to the housing market by Sheppard (1999). Each household will maximize their utility based on its preferences and choose a house and consume other goods. Their optimal choice will be when this maximization of utility is equal to the hedonic price of a characteristic. The equilibrium in the market depends on the preferences and the distribution of consumer incomes (Udell, 2016). However, the housing market is distinctive compared to other markets according to Sheppard (1999). At first, the searching costs to collect information about properties are relatively high. Consumers will search for an expected increase in utility until the searching costs exceed it. Second, housing involves a spatial component. Locations distinguish in transport costs when there have been accounted for all relevant local amenities. Thirdly, the housing market is composed of new and existing houses.

The importance of hedonic analysis of housing markets in conducting cost-benefit analyses of changes in the housing market is also demonstrated by Sheppard (1999) and Udell (2016). They mention the most common implications for the validity of hedonic pricing models. Unobservable variables are correlated with both the explanatory independent and the error term, which harms the endogeneity of the model. This leads to concerns about the impact of variables on residential property valuation and attributes

One of the advantages of a hedonic pricing model is that the price is based on choices consumers will actually make. A disadvantage of the model is that it is based on predictions. Consumers are not reliable in making predictions because of over- and underestimation. Besides that, the data used for the predictions might not to be up to date anymore.

The hedonic price model distinguishes, in general, two types of variables: the physical and locational variables. The model has been developed over time and Xiao (2017) detailed the model to distinguishes four types of variables to value the price of residential properties. This gives the following model:

$$P = f(S, L, N, E)$$

Where S denotes the structural or internal attributes. It represents the physical characteristics of a residential property. L consists of the locational attributes, which represent the distance to major places of work and amenities. It also gives insight about the accessibility of the residential property. N consists of characteristics that determine the quality of the neighbourhood in terms of economic and social status. E denotes the environmental attributes that represent the environmental quality and environmental amenities.

Measuring

The literature is clear about the division of attributes that influence the valuation of residential properties. However, it is still hard to fit some of these surrounding conditions into a hedonic pricing model. A study done by of Can (1998) showed that involving locational effects will improve the precision of coefficients estimated and also will increase the predictive power of the model. The most common methods to obtain the impact of such conditions are ”Neighbourhood effects” and the “Continuous space model”.

When using “Neighbourhood effects”, the areas that will be investigated must be defined separately based on the influence on the influence of the different attributes. One of the main arguments for using “Neighbourhood effects” is that neighbourhood influences are important to understand the persistence of inner city poverty (Wilson, 1987). According to Durlauf (2004), the effects involve two questions. At first, how is the behaviour in a neighbourhood impacted by neighbourhood factors’. Secondly, how will the configuration be across neighbourhoods? The areas differ between studies. Some analyses are based on zip codes, while others choose for the impact in neighbourhoods. Analysing the presence of factors in these areas will create a value for the surrounding conditions, which can be used in the hedonic pricing model for the valuation of residential properties in the area (Sampson, Morenoff & Gannon-Rowley, 2002).

The “Continuous space model” uses another method to assign value of surrounding attributes to the residential property. It draws a fictitious circle around the residential property. The presence of the factors will be observed within the circles, the size of the radius depends on the research. Because the data for each factor is known, it is possible to be included them in the hedonic pricing model very detailed (Sheppard & Udell, 2016). The “Continuous space model” is more precise in establishing the impact of surrounding attributes compared to using “Neighbourhood effects”. For instance, residential properties close to the border of a zip code will by using “Neighbourhood effects” the attributes of the adjacent zip code not taking into account in the hedonic pricing model. These attributes could indeed have their impact on the valuation of the residential property.

Social housing and neighbourhood attractiveness?

Social housing is an important part of the housing provision in countries. It leads to the investment in new buildings and regeneration, and it also provides affordable housing for a great amount of inhabitants. Beyond this traditional business core, the role of housing associations has become more important in neighbourhoods. Housing associations are offering other services and they care more about the environment around their dwellings. Investments to provide facilities and maintenance can be justified as improvements for the quality of life in their neighbourhoods and to maintain the value of their properties. Governments have also become more aware of the economic importance of housing. One of the most important drivers of the economic crisis of 2008 was housing, and the recession afterwards had the largest impact on the sector (Scanlon, Fernández Arrigoitia & Whitehead, 2015).

The housing stock in the Netherlands contained almost 8 million houses in 2018 (CBS, 2019). Housing associations own 29% of the housing stock, and most of the social rented houses are owned by them. Municipalities are also providing social houses, but they own a small fraction of the stock. All municipalities contain a significant amount of social houses, but the concentration is much higher in urban areas. In the municipality of Rotterdam, 56.5% of the housing stock is socially rented (Provincie Zuid Holland, 2018).

Tenants need to meet some conditions to be eligible for social housing. The current conditions according to the National Government (2019) are:

- Tenant need to register with the organisation that is responsible for the distribution of social houses in their municipality.
- A housing permit is needed in some municipalities. The permit requires that the tenant already lives, works or studies in the municipality. These rules differ per municipality.
- Housing associations can set requirement for the tenant's income or family size.
- The tenant's household income cannot be too high. Housing associations must assign 80% of the vacant social houses to households with an maximum income of €38.035 (price level 2019), 10% to households with an income between €38.035 and €42.436 (price level 2019) and 10% to higher incomes.

Some tanants will get priority by assigning a social house. Medical indication, social indication (e.g. family size) and commuting distance can be urgency criteria to get a priority. Due to these conditions the tenants of social houses differ compared to average households. The households that are in social houses are on average: older, less likely to be employed and more likely to be on social benefits, are more likely to be of non-Dutch origin and live in smaller houses (WoON, 2018).

Housing associations in the Netherlands are free to buy and sell their houses. They can have a variety of reasons, according to Elsinga and Wassenberg (2014), to buy from or sell to other landlords or individual households. In general, they want to improve their own financial position or as an incentive for urban regeneration in a particular area. Vacant properties can be sold on the open market and tenanted properties must be offered to the tenant. Tenants have the right to continue renting. Housing associations are allowed to sell below the price on the market, however it is often contracted that the buyer has to sell the house back to the association (Adamse, 2018).

Expected trends for the Netherlands

According to Scanlon, Fernández Arrigoitia and Whitehead (2015), the role of social housing sector will change in the future. However, social housing will still remain a significant percentage of the housing stock. Some of these trends will have their consequences for social housing in the Netherlands and will be further discussed.

The governmental subsidies support investments in new housing and regeneration have, in general, declined and are becoming more targeted. Public expenditures need to be reduced and the market has reduced numerical shortages by themselves. The housing associations in the Netherlands contribute to the government, and new investments need to be funded from their own equity. Elsinga and Wassenberg (2014) mention a change in the regeneration strategies of housing associations. Economic prospects after the crisis of 2008 made households reserved to buy houses. The expected rate of housing sales undermined the business model for urban renewal by the housing associations. Urban regeneration activities were postponed or delayed which resulted in a decrease in demolition, refurbishment and new constructions. The focus of housing associations is changed to inexpensive simple maintenance measures. Even the demand has changed and waiting lists for less valued apartments have become substantial.

Rental benefits depend on the changes in rental policies and the funding of the existing social housing stock. Housing corporations in the Netherlands are relatively free to set their rent within the range for social housing. Increases of the rents could result in more expenditure on rental benefits for the government (Scanlon, Fernández Arrigoitia & Whitehead, 2015).

The increasing demand for social housing leads to pressure on the market. An increased concentration of new entrants that are placed in less desirable locations and the increased demand from migrants and ethnic-minority households results in longer waiting lists and a residualization of the sector. Hoekstra (2017) mentioned that this process will have negative impacts on the housing system in the Netherlands. Problems that could arise are a growing shortage of social houses, unaffordability of rental housing and increased chances of spatial segregation and problem accumulation. Difficulties to obtain affordable houses in the private sector by mainstream households shift their demand. The gap will be filled with shared ownership and near-market-rent housing.

Housing associations have started initiatives in the development of more mixed and environmentally friendly communities. Mixing different types of households in areas can help to reduce the effects of residualization and exclusion. Subsidies and policies can improve the standard in energy efficiency and sustainability.

Social housing and urban regeneration

Governments and policymakers, and even housing associations, use urban regeneration to improve neighbourhoods. Disadvantaged neighbourhoods have, in general, a large share of social housing. Urban regeneration can be described as "all activities, physical and otherwise, intended in the local context to renew existing urban spaces" (Droste, Lelévrier & Wassenberg, 2014). The process is complex and integrates a lot of actors and activities at different scales. Urban regeneration can be divided into two types of policies that are applied to areas with a large share of social housing, *Physically* and *Socially.*

Physical regeneration

Programs for physical regeneration on social housing areas mainly focus on support refurbishment or demolition. De-industrialization and immigration resulted in an oversupply of (social) housing. Other aims of the programs are to improve the quality, outdated floor plans and inadequate dwelling sizes in neighbourhoods. The programs can also be used to stimulate the social mix and reduce the poor living conditions (Bolt, Phillips & van Kempen, 2010).

Concentrations of low-income households are seen as problematic by policymakers. Physical regeneration programs can contribute to a housing mix. The result of this housing mix will be a social mix and more social cohesion in the neighbourhood (Van Kempen & Bolt, 2009). The concept of social cohesion is used in different ways. In general, it can be assumed that it will be related bonding within a neighbourhood and the feeling of being part of a certain group (Atkinson & Kintrea, 2004; Forrest &

Kearns, 2001). The strong connection within a group can be positive, but can also weaken the connection with the rest of the urban society (Healey, 1997). This social fragmentation might lead to weak economic opportunities. Although the effect of social cohesion is uncertain, the expected outcomes of social mixing seems to be positive. It can be expected to lead to social mobility opportunities, more social capital, better amenities, an improved neighbourhood reputation and role-model effects (Kleinhans, 2004). The idea that a social mix in neighbourhoods will lead to common understanding and less prejudices will not always show up. There is no strong evidence found that a mixed neighbourhood will lead to more interaction between neighbours, and it might even have unwanted consequences as coolness and conflicts (Van Kempen & Bolt, 2009).

Social regeneration

Areas with a large share of social housing can often be characterised by high concentrations of low-income, immigrant or unemployed households. The aim of social regeneration programs is to support the residents in these disadvantaged neighbourhoods. According to Musterd (2016), too many vulnerable households in a neighbourhood can result in problem accumulation and synergy effects. The problems in the neighbourhood will be bigger than the sum of all the problems of the households. Training, Education and preparation for the labour market can enhance the employment prospects of the vulnerable households and might reduce the negative effects of spatial segregation and social exclusion (Ginsburg, 1999). The programs can also be used to increase the satisfaction of residents with their housing situation.

The success of the social regeneration programs depends on some key elements mentioned by Ginsburg (1999). Social regeneration is a long term process, so short-term investments have limited impact in the long-term. There is often a mismatch between the needs of the residents of disadvantaged neighbourhoods and the provided services. Local residents and small businesses can be used to create partnerships to achieve more success in local interests.

Hypotheses

It is possible to integrate social housing in the price function for residential properties if it will be counted as an environmental factor. The literature review gave insight about the differences in valuation of residential properties by the environmental factors, which can also be the presence of social housing. The valuation of residential properties is influenced by 4 different categories. These categories are: structural attributes, locational attributes, neighbourhood characteristics and environmental attributes.

Each of these factors has its own interaction with environmental factors. The categories can have their impact on the environmental factors, but it can also work the other way around.

This can be the case when social housing will be counted as environmental factor. The structural attributes of social houses are, in general, different from owner-occupied properties. The quality of social houses is graded by using a point system. The number of points depends the maximum rent of social houses. Points can be awarded for size, quality of the kitchen, quality of bathroom and WOZ-value (Rijksoverheid, 2018). The structural differences have an influence on the valuation of the residential properties.

The impact of social housing on the locational attributes is limited. In general, there is a competition for attractive locations and residents are willing to pay a premium for such locations. Social houses have a maximal rent and therefore their presence in the most desirable locations is limited. These locations will have a competition within the owner-occupied market which will influence the price.

Neighbourhood characteristics will have an interaction effect with social housing. Some neighbourhoods are more likely to have a larger concentration of social houses. The neighbourhood are designed for a large share of social housing and do have sometimes (forced) pull factors for residents of social houses. Urban regeneration programs force some tenants to move to specific places due to their financial position. Social houses will also have their influence on the neighbourhood. Large concentrations of social houses can change the neighbourhood. Neighbourhoods with a large share of social housing can often be characterised by high concentrations of low-income, immigrant or unemployed households. Too many vulnerable households in a neighbourhood result in problem accumulation. The neighbourhood will degenerate, which will have an impact on the valuation of residential properties in it.

The impact of social housing on locational attributes will be limited. Social houses might be located in less desirable places. These locations, e.g. close to highway, will have negative externalities such as air pollution and noise. In addition, neighbourhoods with larger concentrations of social houses have less environmental amenities. The design of the neighbourhood has less green spaces which might have an influence on the valuation of residential properties.

Therefore, the following hypotheses can be stated:

1. There is a negative relationship between the percentage of social houses in a neighbourhood and the price per m2 of residential properties.

2. There is a non-linear negative relationship between the percentage of social houses in a neighbourhood and the price per m2 of residential properties.
3. There is a negative relationship between the number of social houses in the immediate vicinity of a residential property and its price per m2.

Data

The panel dataset is built up from residential property transactions, neighbourhood features and rental house data. The year variable is important because the residential property transactions are listed in time order. The neighbourhood where the residential property is located in another important variable.

Residential property transactions

The data of residential property transactions is received from Brainbay/NVM. The data contains information about house sales in the municipality of Rotterdam between 2004 and 2018. The dataset consist of 58,570 residential properties, which includes, besides the transaction price, several structural attributes. The structural characteristics include the property's year of construction, the surface, the type, the number of rooms, the number of balconies, the number of dormer windows, the number of bathrooms, the parking opportunities, an indication for permanent inhabitant and an indication for partially rented. The variables will be divided in the division of attributes as mentioned in the literature review (Xiao, 2017). In Table 1 are all property specific variables specified.

Type	Variable			Description
Dependent	Logprice_m2		Natural number	Logarithmical price per m2
Structural	BWPER	1	2001-2018	Time period the residential property is built
		2	1991-2000	
		3	1981-1990	
		4	1971-1980	
		5	1960-1970	
		6	1945-1959	
		7	1931-1944	
		8	1906-1930	

	9	1500-1905	
SOORTWONING	2	Simple	Type of residential property
	3	House boat	
	4	Recreation residential property	
	5	Single family residential property	
	6	Canal house	
	7	Mansion	
	8	Living farm	
	9	Bungalow	
	10	Villa	
	11	Cottage	
	12	Estate	
	20	Other sort of apartment	
	21	Ground-floor apartment	
	22	Upstairs apartment	
	23	Maisonnette	
	24	Portico apartment	
	25	Flat Gallery	
	26	Welfare flat	
	27	Ground-floor and upstairs apartment	
SOORTWONING2	1	Single-family house	Type of residential property
	2	Villa	
	3	Farm used as residence	
	4	Mansion	
	5	House Boat	
	6	Bungalow	
	7	Canal house	
	8	Cottage	

	9	Estate	
	11	Apartment with elevator	
	12	Apartment without elevator	
	13	Ground-floor apartment	
TRANSACTIEPRIJS		Natural number	Indicates the transaction price.
DATUM_AANMELDING		Date	Date that the object was enlisted.
DATUM_AFMELDING		Date	Date that the object was checked out.
NKAMERS		Integer	The number of rooms of the residential property.
NBALKON		Integer	The number of balconies.
NDAKKAP		Integer	The number of dormer windows.
NBADK		Integer	The number of bathrooms.
PARKEER	0	No parking opportunity	Indicates the parking opportunity.
	2	Parking place	
	3	Carport and no garage	
	4	Garage and no carport	
	6	Garage and carport	
	8	Garage for more cars	
PERMANENT	0	Not permanently inhabited	Indicates if the residential property is

			permanently inhabited
	1	Permanently inhabited	
GED_VERHUURD	0	Not partially rented	Indicates if the residential property is partially rented.
	1	Partially rented	
BUURT		Afrikaanderwijk, Agniesebuurt, Bergpolder, Beverwaard, Blijdorp, Blijdorpsepolder, Bloemhof, Bospolder, Carnisse, Charlois Zuidrand, Cool, Cs Kwartier, De Esch, Delfshaven, Dijkzigt, Dorp, Feijenoord, Groot IJsselmonde, Heijplaat, Het Lage Land, Hillegersberg Noord, Hillegersberg Zuid, Hillesluis, Hoogvliet Noord, Hoogvliet Zuid, Katendrecht, Kleinpolder, Kop van Zuid, Kop van Zuid – Entrepot, Kralingen Oost, Kralingseveer, Landzicht, Liskwartier, Lombardijen, Middelland, Molenlaankwartier, Nesselande, Nieuw Crooswijk, Nieuwe Werk, Nieuwe Westen, Noord Kethel, Noordereiland, Ommoord, Oosterflank, Oud Charlois, Oud Crooswijk, Oud IJsselmonde, Oud Mathenesse, Oude Noorden, Oude Westen, Overschie, Pendrecht, Pernis, Prinsenland, Provenierswijk,	Indicates the neighbourhood in which the residential property is located

			Rijnpoort, Rubroek, Schiebroek, Schiemond, Schieveen, Spaanse Polder, Spangen, Stadsdriehoek, Strand en Duin, Struisenburg, Tarwewijk, Terbregge, Tussendijk, Vreewijk, Waalhaven, Witte Dorp, Zestienhoven, Zevenkamp, Zuiderpark, Zuidplein, Zuidwijk

Table 1: Property specific variables

Additional data

The neighbourhood features and rental houses data are obtained from Centraal Bureau voor Statistiek (CBS), Buurtmonitor Rotterdam and Leefbarometer. The data from these sources can be linked to the residential properties by using GIS-software. The Nationaal Georegister is used to receive the coordinates of the residential properties by using their zip-codes and house numbers. QGIS was used to map all the data (figure 1), and vectors where used to combine the data by location. Proper data for environmental attributes were not found in the datasets, and therefore these characteristics will be omitted in this research. In Table 2 are all neighbourhood features and rental house data further specified.

The Leefbarometer (Ministerie van Binnelandse Zaken en Koninkrijksrelaties, 2019) rates the quality of life for all neighbourhoods in the Netherlands each two years. It indicates how the living environment fits the conditions and needs of residents. There are 100 indicators used which can be divided in 5 dimensions (dwellings, residents, facilities, safety and physical environment).

Type	Variable		Description
Neighbourhood	BEV_DICHTH[1]	Natural number	Number of inhabitants per km2
	P_N_W_AL[1]	Natural number	Percentage of Non-western immigrants
	P_HHLAAGSTEINKOMENSGROEP2[1 2]	Natural number	Percentage households in the country 40% of lowest

Sources:
[1] CBS – Wijk- en Buurtstatistieken
[2] Rotterdam Buurtmonitor

	AANTAL_MISDADEN[2]	Natural number	Number of crimes committed in the neighbourhood
	AANTAL_NIETWERKENDEN[2]	Natural number	Number of unemployed people in neighbourhood
	LEEFBAROMETER[3]	Integer	Rating of the neighbourhood by the leefbarometer
	A_HUURW[2]	Natural number	Number of rental houses in neighborhood
	A_KOOPW[2]	Natural number	Number of owner occupied houses in neighborhood
	A_ONBEKW[2]	Natural number	Number of houses owner unknown
	AANTAL_CORPORATIEWONINGEN[2]	Natural number	Number of residential properties owned by housing
Locational	AV3_CAFE[1]	Natural number	Average number of bars in 3 kilometers range
	AV3_RESTAU[1]	Natural number	Average number of restaurants in 3 kilometers
	AF_TREINST[1]	Natural number	Distance to nearest train station

Table 2: Neighbourhood features and rental house data

[3] Leefbarometer

Figure 1: Distribution Residential properties in municipality Rotterdam

The data of social houses is obtained from the organization Maaskoepel. This is the umbrella organization of housing associations in Rotterdam. The data consist of 128.965 social houses owned by housing associations in the municipality of Rotterdam. The reference date of the dataset is January 1st, 2018. The data can be used to display the distribution of social houses in Rotterdam. The concentration of social houses is mapped by using Qgis in figure 2.

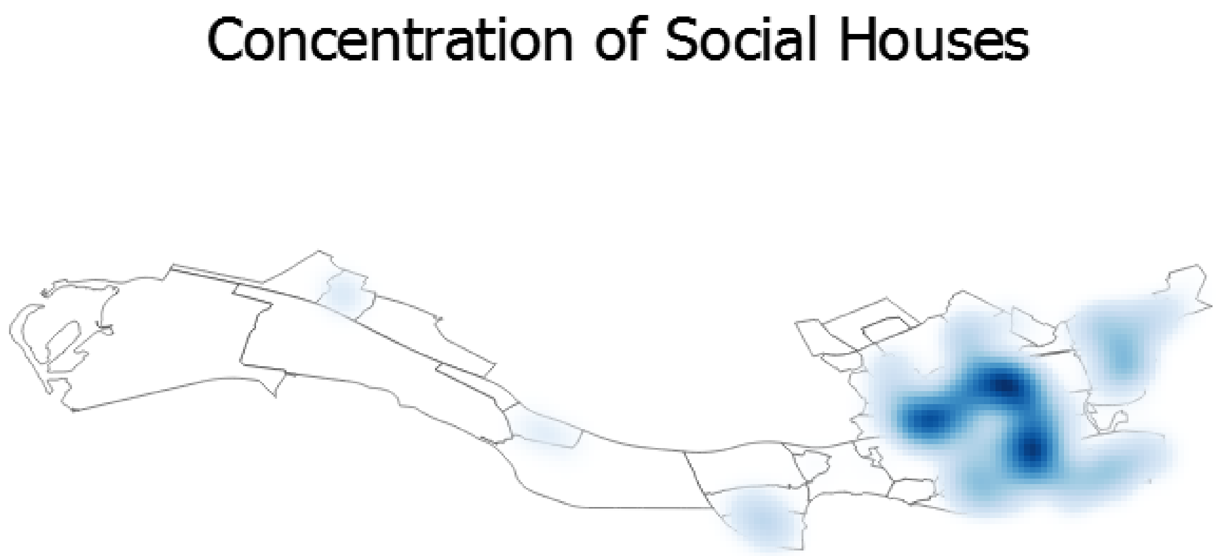

Figure 2: Concentration of Social Houses in Rotterdam

Data adjustments

As every dataset contains the dataset used in this research also outliers. Outliers should be avoided because they can lead to biased conclusions. Relations in the models can be interpreted wrong because some observations are too far away from the other observations. There are three possible reasons for the presence of outliers. *Measurement errors* could create a difference between the measured value of an object and its actual value. *Sampling frame* errors could cause outliers by using inaccurate or incomplete sample frames; the sample is not representing the population well. Another reason could be because of *clerical errors,* where bad translation causes the outliers.

There are three possible solutions to solve outliers. At first, the data can be used as 'normal' values. Secondly, Unreal values can be dropped. Third, data points can be adjusted to less extreme values, which is called winsorizing (Ghosh & Vogt, 2012).

The variable *transactieprijs* has several outliers in the dataset, such as prices above 20,000,000 and below 10,000 euros. Therefore prices below 50,000 and above 7,000,000 euros will be dropped from the dataset. A new variable, *logpricem2*, was created by taking the logarithmical function of price divided by squared meters. The new variable has a normal distributed and this is displayed in figure 3.

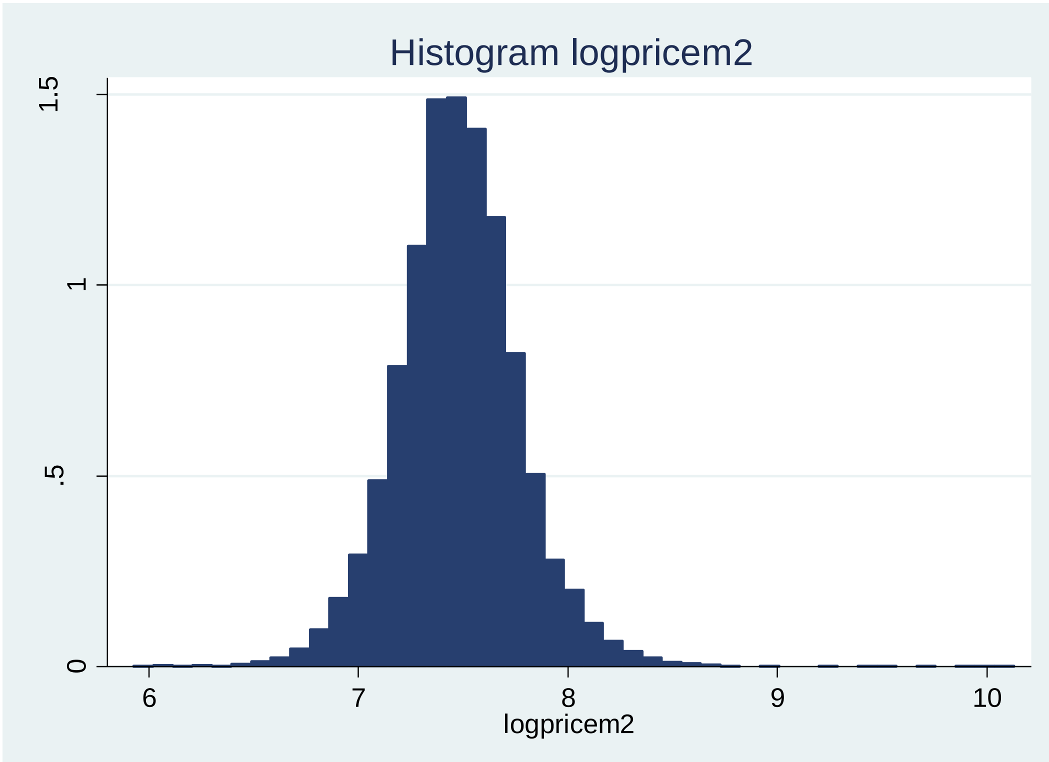

Figure 3: Histogram Logarithmical price per m2

Another problem that occurred in the dataset was of missing values in some instrumental variables. The variables *NBADK*, BEV_DICHTH, P_*N_W_AL*, *AV3_CAFE*, *AV3_RESTAU* and *AF_TREINST* contained missing years in the observations and measurement errors. There are several methods to fill the gaps in the data. *Hot deck-picking* takes a fixed value from another observation in the dataset with the same covariation, *Mean imputation* will fill the gaps with a mean and *Regression imputation* will replace the gaps in a single fitted value. The problem with using these methods is that variation is missing in the filled values. Therefore, in this report is *Multiple Imputation* (MI) used to fill the missing data. All the information of the non-missing values of the observations stays contained. Thereby, a large number of missing observations will lead to larger standard errors, wider confidence intervals and less power compared to MI results (StataCorp, 2019).

MI replaces each missing value in the dataset with a single good estimate. Using MI will assume that the missing data is either missing completely at random (MCAR) or missing at random (MAR). For this dataset are the variables BEV_DICHTH, P_*N_W_AL*, *AV3_CAFE*, *AV3_RESTAU* and *AF_TREINST* MCAR and is *NBADK* MAR. The missing values are summarized in table 3.

				Obs<.		
Variable	**Obs=.**	**Obs>.**	**Obs<.**	**Unique**	**Min**	**Max**
Nbadk	**13,288**		**37,522**	**6**	**1**	**6**
BEV_DICHTH	**8,304**		**42,506**	**>500**	**5**	**20977**
P_N_W_AL	**4,475**		**46,335**	**81**	**0**	**80**
AV3_CAFE	**24,083**		**26,727**	**382**	**0**	**340.9**
AV3_RESTAU	**13,244**		**37,566**	**>500**	**1**	**465.1**
AF_TREINST	**22,206**		**28,604**	**53**	**0.6**	**10.7**

Table 3: Summarized missing values

The patterns of the missing data are presented in table 4. There are 13 patterns in these data from (1,1,1,1,1) till (0,0,0,0,0). The 1 will indicate that all values of the variable are non-missing and the 0 indicates that all values are missing. So, 31% of the dataset consist out of non-missing values. In all the other patterns are some variables missing, and in less than 1% are all the variables missing (StataCorp, 2019).

	Pattern					
Percent	**P_N_W_AL**	**BEV_DICHTH**	**AV3_RESTAU**	**Nbadk**	**AF_TREINST**	**AV3_CAFE**
31%	**1**	**1**	**1**	**1**	**1**	**1**
13	**1**	**1**	**1**	**0**	**1**	**1**
10	**1**	**1**	**1**	**1**	**1**	**0**
8	**0**	**0**	**0**	**1**	**0**	**0**
7	**1**	**1**	**0**	**1**	**0**	**0**
7	**1**	**1**	**1**	**1**	**0**	**0**
6	**1**	**1**	**1**	**1**	**0**	**1**
5	**1**	**0**	**0**	**1**	**0**	**0**
3	**1**	**1**	**1**	**0**	**0**	**1**
3	**1**	**1**	**0**	**0**	**0**	**0**
3	**1**	**1**	**1**	**0**	**1**	**0**
2	**1**	**0**	**0**	**0**	**0**	**0**
2	**1**	**1**	**1**	**0**	**0**	**0**
<1	**0**	**0**	**0**	**0**	**0**	**0**
<1	**0**	**1**	**1**	**1**	**0**	**0**

Table 4: Patterns of missing data

The incomplete data will be analysed by a simulation-based approach when MI is used. The process consists of three steps: In the *Imputation step* will the missing data be replaced with multiple sets of simulated values to complete the data. There will be 20 sets of simulated values in this research. In the next step, the *Data analysis step*, will each imputation separately be tested in the desired analysis. In the last step, the *Pooling step,* Alle the results are combined from the data analyses into a single multiple-imputation model (Medeiros, 2016).

Methodology

The hedonic price model that is needed to test the hypotheses in this research will be estimated using an Ordinary Least Square (OLS) panel regression.

Testing the first hypotheses requires the generation of a new variable. This new variable will be the percentage of social houses in the neighbourhood. The percentage of social housing depends on the overall housing stock in the neighbourhood, thereby controls it for the different sizes of neighbourhoods. The number of residential properties owned by housing associations will be divided by the overall housing stock. A small share of social houses will have a different impact on the valuation of residential properties compared to a larger share. With the new generated variable and the created dataset is it possible to create the following regressions based on Angrist and Pischke (2014) and Stock and Watson (2015).

The dataset consist of panel data. The observations have the same n entities at multiple time periods T. The dataset consist of an unbalanced panel because the panel has some missing data for at least one time period, for at least one entity.

(X_{it}, Y_{it}), $i = 1, \dots, n$ and $t = 1, \dots, T$

Where the first subscript, i, refers to the entity being observed and the second subscript, t, refers to the date at which it is observed.

Fixed effects regressions

The neighbourhood factor remains constant over time because residential properties are located in the same neighbourhood over time. An OLS panel regression with fixed effects will be used. The neighbourhood factor can be hold constant even though it is not possible to measure it. It helps to control for omitted variables in panel data when the omitted variables vary across entities (neighbourhoods) but do not change over time.

The fixed effects regression model has n different intercepts, one for each entity. These intercepts can be represented by a set of binary variables, which will absorb the influences of all omitted variables that differ from one entity to the next but are constant over time.

$$Y_{\mathrm{it}} = \beta_0 + \beta_1 X_{it} + \beta_2 Z_i + u_{it}$$

Where Z_i is an unobserved variable that varies from one neighbourhood to the next but does not change over time.

The regression model can be interpreted as having n intercepts, one for each neighbourhood.

$$Y_{\mathrm{it}} = \beta_1 X_{it} + a_i + u_{it}$$

In this fixed effects regression model are $a_1, \dots, a_n$ treated as unknown intercepts that needs to be estimated, one for each neighbourhood. The interpretation of α_i comes from considering ***logpricem2*** regression line for the i^{th} neighbourhood; this ***logpricem2*** regression line is $a_i + \beta_1 X_{it}$. The slope coefficient of the ***logpricem2*** regression line, β_1, is the same for all neighbourhoods, but the intercept of the ***logpricem2*** regression line varies from one neighbourhood to the next. The intercept a_i represents the 'effect' of being in neighbourhood i, so the terms $a_1, \dots, a_n$ are known as the entity fixed effects. The variation in the entity fixed effects is created by the omitted variables that vary across the neighbourhoods but not over time.

Another way to express the neighbourhood-specific intercepts in the fixed effects regression model is by using binary variables to denote the individual neighbourhoods. Because there are more than two neighbourhoods, additional binary variables are needed to capture all the neighbourhood-specific intercepts. To develop the fixed effects regression model using binary variables, $D1_i$will be a binary variable that equals 1 when $i = 1$ and equals 0 otherwise, and so on. It is not possible to include all n binary variables and a common intercept; otherwise the regressors will be perfectly multicollinear (dummy-trap). So the binary variable for the first group, $D1_i$, will be arbitrarily omitted.

$$Y_{\mathrm{it}} = \beta_0 + \beta_1 X_{it} + \gamma_2 D2_i + \gamma_3 D3_i + \cdots + \gamma_n Dn_i + u_{it}$$

Where $\beta_0, \beta_1, \gamma_2, \dots, \gamma_n$ are unknown coefficients to be estimated. The comparison between the ***logpricem2*** regression lines for each neighbourhood in the two equations can be used to derive the relationship between the coefficients in the fixed effects regression model and the intercepts.

Regression with Time Fixed Effects

Time fixed effects can be used to control for variables that are constant across entities but evolve over time.

$$Y_{\mathrm{it}} = \beta_0 + \beta_1 X_{it} + \beta_2 Z_i + \beta_3 S_t + u_{it}$$

Where S_t is unobserved and where the single t shows the changes over time but remains constant across the neighbourhoods. The variables that determine Y_{it} are represented by $\beta_3 S_t$, thereby if X_{it} and S_t are correlated, omitting S_t from the regression results in omitted variable bias.

Both Entity and Time Fixed Effects

When some omitted variables are constant across neighbourhoods but vary over time while others are constant over time but vary across neighbourhoods, both entity and time effects will be included in the model. This results in an entity and time fixed effects regression model:

$$Y_{\mathrm{it}} = \beta_1 X_{it} + a_i + \lambda_t + u_{it}$$

Where a_i represents the entity fixed effect and λ_t is the time fixed effect. It is also possible to use binary indicators ($n-1$ and $T-1$) along with an intercept.

$$Y_{\mathrm{it}} = \beta_0 + \beta_1 X_{it} + \gamma_2 D2_i + \cdots + \gamma_n Dn_i + \delta_2 B2_t + \cdots + \delta_T BT_t + u_{it}$$

Where $\beta_0, \beta_1, \gamma_2, \ldots, \gamma_n$ and $\delta_2, \ldots, \delta_T$ are unknown coefficients. The combined neighbourhood and time fixed effects regression model corrects for omitted variable bias arising both from unobserved variables that are constant across neighbourhoods and over time.

The fixed effects regression assumptions and standard errors for fixed effects regression

There are four fixed effects regression assumptions.

$Y_{\mathrm{it}} = \beta_1 X_{it} + a_i + u_{it}$, $i = 1, \ldots, n$ and $t = 1, \ldots, T$

The first assumptions is that u_{it} has conditional mean zero, which means that the error term u_{it} has an expected value of zero for all values of the independent variable ($E(u_{it} | X_{i1}, X_{i2}, \ldots, X_{iT}, a_i) = 0$). Secondly, each of the random variables should be independent and identically distributed from their joint distribution ($(X_{i1}, X_{i2}, \ldots, X_{iT}, u_{i1}, u_{i2}, \ldots, u_{iT})$, $i = 1, \ldots, n$). It is not required that the observations will be uncorrelated within the entities. It is possible that X_{it} or u_{it} are auto-correlated (correlated with itself over time). Thirdly, Large outliers are unlikely, so (X_{it}, u_{it}) have nonzero finite fourth moments. Fourth, there is no perfect multicollinearity, so there is no perfect correlation between two or more regressors.

The possible autocorrelation makes it no longer possible to use the heteroscedasticity-robust standard error formula. The heteroscedasticity-robust standard errors are no longer valid to use because they were derived under the false assumption that there was no autocorrelation. The **heteroscedasticity- and autocorrelation-consistent (HAC) standard errors** need to be used when there is both heteroscedasticity and autocorrelation. **Clustered standard errors** are one type of HAC standard errors. These standard errors allow having an arbitrary correlation within a cluster but assuming un-correlation across them.

Hedonic housing price model

The single hedonic pricing model (Rosen, 1974) is based on the theory that housing price P is composed from different factors with error term (ε) into the following function:

$$P(x) = f(x) + \varepsilon$$

The different factors that are included in the hedonic pricing model are described and assigned to a category in the data review. The hedonic pricing model uses $f(x)$ as the function of these factors. Implementing these factors into the hedonic pricing model will result in:

$$P(x) = C + \sum \beta_m STR + \sum \beta_n LOC + \sum \beta_o NGH + \sum \beta_p ENV^{4} + \varepsilon$$

Where m, n, o, p are independent parameters, C the constant and structural attributes (STR), locational attributes (LOC), neighbourhood characteristics (NGH) and environmental attributes (ENV) are included in the model.

When this hedonic pricing model will be implemented as OLS panel regression with Entity and Time fixed effects, it will result in the following function:

$$P(x)_{it} = \sum \beta_m STR_{it} + \sum \beta_n LOC_{it} + \sum \beta_o NGH_{it} + a_i + \lambda_t + u_{it}$$

Where a_i represents the entity fixed effect and λ_t is the time fixed effect. The model will be using Clustered standard errors for neighbourhoods.

[4] Proper data for environmental attributes were not found in the datasets, and therefore these characteristics will be omitted in further models.

The variables BEV_DICHTH, P_*N_W_AL*, *AV3_CAFE*, *AV3_RESTAU, AF_TREINST* and *NBADK* will be imputed fill the missing data in the variables. Using a multivariate normal model assumes that all the imputed variables will follow a multivariate normal distribution. At least 20 imputations are used to reduce the sampling error due to imputations.

Hypotheses 1 will be tested if there is a negative relationship between the percentage of social houses in a neighbourhood and the logarithmical price per m2 by using an OLS panel regression with Entity and Time fixed effects. The logarithmical price per m2 will be the independent variable and the percentage of social houses in the neighbourhood as independent variable. Furthermore, several control variables are added resulting in the following OLS panel regression with Entity and Time fixed effects:

$$\begin{aligned} Log\ price\ m2 = \ & \beta_1 * P\_socialhouses(T) + \beta_2 * i.jaar\ (X1) + \beta_3 * i.construction\ period\ (X2) \\ & + \beta_4 * i.parking\ opportunities\ (X3) + \beta_5 * i.type\ (X4) + \beta_6 * number\ rooms\ (X5) \\ & + \beta_7 * number\ of\ bathrooms\ (X6) + \beta_8 * number\ of\ balconies\ (X7) + \beta_9 \\ & * number\ of\ dormer\ windows\ (X8) + \beta_{10} * permanently\ inhabitat\ (X9) + \beta_{11} \\ & * partually\ rented\ (X10) + \beta_{12} * P\_NWAL(X11) + \beta_{13} * inhabitants\ km2\ (X12) \\ & + \beta_{14} * crimes\ (X13) + \beta_{15} * P\_\ hhlowestincome\ (X14) + \beta_{16} * unemployed\ (X15) \\ & + \beta_{17} * leefbarometer\ (X16) + \beta_{18} * restaurant\ (X17) + \beta_{19} * bar\ (X18) + \beta_{20} \\ & * trainstation\ (X19), fe\ vce(cluster\ buurt) \end{aligned}$$

The same type of model can be used to analyse the second hypotheses. The variable percentage of social houses will be split in different categories. Each category takes a step of 5% in the share of social houses, so >95% means that more than 95% of the houses in a neighbourhood are social houses. The share of social houses in the total housing stock of the neighbourhood is changed over time. Neighbourhoods will therefore differ in categories from year to year. The categorical index is checked on multiple intervals. Changes in the share of social houses in a neighbourhood were in most neighbourhoods relatively small. Larger intervals are less likely to obtain a change in categories of the neighbourhoods. Larger categorical indexes resulted in insignificant outcomes and are therefore omitted from this research. The categorical index of the share of social houses will be:

1	>95%
2	90-95%
3	85-90%
4	80-85%
5	75-80%
6	70-75%

7	65-70&
8	60-65%
9	55-60%
10	50-55%
11	45-50%
12	40-45%
13	35-40%
14	30-35%
15	25-30%
16	20-25%
17	15-20%
18	10-15%
19	5-10%
20	<5%

Table 5: Categorical index share of social houses in neighbourhood

The share of social houses can also categorized by quartiles. Each category contains in this case 25% of the dataset. Because of the limited change of neighbourhoods between categories are the categories indexed by deciles. Each category contains 10% if the dataset. This index will be:

1	>90%
2	80-90%
3	70-80%
4	60-70%
5	50-60%
6	40-50%
7	30-40&
8	20-30%
9	10-20%
10	<10%

Table 6: Categorical index by deciles share of social houses in neighbourhood

After adding several control variables, the following the following OLS panel regression with Entity and Time fixed effects will be used to test the second hypotheses:

$$Log\ price\ m2 = \beta_1 * i.P\_socialhouses(T) + \beta_2 * i.jaar\ (X1) + \beta_3 * i.construction\ period\ (X2) + \beta_4 * i.parking\ opportunities\ (X3) + \beta_5 * i.type\ (X4) + \beta_6 * number\ rooms\ (X5) + \beta_7 * number\ of\ bathrooms\ (X6) + \beta_8 * number\ of\ balconies\ (X7) + \beta_9 * number\ of\ dormer\ windows\ (X8) + \beta_{10} * permanently\ inhabitat\ (X9) + \beta_{11} * partually\ rented\ (X10) + \beta_{12} * P\_NWAL(X11) + \beta_{13} * inhabitants\ km2\ (X12) + \beta_{14} * crimes\ (X13) + \beta_{15} * P\_\ hhlowestincome\ (X14) + \beta_{16} * unemployed\ (X15) + \beta_{17} * leefbarometer\ (X16) + \beta_{18} * restaurant\ (X17) + \beta_{19} * bar\ (X18) + \beta_{20} * trainstation\ (X19), fe\ vce(cluster\ buurt)$$

The third hypotheses can be tested by generating new variables. These variables are the number of social houses in a radius of 100, 300 and 500 around the residential properties. The radius of 300 meters is based on the fact that the social houses are never located further than 2 blocks away. The maximum walking distance of 3.5 makes it assumable that residents could be inconvenienced of the social houses. The radius of 100 and 500 meters are chosen to control for unnoticed and overestimated effects of using a smaller of larger radius.

The residential properties and social houses are geocoded and GIS-software is used to calculate the number of social houses in 100, 300 and 500 meter radius. The plug-inn MMGIS is used to create a buffer of 300 meters around each residential property. An algorithm makes it possible to count the number of social houses in these created polygons. The new generated variables makes it possible to trace the intensity of the number of social houses per residential property. A small amount of social houses will have another impact than if this number is considerably higher. The OLS panel regressions with Entity and Time fixed effects used to test the third hypotheses will be:

$$Log\ price\ m2 = \beta_1 * Number\ of\ social\ houses\ in\ 300\ meters\ radius(T) + \beta_2 * i.jaar\ (X1) + \beta_3 * i.construction\ period\ (X2) + \beta_4 * i.parking\ opportunities\ (X3) + \beta_5 * i.type\ (X4) + \beta_6 * number\ rooms\ (X5) + \beta_7 * number\ of\ bathrooms\ (X6) + \beta_8 * number\ of\ balconies\ (X7) + \beta_9 * number\ of\ dormer\ windows\ (X8) + \beta_{10} * permanently\ inhabitat\ (X9) + \beta_{11} * partually\ rented\ (X10) + \beta_{12} * P\_NWAL(X11) + \beta_{13} * inhabitants\ km2\ (X12) + \beta_{14} * crimes\ (X13) + \beta_{15} * P\_\ hhlowestincome\ (X14) + \beta_{16} * unemployed\ (X15) + \beta_{17} * leefbarometer\ (X16) + \beta_{18} * restaurant\ (X17) + \beta_{19} * bar\ (X18) + \beta_{20} * trainstation\ (X19), fe\ vce(cluster\ buurt)$$

The models are tested with a significance level of 5%

Results

The relationship between the percentage of social houses and the logarithmical price per m2 needs to be analysed for hypotheses 1. The share of social houses in a neighbourhoods are regressed on the logarithmical price per m2 using an OLS panel regression with Entity and Time fixed effects. The results of this regression are shown in table 6 (T1). The percentage of social houses in a neighbourhood has a non-significant (5% level), negative effect on the logarithmical price per m2. A percent point increase in the share of social houses in a neighbourhood will lower the price per m2 by 10.75%. However, the variable is not significant and therefore is it not possible to be sure about the impact on the price per m2. The constant in the model is significant (5% level) and has the value of 7.742982. This means that the starting point of the change in the price per m2 is 774.3%

The hedonic price model has an inherent risk of *omitted variable bias* (OVB). This model uses some tools to avoid the presence of OVB. It is already described in the data and methodological that all the observations are independently distributed and do not have outliers. There are also control variables added to the model as prevention. The risk of OVB is therefore limited.

Most of the control variables in the model have a significant impact on the change in the price per m2, displayed in table 6 (T1). The R-squared of the panel regression with Entity and Time fixed effects is 0.255654. This describes the percentage of variance in the change in price per m2 that is declared by the model. This is relatively low for a hedonic price model. One of the reasons could be that there is a lack of micro data for the observations. Adding this type of data into the hedonic regression models can increase the explanatory power of it. The other variables influence the model as expected.

Variables		**T1**	**T2**
Percentage social houses		-.1075158	
	90-95%		.0411964**
	85-90%		.111859*
	80-85%		.1945182***
	75-80%		.258269***
	70-75%		.2617692***
	65-70&		.2840806***
	60-65%		.2958655***
	55-60%		.289776***
	50-55%		.2787823***
	45-50%		.2785559***
	40-45%		.274379***
	35-40%		.2766705***

	30-35%		.2914324***
	25-30%		.3405223***
	20-25%		.2957748***
	15-20%		.3099055***
	10-15%		.2967644***
	5-10%		(Omitted)
	<5%		(Omitted)
Year	2007	.0208281***	.0229552***
	2008	.0484787***	.0496594***
	2009	.0219219**	.0240431**
	2010	.0178939*	.0214788**
	2011	.0258507***	.0297423***
	2012	.0040969	.0157466
	2013	-.0508604*	-.0393361
	2014	-.0153467	-.0042087
Construction Period	1991-2000	-.0366591**	-.0361563**
	1981-1990	-.1582655***	-.158378***
	1971-1980	-.1972471***	-.1967289***
	1960-1970	-.2077166***	-.2069092***
	1945-1959	-.1519028***	-.1521955***
	1931-1944	-.1731724***	-.173674***
	1906-1930	-.1698002***	-.1699675***
	1500-1905	-.1858295***	-.1859767***
Parking opportunities	Parking place	.0967893***	.0964102***
	Carport and no garage	.108488***	.1083193***
	Garage and no carport	.1038802***	.1038499***
	Garage and carport	.1715266***	.1697862***
	Garage for more cars	.1824765***	.1822261***
Type	Villa	.2969186***	.2964037***
	Farm used as residence	.1914857**	.1941698**
	Mansion	.1028452***	.1022104***
	House Boat	.1182119*	.1188671*
	Bungalow	.2132797***	.2149569***
	Canal house	.2631148***	.2644721***
	Cottage	.3557582***	.3532696***
	Estate	.5865269***	.593825***
	Apartment with elevator	-.0783725***	-.079098***
	Apartment without	-.1024946***	-.1027494***
	Ground-floor apartment	-.018039	-.0183628
Number of rooms		-.0286327***	-.028601***
Number of bathrooms		.0523321***	.0520641***
Number of balconies		-.0148271***	-.0146421***
Number of dormer windows		.01517*	.0156084*
Permanently inhabited		.0052553	.0068361
Partially rented		-.2519116*	-.2485023*

Percentage non-western immigrants	-.0010659***	-.0010801***
Inhabitants per km2	-	0.
Number of crimes	.0000366**	.0000397***
Percentage households lowest income	-.0005079	-.000648
Number of unemployed people	-.0000515**	-.0000478**
Leefbarometer	.0104629	.0087367
Number of bars in 3km	-.0009905***	-.0010118***
Number of restaurants in 3km	.0009747***	.0009817***
Distance till nearest Train station	-.0090768***	-.0087274***
Constant	7.742982***	7.441818***
Number of observations	31,480	31,480
Number of groups	69	69
R-Squared	.255654	.2568608
Legend: *** p<.01, ** p<.05, * p<0.1		

Table 6: Panel regressions with Entity and Time fixed effects on logarithmical price per m2

For hypotheses 2, the nonlinear relationship between the share of social houses in a neighbourhood and the change in price per m2 needs to be tested. An OLS panel regression with Entity and Time fixed effects with several control variables is used again to analyse this relationship, as displayed in Table 6 (T2). Using different categories for the share of social houses in a neighbourhood has a significant impact on the change in price per m2. The coefficients are, according to the *joint significance test* (table 7), jointly significant different from 0 (5% level). Individually, besides 85-90% which is not significant and 5-10% and <5% which are omitted, are the other categories significant (5% level) and have a positive impact on the change in price per m2 taking >95% as a baseline. There seems to be an obvious trend in the points estimate. The lower the share of social houses in a neighbourhood, the higher the change in price per m2 will be. This effect seems to flatten after a certain point (figure 4). Although it is difficult to claim, it is found that the results are in line with the expectation. The model indicates a negative price effect of the share of social houses in a neighbourhood.

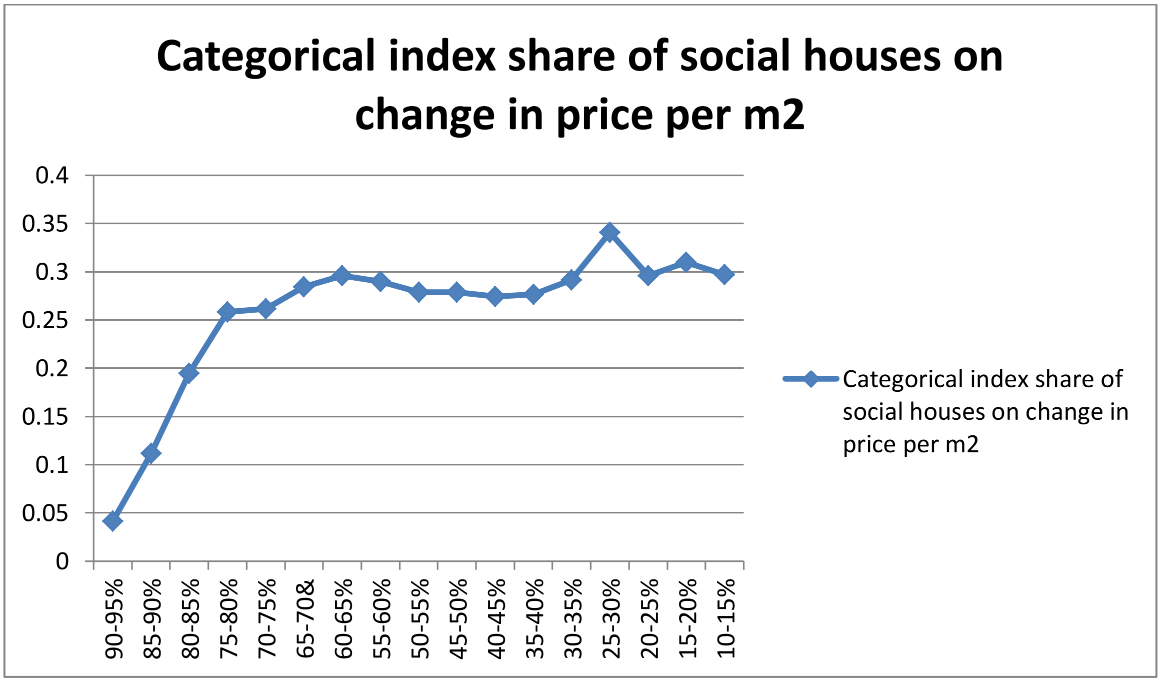

Figure 4: Categorical index share of social houses on change in price per m2

Most of the control variables in the model have a significant impact on the change in the price per m2, displayed in table 6 (T2). The R-squared of the panel regression with Entity and Time fixed effects is 0.2568608. The model with a categorical index for the share of social houses in a neighbourhood has some more explanatory power in the variance of the independent variables which will influence the dependent variables. The main reason will be that most of the categorical variables are significant, compared to using it as a continuous variable where it was insignificant.

(1)	90-95% = 0
(2)	85-90% = 0
(3)	80-85% = 0
(4)	75-80% = 0
(5)	70-75% = 0
(6)	65-70& = 0
(7)	60-65% = 0
(8)	55-60% = 0
(9)	50-55% = 0
(10)	45-50% = 0
(11)	40-45% = 0
(12)	35-40% = 0
(13)	30-35% = 0

(14)	25-30% = 0
(15)	20-25% = 0
(16)	15-20% = 0
(17)	10-15% = 0
F(17, 64.4) = 4.40	
Prob > F = 0.0000	

Table 7: Joint significant test categorical index share of social houses in neighbourhood

The same analysis is used to test the deciles where all categories contain 10% of the dataset. Using different categories for the deciles of shares of social houses in a neighbourhood has no significant impact on the change in price per m2, as shown in Table 8 (T3). Each category is insignificant (5% level) and the coefficients are, according to the *joint significance test* (table 9), jointly not significant different from 0 (5% level). Therefore, it is not possible to evaluate the impact on the change in price per m2.

Variables		**T3**
Percentage social houses	80-90%	-.0076893
	70-80%	-.0089183
	60-70%	-.026741
	50-60%	-.0203383
	40-50%	-.0082759
	30-40&	.0147731
	20-30%	.0137684
	10-20%	.005021
	<10%	(omitted)
Year	2007	.0221732***
	2008	.0506407***
	2009	.0244289**
	2010	.021304**
	2011	.0295453***
	2012	.0092105
	2013	-.045675*
	2014	-.0104228
Construction Period	1991-2000	-.0358309**
	1981-1990	-.157927***
	1971-1980	-.1967468***
	1960-1970	-.207635***
	1945-1959	-.1517514***
	1931-1944	-.1729224***
	1906-1930	-.1694055***
	1500-1905	-.1858383***
Parking opportunities	Parking place	.096647***

Type	Carport and no garage	.1083154***
	Garage and no carport	.1036161***
	Garage and carport	.1707974***
	Garage for more cars	.1822015***
	Villa	.2965427***
	Farm used as residence	.1900799**
	Mansion	.102629***
	House Boat	.118734*
	Bungalow	.2139131***
	Canal house	.2625359***
	Cottage	.35374***
	Estate	.5851371***
	Apartment with elevator	-.0782764***
	Apartment without	-.102569***
	Ground-floor apartment	-.0183927
Number of rooms		-.0287004***
Number of bathrooms		.0525326***
Number of balconies		-.0149223***
Number of dormer windows		.0160255*
Permanently inhabited		.0060758
Partially rented		-.2495245*
Percentage non-western immigrants		-.0010279***
Inhabitants per km2		-
Number of crimes		.0000341**
Percentage households lowest		-.0005233
Number of unemployed people		-.0000482**
Leefbarometer		.0125627
Number of bars in 3km		-.0009879***
Number of restaurants in 3km		.0009625***
Distance till nearest Train station		-.0091674***
Constant		7.691343***
Number of observations		31,480
Number of groups		69
R-Squared		.25558985
Legend: *** p<.01, ** p<.05, * p<0.1		

Table 8: Panel regressions with Entity and Time fixed effects on logarithmical price per m2

(1)	90-80% = 0
(2)	80-70% = 0
(3)	70-60% = 0
(4)	60-50% = 0
(5)	50-40% = 0
(6)	40-30& = 0
(7)	30-20% = 0

(8)	20-10% = 0
F(8, 66.0) = 1.11	
Prob > F = 0.3676	

Table 9: Joint significant test categorical index centiles share of social houses in neighbourhood

The relationship between the amount of social houses in 100, 300, and 500 meters radius and the price per m2 of residential properties needs to be tested for hypothesis 3. The amount of social houses in the ranges needs to be regressed on the change in price per m2. According to the results in Table 10 (T4), the amount of social houses in 300 meters around a residential property has a significant (5% level) negative effect on the change in price per m2. An extra social house will decrease the price per m2 by 0.00914%. The associated P-value is 0.000, which is smaller than 0.05, so the amount of social houses in 300 meter radius around a residential property has a significant effect on the change in price per m2. It has a negative impact with a confidence interval of (-0.0001345; -0.0000482) per social house.

Testing for the other distances, displayed in Table 10 (T5 and T6), confirms that the amount of social houses in the immediate vicinity has a significant (5% level) negative impact on the change in price per m2. An extra social house will decrease the price per m2 by 0.04931% in 100 meter radius and 0.00282% for 500 meter range. This is not in line with the expectations of the model. The expectation was that a smaller range would underestimate, and a larger range would overestimate the effect of social houses on residential property valuation. Comparing the R-squares of the Models (0.26624807 of 100 meters radius, 0.26336842 for 300 meters radius and 0.25752136), shows that the model with 100 meters radius has the most explanatory power. Table 10 (T7) concludes that the effect of immediate vicinity of social houses will decrease. An extra social house within a 100 meter radius will significantly decrease the price per m2 by 0.04282%. In the 100-300 meters radius will it significantly decrease the price by 0.00609%. The 300-500 shows an increase of 0.000824% in the price per m2, however this effect is not significant and cannot be interpreted. The effects still seems to diminish over distance. This seems to be logical because housing associations often own a whole block of houses which makes the concentration in the immediate vicinity relatively high.

Variables	T4	T5	T6	T7
Number of social houses in 300 meters	- .0000914***			

Number of social houses in 100 meters			-.0004931***		-.0004282***
Number of social houses in 500 meters				-.0000282**	
Number of social houses in 100-300					-.0000609***
Number of social houses in 300-500					.00000824
Year	2007	.020371***	.0196611***	.0201258***	.019959***
	2008	.0486388***	.0478772***	.0481746***	.0483529***
	2009	.0208713**	.0212688**	.0210115**	.0210126**
	2010	.0177481**	.0179774**	.0174344*	.0179639**
	2011	.026077***	.0260819***	.0260266***	.0260666***
	2012	-.000038	.0001415	-.0027276	.0016304
	2013	-.0550801**	-.0541053**	-.0567654**	-.0533141**
	2014	-.0215369	-.0202475	-.0224276	-.0200772
Construction Period	1991-2000	-	-	-	-
	1981-1990	-	-	-	-
	1971-1980	-	-.208518***	-	-
	1960-1970	-	-	-	-
	1945-1959	-	-	-	-
	1931-1944	-	-	-	-
	1906-1930	-	-	-	-
	1500-1905	-	-	-.183869***	-
Parking opportunities	Parking place	.088154***	.0848341***	.0900594***	.0838807***
	Carport and	.0996355***	.0950635***	.1001788***	.0951722***
	Garage and no	.0936996***	.0944942***	.097482***	.0914178***
	Garage and	.153354***	.1518083***	.1572112***	.14928***
	Garage for	.1755319***	.1770017***	.1799559***	.1739975***
Type	Villa	.292956***	.2953803***	.2944428***	.2934762***
	Farm used as	.1828023**	.1818633**	.1829022**	.1812207**
	Mansion	.1043524***	.1029472***	.1045164***	.1034579***
	House Boat	.1084394*	.1017235*	.1079885*	.1014637***
	Bungalow	.2161696***	.2115387***	.2166977***	.2128663***
	Canal house	.2779237***	.2714803***	.2864434***	.2735974***
	Cottage	.3439336***	.3535144***	.3443695***	.3488793***
	Estate	.6048926***	.6836926***	.5894739***	.6739351***
	Apartment	-	-	-	-.06742***

	Apartment	-	-	-	-
	Ground-floor	-.0102821	-.0128247	-.0134736	-.0094957
Number of rooms		-.028266***	-	-	-.028878***
Number of bathrooms		.051286***	.0505055***	.0518772***	.0503024***
Number of balconies		-	-	-	-
Number of dormer		.0137955	.0135639	.0154422*	.0127086
Permanently		.0052434	.0053803	.0066689	.0045529
Partially rented		-.23945	-.2495193*	-.2424268	-.2437985*
Percentage non-		-	-	-	-
Inhabitants per km2		-	-	-.0000024*	-.00000237*
Number of crimes		.0000276*	.0000268*	.0000279*	.0000263*
Percentage		-.000436	-.0004483	-.0003972	-.000469
Number of		-.0000475**	-.0000497**	-.0000503**	-.0000474**
Leefbarometer		.0165187	.0175435	.0177099	.016542
Number of bars in		-	-	-	-
Number of		.0009497***	.0009457***	.0009519***	.0009447***
Distance till nearest		-	-	-	-
Constant		7.723512***	7.709387***	7.711435***	7.727572***
Number of		31,653	31,653	31,653	31,653
Number of groups		71	71	71	71
R-Squared		.26336842	.26624807	.25752136	.26926345

Legend: *** p<.01, ** p<.05, * p<0.1

Table 10: Panel regressions with Entity and Time fixed effects on logarithmical price per m2

Discussion and Limitations

The valuation of residential properties is affected by different characteristics and attributes in and around the properties. The effects of the different environmental factors as mentioned in the literature review were significant in the used models. The same effect was expected for the presence of social houses and their contribution to the neighbourhood attractiveness. The tenants of social houses are on average: older, less likely to be employed and more likely to be on social benefits, are more likely to be of non-Dutch origin and live in smaller houses (WoOn, 2018). High concentrations of them are seen as problematic and expected was that it would have a negative impact on the valuation of residential properties.

The literature also mentioned that urban regeneration programs are used to improve neighbourhoods. The programs are described as “all activities, physical and otherwise, intended in the local context to renew existing urban spaces” (Droste, Lelévrier & Wassenberg, 2014). Disadvantaged neighbourhoods have, in general, a large share of social houses and are therefore more likely to be treated in the urban regeneration programs. However, the programs often mismatch between the needs of the residents and the provided services.

The models used in this research cannot prove the benefits of these programs. The amount of social houses in the immediate vicinity of a residential property has a negative impact on the price per m2. This effect decreases over distance. The share of social houses in a neighbourhood seems to have a non-linear impact on the valuation of residential properties. However, the different show that used methods outcomes are not in line with each other. It can therefore not be stated that the share of social houses in a neighbourhood have an effect on the valuation of residential properties.

This study also has its limitations that could have had an impact on the results from this research. The internal validity needs to be further investigated. The used models can be subjected to endogeneity. With endogeneity is there a correlation between the coefficients and the error term. It can be caused by simultaneous and reversed causality. Social houses and the price of residential properties can influence each other, or the dependent and independent variables are swapped. The price of residential properties can influence the share of social houses because it might be attractive for housing associations to sell the social houses. This research focuses on the influence of social houses on the price of residential properties and several factors are added that have also their influence on the valuation of residential properties in order to attempt to remove the causality. Endogeneity can also be caused by *Selection bias*. The used data would not be random and representative. The used data is collected over the same time. Most of the data from the NVM/Brainbay, CBS, Buurtmonitor Rotterdam and Leefbarometer was available for the time period 2006-2014. Missing data is adjusted or imputed. The data and methodology section already mentioned that, furthermore the data is normally distributed. The data of Maaskoepel is not collected over the same time. The reference date is January 1st, 2018 which is later than the other obtained data. This might bias the outcome of the third hypotheses because the stock of the housing associations changes over time. However, the data is used indicate the effects on a micro-level.

Furthermore, the whole stock is owned by housing associations and not a sub-sample where some neighbourhoods could be more influenced than others.

The internal validity can also be affected when the OVB is violated. In that case a number of important variables are missing in the model, which means that the effect of the independent variable will be overvalued. Control variables are added to the model in this research to solve this problem. However, data on a micro-level was missing in this research which has an impact on the explanatory power of the model. The explanatory power of this model was relatively low for a hedonic pricing model, and more control variables had to be added. Despite this, the influence of social houses is limited in the models compared to other factors that have a major influence on the change in price per m2, which makes it seem that those factors are rather overestimated.

Finally, the *sample selection bias* could have an influence on the results. This research uses a relatively small sample for the municipality of Rotterdam. Certain neighbourhoods had only a small amount of residential properties. Another problem was that the change in share of social houses for some neighbourhoods was limited. Housing associations did not want to give information about their changes in housing stock. Despite the limited selection of data used in this research, the data were normally and independently distributed across the municipality of Rotterdam.

A number of recommendations can be made on further research, taking the insights of the limitations of this research into account. At first, the dataset could be expanded to widen the scope of the research. Adding more valuations of residential properties will increase the amount for some neighbourhoods where the amount was now small. More detailed information about the change in the social housing stock will make it possible to analyse the impact of changing the composition of neighbourhoods. Specifically on the amount of rent might also an option to wider the scope of this research; low-segments might have a different impact on high-segment social houses. More control variables can be added to increase the explanatory power of the models. This research could also be applied to other cities or rural areas. Not every location is the same, which might result in different outcomes.

The government and policymakers can take advantages of the outcomes of this research. Policy can be made concerning the amount of social houses in a neighbourhood. Too many social houses in a neighbourhood has a negative impact on the valuation of residential properties. The composition of the housing stock needs to change and urban regeneration programs can help with that. Social housing in the immediate vicinity seems to have the largest impact in the valuation of residential property prices. A better mix in blocks between types of houses seems to be ideal but is difficult to achieve. Most houses in blocks are of the same type, and they are therefore social houses, private rented or owner occupied.

Conclusion

The aim of this research was to answer some hypotheses. Hypothesis 1 stated that there should be a negative relationship between the percentage of social houses in a neighbourhood and the price per m2 of residential properties. Table 6 (T1) displayed that there is no significant effect of the percentage of social houses in a neighbourhood on the price per m2 of residential properties. Therefore, this hypothesis cannot be rejected. The second hypothesis stated that there would be a nonlinear negative relationship between the share of social houses in a neighbourhood and the price per m2 of residential properties. The categorical index of shares of social houses in a neighbourhood is jointly significant from 0, displayed in table 7. Furthermore, table 6 (T2) shows that there is a negative price effect of the share of social houses in a neighbourhood. The trend in figure 4 seems to be that the lower the share of social houses in a neighbourhood, the higher will be the change in price per m2. The effect flattens after a certain point and it is nonlinear. When the categories are indexed by deciles, they categories are insignificant. Therefore, second hypothesis will not be rejected. The third hypotheses stated that there is a negative relationship between the amount of social houses in the immediate vicinity of residential properties and their price per m2. Table 10 (T4) showed that there is a significant negative effect between the price per m2 of residential properties and the amount of social houses in a 300 meters radius. The hypotheses could therefore not be rejected. The negative price effect of an extra social house seems to diminish over distance, as displayed in Table 10 (T7).

The negative externalities of social houses seem to dominate in the valuation of residential property prices. The negative price effect of the share of social houses is nonlinear and starts out flat (figure 3). A small share of social houses is the most desirable situation. The main question of this research is answered by the conclusion that social houses have a particularly negative effect on the valuation of residential properties in Rotterdam. The negative externalities will presumably dominate over the price pressure by social houses on the housing market. Noticed should be that there is already a strong positive price pressure with a different origin in Rotterdam (e.g. employment opportunities), this is partly controlled for in the model.

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Raw STATA output

```
. misstable summarize nbadk BEV_DICHTH P_N_W_AL AV3_CAFE AV3_RESTAU AF_TREINS
                                                              Obs<.
```

Variable	Obs=.	Obs>.	Obs<.	Unique values	Min	Max
nbadk	13,288		37,522	6	1	6
BEV_DICHTH	8,304		42,506	>500	5	20977
P_N_W_AL	4,475		46,335	81	0	80
AV3_CAFE	24,083		26,727	382	0	340.9
AV3_RESTAU	13,244		37,566	>500	1	465.1
AF_TREINST	22,206		28,604	53	.6	10.7

```
. misstable patterns nbadk BEV_DICHTH P_N_W_AL AV3_CAFE AV3_RESTAU AF_TREINS

      Missing-value patterns
        (1 means complete)
```

Percent	Pattern 1	2	3	4	5	6
31%	1	1	1	1	1	1
13	1	1	1	0	1	1
10	1	1	1	1	1	0
8	0	0	0	1	0	0
7	1	1	0	1	0	0
7	1	1	1	1	0	0
6	1	1	1	1	0	1
5	1	0	0	1	0	0
3	1	1	1	0	0	1
3	1	1	0	0	0	0
3	1	1	1	0	1	0
2	1	0	0	0	0	0
2	1	1	1	0	0	0
<1	0	0	0	0	0	0
<1	0	1	1	1	0	0
100%						

```
Variables are  (1) P_N_W_AL  (2) BEV_DICHTH  (3) AV3_RESTAU  (4) nbadk  (5) AF_TREINST  (6) AV3_CAFE
```

```
. mi estimate: xtreg logpricem2 p_huurco i.jaar i.bwper2 i.parkeer i.soortwoning2 nkamers nbadk nbalkon ndakkap permanent ged
> _verhuurd P_N_W_AL BEV_DICHTH aantal_misdaden p_hhlaagsteinkomensgroep2 aantal_nietwerkenden leefbarometer AV3_CAFE AV3_RES
> TAU AF_TREINS, fe vce(cluster buurt)

Multiple-imputation estimates                   Imputations      =         20
Fixed-effects (within) regression               Number of obs    =     31,480

Group variable: buurt                           Number of groups =         69
                                                Obs per group:
                                                             min =          2
                                                             avg =      456.2
                                                             max =      2,013
                                                Average RVI      =     2.2931
                                                Largest FMI      =     0.7328
                                                Complete DF      =         68
DF adjustment:   Small sample                   DF:     min      =      12.99
                                                        avg      =      62.24
                                                        max      =      66.04
Model F test:       Equal FMI                   F(  48,    57.5) =     162.03
Within VCE type:       Robust                   Prob > F         =     0.0000

                                 (Within VCE adjusted for 69 clusters in buurt)
```

logpricem2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
p_huurco	-.1075158	.1540552	-0.70	0.488	-.4151536	.200122
jaar						
2007	.0208281	.0064355	3.24	0.002	.0079706	.0336855
2008	.0484787	.0090638	5.35	0.000	.0303756	.0665817
2009	.0219219	.0093985	2.33	0.023	.0031497	.0406942
2010	.0178939	.0091228	1.96	0.054	-.0003283	.036116
2011	.0258507	.0095564	2.71	0.009	.0067626	.0449389
2012	.0040969	.0264634	0.15	0.877	-.0487479	.0569418
2013	-.0508604	.0270302	-1.88	0.064	-.1048357	.003115
2014	-.0153467	.0282648	-0.54	0.589	-.0717839	.0410905
bwper2						
1991-2000	-.0366591	.0140317	-2.61	0.011	-.0646758	-.0086425
1981-1990	-.1582655	.0210564	-7.52	0.000	-.2003062	-.1162247
1971-1980	-.1972471	.0180606	-10.92	0.000	-.2333074	-.1611868
1960-1970	-.2077166	.0178216	-11.66	0.000	-.2432992	-.172134
1945-1959	-.1519028	.0195407	-7.77	0.000	-.1909174	-.1128883
1931-1944	-.1731724	.0256273	-6.76	0.000	-.2243387	-.1220062
1906-1930	-.1698002	.0255346	-6.65	0.000	-.2207812	-.1188193
1500-1905	-.1858295	.0274626	-6.77	0.000	-.24066	-.1309991
parkeer						
Parking place	.0967893	.009196	10.53	0.000	.0784266	.115152
Carport and no garage	.108488	.0180379	6.01	0.000	.0724731	.1445028
Garage and no carport	.1038802	.0171588	6.05	0.000	.0696209	.1381396
Garage and carport	.1715266	.0222727	7.70	0.000	.1270401	.216013
Garage for more cars	.1824765	.0294614	6.19	0.000	.1236535	.2412996
soortwoning2						
Villa	.2969186	.0318991	9.31	0.000	.2332248	.3606125
Farm used as residence	.1914857	.0740199	2.59	0.012	.043673	.3392984
Mansion	.1028452	.0186314	5.52	0.000	.0656449	.1400456
House boat	.1182119	.0652452	1.81	0.075	-.0121129	.2485366
Bungalow	.2132797	.0601987	3.54	0.001	.0930819	.3334776
Canal house	.2631148	.0607005	4.33	0.000	.1418759	.3843538
Cottage	.3557582	.0737044	4.83	0.000	.2085529	.5029635
Estate	.5865269	.0734909	7.98	0.000	.4277442	.7453097
Apartment with elevator	-.0783725	.0193556	-4.05	0.000	-.1170177	-.0397274
Apartment without elevator	-.1024946	.0172761	-5.93	0.000	-.1369876	-.0680016
Ground-floor apartment	-.018039	.0209092	-0.86	0.391	-.0597854	.0237074
nkamers	-.0286327	.0044447	-6.44	0.000	-.0375069	-.0197585
nbadk	.0523321	.0130063	4.02	0.000	.0263409	.0783233
nbalkon	-.0148271	.0042242	-3.51	0.001	-.023262	-.0063922
ndakkap	.01517	.0085202	1.78	0.080	-.0018428	.0321828
permanent	.0052553	.0115776	0.45	0.651	-.0178865	.028397
ged_verhuurd	-.2519116	.1480274	-1.70	0.094	-.5474681	.0436449
P_N_W_AL	-.0010659	.0002962	-3.60	0.001	-.0016625	-.0004694
BEV_DICHTH	-3.17e-06	1.30e-06	-2.44	0.019	-5.81e-06	-5.43e-07
aantal_misdaden	.0000366	.000015	2.43	0.018	6.53e-06	.0000666
p_hhlaagsteinkomensgroep2	-.0005079	.0005044	-1.01	0.318	-.001515	.0004992
aantal_nietwerkenden	-.0000515	.0000201	-2.56	0.013	-.0000916	-.0000114
leefbarometer	.0104629	.0117739	0.89	0.377	-.0130457	.0339716
AV3_CAFE	-.0009905	.0001233	-8.03	0.000	-.0012381	-.000743
AV3_RESTAU	.0009747	.0000994	9.80	0.000	.0007749	.0011744
AF_TREINST	-.0090768	.0012442	-7.30	0.000	-.0115875	-.0065662
_cons	7.742982	.1112335	69.61	0.000	7.520866	7.965098
sigma_u	.12108371					
sigma_e	.19270846					
rho	.28304792	(fraction of variance due to u_i)				

Note: sigma_u and sigma_e are combined in the original metric.

R^2 over imputed data = .255654

```
. mi estimate: xtreg logpricem2 i.p_huur2 i.jaar i.bwper2 i.parkeer i.soortwoning2 nkamers nbadk nbalkon ndakkap  permanent ged_v
> erhuurd P_N_W_AL  BEV_DICHTH aantal_misdaden p_hhlaagsteinkomensgroep2 aantal_nietwerkenden leefbarometer AV3_CAFE AV3_RESTAU A
> F_TREINS, fe vce(cluster buurt)

Multiple-imputation estimates                   Imputations       =         20
Fixed-effects (within) regression               Number of obs     =     31,480

Group variable: buurt                           Number of groups  =         69
                                                Obs per group:
                                                              min =          2
                                                              avg =      456.2
                                                              max =      2,013
                                                Average RVI       =     4.5789
                                                Largest FMI       =     0.6992
                                                Complete DF       =         68
DF adjustment:   Small sample                   DF:     min       =      14.41
                                                        avg       =      61.31
                                                        max       =      66.03
Model F test:       Equal FMI                   F(  64,    46.6)  =     104.06
Within VCE type:       Robust                   Prob > F          =     0.0000

                                (Within VCE adjusted for 69 clusters in buurt)
```

logpricem2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
p_huur2						
90-95%	.0411964	.0189877	2.17	0.039	.0021658	.0802271
85-90%	.111859	.0563203	1.99	0.051	-.000694	.2244119
80-85%	.1945182	.0505714	3.85	0.000	.0933556	.2956808
75-80%	.258269	.0548496	4.71	0.000	.1484491	.3680888
70-75%	.2617692	.0578259	4.53	0.000	.1460672	.3774711
65-70%	.2840806	.0595308	4.77	0.000	.1650058	.4031555
60-65%	.2958655	.0605136	4.89	0.000	.1748387	.4168924
55-60%	.289776	.0607578	4.77	0.000	.1682754	.4112765
50-55%	.2787823	.0615235	4.53	0.000	.1557595	.4018051
45-50%	.2785559	.0663646	4.20	0.000	.145881	.4112308
40%-45	.274379	.06731	4.08	0.000	.1397987	.4089593
35%-40%	.2766705	.0693394	3.99	0.000	.1380698	.4152712
30%-35%	.2914324	.0712894	4.09	0.000	.148934	.4339308
25%-30%	.3405223	.071112	4.79	0.000	.1983824	.4826621
20%-25%	.2957748	.0764417	3.87	0.000	.1430045	.448545
15%-20%	.3099055	.0778721	3.98	0.000	.154298	.4655131
10%-15%	.2967644	.0786763	3.77	0.000	.139553	.4539758
5%-10%	0	(omitted)				
<5%	0	(omitted)				
jaar						
2007	.0229552	.0069815	3.29	0.002	.0090082	.0369021
2008	.0496594	.0092444	5.37	0.000	.0311955	.0681233
2009	.0240431	.0095993	2.50	0.015	.0048695	.0432166
2010	.0214788	.0095691	2.24	0.028	.0023654	.0405921
2011	.0297423	.0099686	2.98	0.004	.009831	.0496536
2012	.0157466	.0259161	0.61	0.546	-.0360066	.0674998
2013	-.0393361	.0260468	-1.51	0.136	-.0913491	.0126768
2014	-.0042087	.0262209	-0.16	0.873	-.0565654	.048148
bwper2						
1991-2000	-.0361563	.0139473	-2.59	0.012	-.0640044	-.0083082
1981-1990	-.158378	.0210344	-7.53	0.000	-.2003748	-.1163812
1971-1980	-.1967289	.0180541	-10.90	0.000	-.2327764	-.1606813
1960-1970	-.2069092	.0179204	-11.55	0.000	-.2426891	-.1711294
1945-1959	-.1521955	.0196081	-7.76	0.000	-.1913445	-.1130465
1931-1944	-.173674	.025722	-6.75	0.000	-.2250293	-.1223187
1906-1930	-.1699675	.0254669	-6.67	0.000	-.2208133	-.1191216
1500-1905	-.1859767	.0274388	-6.78	0.000	-.2407595	-.131194
parkeer						
Parking place	.0964102	.0091468	10.54	0.000	.0781459	.1146746
Carport and no garage	.1083193	.0177434	6.10	0.000	.0728925	.143746
Garage and no carport	.1038499	.017213	6.03	0.000	.0694822	.1382177

Garage and carport	.1697862	.0217407	7.81	0.000	.1263618	.2132106
Garage for more cars	.1822261	.0294994	6.18	0.000	.1233271	.2411251
soortwoning2						
Villa	.2964037	.0320319	9.25	0.000	.2324448	.3603627
Farm used as residence	.1941698	.0747339	2.60	0.012	.044932	.3434076
Mansion	.1022104	.0187206	5.46	0.000	.064832	.1395888
House boat	.1188671	.0662472	1.79	0.077	-.013458	.2511921
Bungalow	.2149569	.0600726	3.58	0.001	.0950111	.3349027
Canal house	.2644721	.0591376	4.47	0.000	.1463517	.3825926
Cottage	.3532696	.0746702	4.73	0.000	.2041395	.5023997
Estate	.593825	.0750159	7.92	0.000	.4333568	.7542932
Apartment with elevator	-.079098	.0193397	-4.09	0.000	-.1177115	-.0404845
Apartment without elevator	-.1027494	.0173166	-5.93	0.000	-.1373234	-.0681755
Ground-floor apartment	-.0183628	.0209198	-0.88	0.383	-.0601304	.0234047
nkamers	-.028601	.0044395	-6.44	0.000	-.0374648	-.0197373
nbadk	.0520641	.0130247	4.00	0.000	.0260362	.078092
nbalkon	-.0146421	.0042274	-3.46	0.001	-.0230835	-.0062007
ndakkap	.0156084	.0083798	1.86	0.067	-.001124	.0323408
permanent	.0068361	.0114696	0.60	0.553	-.0160893	.0297615
ged_verhuurd	-.2485023	.1484963	-1.67	0.099	-.5449946	.0479901
P_N_W_AL	-.0010801	.0002998	-3.60	0.001	-.0016841	-.0004761
BEV_DICHTH	-3.08e-06	1.30e-06	-2.37	0.023	-5.72e-06	-4.47e-07
aantal_misdaden	.0000397	.0000136	2.92	0.005	.0000125	.0000668
p_hhlaagsteinkomensgroep2	-.000648	.0005013	-1.29	0.201	-.001649	.0003531
aantal_nietwerkenden	-.0000478	.0000225	-2.12	0.038	-.0000928	-2.76e-06
leefbarometer	.0087367	.0116697	0.75	0.457	-.0145638	.0320372
AV3_CAFE	-.0010118	.000125	-8.09	0.000	-.0012627	-.0007608
AV3_RESTAU	.0009817	.0001	9.82	0.000	.0007807	.0011826
AF_TREINST	-.0087274	.0012168	-7.17	0.000	-.0111883	-.0062665
_cons	7.441818	.0815387	91.27	0.000	7.278941	7.604696
sigma_u	.17287575					
sigma_e	.19260132					
rho	.44618467	(fraction of variance due to u_i)				

Note: sigma_u and sigma_e are combined in the original metric.

R2 over imputed data = .2568608

```
. mi test 2.p_huur2 3.p_huur2 4.p_huur2 5.p_huur2 6.p_huur2 7.p_huur2 8.p_huur2 9.p_huur2 10.p_huur2 11.p_huur2 12.p_huur2 1
> 3.p_huur2 14.p_huur2 15.p_huur2 16.p_huur2 17.p_huur2 18.p_huur2
note: assuming equal fractions of missing information

 ( 1)  2.p_huur2 = 0
 ( 2)  3.p_huur2 = 0
 ( 3)  4.p_huur2 = 0
 ( 4)  5.p_huur2 = 0
 ( 5)  6.p_huur2 = 0
 ( 6)  7.p_huur2 = 0
 ( 7)  8.p_huur2 = 0
 ( 8)  9.p_huur2 = 0
 ( 9)  10.p_huur2 = 0
 (10)  11.p_huur2 = 0
 (11)  12.p_huur2 = 0
 (12)  13.p_huur2 = 0
 (13)  14.p_huur2 = 0
 (14)  15.p_huur2 = 0
 (15)  16.p_huur2 = 0
 (16)  17.p_huur2 = 0
 (17)  18.p_huur2 = 0

       F( 17,   64.4) =    4.40
            Prob > F =    0.0000
```

```
. mi estimate: xtreg logpricem2 i.p_huur4 i.jaar i.bwper2 i.parkeer i.soortwoning2 nkamers nbadk nbalkon ndakkap  permanent
> ged_verhuurd P_N_W_AL  BEV_DICHTH aantal_misdaden p_hhlaagsteinkomensgroep2 aantal_nietwerkenden leefbarometer AV3_CAFE AV
> 3_RESTAU AF_TREINS, fe vce(cluster buurt)

Multiple-imputation estimates                    Imputations       =         20
Fixed-effects (within) regression                Number of obs     =     31,480

Group variable: buurt                            Number of groups  =         69
                                                 Obs per group:
                                                              min =          2
                                                              avg =      456.2
                                                              max =      2,013
                                                 Average RVI       =     2.1071
                                                 Largest FMI       =     0.7094
                                                 Complete DF       =         68
DF adjustment:   Small sample                    DF:     min       =      13.97
                                                         avg       =      62.83
                                                         max       =      66.01
Model F test:       Equal FMI                    F(  55,    58.4)  =     240.52
Within VCE type:       Robust                    Prob > F          =     0.0000

                                                (Within VCE adjusted for 69 clusters in buurt)
```

logpricem2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
p_huur4						
80-90%	-.0076893	.0210049	-0.37	0.715	-.0496321	.0342535
70-80%	-.0089183	.0280609	-0.32	0.752	-.0649481	.0471114
60-70%	-.026741	.0296415	-0.90	0.370	-.0859291	.0324471
50-60%	-.0203383	.0355959	-0.57	0.570	-.0914134	.0507368
40-50%	-.0082759	.0412609	-0.20	0.842	-.0906667	.0741149
30-40%	.0147731	.046129	0.32	0.750	-.0773404	.1068865
20-30%	.0137684	.0540197	0.25	0.800	-.0940957	.1216325
10-20%	.005021	.052334	0.10	0.924	-.0994804	.1095225
<10%	0	(omitted)				
jaar						
2007	.0221732	.0066413	3.34	0.001	.0089073	.0354391
2008	.0506407	.0090342	5.61	0.000	.0325987	.0686828
2009	.0244289	.0096597	2.53	0.014	.0051384	.0437194
2010	.021304	.0088504	2.41	0.019	.003628	.03898
2011	.0295453	.0095187	3.10	0.003	.0105319	.0485588
2012	.0092105	.0251691	0.37	0.716	-.0410487	.0594697
2013	-.045675	.0252072	-1.81	0.075	-.0960089	.0046589
2014	-.0104228	.0261596	-0.40	0.692	-.0626554	.0418098
bwper2						
1991-2000	-.0358309	.0141342	-2.54	0.014	-.0640528	-.0076089
1981-1990	-.157927	.0211148	-7.48	0.000	-.2000847	-.1157694
1971-1980	-.1967468	.0181623	-10.83	0.000	-.2330104	-.1604831
1960-1970	-.207635	.0179795	-11.55	0.000	-.2435331	-.171737
1945-1959	-.1517514	.0196692	-7.72	0.000	-.191023	-.1124799
1931-1944	-.1729224	.0257492	-6.72	0.000	-.2243322	-.1215126
1906-1930	-.1694055	.0256248	-6.61	0.000	-.2205673	-.1182437
1500-1905	-.1858383	.027661	-6.72	0.000	-.2410671	-.1306096
parkeer						
Parking place	.096647	.0091606	10.55	0.000	.0783554	.1149387
Carport and no garage	.1083154	.0178849	6.06	0.000	.0726034	.1440274
Garage and no carport	.1036161	.0172098	6.02	0.000	.0692544	.1379777
Garage and carport	.1707974	.0222835	7.66	0.000	.1262921	.2153026
Garage for more cars	.1822015	.0293508	6.21	0.000	.1235992	.2408038
soortwoning2						
Villa	.2965427	.0318822	9.30	0.000	.2328841	.3602012
Farm used as residence	.1900799	.0743546	2.56	0.013	.0415994	.3385603
Mansion	.102629	.01858	5.52	0.000	.0655308	.1397272
House boat	.118734	.0656532	1.81	0.075	-.012367	.2498351
Bungalow	.2139131	.060418	3.54	0.001	.0932788	.3345473
Canal house	.2625359	.0601481	4.36	0.000	.142411	.3826609
Cottage	.35374	.07372	4.80	0.000	.2065263	.5009538
Estate	.5851371	.0704091	8.31	0.000	.434091	.7361832
Apartment with elevator	-.0782764	.0192267	-4.07	0.000	-.1166646	-.0398881
Apartment without elevator	-.102569	.0172237	-5.96	0.000	-.1369579	-.0681801

Ground-floor apartment	-.0183927	.0209546	-0.88	0.383	-.0602303	.0234449
nkamers	-.0287004	.0044494	-6.45	0.000	-.0375839	-.0198169
nbadk	.0525326	.0128912	4.08	0.000	.0267675	.0782976
nbalkon	-.0149223	.0042385	-3.52	0.001	-.023386	-.0064587
ndakkap	.0160255	.0084865	1.89	0.063	-.0009194	.0329705
permanent	.0060758	.0118938	0.51	0.611	-.0177022	.0298539
ged_verhuurd	-.2495245	.1481785	-1.68	0.097	-.5453828	.0463338
P_N_W_AL	-.0010279	.0002841	-3.62	0.001	-.0015995	-.0004564
BEV_DICHTH	-3.03e-06	1.18e-06	-2.56	0.014	-5.41e-06	-6.52e-07
aantal_misdaden	.0000341	.000015	2.27	0.026	4.14e-06	.000064
p_hhlaagsteinkomensgroep2	-.0005233	.0004796	-1.09	0.279	-.001481	.0004343
aantal_nietwerkenden	-.0000482	.0000207	-2.33	0.023	-.0000895	-6.97e-06
leefbarometer	.0125627	.0120099	1.05	0.299	-.0114174	.0365428
AV3_CAFE	-.0009879	.0001204	-8.20	0.000	-.00123	-.0007458
AV3_RESTAU	.0009625	.0000973	9.89	0.000	.0007665	.0011585
AF_TREINST	-.0091674	.001343	-6.83	0.000	-.0118738	-.0064609
_cons	7.691343	.0849432	90.55	0.000	7.52173	7.860955
sigma_u	.12519305					
sigma_e	.19273833					
rho	.29672275	(fraction of variance due to u_i)				

Note: **sigma_u** and **sigma_e** are combined in the original metric.

R2 over imputed data = .25558985

```
. mi test 2.p_huur4 3.p_huur4 4.p_huur4 5.p_huur4 6.p_huur4 7.p_huur4 8.p_huur4 9.p_huur4 10.p_huur4
note: assuming equal fractions of missing information

 ( 1)  2.p_huur4 = 0
 ( 2)  3.p_huur4 = 0
 ( 3)  4.p_huur4 = 0
 ( 4)  5.p_huur4 = 0
 ( 5)  6.p_huur4 = 0
 ( 6)  7.p_huur4 = 0
 ( 7)  8.p_huur4 = 0
 ( 8)  9.p_huur4 = 0
 ( 9)  10o.p_huur4 = 0
       Constraint 9 dropped

       F(  8,   66.0) =    1.11
            Prob > F =    0.3676
```

```
. mi estimate: xtreg logpricem2 a_socialhouses300m i.jaar i.bwper2 i.parkeer i.soortwoning2 nkamers nbadk nbalkon ndakkap  p
> ermanent ged_verhuurd P_N_W_AL  BEV_DICHTH aantal_misdaden p_hhlaagsteinkomensgroep2 aantal_nietwerkenden leefbarometer AV
> 3_CAFE AV3_RESTAU AF_TREINS, fe vce(cluster buurt)

Multiple-imputation estimates                  Imputations       =         20
Fixed-effects (within) regression              Number of obs     =     31,653

Group variable: buurt                          Number of groups  =         71
                                               Obs per group:
                                                             min =          2
                                                             avg =      445.8
                                                             max =      2,013
                                               Average RVI       =     2.1638
                                               Largest FMI       =     0.7258
                                               Complete DF       =         70
DF adjustment:   Small sample                  DF:     min       =      13.52
                                                       avg       =      64.37
                                                       max       =      68.05
Model F test:       Equal FMI                  F(  48,    60.0)  =     200.64
Within VCE type:       Robust                  Prob > F          =     0.0000

                                    (Within VCE adjusted for 71 clusters in buurt)
```

logpricem2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
a_socialhouses300m	-.0000914	.0000216	-4.22	0.000	-.0001345	-.0000482
jaar						
2007	.020371	.0063878	3.19	0.002	.0076181	.033124
2008	.0486388	.008919	5.45	0.000	.0308365	.0664411
2009	.0208713	.0093062	2.24	0.028	.0022969	.0394456
2010	.0177481	.0086923	2.04	0.045	.0003985	.0350976
2011	.026077	.008553	3.05	0.003	.0090011	.0431529
2012	-.000038	.0265879	-0.00	0.999	-.0531009	.0530249
2013	-.0550801	.026822	-2.05	0.044	-.1086087	-.0015514
2014	-.0215369	.0280347	-0.77	0.445	-.0774823	.0344084
bwper2						
1991-2000	-.0410729	.0137158	-2.99	0.004	-.0684445	-.0137014
1981-1990	-.1580164	.0189146	-8.35	0.000	-.1957609	-.1202719
1971-1980	-.2066278	.0167014	-12.37	0.000	-.2399566	-.1732991
1960-1970	-.2160846	.0168562	-12.82	0.000	-.2497216	-.1824475
1945-1959	-.1597297	.0176539	-9.05	0.000	-.1949586	-.1245008
1931-1944	-.1860344	.0228036	-8.16	0.000	-.2315384	-.1405304
1906-1930	-.1722734	.0243815	-7.07	0.000	-.2209262	-.1236206
1500-1905	-.1805223	.0271092	-6.66	0.000	-.2346198	-.1264249
parkeer						
Parking place	.088154	.008587	10.27	0.000	.0710172	.1052908
Carport and no garage	.0996355	.0179863	5.54	0.000	.0637412	.1355297
Garage and no carport	.0936996	.0168622	5.56	0.000	.0600504	.1273489
Garage and carport	.153354	.024559	6.24	0.000	.1043353	.2023727
Garage for more cars	.1755319	.0287619	6.10	0.000	.1181371	.2329267
soortwoning2						
Villa	.292956	.0320674	9.14	0.000	.2289631	.3569488
Farm used as residence	.1828023	.0713485	2.56	0.013	.0404048	.3251998
Mansion	.1043524	.018484	5.65	0.000	.0674661	.1412388
House boat	.1084394	.0601136	1.80	0.076	-.0115372	.228416
Bungalow	.2161696	.0611417	3.54	0.001	.0941576	.3381815
Canal house	.2779237	.0535962	5.19	0.000	.1709352	.3849121
Cottage	.3439336	.0715566	4.81	0.000	.2011194	.4867479
Estate	.6048926	.068091	8.88	0.000	.4583653	.75142
Apartment with elevator	-.0673288	.0247329	-2.72	0.008	-.1166827	-.017975
Apartment without elevator	-.0949796	.018299	-5.19	0.000	-.1314951	-.0584641
Ground-floor apartment	-.0102821	.0217709	-0.47	0.638	-.0537255	.0331613
nkamers	-.028266	.0044871	-6.30	0.000	-.0372199	-.0193121
nbadk	.051286	.0124229	4.13	0.000	.0264718	.0761001
nbalkon	-.0151823	.0041249	-3.68	0.000	-.0234146	-.00695
ndakkap	.0137955	.008623	1.60	0.114	-.0034124	.0310034
permanent	.0052434	.0120601	0.43	0.665	-.0188488	.0293356
ged_verhuurd	-.23945	.145903	-1.64	0.105	-.5306046	.0517046
P_N_W_AL	-.0011807	.0002986	-3.95	0.000	-.0017804	-.0005809
BEV_DICHTH	-2.36e-06	1.27e-06	-1.85	0.070	-4.91e-06	2.02e-07

	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
aantal_misdaden	.0000276	.000014	1.97	0.053	-3.09e-07	.0000556
p_hhlaagsteinkomensgroep2	-.000436	.0005103	-0.85	0.396	-.0014545	.0005824
aantal_nietwerkenden	-.0000475	.0000208	-2.28	0.026	-.000089	-5.87e-06
leefbarometer	.0165187	.0123441	1.34	0.185	-.0081151	.0411524
AV3_CAFE	-.0009893	.0001202	-8.23	0.000	-.0012307	-.0007478
AV3_RESTAU	.0009497	.0000952	9.97	0.000	.000758	.0011415
AF_TREINST	-.0088816	.0012073	-7.36	0.000	-.0113146	-.0064485
_cons	7.723512	.0776937	99.41	0.000	7.568456	7.878567
sigma_u	.11618038					
sigma_e	.19182928					
rho	.26836699	(fraction of variance due to u_i)				

Note: sigma_u and sigma_e are combined in the original metric.

R2 over imputed data = 0.26336842

```
. mi estimate: xtreg logpricem2 a_socialhouses100m i.jaar i.bwper2 i.parkeer i.soortwoning2 nkamers nbadk nbalkon ndakk
> ap  permanent ged_verhuurd P_N_W_AL  BEV_DICHTH aantal_misdaden p_hhlaagsteinkomensgroep2 aantal_nietwerkenden leefba
> rometer AV3_CAFE AV3_RESTAU AF_TREINS, fe vce(cluster buurt)

Multiple-imputation estimates                   Imputations       =         20
Fixed-effects (within) regression               Number of obs     =     31,653

Group variable: buurt                           Number of groups  =         71
                                                Obs per group:
                                                              min =          2
                                                              avg =      445.8
                                                              max =      2,013
                                                Average RVI       =     2.2038
                                                Largest FMI       =     0.6869
                                                Complete DF       =         70
DF adjustment:   Small sample                   DF:     min       =      15.22
                                                        avg       =      64.35
                                                        max       =      68.00
Model F test:       Equal FMI                   F(  48,    59.7)  =     199.92
Within VCE type:       Robust                   Prob > F          =     0.0000

                                               (Within VCE adjusted for 71 clusters in buurt)
```

logpricem2	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
a_socialhouses100m	-.0004931	.0000888	-5.56	0.000	-.0006702	-.000316
jaar						
2007	.0196611	.0062206	3.16	0.002	.0072414	.0320807
2008	.0478772	.0088722	5.40	0.000	.0301681	.0655862
2009	.0212688	.0092127	2.31	0.024	.0028811	.0396565
2010	.0179774	.0087961	2.04	0.045	.0004204	.0355343
2011	.0260819	.0086287	3.02	0.004	.0088553	.0433085
2012	.0001415	.0264604	0.01	0.996	-.0526669	.0529498
2013	-.0541053	.0267413	-2.02	0.047	-.1074729	-.0007378
2014	-.0202475	.028084	-0.72	0.473	-.0762911	.0357962

bwper2						
1991-2000	-.0427102	.0143577	-2.97	0.004	-.0713623	-.0140581
1981-1990	-.1583487	.0215531	-7.35	0.000	-.2013579	-.1153394
1971-1980	-.208518	.0197436	-10.56	0.000	-.2479167	-.1691192
1960-1970	-.2142108	.0183155	-11.70	0.000	-.2507597	-.1776619
1945-1959	-.1634969	.0200032	-8.17	0.000	-.2034133	-.1235806
1931-1944	-.1869284	.0241755	-7.73	0.000	-.2351698	-.138687
1906-1930	-.1704513	.0252648	-6.75	0.000	-.2208666	-.120036
1500-1905	-.1841025	.0281257	-6.55	0.000	-.240228	-.1279771
parkeer						
Parking place	.0848341	.0085532	9.92	0.000	.0677647	.1019035
Carport and no garage	.0950635	.0181491	5.24	0.000	.0588447	.1312823
Garage and no carport	.0944942	.0167488	5.64	0.000	.0610713	.1279171
Garage and carport	.1518083	.0228652	6.64	0.000	.1061684	.1974481
Garage for more cars	.1770017	.0284501	6.22	0.000	.1202289	.2337744
soortwoning2						
Villa	.2953803	.0319473	9.25	0.000	.2316273	.3591334
Farm used as residence	.1818633	.0716634	2.54	0.013	.0388379	.3248887
Mansion	.1029472	.0183556	5.61	0.000	.0663171	.1395772
House boat	.1017235	.0568825	1.79	0.078	-.0118071	.2152542
Bungalow	.2115387	.0616829	3.43	0.001	.0884472	.3346302
Canal house	.2714803	.065836	4.12	0.000	.1400775	.4028831
Cottage	.3535144	.0737729	4.79	0.000	.2062788	.5007499
Estate	.6836926	.0694507	9.84	0.000	.5358447	.8315405
Apartment with elevator	-.0723519	.0217605	-3.32	0.001	-.1157746	-.0289291
Apartment without elevator	-.0970608	.0178953	-5.42	0.000	-.1327707	-.0613509
Ground-floor apartment	-.0128247	.0216368	-0.59	0.555	-.0560004	.0303511
nkamers	-.0293367	.0043569	-6.73	0.000	-.0380307	-.0206426
nbadk	.0505055	.0127829	3.95	0.000	.0249765	.0760345
nbalkon	-.0153969	.0038497	-4.00	0.000	-.02308	-.0077137
ndakkap	.0135639	.0088157	1.54	0.129	-.0040284	.0311563
permanent	.0053803	.0119831	0.45	0.655	-.0185576	.0293182
ged_verhuurd	-.2495193	.1443125	-1.73	0.088	-.5375002	.0384615
P_N_W_AL	-.0011551	.000299	-3.86	0.000	-.0017563	-.0005539
BEV_DICHTH	-2.42e-06	1.25e-06	-1.93	0.059	-4.94e-06	9.84e-08
aantal_misdaden	.0000268	.0000138	1.95	0.055	-6.15e-07	.0000543
p_hhlaagsteinkomensgroep2	-.0004483	.0005081	-0.88	0.381	-.0014622	.0005657
aantal_nietwerkenden	-.0000497	.0000204	-2.44	0.017	-.0000904	-9.10e-06
leefbarometer	.0175435	.0122212	1.44	0.156	-.0068449	.0419319
AV3_CAFE	-.0009817	.0001183	-8.29	0.000	-.0012192	-.0007442
AV3_RESTAU	.0009457	.0000939	10.07	0.000	.0007567	.0011347
AF_TREINST	-.0087914	.001207	-7.28	0.000	-.0112241	-.0063587
_cons	7.709387	.0777669	99.13	0.000	7.554185	7.864588
sigma_u	.11554668					
sigma_e	.19145398					
rho	.26699048	(fraction of variance due to u_i)				

Note: **sigma_u** and **sigma_e** are combined in the original metric.

R2 over imputed data = 0.26624807

```
. mi estimate: xtreg logpricem2 a_socialhouses500m i.jaar i.bwper2 i.parkeer i.soortwoning2 nkamers nbadk nbalkon ndakkap
>   permanent ged_verhuurd P_N_W_AL  BEV_DICHTH aantal_misdaden p_hhlaagsteinkomensgroep2 aantal_nietwerkenden leefbarome
> ter AV3_CAFE AV3_RESTAU AF_TREINS, fe vce(cluster buurt)

Multiple-imputation estimates                  Imputations       =         20
Fixed-effects (within) regression              Number of obs     =     31,653

Group variable: buurt                          Number of groups  =         71
                                               Obs per group:
                                                             min =          2
                                                             avg =      445.8
                                                             max =      2,013
                                               Average RVI       =     2.1599
                                               Largest FMI       =     0.7194
                                               Complete DF       =         70
DF adjustment:   Small sample                  DF:      min      =      13.80
                                                        avg      =      64.34
                                                        max      =      68.03
Model F test:       Equal FMI                  F(  48,    60.0)  =     185.46
Within VCE type:       Robust                  Prob > F          =     0.0000

                                      (Within VCE adjusted for 71 clusters in buurt)

------------------------------------------------------------------------------------
        logpricem2 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
a_socialhouses500m |  -.0000282   .0000108    -2.60   0.011    -.0000498   -6.54e-06
                   |
              jaar |
             2007  |   .0201258   .0064104     3.14   0.003     .0073277    .0329238
             2008  |   .0481746   .0089691     5.37   0.000     .0302722    .0660771
             2009  |   .0210115   .0092889     2.26   0.027     .0024718    .0395513
             2010  |   .0174344   .0087761     1.99   0.051    -.0000826    .0349514
             2011  |   .0260266   .0086542     3.01   0.004     .0087486    .0433046
             2012  |  -.0027276   .0269058    -0.10   0.920    -.0564247    .0509695
             2013  |  -.0567654   .0270227    -2.10   0.039    -.1106943   -.0028365
             2014  |  -.0224276   .0283429    -0.79   0.432    -.0789877    .0341325
```

bwper2						
1991-2000	-.0418092	.0140082	-2.98	0.004	-.0697642	-.0138543
1981-1990	-.1622205	.0201856	-8.04	0.000	-.2025011	-.12194
1971-1980	-.2041301	.0173477	-11.77	0.000	-.2387484	-.1695117
1960-1970	-.2140515	.0172428	-12.41	0.000	-.24846	-.1796429
1945-1959	-.1565446	.0181404	-8.63	0.000	-.1927442	-.120345
1931-1944	-.1823808	.0240606	-7.58	0.000	-.2303932	-.1343685
1906-1930	-.1743288	.0250624	-6.96	0.000	-.2243403	-.1243174
1500-1905	-.183869	.0272006	-6.76	0.000	-.2381487	-.1295893
parkeer						
Parking place	.0900594	.0087422	10.30	0.000	.0726128	.107506
Carport and no garage	.1001788	.0178628	5.61	0.000	.0645311	.1358266
Garage and no carport	.097482	.0171242	5.69	0.000	.06331	.1316541
Garage and carport	.1572112	.0243187	6.46	0.000	.1086716	.2057508
Garage for more cars	.1799559	.029097	6.18	0.000	.1218924	.2380195
soortwoning2						
Villa	.2944428	.0320944	9.17	0.000	.2303961	.3584894
Farm used as residence	.1829022	.0718404	2.55	0.013	.0395229	.3262816
Mansion	.1045164	.0185801	5.63	0.000	.0674384	.1415945
House boat	.1079885	.0635918	1.70	0.094	-.0189269	.2349039
Bungalow	.2166977	.0601097	3.61	0.001	.0967448	.3366506
Canal house	.2864434	.0550397	5.20	0.000	.1765762	.3963106
Cottage	.3443695	.0734701	4.69	0.000	.1977377	.4910014
Estate	.5894739	.06877	8.57	0.000	.441772	.7371758
Apartment with elevator	-.0713666	.0220213	-3.24	0.002	-.11531	-.0274232
Apartment without elevator	-.0979296	.0178764	-5.48	0.000	-.1336019	-.0622572
Ground-floor apartment	-.0134736	.0214516	-0.63	0.532	-.05628	.0293328
nkamers	-.0283696	.0044866	-6.32	0.000	-.0373225	-.0194168
nbadk	.0518772	.0125379	4.14	0.000	.0268331	.0769213
nbalkon	-.0152685	.0041911	-3.64	0.001	-.0236329	-.0069042
ndakkap	.0154422	.0085564	1.80	0.076	-.0016327	.0325172
permanent	.0066689	.0116548	0.57	0.569	-.0166161	.029954
ged_verhuurd	-.2424268	.1471681	-1.65	0.104	-.536106	.0512523
P_N_W_AL	-.0011798	.0003005	-3.93	0.000	-.0017834	-.0005763
BEV_DICHTH	-2.40e-06	1.28e-06	-1.87	0.067	-4.97e-06	1.77e-07
aantal_misdaden	.0000279	.0000143	1.95	0.055	-6.57e-07	.0000565
p_hhlaagsteinkomensgroep2	-.0003972	.0005155	-0.77	0.444	-.0014261	.0006316
aantal_nietwerkenden	-.0000503	.0000205	-2.45	0.017	-.0000913	-9.41e-06
leefbarometer	.0177099	.0124324	1.42	0.159	-.0071	.0425198
AV3_CAFE	-.0009888	.0001207	-8.19	0.000	-.0012311	-.0007465
AV3_RESTAU	.0009519	.0000962	9.90	0.000	.0007582	.0011456
AF_TREINST	-.0089448	.0012172	-7.35	0.000	-.0113992	-.0064904
_cons	7.711435	.0805543	95.73	0.000	7.550672	7.872199
sigma_u	.1163023					
sigma_e	.19258911					
rho	.26722802	(fraction of variance due to u_i)				

Note: **sigma_u** and **sigma_e** are combined in the original metric.

.

R2 over imputed data = 0.25752136

```
. mi estimate: xtreg logpricem2  a_socialhouses100m a_socialhouses300m a_socialhouses500m i.jaar i.bwper2 i.parkeer i.soort
> woning2 nkamers nbadk nbalkon ndakkap  permanent ged_verhuurd P_N_W_AL  BEV_DICHTH aantal_misdaden p_hhlaagsteinkomensgro
> ep2 aantal_nietwerkenden leefbarometer AV3_CAFE AV3_RESTAU AF_TREINS, fe vce(cluster buurt)

Multiple-imputation estimates                   Imputations       =         20
Fixed-effects (within) regression               Number of obs     =     31,653

Group variable: buurt                           Number of groups  =         71
                                                Obs per group:
                                                              min =          2
                                                              avg =      445.8
                                                              max =      2,013
                                                Average RVI       =     2.1041
                                                Largest FMI       =     0.6946
                                                Complete DF       =         70
DF adjustment:   Small sample                   DF:     min       =      14.87
                                                        avg       =      64.52
                                                        max       =      68.00
Model F test:       Equal FMI                   F(  50,   60.2)   =     206.83
Within VCE type:       Robust                   Prob > F          =     0.0000

                                       (Within VCE adjusted for 71 clusters in buurt)
```

logpricem2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
a_socialhouses100m	-.0003673	.0000689	-5.33	0.000	-.0005049	-.0002298
a_socialhouses300m	-.0000691	.0000211	-3.27	0.002	-.0001113	-.0000269
a_socialhouses500m	8.24e-06	.0000125	0.66	0.511	-.0000166	.0000331
jaar						
2007	.019959	.0062538	3.19	0.002	.0074731	.0324448
2008	.0483529	.0088628	5.46	0.000	.0306626	.0660432
2009	.0210126	.0092678	2.27	0.027	.002515	.0395103
2010	.0179639	.0087377	2.06	0.044	.0005235	.0354042
2011	.0260666	.0085427	3.05	0.003	.0090116	.0431215
2012	.0016304	.0263771	0.06	0.951	-.0510118	.0542727
2013	-.0533141	.0266669	-2.00	0.050	-.1065333	-.0000948
2014	-.0200772	.0279279	-0.72	0.475	-.0758094	.0356549

bwper2						
1991-2000	-.0427446	.0142225	-3.01	0.004	-.0711271	-.0143621
1981-1990	-.1567621	.0200024	-7.84	0.000	-.196677	-.1168472
1971-1980	-.2103118	.0186148	-11.30	0.000	-.2474583	-.1731653
1960-1970	-.2165781	.017711	-12.23	0.000	-.2519208	-.1812353
1945-1959	-.1646959	.0188827	-8.72	0.000	-.2023766	-.1270153
1931-1944	-.1901202	.023338	-8.15	0.000	-.2366905	-.1435499
1906-1930	-.1705298	.0247057	-6.90	0.000	-.2198295	-.1212302
1500-1905	-.1807201	.0275831	-6.55	0.000	-.2357631	-.1256771
parkeer						
Parking place	.0838807	.0083181	10.08	0.000	.0672803	.100481
Carport and no garage	.0951722	.0179264	5.31	0.000	.0593975	.1309468
Garage and no carport	.0914178	.0164716	5.55	0.000	.0585479	.1242876
Garage and carport	.14928	.0234267	6.37	0.000	.1025201	.1960398
Garage for more cars	.1739975	.0283978	6.13	0.000	.1173293	.2306657
soortwoning2						
Villa	.2934762	.0320164	9.17	0.000	.2295853	.3573671
Farm used as residence	.1812207	.0713966	2.54	0.013	.0387276	.3237139
Mansion	.1034579	.0182997	5.65	0.000	.0669394	.1399763
House boat	.1014637	.0555257	1.83	0.072	-.0093597	.2122871
Bungalow	.2128663	.0617567	3.45	0.001	.0896275	.3361051
Canal house	.2735974	.0616673	4.44	0.000	.150512	.3966828
Cottage	.3488793	.0733894	4.75	0.000	.202409	.4953496
Estate	.6739351	.0690038	9.77	0.000	.5267476	.8211225
Apartment with elevator	-.06742	.0241004	-2.80	0.007	-.1155119	-.0193281
Apartment without elevator	-.0940863	.0182876	-5.14	0.000	-.1305792	-.0575935
Ground-floor apartment	-.0094957	.0217952	-0.44	0.664	-.0529876	.0339962
nkamers	-.028878	.0043885	-6.58	0.000	-.0376352	-.0201208
nbadk	.0503024	.0125781	4.00	0.000	.0251815	.0754234
nbalkon	-.0153359	.0038716	-3.96	0.000	-.0230628	-.0076091
ndakkap	.0127086	.008804	1.44	0.153	-.0048604	.0302777
permanent	.0045529	.0122806	0.37	0.712	-.0199778	.0290836
ged_verhuurd	-.2437985	.143816	-1.70	0.095	-.5307887	.0431916
P_N_W_AL	-.0011645	.0002995	-3.89	0.000	-.0017666	-.0005625
BEV_DICHTH	-2.37e-06	1.26e-06	-1.88	0.066	-4.90e-06	1.59e-07
aantal_misdaden	.0000263	.0000139	1.90	0.062	-1.39e-06	.000054
p_hhlaagsteinkomensgroep2	-.000469	.0005068	-0.93	0.358	-.0014805	.0005425
aantal_nietwerkenden	-.0000474	.0000207	-2.29	0.025	-.0000888	-6.07e-06
leefbarometer	.016542	.0122196	1.35	0.180	-.0078432	.0409271
AV3_CAFE	-.0009834	.0001185	-8.30	0.000	-.0012212	-.0007455
AV3_RESTAU	.0009447	.0000938	10.07	0.000	.0007559	.0011336
AF_TREINST	-.0087704	.0012012	-7.30	0.000	-.0111906	-.0063501
_cons	7.727572	.0792894	97.46	0.000	7.569332	7.885812
sigma_u	.11556087					
sigma_e	.19106624					
rho	.26783289	(fraction of variance due to u_i)				

Note: **sigma_u** and **sigma_e** are combined in the original metric.

R2 over imputed data = .26926345

```
. mi estimate: xtreg logpricem2 a_socialhouses100m a_100300m a_300500m i.jaar i.bwper2 i.parkeer i.soortwoning2 nkamers nbad
> k nbalkon ndakkap  permanent ged_verhuurd P_N_W_AL  BEV_DICHTH aantal_misdaden p_hhlaagsteinkomensgroep2 aantal_nietwerken
> den leefbarometer AV3_CAFE AV3_RESTAU AF_TREINS, fe vce(cluster buurt)

Multiple-imputation estimates                  Imputations       =         20
Fixed-effects (within) regression              Number of obs     =     31,653

Group variable: buurt                          Number of groups  =         71
                                               Obs per group:
                                                             min =          2
                                                             avg =      445.8
                                                             max =      2,013
                                               Average RVI       =     2.1041
                                               Largest FMI       =     0.6946
                                               Complete DF       =         70
DF adjustment:   Small sample                  DF:     min       =      14.87
                                                       avg       =      64.52
                                                       max       =      68.00
Model F test:       Equal FMI                  F(  50,    60.2)  =     206.83
Within VCE type:       Robust                  Prob > F          =     0.0000

                                              (Within VCE adjusted for 71 clusters in buurt)
```

logpricem2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
a_socialhouses100m	-.0004282	.0000746	-5.74	0.000	-.000577	-.0002794
a_100300m	-.0000609	.0000169	-3.60	0.001	-.0000946	-.0000271
a_300500m	8.24e-06	.0000125	0.66	0.511	-.0000166	.0000331
jaar						
2007	.019959	.0062538	3.19	0.002	.0074731	.0324448
2008	.0483529	.0088628	5.46	0.000	.0306626	.0660432
2009	.0210126	.0092678	2.27	0.027	.002515	.0395103
2010	.0179639	.0087377	2.06	0.044	.0005235	.0354042
2011	.0260666	.0085427	3.05	0.003	.0090116	.0431215
2012	.0016304	.0263771	0.06	0.951	-.0510118	.0542727
2013	-.0533141	.0266669	-2.00	0.050	-.1065333	-.0000948
2014	-.0200772	.0279279	-0.72	0.475	-.0758094	.0356549
bwper2						
1991-2000	-.0427446	.0142225	-3.01	0.004	-.0711271	-.0143621
1981-1990	-.1567621	.0200024	-7.84	0.000	-.196677	-.1168472
1971-1980	-.2103118	.0186148	-11.30	0.000	-.2474583	-.1731653
1960-1970	-.2165781	.017711	-12.23	0.000	-.2519208	-.1812353
1945-1959	-.1646959	.0188827	-8.72	0.000	-.2023766	-.1270153
1931-1944	-.1901202	.023338	-8.15	0.000	-.2366905	-.1435499
1906-1930	-.1705298	.0247057	-6.90	0.000	-.2198295	-.1212302
1500-1905	-.1807201	.0275831	-6.55	0.000	-.2357631	-.1256771
parkeer						
Parking place	.0838807	.0083181	10.08	0.000	.0672803	.100481
Carport and no garage	.0951722	.0179264	5.31	0.000	.0593975	.1309468
Garage and no carport	.0914178	.0164716	5.55	0.000	.0585479	.1242876
Garage and carport	.14928	.0234267	6.37	0.000	.1025201	.1960398
Garage for more cars	.1739975	.0283978	6.13	0.000	.1173293	.2306657
soortwoning2						
Villa	.2934762	.0320164	9.17	0.000	.2295853	.3573671
Farm used as residence	.1812207	.0713966	2.54	0.013	.0387276	.3237139
Mansion	.1034579	.0182997	5.65	0.000	.0669394	.1399763
House boat	.1014637	.0555257	1.83	0.072	-.0093597	.2122871
Bungalow	.2128663	.0617567	3.45	0.001	.0896275	.3361051
Canal house	.2735974	.0616673	4.44	0.000	.150512	.3966828
Cottage	.3488793	.0733894	4.75	0.000	.202409	.4953496
Estate	.6739351	.0690038	9.77	0.000	.5267476	.8211225

Apartment with elevator	-.06742	.0241004	-2.80	0.007	-.1155119	-.0193281
Apartment without elevator	-.0940863	.0182876	-5.14	0.000	-.1305792	-.0575935
Ground-floor apartment	-.0094957	.0217952	-0.44	0.664	-.0529876	.0339962
nkamers	-.028878	.0043885	-6.58	0.000	-.0376352	-.0201208
nbadk	.0503024	.0125781	4.00	0.000	.0251815	.0754234
nbalkon	-.0153359	.0038716	-3.96	0.000	-.0230628	-.0076091
ndakkap	.0127086	.008804	1.44	0.153	-.0048604	.0302777
permanent	.0045529	.0122806	0.37	0.712	-.0199778	.0290836
ged_verhuurd	-.2437985	.143816	-1.70	0.095	-.5307887	.0431916
P_N_W_AL	-.0011645	.0002995	-3.89	0.000	-.0017666	-.0005625
BEV_DICHTH	-2.37e-06	1.26e-06	-1.88	0.066	-4.90e-06	1.59e-07
aantal_misdaden	.0000263	.0000139	1.90	0.062	-1.39e-06	.000054
p_hhlaagsteinkomensgroep2	-.000469	.0005068	-0.93	0.358	-.0014805	.0005425
aantal_nietwerkenden	-.0000474	.0000207	-2.29	0.025	-.0000888	-6.07e-06
leefbarometer	.016542	.0122196	1.35	0.180	-.0078432	.0409271
AV3_CAFE	-.0009834	.0001185	-8.30	0.000	-.0012212	-.0007455
AV3_RESTAU	.0009447	.0000938	10.07	0.000	.0007559	.0011336
AF_TREINST	-.0087704	.0012012	-7.30	0.000	-.0111906	-.0063501
_cons	7.727572	.0792894	97.46	0.000	7.569332	7.885812
sigma_u	.11556087					
sigma_e	.19106624					
rho	.26783289	(fraction of variance due to u_i)				

Note: **sigma_u** and **sigma_e** are combined in the original metric.

```
.
. estimate store t18
```

R2 over imputed data =.26926345