

GOOD BONES AND FIXER-UPPERS: HOUSING QUALITY AND NEIGHBOURHOOD SPILLOVER EFFECTS IN ROTTERDAM

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The views stated in this thesis are those of the author and not necessarily those of the supervisor second assessor,
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Abstract

The current housing market in Rotterdam is showing a similar increase in prices and demand as the other large cities in the Netherlands. The goal of this study is to find out what the effect of neighbourhood spillover effects of quality are on the housing prices in Rotterdam and if this effect follows a trend over time. Through comparison of maps and statistical analyses for different time periods, the effects and trends were researched. The data included houses sold during the period 2010-2020 in the municipality of Rotterdam. The results do not show a clear trend, neither for improvement of the quality of homes over time nor for the neighbourhood spillover effects of quality over time. However, the results do show that the average quality of an area significantly affects the housing price and that there are neighbourhood spillover effects of quality on the housing price. This is not in line with previous research conducted in other municipalities. Further research should aim to assess these differences, which could be due to the unique and heterogeneous housing stock of Rotterdam. Due to the heterogeneous housing stock, other factors than just the location may be better suited to group similar housing stock when creating policies in Rotterdam.

The effect of the quality of the area is not large enough to make a difference in whether someone can afford a home or not. Surprisingly, the effect for 4-digit postal code areas was the largest compared to the 6-, 5- and 3-digit postal code areas. This would be an interesting subject for further research.

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1. Introduction

The state of the housing market in the Netherlands has received a lot of attention in the last few years. The prices are going through the roof and the demand keeps increasing (CBS, 2020b). Many prospective buyers are struggling to find affordable housing in a location that suits their needs. A popular city for young professionals is Rotterdam, the second largest city in the Netherlands (CBS, 2020). This increasing demand and popularity influences the housing market of Rotterdam and in particular the housing price. Important to establish then is what determines the price of a home in Rotterdam. As can be expected, things such as the size of home, the number of rooms, and its quality partly determine the price of a home. However, other factors such as the construction period of a home and the neighbourhood it's located in can have a large effect on the price. The popularity of certain neighbourhoods varies over time. Neighbourhoods that might formerly be known as a "bad" neighbourhood due to low quality housing and, or, a high crime rate can become the 'place to be' a couple of years later due to gentrification. A more thorough explanation of gentrification will be given in the theoretical framework. An example of this is the neighbourhood 'Katendrecht', which used to be considered a problem area with a lot of low income households and a high crime rate, but is now the most popular amongst young people or young families (Vocke, 2019). What used to be in decay is now filled with trendy shops and facilities.

There is no shortage of papers on the housing market in the Netherlands. However, the academic literature tends to focus on gentrification in general. Mostly, the focus in academic literature is on the effect of gentrification, but also decay and renewal specifically, on the inhabitants of neighbourhoods and/or on individual prices. While most papers do mention the effects of decay and renewal on individual homes or on the market, not a lot of the literature includes the neighbourhood spillover effects (Helms, 2012). This paper hopes to close part of that gap in academic literature by looking at the neighbourhood spillover effects of quality and the effect of the quality of homes in the neighbourhood on the housing prices. The city of Rotterdam was chosen due to its unique housing stock. The bombings in the Second World War have made revitalization of the housing stock a continuing pressing issue for the city. Usually, the city centre is the oldest and the neighbourhoods get newer and more modern the further away they are from the city centre. The neighbourhoods of Rotterdam do not follow this typical pattern because the city centre was severely bombed during the war. Therefore, the possible neighbourhood effects can differ from other cities because the housing stock in neighbourhoods

is more heterogeneous. This paper will focus on the research question whether there are neighbourhood spillover effects of the quality of surrounding homes on the price of a home and, if there are, whether these effects follow a trend over time. Although usually there are neighbourhood spillover effects and they follow a trend over time, it can be expected that due to the differences in housing stock within different areas in Rotterdam the results of this research could differ from these expectations.

The paper starts with a literature review on gentrification, decay and renewal of houses, and neighbourhood spillover effects. The literature will then focus specifically on the city of Rotterdam. The data used in the current research spans over the period 2010-2020 and is obtained from the municipality of Rotterdam and the Nederlandse Coöperatieve Vereniging van Makelaars en Taxateurs (NVM). Based on previous academic literature and the data available, a method was conducted to research the neighbourhood spillover effects of quality on the housing price and to examine these effects over time. The average quality of a postal code area in a specific year was matched with each individual house sold in the dataset. This method will be explained in more detail in the third and fourth chapter. The results of the data analysis will be presented in chapter 5 in the results section. The limitations of the research will be discussed in the sixth chapter, which will include a discussion on how the results match with previous academic literature. Lastly, the conclusion will be presented.

2. Theoretical Framework

The conceptual framework provides a foundation for the construction of the different hypotheses this research will explore. The first section explains the term gentrification and describes what factors need to be present for the process of gentrification to arise in a certain area. The second section focuses on the concept of urban revitalization and housing maintenance. The third section explains where and how these different concepts implicate neighbourhood spillover effects. Lastly, the theoretical explanation applies these insights to the situation in Rotterdam. Examining the current situation in the housing market and relevant factors for gentrification and urban renewal will prepare the ground for hypotheses about the existence of neighbourhood spillover effects in the city of Rotterdam.

Gentrification

The concept of gentrification is something that is extensively researched in academic literature. Because renovation of the housing stock, which is the focus of this research, is such a large part of what gentrification entails most research on decay and renewal and its effects on neighbourhoods and surround housing prices immediately focusses on gentrification as a whole. Therefore, for the sake of completeness gentrification is included in the theoretical part of this research. This paragraph will explore what gentrification is, what factors need to be present for the phenomenon to occur and what the upsides and downsides are of the phenomenon.

What is gentrification ?

The economic literature defines gentrification in different ways, but all definitions circle around a similar core: change in low-income urban areas. Byrne (2003) calls gentrification the process by which people with a higher income change the physical and social fabric of lower-income urban areas to better fit their needs and preferences (Byrne, 2003). Gentrification can improve the quality of building and neighbourhoods in cities due to the renovation of new buildings. For this reason, the term gentrification also describes the action of ‘upgrading’ urban areas with a low average income, low housing values, or high poverty rates (Kolko, 2007). The broadest definition of gentrification uses the term to capture the replacement of low-income households in a neighbourhood by higher-income households (Guirrieri et al., 2013). This paper uses

Byrne's definition (2003) to describe gentrification because it includes the tangible shifts in housing but also the change in social dynamics. Because an improvement in the quality of homes is both a precursor of gentrification and part of the gentrification process, some general context on gentrification is given in this chapter as for what the consequences of neighbourhood spillover effects of quality and the effect of an improvement of quality on the housing prices can be.

In Byrne's understanding of gentrification, preferences play a key role. When considering where to live, people can maximize their utility by optimizing their commuting costs and housing costs (Alonso, 1964). In theory, living in the suburbs would be optimal for people that prefer to live in a larger space, because a person can get more space for the same price per square foot. However, in terms of commuting costs, living closer to the city centre is optimal (Brueckner & Rosenthal, 2009). If the income elasticity of demand for land, and therefore housing, is greater than the income elasticity of the travel costs, affluent people will live in the suburbs. Gentrification arises when there is a shift. For some people, the income elasticity for travel time becomes more than the income elasticity for land, and therefore they prefer to live close to the city centre (Glaeser et al., 2000). When these people move toward the city centre, they often move to lower-income areas because those are often closer to the city centre (Mills & Lubuele, 1997). These areas are then profoundly affected by this group's social and physical preferences for housing and neighbourhood life.

What factors make it likely that gentrification will occur in a neighbourhood?

Not all neighbourhoods are likely to gentrify. Exploring the factors that determine which neighbourhoods gentrify and why can be useful for both policy makers and real estate investors. Knowing these factors can make urban revitalization policy more targeted and effective. For real estate investors, this information is necessary for the lucrative practice of 'flipping houses': buying cheap housing, renovating it, and then selling with a profit.

Both policy makers and investors assume that gentrification will continue to be a factor in the housing market. This is a shift: in literature from the late 20th century, gentrification was assumed to be temporary (Smith, 1982). The different lifestyle of the baby boom generation compared to previous generations, the high costs of suburban living, and the low housing vacancy rates seemed like a perfect storm pushing people away from the suburbs and towards

the city centres. The assumption was that these effects were only temporary, with the revival of city centres coming to an end in the long run (Smith, 1982). But although society and the housing market have changed substantially since then, gentrification has persisted. With gentrification still an important dynamic today, the question of which factors predict gentrification remains important across the board. Although gentrification has some downsides that should not be forgotten, which will be further discussed in a later chapter in the paper, the revitalization gentrification brings to a city is a positive thing. Therefore, seeing what factors predict gentrification and therefore the revitalization of a city is important because this paper not only looks at the effect of renovation on housing prices but also looks at the neighbourhood spillover effects of renovation.

The factors that determine whether or not a neighbourhood is attractive for gentrification are not the same for all cities. The build of a specific city and the setup of its neighbourhoods and transport facilities create differences in what is most important. In spite of this variation, there are three general factors that affect the likelihood of gentrification in a given neighbourhood: its location, the housing stock, and demographics (Kolko, 2007). This paper will discuss each of these factors and how they affect gentrification and there for renovation of homes and the effect that has on the housing prices.

Location

The location of a neighbourhood influences whether or not people want to live there. The proximity to amenities can make a certain neighbourhood less or more attractive for (potential) residents (Kolko, 2007). Most amenities and job opportunities can be found in the city centre (Glaeser et al., 2000), which means that neighbourhoods close to the city centre are likely to be most attractive for residents. Proximity to the city centre is especially important for high-income people in larger cities (Kolko, 2007). For these people with a higher income, a short commute is especially appealing because their commuting costs are higher than for people with a lower income (Wheaton, 1977). Since people with a higher income earn more money in the same time than people with a lower income, losing time for their commute results in a bigger loss of money. With this reasoning a rich person's time is worth more. Living closer to the city centre saves time, but so does having access to good transport facilities. Improvements to infrastructure and/or facilities can make neighbourhoods that were previously deemed unattractive popular again (Rigolon & Németh, 2019b). All in all, a neighbourhood with good

access to the central business district, amenities, and public transport will be attractive to higher-income people and therefore more likely to gentrify (Chapple et al., 2017). These neighbourhoods often have an older housing stock as well. Other aspects of the location of neighbourhoods also influence the likeliness that a neighbourhood is going to gentrify but because this paper focusses on the renovation of housing stock they are not further discussed.

The housing stock

Alongside the location of neighbourhoods, the type of housing stock is also a factor that indicates whether or not a neighbourhood is likely to gentrify (Kolko, 2007). Broadly speaking, a historic housing stock is considered attractive and therefore more likely to gentrify (Chapelle et al., 2017). For example, in the Netherlands houses built in the 1930s are particularly popular. This is not only due to the preferable locations where these types of houses were built, but also due to their features: stained glass windows, bay windows and so on (Het Parool, 2021). But older houses also come with challenges. The older a house gets, the more it deteriorates and the smaller the enjoyment of living there becomes. If the deterioration is bad enough, it is profitable to renovate the house. The worse the state of the house is, the more it benefits from renovation and redevelopment (Kolko, 2007). Therefore, in theory, the oldest houses that are in the worst state are most likely to get renovated. Renovating houses is part of the gentrification process (Byrne, 2003). However, only the houses with a good location get renovated because the age and look of a home is not enough to make the home to be attractive for renovation.

Redevelopment and renovation of the housing stock in a neighbourhood can be a sign that the neighbourhood is gentrifying (Kolko, 2007). In a gentrifying neighbourhood, the number of housing units increases. This is not only due to new building and development, but also due to the renovation and transformation of the existing housing stock. For example, one-family homes might be transformed into several different apartments. The type of housing stock can increase the popularity of a neighbourhood, with the preference for historic buildings as an example. When combined with an attractive location, the housing stock – both existing and transformed through new development – creates a pathway to gentrification of an entire neighbourhood. Large scale renovation of the housing stock can be a sign that the neighbourhood is gentrifying meaning housing prices will increase.

Demographics of a neighbourhood

The changes in demographics of a neighbourhood are also a relevant factor in a neighbourhood's potential gentrification. This paper is brief about the demographic context, since demographics are not as important for the physical state of houses, which is the point of interest in this research. However, the type of residents also influence how likely it is a home gets renovated. People with lower income and/or older people are less likely to renovate a home (Davey, 2006).

The process of gentrification changes neighbourhoods where most people have lower income into neighbourhoods with higher-income residents (Byrne, 2003). Whilst in the beginning the neighbourhood's residents are predominantly less affluent, over time as the neighbourhood is gentrified by people with a higher income, the share of affluent people in the neighbourhood grows. In general, the higher-income people moving into lower-income neighbourhood are white with no children (Kolko, 2007; Kirkland, 2008). Gentrification is usually partly the result of affluent white young people moving into a neighbourhood that previously were home to a more diverse population with a lower income. These new residents of the neighbourhood have different preferences, and as this group grows, the neighbourhood adapts to their needs. When neighbourhoods gentrify, the number of households increases, but the number of residents younger than 18 decreases. Gentrification changes the constitution of a neighbourhood, but does not necessarily lead to an increase in inhabitants (Kolko, 2007). Changes in the type of people living in a neighbourhood can indicate that gentrification is underway.

In summation, a neighbourhood that has an older housing stock, close to the city centre, with green amenities and proximity to wealthier neighbourhoods, is a prime candidate for gentrification.

Decay and Renewal

Gentrification broadly describes a neighbourhood's transition from poor quality housing and low-income residents to an affluent neighbourhood with high quality housing. Decay and then the renewal of housing are always part of the broader gentrification process (Helms, 2003). Decay and renewal refer only to the state of the real estate itself, while gentrification also covers neighbourhood factors, such as location and transport. Distinguishing between the gentrification of a neighbourhood and its renewal is helpful in considering the effects on the incumbent residents. Gentrification can lead to displacement, when the housing prices go up to such an extent that the incumbent residents cannot afford to live in the neighbourhood anymore. Only affluent residents can afford to benefit from the renewal. When a neighbourhood is revitalized or renewed, the housing improves in the same manner as with gentrification, but there is no displacement of the incumbent residents (National Low Income Housing Coalition, 2019). Decay and renewal overlap with gentrification, but they are not the same thing.

Over time, real estate decays until it is either renovated or torn down and replaced. The cycle of decay and renewal in a neighbourhood can take up to 100 years (Rosenthal, 2008). Because of decay, the older a building is the more likely it is to get renovated (Helms, 2003). When a dwelling is in a good state and of high quality, rich residents live there. When the property deteriorates and the quality diminishes, low-income households move in. The lack of maintenance by homeowners lowers prices and makes it affordable for less affluent people to move in (Dildine & Massey, 1974). Less affluent people moving into a neighbourhood is not the cause of decay, but a result of it. Under certain conditions, decaying real estate can be renovated and improved to such an extent that it becomes attractive again for rich households (Rosenthal, 2008). In this case, changes in the housing stock may lead to gentrification.

However, not all housing renovation leads to gentrification. Most renovations are done by incumbent residents who own their homes. While these renovations may increase the price of the homes, or at least prevent decay from lowering these prices, this "incumbent upgrading" does not alter the neighbourhood as gentrification does (Helms, 2003). People with a higher income have more money to possibly invest in their homes. Furthermore, homeowners invest more in their homes when it comes to renovation because it is their own property. People who rent their place have less incentive to renovate (Helms, 2003).

Research by Vigdor (2010) shows that the price increases that result from different houses in a neighbourhood getting renovated is higher than the willingness to pay for these changes in neighbourhood quality of the residents. The other way around, the decay of housing in a neighbourhood lowers the rents and property values but is perceived as more bothersome. So the increase in quality of life for residents in a neighbourhood that is being revitalized is less compared to the decrease in quality of life for residents in a neighbourhood where there is decay. When it comes to abandoned houses, people are willing to pay a certain price to not live close to it (Vigdor, 2010).

Renters have a different relationship with renewal and decay. Vigdor (2010) shows that when homeowners renew homes in a neighbourhood, renters may find that rents increase beyond their willingness to pay. Conversely, decay may lead to lower property values, and with that, lower rents, but residents will no longer enjoy living there. Residents are even willing to pay to not live close to abandoned houses (Vigdor, 2010). The increase in quality of life for renting residents in a neighbourhood that is being revitalized is less than the decrease in quality of life for residents in a neighbourhood where there is decay. While gentrification and incumbent renewal benefits mostly homeowners due to the increase in value of their home, renting residents benefit considerably less from revitalization even though decay does affect them.

In short, decay lowers the value of property and the quality of life in a neighbourhood. However, decaying homes also present opportunities for renewal and revitalization of a neighbourhood.

Upsides and downsides of gentrification

Gentrification is a two-sided phenomenon. On the one hand, the city improves through more amenities and better quality housing. On the other hand, people with lower income are no longer able to live in their own neighbourhoods, because the prices are being driven up. This effect is called displacement, and it can be broken up in two types: direct and indirect. Direct displacement occurs when a resident of a neighbourhood has to move involuntarily due to increases in prices. Indirect displacement occurs when after a resident moves voluntarily, the housing prices increase and therefore low costs housing disappears from the neighbourhood (Byrne, 2003). A neighbourhood that used to be available for low-income households has then become too expensive, indirectly displacing these people. The more affluent people moving

into the neighbourhood not only drive up prices by renovating the buildings, but also through their demand for higher quality (Byrne, 2003). It is hard to determine how many people are affected by displacement as a result of price hikes (Byrne, 2003).

For residents who remain in the neighbourhood, gentrification may have upsides. Gentrification can lead to more investment in transport facilities, for example, which improves the neighbourhood as a whole (Rigolon & Németh, 2019a). The increase in property prices, however, is mainly beneficial for the homeowners in the neighbourhood and for the municipality in general (Kolko, 2007). People who rent their home do not benefit from the value increase. Some argue that the poorer residents in the neighbourhood may benefit from the spillover effects of the improved economy in the neighbourhood, but empirical evidence on this effect is hard to obtain (Jenkins & Mayer, 1990). Some cities try to stimulate gentrification to improve less affluent neighbourhoods, but these measures mostly benefit the rich rather than the less affluent residents for whom the policy was created (Rigolon & Németh, 2019a; Brueckner & Rosenthal, 2009).

Briefly put, the renovation and new development of housing, business, and transport facilities likely improves the quality of living for the residents of a gentrifying neighbourhood. These investments in the neighbourhoods are only done when people see potential in the neighbourhood. However, residents may not be able to experience these benefits, because the increase in prices and decrease of low-cost housing creates displacement. Policies that aim to improve the life of less affluent residents often primarily benefit people who are already well off.

Neighbourhood spillover effects

When choosing where to live, people not only look at the neighbourhood where the house stands but also the surrounding neighbourhoods. Neighbourhoods and their property values form spatial clusters and are spatially dependent (Jun, 2016). This means that things that have a close proximity together are more likely to be related in ways other than location. This is also explained in the first law of geography by Tobler (1970): “everything is related to everything else, but near things are more related than distant things”. Neighbourhood spillover effects can be within a neighbourhood and between neighbourhoods. Because gentrification leads to (in)direct displacement, with poor residents moving away and more affluent residents moving in, gentrifying neighbourhoods experience an increase in income inequality (Byrne, 2003). Research by Christafore and Leguizamon (2018) shows that this increase in income inequality is not just present in the gentrified neighbourhood, but also in the surrounding neighbourhoods, an example of neighbourhood spillover effects of gentrification.

Like gentrification, housing renovation is spatially interdependent. Renovation increases neighbourhood quality, but neighbourhood quality also increases whether or not all people renovate their homes. It works both ways (Helms, 2012). If one resident decides to renovate their house, the marginal returns for nearby households are likely to increase if they decide to renovate as well. There is an increase in marginal returns for the renovation of a decayed home if the rest of the neighbourhood is renovated, because the combined renovated homes improve the overall quality of the neighbourhood. There is no statistical evidence for the “free rider effect”, which would occur when someone profits from the improvement in neighbourhood quality caused by their neighbour’s renovation of their house, without doing any renovations themselves (Helm, 2012). On top of the increase in marginal returns for renovations that results from neighbours renovating their houses, renovation in a neighbourhood can also function as a signal that the area is promising and on the upswing. Such signalling is not only relevant for people who are searching for a new place, but also for real estate developers seeking to invest in neighbourhoods where gentrification is likely to occur.

Income and renovation

An owner occupant who is not satisfied with their home has different options for improving their situation. They can move to a new place, but they can also renovate and improve their current home to better fit their needs. Housing is a normal good, which means that an income increase results in increased consumption of the good. For housing, this means that a rise in income increases the likelihood of both moving and alterations to the current house (Fisher & Williams, 2010). People prefer to move over improvements and alterations (Potepan, 1989). But in the current Dutch housing market, moving has become more difficult due to the low supply of housing (ABF Research, 2021). This makes renovations a more attractive solution for households that have seen a shift in housing preferences. Renovation can be anything from renewing the kitchen and bathroom to adding extra space in the form of an extension or extra floor. Therefore, with the increase in housing prices in the Netherlands breaking records, and with income not increasing with the same amount, renovation has become increasingly relevant. These increases in quality of housing influences not only the housing price of the home that is renovated but also surrounding homes. The effect of an increase in the quality of surrounding homes on the housing price is researched in this paper.

The city of Rotterdam

The city of Rotterdam is the second most populous city of the Netherlands (CBS, 2020). It is famous for its large harbour as well as its iconic buildings and places, which often receive their own nicknames (Mutsaers, 2020). For example, the city's famous Erasmusbridge got the nickname the Swan. The city used to have fewer affluent inhabitants compared to other big Dutch cities, because of the dominance of the maritime and logistics sector and their employment of low-wage workers. However, the city is increasing in popularity with young highly educated professionals, due to its many employment possibilities, a vibrant city centre, and many amenities (Doucet et al., 2011).

The housing stock in Rotterdam differs significantly from other big cities in the Netherlands, such as Amsterdam and Utrecht. This is mostly due to the bombing of the city's historic centre during the Second World War. As figure 1 shows, a large part of the city was ruined by the fires that resulted from the bombing. In the figure every red dot represents a bomb hit and everything

within the red line represents what was damaged by the fires due to the bombings. The old city centre was almost entirely destroyed.

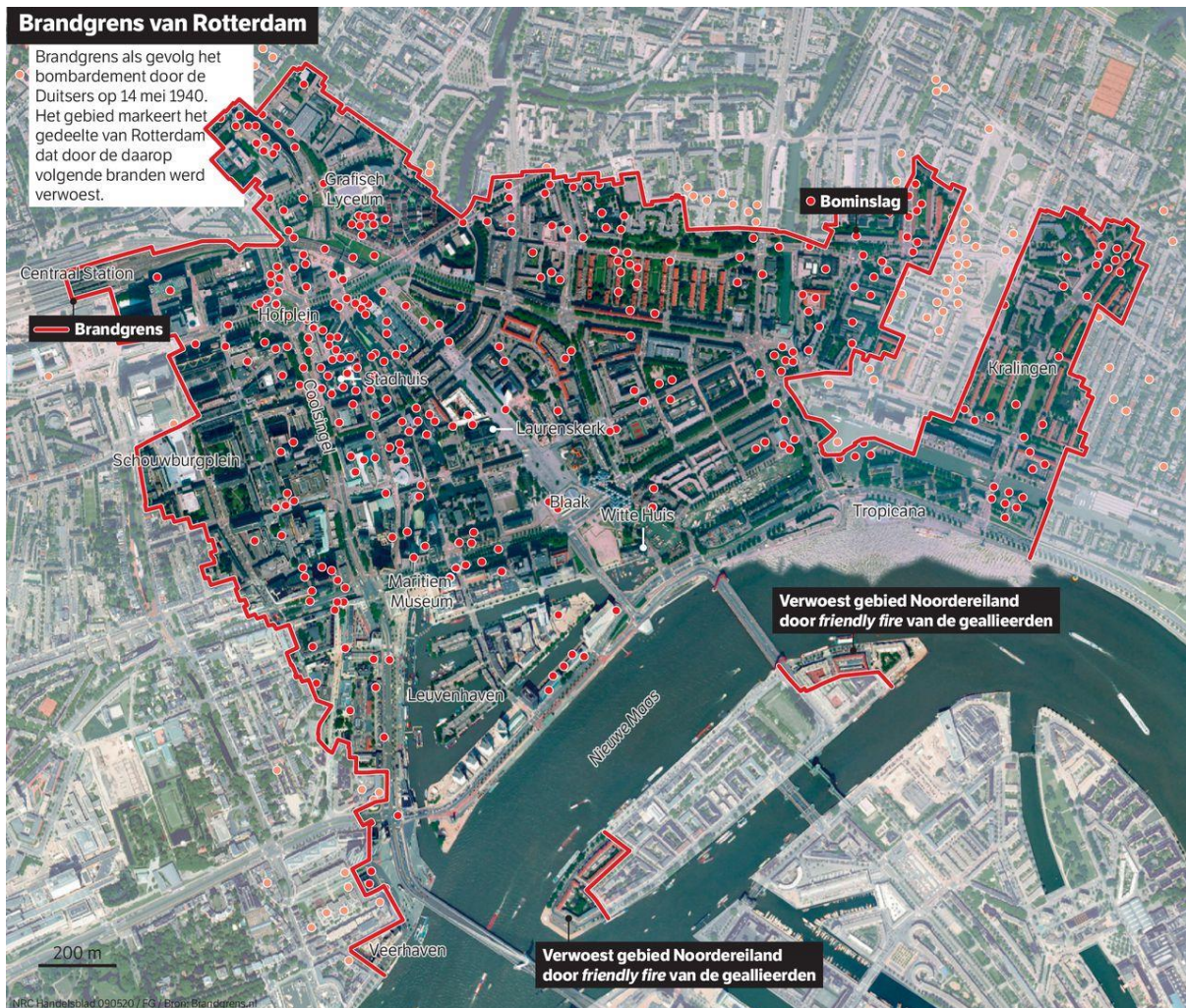


Figure 1: The bombs and fires in the city of Rotterdam during World War II Source: (NRC Handelsblad, 2020)

Rotterdam's history makes that the city is an interesting focus for research on the housing market and specifically the renewal of homes. In Rotterdam, the housing stock available on a given street or in a given neighbourhood varies much more than in other Dutch cities. With historic housing right next to more recently built houses, neighbourhoods in Rotterdam are less homogenous and uniform than in other cities. Therefore, testing the effect of an improvement in quality of surrounding homes, and whether this follows a trend over time could lead to different results than what previous academic literature would expect. Unexpected outcomes could be interesting for policy makers of the city of Rotterdam to know that following the policies from other cities might lead to different results in Rotterdam. The possibility for different results makes Rotterdam an interesting city to research.

In terms of demographics, the city's growing number of high-income households and the pressure on the housing market are notable. In Rotterdam, the number of young people (20-39 years old) is relatively large (Gemeente Rotterdam, 2020). The people in this age group have relatively small households and are trying to find a place to live in the city. A large part of this group is highly educated and they earn a high income. There are not enough houses for this group, either because there are not enough houses of the right price class or because they cannot afford to live in their preferred neighbourhoods. Consequently, they move to the less affluent neighbourhoods. This has resulted in direct and indirect displacement: the less affluent citizens of Rotterdam have expressed dissatisfaction with the pressure that this influx of higher-income people has put on their neighbourhoods to make room for the more affluent new citizens (Trouw, 2019). This is an important sign that gentrification is underway in large parts of Rotterdam. But what about renewal?

Several indicators for renewal and gentrification jump out in the case of Rotterdam. In spite of the impact of bombing, the housing stock in Rotterdam is relatively old. In 2020, around 30 percent of the houses in Rotterdam were built before 1945 (Gemeente Rotterdam, 2020). Neighbourhoods like "Nieuwe Westen" and "Oude Noorden" especially contain a lot of older homes (Netherlands building ages, 2021). These historic houses are popular (Het Parool, 2021) and lend themselves to renewal and renovation efforts. According to the municipality of Rotterdam, part of the city's housing stock is not in good enough state for future residents (Gemeente Rotterdam, 2021). This makes renewal a necessity. Additionally, because parts of the city of Rotterdam were previously used for harbour activities, there are large swaths of land that can be completely renewed and built for people with a high income (Karsten, 2006). These location-specific factors have made renewal an especially pressing question in Rotterdam.



Figure 2: Old housing directly next to new housing due to the fires, Rechter Rottekade. Source: Google maps

In the past, the municipality of Rotterdam has pursued policies that were meant to stimulate renewal and gentrification in the city (Doucet et al., 2011; Karsten, 2006). Rotterdam was not the only city to do so in the Netherlands. The Dutch government has stimulated housing associations and other real estate investors to invest in disadvantaged neighbourhoods, in order to gentrify them and create more housing for the middle class (Uitermark et al., 2007). In 2004, the municipality of Rotterdam introduced the concept of “klushuizen” (fixer uppers) to address the decay of housing in the city. These were homes in working-class neighbourhoods that could be bought for very low prices, and people could receive subsidies if they promised to renovate them (NU.nl, 2004; Rijksdienst voor Ondernemend Nederland & Ministerie van Binnenlandse Zaken en Koninkrijksrelaties, 2014). More recently, the municipality of Rotterdam has invested in the renewal of housing in the south part of the city to develop homes for the middle class (Algemeen Dagblad, 2019). These efforts have not been met with enthusiasm by all residents. The plan to demolish houses in the Carnisse neighbourhood to replace them with larger middle class homes is a good example. The plan was to demolish 216 smaller houses inhabited by low-income residents and replace them with 42 one-family homes and 118 large apartments for the middle class or higher (Algemeen Dagblad, 2020; Recht op de Stad, 2021). This is a policy of renewal that encourages gentrification and, by extension, displacement. These policy efforts

show that the renewal of less affluent parts of Rotterdam is definitely a priority for the municipality.

To summarize, the renovation of homes can have gentrification as a consequence, but renovation can be seen as a separate process. Renovation can happen on a neighbourhood wide level as a result of policy or on an individual level when a homeowner decides to renovate. Rotterdam has a unique housing stock where renovation has become necessary for the future.

Because an improvement of the quality of the housing stock is such a large precursor of gentrification, this paper will look into renovation in the city of Rotterdam, its effect on price, where it has taken place and if there are neighbourhood spillover effects. Specifically, this paper will research the effect on the housing price of an improvement of the average quality of housing in surround areas of different sizes. Moreover, this paper will look into whether or not there is a visible time-trend in the improvement of quality in neighbourhood.

3. Data description

For this research two data sets were combined. One was obtained from the Dutch national real estate brokers association, De Nederlandse Coöperatieve Vereniging van Makelaars en Taxateurs (NVM). The data obtained from the NVM consists of data of the houses sold in the municipality of Rotterdam between the period of 2010 to 2020. This data set includes, amongst other things, housing characteristics, addresses, and the selling prices of the houses sold in Rotterdam of the period 2010-2020. Each time a house was sold, a data entry was made. Therefore, in the NVM dataset, houses can be mentioned multiple times. A PDOK geocoder (PDOK Geocoder v.2.3.1, 2021) was used to create coordinates for every data entry of the NVM.

Furthermore, the second dataset was obtained from the municipality of Rotterdam which contains data on renovation of houses in Rotterdam per neighbourhood in 2020. The data from the municipality is collected per neighbourhood and not per individual house, in contrast to the NVM data set.

Because the dataset may contain measurement errors, any extraordinary values of variables that can be assumed to be false are removed from the dataset. Without removing these outliers, the results of the analysis can give a wrong conclusion. An example of such an outlier is a home that is said to have zero square metres. For this dataset it is assumed that a home cannot have zero m² or m³ and has to have more than one m² of usable floor area (UFA). This is required by law and therefore data entries with fewer than one m² of UFA are removed (Artikel 4.21 | Bouwbesluit Online, 2020). Furthermore, it is assumed that the original and last listed price of a sold home are more than one euro. Additionally, the assumption is made that the price of a home is below 20 million euros because no house in that price category has ever been sold in the municipality of Rotterdam sold (Algemeen Dagblad, 2021; Van Riessen, 2021). Therefore, the limit of 20 million euros is assumed to be correct¹. Lastly, it is also assumed that the houses sold have less than 99.999 m³. Again, this is based on the fact that there has not been a house sold with that much space in Rotterdam (Bayhouse, 2021). To check whether there are any outliers left, a histogram was made for each variable used to filter the dataset. The histograms for the variables included can be found in the appendix in figures 9-13. Using these assumptions several outliers were removed from the dataset making it more realistic and therefore more

¹ *There is talk of an apartment being built in Katendrecht in that price category but that apartment building has not been built yet build and the apartment has not been sold (Bayhouse, 2021)*

useful for research. The dataset before removing the outliers contains 43,601 observations, and 42,696 observations remain after filtering the outliers. Fortunately, enough observations are left to use the data for this research. Part of the research done in this paper uses postal codes. The first two digits of a postal code refer to the region and the second set of two digits refer to the neighbourhood in a medium or large sized town/city, or in a small village to just the village itself. The last two digits specify the location further to around 25 homes, business locations or postal boxes (PostNL, 2021).

4. Methodology

After filtering out the data outliers, a data set with data from 42,696 house transactions is used for the analysis. Each data entry is of a house that is sold during the period 2010-2020. If a house is sold more than once in the period 2010-2020 it appears again as a new data entry. Therefore, an address can occur more than once in the dataset. The data is used to test whether the price of a home is influenced by the change of quality of houses in the neighbourhood and whether the change in quality follows a trend over time. Considering several components are very important in establishing what price a house is sold for, a regression is run to see whether these components are statistically significant for the city of Rotterdam as well (Kolko, 2007; Chapelle et al., 2017, Byrne, 2003; Helms, 2003). As mentioned in previous literature, these components are important because they influence the attractiveness of a home for the buyer. These components are: size in m², size in m³, building year, the type of housing, whether the home has a garden and/or parking facilities and location factors such as whether a home is close to water or the city centre. The types of housing and apartments are distinguished in different categories that can be found in table 1. As previously done in academic literature on the housing market (Baker et.al, 2020), fixed effects are added to the regression for the year in which a house is sold and the neighbourhoods. The fixed effects are added so the results show the changes in price within the group of the houses sold over time and within neighbourhoods. If the regression would also look at the changes between houses sold over time and between neighbourhoods the estimates could possibly be biased because things such as general price increases over time and differences in neighbourhoods would be included in the model. Therefore, to avoid possible biased estimates the fixed effects for neighbourhoods and time have been included in the model.

To test whether the quality of a house and the quality of surrounding houses has a statistically significant effect on the selling price, an OLS regression is run with fixed effects for the year a house is sold and the neighbourhood. The neighbourhood fixed effects control for any other factors that could influence the price of a home such as the reputation of the neighbourhood. The quality of a house is measured by the realtors associated with the NVM. In this paper, the neighbourhood of a home and the area surrounding a home are not exactly the same. When the neighbourhood of a home is mentioned it refers to the neighbourhood a home is in according to the Dutch government. In this paper, the area of a home refers to the postal code of that home. This can be a 6-, 5-, 4-, or 3-digit number. The postal codes and neighbourhoods often match, but not for every home. To assess the effect of the quality of surrounding houses on the price of a home the average quality per postal code area is added to the regression. Specifically, a variable was made for the average quality for each combination of the year a house was sold and the postal code of the house. For example, if a house was sold in 2010 with the postal code 30110102, where the last number represent the letters that are used in Dutch postal codes, an average quality for homes for that year and that area can be calculated. Each home is matched with the right average quality in the regressions to measure the effect of the quality of the surrounding houses. To see how far these neighbourhood spillover effects of quality go, multiple regression models are made. These regression models test the effect of the average quality of the area on the housing price for increasingly larger areas. The 4-digit postal code areas are roughly the same size of the neighbourhoods, containing more than thousands of homes, whilst the 6-digit postal code areas contain around 25 homes, business locations or postal boxes (PostNL, 2021; AlleCijfers, 2021). However, not all the homes in the areas are included because the data contains only the houses sold during 2010-2020. The data used is the data provided by the NVM. The first group of models include all data, the second group of models includes only the houses sold in the period of 2010 to 2015 and the third group of models includes the houses sold from the period of 2016 to 2020. This divide in periods is chosen based on the trend in the housing market over the past few years. After the Great Recession of 2008-2009 the housing prices in all of the Netherlands were low and had to recover. In 2015 the housing market in all of the Netherlands was recovered and the housing prices were rising again (CBS, 2020b). As a result of the variable price being skewed to the left-hand side, as can be seen in the histogram of price in figure 13, the log of the price is used in the regression models. Lastly, because the quality scale of the NVM also includes a negative number as a category (-1), a dummy variable was created for when the average quality of an area was positive or

negative to see if there is a difference in effect between areas with a positive average quality of homes and areas with a negative score for the average quality of homes.

Furthermore, to see whether there are neighbourhood spillover effects of sold houses being renovated during the period of 2010-2020 in Rotterdam, a map with the most frequently occurring quality score of houses sold in each neighbourhood was made for each year. In this research, the maps of each year will be compared to see if there are noticeable changes.

Together with the comparison of the maps to answer the hypothesis if there are neighbourhood spillover effects of quality over time, the variable that measures the quality of a home was tested for spatial autocorrelation, to see if homes of the same quality become more clustered over time through neighbourhood spillover effects. In previous academic literature, Moran's I has been used to measure for spatial autocorrelation (Can, 1990), and research has been done on spatial effects of quality of neighbourhoods but with different measures of quality (Dubin, 1992). Spatial autocorrelation, and in this research specifically Moran's I, is calculated to see whether there is a relation between nearby units of the same variable. Moran's I is scored from -1 to +1, if the coefficient is larger than 0 there is positive spatial autocorrelation and if the coefficient is lower than zero there is negative spatial autocorrelation (Getis, 2007). Because of the usage of Moran's I in previous literature, the Moran's I is calculated to test for spatial autocorrelation per year and per specific neighbourhood to see whether houses of different quality categories are clustered together and whether they become more clustered together over time.

The regressions test for the effect of the quality of surrounding homes on the housing price within different sizes of areas, whilst the maps and Moran's I are descriptive tools for possible neighbourhood spillover effects over time.

5. Results

As mentioned in the methodology, the following variables have been included in an OLS regression as independent variables because previous literature has used them to explain the selling price of a house: m2, quality, proximity to the city centre, attractiveness of the location, construction period, whether a home has a garden and/or parking facilities, type of housing, and type of apartment (Chapelle et al., 2017; Kolko, 2007; Byrne, 2003; Helms, 2003). Furthermore, the average quality of an area matched with the right year and postal code combinations are added to the regressions to measure the neighbourhood spillover effect of quality on the price of a house. A summary and explanation of these variables can be found in table 1. For the categorical variables *ligcentr*, *ligmooi*, *construction_period*, *soorthuis*, *soortapp*, *parkeer* and *tuinlig* the reference category is made italic. some categories are left out automatically in the regressions because not all separate categories occur in the data set.

To avoid any biased estimated for the effect on the dependent variable price, the independent variables were checked for multicollinearity. The correlation between the quality of a home and price will be researched further for spatial correlation. M3 is not included in the regression because the number of m3 of a house is largely based on the number of m2 and both variables say something about the size of the house. There are other variables included in the regression with a high correlation but because those variables each say something different about a house, they are kept in the regression. For example, if the house sold is an apartment, that is likely to say something about the size of the house but that is not all that the variable tells us. All variables included in the regression have a statistically significant correlation with a p-value that is smaller than 1% to the dependent variable the log of price. There are no independent variables that are perfectly correlated with each other. All correlations and covariances can be found in the appendix in table 12-14.

Variable	Variable name in data set	Explanation
M ²	m2	Square metres
Quality	Kwaliteit	Quality scale from -1 to 2
Proximity to the city center	Ligcentr	-1 Not a home 0 Outside the urban area 1 No information known 2 In residential area 3 In city center
Attractiveness of location	Ligmooi	-1 Not a home 0 No information known 1 Next to the edge of a forest

		2 Next to water 3 Next to park 4 Nothing obstructing the view
Year the house was build	Construction_period	-1 Not a home 0 <i>Unknown, before 1500, after transaction year</i> 1 1500-1905 2 1906-1930 3 1931-1944 4 1945-1959 5 1960-1970 6 1971-1980 7 1981-1990 8 1991-2000 9 >2001
Type of house	Soorthuis	0 Different type of housing 1 mobile home 2 Simple 3 Houseboat 4 Recreational housing 5 One family home 6 House on the canal 7 Manor house 8 Farmhouse 9 Bungalow 10 Standalone house 12 Estate 13 <i>Not a home</i>
Type of apartment	soortapp	0 Different type apartment 1 Downstairs apartment 2 Upstairs apartment 3 Maisonnette 4 Staircase porch apartment 5 Gallery apartment 6 Nursing home apartment 7 Down- and upstarts apartment 8 <i>Not an apartment</i>
Parking facilities present	parkeer	0 <i>No parking facilities present</i> 1 Parking facilities present
Garden present	Tuinligg	0 <i>Unknown or no garden present</i> 1 Garden present

Table 1: Variables and explanations

As mentioned in the methodology, fixed effects were added for the variable year and neighbourhood. Including the fixed effects for time will filter out any changes in the variables that occur only because time passed (Woolridge, 2012). Furthermore, the neighbourhood fixed effects ensure that the effects of the independent variables on the price of a home only look at the within variation and not the between variation. Therefore, the fixed effects in the regression help with making a better interpretation of what the actual unbiased effect of the different variables is on the price of a home.

Heteroskedasticity occurs when the variance of the unobserved error is not constant and needs to be corrected for to meet all of Gauss-Markov assumptions of an OLS regression (Woolridge, 2012). To avoid problems with heteroskedasticity, all models have robust standard errors.

The situation in 2020:

According to the municipality, all houses in Rotterdam need some sort of renovation (Gemeente Rotterdam, 2020a). Therefore, a map was made with four categories of the costs per house per neighbourhood to see what the general state of the houses in a neighbourhood are. To better compare whether the data from the municipality and the data from the NVM are the same, there are four categories made for the average cost of renovation of a home per neighbourhood to match with the four categories of the NVM. When comparing this map of the quality of houses in 2020 based on the data of the municipality in figure 3 to the map of the quality of houses sold in Rotterdam based on the data of the NVM in figure 4, some differences emerge.

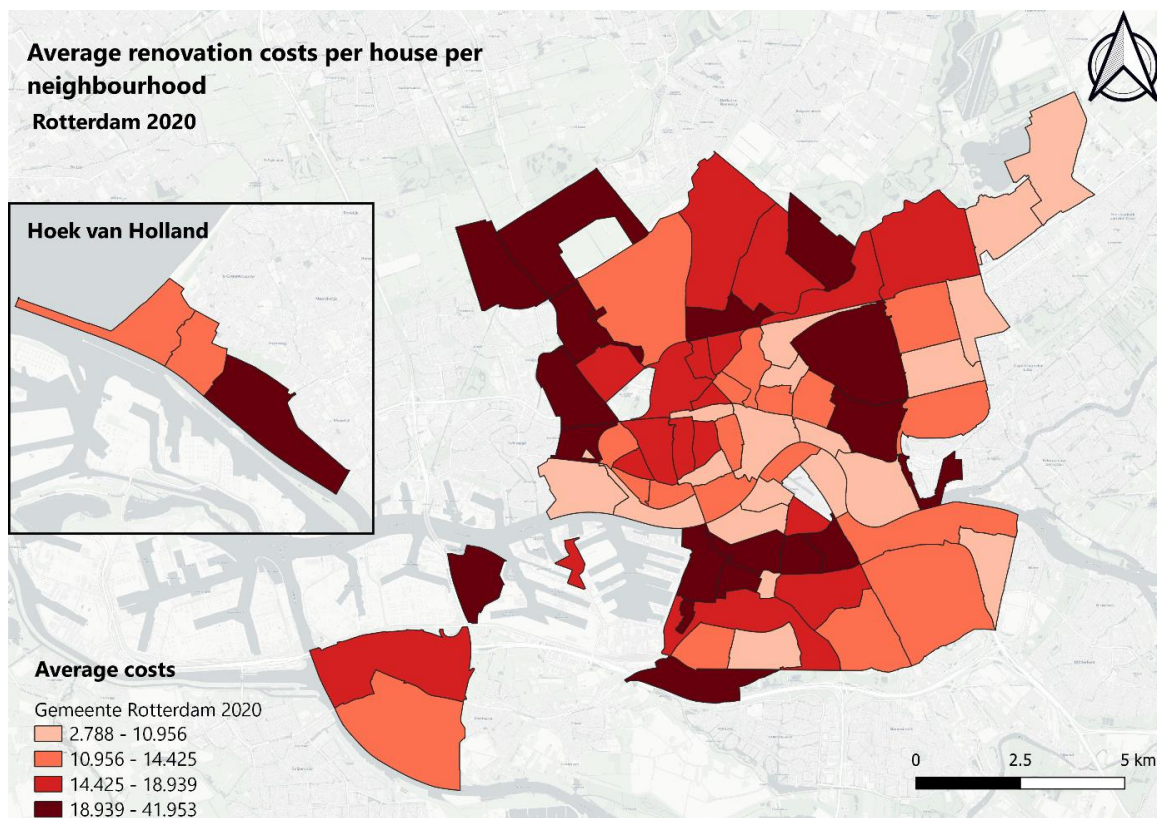


Figure 3: Average renovation costs per house per neighbourhood in 2020. Source data: Gemeente Rotterdam (2020)



Figure 4: Quality of houses sold per neighbourhood 2020. Source data: NVM (2020)

Especially in the city centre, the maps show different results. Although the data from the municipality includes all homes, the data provided by the NVM includes more than just the year 2020. Therefore, comparing the information taken from both datasets is useful. However, for the year 2020 it could be argued that the data provided by the municipality of Rotterdam is better because it includes all homes and not just the houses sold. For the overall analysis the data from the NVM provides more thorough information. According to the data provided by the municipality of Rotterdam, the North West of the city, the neighbourhoods 'Spaanse Polder' and 'Noord Kethel', and just south of the river Maas, the neighbourhoods 'Charlois Zuid Rand' and 'Carnisse', the renovation costs are highest per house. However, the NVM data does not put those neighbourhoods in the same category. In the neighbourhood 'Kop van Zuid' the average renovation costs per home were calculated to be lowest of the entire city, which is not surprising because the neighbourhood is quite new and there are a lot of homes being built there (*Kennisgeving bestemmingsplan 'Kop van Zuid' en m.e.r.-beoordelingsbesluit*, 2021 15 April). This neighbourhood is also included in the lists of the NVM as a neighbourhood with a high quality of homes but not one of the highest. According to the data of the NVM the houses with the lowest quality are found in the North and North East of Rotterdam whilst the higher quality houses are more in the city centre.

When tested whether the quality score given by the NVM corresponds with the score given by the municipality of Rotterdam, only 17 of the 79 neighbourhoods had a similar score. The correlation between the categories for quality of the datasets is -0.1971. The table with all the scores and comparisons can be found in table 15 in the appendix. The differences between the two datasets could be explained by several different factors. Firstly, the NVM data is based solely on the houses sold while the data of the municipality is based on all houses. However, the NVM data provides more information about the homes, such as the size, whilst the data from the municipality only refers to the quality. It could be possible that most of the houses sold in certain neighbourhoods are of a low quality because those are the only houses that people can afford. It is also possible that for some neighbourhoods only the houses with a very high quality are sold because people who want to live in that area do not want to invest in the renovation of a home. Secondly, the NVM data does not include houses that are rented out rather than sold. Thirdly, the quality measures in both the NVM data and the municipality data are based on what employees of the respective organisations filled in and could be subject to measurement errors. Lastly, the measurement of quality of the houses in Rotterdam conducted by the municipality was a one-time measurement whilst the data of the NVM spans over

different years and different moments within a year. The realtors of the NVM filling in the data could change their view on what qualifies as a certain rank for quality.

Moran's I:

The Moran's I is calculated for each year at an individual housing level to see if there are neighbourhood spillover effects of the quality of housing in Rotterdam over time during the period 2010-2020. Using Moran's I, the spatial autocorrelation of a variable can be calculated. For the variable quality of a home, the Moran's I is statistically significant in all years included in the data set by the NVM, as can be seen in table 2. In all years there is positive spatial autocorrelation measured which means that it can be assumed that high quality homes cluster together in Rotterdam. Despite the Moran's I being statistically significant, the effect is not very large, meaning it is close to zero and there is little spatial autocorrelation measured. The low score for spatial autocorrelation means that houses of the same quality are not very clustered together. In the period 2010-2015, Moran's I was on average 0.132 whilst in the period 2016-2020 the average Moran's I was 0.139. This is an increase of slightly more than 5%. Whether it is a trend that higher quality houses are becoming more spatially clustered over time is a subject for further research.

Year	Observed	Expected	sd	P-value
2010	0.1222493	-0.0002925688	0.001342818	0
2011	0.1172437	-0.0003196931	0.001371213	0
2012	0.1377051	-0.0003372681	0.001391689	0
2013	0.1331086	-0.003793627	0.001718005	0
2014	0.146474	-0.000256476	0.001174581	0
2015	0.1364027	-0.0002089864	0.0009680032	0
2016	0.1119562	-0.0001829826	0.0009071168	0
2017	0.1368135	-0.0002129925	0.001192252	0
2018	0.151902	-0.0002558854	0.001405304	0
2019	0.1393128	-0.0002657454	0.001109867	0
2020	0.1562849	-0.0002485707	0.001089076	0

Table 2: Moran's I over time

Quality of houses sold in Rotterdam over time:

In general, the share of houses sold with a quality of the higher category 1 and 2 as scored by the NVM has decreased over time. Whilst in 2010 69% of the houses sold had a category 1 or 2, that percentage dropped to 67% in 2015 and to 58% in 2020. The share of houses sold with the lowest category score has increased in the same period. This share of houses represented 27% in 2010, 30% in 2015 and 40% in 2020. The share of houses per category per year can be found in figures 14-24 in the Appendix. The most common quality category per neighbourhood can also be seen visually with the maps made from the NVM data.

During the period 2010-2020 the housing prices for all neighbourhoods increased. Figure 5 shows the increase of the average housing price per neighbourhood in 2020 compared to 2010. In the neighbourhood “Landzicht” the average housing price increased the most during 2010-2020 with the average housing price being almost 3 times as high in 2020 than in 2010, whilst the average housing price in the neighbourhood “Schiemond” only increased with almost 20% in the same period.

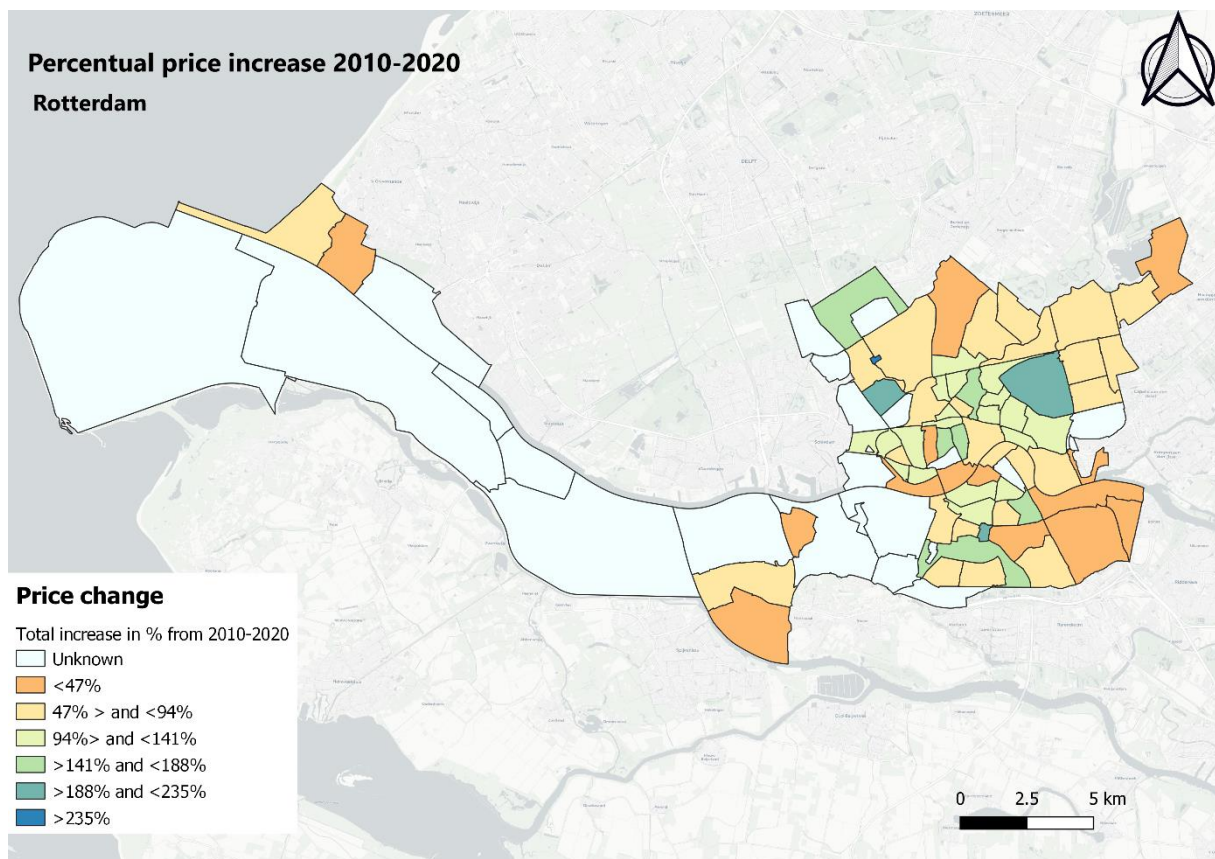


Figure 5: Percentual price increase of the average housing price 2010-2020

Maps were created based on the NVM data for each year between 2010 and 2020. When comparing these maps it can be seen that the most common quality category of houses sold per neighbourhood changes over time. All maps can be found in the appendix in figures 25-35. When comparing 2010 to 2015 and 2020 (see figures 6, 7 and 8 below) the maps show that overall there are more neighbourhoods where the majority of the houses sold are in the lowest quality scale. The lower quality houses of the houses sold in the north west were only found in the neighbourhoods ‘Zevenkamp’ and ‘Oosterflank’ at first but over time it can be seen that for the houses sold in all the northern neighbourhoods the quality category most often given is of the lowest quality. This could partly be because of the age of the housing stock in those neighbourhoods, but when looking at what year the houses in those neighbourhoods were built (see figure 38 in the appendix), this does not seem to be the only explanation. In some of these northern neighbourhoods such as ‘Overschie’, the housing stock is relatively young compared to neighbourhoods such as ‘Schiebroek’, but in both neighbourhoods the quality of the houses is considered low.



Figure 6: *Quality of houses sold per neighbourhood 2010. Source data: NVM (2020)*



Figure 7: *Quality of houses sold per neighbourhood 2015. Source data: NVM (2020)*

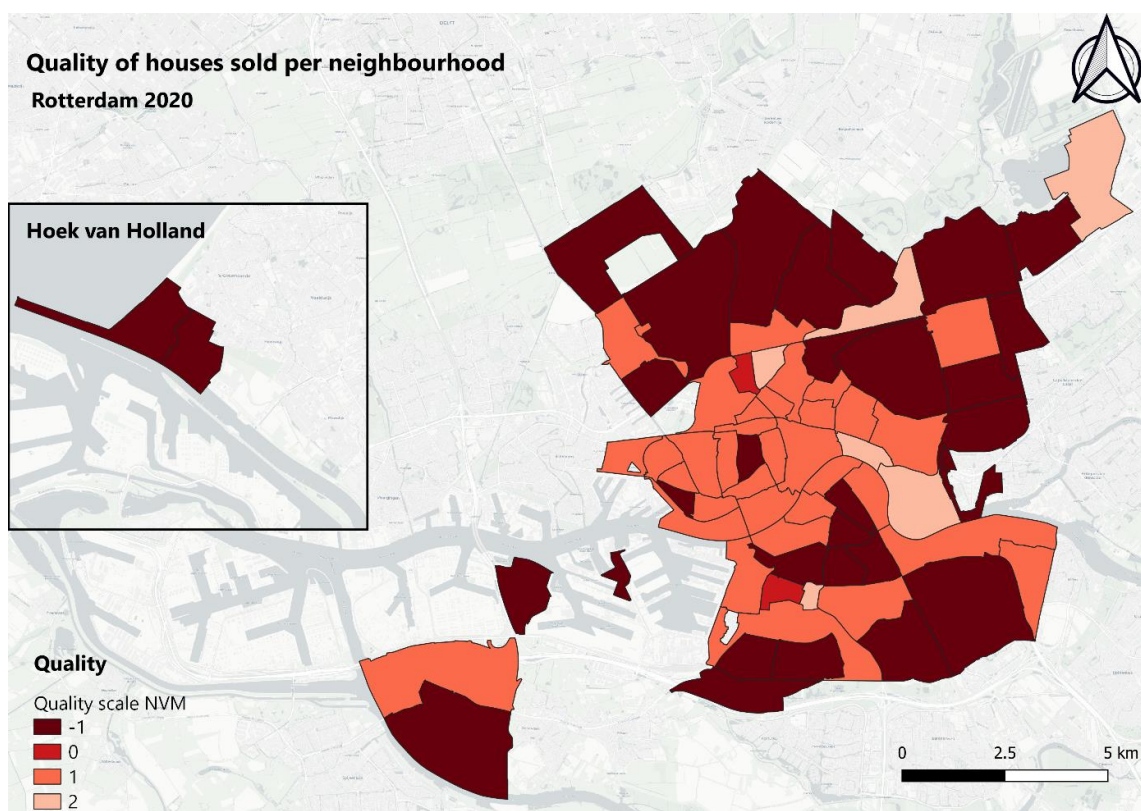


Figure 8: *Quality of houses sold per neighbourhood 2020. Source data: (NVM 2020)*

In the city centre of Rotterdam the quality of the sold housing stock is almost consistently high. Some neighbourhoods, such as ‘Oude Westen’ and ‘Cool’ have some years where the houses sold were of a bit higher or lower quality, but overall the neighbourhoods in the city centre consistently score in the higher categories.

In the most southern neighbourhoods of Rotterdam the quality has deteriorated over time. In neighbourhoods such as ‘Hillesluis’, where the quality in the year 2015 was scored with a 1, the score drops to lower quality categories from 2016 onwards.

Neither the maps nor Moran’s I can give a definitive conclusion on whether there is a general, identifiable trend in the changes of quality over time in the period 2010-2020 in the city of Rotterdam. Therefore, they can only be used as descriptive tools to show the changes during the period 2010-2020.

Regression models:

The size of house is one of the main factors deciding the attractiveness and price of a home (Zahirovich-Herbert & Gibler, 2014). Adding one square meter to a house that is already quite large is likely to have a smaller effect on the price compared to extra space for a relatively smaller house. To test whether this is the case, separate regression models are run with regular m2 as an independent variable or with the log of m2 as an independent variable, for the period 2010-2020. Unsurprisingly, for all models, square metres or the log of square meters had a statistically significant effect on price at a 1% significance level. All the models that had logm2 as an independent variable had a higher R-squared and Adjusted R-squared compared to their counterpart that had regular square metres as an independent variable, which means that more of the price of house can be explained by the independent variables. Therefore, the models with logm2 are used for the analysis to see whether the quality of surrounding neighbourhoods has an effect on the price of a home. The models without the log of m2 can be found in the appendix in tables 16-19.

Full period

For the period 2010-2020, 42,695 observations were included in the regression. For all postal code and year combinations, meaning 6-, 5-, 4-, and 3-digit postal codes, the R-squared and Adjusted R-Squared are higher than 0.86. This means a substantial amount of the price of a home can be explained by the factors included in the regression. The quality of a home has a

statistically significant effect at a 1% level on the price of a home. In each model a dummy variable, *mean_qualitypos*, is included which tests whether there is a statistically significant difference in effect on the price of a home when the average quality of an area is positive or negative. When the fixed effects are not included in the model the R-squared is lower compared to the models that do include the neighbourhood and year fixed effects. When only including neighbourhood fixed effects, the effect of the average quality of a surrounding area is only significant for the 6-digit postal code size at a 1% significance level, not for the other sizes. Moreover, the effect of the average quality of surrounding homes in a 6-digit postal code area is larger when only including neighbourhood fixed effects, compared to when both year and neighbourhood fixed effects are added to the regression. When only including year fixed effects and not considering neighbourhood fixed effects the R-squared is also lower compared to the full model with both neighbourhood and year fixed effects. Most notably, the effect of the log of squared meters on the price in the model with only year fixed effects is larger than the model that includes fixed effects for both year and neighbourhood showing that the effect of the size of a home on price is overestimated when not including neighbourhood fixed effects. The effect of the average quality of surrounding homes in a 6-digit postal code area on the price of a home when only including year fixed effects is smaller compared to the model which includes both year and neighbourhood fixed effects. This could suggest that without neighbourhood fixed effects the effect of the average quality of surrounding homes on the housing price is underestimated. The models without any fixed effects or only one fixed effect can be found in the Appendix in figures 39-50.

<i>Dependent variable: Logprice</i>						
N	F (38,42567)	Prob > F	R-squared	Adj R-squared	Within R-squared	Root MSE
42,695	2448.31	0.0000	0.8619	0.8615	0.7153	0.2211
	Coef.	Robust std. Error	T	P> t	[95 % Confidence interval]	
Logm2	0.796604	0.0050915	156.46	0.000	0.7866246	0.8065834
Kwaliteit	0.112021	0.0041823	26.78	0.000	0.1038235	0.1202185
qualityPC6	0.0012712	0.0001004	12.66	0.000	0.0010744	0.0014681
Mean_quality6pos	-0.0020493	0.006507	-0.31	0.753	-0.0148032	0.0107046

Table 3: Output model full period 6-digit postal code

<i>Dependent variable: Logprice</i>						
N	F (38,42567)	Prob > F	R-squared	Adj R-squared	Within R-squared	Root MSE
42,695	2434.34	0.0000	0.8616	0.8612	0.7146	0.2214
	Coef.	Robust std. Error	T	P> t	[95 % Confidence interval]	
Logm2	0.7989008	0.0050885	157.00	0.000	0.7889272	0.8088744
Kwaliteit	0.148723	0.0031108	47.81	0.000	0.1426259	0.1548202
qualityPC5	0.0000816	0.0000162	5.05	0.000	0.0000499	0.0001132
Mean_quality5pos	-0.0167976	0.0053045	-3.17	0.002	-0.0271946	-0.0064007

Table 4: Output model full period 5-digit postal code

For 6-digit postal codes areas, the difference between a negative or positive average quality of the area, measured by the variable *mean_quality6pos*, is insignificant at a 5% significance level. When looking at the effect of the average quality of homes in the same postal code area with a 6-digit postal codes, it shows that an increase in the average quality of the area with 1 point increases the price of a home with approximately 0.12712%, all else equal. This effect is statistically significant at a 1% significance level. This means that the quality of the surrounding homes correlate with the price in 6-digit postal code areas. An increase in the average quality of a 5-digit postal code area of 1 point increases the price of a home approximately with 0.00816%, all else equal. This effect is statistically significant at a 1% significance level. Unlike the 6-digit postal code areas, the difference in effect on price between a positive and a negative average quality of a 5-digit area is statistically significant at a 1% level, all else equal, as can be seen by the variable *mean_quality5pos*. This means that the difference in effect for positive average quality values on price is smaller for positive average quality values than for negative average quality values in 5-digit postal codes areas. The effect shows that an improvement of a previously negatively rated area in terms of quality has a larger effect on the housing price than an improvement in an area where the average quality was already positive. For a 4-digit postal code area, the effects of the average quality in an area and whether that value is positive or not, are larger compared to 5-digit postal codes areas. An increase in the average quality of a 4-digit postal code area of 1 point increases the price of a home approximately with 0.01545%, all else equal. This effect is statistically significant at a 1% significance level. The effect on price of a positive average quality in a 4-digit postal code area is smaller compared to the effect of a negative average quality in a 4-digit postal code area, just as in 5-digit postal code areas, but this effect is more pronounced in 4-digit postal code areas. .

<i>Dependent variable: Logprice</i>						
N	F (38,42567)	Prob > F	R-squared	Adj R-squared	Within R-squared	Root MSE
42,695	2437.84	0.0000	0.8616	0.8612	0.7147	0.2213
	Coef.	Robust std. Error	T	P> t	[95 % Confidence interval]	
Logm2	0.79897	0.0050904	156.96	0.000	0.7889928	0.8089473
Kwaliteit	0.1490317	0.0031196	47.77	0.000	0.1429172	0.1551462
qualityPC4	0.0001545	0.0000325	4.76	0.000	0.0000909	0.0002182
Mean_quality4pos	-0.0477965	0.0072462	-6.60	0.000	-0.0619993	-0.0335938

Table 5: Output model full period 4-digit postal code

<i>Dependent variable: Logprice</i>						
N	F (38,42567)	Prob > F	R-squared	Adj R-squared	Within R-squared	Root MSE
42,695	2431.96	0.0000	0.8617	0.8613	0.7148	0.2213
	Coef.	Robust std. Error	T	P> t	[95 % Confidence interval]	
Logm2	0.7985989	0.0050977	156.66	0.000	0.7886074	0.8085905
Kwaliteit	0.1497379	0.0031134	48.09	0.000	0.1436355	0.1558403
qualityPC3	0.00036396	0.0002054	1.77	0.077	-0.0000388	0.0007665
Mean_quality3pos	0.0323644	0.0085888	3.77	0.000	0.0155301	0.0491986

Table 6: Output model full period 3-digit postal code

For 3-digit postal codes areas the effect of the average quality of an area on the price of a home is not significant at a 5% significance level. However, the difference between a positive average quality of an area and a negative average quality of an area is significant. The former is unsurprising because the larger the area the less likely it is that all those houses in that area affect each other. This follows the first law of geography; all things are related to each other but things that are closer to each other are more strongly related (Tobler, 1970). However, the model for 4-digit postal codes shows a larger effect size of quality of a home on the selling price than the model with 6- and 5-digit postal codes, which does not follow that same first law of geography. The effect is significant in all three models. This could possibly be due to the heterogeneity of the housing stock which means that houses close together in space do not have many other similarities except their location. Therefore, the first law of geography does not hold anymore because being close to each other does not mean being more strongly related. For all different area sizes the effect on price of whether a home has a garden

or parking facilities is larger compared to the effect of the average quality of surrounding homes.

All full models for each different area size can be found in the Appendix in tables 20-23.

Period 2010-2015

In the regression model for homes sold in the period 2010-2015, 20,837 observations were used. Just like in the previous model, the average quality of surrounding homes in areas from different sizes were used to measure the spillover effects of quality on the prices of homes. The R-Squared and the Adjusted R-Squared for all models created for the period 2010-2015 are higher than 0.80, which means that a substantial proportion, more than three quarters, of the price of a home can be explained by the variables included in the model. For each different regression the quality of a home had a statistically significant positive effect on the price of the same home at a 1% significance level, all else equal. An increase of 1 point on the quality scale of a home increased the price of that same home with more than 10% in the model with 6-digit postal code areas, all else equal, and more than 15% in the other area sizes. Compared to the models that include the full period from 2010-2020, in the models that only includes the period 2010-2015 more construction periods have a statistically significant effect on the price of homes. Only when a house is built in the 1960's the construction period does not have a statistically significant effect on the housing price.

<i>Dependent variable: Logprice</i>						
N	F (38,20715)	Prob > F	R-squared	Adj R-squared	Within R-squared	Root MSE
20,837	1451.92	0.0000	0.8021	0.8009	0.6829	0.2452
	Coef.	Robust std. Error	T	P> t 	[95 % Confidence interval]	
Logm2	0.8287278	0.0079884	103.74	0.000	0.8130699	0.8443858
Kwaliteit	0.1175619	0.0063693	18.46	0.000	0.1050775	0.1300463
qualityPC6	0.0009863	0.0001511	6.53	0.000	0.0006902	0.0012824
Mean_quality6pos	0.0255948	0.0108385	2.36	0.018	0.0043505	0.0468391

Table 7: Output model 2010-2015, 6-digit postal code

<i>Dependent variable: Logprice</i>						
N	F (38,20715)	Prob > F	R-squared	Adj R-squared	Within R-squared	Root MSE
20,837	1447.32	0.0000	0.8018	0.8007	0.6824	0.2453
	Coef.	Robust std. Error	T	P> t	[95 % Confidence interval]	
Logm2	0.8298141	0.0079896	103.86	0.000	0.8141537	0.8454744
Kwaliteit	0.1520141	0.0047061	32.30	0.000	0.1427897	0.1612385
qualityPC5	0.0000892	0.0000252	3.54	0.000	0.0000398	0.0001386
Mean_quality5pos	-0.0078346	0.0086359	-0.91	0.364	-0.0247616	0.0090924

Table 8: Output model 2010-2015, 5-digit postal code

Unsurprisingly, the effect of the average quality of the area of a home has a smaller effect on the price compared to the quality of the home itself. When looking at the effect of the average quality of homes in a 6-digit postal code area on the price of a home, the model in table 7 shows that an increase of 1 of the average quality increases the price of a home with approximately 0.09863%, all else equal. This effect is statistically significant at a 1% significance level. However, the difference in effect between areas with a negative average quality and areas with a positive average quality is not statistically significant at a 1% significance level. At a 5% significance level this effect, shown by the variable *mean_quality6pos*, is significant and can be interpreted. This shows that the effect of the average quality for homes located in areas with a negative average quality is higher compared to homes located in areas with a positive average quality. This differs from the effect measured when expanding the area to a 5-digit postal code, where the difference between negative or positive average quality in the area is non-significant. In a 5-digit postal code area, an improvement of 1 of the average quality of the area increases the price with approximately 0.00892%, all else equal. For a home that is worth €300.000,- euros this would mean that an increase in the average quality of a home would increase the price with less than €30 euros. So, although this effect is statistically significant, it is not likely to make a huge difference in whether someone can afford a certain home or not.

<i>Dependent variable: Logprice</i>						
N	F (38,20715)	Prob > F	R-squared	Adj R-squared	Within R-squared	Root MSE
20,837	1446.74	0.0000	0.8020	0.8009	0.6827	0.2452
	Coef.	Robust std. Error	T	P> t	[95 % Confidence interval]	
Logm2	0.8298417	0.0079962	103.78	0.000	0.8141685	0.8455149
Kwaliteit	0.1516875	0.0047342	32.04	0.000	0.1424081	0.160967
qualityPC4	0.0002637	0.0000518	5.09	0.000	0.0001622	0.0003652
Mean_quality4pos	-0.068931	0.0123637	-5.58	0.000	-0.0931649	-0.0446971

Table 9: Output model 2010-2015, 4-digit postal code

<i>Dependent variable: Logprice</i>						
N	F (38,20715)	Prob > F	R-squared	Adj R-squared	Within R-squared	Root MSE
20,837	1443.90	0.0000	0.8017	0.8005	0.6822	0.2454
	Coef.	Robust std. Error	T	P> t	[95 % Confidence interval]	
Logm2	0.8295589	0.0080002	103.69	0.000	0.8138779	0.8452399
Kwaliteit	0.1533852	0.0047123	32.55	0.000	0.1441486	0.1626217
qualityPC3	-0.00008	0.0004466	-0.18	0.858	-0.0009554	0.0007954
Mean_quality3pos	0.0066396	0.0251309	0.26	0.792	-0.042619	0.0558982

Table 10: Output model 2010-2015, 3-digit postal code

The effect of the average quality of an area with a 4-digit postal code is larger than that of 5-digit postal code areas but smaller than that of 6-digit postal code areas. When the average quality of a 4-digit postal code area increases with 1, the price of a home in that area increases with 0.026%, all else equal. This effect is larger when an area with a negative average postal code increases with 1 compared to a similar increase in an area that already had a positive average quality, all else equal. Both of these effects are statistically significant at a 1% significance level. At the largest area included in the regression, a 3-digit postal code area, there are no statistically significant neighbourhood spillover effects for quality. The full models for all different area sizes for period 2010-2015 can be found in the appendix in tables 24-27.

Period 2016-2020

Although the period 2016-2020 has one year fewer included in the model compared to the period 2010-2015, the model includes more observations. For this period, 21,857 house transactions were included in the model. For all area sizes more than 90% of the price of a home could be explained by the variables included in the model. An increase of 1 on the NVM quality scale of a home increases the price of that same home with more than 10%, all else equal, for all area sizes. Whilst in the models that were created for the period 2010-2015 the construction period had a statistically significant effect on the housing price, in the models that cover the period 2016-2020, similar to the full time period models, less construction periods have a statistically significant effect on price. Comparably to the previous models, in the models made for the period 2016-2020 whether a home has a garden or parking facilities has a statistically significant effect on the price of a home.

<i>Dependent variable: Logprice</i>						
N	F (37,21738)	Prob > F	R-squared	Adj R-squared	Within R-squared	Root MSE
21,857	15825.98	0.0000	0.9010	0.9005	0.7730	0.1816
	Coef.	Robust std. Error	T	P> t 	[95 % Confidence interval]	
Logm2	0.7537525	0.0060202	125.20	0.000	0.7419525	0.7655525
Kwaliteit	0.1011358	0.0051411	19.67	0.000	0.0910588	0.1112128
qualityPC6	0.0013601	0.0001277	10.65	0.000	0.0011099	0.0016103
Mean_quality6pos	-0.0253151	0.007208	-3.51	0.000	-0.0394433	-0.0111868

Table 11: Output model 2016-2020, 6-digit postal code

The price of a home increases with approximately 0.136% when the average quality of the 6-digit postal code increases with 1, all else equal. This effect is larger for areas with a negative average quality compared to areas with a positive average quality, all else equal. Both of these effects are statistically significant at a 1% significance level. When the area size increases to a 5-, 4- or 3-digit postal code, the average quality of the area has no statistically significant effect on the price of a home, all else equal. A possible explanation for this could be the state of the housing market during the period 2016-2020. With a high demand for homes, the prices in the Netherlands in general, and in Rotterdam were going up in that period. This means that buyers had fewer options and faced higher competition from other buyers (CBS, 2020b). Therefore, the quality of surrounding homes might have become less important to buyers and the focus

was more on the actual qualities of the home itself and less on its surroundings. The fact that whether the home is located in an attractive area is statistically significant at a 1% significance might also suggest that buyers focussed on the potential of an area and not necessarily on the state of the area at the moment of transaction. The high R-squared and Adjusted R-Squared show that the other factors included in the model explain a large portion of the price but that the only locational factor that is considered relevant is the attractiveness of an area.

During the period 2010-2020 the housing market in Rotterdam has changed a lot. When comparing the models, the outcomes show that during the period 2016-2020 the variables included in the model explained most of the variance of the price of a home. In 2010-2015 the least amount of the variance of the price could be explained by the variables in the regression model. However, it is still a relatively large portion. As could be expected, the 3-digit postal code area, which is the largest area, showed no statistically significant effect of the average quality in the area on the price of a home in all different models. Especially with the heterogenous nature of the housing stock in Rotterdam, the difference in houses in larger areas is too big to have a sole effect on the price of a home. During the period 2010-2015, the effect of the quality of the home itself was the largest compared to the model for the entire time period and for the period 2016-2020. A possibly explanation for this could be that there was less competition in the housing market during that period with supply being high and the demand for housing low, which means that buyers could afford to be more critical of the quality of a home and were less likely to buy a fixer-upper because they could afford a good quality home already.

Although statistically significant, in all of the periods the effect of the average quality of an area on price was quite small in all the time periods. The change in price would likely not have made a difference in whether or not a buyer would be able to afford a home, making the effect on the lives of residents or potential buyers small. An increase of 0.12712% of the price of a home, which was the largest possible statistically significant increase measured, on the average price of a home in 2020 which was € 334.488, equals to around 425 euros making it unlikely that it makes a difference on whether a person can buy that home or not (CBS, 2021). However, if the entire neighbourhood experiences a price increase like that, the collective effect could turn out to be substantial. All full models of the period 2016-2020 can be found in the Appendix in table 28-31.

To conclude, the models show that there are neighbourhood spillover effects for the effect on price for the quality of homes. These effects vary in size depending on the size of the area, showing the largest effects in 4-digit postal code areas.

6. Discussion & Limitations

According to previous literature, older housing stock in neighbourhoods close to the city centre with green facilities is most likely to be renovated and gentrified. A large part of what gentrification entails is the renovation of housing stock and the increase in housing prices that come with the improvement in quality. This renovation in certain areas will then would have to lead to more renovation in neighbouring areas due to neighbourhood spillover effects. This paper has tried to research whether the quality of surrounding homes influence the housing price and whether there are neighbourhood spillover effects for the quality of homes for the city of Rotterdam during the period 2010-2020 and if so, where these changes occurred over time. Based on literature, one could assume that this process starts in places where all factors needed for renovation and gentrification are present and then spreads out like an oil spill. Through statistical analysis and the creation of maps this paper has tried to research this phenomenon.

The consensus in academic literature is that the renovation of homes increases the housing price and that renovation has neighbourhood spillover effects. However, this paper has researched a unique housing stock so therefore outcomes could be different. The regression models show that the price of a home is influenced by the average quality of homes in the area, despite heterogeneity of the housing stock in those areas. This effect becomes smaller as the area gets larger, which is in line with the expectations based on previous literature. However, what is surprising is that for the models of the full time period and the period 2010-2015, which can be found in table 22 and 26 in the Appendix, the effect of a 4-digit postal code area is the larger compared to the 6- and 5- digit postal code area. Reputation of a neighbourhood, which is roughly the same as the 4-digit postal code area, is unlikely to be the explanation for this because the regressions include neighbourhood fixed effects. A possible explanation for this larger effect could be that for smaller areas, such as 6-digit or 5-digit postal code areas, the heterogeneity of the housing stock in areas results in a smaller effect of the average quality of homes on price. Part of the effect of the average quality of an area on the housing price for those smaller area sizes could possibly have little to do with the actual quality but more so with the heterogeneity of the area. The neighbourhood fixed effects might not compensate for this due to the heterogeneity of the housing stock. Due to the lack of similarities in housing stock, the neighbourhood effects are likely to not be uniform enough to be filtered out. Therefore, the effect of the average quality of housing in 6- and 5-digit postal code areas is underestimated and consequently the effect in the 4-digit postal code is bigger. This heterogeneity could be an

explanation on why the effects of 6-, 5- and 4-digit postal codes do not follow the expected trend. This larger effect of the 4-digit postal code area should definitely be included in further research.

This research shows that the renovation of houses in Rotterdam does not follow the typical pattern over time as previously described in academic literature. Usually the city centre has the oldest housing stock and the further away from the centre the newer the housing gets because homes keep being added to the city. This difference could be due to the data used but also due to Rotterdam's unique nature. As a consequence of the bombings and fires during the Second World War the city's structure and age of housing stock is different from not only other cities in the Netherlands but also other cities used in previous research. People living in the same neighbourhood and enjoying the same amenities can live in housing that is not only built differently but also built decades apart. These differences in homes mean that not only do the homes look different, they also have a different quality and decay at different rates and times. This paper shows that there are no visible time trends in terms of renovation which can most likely be explained due to the heterogeneous nature of the neighbourhoods. Whether the popularity of certain areas in Rotterdam can also be contributed to the looks of the homes is a subject for further research. Perhaps looking at smaller clusters of houses can show a different trend on whether high quality homes cluster together. This would be a subject for further research.

Because gentrification leads to more than higher housing prices and renovated homes, this paper cannot draw any definitive conclusions on whether there is full gentrification in areas in Rotterdam because it only looks at the effect of an increase in quality on housing prices and possible neighbourhood spillover effects. Other studies also mentioned marginal returns for renovation meaning that when someone renovates their home their neighbour also profits from that (Munneke & Womack, 2015; Helms, 2012). To draw any conclusions on possible marginal returns in Rotterdam, a more thorough research on an individual housing level has to be conducted where not only the location of the homes is used to group them but perhaps also other factors to compensate for the heterogeneity of the housing stock. Furthermore, because this research only includes houses sold during 2010-2020 and not all houses, making conclusions on marginal returns would be too premature. Previous research shows that most renovations are done by incumbent residents that own their home and that the benefits from

renovation are not felt by the people who rent their home (Helms, 2003; Kolko, 2007). This paper does not look at possible effects of renovation on the rent of homes.

An important limitation of this research paper comes from the dataset. The NVM dataset only looks at the houses sold in Rotterdam during 2010-2020. Therefore, this does not include all housing in Rotterdam because not every house has been sold during this period. Homes that are not sold during this period could have experienced an increase in value that is not included in this research. Due to the shortage in appropriate housing in the past couple of years it has been more difficult for people to move. With the fast rising housing prices, prospective buyers, and starters on the market in particular, experience difficulty buying a home. Consequently, renovation is the best possible solution to have a home that fits their needs, for people who cannot afford to move. These houses and people cannot be found in the dataset by the NVM because it only focuses on houses sold.

Furthermore, it is hard to control for any bias towards which type of housing is sold in this model. For example, it could be possible that houses in certain neighbourhoods are of low quality because those are the only houses that people can afford to buy in that neighbourhood due to the rest of the housing being too expensive. This could also work the other way around; it could be possible that in certain neighbourhoods people only want to buy a renovated home or a home with a high quality because they only want to live in that neighbourhood if the house is of a high enough quality to compensate for the lack of attractiveness of the neighbourhood. It is not possible to control for these potential effects and biases in this research.

Moreover, any extra builds, whether these were completely new homes or homes that were demolished and rebuilt, are not included in the dataset unless they were sold. These homes or just the plans of these new homes can influence the reputation a neighbourhood has. The plans for new high quality houses can signal that the neighbourhood is becoming more popular and therefore increase the demand for houses in that area.

Additionally, the dataset from the NVM is not completely objective. The quality scale is filled in by the realtors themselves when they view a home. This means there will also be a partial personal preference and value judgement when filling in the quality scale for the home. It would have been better to have the data for renovation costs per neighbourhood from the municipality of Rotterdam to compare to the NVM dataset, as was done for 2020. A comparison or combination of the datasets would provide a corroboration of the conclusions drawn and a more thorough research.

The regression models measure the effect of the average quality of an area on the price of a home. A limitation to this method is that the average quality of an area, especially a larger one, does not easily improve with a whole point. Therefore, any changes in quality and their effect on the price of a home can only be seen when a large portion of the homes in an area all improve or deteriorate. A second limitation to this method is that the effect of the average quality of homes that are outside the municipality of Rotterdam, but close enough to homes located within the city limits of Rotterdam to influence the area, are not included in the model because the dataset only includes homes sold in the municipality of Rotterdam. If the housing stock outside of the municipality of Rotterdam is more homogeneous then perhaps the spillover effects could be more noticeable. Moreover, possibly a difference can be seen between houses that are more similar in nature but outside of the municipality of Rotterdam and houses that are in the same area but less similar.

To conclude, this research has shown that there are neighbourhood spillover effects on the price of a home from the quality of surrounding homes. There is no trend visible for the renovation of homes over time in Rotterdam during 2010-2020 in the descriptive tests done with the comparison of the maps and the changes in Moran's I. More statistical tests should be done before any definitive conclusions can be drawn on whether there is a time trend or not. This could possibly be due to the unique housing stock of Rotterdam. The different distribution of old housing due to the bombs of WOII might change the way neighbourhood spillover effects occur in Rotterdam. Comparative research in a different city could be a great way to see if the neighbourhood spillover effects in Rotterdam are unique or follow a trend that is similar in other major Dutch cities.

7. Conclusion:

The current housing market in the Netherlands is in such a dire state that houses with a very low quality are also sold for a very high price. This not only affects renovation efforts but also the ability for people to move and the attractiveness of moving. Firstly, the current state of the housing market could result in people renovating their homes to better fit their needs instead of moving. The increase in housing prices can make it more difficult for people to move and changing their current home could be the better option. One could argue that housing prices increased in all price ranges, so any increase in price of a new home is accompanied with an increase in the price of the current home. Although this is mostly true, this does not mean that a person can easily buy a new home with the extra money they get from the sale of their current home. Secondly, the current high prices in the housing market can make low income neighbourhoods more popular because these are the places that are still affordable.

Although this paper does not show clear trends in the renovation of homes in the city of Rotterdam during 2010-2020, it does not mean that there is no consistent renewal in certain areas of the city. As shown in the data collected by the municipality of Rotterdam there is a large need for renovation and the quality of housing in certain areas is very bad. The increase in popularity of the city means that more people want to live there and want to invest in the city. Previous literature and the statistical analysis show that there are neighbourhood spillover effects for the quality of housing. However, in this research these effects, while statistically significant, are relatively small compared to the overall price of a home, most often less than 1%. If all houses in the area increased then the overall value of the area would become better even if only a portion of the homes is renovated. This could be an indication that the heterogeneous housing stock in neighbourhoods in Rotterdam requires research that is more focussed on an even smaller scale than 6-digit postal codes, or a different way for categorizing homes. This is important for the policy makers in Rotterdam. The diverse housing stock and neighbourhoods require special attention and policy. When creating policy, perhaps other factors than location could be used to group similar areas instead of dividing per neighbourhood. The housing stock of Rotterdam is unique in many ways and requires specific policies to keep this interesting city in good shape.

For the people of Rotterdam the results in this paper show that they cannot profit a lot from the improvements of their neighbours' houses. The quality of the area of home has an influence on the price but it is a relatively small effect compared to other factors that make up a housing

price. As mentioned previously in this paper, further research should assess whether the neighbourhood spillover effects are different than in other places because in relatively small areas there are large differences in types of housing. For the municipality of Rotterdam, investing in the improvement of the quality of the housing stock is essential. However, projects such as the one in Carnisse where old, low quality, and lower cost homes are replaced by fewer high quality and more expensive homes is not always the best solution. It does increase the quality of the housing stock, but with the shortage of homes and especially affordable homes these projects are not necessarily an improvement for the people of Rotterdam.

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9. Appendix

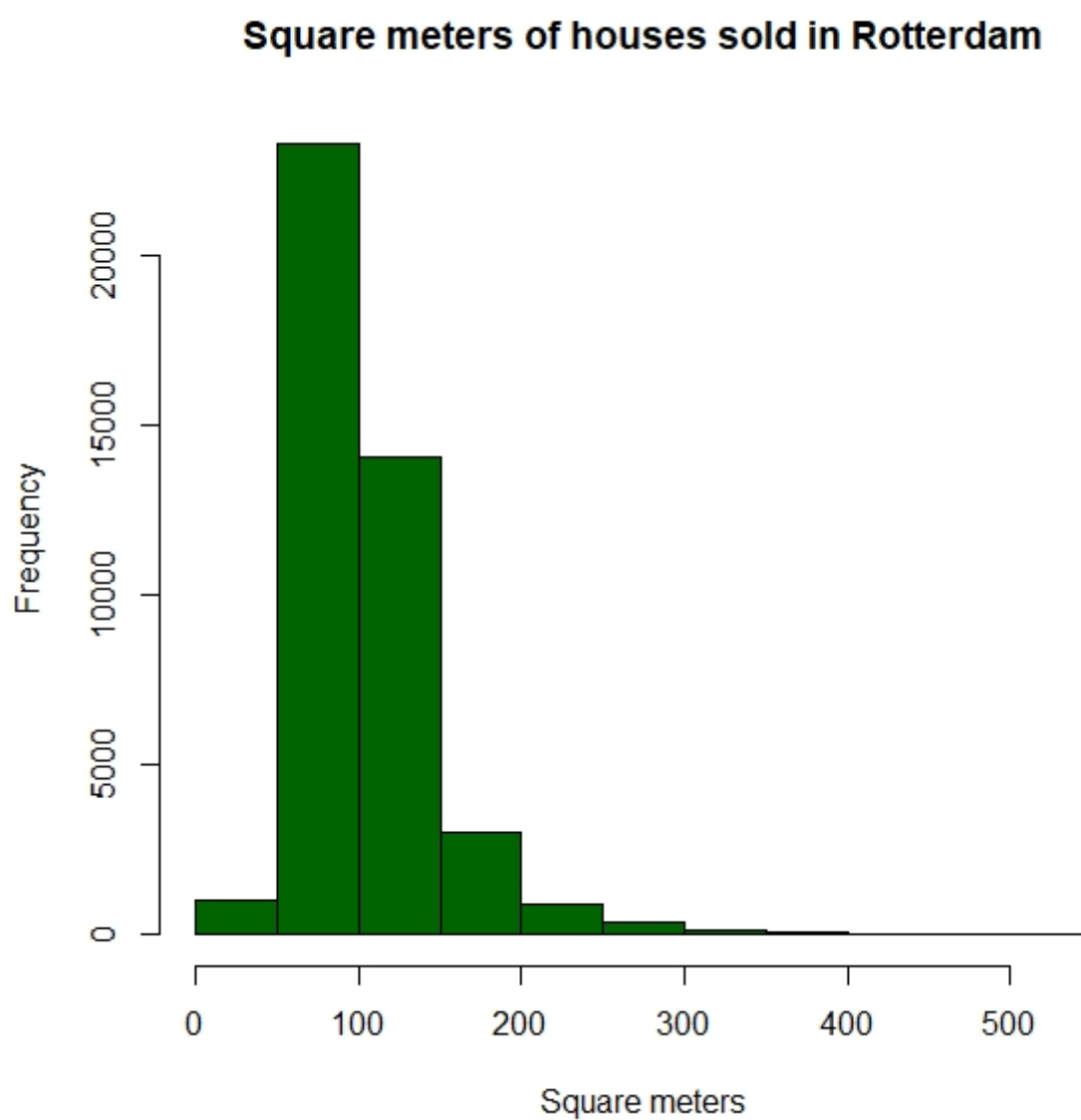


Figure 9: Histogram m2. Source data: NVM (2020)

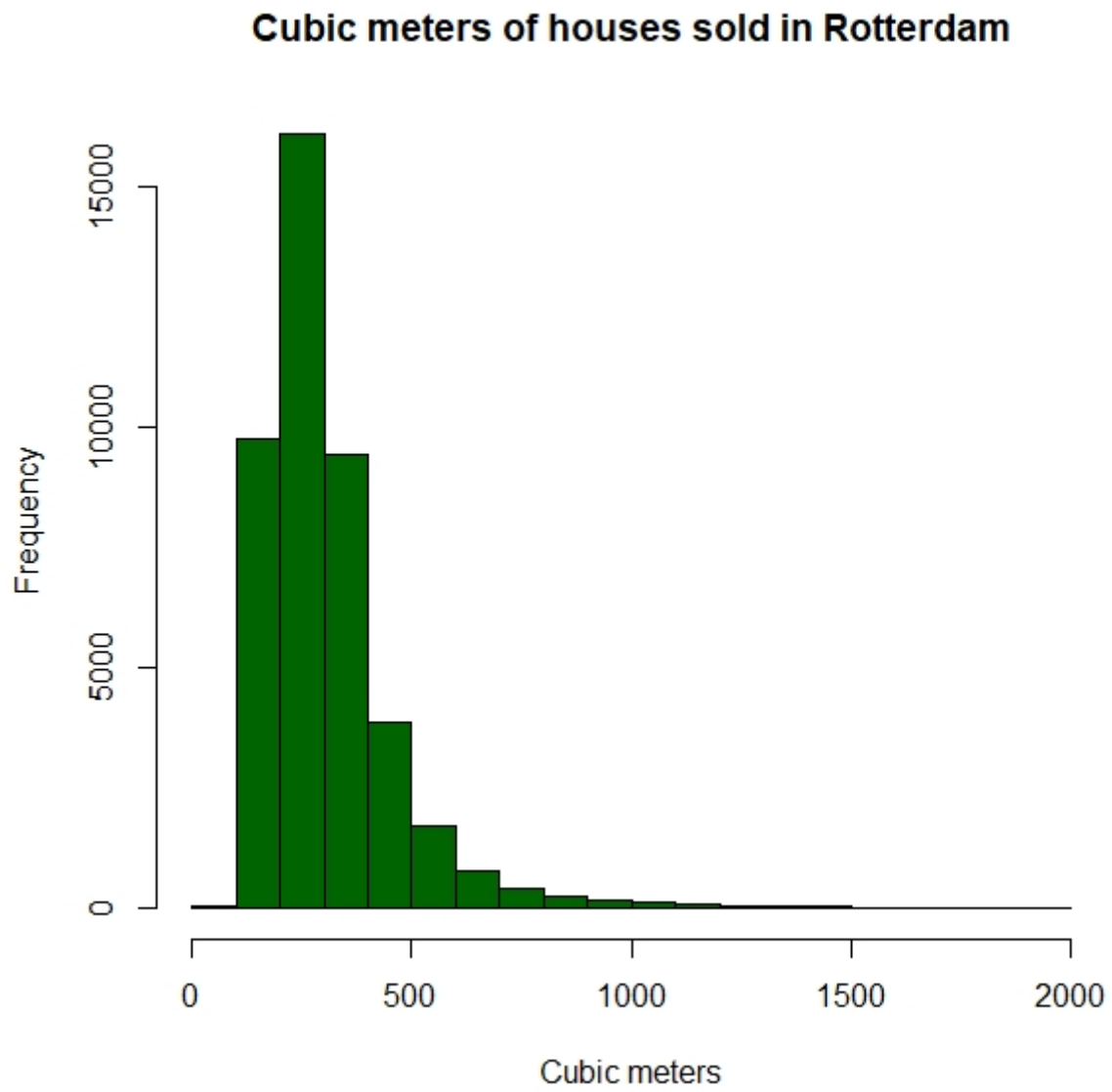


Figure 10: Histogram m3. Source data: NVM (2020)

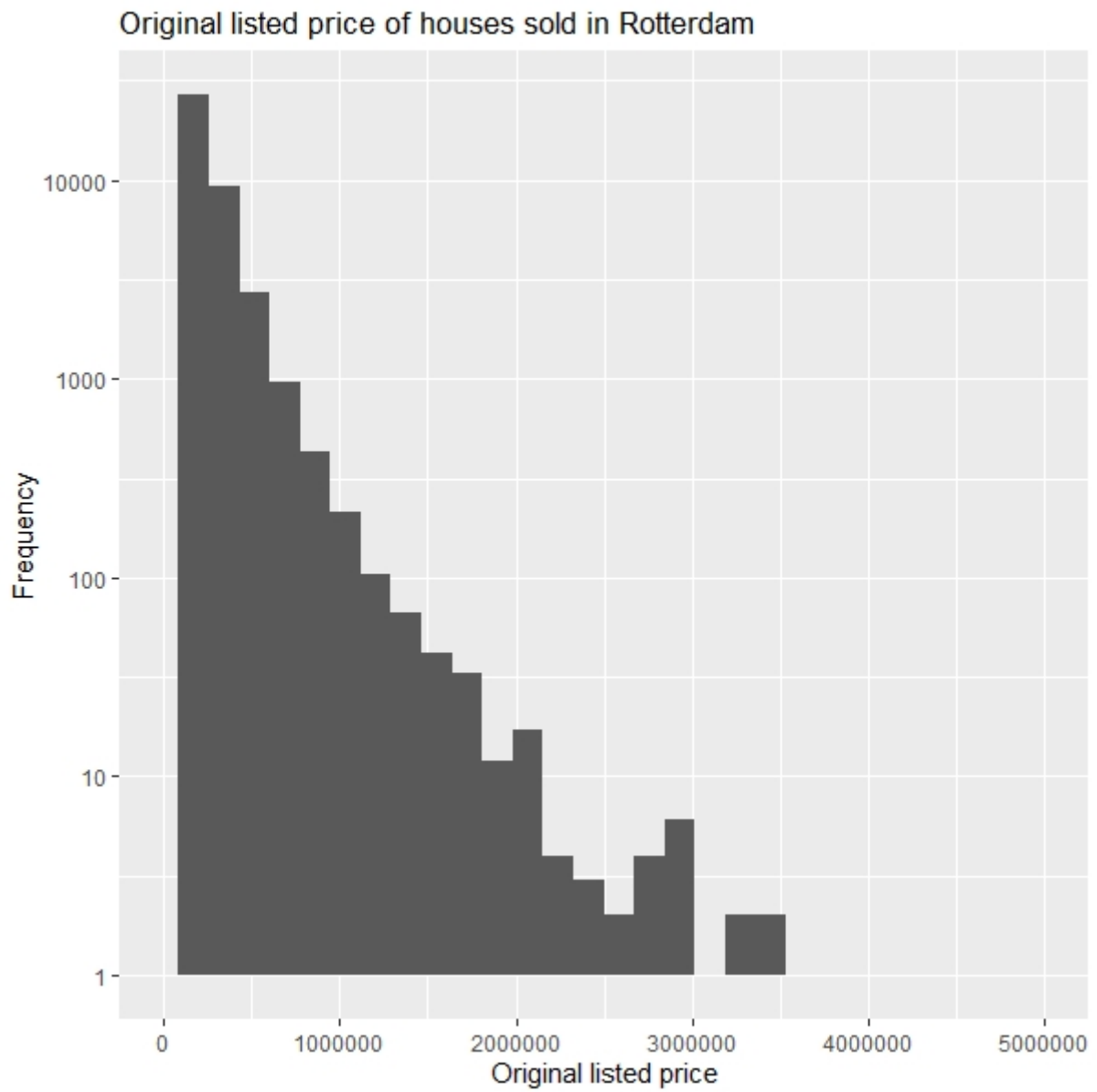


Figure 11: Histogram original listed price. Source data: NVM (2020)

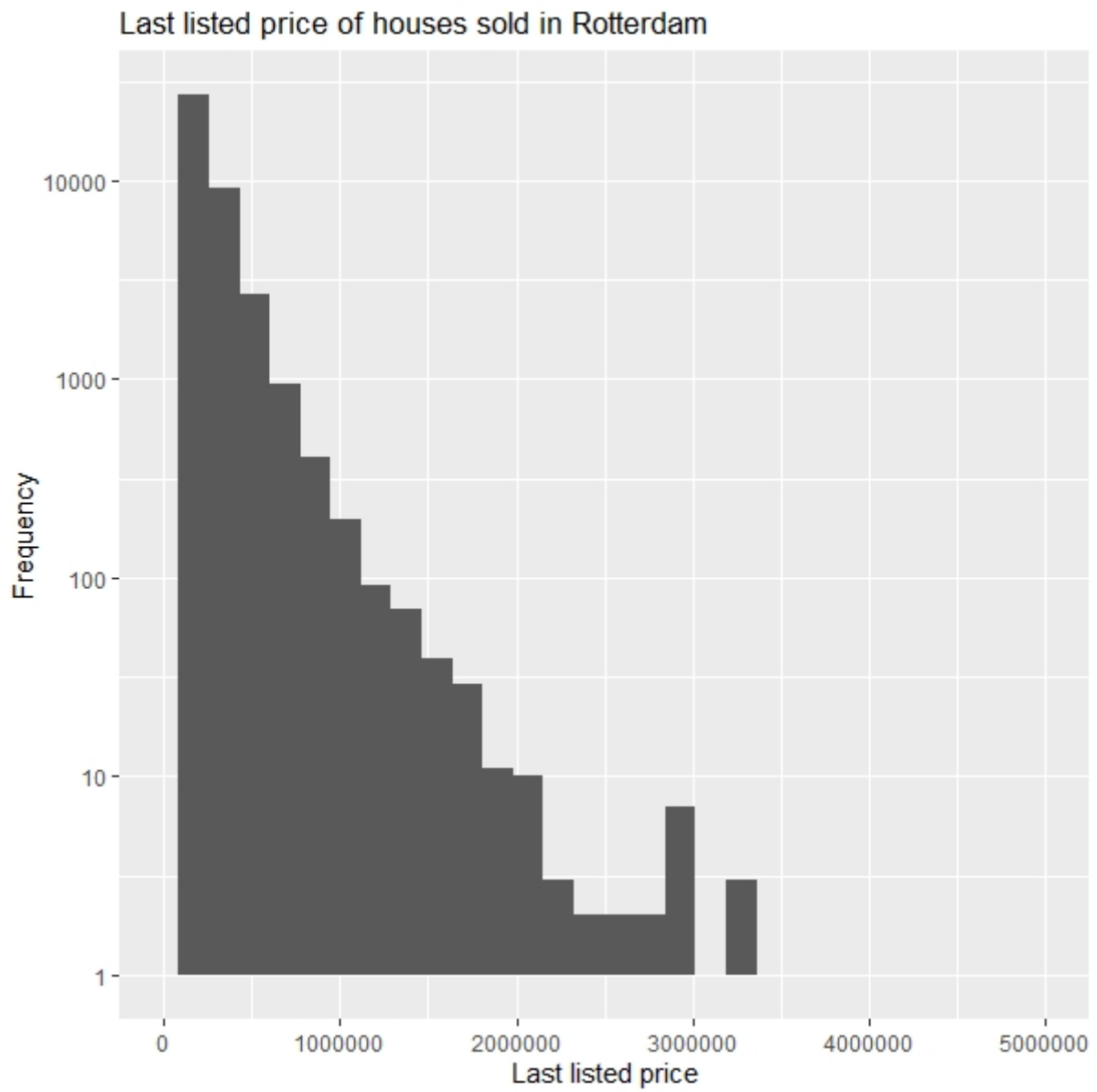


Figure 12: Histogram last listed price. Source data: NVM (2020)

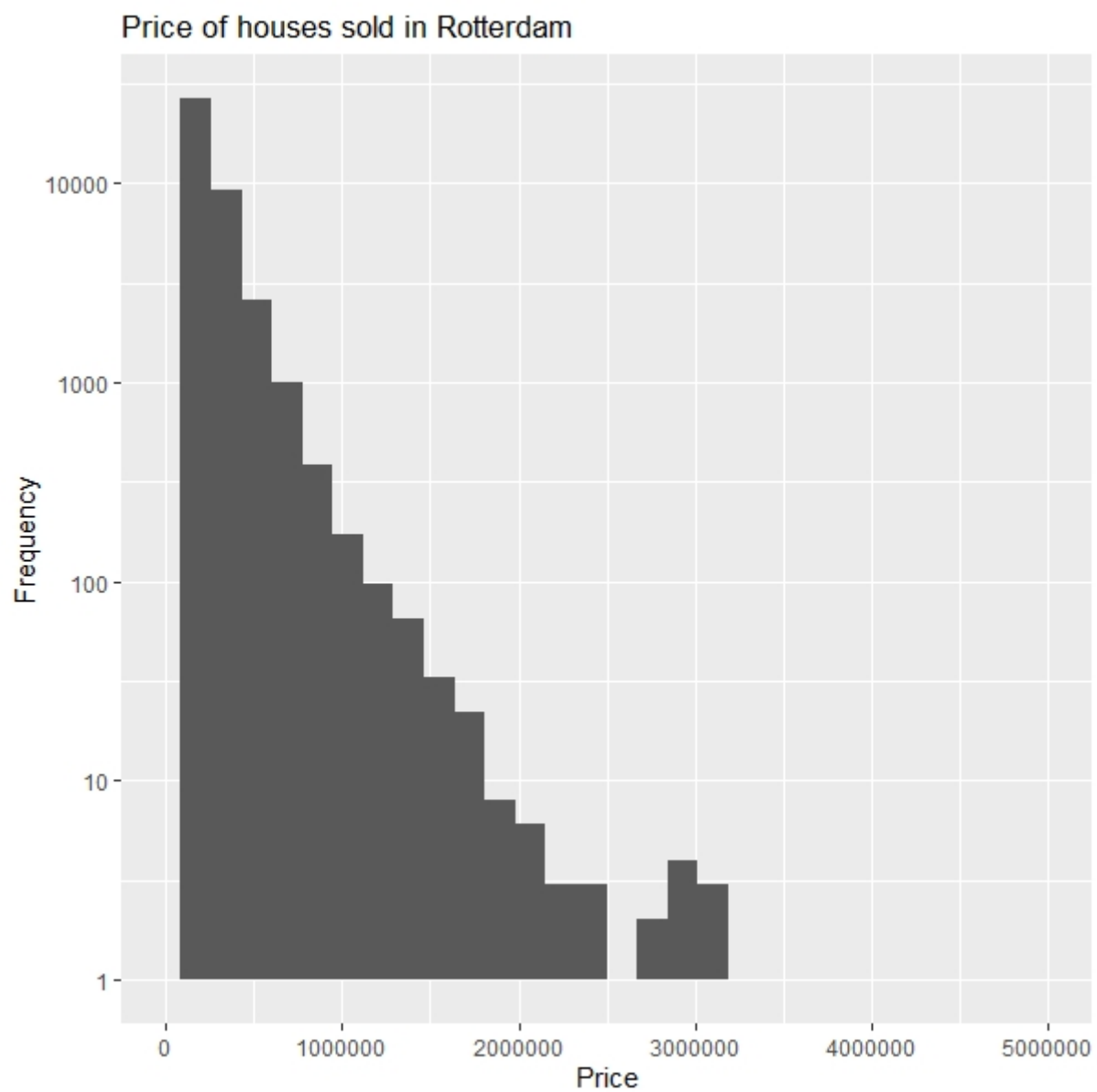


Figure 13: Histogram price. Source data: NVM (2020)

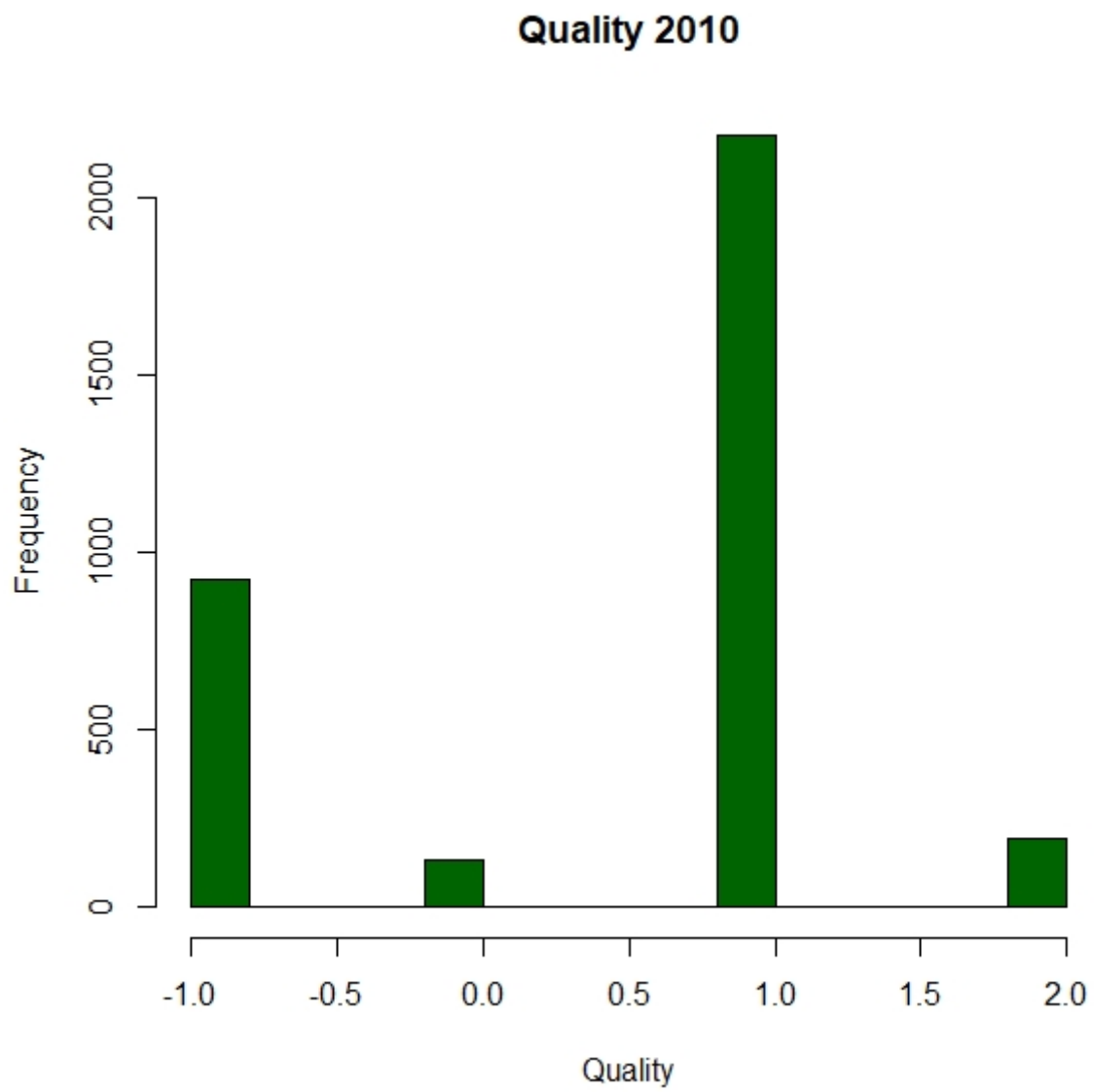


Figure 14: Frequency table quality 2010. Source data: NVM(2020)

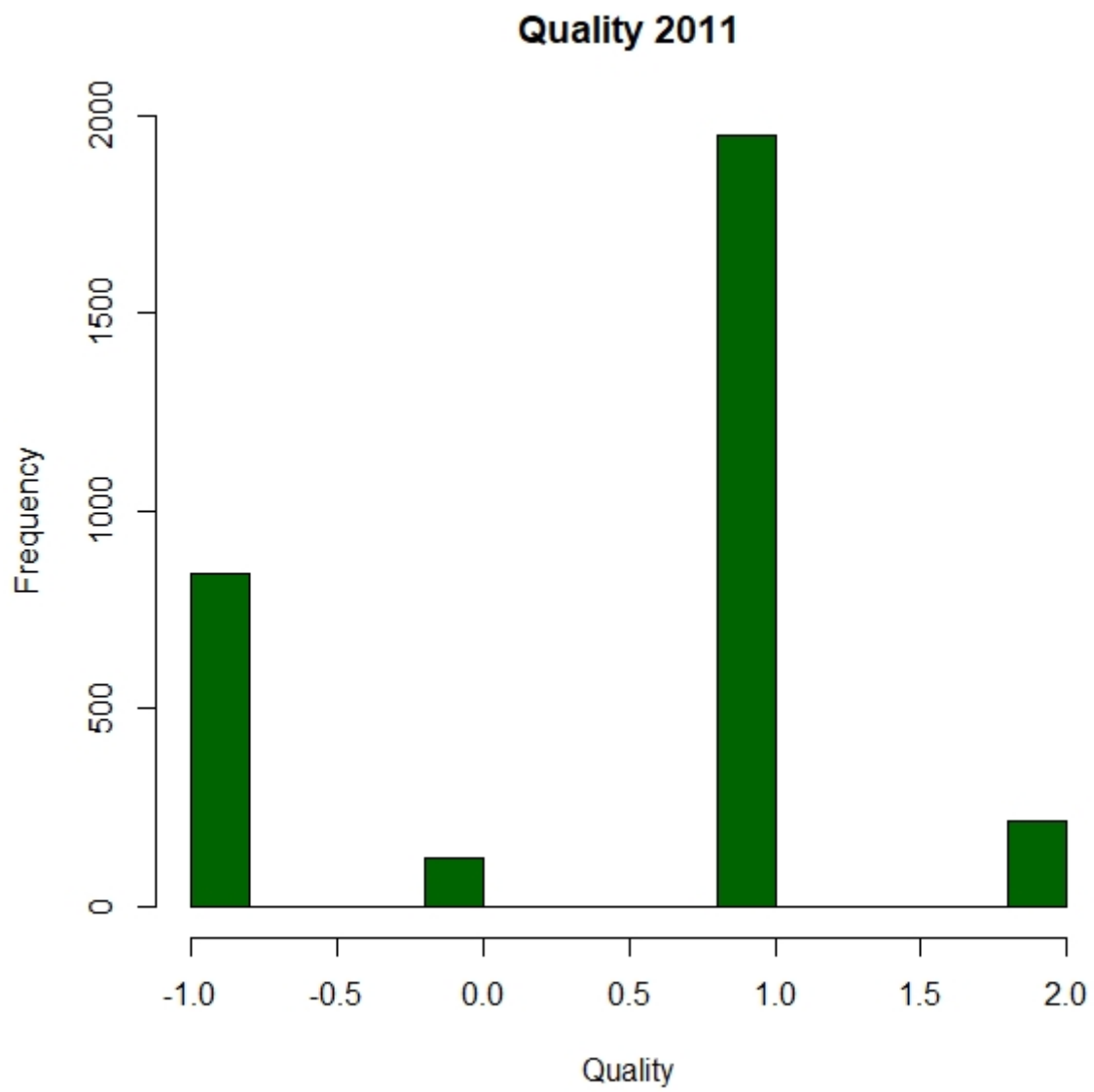


Figure 15: Frequency table quality 2011. Source data: NVM(2020)

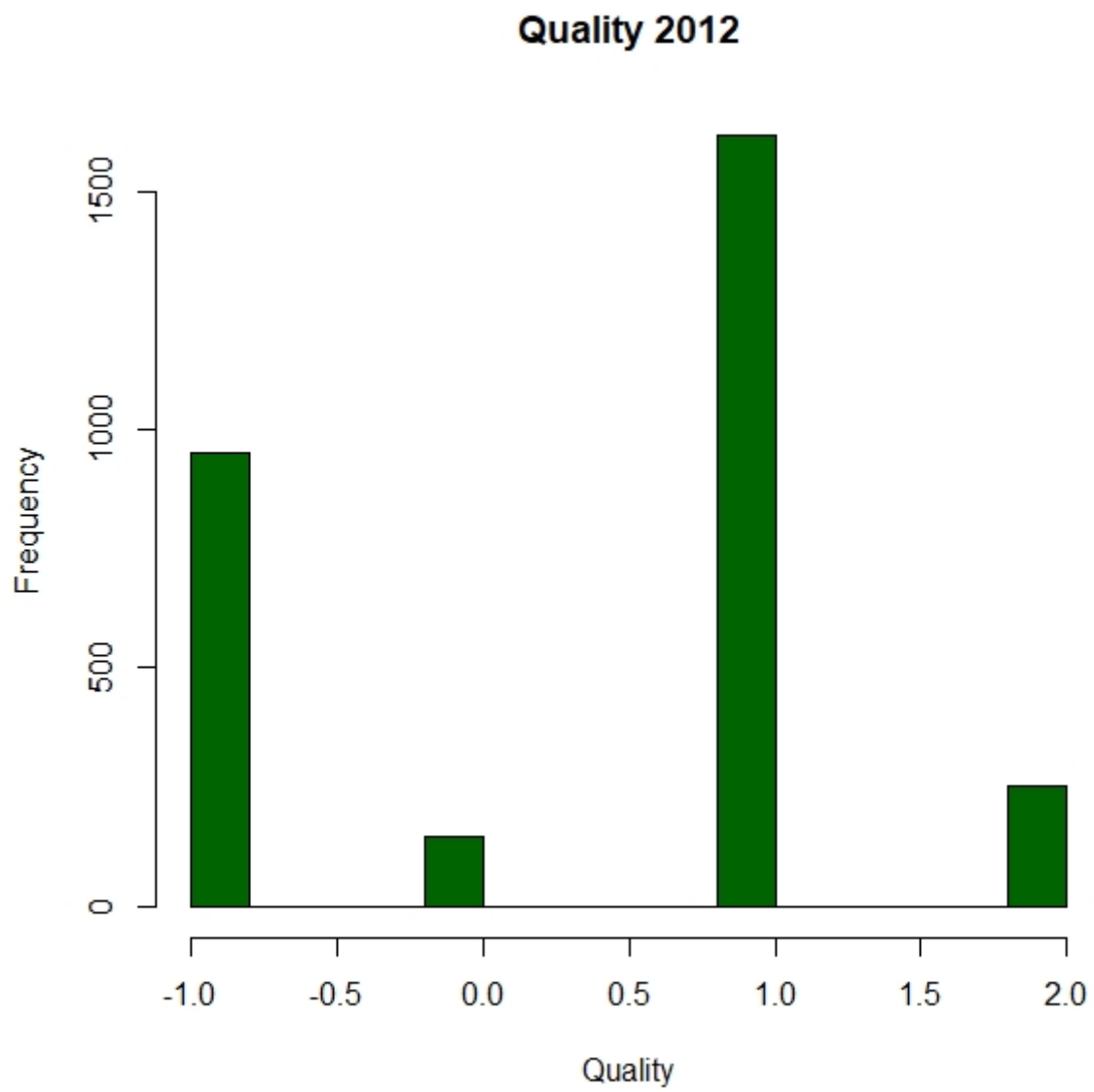


Figure 16: Frequency table quality 2012. Source data: NVM(2020)

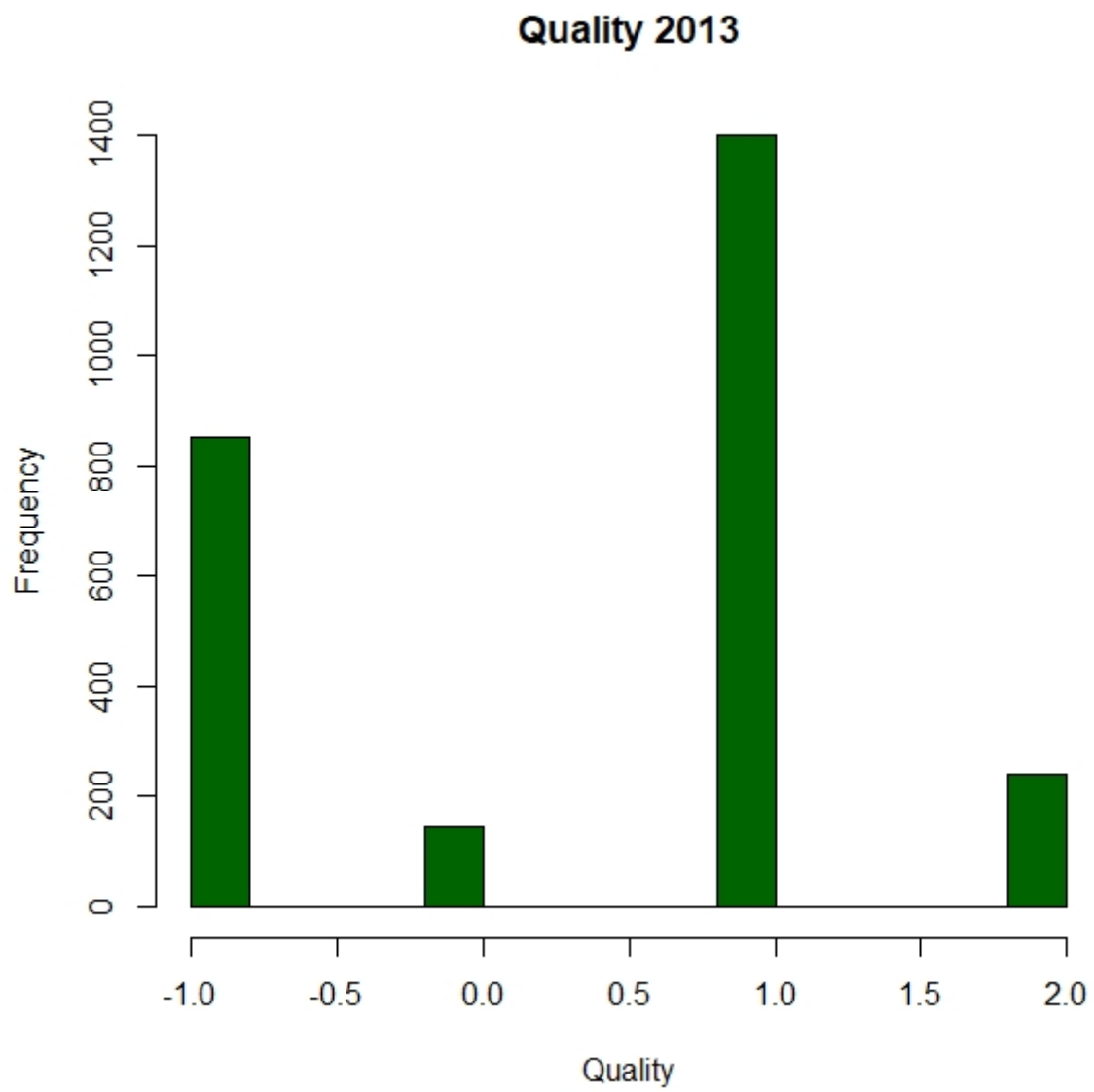


Figure 17: Frequency table quality 2013. Source data: NVM(2020)

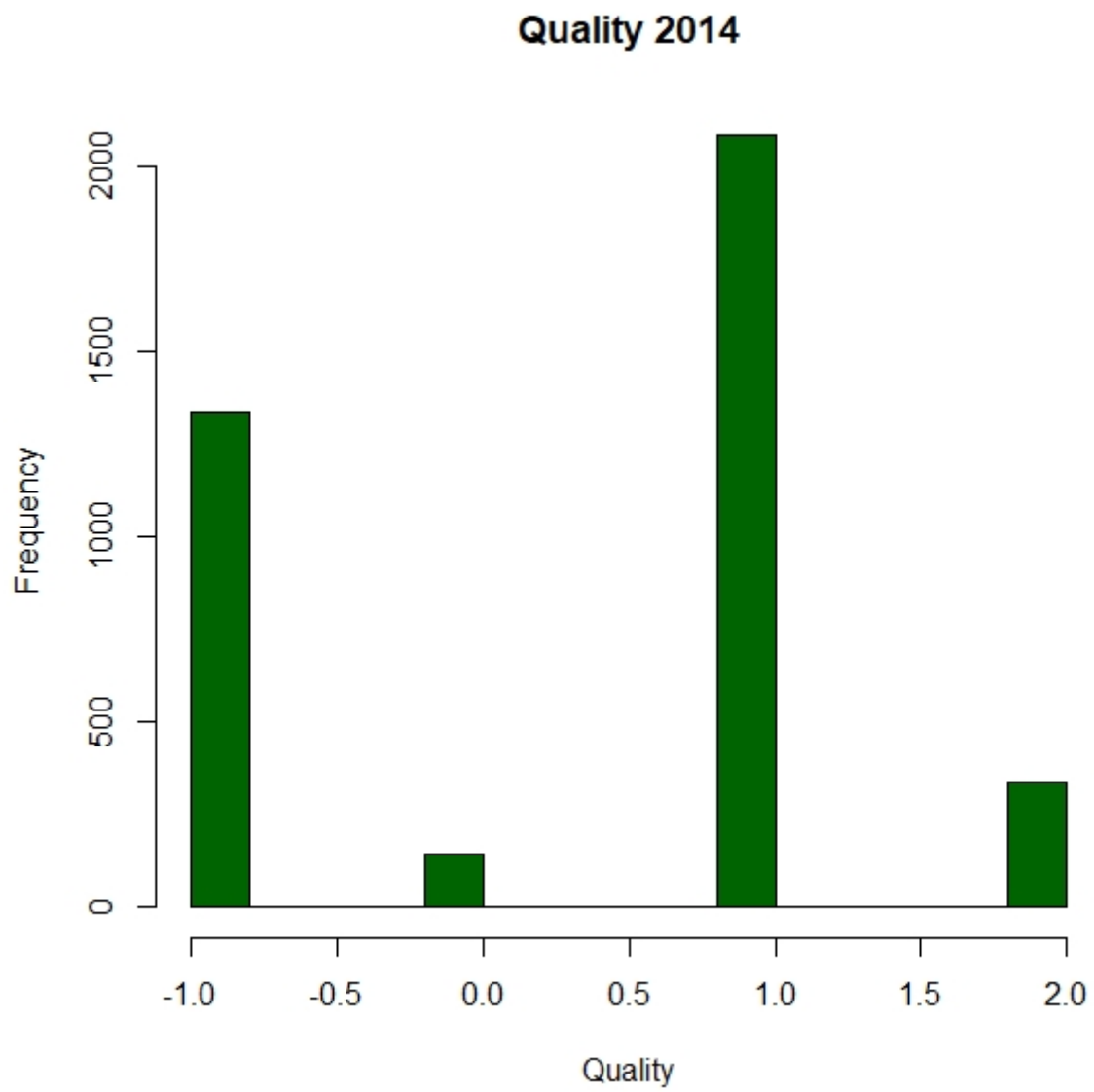


Figure 18: Frequency table quality 2014. Source data: NVM(2020)

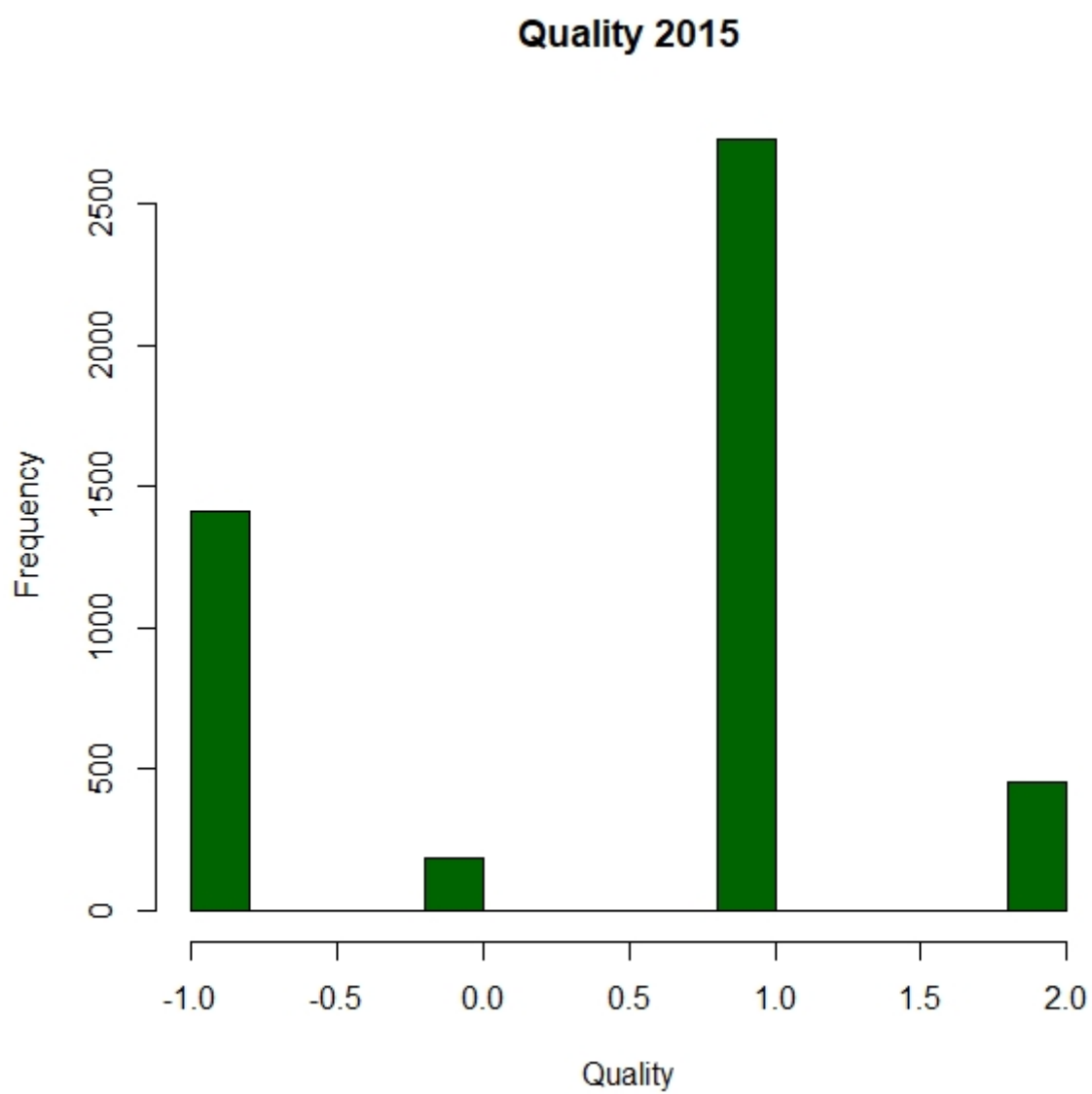


Figure 19: Frequency table quality 2015. Source data: NVM(2020)

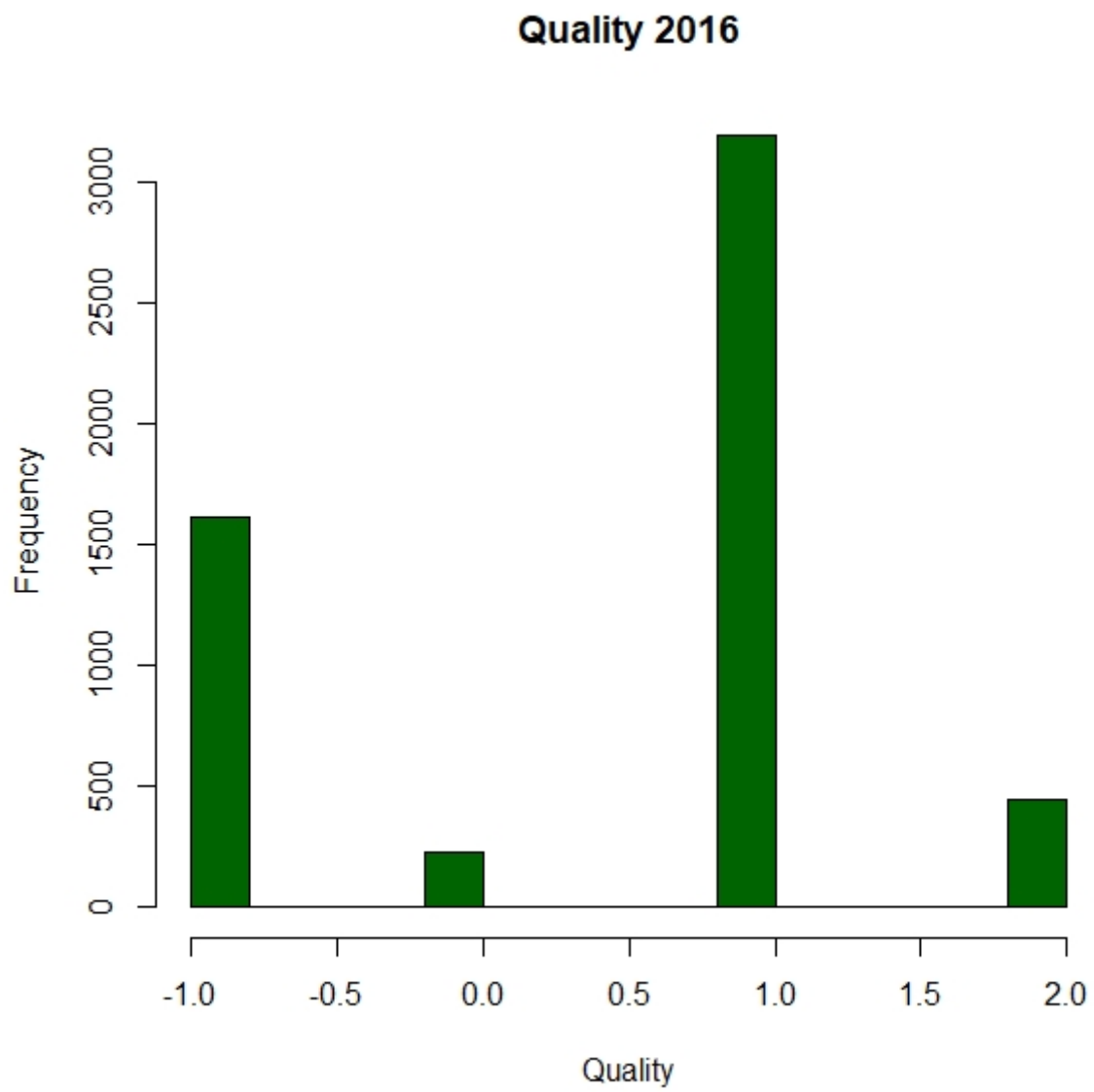


Figure 20: Frequency table quality 2016. Source data: NVM(2020)

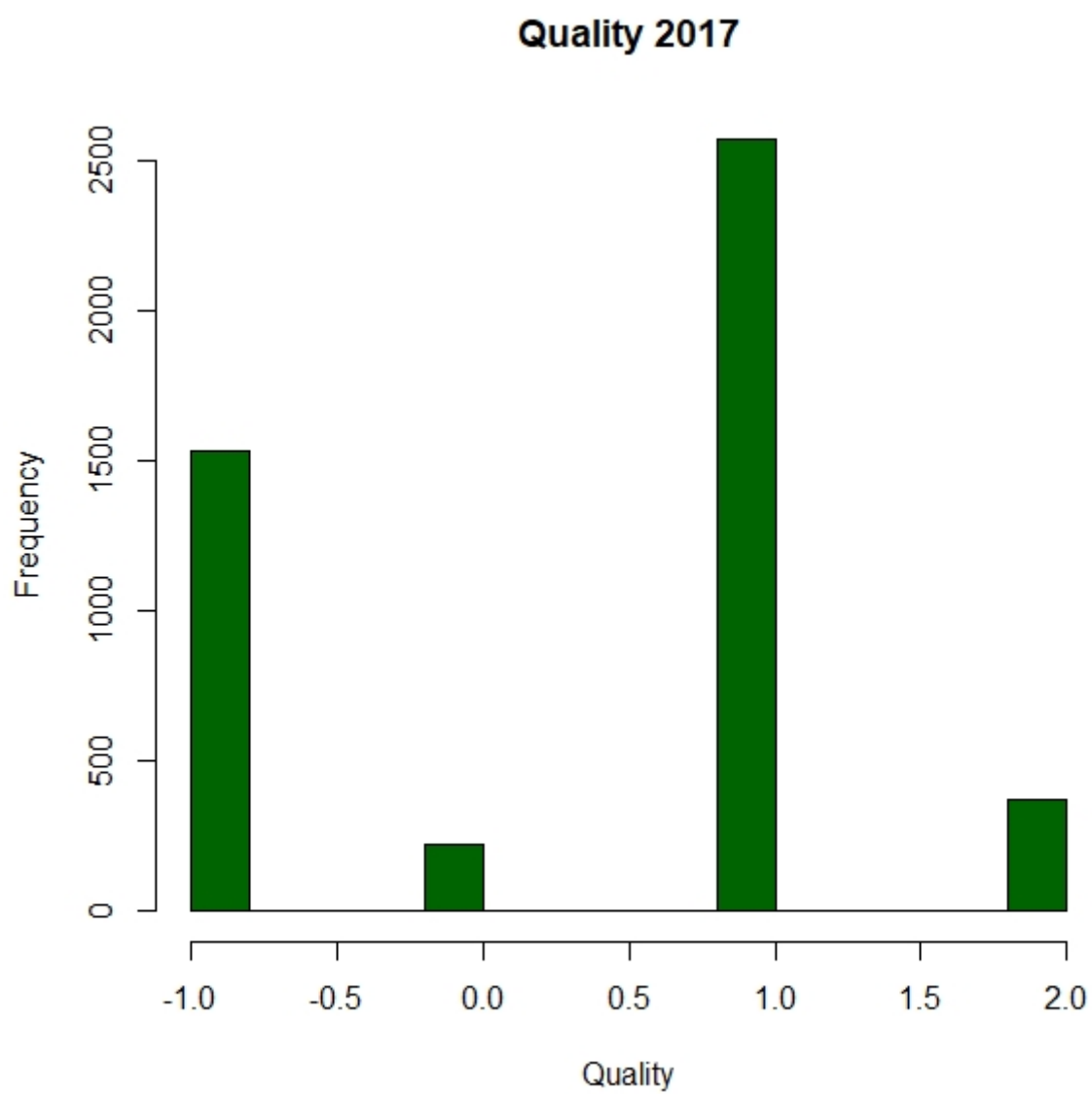


Figure 21: Frequency table quality 2017. Source data: NVM(2020)

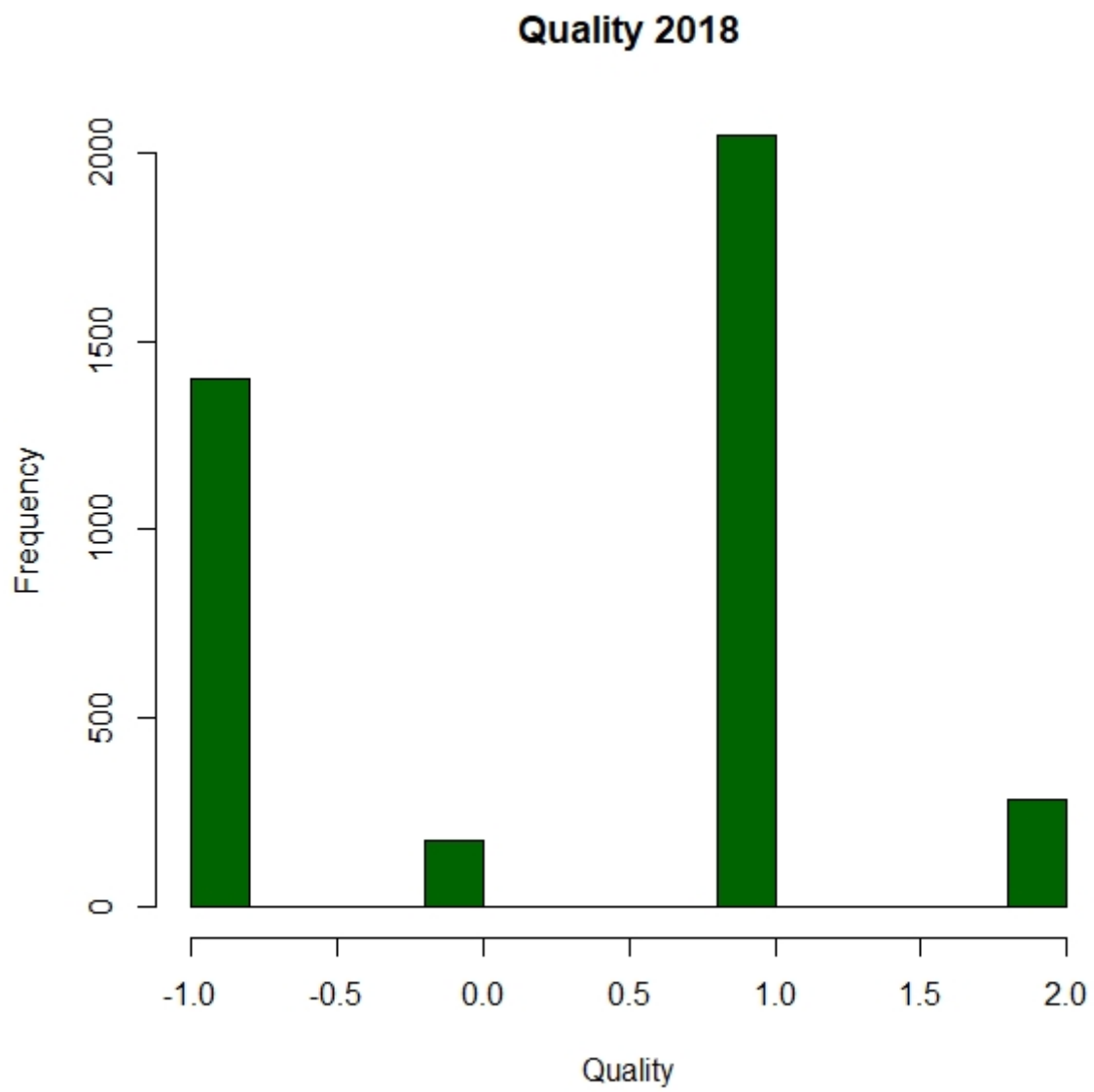


Figure 22: Frequency table quality 2018. Source data: NVM(2020)

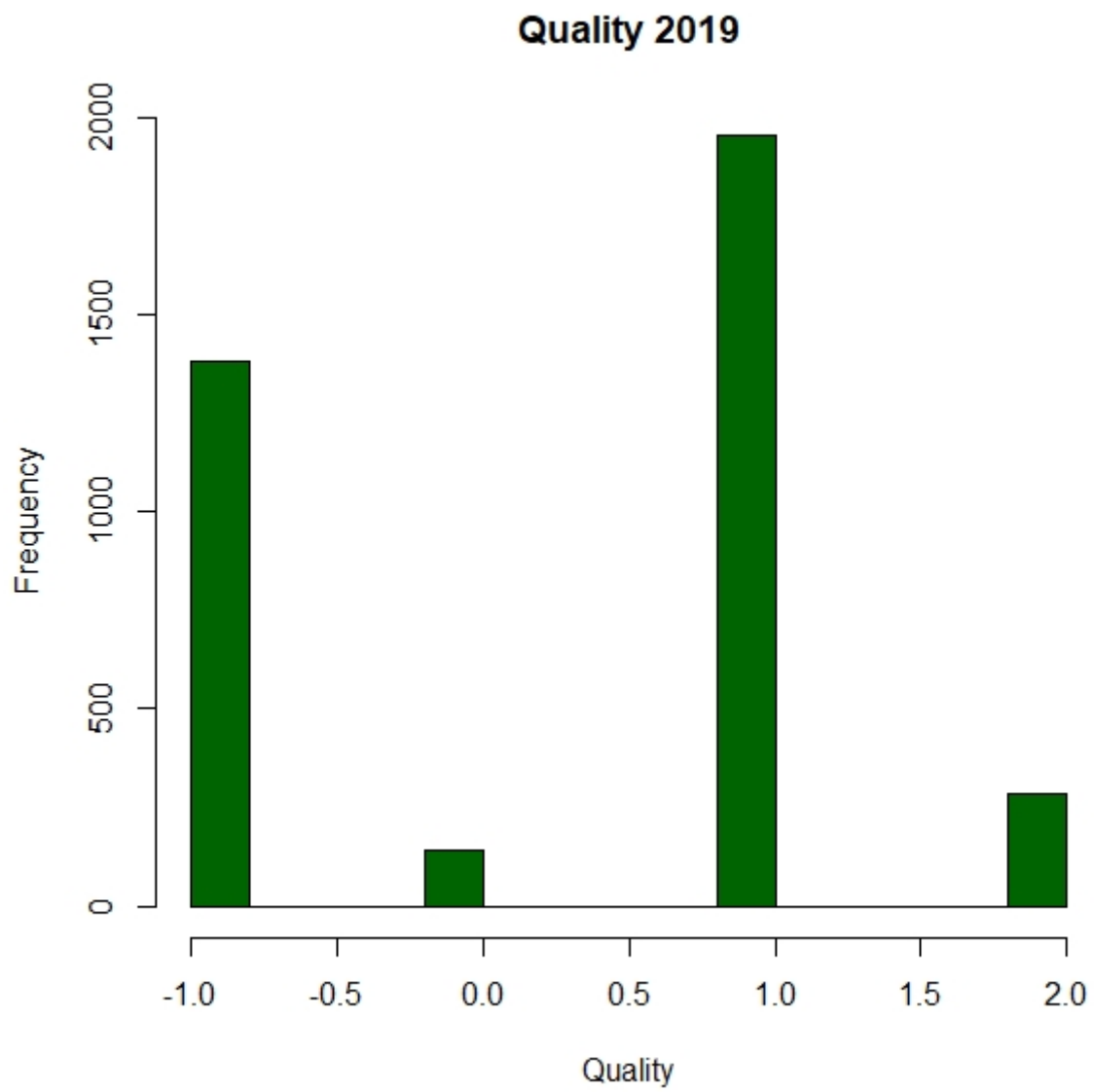


Figure 23: Frequency table quality 2019. Source data: NVM(2020)

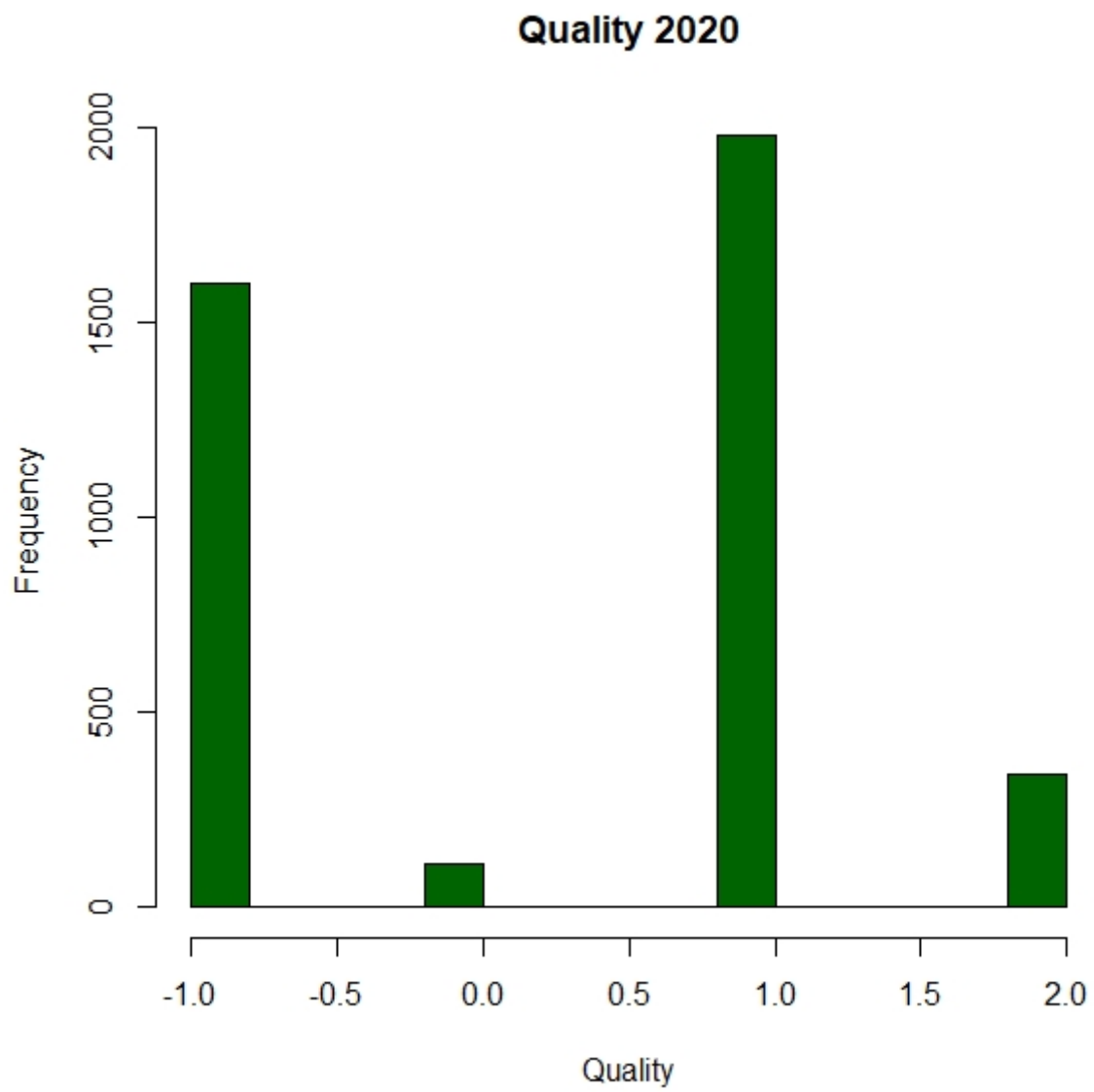


Figure 24: Frequency table quality 2020. Source data: NVM(2020)


```
. pwcorr logprice logm2 kwaliteit qualityPC6 qualityPC5 qualityPC4 qualityPC3 ligcentr ligmo
> oi construction_period soorthuis2 soortapp2 parkeer tuinlig, sig star(.01)
```

	logprice	logm2	kwaliteit	qualityPC6	qualityPC5	qualityPC4	qualityPC3	ligcentr	ligmo
logprice	1.0000								
logm2	0.7523*	1.0000							
kwaliteit	-0.2881*	-0.4525*	1.0000						
qualityPC6	-0.1404*	-0.3044*	0.8652*	1.0000					
qualityPC5	-0.1491*	-0.2801*	0.5875*	0.5265*	1.0000				
qualityPC4	-0.1157*	-0.2546*	0.5532*	0.4854*	0.8934*	1.0000			
qualityPC3	-0.2380*	-0.2733*	0.4354*	0.3800*	0.6905*	0.7343*	1.0000		
ligcentr	0.0548*	0.0008	0.0343*	0.0485*	0.0956*	0.1002*	0.1011*	1.0000	
ligmo	0.0819*	0.0212*	0.1519*	0.1530*	0.0616*	0.0419*	0.0255*	0.0000	1.0000
constructi~d	0.1332*	0.0748*	-0.0614*	-0.0205*	-0.1446*	-0.1724*	-0.1142*	0.0000	0.0000
soorthuis2	-0.2942*	-0.4412*	0.9149*	0.7230*	0.5986*	0.5719*	0.4424*	0.0000	0.0000
soortapp2	0.3419*	0.4569*	-0.8359*	-0.6563*	-0.5768*	-0.5619*	-0.4376*	0.0000	0.0000
parkeer	0.3740*	0.3343*	-0.1220*	-0.0443*	-0.1014*	-0.0976*	-0.1248*	0.0000	0.0000
tuinlig	0.2325*	0.3039*	-0.5229*	-0.4110*	-0.3669*	-0.3481*	-0.2941*	0.0000	0.0000
	ligcentr	ligmo	constr~d	soorth~2	soorta~2	parkeer	tuinlig		
ligcentr	1.0000								
ligmo	0.0983*	1.0000							
constructi~d	0.0532*	0.1412*	1.0000						
soorthuis2	0.0175*	0.1408*	-0.0987*	1.0000					
soortapp2	-0.0085	-0.0555*	0.2113*	-0.8656*	1.0000				
parkeer	0.0245*	0.1086*	0.2775*	-0.1072*	0.1889*	1.0000			
tuinlig	0.0122	-0.1105*	-0.0101	-0.5637*	0.4322*	0.0590*	1.0000		

Table 12: Correlation table

```
. correlate logprice logm2 kwaliteit qualityPC6 qualityPC5 qualityPC4 qualityPC3 ligcentr li
> gmooi construction_period soorthuis2 soortapp2 parkeer tuinlig, covariance
(obs=42,696)
```

	logprice	logm2	kwalit~t	qualit~6	qualit~5	qualit~4	qualit~3	ligcentr
logprice	.35297							
logm2	.163442	.133727						
kwaliteit	-.1751	-.169289	1.04661					
qualityPC6	-1.82903	-2.44124	19.409	480.822				
qualityPC5	-16.7433	-19.361	113.615	2182.38	35735.8			
qualityPC4	-11.2194	-15.193	92.3658	1737.35	27565.7	26638.4		
qualityPC3	-4.35999	-3.08103	13.7352	256.886	4024.82	3695.18	950.683	
ligcentr	.017702	.000164	.019063	.578087	9.82706	8.89431	1.69466	.295531
ligmooi	.075681	.012044	.241719	5.21842	18.1101	10.634	1.22446	.083112
constructi~d	.197623	.068294	-.156857	-1.12182	-68.2764	-70.2855	-8.79022	.072224
soorthuis2	-.6415	-.592203	3.4358	58.1936	415.359	342.636	50.0665	.034895
soortapp2	.52547	.432234	-2.21215	-37.2252	-282.03	-237.206	-34.9043	-.011935
parkeer	.306354	.168559	-.17205	-1.34043	-26.4331	-21.9543	-5.30425	.018329
tuinlig	.361702	.291023	-1.4009	-23.602	-181.61	-148.793	-23.7486	.017368
	ligmooi	constr~d	soorth~2	soorta~2	parkeer	tuinlig		
ligmooi	2.41859							
constructi~d	.548484	6.23641						
soorthuis2	.803488	-.904793	13.4738					
soortapp2	-.223383	1.36524	-8.21914	6.69108				
parkeer	.232954	.955459	-.542757	.673769	1.90131			
tuinlig	-.449845	-.066177	-5.41775	2.92749	.21292	6.85691		

Table 13: Covariance table

Variable	Correlation with price	Significant
m2	0.6843197	p-value < 0.01
kwaliteit	-0.2584532	p-value < 0.01
Ligmooi	0.05435654	p-value < 0.01
ligcentr	0.01859235	p-value < 0.01
Construction_period	0.04344887	p-value < 0.01
Soorthuis	0.4304547	p-value < 0.01
Soortapp	-0.2758456	p-value < 0.01
Year	0.2526129	p-value < 0.01
Parkeer	0.3073052	p-value < 0.01
Garden	0.181138	p-value < 0.01
All neighbourhoods	-0.05034275	p-value < 0.01

Table 14: Correlation with dependent variable

Neighbourhood (Gemeente Rotterdam, 2020)	Score (2020)	NVM	Score Municipality (2020)	Same
Afrikaanderwijk	-1		1	No
Agniesebuurt	1		0	No
Bergpolder	1		1	Yes
Beverwaard	-1		-1	Yes
Blijdorp	1		1	Yes
Bloemhof	-1		2	No
Bospolder	1		0	No
Cs Kwartier	1		-1	No
Carnisse	1		2	No
Charlois Zuidrand	-1		2	No
Cool	1		0	No
De Esch	1		-1	No
Delfshaven	1		0	No
Dijkzigt	1		-1	No
Dorp	-1		1	No
Feijenoord	1		-1	No
Groot IJsselmonde	1		0	No

Heijplaat	1	1	Yes
Het Lage Land	1	0	No
Hillegersberg Noord	1	1	Yes
Hillegersberg Zuid	-1	2	No
Hillesluis	1	2	No
Hoogvliet Noord	-1	1	No
Hoogvliet Zuid	-1	0	No
Katendrecht	1	-1	No
Kleinpolder	-1	1	No
Kop van Zuid	1	-1	No
Kop van Zuid-Entrepot	1	-1	No
Kralingen Oost	1	2	No
Kralingen West	1	0	No
Kralingse Bos	-1/1	2	No
Kralingseveer	-1	2	No
Landzicht	-1	2	No
Liskwartier	1	1	Yes
Lombardijen	1	0	No

Middelland	1	1	Yes
Molenlaankwartier	-1	2	No
Nesselande	-1	-1	Yes
Nieuw Crooswijk	-1	-1	Yes
Nieuw Mathenesse	X	-1	No
Nieuwe Werk	1	0	No
Nieuwe Westen	1	1	Yes
Noord Kethel	X	2	No
Noordereiland	1	0	No
Ommoord	-1	1	No
Oosterflank	-1	-1	Yes
Oud Charlois	1	2	No
Oud Mathenesse	1	2	No
Oud Crooswijk	1	-1	No
Oud IJsselmonde	1	0	No
Oude Noorden	1	0	No
Oude Westen	1	1	Yes
Overschie	-1	2	No
Pendrecht	2	0	No

Pernis	-1	2	No
Prinsenland	-1	-1	Yes
Provenierswijk	1	1	Yes
Rijnpoort	X	2	No
Rozenburg	X	1	No
Rubroek	1	0	No
's-Gravenland	-1	0	No
Schiebroek	-1	1	No
Schiemond	1	-1	No
Schieveen	-1	2	No
Spaanse Polder	X	2	No
Spangen	1	0	No
Stadsdriehoek	1	-1	No
Strand en Duin	-1	0	No
Struisenburg	1	-1	No
Tarwewijk	1	2	No
Terbregge	-1	1	No
Tussendijken	1	1	Yes
Vreewijk	-1	1	No

Wielewaal	X	2	No
Witte Dorp	X	-1	No
Zestienhoven	-1	0	No
Zevenkamp	-1	-1	Yes
Zuiderpark	1	1	Yes
Zuidplein	1	-1	No
Zuidwijk	1	-1	No

Table 15: Difference per neighbourhood between data Gemeente Rotterdam (2020) and NVM (2020)



Figure 25: Quality of houses sold per neighbourhood 2010. Source data: NVM (2020)

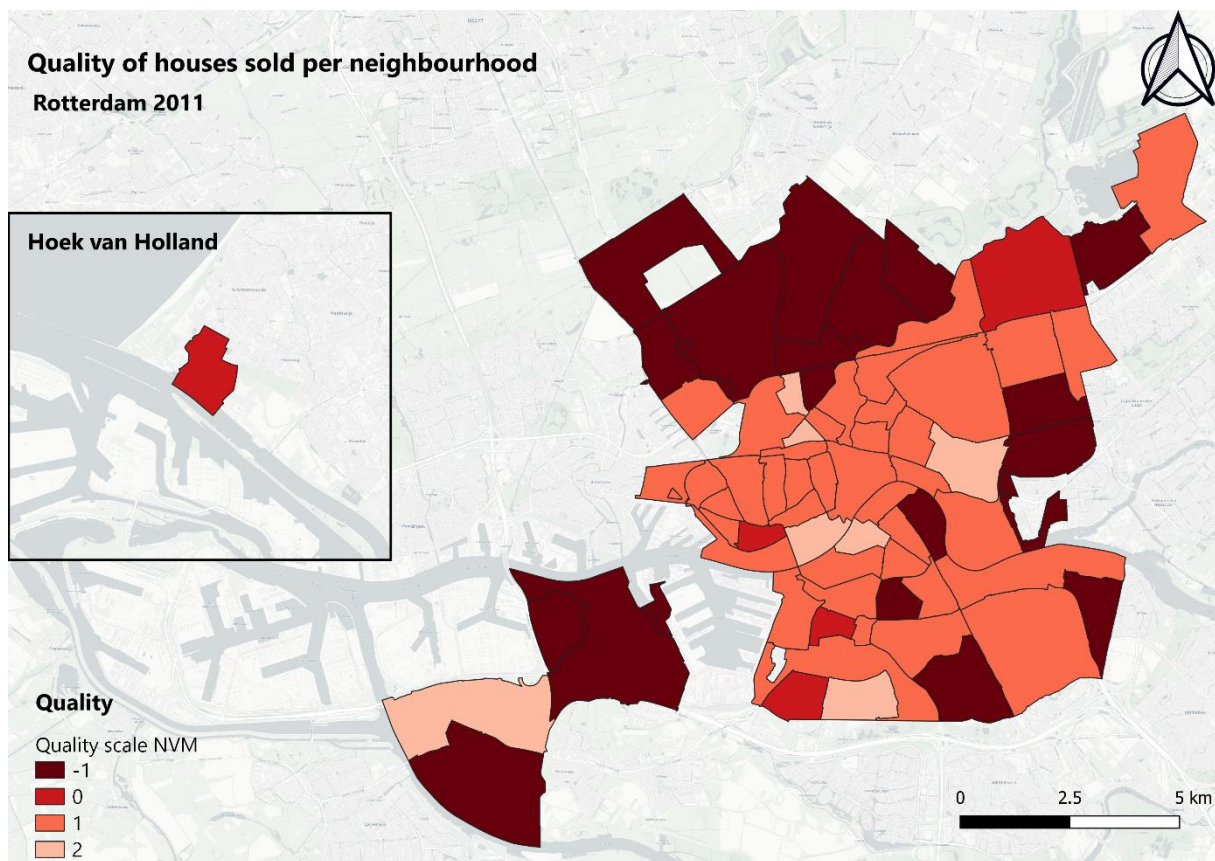


Figure 26: *Quality of houses sold per neighbourhood 2011. Source data: NVM (2020)*

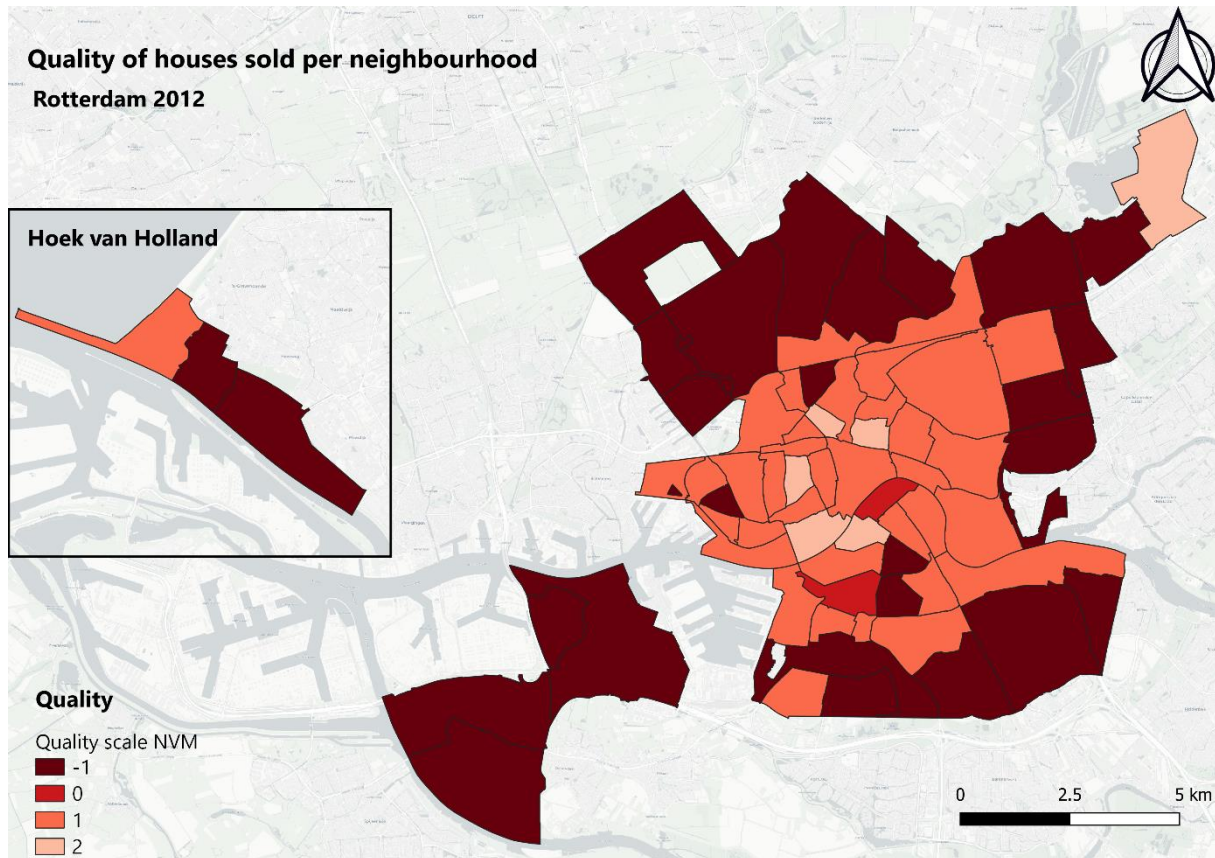


Figure 27: *Quality of houses sold per neighbourhood 2012. Source data: NVM (2020)*



Figure 28: *Quality of houses sold per neighbourhood 2013. Source data: NVM (2020)*

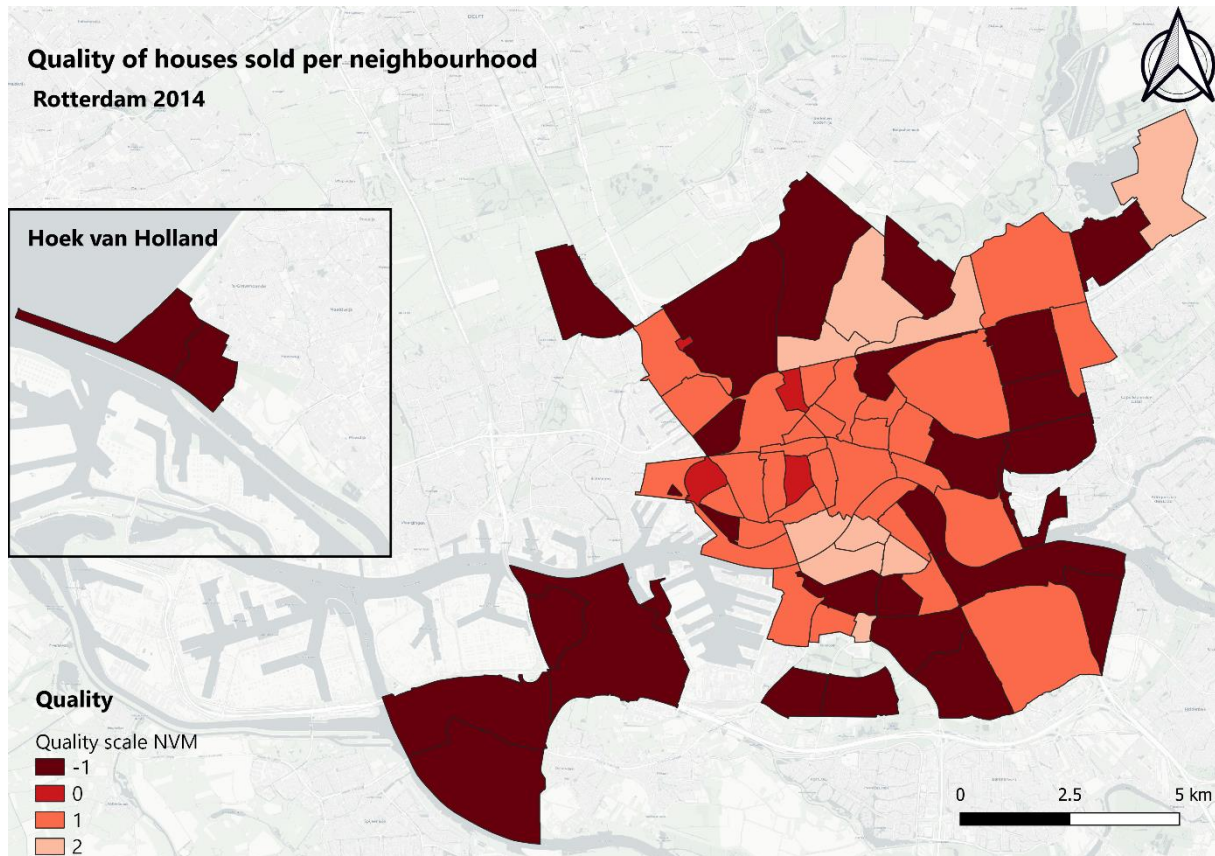


Figure 29: *Quality of houses sold per neighbourhood 2014. Source data: NVM (2020)*

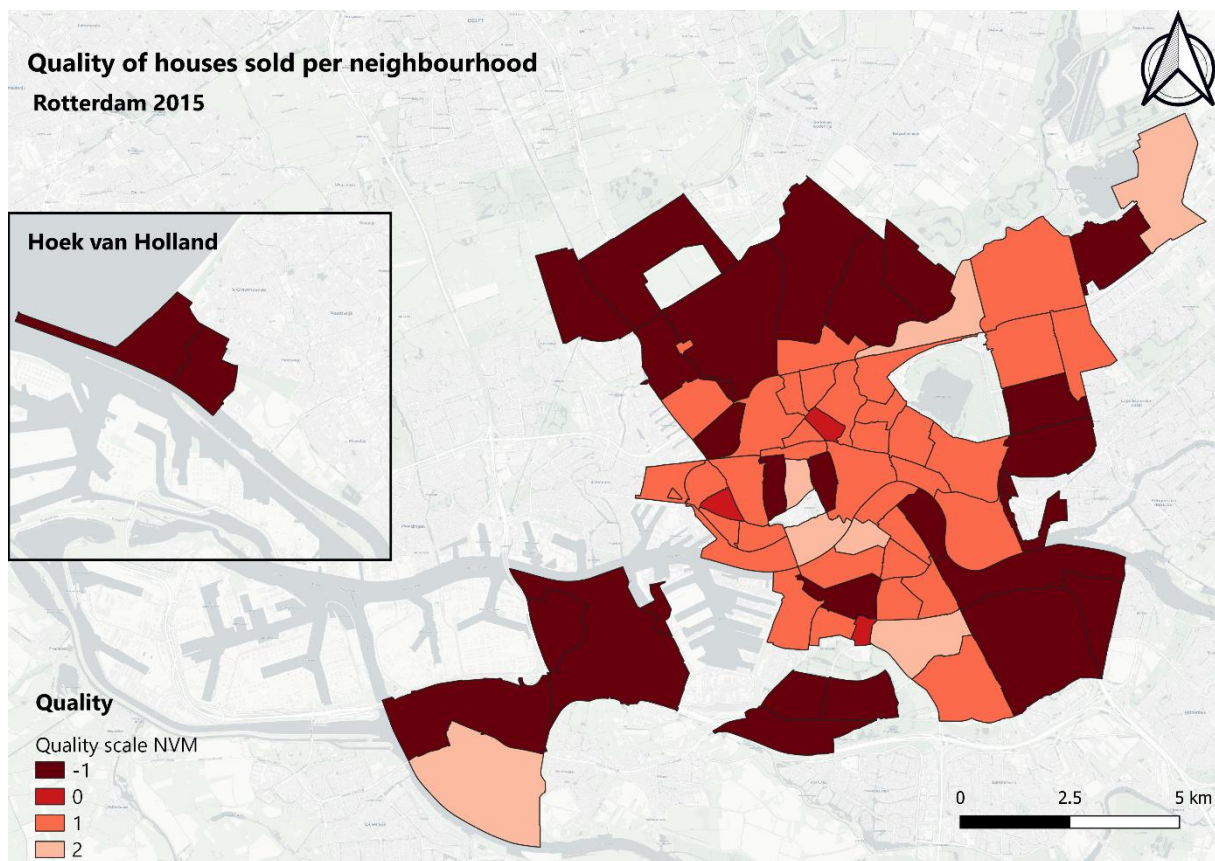


Figure 30: Quality of houses sold per neighbourhood 2015. Source data: NVM (2020)



Figure 31: Quality of houses sold per neighbourhood 2016. Source data: NVM (2020)



Figure 32: Quality of houses sold per neighbourhood 2017. Source data: NVM (2020)



Figure 33: Quality of houses sold per neighbourhood 2018. Source data: NVM (2020)

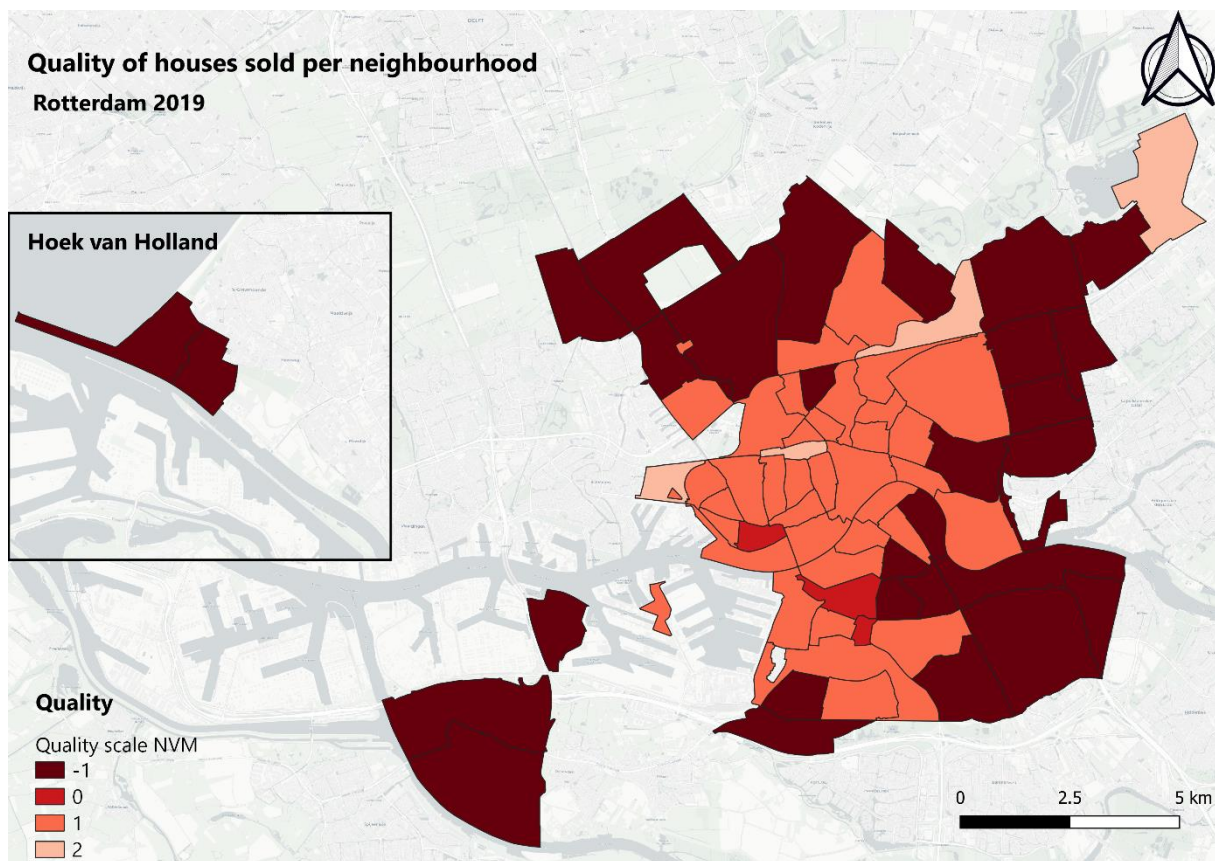


Figure 34: Quality of houses sold per neighbourhood 2019. Source data: NVM (2020)



Figure 35: Quality of houses sold per neighbourhood 2020. Source data: NVM (2020)

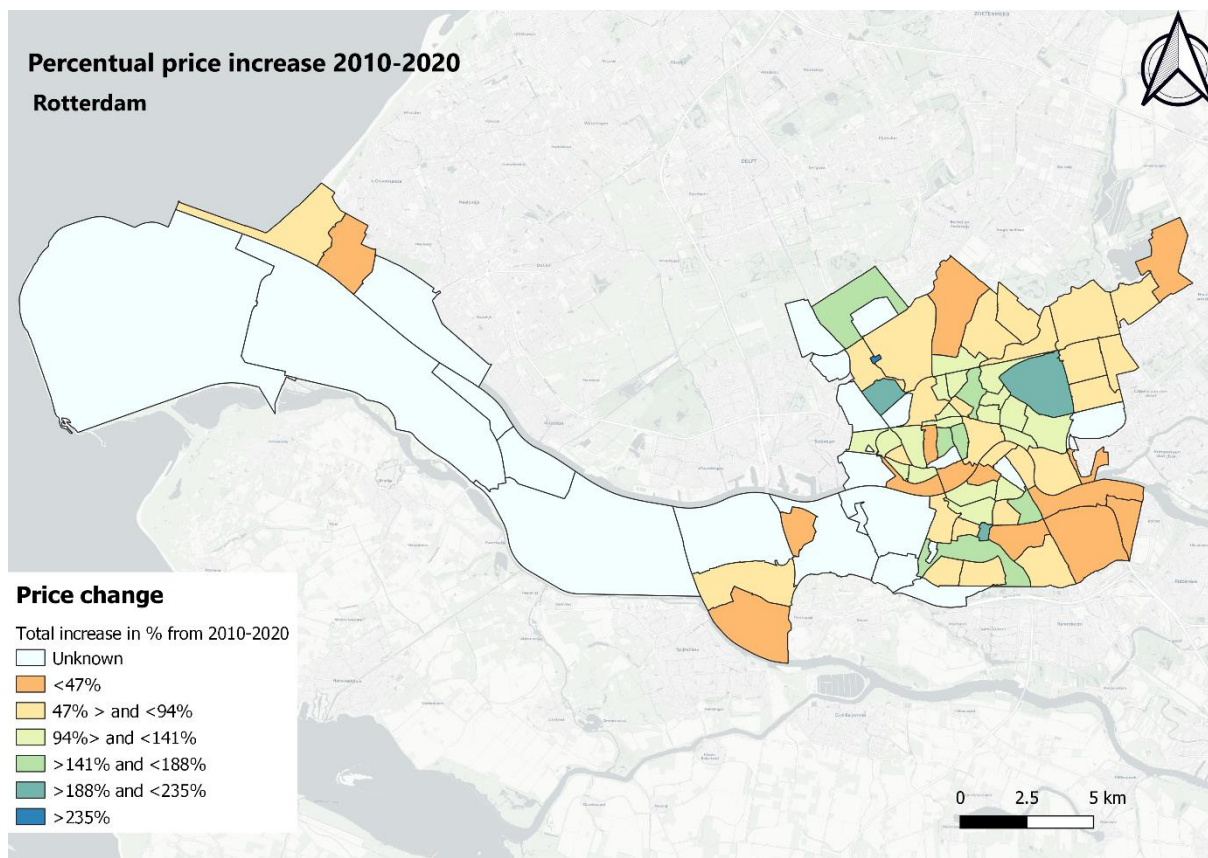


Figure 36: Percentual price increase 2010-2020

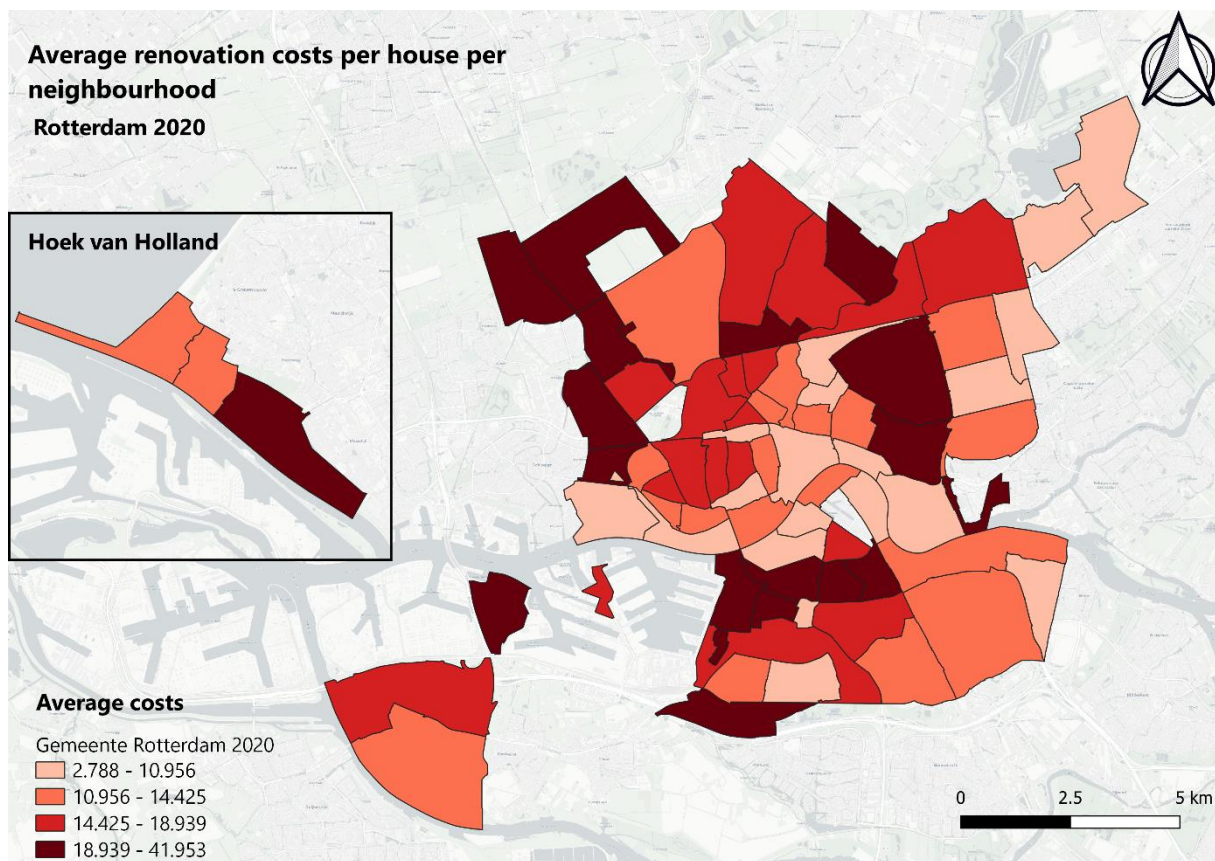


Figure 37: Average renovation costs per house per neighbourhood in 2020. Source data: Gemeente Rotterdam (2020)

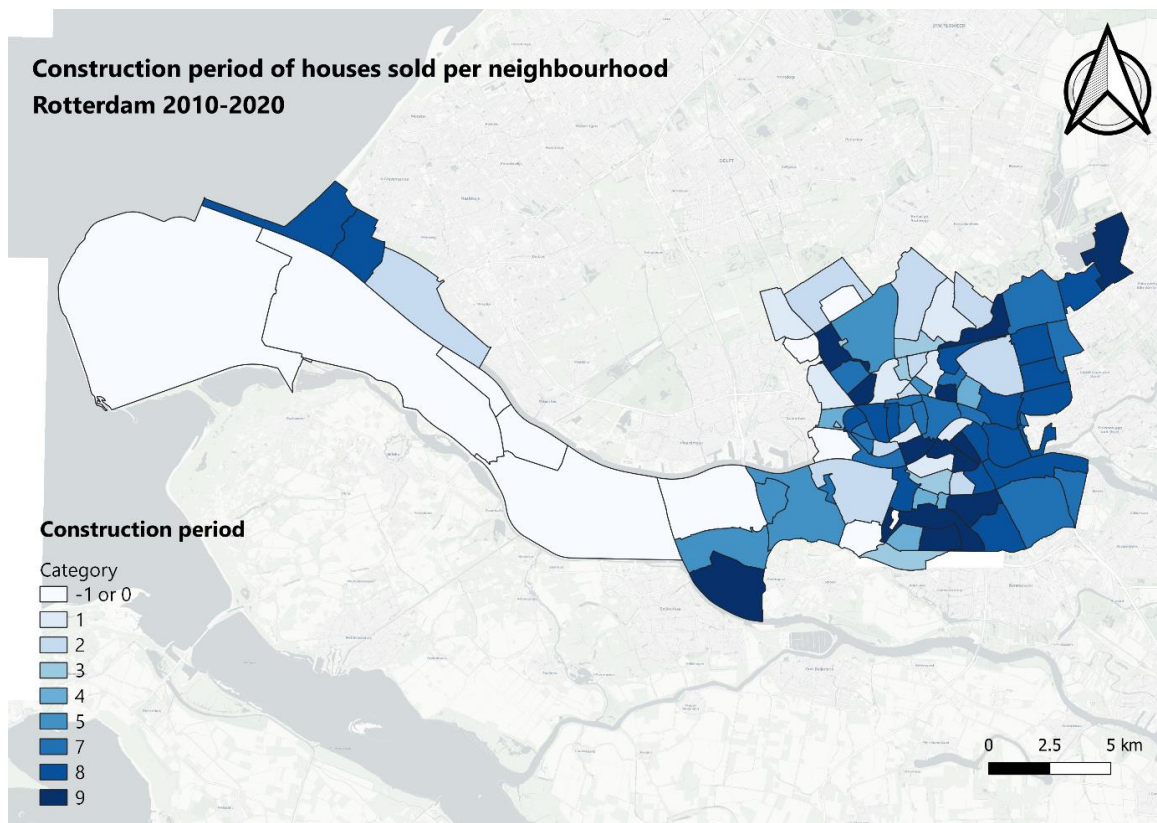


Figure 38: Construction period of houses sold per neighbourhood. Source data: NVM (2020)

```
. reghdfc logprice m2 kwaliteit qualityPC6 mean_quality6pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis2 i.s
> oortapp2 ib8.soortapp2 i.parkeer2 i.tuinlig2, absorb(x_buurtnaam year)vce(robust)
(dropped 1 singleton observations)
(MWFE estimator converged in 5 iterations)
note: 7.soortapp2 omitted because of collinearity
```

```
HDFE Linear regression      Number of obs   =    42,695
Absorbing 2 HDFE groups    F(   38, 42567) =   1605.76
                           Prob > F           =    0.0000
                           R-squared            =    0.8494
                           Adj R-squared       =    0.8490
                           Within R-sq.       =    0.6895
                           Root MSE        =    0.2309
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
m2	.0065047	.0000674	96.45	0.000	.0063725	.0066369
kwaliteit	.1197212	.004292	27.89	0.000	.1113088	.1281336
qualityPC6	.0015121	.0001035	14.61	0.000	.0013092	.0017149
mean_quality6pos	-.0106074	.0067496	-1.57	0.116	-.0238367	.0026219
ligcentr						
1	-.1818913	.063833	-2.85	0.004	-.3070052	-.0567774
2	-.1847322	.0637908	-2.90	0.004	-.3097633	-.059701
3	-.144328	.0639457	-2.26	0.024	-.2696629	-.0189932
ligmooi						
1	.034437	.0197931	1.74	0.082	-.0043579	.073232
2	.1079757	.0041618	25.94	0.000	.0998186	.1161328
3	.035175	.0059948	5.87	0.000	.023425	.0469249
4	.0380833	.0032077	11.87	0.000	.0317961	.0443705
construction_period						
1	-.1394737	.0720461	-1.94	0.053	-.2806855	.0017381
2	-.1286894	.0718713	-1.79	0.073	-.2695586	.0121798
3	-.1495423	.0718849	-2.08	0.038	-.2904382	-.0086465
4	-.1913509	.0718587	-2.66	0.008	-.3321954	-.0505064
5	-.2505094	.0719163	-3.48	0.000	-.3914667	-.1095521
6	-.2103149	.071877	-2.93	0.003	-.3511953	-.0694346
7	-.1960498	.0718798	-2.73	0.006	-.3369356	-.055164
8	-.0504743	.0717887	-0.70	0.482	-.1911816	.0902331
9	.0034322	.0717869	0.05	0.962	-.1372715	.1441359
soorthuis2						
2	.2174758	.0205266	10.59	0.000	.1772433	.2577084
3	.1926892	.0969002	1.99	0.047	.0027629	.3826156
4	-.3566898	.4387618	-0.81	0.416	-1.216671	.503292
5	.3469367	.018828	18.43	0.000	.3100335	.3838399
6	.2839085	.1248292	2.27	0.023	.0392408	.5285761
7	.3339308	.0201252	16.59	0.000	.294485	.3733766
8	.2941989	.1062626	2.77	0.006	.0859221	.5024757
9	.5882066	.0307927	19.10	0.000	.5278524	.6485608
10	.460072	.0239058	19.25	0.000	.4132162	.5069279
11	.4221357	.1148458	3.68	0.000	.1970356	.6472357
soortapp2						
1	-.0834776	.0142499	-5.86	0.000	-.1114076	-.0555476
2	-.1070942	.0145305	-7.37	0.000	-.1355742	-.0786142
3	-.1106756	.014843	-7.46	0.000	-.1397682	-.081583
4	-.1203809	.0145768	-8.26	0.000	-.1489517	-.09181
5	-.1270825	.0149575	-8.50	0.000	-.1563995	-.0977655
6	.1193697	.0167476	7.13	0.000	.0865442	.1521953
7	0	(omitted)				
1.parkeer2	.1106362	.0037287	29.67	0.000	.1033278	.1179446
1.tuinlig2	.0581699	.003914	14.86	0.000	.0504983	.0658415
_cons	11.66011	.0980185	118.96	0.000	11.46799	11.85223

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs
x_buurtnaam	80	0	80
year	11	1	10

```
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.
```

Table 16: Regression output full period without log 6-digit postal code

```
. reghdfe logprice m2 kwaliteit qualityPC5 mean_quality5pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis2 i.s
> oortapp2 ib8.soortapp2 i.parkeer2 i.tuinlig2, absorb(x_buurtnaam year)vce(robust)
(dropped 1 singleton observations)
(MWFE estimator converged in 5 iterations)
note: 7.soortapp2 omitted because of collinearity
```

```
HDFE Linear regression      Number of obs   =    42,695
Absorbing 2 HDFE groups    F(   38, 42567) =   1589.07
                           Prob > F           =    0.0000
                           R-squared           =    0.8489
                           Adj R-squared      =    0.8485
                           Within R-sq.      =    0.6885
                           Root MSE       =    0.2313
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
m2	.0065252	.0000677	96.44	0.000	.0063926	.0066578
kwaliteit	.1619142	.0031857	50.83	0.000	.1556701	.1681583
qualityPC5	.0000875	.000017	5.15	0.000	.0000542	.0001208
mean_quality5pos	-.0216096	.0055478	-3.90	0.000	-.0324833	-.0107359
ligcentr						
1	-.1800047	.0640497	-2.81	0.005	-.3055433	-.0544662
2	-.1829299	.0640087	-2.86	0.004	-.3083882	-.0574716
3	-.1422412	.0641615	-2.22	0.027	-.2679989	-.0164835
ligmooi						
1	.0361072	.0198086	1.82	0.068	-.002718	.0749323
2	.1083047	.0041694	25.98	0.000	.1001326	.1164769
3	.0359888	.0059968	6.00	0.000	.0242348	.0477427
4	.0386645	.0032138	12.03	0.000	.0323653	.0449636
construction_period						
1	-.1631911	.0754564	-2.16	0.031	-.3110871	-.015295
2	-.1533847	.0752886	-2.04	0.042	-.3009519	-.0058176
3	-.1761039	.0753014	-2.34	0.019	-.3236961	-.0285116
4	-.218131	.0752692	-2.90	0.004	-.3656602	-.0706019
5	-.2761478	.0753414	-3.67	0.000	-.4238184	-.1284772
6	-.2372517	.0752913	-3.15	0.002	-.3848241	-.0896792
7	-.2244672	.0752986	-2.98	0.003	-.372054	-.0768805
8	-.0764322	.0752099	-1.02	0.310	-.2238451	.0709806
9	-.0197595	.0752135	-0.26	0.793	-.1671794	.1276604
soorthuis2						
2	.2643735	.01874	14.11	0.000	.2276427	.3011044
3	.2412597	.0971923	2.48	0.013	.0507609	.4317585
4	-.3042807	.4402611	-0.69	0.489	-1.167201	.5586398
5	.394177	.0169176	23.30	0.000	.3610182	.4273359
6	.3341175	.1252567	2.67	0.008	.0886118	.5796232
7	.380517	.0185111	20.56	0.000	.3442349	.4167992
8	.3371382	.1064	3.17	0.002	.1285922	.5456842
9	.6356441	.0296632	21.43	0.000	.5775036	.6937847
10	.5056679	.0225644	22.41	0.000	.4614413	.5498945
11	.4638352	.1149296	4.04	0.000	.238571	.6890994
soortapp2						
1	-.0820527	.0142553	-5.76	0.000	-.1099934	-.054112
2	-.1051371	.0145393	-7.23	0.000	-.1336344	-.0766399
3	-.1112127	.0148764	-7.48	0.000	-.1403707	-.0820547
4	-.1181299	.0146073	-8.09	0.000	-.1467606	-.0894992
5	-.1257082	.0150266	-8.37	0.000	-.1551607	-.0962557
6	.1511333	.0166254	9.09	0.000	.1185471	.1837195
7	0	(omitted)				
1.parkeer2	.1115857	.0037456	29.79	0.000	.1042442	.1189271
1.tuinlig2	.0586929	.003915	14.99	0.000	.0510194	.0663664
_cons	11.68825	.1005733	116.22	0.000	11.49113	11.88538

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs
x_buurtnaam	80	0	80
year	11	1	10

```
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```

Table 17: Regression output full period without log 5-digit postal code


```
. reghdfe logprice m2 kwaliteit qualityPC4 mean_quality4pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis2 i.s
> oortapp2 ib8.soortapp2 i.parkeer2 i.tuinlig2, absorb(x_buurtnaam year)vce(robust)
(dropped 1 singleton observations)
(MWFE estimator converged in 5 iterations)
note: 7.soortapp2 omitted because of collinearity
```

```
HDFE Linear regression      Number of obs   =    42,695
Absorbing 2 HDFE groups    F(   38, 42567) =   1581.61
                           Prob > F           =    0.0000
                           R-squared           =    0.8490
                           Adj R-squared      =    0.8485
                           Within R-sq.      =    0.6886
                           Root MSE       =    0.2312
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
m2	.0065248	.0000676	96.54	0.000	.0063923	.0066573
kwaliteit	.1623323	.0031914	50.87	0.000	.1560771	.1685875
qualityPC4	.0001524	.000034	4.49	0.000	.0000858	.000219
mean_quality4pos	-.049484	.0075632	-6.54	0.000	-.0643079	-.03466
ligcentr						
1	-.1818105	.0641301	-2.84	0.005	-.3075068	-.0561143
2	-.1845798	.0640893	-2.88	0.004	-.3101961	-.0589636
3	-.1443483	.0642414	-2.25	0.025	-.2702627	-.0184338
ligmooi						
1	.0371085	.0197902	1.88	0.061	-.0016808	.0758977
2	.1085793	.0041705	26.04	0.000	.100405	.1167536
3	.0360543	.0060009	6.01	0.000	.0242923	.0478162
4	.0386924	.0032148	12.04	0.000	.0323913	.0449934
construction_period						
1	-.159296	.0749102	-2.13	0.033	-.3061214	-.0124705
2	-.1490442	.0747384	-1.99	0.046	-.2955329	-.0025556
3	-.1715372	.0747524	-2.29	0.022	-.3180534	-.0250211
4	-.2137605	.0747215	-2.86	0.004	-.3602161	-.0673049
5	-.2724078	.0747914	-3.64	0.000	-.4190005	-.1258152
6	-.2334853	.0747459	-3.12	0.002	-.3799887	-.0869819
7	-.2204468	.0747501	-2.95	0.003	-.3669585	-.0739352
8	-.0717904	.0746584	-0.96	0.336	-.2181223	.0745416
9	-.0151585	.0746652	-0.20	0.839	-.1615038	.1311869
soorthuis2						
2	.2630921	.0187637	14.02	0.000	.2263149	.2998693
3	.2390351	.0973468	2.46	0.014	.0482335	.4298367
4	-.3080322	.4428216	-0.70	0.487	-1.175971	.559907
5	.3940241	.0169635	23.23	0.000	.3607753	.427273
6	.3325581	.1235944	2.69	0.007	.0903106	.5748055
7	.380312	.0185305	20.52	0.000	.3439918	.4166323
8	.3364511	.1061679	3.17	0.002	.12836	.5445422
9	.6349861	.0297608	21.34	0.000	.5766544	.6933179
10	.5059242	.0226162	22.37	0.000	.4615961	.5502524
11	.466109	.1149641	4.05	0.000	.2407771	.6914409
soortapp2						
1	-.0817965	.0142844	-5.73	0.000	-.1097941	-.0537989
2	-.1046564	.0145706	-7.18	0.000	-.133215	-.0760978
3	-.1110635	.0149167	-7.45	0.000	-.1403005	-.0818264
4	-.1174173	.0146394	-8.02	0.000	-.1461107	-.0887238
5	-.1252363	.0150576	-8.32	0.000	-.1547494	-.0957232
6	.1527051	.0165538	9.22	0.000	.1202593	.1851508
7	0	(omitted)				
1.parkeer2	.1113952	.0037454	29.74	0.000	.1040542	.1187363
1.tuinlig2	.0589161	.0039117	15.06	0.000	.0512491	.0665832
_cons	11.69227	.1002286	116.66	0.000	11.49582	11.88872

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs
x_buurtnaam	80	0	80
year	11	1	10

```
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```

Table 18: Regression output full period without log 4-digit postal code

```
. reghdfc logprice m2 kwaliteit qualityPC3 mean_quality3pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis2 i.s
> oortapp2 ib8.soortapp2 i.parkeer2 i.tuinlig2, absorb(x_buurtnaam year)vce(robust)
(dropped 1 singleton observations)
(MWFE estimator converged in 5 iterations)
note: 7.soortapp2 omitted because of collinearity
```

```
HDFE Linear regression      Number of obs   =    42,695
Absorbing 2 HDFE groups    F( 38, 42567) =   1578.91
                           Prob > F           =    0.0000
                           R-squared           =    0.8490
                           Adj R-squared      =    0.8486
                           Within R-sq.      =    0.6887
                           Root MSE       =    0.2312
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
m2	.0065197	.0000676	96.45	0.000	.0063872	.0066522
kwaliteit	.1630429	.0031863	51.17	0.000	.1567977	.169288
qualityPC3	.0004633	.0002146	2.16	0.031	.0000427	.0008838
mean_quality3pos	.0258735	.0091145	2.84	0.005	.0080089	.043738
ligcentr						
1	-.1824544	.064089	-2.85	0.004	-.3080701	-.0568387
2	-.1854651	.0640483	-2.90	0.004	-.3110011	-.0599292
3	-.1442097	.0642021	-2.25	0.025	-.2700471	-.0183722
ligmooi						
1	.035749	.0197891	1.81	0.071	-.0030379	.074536
2	.1085882	.0041732	26.02	0.000	.1004087	.1167676
3	.0354047	.006002	5.90	0.000	.0236407	.0471688
4	.0389015	.0032112	12.11	0.000	.0326074	.0451955
construction_period						
1	-.161319	.0747304	-2.16	0.031	-.307792	-.014846
2	-.1501593	.0745543	-2.01	0.044	-.2962872	-.0040315
3	-.1725985	.0745667	-2.31	0.021	-.3187507	-.0264464
4	-.2155938	.0745367	-2.89	0.004	-.3616873	-.0695003
5	-.2728993	.0746104	-3.66	0.000	-.4191372	-.1266614
6	-.2354494	.0745627	-3.16	0.002	-.3815937	-.089305
7	-.2210794	.0745623	-2.97	0.003	-.367223	-.0749357
8	-.0726174	.0744784	-0.98	0.330	-.2185966	.0733618
9	-.0170299	.0744833	-0.23	0.819	-.1630186	.1289587
soorthuis2						
2	.2684826	.0187311	14.33	0.000	.2317693	.3051959
3	.2446383	.0978667	2.50	0.012	.0528176	.4364589
4	-.3049851	.4380364	-0.70	0.486	-1.163545	.5535749
5	.3973457	.0169126	23.49	0.000	.3641966	.4304947
6	.331882	.123967	2.68	0.007	.0889042	.5748598
7	.382231	.0185009	20.66	0.000	.3459688	.4184931
8	.3381047	.1055456	3.20	0.001	.1312333	.5449761
9	.6363567	.0295993	21.50	0.000	.5783416	.6943719
10	.5090893	.0225334	22.59	0.000	.4649234	.5532552
11	.4689049	.1149283	4.08	0.000	.2436432	.6941666
soortapp2						
1	-.0819863	.0142544	-5.75	0.000	-.1099252	-.0540474
2	-.1045228	.0145397	-7.19	0.000	-.1330209	-.0760247
3	-.110855	.0148775	-7.45	0.000	-.1400152	-.0816948
4	-.1175513	.0146077	-8.05	0.000	-.1461826	-.0889199
5	-.1251424	.0150261	-8.33	0.000	-.1545938	-.095691
6	.1501468	.0165105	9.09	0.000	.1177858	.1825078
7	0	(omitted)				
1.parkeer2	.1118202	.003748	29.83	0.000	.104474	.1191664
1.tuinlig2	.0590755	.00391	15.11	0.000	.0514117	.0667392
_cons	11.65581	.1002513	116.27	0.000	11.45932	11.8523

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs
x_buurtnaam	80	0	80
year	11	1	10

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Table 19: Regression output full period without log 3-digit postal code

```
. reghdfc logprice logm2 kwaliteit qualityPC6 mean_quality6pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis2
> i.soortapp2 ib8.soortapp2 i.parkeer2 i.tuinlig2, absorb(x_buurtnaam year)vce(robust)
(dropped 1 singleton observations)
(MWFE estimator converged in 5 iterations)
note: 7.soortapp2 omitted because of collinearity
```

```
HDFE Linear regression      Number of obs   =    42,695
Absorbing 2 HDFE groups    F(   38, 42567) =   2448.31
                           Prob > F           =    0.0000
                           R-squared            =    0.8619
                           Adj R-squared       =    0.8615
                           Within R-sq.       =    0.7153
                           Root MSE        =    0.2211
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.796604	.0050915	156.46	0.000	.7866246	.8065834
kwaliteit	.112021	.0041823	26.78	0.000	.1038235	.1202185
qualityPC6	.0012712	.0001004	12.66	0.000	.0010744	.0014681
mean_quality6pos	-.0020493	.006507	-0.31	0.753	-.0148032	.0107046
ligcentr						
1	-.1507669	.0564507	-2.67	0.008	-.2614113	-.0401224
2	-.1553231	.0563949	-2.75	0.006	-.2658583	-.0447879
3	-.1138281	.0565841	-2.01	0.044	-.224734	-.0029222
ligmooi						
1	.0466681	.0189999	2.46	0.014	.0094279	.0839083
2	.1067667	.003957	26.98	0.000	.0990108	.1145225
3	.0356291	.0057542	6.19	0.000	.0243509	.0469074
4	.0353176	.0030753	11.48	0.000	.0292899	.0413454
construction_period						
1	-.135187	.0621678	-2.17	0.030	-.2570372	-.0133369
2	-.1303775	.0620242	-2.10	0.036	-.2519461	-.0088088
3	-.1510564	.0620621	-2.43	0.015	-.2726994	-.0294134
4	-.1755881	.0620377	-2.83	0.005	-.2971832	-.053993
5	-.2350592	.0620971	-3.79	0.000	-.3567706	-.1133477
6	-.2080254	.0620568	-3.35	0.001	-.329658	-.0863927
7	-.1996861	.0620589	-3.22	0.001	-.3213228	-.0780495
8	-.0771845	.0619514	-1.25	0.213	-.1986106	.0442415
9	-.0284401	.0619473	-0.46	0.646	-.1498579	.0929777
soorthuis2						
2	.2169699	.0204343	10.62	0.000	.1769183	.2570216
3	.2229814	.082784	2.69	0.007	.060723	.3852397
4	-.1823062	.3645667	-0.50	0.617	-.8968641	.5322518
5	.3446005	.0186605	18.47	0.000	.3080255	.3811755
6	.3996788	.0982035	4.07	0.000	.207198	.5921595
7	.4336253	.0195538	22.18	0.000	.3952995	.4719512
8	.5672511	.0720222	7.88	0.000	.4260861	.7084161
9	.6227079	.0299077	20.82	0.000	.5640881	.6813276
10	.6805088	.0220742	30.83	0.000	.6372429	.7237748
11	.7311271	.0892372	8.19	0.000	.5562204	.9060337
soortapp2						
1	-.0255004	.0139847	-1.82	0.068	-.0529107	.0019098
2	-.0822956	.0143021	-5.75	0.000	-.110328	-.0542632
3	-.1030164	.0146395	-7.04	0.000	-.1317102	-.0743227
4	-.0678607	.0143108	-4.74	0.000	-.0959102	-.0398113
5	-.0735707	.0146702	-5.01	0.000	-.1023246	-.0448168
6	.1784155	.0163559	10.91	0.000	.1463576	.2104734
7	0	(omitted)				
1.parkeer2	.1025411	.0035004	29.29	0.000	.0956803	.109402
1.tuinlig2	.047034	.0036739	12.80	0.000	.0398332	.0542348
_cons	8.644871	.0886207	97.55	0.000	8.471172	8.818569

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs
x_buurtnaam	80	0	80
year	11	1	10

end of do-file

Table 20: Regression output full period with log 6-digit postal code

```
. reghdfe logprice logm2 kwaliteit qualityPC5 mean_quality5pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis2
> i.soortapp2 ib8.soortapp2 i.parker2 i.tuinlig2, absorb(x_buurtnaam year)vce(robust)
(dropped 1 singleton observations)
(MWFE estimator converged in 5 iterations)
note: 7.soortapp2 omitted because of collinearity
```

```
HDFE Linear regression      Number of obs   =    42,695
Absorbing 2 HDFE groups    F(   38, 42567) =   2434.34
                           Prob > F           =    0.0000
                           R-squared            =    0.8616
                           Adj R-squared       =    0.8612
                           Within R-sq.       =    0.7146
                           Root MSE        =    0.2214
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.7989008	.0050885	157.00	0.000	.7889272	.8088744
kwaliteit	.148723	.0031108	47.81	0.000	.1426259	.1548202
qualityPC5	.0000816	.0000162	5.05	0.000	.0000499	.0001132
mean_quality5pos	-.0167976	.0053045	-3.17	0.002	-.0271946	-.0064007
ligcentr						
1	-.1489576	.0566282	-2.63	0.009	-.25995	-.0379652
2	-.1536159	.0565734	-2.72	0.007	-.2645009	-.042731
3	-.111951	.0567619	-1.97	0.049	-.2232053	-.0006966
ligmooi						
1	.0478229	.0189929	2.52	0.012	.0105964	.0850493
2	.1068687	.0039625	26.97	0.000	.0991021	.1146352
3	.0362882	.0057531	6.31	0.000	.025012	.0475644
4	.0357251	.0030812	11.59	0.000	.029686	.0417643
construction_period						
1	-.1548765	.0649897	-2.38	0.017	-.2822576	-.0274954
2	-.1511019	.0648497	-2.33	0.020	-.2782087	-.0239952
3	-.1731426	.0648868	-2.67	0.008	-.3003221	-.0459631
4	-.1976955	.0648533	-3.05	0.002	-.3248094	-.0705817
5	-.2560549	.0649298	-3.94	0.000	-.3833186	-.1287911
6	-.2302588	.064877	-3.55	0.000	-.3574191	-.1030986
7	-.223153	.0648835	-3.44	0.001	-.3503259	-.0959802
8	-.0986558	.0647799	-1.52	0.128	-.2256257	.0283142
9	-.0478087	.0647827	-0.74	0.461	-.174784	.0791667
soorthuis2						
2	.2538703	.0186843	13.59	0.000	.2172486	.2904919
3	.260971	.0828721	3.15	0.002	.0985401	.4234019
4	-.1399398	.365041	-0.38	0.701	-.8554275	.5755478
5	.3816499	.01678	22.74	0.000	.3487608	.4145389
6	.4395529	.0987624	4.45	0.000	.2459766	.6331292
7	.4703956	.0178898	26.29	0.000	.4353313	.50546
8	.601979	.0717258	8.39	0.000	.461395	.742563
9	.6596097	.0287363	22.95	0.000	.6032859	.7159335
10	.7168327	.0206166	34.77	0.000	.6764238	.7572415
11	.7639689	.0889737	8.59	0.000	.5895787	.9383592
soortapp2						
1	-.0238646	.014012	-1.70	0.089	-.0513284	.0035991
2	-.0803115	.0143351	-5.60	0.000	-.1084085	-.0522144
3	-.1031852	.0146955	-7.02	0.000	-.1319888	-.0743817
4	-.0655027	.0143613	-4.56	0.000	-.0936513	-.0373542
5	-.0718406	.0147581	-4.87	0.000	-.1007668	-.0429143
6	.2074009	.0162824	12.74	0.000	.1754871	.2393148
7	0	(omitted)				
1.parker2	.1032627	.0035117	29.40	0.000	.0963796	.1101458
1.tuinlig2	.0474415	.0036722	12.92	0.000	.0402439	.0546392
_cons	8.660077	.0905667	95.62	0.000	8.482564	8.837589

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs
x_buurtnaam	80	0	80
year	11	1	10

```
.
end of do-file
```

Table 21: Regression output full period with log 5-digit postal code

```
. reghdfc logprice logm2 kwaliteit qualityPC4 mean_quality4pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis2
> i.soortapp2 ib8.soortapp2 i.parkeer2 i.tuinlig2, absorb(x_buurtnaam year)vce(robust)
(dropped 1 singleton observations)
(MWFE estimator converged in 5 iterations)
note: 7.soortapp2 omitted because of collinearity
```

```
HDFE Linear regression      Number of obs   =    42,695
Absorbing 2 HDFE groups    F(   38, 42567) =   2437.84
                           Prob > F           =    0.0000
                           R-squared            =    0.8616
                           Adj R-squared       =    0.8612
                           Within R-sq.       =    0.7147
                           Root MSE        =    0.2213
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.79897	.0050904	156.96	0.000	.7889928	.8089473
kwaliteit	.1490317	.0031196	47.77	0.000	.1429172	.1551462
qualityPC4	.0001545	.0000325	4.76	0.000	.0000909	.0002182
mean_quality4pos	-.0477965	.0072462	-6.60	0.000	-.0619993	-.0335938
ligcentr						
1	-.1504156	.056645	-2.66	0.008	-.261441	-.0393902
2	-.1548935	.0565904	-2.74	0.006	-.2658117	-.0439753
3	-.1137234	.0567775	-2.00	0.045	-.2250084	-.0024383
ligmooi						
1	.0490549	.01898	2.58	0.010	.0118538	.086256
2	.1071677	.0039636	27.04	0.000	.0993989	.1149364
3	.0364194	.005756	6.33	0.000	.0251375	.0477013
4	.0358052	.0030816	11.62	0.000	.0297653	.0418452
construction_period						
1	-.1510902	.0645549	-2.34	0.019	-.2776191	-.0245613
2	-.1468964	.0644131	-2.28	0.023	-.2731473	-.0206455
3	-.1688457	.064451	-2.62	0.009	-.2951709	-.0425205
4	-.1934699	.0644189	-3.00	0.003	-.3197322	-.0672077
5	-.252648	.0644936	-3.92	0.000	-.3790567	-.1262394
6	-.2265887	.0644453	-3.52	0.000	-.3529028	-.1002747
7	-.2193636	.0644482	-3.40	0.001	-.3456834	-.0930438
8	-.0944076	.0643417	-1.47	0.142	-.2205185	.0317034
9	-.0433141	.0643478	-0.67	0.501	-.1694371	.0828088
soorthuis2						
2	.2517116	.0187129	13.45	0.000	.215034	.2883893
3	.2588426	.0830255	3.12	0.002	.096111	.4215743
4	-.1438521	.3680165	-0.39	0.696	-.8651716	.5774674
5	.3807404	.0168328	22.62	0.000	.3477477	.4137331
6	.4379882	.0968273	4.52	0.000	.2482047	.6277717
7	.4697884	.0179162	26.22	0.000	.4346722	.5049046
8	.5997771	.0718919	8.34	0.000	.4588675	.7406867
9	.6585824	.0288228	22.85	0.000	.6020892	.7150756
10	.7163382	.0206575	34.68	0.000	.6758492	.7568273
11	.7652152	.0888312	8.61	0.000	.5911042	.9393262
soortapp2						
1	-.0235879	.0140405	-1.68	0.093	-.0511076	.0039318
2	-.0798267	.0143664	-5.56	0.000	-.1079851	-.0516683
3	-.103053	.0147358	-6.99	0.000	-.1319355	-.0741705
4	-.0647586	.0143937	-4.50	0.000	-.0929705	-.0365466
5	-.0712932	.01479	-4.82	0.000	-.1002819	-.0423045
6	.2074366	.0161955	12.81	0.000	.175693	.2391802
7	0	(omitted)				
1.parkeer2	.1030428	.0035116	29.34	0.000	.09616	.1099257
1.tuinlig2	.0476175	.0036679	12.98	0.000	.0404283	.0548068
_cons	8.663304	.0903125	95.93	0.000	8.48629	8.840318

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs
x_buurtnaam	80	0	80
year	11	1	10

end of do-file

Table 22: Regression output full period with log 4-digit postal code

```
. reghdfe logprice logm2 kwaliteit qualityPC3 mean_quality3pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis2
> i.soortapp2 ib8.soortapp2 i.parker2 i.tuinlig2, absorb(x_buurtnaam year)vce(robust)
(dropped 1 singleton observations)
(MWFE_estimator converged in 5 iterations)
note: 7.soortapp2 omitted because of collinearity
```

```
HDFE Linear regression      Number of obs   =    42,695
Absorbing 2 HDFE groups    F( 38, 42567) =   2431.96
                           Prob > F             =    0.0000
                           R-squared              =    0.8617
                           Adj R-squared         =    0.8613
                           Within R-sq.         =    0.7148
                           Root MSE          =    0.2213
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.7985989	.0050977	156.66	0.000	.7886074	.8085905
kwaliteit	.1497379	.0031134	48.09	0.000	.1436355	.1558403
qualityPC3	.0003639	.0002054	1.77	0.077	-.0000388	.0007665
mean_quality3pos	.0323644	.0085888	3.77	0.000	.0155301	.0491986
ligcentr						
1	-.1511976	.0565268	-2.67	0.007	-.2619912	-.0404039
2	-.1559262	.0564721	-2.76	0.006	-.2666127	-.0452398
3	-.1137421	.0566609	-2.01	0.045	-.2247985	-.0026857
ligmooi						
1	.0476757	.0189747	2.51	0.012	.010485	.0848664
2	.1071928	.0039658	27.03	0.000	.0994198	.1149658
3	.0357593	.0057562	6.21	0.000	.024477	.0470415
4	.0360397	.0030767	11.71	0.000	.0300094	.04207
construction_period						
1	-.1527622	.0641451	-2.38	0.017	-.2784879	-.0270365
2	-.1476106	.0639975	-2.31	0.021	-.273047	-.0221743
3	-.1695262	.0640337	-2.65	0.008	-.2950335	-.0440189
4	-.1948936	.0640027	-3.05	0.002	-.3203401	-.0694472
5	-.252703	.0640819	-3.94	0.000	-.3783048	-.1271011
6	-.2280695	.0640316	-3.56	0.000	-.3535728	-.1025663
7	-.2195326	.0640289	-3.43	0.001	-.3450306	-.0940346
8	-.0948182	.0639302	-1.48	0.138	-.2201226	.0304863
9	-.0447926	.0639346	-0.70	0.484	-.1701056	.0805204
soorthuis2						
2	.2568426	.0186832	13.75	0.000	.2202231	.2934621
3	.2645581	.0837643	3.16	0.002	.1003785	.4287378
4	-.1411787	.363393	-0.39	0.698	-.8534362	.5710788
5	.3839618	.0167829	22.88	0.000	.351067	.4168566
6	.4367138	.0974339	4.48	0.000	.2457415	.6276861
7	.4715228	.0178869	26.36	0.000	.4364641	.5065815
8	.6004584	.0713081	8.42	0.000	.4606931	.7402238
9	.6596033	.0286839	23.00	0.000	.6033823	.7158244
10	.7191025	.0205962	34.91	0.000	.6787336	.7594713
11	.7676427	.0886906	8.66	0.000	.5938073	.941478
soortapp2						
1	-.0237192	.0140117	-1.69	0.090	-.0511825	.003744
2	-.0795939	.0143365	-5.55	0.000	-.1076937	-.051494
3	-.1028134	.0146972	-7.00	0.000	-.1316202	-.0740065
4	-.0648028	.0143632	-4.51	0.000	-.092955	-.0366507
5	-.0710846	.0147597	-4.82	0.000	-.100014	-.0421553
6	.2045696	.0161493	12.67	0.000	.1729166	.2362226
7	0	(omitted)				
1.parker2	.1034307	.0035145	29.43	0.000	.0965423	.1103191
1.tuinlig2	.0477783	.0036669	13.03	0.000	.0405911	.0549655
_cons	8.630394	.0899097	95.99	0.000	8.45417	8.806619

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs
x_buurtnaam	80	0	80
year	11	1	10

```
.
end of do-file
```

Table 23: Regression output full period with log 3-digit postal code

```
. reghdfe logprice logm2 kwaliteit qualityPC6 mean_quality6pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis2
> i.soortapp2 ib8.soortapp2 i.parkeer2 i.tuinlig2, absorb(x_buurtnaam year)vce(robust)
(MWFE estimator converged in 5 iterations)
note: 7.soortapp2 omitted because of collinearity
```

```
HDFE Linear regression      Number of obs   =    20,837
Absorbing 2 HDFE groups    F(   38, 20715) =   1451.92
                           Prob > F           =    0.0000
                           R-squared            =    0.8021
                           Adj R-squared       =    0.8009
                           Within R-sq.       =    0.6829
                           Root MSE        =    0.2452
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.8287278	.0079884	103.74	0.000	.8130699	.8443858
kwaliteit	.1175619	.0063693	18.46	0.000	.1050775	.1300463
qualityPC6	.0009863	.0001511	6.53	0.000	.0006902	.0012824
mean_quality6pos	.0255948	.0108385	2.36	0.018	.0043505	.0468391
ligcentr						
1	-.1376399	.0519247	-2.65	0.008	-.2394164	-.0358634
2	-.1489055	.0518801	-2.87	0.004	-.2505945	-.0472164
3	-.0967491	.0522358	-1.85	0.064	-.1991354	.0056371
ligmooi						
1	.0587516	.0407729	1.44	0.150	-.0211664	.1386697
2	.1058491	.0064223	16.48	0.000	.093261	.1184372
3	.0307056	.010352	2.97	0.003	.0104149	.0509962
4	.0315722	.0049238	6.41	0.000	.0219211	.0412233
construction_period						
1	.1283487	.0146864	8.74	0.000	.0995623	.1571352
2	.1319304	.0120301	10.97	0.000	.1083505	.1555103
3	.120257	.0116211	10.35	0.000	.0974787	.1430353
4	.1151479	.0116863	9.85	0.000	.0922418	.138054
5	.0345233	.0101507	3.40	0.001	.0146273	.0544194
6	.0723296	.0109643	6.60	0.000	.0508386	.0938205
7	.0873437	.011437	7.64	0.000	.0649262	.1097611
8	.2238054	.0105928	21.13	0.000	.2030426	.2445681
9	.2601246	.0131705	19.75	0.000	.2343094	.2859399
soorthuis2						
2	.246934	.0380713	6.49	0.000	.1723113	.3215567
3	.3813738	.0941676	4.05	0.000	.1967979	.5659496
4	.6981883	.0375526	18.59	0.000	.6245823	.7717943
5	.376164	.0358715	10.49	0.000	.305853	.446475
6	.3526868	.2252639	1.57	0.117	-.0888481	.7942216
7	.4739455	.0371302	12.76	0.000	.4011674	.5467236
8	.5477573	.1012962	5.41	0.000	.3492089	.7463058
9	.6326307	.0505812	12.51	0.000	.5334875	.7317739
10	.7414656	.0405234	18.30	0.000	.6620365	.8208947
11	.9520265	.1165063	8.17	0.000	.7236649	1.180388
soortapp2						
1	.0122763	.0271558	0.45	0.651	-.0409511	.0655037
2	-.0568566	.0280633	-2.03	0.043	-.1118627	-.0018504
3	-.0726473	.0282062	-2.58	0.010	-.1279337	-.017361
4	-.0546394	.0280994	-1.94	0.052	-.1097163	.0004376
5	-.0563329	.0286141	-1.97	0.049	-.1124188	-.0002471
6	.1201912	.0300464	4.00	0.000	.0612979	.1790845
7	0	(omitted)				
1.parkeer2	.1159152	.0058237	19.90	0.000	.1045003	.12733
1.tuinlig2	.0538001	.005645	9.53	0.000	.0427355	.0648647
_cons	7.996924	.0721235	110.88	0.000	7.855556	8.138292

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs
x_buurtnaam	79	0	79
year	6	1	5

```
.
end of do-file
```

Table 24: Regression output period 2010-2015 with log 6-digit postal code

```
. reghdfe logprice logm2 kwaliteit qualityPC5 mean_quality5pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis2
> i.soortapp2 ib8.soortapp2 i.parker2 i.tuinlig2, absorb(x_buurtnaam year)vce(robust)
(MWFE_estimator converged in 5 iterations)
note: 7.soortapp2 omitted because of collinearity
```

HDFE Linear regression	Number of obs	=	20,837
Absorbing 2 HDFE groups	F(38, 20715)	=	1447.32
	Prob > F	=	0.0000
	R-squared	=	0.8018
	Adj R-squared	=	0.8007
	Within R-sq.	=	0.6824
	Root MSE	=	0.2453

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.8298141	.0079896	103.86	0.000	.8141537	.8454744
kwaliteit	.1520141	.0047061	32.30	0.000	.1427897	.1612385
qualityPC5	.0000892	.0000252	3.54	0.000	.0000398	.0001386
mean_quality5pos	-.0078346	.0086359	-0.91	0.364	-.0247616	.0090924
ligcentr						
1	-.1349146	.052201	-2.58	0.010	-.2372328	-.0325965
2	-.1460595	.0521533	-2.80	0.005	-.2482841	-.043835
3	-.0945616	.0525056	-1.80	0.072	-.1974766	.0083535
ligmooi						
1	.0594041	.0407479	1.46	0.145	-.020465	.1392732
2	.1050001	.0064144	16.37	0.000	.0924275	.1175728
3	.0306353	.0103553	2.96	0.003	.010338	.0509325
4	.0318041	.0049249	6.46	0.000	.0221508	.0414574
construction_period						
1	.1278719	.0146978	8.70	0.000	.0990632	.1566807
2	.1298468	.012105	10.73	0.000	.10612	.1535736
3	.1176202	.0116379	10.11	0.000	.094809	.1404314
4	.1131416	.0116917	9.68	0.000	.090225	.1360582
5	.0344139	.0101471	3.39	0.001	.0145247	.0543031
6	.0705879	.0110012	6.42	0.000	.0490247	.0921511
7	.0855417	.0114745	7.45	0.000	.0630508	.1080326
8	.2227135	.0106166	20.98	0.000	.2019041	.2435229
9	.2605068	.0132876	19.61	0.000	.234462	.2865516
soorthuis2						
2	.267014	.034542	7.73	0.000	.1993089	.334719
3	.3979036	.0930911	4.27	0.000	.2154378	.5803694
4	.7229102	.0336736	21.47	0.000	.6569074	.7889131
5	.3956715	.0321651	12.30	0.000	.3326255	.4587175
6	.3762648	.2262494	1.66	0.096	-.0672018	.8197314
7	.4936595	.0337817	14.61	0.000	.4274446	.5598743
8	.5672272	.1003746	5.65	0.000	.3704852	.7639692
9	.6503649	.0480154	13.54	0.000	.556251	.7444788
10	.7605269	.037515	20.27	0.000	.6869945	.8340593
11	.9676507	.1158157	8.36	0.000	.7406428	1.194659
soortapp2						
1	.0141133	.027297	0.52	0.605	-.039391	.0676176
2	-.0549394	.0282014	-1.95	0.051	-.1102163	.0003375
3	-.0717558	.0283567	-2.53	0.011	-.1273371	-.0161746
4	-.052354	.0282592	-1.85	0.064	-.1077441	.0030362
5	-.0540818	.0288891	-1.87	0.061	-.1107067	.0025432
6	.1486533	.0300675	4.94	0.000	.0897187	.207588
7	0 (omitted)					
1.parker2	.1165232	.0058486	19.92	0.000	.1050594	.127987
1.tuinlig2	.0536545	.0056373	9.52	0.000	.042605	.064704
_cons	7.999725	.0711877	112.38	0.000	7.860192	8.139259

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs
x_buurtnaam	79	0	79
year	6	1	5

.
end of do-file

Table 25: Regression output period 2010-2015 with log 5-digit postal code


```
. reghdfe logprice logm2 kwaliteit qualityPC4 mean_quality4pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis2
> i.soortapp2 ib8.soortapp2 i.parker2 i.tuinlig2, absorb(x_buurtnaam year)vce(robust)
(MWFE estimator converged in 5 iterations)
note: 7.soortapp2 omitted because of collinearity
```

```
HDFE Linear regression      Number of obs   =    20,837
Absorbing 2 HDFE groups    F(   38, 20715) =   1446.74
                           Prob > F           =    0.0000
                           R-squared           =    0.8020
                           Adj R-squared      =    0.8009
                           Within R-sq.     =    0.6827
                           Root MSE       =    0.2452
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.8298417	.0079962	103.78	0.000	.8141685	.8455149
kwaliteit	.1516875	.0047342	32.04	0.000	.1424081	.160967
qualityPC4	.0002637	.0000518	5.09	0.000	.0001622	.0003652
mean_quality4pos	-.068931	.0123637	-5.58	0.000	-.0931649	-.0446971
ligcentr						
1	-.135243	.0525945	-2.57	0.010	-.2383323	-.0321537
2	-.1459226	.0525505	-2.78	0.005	-.2489257	-.0429196
3	-.0958596	.0529	-1.81	0.070	-.1995478	.0078286
ligmooi						
1	.0591603	.0406761	1.45	0.146	-.020568	.1388887
2	.1055028	.006425	16.42	0.000	.0929092	.1180964
3	.0302617	.0103662	2.92	0.004	.0099432	.0505803
4	.0319268	.0049275	6.48	0.000	.0222684	.0415851
construction_period						
1	.1226906	.0146828	8.36	0.000	.0939112	.15147
2	.1241528	.0120729	10.28	0.000	.1004889	.1478167
3	.1118895	.0115709	9.67	0.000	.0892097	.1345694
4	.1073634	.0115995	9.26	0.000	.0846274	.1300993
5	.0265718	.0102702	2.59	0.010	.0064415	.0467022
6	.0631252	.0109389	5.77	0.000	.0416841	.0845662
7	.0786066	.011414	6.89	0.000	.0562343	.1009789
8	.2167188	.0106177	20.41	0.000	.1959073	.2375303
9	.2556929	.0131175	19.49	0.000	.2299816	.2814041
soorthuis2						
2	.2607641	.0346621	7.52	0.000	.1928236	.3287045
3	.397117	.0949507	4.18	0.000	.2110062	.5832279
4	.7166673	.0334893	21.40	0.000	.6510257	.7823089
5	.3916585	.0323385	12.11	0.000	.3282726	.4550445
6	.3784932	.2230941	1.70	0.090	-.0587887	.8157751
7	.4915873	.0339024	14.50	0.000	.4251359	.5580386
8	.5599891	.1000631	5.60	0.000	.3638575	.7561207
9	.6465297	.048224	13.41	0.000	.5520069	.7410525
10	.7582943	.0376898	20.12	0.000	.6844193	.8321693
11	.9656047	.1154136	8.37	0.000	.739385	1.191824
soortapp2						
1	.0143775	.0274091	0.52	0.600	-.0393466	.0681016
2	-.0544653	.0283162	-1.92	0.054	-.1099673	.0010367
3	-.0713684	.0284735	-2.51	0.012	-.1271787	-.0155581
4	-.0510396	.0283733	-1.80	0.072	-.1066536	.0045743
5	-.0533042	.0289942	-1.84	0.066	-.1101351	.0035267
6	.1432899	.0300269	4.77	0.000	.0844347	.202145
7	0	(omitted)				
1.parker2	.1165123	.0058354	19.97	0.000	.1050744	.1279501
1.tuinlig2	.0538714	.0056223	9.58	0.000	.0428514	.0648915
_cons	8.00398	.071206	112.41	0.000	7.86441	8.143549

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs
x_buurtnaam	79	0	79
year	6	1	5

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Table 26: Regression output period 2010-2015 with log 4-digit postal code

```
. reghdfe logprice logm2 kwaliteit qualityPC3 mean_quality3pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis2
> i.soortapp2 ib8.soortapp2 i.parkeer2 i.tuinlig2, absorb(x_buurtnaam year)vce(robust)
(MWFE_estimator converged in 5 iterations)
note: 7.soortapp2 omitted because of collinearity
```

```
HDFE Linear regression      Number of obs   =    20,837
Absorbing 2 HDFE groups    F(   38, 20715) =   1443.90
                           Prob > F             =    0.0000
                           R-squared              =    0.8017
                           Adj R-squared         =    0.8005
                           Within R-sq.         =    0.6822
                           Root MSE           =    0.2454
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.8295589	.0080002	103.69	0.000	.8138779	.8452399
kwaliteit	.1533852	.0047123	32.55	0.000	.1441486	.1626217
qualityPC3	-.00008	.0004466	-0.18	0.858	-.0009554	.0007954
mean_quality3pos	.0066396	.0251309	0.26	0.792	-.042619	.0558982
ligcentr						
1	-.1376757	.0520086	-2.65	0.008	-.2396167	-.0357347
2	-.1488948	.0519735	-2.86	0.004	-.250767	-.0470225
3	-.0968044	.052314	-1.85	0.064	-.1993439	.0057352
ligmooi						
1	.0588984	.0407479	1.45	0.148	-.0209707	.1387674
2	.1055891	.006429	16.42	0.000	.0929878	.1181904
3	.03058	.0103472	2.96	0.003	.0102986	.0508613
4	.0320171	.0049284	6.50	0.000	.0223571	.0416772
construction_period						
1	.1267289	.0148057	8.56	0.000	.0977085	.1557494
2	.1309367	.0121607	10.77	0.000	.1071008	.1547726
3	.1183503	.0117664	10.06	0.000	.0952874	.1414133
4	.1134174	.0118157	9.60	0.000	.0902578	.1365771
5	.0338876	.0103422	3.28	0.001	.013616	.0541592
6	.0700285	.0111383	6.29	0.000	.0481966	.0918603
7	.0858852	.0116317	7.38	0.000	.0630862	.1086842
8	.2234589	.01065	20.98	0.000	.202584	.2443337
9	.2610907	.0131528	19.85	0.000	.2353101	.2868712
soorthuis2						
2	.2672113	.0345797	7.73	0.000	.1994325	.3349902
3	.3969394	.0935521	4.24	0.000	.2135699	.5803089
4	.7162091	.0337064	21.25	0.000	.6501419	.7822762
5	.3963347	.0322218	12.30	0.000	.3331774	.459492
6	.3736938	.2247525	1.66	0.096	-.0668387	.8142263
7	.4942611	.0338294	14.61	0.000	.4279528	.5605693
8	.5658259	.100286	5.64	0.000	.3692574	.7623944
9	.6516045	.0480052	13.57	0.000	.5575106	.7456985
10	.7628204	.0375562	20.31	0.000	.6892073	.8364335
11	.9694994	.1152706	8.41	0.000	.7435601	1.195439
soortapp2						
1	.0150675	.0273641	0.55	0.582	-.0385684	.0687034
2	-.0537848	.0282777	-1.90	0.057	-.1092113	.0016418
3	-.0705437	.0284202	-2.48	0.013	-.1262495	-.014838
4	-.0507846	.0283403	-1.79	0.073	-.1063338	.0047646
5	-.0528955	.0289476	-1.83	0.068	-.1096351	.003844
6	.1465182	.0303063	4.83	0.000	.0871155	.2059209
7	0	(omitted)				
1.parkeer2	.1169194	.0058504	19.98	0.000	.1054522	.1283865
1.tuinlig2	.0535825	.0056322	9.51	0.000	.0425429	.0646221
_cons	8.029009	.0736435	109.03	0.000	7.884662	8.173356

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs
x_buurtnaam	79	0	79
year	6	1	5

```
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```

Table 27: Regression output period 2010-2015 with log 3-digit postal code

```
. reghdfe logprice logm2 kwaliteit qualityPC6 mean_quality6pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis2
> i.soortapp2 ib8.soortapp2 i.parkeer2 i.tuinlig2, absorb(x_buurtnaam year)vce(robust)
(dropped 2 singleton observations)
(MWFE estimator converged in 4 iterations)
note: 7.soortapp2 omitted because of collinearity
```

```
HDFE Linear regression      Number of obs   =    21,857
Absorbing 2 HDFE groups    F(   37, 21738) =   1582.98
                           Prob > F           =    0.0000
                           R-squared           =    0.9010
                           Adj R-squared      =    0.9005
                           Within R-sq.      =    0.7730
                           Root MSE       =    0.1816
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.7537525	.0060202	125.20	0.000	.7419525	.7655525
kwaliteit	.1011358	.0051411	19.67	0.000	.0910588	.1112128
qualityPC6	.0013601	.0001277	10.65	0.000	.0011099	.0016103
mean_quality6pos	-.0253151	.007208	-3.51	0.000	-.0394433	-.0111868
ligcentr						
1	-.1549255	.0845177	-1.83	0.067	-.3205864	.0107354
2	-.150558	.0845408	-1.78	0.075	-.3162642	.0151482
3	-.1256391	.0846867	-1.48	0.138	-.2916313	.0403531
ligmooi						
1	.0398958	.0124897	3.19	0.001	.015415	.0643766
2	.1029889	.0045296	22.74	0.000	.0941105	.1118674
3	.0367182	.0053668	6.84	0.000	.0261989	.0472375
4	.0358322	.003342	10.72	0.000	.0292817	.0423827
construction_period						
1	-.1551647	.0709015	-2.19	0.029	-.2941368	-.0161926
2	-.1301517	.070816	-1.84	0.066	-.2689563	.0086529
3	-.1714733	.070883	-2.42	0.016	-.3104092	-.0325375
4	-.2202684	.07085	-3.11	0.002	-.3591396	-.0813972
5	-.2610718	.0707996	-3.69	0.000	-.3998442	-.1222995
6	-.2423081	.0708873	-3.42	0.001	-.3812525	-.1033638
7	-.2316379	.070791	-3.27	0.001	-.3703934	-.0928825
8	-.1288424	.0706532	-1.82	0.068	-.2673279	.009643
9	-.0658863	.0706439	-0.93	0.351	-.2043535	.072581
soorthuis2						
2	.169906	.0185828	9.14	0.000	.1334825	.2063296
3	.0357678	.1324916	0.27	0.787	-.2239253	.2954609
4	-.3982788	.3913404	-1.02	0.309	-1.165335	.3687769
5	.3093089	.0159305	19.42	0.000	.2780839	.3405339
6	.4417712	.0627721	7.04	0.000	.3187332	.5648091
7	.3914883	.0173106	22.62	0.000	.3575582	.4254183
8	.5917731	.0766173	7.72	0.000	.4415975	.7419487
9	.600257	.0346768	17.31	0.000	.5322879	.6682261
10	.6381687	.0212913	29.97	0.000	.5964361	.6799012
11	.4185064	.0813251	5.15	0.000	.2591032	.5779096
soortapp2						
1	-.0494388	.0126256	-3.92	0.000	-.0741858	-.0246917
2	-.0908927	.0124676	-7.29	0.000	-.1153301	-.0664553
3	-.1201348	.0132944	-9.04	0.000	-.1461928	-.0940767
4	-.0647276	.0126281	-5.13	0.000	-.0894795	-.0399756
5	-.0730365	.0129404	-5.64	0.000	-.0984006	-.0476725
7	0	(omitted)				
1.parkeer2	.0932489	.0040848	22.83	0.000	.0852425	.1012553
1.tuinlig2	.0387396	.0045487	8.52	0.000	.0298239	.0476553
_cons	9.072503	.1142612	79.40	0.000	8.848543	9.296464

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs
x_buurtnaam	78	0	78
year	5	1	4

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Table 28: Regression output period 2016-2020 with log 6-digit postal code

```
. reghdfe logprice logm2 kwaliteit qualityPC5 mean_quality5pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis2
> i.soortapp2 ib8.soortapp2 i.parkeer2 i.tuinlig2, absorb(x_buurtnaam year)vce(robust)
(dropped 2 singleton observations)
(MWFE estimator converged in 4 iterations)
note: 7.soortapp2 omitted because of collinearity
```

```
HDFE Linear regression      Number of obs   =    21,857
Absorbing 2 HDFE groups    F(   37, 21738) =   1571.86
                           Prob > F           =    0.0000
                           R-squared           =    0.9005
                           Adj R-squared       =    0.9000
                           Within R-sq.      =    0.7720
                           Root MSE       =    0.1821
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.7560481	.0060332	125.31	0.000	.7442225	.7678737
kwaliteit	.1358779	.0037769	35.98	0.000	.1284749	.1432808
qualityPC5	.0000183	.0000204	0.90	0.370	-.0000217	.0000582
mean_quality5pos	.0085347	.0062617	1.36	0.173	-.0037387	.0208081
ligcentr						
1	-.1561732	.0848062	-1.84	0.066	-.3223996	.0100532
2	-.1516929	.0848303	-1.79	0.074	-.3179664	.0145807
3	-.1256914	.0849771	-1.48	0.139	-.2922528	.04087
ligmooi						
1	.0404338	.0124525	3.25	0.001	.016026	.0648417
2	.103317	.0045516	22.70	0.000	.0943955	.1122385
3	.0372865	.0053853	6.92	0.000	.0267309	.0478422
4	.0358285	.0033532	10.68	0.000	.029256	.042401
construction_period						
1	-.1793056	.073579	-2.44	0.015	-.3235259	-.0350854
2	-.1535289	.0735351	-2.09	0.037	-.297663	-.0093948
3	-.1963264	.0735893	-2.67	0.008	-.3405669	-.052086
4	-.2466978	.0735382	-3.35	0.001	-.3908381	-.1025575
5	-.2853752	.0735069	-3.88	0.000	-.4294541	-.1412962
6	-.2696719	.0735701	-3.67	0.000	-.4138747	-.1254691
7	-.2601286	.0734811	-3.54	0.000	-.4041569	-.1161003
8	-.1530035	.0733621	-2.09	0.037	-.2967987	-.0092084
9	-.0896216	.0733583	-1.22	0.222	-.2334091	.054166
soorthuis2						
2	.2225576	.0176751	12.59	0.000	.1879131	.2572021
3	.0840514	.1330062	0.63	0.527	-.1766506	.3447533
4	-.3409645	.3892284	-0.88	0.381	-1.103881	.4219515
5	.3613041	.0148692	24.30	0.000	.3321594	.3904487
6	.4891952	.0627631	7.79	0.000	.3661749	.6122154
7	.4397031	.0164449	26.74	0.000	.4074699	.4719363
8	.644824	.0765915	8.42	0.000	.494699	.7949489
9	.6509719	.0342069	19.03	0.000	.5839238	.71802
10	.6887777	.0205727	33.48	0.000	.6484537	.7291017
11	.4690856	.0813502	5.77	0.000	.3096332	.628538
soortapp2						
1	-.0486357	.012616	-3.86	0.000	-.0733639	-.0239074
2	-.0895427	.01246	-7.19	0.000	-.1139653	-.0651202
3	-.1217946	.0133035	-9.16	0.000	-.1478705	-.0957187
4	-.0632151	.012625	-5.01	0.000	-.087961	-.0384692
5	-.072686	.0129347	-5.62	0.000	-.098039	-.0473329
7	0	(omitted)				
1.parkeer2	.0939195	.0040988	22.91	0.000	.0858856	.1019534
1.tuinlig2	.0397269	.0045427	8.75	0.000	.0308228	.0486309
_cons	9.08428	.1161661	78.20	0.000	8.856586	9.311974

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs
x_buurtnaam	78	0	78
year	5	1	4

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end of do-file

Table 29: Regression output period 2016-2020 with log 5-digit postal code

```
. reghdfe logprice logm2 kwaliteit qualityPC4 mean_quality4pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis2
> i.soortapp2 ib8.soortapp2 i.parker2 i.tuinlig2, absorb(x_buurtnaam year)vce(robust)
(dropped 2 singleton observations)
(MWFE estimator converged in 4 iterations)
note: 7.soortapp2 omitted because of collinearity
```

```
HDFE Linear regression      Number of obs   =    21,857
Absorbing 2 HDFE groups    F(   37, 21738) =   1568.67
                           Prob > F           =    0.0000
                           R-squared            =    0.9006
                           Adj R-squared       =    0.9001
                           Within R-sq.       =    0.7721
                           Root MSE        =    0.1820
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.7557611	.0060363	125.20	0.000	.7439295	.7675926
kwaliteit	.1360623	.003771	36.08	0.000	.1286708	.1434538
qualityPC4	-.0000338	.0000409	-0.83	0.408	-.0001139	.0000463
mean_quality4pos	.0351985	.0090769	3.88	0.000	.017407	.05299
ligcentr						
1	-.1570092	.0850101	-1.85	0.065	-.3236353	.0096169
2	-.1524789	.0850336	-1.79	0.073	-.3191509	.0141932
3	-.1261787	.0851772	-1.48	0.139	-.2931322	.0407748
ligmooi						
1	.0408266	.0124498	3.28	0.001	.016424	.0652292
2	.1034272	.0045488	22.74	0.000	.0945112	.1123431
3	.0368886	.005377	6.86	0.000	.0263493	.047428
4	.0359408	.0033473	10.74	0.000	.0293799	.0425017
construction_period						
1	-.1788824	.0731338	-2.45	0.014	-.3222301	-.0355348
2	-.1521654	.0730769	-2.08	0.037	-.2954014	-.0089294
3	-.1953843	.0731268	-2.67	0.008	-.3387181	-.0520504
4	-.2459228	.0730819	-3.37	0.001	-.3891687	-.1026768
5	-.2848416	.0730443	-3.90	0.000	-.4280137	-.1416695
6	-.2693572	.0731144	-3.68	0.000	-.4126669	-.1260476
7	-.2591985	.0730144	-3.55	0.000	-.4023121	-.1160849
8	-.1519383	.0728957	-2.08	0.037	-.2948192	-.0090573
9	-.0883342	.0729007	-1.21	0.226	-.2312249	.0545565
soorthuis2						
2	.2229454	.0176276	12.65	0.000	.1883939	.2574968
3	.0817287	.1330604	0.61	0.539	-.1790794	.3425368
4	-.3357732	.3848613	-0.87	0.383	-1.090129	.418583
5	.3610213	.0148129	24.37	0.000	.3319871	.3900556
6	.4878517	.0628802	7.76	0.000	.3646019	.6111015
7	.439428	.0164171	26.77	0.000	.4072493	.4716067
8	.6440749	.0762205	8.45	0.000	.4946771	.7934726
9	.6522942	.0341478	19.10	0.000	.585362	.7192265
10	.6881289	.0205228	33.53	0.000	.6479027	.728355
11	.4690014	.0813464	5.77	0.000	.3095565	.6284464
soortapp2						
1	-.048638	.0126018	-3.86	0.000	-.0733384	-.0239377
2	-.089255	.0124439	-7.17	0.000	-.1136459	-.0648641
3	-.1208638	.0132893	-9.09	0.000	-.1469118	-.0948158
4	-.0628835	.0126095	-4.99	0.000	-.0875989	-.038168
5	-.0725723	.0129196	-5.62	0.000	-.0978956	-.047249
7	0	(omitted)				
1.parker2	.0939713	.0041013	22.91	0.000	.0859324	.1020102
1.tuinlig2	.0397237	.0045437	8.74	0.000	.0308179	.0486296
_cons	9.082309	.1164286	78.01	0.000	8.8541	9.310518

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs
x_buurtnaam	78	0	78
year	5	1	4

end of do-file

Table 30: Regression output period 2016-2020 with log 4-digit postal code

```
. reghdfe logprice logm2 kwaliteit qualityPC3 mean_quality3pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis2
> i.soortapp2 ib8.soortapp2 i.parkeer2 i.tuinlig2, absorb(x_buurtnaam year)vce(robust)
(dropped 2 singleton observations)
(MWFE estimator converged in 5 iterations)
note: 7.soortapp2 omitted because of collinearity
```

```
HDFE Linear regression      Number of obs   =    21,857
Absorbing 2 HDFE groups    F(   37, 21738) =   1581.55
                           Prob > F           =    0.0000
                           R-squared           =    0.9010
                           Adj R-squared      =    0.9004
                           Within R-sq.     =    0.7729
                           Root MSE       =    0.1817
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.7563592	.0060262	125.51	0.000	.7445474	.7681709
kwaliteit	.1355204	.0037621	36.02	0.000	.1281464	.1428945
qualityPC3	.0000142	.0002556	0.06	0.956	-.0004869	.0005152
mean_quality3pos	.0542599	.0098257	5.52	0.000	.0350008	.0735189
ligcentr						
1	-.158079	.0844758	-1.87	0.061	-.3236578	.0074998
2	-.1537152	.0844964	-1.82	0.069	-.3193343	.011904
3	-.1275516	.0846466	-1.51	0.132	-.2934652	.038362
ligmooi						
1	.0422329	.0123254	3.43	0.001	.0180742	.0663917
2	.1039516	.0045469	22.86	0.000	.0950392	.1128639
3	.0373035	.0053544	6.97	0.000	.0268085	.0477985
4	.0365867	.0033506	10.92	0.000	.0300192	.0431541
construction_period						
1	-.1777856	.0728153	-2.44	0.015	-.3205089	-.0350622
2	-.1517229	.0727572	-2.09	0.037	-.2943323	-.0091134
3	-.1950802	.0728053	-2.68	0.007	-.3377839	-.0523766
4	-.245086	.0727617	-3.37	0.001	-.3877043	-.1024677
5	-.2845271	.0727267	-3.91	0.000	-.4270767	-.1419775
6	-.2681095	.0728002	-3.68	0.000	-.4108032	-.1254157
7	-.2581492	.0726966	-3.55	0.000	-.4006398	-.1156585
8	-.1521474	.0725747	-2.10	0.036	-.2943992	-.0098955
9	-.088234	.0725808	-1.22	0.224	-.2304977	.0540297
soorthuis2						
2	.2208792	.0176251	12.53	0.000	.1863328	.2554256
3	.0857372	.1334956	0.64	0.521	-.175924	.3473984
4	-.3373805	.3934655	-0.86	0.391	-1.108602	.4338406
5	.3597653	.014803	24.30	0.000	.3307503	.3887804
6	.4858175	.0625678	7.76	0.000	.3631801	.608455
7	.4388855	.0163965	26.77	0.000	.4067471	.4710238
8	.6353645	.0774451	8.20	0.000	.4835665	.7871625
9	.6467509	.033874	19.09	0.000	.5803553	.7131464
10	.6865945	.0204677	33.55	0.000	.6464764	.7267126
11	.463272	.0818238	5.66	0.000	.3028914	.6236526
soortapp2						
1	-.0486014	.0125878	-3.86	0.000	-.0732745	-.0239284
2	-.0885885	.0124288	-7.13	0.000	-.1129498	-.0642271
3	-.1214123	.0132657	-9.15	0.000	-.147414	-.0954107
4	-.0624691	.0125881	-4.96	0.000	-.0871428	-.0377954
5	-.0709981	.012903	-5.50	0.000	-.0962889	-.0457073
7	0 (omitted)					
1.parkeer2	.0934777	.0040912	22.85	0.000	.0854586	.1014968
1.tuinlig2	.0399015	.0045272	8.81	0.000	.0310279	.0487751
_cons	9.054657	.115667	78.28	0.000	8.827941	9.281373

Absorbed degrees of freedom:

Absorbed FE	Categories	- Redundant	= Num. Coefs
x_buurtnaam	78	0	78
year	5	1	4

```
.
end of do-file
```

Table 31: Regression output period 2016-2020 with log 3-digit postal code

```
. reg logprice logm2 kwaliteit qualityPC6 mean_quality6pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis
> 2 i.soortapp2 ib8.soortapp2 i.parker2 i.tuinlig2, robust
note: 7.soortapp2 omitted because of collinearity
```

```
Linear regression               Number of obs   =    42,696
                               F(37, 42657)       =          .
                               Prob > F           =          .
                               R-squared           =    0.6404
                               Root MSE        =    .35644
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.9980012	.0075329	132.49	0.000	.9832365	1.012766
kwaliteit	.1236062	.0070938	17.42	0.000	.1097022	.1375103
qualityPC6	.0015013	.0001722	8.72	0.000	.0011637	.0018389
mean_quality6pos	.0271647	.0108079	2.51	0.012	.005981	.0483484
ligcentr						
1	-.08335	.0569166	-1.46	0.143	-.1949077	.0282077
2	-.0970385	.0567901	-1.71	0.088	-.2083481	.0142711
3	.0810575	.0570963	1.42	0.156	-.0308525	.1929674
ligmooi						
1	.2377188	.0225711	10.53	0.000	.1934791	.2819586
2	.1267515	.0056898	22.28	0.000	.1155994	.1379037
3	.0639966	.0085296	7.50	0.000	.0472785	.0807148
4	.0359268	.0048532	7.40	0.000	.0264145	.0454392
construction_period						
1	-.2862587	.0985875	-2.90	0.004	-.4794921	-.0930253
2	-.3273147	.0983064	-3.33	0.001	-.5199973	-.1346322
3	-.3166761	.0982783	-3.22	0.001	-.5093035	-.1240488
4	-.3148017	.0982885	-3.20	0.001	-.5074491	-.1221542
5	-.4370549	.098312	-4.45	0.000	-.6297484	-.2443614
6	-.4321542	.0983201	-4.40	0.000	-.6248635	-.2394449
7	-.3715729	.0982832	-3.78	0.000	-.5642099	-.178936
8	-.2628396	.0982103	-2.68	0.007	-.4553336	-.0703455
9	-.203851	.098216	-2.08	0.038	-.3963563	-.0113457
soorthuis2						
2	.0920053	.0292961	3.14	0.002	.0345844	.1494262
3	.1772705	.0734112	2.41	0.016	.0333832	.3211578
4	-.1334347	.3355964	-0.40	0.691	-.7912102	.5243407
5	.3016697	.0268028	11.26	0.000	.2491357	.3542036
6	.2533125	.1514359	1.67	0.094	-.0435048	.5501298
7	.4701527	.0281848	16.68	0.000	.4149099	.5253955
8	.3135322	.0839061	3.74	0.000	.1490745	.4779899
9	.6023327	.047202	12.76	0.000	.5098158	.6948496
10	.7186437	.0307882	23.34	0.000	.6582981	.7789892
11	.6726362	.101143	6.65	0.000	.474394	.8708784
soortapp2						
1	-.0305998	.0208158	-1.47	0.142	-.0713992	.0101996
2	-.0773946	.0208549	-3.71	0.000	-.1182706	-.0365186
3	-.1721662	.0215537	-7.99	0.000	-.2144119	-.1299205
4	-.0570219	.0209811	-2.72	0.007	-.0981453	-.0158986
5	-.0664164	.0214586	-3.10	0.002	-.1084757	-.0243571
6	-.1089036	.0218017	-5.00	0.000	-.1516353	-.0661718
7	0	(omitted)				
1.parker2	.1034152	.0051804	19.96	0.000	.0932615	.1135688
1.tuinlig2	.0400296	.0056298	7.11	0.000	.0289952	.0510641
_cons	7.803121	.1212932	64.33	0.000	7.565384	8.040858

```
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```

Figure 39: Regression result full period without any fixed effects 6-digit postal code

```
. reg logprice logm2 kwaliteit qualityPC5 mean_quality5pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis
> 2 i.soortapp2 ib8.soortapp2 i.parker2 i.tuinlig2, robust
note: 7.soortapp2 omitted because of collinearity
```

```
Linear regression               Number of obs   =    42,696
                               F(38, 42657)       =   2096.45
                               Prob > F           =    0.0000
                               R-squared          =    0.6402
                               Root MSE       =    .35653
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	1.000506	.007555	132.43	0.000	.9856979	1.015314
kwaliteit	.1732712	.0053346	32.48	0.000	.1628152	.1837272
qualityPC5	.0001056	.0000181	5.83	0.000	.0000701	.0001411
mean_quality5pos	.0010693	.0069641	0.15	0.878	-.0125806	.0147191
ligcentr						
1	-.0843173	.0571316	-1.48	0.140	-.1962964	.0276618
2	-.0961965	.0570153	-1.69	0.092	-.2079475	.0155546
3	.0712949	.0573267	1.24	0.214	-.0410666	.1836565
ligmooi						
1	.2419814	.0225959	10.71	0.000	.1976931	.2862697
2	.1263561	.0056969	22.18	0.000	.1151901	.1375222
3	.0664588	.0085206	7.80	0.000	.0497583	.0831593
4	.0366849	.0048501	7.56	0.000	.0271787	.0461911
construction_period						
1	-.3076933	.1003769	-3.07	0.002	-.504434	-.1109527
2	-.3479806	.1000999	-3.48	0.001	-.5441784	-.1517829
3	-.3411134	.1000742	-3.41	0.001	-.5372608	-.144966
4	-.3341927	.1000613	-3.34	0.001	-.5303148	-.1380706
5	-.4461021	.1000997	-4.46	0.000	-.6422995	-.2499046
6	-.4448224	.1001002	-4.44	0.000	-.6410208	-.248624
7	-.3909003	.1000565	-3.91	0.000	-.587013	-.1947876
8	-.2801257	.0999962	-2.80	0.005	-.4761201	-.0841312
9	-.2203551	.1000021	-2.20	0.028	-.4163611	-.024349
soorthuis2						
2	.1407695	.0272277	5.17	0.000	.0874028	.1941362
3	.2120575	.0721241	2.94	0.003	.0706929	.3534221
4	-.0837358	.331768	-0.25	0.801	-.7340076	.5665359
5	.3508661	.024564	14.28	0.000	.3027202	.399012
6	.2887231	.1499584	1.93	0.054	-.0051983	.5826446
7	.5155123	.026253	19.64	0.000	.4640559	.5669687
8	.3709259	.0834023	4.45	0.000	.2074557	.5343961
9	.648988	.0457989	14.17	0.000	.5592212	.7387548
10	.7698837	.0290826	26.47	0.000	.7128813	.8268861
11	.7179994	.0998615	7.19	0.000	.522269	.9137298
soortapp2						
1	-.0290342	.0208947	-1.39	0.165	-.0699881	.0119197
2	-.0754171	.0209496	-3.60	0.000	-.1164787	-.0343555
3	-.1710357	.0216512	-7.90	0.000	-.2134725	-.1285988
4	-.0539549	.0210779	-2.56	0.010	-.0952679	-.0126418
5	-.060249	.0215906	-2.79	0.005	-.102567	-.017931
6	-.0359169	.0217816	-1.65	0.099	-.0786093	.0067755
7	0	(omitted)				
1.parker2	.1045547	.0051811	20.18	0.000	.0943996	.1147098
1.tuinlig2	.042346	.0056457	7.50	0.000	.0312803	.0534116
_cons	7.813356	.1227524	63.65	0.000	7.572759	8.053954

```
.
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```

Figure 40: Regression result full period without any fixed effects 5-digit postal code


```
. reg logprice logm2 kwaliteit qualityPC4 mean_quality4pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis
> 2 i.soortapp2 ib8.soortapp2 i.parkeer2 i.tuinlig2, robust
note: 7.soortapp2 omitted because of collinearity
```

```
Linear regression               Number of obs   =    42,696
                               F(38, 42657)      =   2108.11
                               Prob > F          =    0.0000
                               R-squared         =    0.6413
                               Root MSE      =    .35597
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	1.001133	.0075443	132.70	0.000	.9863455	1.01592
kwaliteit	.1728436	.0053264	32.45	0.000	.1624037	.1832835
qualityPC4	.0002639	.0000221	11.95	0.000	.0002206	.0003072
mean_quality4pos	-.0281288	.0069957	-4.02	0.000	-.0418405	-.0144172
ligcentr						
1	-.0842547	.0574086	-1.47	0.142	-.1967767	.0282672
2	-.0918933	.0572892	-1.60	0.109	-.2041813	.0203947
3	.057301	.0576309	0.99	0.320	-.0556566	.1702587
ligmooi						
1	.2465738	.0225699	10.92	0.000	.2023363	.2908114
2	.1252532	.0056817	22.05	0.000	.1141169	.1363894
3	.0691843	.008514	8.13	0.000	.0524967	.0858719
4	.0371519	.0048359	7.68	0.000	.0276734	.0466305
construction_period						
1	-.3036577	.0996997	-3.05	0.002	-.499071	-.1082445
2	-.3409093	.0994204	-3.43	0.001	-.5357752	-.1460433
3	-.3426346	.0993834	-3.45	0.001	-.537428	-.1478411
4	-.3298379	.0993774	-3.32	0.001	-.5246196	-.1350562
5	-.4313366	.0994334	-4.34	0.000	-.6262279	-.2364452
6	-.4325968	.0994318	-4.35	0.000	-.627485	-.2377086
7	-.3844539	.0993756	-3.87	0.000	-.579232	-.1896757
8	-.2745603	.0993104	-2.76	0.006	-.4692107	-.0799099
9	-.2147019	.099322	-2.16	0.031	-.4093749	-.0200288
soorthuis2						
2	.1448718	.027239	5.32	0.000	.0914828	.1982607
3	.20588	.0721069	2.86	0.004	.064549	.347211
4	-.0720944	.3304436	-0.22	0.827	-.7197703	.5755814
5	.3555372	.024534	14.49	0.000	.3074501	.4036243
6	.2788739	.1450121	1.92	0.054	-.0053526	.5631005
7	.5201867	.0262523	19.81	0.000	.4687316	.5716418
8	.3747545	.0826261	4.54	0.000	.2128057	.5367033
9	.656634	.0456047	14.40	0.000	.567248	.74602
10	.7733694	.0290014	26.67	0.000	.7165261	.8302127
11	.7287144	.0998192	7.30	0.000	.5330669	.9243619
soortapp2						
1	-.0310695	.020926	-1.48	0.138	-.0720848	.0099458
2	-.0788351	.0209923	-3.76	0.000	-.1199805	-.0376897
3	-.1708191	.0216683	-7.88	0.000	-.2132894	-.1283489
4	-.0551657	.0211088	-2.61	0.009	-.0965394	-.0137919
5	-.0570556	.0216214	-2.64	0.008	-.099434	-.0146773
6	-.0192956	.0217558	-0.89	0.375	-.0619373	.0233461
7	0	(omitted)				
1.parkeer2	.1041028	.0051721	20.13	0.000	.0939655	.1142402
1.tuinlig2	.0426067	.0056379	7.56	0.000	.0315563	.0536571
_cons	7.784712	.1222784	63.66	0.000	7.545044	8.02438

```
.
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```

Figure 41: Regression result full period without any fixed effects 4-digit postal code

```
. reg logprice logm2 kwaliteit qualityPC3 mean_quality3pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthuis
> 2 i.soortapp2 ib8.soortapp2 i.parker2 i.tuinlig2, robust
note: 7.soortapp2 omitted because of collinearity
```

```
Linear regression               Number of obs   =    42,696
                               F(37, 42657)       =          .
                               Prob > F           =          .
                               R-squared           =    0.6459
                               Root MSE        =    .35368
```

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.9914823	.007461	132.89	0.000	.9768585	1.006106
kwaliteit	.1732981	.0053321	32.50	0.000	.1628471	.183749
qualityPC3	-.0007087	.0001089	-6.51	0.000	-.0009222	-.0004953
mean_quality3pos	-.0847058	.0067665	-12.52	0.000	-.0979682	-.0714433
ligcentr						
1	-.0581253	.0570217	-1.02	0.308	-.1698889	.0536383
2	-.0804433	.0568926	-1.41	0.157	-.1919539	.0310674
3	.1352299	.0572822	2.36	0.018	.0229556	.2475042
ligmooi						
1	.2145853	.0224897	9.54	0.000	.170505	.2586655
2	.1208415	.0056444	21.41	0.000	.1097783	.1319046
3	.0575477	.0084624	6.80	0.000	.0409612	.0741342
4	.0360476	.0048214	7.48	0.000	.0265975	.0454977
construction_period						
1	-.2897376	.101783	-2.85	0.004	-.4892342	-.090241
2	-.3508494	.1015172	-3.46	0.001	-.5498251	-.1518737
3	-.3277591	.1015155	-3.23	0.001	-.5267315	-.1287866
4	-.3448319	.1014884	-3.40	0.001	-.5437511	-.1459127
5	-.4724226	.1015042	-4.65	0.000	-.6713728	-.2734724
6	-.4508635	.1015117	-4.44	0.000	-.6498284	-.2518985
7	-.3841517	.1014728	-3.79	0.000	-.5830404	-.1852631
8	-.2781493	.1014071	-2.74	0.006	-.4769091	-.0793895
9	-.2321091	.1014304	-2.29	0.022	-.4309146	-.0333036
soorthuis2						
2	.0894557	.0268509	3.33	0.001	.0368274	.1420839
3	.1816506	.075499	2.41	0.016	.0336711	.32963
4	-.1619146	.3289651	-0.49	0.623	-.8066927	.4828634
5	.2912987	.0241791	12.05	0.000	.2439071	.3386903
6	.2938595	.1511693	1.94	0.052	-.0024352	.5901542
7	.4633394	.0258783	17.90	0.000	.4126175	.5140613
8	.2747068	.0830634	3.31	0.001	.1119009	.4375126
9	.6042455	.0461128	13.10	0.000	.5138635	.6946275
10	.7022282	.0286076	24.55	0.000	.6461567	.7582997
11	.6619619	.0992119	6.67	0.000	.4675047	.8564191
soortapp2						
1	-.028775	.0207118	-1.39	0.165	-.0693706	.0118206
2	-.0757853	.0207581	-3.65	0.000	-.1164715	-.0350991
3	-.1777858	.0214724	-8.28	0.000	-.2198722	-.1356995
4	-.0524843	.0208797	-2.51	0.012	-.093409	-.0115596
5	-.0710406	.0213723	-3.32	0.001	-.1129307	-.0291506
6	-.0872878	.0212786	-4.10	0.000	-.1289943	-.0455814
7	0	(omitted)				
1.parker2	.1021346	.0051257	19.93	0.000	.092088	.1121811
1.tuinlig2	.0297435	.0055567	5.35	0.000	.0188522	.0406348
_cons	8.006093	.1237225	64.71	0.000	7.763594	8.248591

```
.
end of do-file
```

Figure 42: Regression result full period without any fixed effects 3-digit postal code

Fixed-effects (within) regression	Number of obs	=	42,696
Group variable: year	Number of groups	=	11
R-sq:	Obs per group:		
within = 0.7205	min =		2,637
between = 0.7595	avg =		3,881.5
overall = 0.6385	max =		5,466
	<u>F(10,10)</u>	=	.
corr(u_i, Xb) = 0.0650	Prob > F	=	.
(Std. Err. adjusted for 11 clusters in year)			

	logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
	logm2	.9550317	.0158402	60.29	0.000	.9197375 .9903258
	kwaliteit	.1121987	.007378	15.21	0.000	.0957595 .1286379
	qualityPC6	.0019255	.0002652	7.26	0.000	.0013347 .0025164
	mean_quality6pos	.0328629	.0201862	1.63	0.135	-.0121149 .0778406
	ligcentr					
	1	-.1076748	.0875235	-1.23	0.247	-.3026893 .0873397
	2	-.1269246	.0854878	-1.48	0.168	-.3174033 .0635542
	3	.0580502	.0840832	0.69	0.506	-.1292988 .2453992
	ligmooi					
	1	.202925	.0290555	6.98	0.000	.1381853 .2676666
	2	.1190027	.0063618	18.71	0.000	.1048278 .1331774
	3	.0575703	.0076928	7.48	0.000	.0404296 .074711
	4	.0360027	.0044934	8.01	0.000	.0259907 .0460147
construction_period						
	1	-.0877512	.0977335	-0.90	0.390	-.3055149 .1300126
	2	-.1127004	.0960847	-1.17	0.268	-.3267905 .1013897
	3	-.1183888	.0907637	-1.30	0.221	-.3206229 .0838453
	4	-.1137345	.0967098	-1.18	0.267	-.3292172 .1017483
	5	-.2483428	.0982123	-2.53	0.030	-.4671733 -.0295122
	6	-.2284675	.0957902	-2.39	0.038	-.4419013 -.0150337
	7	-.168663	.0954721	-1.77	0.108	-.3813882 .0440621
	8	-.0544377	.0922755	-0.59	0.568	-.2600403 .1511649
	9	-.0474735	.0938919	-0.51	0.624	-.2566776 .1617307
soorthuis2						
	2	.1229217	.0498728	2.46	0.033	.0117981 .2340453
	3	.2822286	.1271835	2.22	0.051	-.0011538 .565611
	4	-.1320567	.2857811	-0.46	0.654	-.7688167 .5047032
	5	.3015711	.0456729	6.60	0.000	.1998056 .4033366
	6	.247549	.111729	2.22	0.051	-.0013987 .4964967
	7	.4926349	.0429383	11.47	0.000	.3969624 .5883074
	8	.3632358	.092463	3.93	0.003	.1572154 .5692562
	9	.6129518	.0740201	8.28	0.000	.4480246 .7778789
	10	.7240419	.0487661	14.85	0.000	.6153842 .8326995
	11	.7291653	.1836987	3.97	0.003	.3198591 1.138472
soortapp2						
	1	-.0042413	.027197	-0.16	0.879	-.0648401 .0563574
	2	-.0276675	.020583	-1.34	0.209	-.0735293 .0181943
	3	-.1169531	.0245032	-4.77	0.001	-.1715497 -.0623565
	4	-.0395195	.0249818	-1.58	0.145	-.0951825 .0161434
	5	-.0391946	.0231918	-1.69	0.122	-.0908691 .0124798
	6	.0995345	.0217454	4.58	0.001	.0510826 .1479863
	7	0 (omitted)				
1.parkeer2		.1308976	.0079843	16.39	0.000	.1131075 .1486876
1.tuinlig2		.0558692	.0069493	8.04	0.000	.0403853 .0713532
_cons		7.782582	.1268878	61.33	0.000	7.499859 8.065306
	sigma_u	.22845802				
	sigma_e	.28631565				
	rho	.3890078	(fraction of variance due to u_i)			

Figure 43: Regression results full period with year fixed effect 6-digit postal code

Fixed-effects (within) regression	Number of obs	=	42,696
Group variable: year	Number of groups	=	11
R-sq:	Obs per group:		
within = 0.7215	min =		2,637
between = 0.7478	avg =		3,881.5
overall = 0.6378	max =		5,466
	<u>F(10,10)</u>	=	.
corr(u_i, Xb) = 0.0621	Prob > F	=	.
(Std. Err. adjusted for 11 clusters in year)			

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.9592863	.0167728	57.19	0.000	.9219141	.9966585
kwaliteit	.173489	.00692	25.07	0.000	.1580703	.1889077
qualityPC5	.0002409	.0000647	3.72	0.004	.0000967	.000385
mean_quality5pos	-.0226548	.0223665	-1.01	0.335	-.0724904	.0271809
ligcentr						
1	-.1048793	.0861538	-1.22	0.251	-.2968418	.0870832
2	-.119172	.0848923	-1.40	0.191	-.3083238	.0699798
3	.0399746	.0813444	0.49	0.634	-.141272	.2212213
ligmooi						
1	.2105668	.029204	7.21	0.000	.1454963	.2756374
2	.1175547	.0063896	18.40	0.000	.1033177	.1317917
3	.0626123	.0080055	7.82	0.000	.0447748	.0804497
4	.0370064	.0045439	8.14	0.000	.0268819	.0471308
construction_period						
1	-.1146749	.0991312	-1.16	0.274	-.335553	.1062033
2	-.1387265	.0973278	-1.43	0.185	-.3555864	.0781335
3	-.1546073	.0946695	-1.63	0.133	-.365544	.0563295
4	-.1389516	.0998404	-1.39	0.194	-.36141	.0835067
5	-.2534245	.098122	-2.58	0.027	-.4720539	-.0347952
6	-.240596	.0965569	-2.49	0.032	-.4557383	-.0254537
7	-.1939358	.0985706	-1.97	0.077	-.4135647	.025693
8	-.0778715	.0954249	-0.82	0.433	-.2904914	.1347485
9	-.069104	.0967551	-0.71	0.491	-.2846878	.1464798
soorthuis2						
2	.1872442	.042178	4.44	0.001	.0932658	.2812226
3	.3286201	.1160627	2.83	0.018	.0700162	.5872241
4	-.0609646	.2811796	-0.22	0.833	-.6874719	.5655426
5	.3679286	.0336623	10.93	0.000	.2929244	.4429327
6	.2953647	.1101451	2.68	0.023	.0499461	.5407833
7	.5555102	.0322444	17.23	0.000	.4836651	.6273553
8	.441087	.0885413	4.98	0.001	.2438048	.6383693
9	.6772744	.066386	10.20	0.000	.5293571	.8251917
10	.7943903	.0373791	21.25	0.000	.7111044	.8776761
11	.7919074	.1744873	4.54	0.001	.4031256	1.180689
soortapp2						
1	-.0036356	.0264149	-0.14	0.893	-.0624918	.0552206
2	-.0276581	.020298	-1.36	0.203	-.072885	.0175688
3	-.1163579	.0246107	-4.73	0.001	-.1711939	-.061522
4	-.0376895	.0243274	-1.55	0.152	-.0918943	.0165152
5	-.0304456	.0228645	-1.33	0.213	-.0813908	.0204996
6	.2055282	.0186519	11.02	0.000	.1639691	.2470873
7	0 (omitted)					
1.parkeer2	.1320661	.0079583	16.59	0.000	.114334	.1497982
1.tuinlig2	.0593906	.0061146	9.71	0.000	.0457664	.0730149
_cons	7.764395	.1136644	68.31	0.000	7.511135	8.017655
sigma_u	.22983889					
sigma_e	.2857631					
rho	.39279725	(fraction of variance due to u_i)				

Figure 44: Regression results full period with year fixed effect 5-digit postal code

```
. xtreg logprice logm2 kwaliteit qualityPC4 mean_quality4pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthu
> is2 i.soortapp2 ib8.soortapp2 i.parkeer2 i.tuinlig2, fe robust
note: 7.soortapp2 omitted because of collinearity
```

```
Fixed-effects (within) regression      Number of obs   =    42,696
Group variable: year                  Number of groups  =     11
```

```
R-sq:                                Obs per group:
    within = 0.7233                    min =      2,637
    between = 0.7401                   avg =    3,881.5
    overall = 0.6391                   max =    5,466
```

```
corr(u_i, Xb) = 0.0617                F(10,10)         =      .
                                      Prob > F           =      .
```

(Std. Err. adjusted for 11 clusters in year)

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.9590744	.0167747	57.17	0.000	.921698	.9964508
kwaliteit	.1746205	.0064128	27.23	0.000	.1603319	.1889091
qualityPC4	.0003862	.000072	5.37	0.000	.0002258	.0005466
mean_quality4pos	-.041971	.0197374	-2.13	0.059	-.0859488	.0020067
ligcentr						
1	-.1094153	.0871691	-1.26	0.238	-.3036401	.0848095
2	-.1195474	.0858338	-1.39	0.194	-.310797	.0717022
3	.0224453	.0819638	0.27	0.790	-.1601814	.205072
ligmooi						
1	.215355	.028766	7.49	0.000	.1512602	.2794497
2	.1167193	.0064871	17.99	0.000	.1022651	.1311734
3	.0650896	.0083955	7.75	0.000	.0463833	.0837958
4	.0376845	.0045503	8.28	0.000	.0275459	.0478231
construction_period						
1	-.1078472	.0984509	-1.10	0.299	-.3272094	.111515
2	-.127197	.0959459	-1.33	0.214	-.3409778	.0865838
3	-.1512441	.0930261	-1.63	0.135	-.3585192	.056031
4	-.1304135	.098329	-1.33	0.214	-.3495041	.0886771
5	-.2349815	.095963	-2.45	0.034	-.4488004	-.0211627
6	-.224006	.0951674	-2.35	0.040	-.4360522	-.0119598
7	-.1820997	.096561	-1.89	0.089	-.397251	.0330516
8	-.0665137	.0932439	-0.71	0.492	-.2742741	.1412467
9	-.0587339	.0952232	-0.62	0.551	-.2709044	.1534366
soorthuis2						
2	.1951698	.037944	5.14	0.000	.1106254	.2797142
3	.3201946	.1153138	2.78	0.020	.0632594	.5771298
4	-.0483387	.2780892	-0.17	0.865	-.6679601	.5712827
5	.3752976	.0291927	12.86	0.000	.3102523	.4403429
6	.2799578	.1060986	2.64	0.025	.0435555	.5163601
7	.5610039	.0294716	19.04	0.000	.4953372	.6266706
8	.4485926	.0878268	5.11	0.000	.2529023	.6442829
9	.6877989	.063317	10.86	0.000	.5467199	.828878
10	.7991891	.0343918	23.24	0.000	.7225593	.8758189
11	.8072652	.1712173	4.71	0.001	.4257692	1.188761
soortapp2						
1	-.0052427	.0261588	-0.20	0.845	-.0635283	.0530428
2	-.030133	.0200599	-1.50	0.164	-.0748293	.0145634
3	-.1147328	.0239121	-4.80	0.001	-.1680123	-.0614533
4	-.0376484	.0242572	-1.55	0.152	-.0916969	.0164001
5	-.0261007	.0223739	-1.17	0.270	-.0759529	.0237515
6	.224447	.0177143	12.67	0.000	.184977	.2639169
7	0 (omitted)					
1.parkeer2	.1317079	.0082389	15.99	0.000	.1133505	.1500654
1.tuinlig2	.0597527	.0060586	9.86	0.000	.0462533	.0732522
_cons	7.743786	.1163847	66.54	0.000	7.484465	8.003108
sigma_u	.23001526					
sigma_e	.28484099					
rho	.39470654	(fraction of variance due to u_i)				

```
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```

Figure 45: Regression results full period with year fixed effect 4-digit postal code

```
. xtreg logprice logm2 kwaliteit qualityPC3 mean_quality3pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthu
> is2 i.soortapp2 ib8.soortapp2 i.parkeer2 i.tuinlig2, fe robust
note: 7.soortapp2 omitted because of collinearity
```

```
Fixed-effects (within) regression      Number of obs   =    42,696
Group variable: year                  Number of groups  =     11
```

```
R-sq:                                Obs per group:
    within = 0.7200                    min =      2,637
    between = 0.7625                   avg =    3,881.5
    overall = 0.6418                   max =    5,466
```

```
corr(u_i, Xb) = 0.0710                F(10,10)         =      .
                                      Prob > F           =      .
```

(Std. Err. adjusted for 11 clusters in year)

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.9555282	.0159496	59.91	0.000	.9199903	.9910662
kwaliteit	.177212	.0062242	28.47	0.000	.1633436	.1910804
qualityPC3	-.0004693	.0005094	-0.92	0.379	-.0016044	.0006658
mean_quality3pos	-.0193703	.038157	-0.51	0.623	-.1043894	.0656488
ligcentr						
1	-.0964307	.0851637	-1.13	0.284	-.2861873	.093326
2	-.1210532	.08424	-1.44	0.181	-.3087517	.0666452
3	.0870117	.0777262	1.12	0.289	-.0861731	.2601966
ligmooi						
1	.1944435	.0296556	6.56	0.000	.1283667	.2605204
2	.1168878	.0069006	16.94	0.000	.1015123	.1322634
3	.0553147	.0084038	6.58	0.000	.0365899	.0740396
4	.0366949	.0044623	8.22	0.000	.0267524	.0466375
construction_period						
1	-.1067605	.1071659	-1.00	0.343	-.3455409	.13202
2	-.1387456	.1084101	-1.28	0.230	-.3802983	.1028071
3	-.1382394	.105276	-1.31	0.218	-.3728089	.0963301
4	-.1424028	.1109753	-1.28	0.228	-.3896711	.1048656
5	-.2802904	.1097672	-2.55	0.029	-.524867	-.0357137
6	-.2546388	.1061028	-2.40	0.037	-.4910505	-.018227
7	-.1920906	.1066186	-1.80	0.102	-.4296516	.0454705
8	-.0779111	.102966	-0.76	0.467	-.3073337	.1515114
9	-.0741227	.1074909	-0.69	0.506	-.3136275	.165382
soorthuis2						
2	.1525203	.0395371	3.86	0.003	.0644262	.2406143
3	.3120547	.1201786	2.60	0.027	.0442801	.5798294
4	-.1131374	.2847126	-0.40	0.699	-.7475166	.5212417
5	.3278017	.0305037	10.75	0.000	.2598351	.3957682
6	.2923183	.1103696	2.65	0.024	.0463994	.5382372
7	.5185542	.0301296	17.21	0.000	.4514212	.5856871
8	.3749914	.0903568	4.15	0.002	.173664	.5763188
9	.6423537	.0645164	9.96	0.000	.4986022	.7861053
10	.7456317	.0353417	21.10	0.000	.6668854	.824378
11	.750002	.1667984	4.50	0.001	.378352	1.121652
soortapp2						
1	-.0001794	.0270415	-0.01	0.995	-.0604317	.0600728
2	-.0224568	.0199179	-1.13	0.286	-.0668368	.0219231
3	-.1180656	.0243034	-4.86	0.001	-.172217	-.0639142
4	-.0327604	.024861	-1.32	0.217	-.0881543	.0226334
5	-.0372794	.0229766	-1.62	0.136	-.0884743	.0139156
6	.1382386	.0197501	7.00	0.000	.0942327	.1822445
7	0	(omitted)				
1.parkeer2	.1309816	.0076513	17.12	0.000	.1139335	.1480298
1.tuinlig2	.0523621	.0058833	8.90	0.000	.0392533	.0654709
_cons	7.904684	.1334661	59.23	0.000	7.607303	8.202065
sigma_u	.22548216					
sigma_e	.28657149					
rho	.38237163	(fraction of variance due to u_i)				

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```

Figure 46: Regression results full period with year fixed effect 3-digit postal code

```
. *Regression for PC6
. xtreg logprice logm2 kwaliteit qualityPC6 mean_quality6pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthu
> is2 i.soortapp2 ib8.soortapp2 i.parkeer2 i.tuinlig2, fe robust
note: 7.soortapp2 omitted because of collinearity
```

```
Fixed-effects (within) regression      Number of obs   =    42,696
Group variable: neighbourh~d          Number of groups  =     81
```

```
R-sq:                                Obs per group:
    within = 0.5785                    min =          1
    between = 0.7431                   avg =        527.1
    overall = 0.6245                    max =       2,151
```

```
corr(u_i, Xb) = 0.1915                F(37,80)         =
                                         Prob > F         =
```

(Std. Err. adjusted for 81 clusters in neighbourhood)

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.8516815	.0219943	38.72	0.000	.8079115	.8954515
kwaliteit	.120712	.0134193	9.00	0.000	.0940067	.1474172
qualityPC6	.0008801	.0003171	2.78	0.007	.000249	.0015111
mean_quality6pos	.0001854	.0180678	0.01	0.992	-.0357706	.0361414
ligcentr						
1	-.1141855	.0469534	-2.43	0.017	-.2076257	-.0207453
2	-.1128834	.0461547	-2.45	0.017	-.2047342	-.0210326
3	-.0699814	.0562663	-1.24	0.217	-.1819549	.0419922
ligmooi						
1	.0916163	.0337127	2.72	0.008	.0245259	.1587066
2	.1119465	.0127395	8.79	0.000	.086594	.1372989
3	.0391523	.0109545	3.57	0.001	.0173521	.0609525
4	.0326761	.006431	5.08	0.000	.0198779	.0454742
construction_period						
1	-.3366672	.1946682	-1.73	0.088	-.7240693	.050735
2	-.3534649	.1958463	-1.80	0.075	-.7432115	.0362817
3	-.3667624	.1946734	-1.88	0.063	-.7541749	.02065
4	-.3958849	.1939917	-2.04	0.045	-.7819407	-.009829
5	-.4657128	.1966245	-2.37	0.020	-.8570081	-.0744175
6	-.4435319	.197169	-2.25	0.027	-.8359107	-.051153
7	-.4282325	.1980245	-2.16	0.034	-.8223138	-.0341512
8	-.3095605	.1967257	-1.57	0.120	-.7010571	.0819362
9	-.2082288	.1959399	-1.06	0.291	-.5981616	.181704
soorthuis2						
2	.1608531	.0491841	3.27	0.002	.0629736	.2587327
3	.1817066	.07701	2.36	0.021	.0284517	.3349614
4	-.1674813	.3780599	-0.44	0.659	-.9198446	.584882
5	.3224712	.0446698	7.22	0.000	.2335754	.411367
6	.371017	.1454322	2.55	0.013	.0815976	.6604364
7	.3969241	.0452869	8.76	0.000	.3068003	.4870479
8	.4466061	.0898489	4.97	0.000	.2678011	.6254112
9	.5826081	.0675522	8.62	0.000	.448175	.7170413
10	.6481928	.0531629	12.19	0.000	.5423954	.7539903
11	.636109	.09604	6.62	0.000	.4449834	.8272347
soortapp2						
1	-.0534683	.0235009	-2.28	0.026	-.1002366	-.0067001
2	-.1309326	.0244239	-5.36	0.000	-.1795377	-.0823275
3	-.1654826	.0295196	-5.61	0.000	-.2242286	-.1067367
4	-.0884708	.0252041	-3.51	0.001	-.1386287	-.038313
5	-.1028877	.0245843	-4.19	0.000	-.1518121	-.0539634
6	-.0598276	.034955	-1.71	0.091	-.1293903	.009735
7	0 (omitted)					
1.parkeer2	.0739022	.0122891	6.01	0.000	.0494461	.0983583
1.tuinlig2	.0293317	.0096005	3.06	0.003	.010226	.0484373
_cons	8.623181	.2223722	38.78	0.000	8.180646	9.065715
sigma_u	.21140404					
sigma_e	.31122431					
rho	.31572563	(fraction of variance due to u_i)				

```
.
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```

Figure 47: Regression result full period neighbourhood fixed effect 6-digit postal code


```
. xtreg logprice logm2 kwaliteit qualityPC4 mean_quality4pos i.ligcentr i.ligmooi i.construction_period i.soorthuis2 ib13.soorthu
> is2 i.soortapp2 ib8.soortapp2 i.parkeer2 i.tuinlig2, fe robust
note: 7.soortapp2 omitted because of collinearity
```

```
Fixed-effects (within) regression      Number of obs   =    42,696
Group variable: neighbourh~d          Number of groups =      81
```

```
R-sq:                                Obs per group:
    within = 0.5782                    min =          1
    between = 0.7341                   avg =       527.1
    overall = 0.6207                    max =       2,151
```

```
corr(u_i, Xb) = 0.1698                F(38,80)         =    2.02e+10
                                      Prob > F          =    0.0000
```

(Std. Err. adjusted for 81 clusters in neighbourhood)

logprice	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
logm2	.8528801	.0221179	38.56	0.000	.808864	.8968961
kwaliteit	.1474365	.0118931	12.40	0.000	.1237684	.1711046
qualityPC4	-.0000472	.0003431	-0.14	0.891	-.00073	.0006356
mean_quality4pos	-.0009644	.0628936	-0.02	0.988	-.1261266	.1241977
ligcentr						
1	-.114604	.0470814	-2.43	0.017	-.208299	-.0209091
2	-.1135653	.0461491	-2.46	0.016	-.2054049	-.0217257
3	-.0698689	.0568234	-1.23	0.222	-.1829511	.0432134
ligmooi						
1	.0922824	.0329526	2.80	0.006	.0267047	.1578602
2	.1121621	.0127165	8.82	0.000	.0868554	.1374687
3	.0393383	.0112565	3.49	0.001	.0169372	.0617394
4	.0330513	.0065684	5.03	0.000	.0199797	.0461229
construction_period						
1	-.3487522	.1978471	-1.76	0.082	-.7424804	.044976
2	-.3649049	.199039	-1.83	0.070	-.7610052	.0311954
3	-.3789853	.1978594	-1.92	0.059	-.772738	.0147674
4	-.408539	.1972548	-2.07	0.042	-.8010886	-.0159894
5	-.477126	.1998549	-2.39	0.019	-.87485	-.0794021
6	-.4563621	.2004824	-2.28	0.025	-.8553349	-.0573894
7	-.4410918	.2013172	-2.19	0.031	-.8417258	-.0404577
8	-.3208667	.1998873	-1.61	0.112	-.7186551	.0769217
9	-.2189068	.1991006	-1.10	0.275	-.6151296	.177316
soorthuis2						
2	.1868352	.0439856	4.25	0.000	.0993011	.2743694
3	.203957	.0750362	2.72	0.008	.0546302	.3532838
4	-.1435167	.3770186	-0.38	0.704	-.8938076	.6067742
5	.348943	.0402259	8.67	0.000	.2688909	.4289951
6	.3953509	.145114	2.72	0.008	.1065648	.6841371
7	.42239	.0412403	10.24	0.000	.3403192	.5044608
8	.4712961	.0871152	5.41	0.000	.2979313	.6446609
9	.6084792	.0653402	9.31	0.000	.478448	.7385104
10	.6746334	.0502787	13.42	0.000	.5745756	.7746912
11	.6617232	.0954073	6.94	0.000	.4718565	.8515898
soortapp2						
1	-.0516434	.0231653	-2.23	0.029	-.0977439	-.0055429
2	-.1287027	.0245727	-5.24	0.000	-.177604	-.0798015
3	-.1646187	.0298731	-5.51	0.000	-.224068	-.1051694
4	-.0858926	.0254231	-3.38	0.001	-.1364862	-.0352989
5	-.1007935	.0249662	-4.04	0.000	-.1504779	-.0511091
6	-.0387367	.0334861	-1.16	0.251	-.1053761	.0279027
7	0	(omitted)				
1.parkeer2	.0744866	.0121971	6.11	0.000	.0502135	.0987596
1.tuinlig2	.0296238	.0096185	3.08	0.003	.0104823	.0487652
_cons	8.660485	.2323447	37.27	0.000	8.198104	9.122866
sigma_u	.2140748					
sigma_e	.31133287					
rho	.32102304	(fraction of variance due to u_i)				

```
.
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```

Figure 49: Regression result full period neighbourhood fixed effect 4-digit postal code

