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The effects of restaurants on the house transaction prices in Rotterdam

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Management Summary

This paper assesses the effect of restaurants on house prices in Rotterdam. This research adds an important layer to the existing literature, namely that the impact of restaurants is heterogeneous over space. Glaeser, Kolko and Saiz (2001) stated that cities should have a large variety of consumer goods and services in order to grow as a consumer city, which can contribute to the quality of life and attractiveness of a city. Home owners derive utility from the presence of amenities, either by direct consumption or simply by enjoying a vibrant urban environment. The utility is capitalized in the house prices, as house prices are affected by location characteristics and the proximity to such amenities (Li & Brown, 1980).

In order to measure the effects of restaurants and location characteristics on house prices, analyses of the spatial structure of Rotterdam have been made via multi-level modelling. The results show clear evidence of spatial heterogeneity in the effect of restaurants on house prices. Furthermore, here is no statistical evidence that restaurants inside the city centre have a positive significant effect on the house transaction prices. However, restaurants outside the city centre do have a significant positive effect on the house transaction prices. This finding raises questions on how the effect of restaurants in particular and consumer amenities in general, should be incorporated in housing models.

These results complement earlier studies on the effect of restaurants and house prices. Various contributions delved into the diverse aspects of restaurants as a consumer amenity. Such as the quality, quantity, price levels (Kuang, 2017) and diversity of restaurants (Schiff, 2014). The key addition of this research is that the effect of restaurants on the house transaction prices does not solely depend on these previously identified restaurant factors, but is also highly dependent on *where* the restaurants are situated.

The results in this paper are relevant in the wider debate on amenities. The findings are academically relevant as restaurants can serve as a proxy for other amenities and it is socially relevant because it reveals a deeper understanding of the role restaurants play in urban attractiveness. A such, policymaking in urban development can incorporate the results in spatial planning by recognising the different value of amenities in different place.

1. Introduction

Almost everyone enjoys a day in which they visit a restaurant. Especially in Rotterdam, where there is an abundance in cuisines and the convenience of home delivery restaurants. One is left to wonder whether the proximity to restaurants adds the same value to the house transaction prices as it does to the stomach. This report has been conducted in collaboration with the NVM (Dutch Association of Real Estate Agents) to find the effect of restaurants on the transaction prices in different neighbourhoods in Rotterdam.

1.1 Problem statement

The real estate market in the Netherlands is in a turbulent phase. According to the statistics of the CBS, the house prices increased by more than 10% between 2017 and 2018 nationally. In the four biggest cities Amsterdam (~16%), Rotterdam (~15%), The Hague (~12.4%) and Utrecht (~12.7%) the effect is even greater. The increase in house prices leads to an affordability problem. Which has been especially hard for the middle class tenants, elderly people and people who are looking to purchase a house for the first time. The uncertainty and a low consumer confidence in the economy has also led to a trend in which house owners will look to purchase a house first, before selling their own house. Which leads to fewer houses on sale. This negative spiral is reflected by the decrease in the number of transactions, which in the cities have even decreased with more than 10% (ING, 2018; Business Insider Nederland, 2019; Rabobank, 2019).

The former chairman of the NVM (dutch association of estate agents and appraisers), Ger Jaarsma, stated that the biggest bottleneck is the deficit of houses in and near the cities. This is due to the lack of new construction these past few years, which has led to a shortage of 200,000 houses. The problems concerning high transaction prices and the deficit in housing will continue as the shortage in supply will not be overcome within such a short timeframe (Kleyngeld, 2018).

1.2 Relevance of this study

An interesting question is why do people want to live in and near the cities. The house prices are higher and yet there is an ongoing high demand. Jaarsma state that there is a trend in which people want to live, work and recreate in the same area. Which means that there is not only a need for housing, but also space for green, firms and infrastructure. This statement can be further supported by the research of Koster and Rouwendal (2012). They have found empirical evidence that house prices are higher in areas with a mixed variety of land use. This has the implication that it increases the willingness to pay by multiple parties and that that household density has a negative effect on the house prices.

Housing and amenities go hand in hand and it is expected that there will be 20 to 30 new agglomerations in the Netherlands.In this report, the effect of these amenities and the locational factors on the house prices will be studied.

Rappaport (2008) found that consumption amenities have a higher effect on the house prices than the wages of the people residing in those areas. The author also concluded that consumption amenities are becoming an increasingly more important factor that people will look to when choosing to settle in a new home. Restaurants are key consumption amenities in the urban environment and this research will focus on studying the effects of restaurants on house transaction prices. This topic is yet underexplored and the challenge is to bring a new layer of depth to the existing literature.

There is an unspoken assumption that more consumer amenities will bring more benefit/utiliy to the house prices. This report will challenge that assumption by researching whether the effects of restaurants are spatially heterogeneous or monotone[1]. The results could show a new insight to entrepreneurs, restaurant owners, investors, real estate agents and appraisers, policymakers, home owners and other parties. As it answers the question whether it makes a difference in which neighbourhood restaurants are situated and how house prices are affected by it. This can help in decision making in terms of development, taxing, marketing, investing, and residence.

1.3 Research question and hypotheses

To discover whether there is a distinction between different neighbourhoods and which role restaurants play, the following research question and hypothese have been formulated.

Research question:
What are the effects of restaurants in different neighbourhoods of Rotterdam on the house prices?

- ❖ *Hypothesis 1: Restaurants have a significant positive effect on the house transaction prices.*

The effect of restaurants on the house transaction prices is central in this study. This hypothesis will be tested with the hedonic pricing method and multi-level modelling.

- ❖ *Hypothesis 2: There is a significant difference in transaction prices between neighbourhoods.*

There are many aspects which can set neighbourhoods apart from each other and it is interesting to see whether all these factors added up will display a significant difference on the house transaction prices between different neighbourhoods. The added value of this hypothesis is to give an insight to the externalities (both positive and negative) of different neighbourhoods and how this affects the house prices.

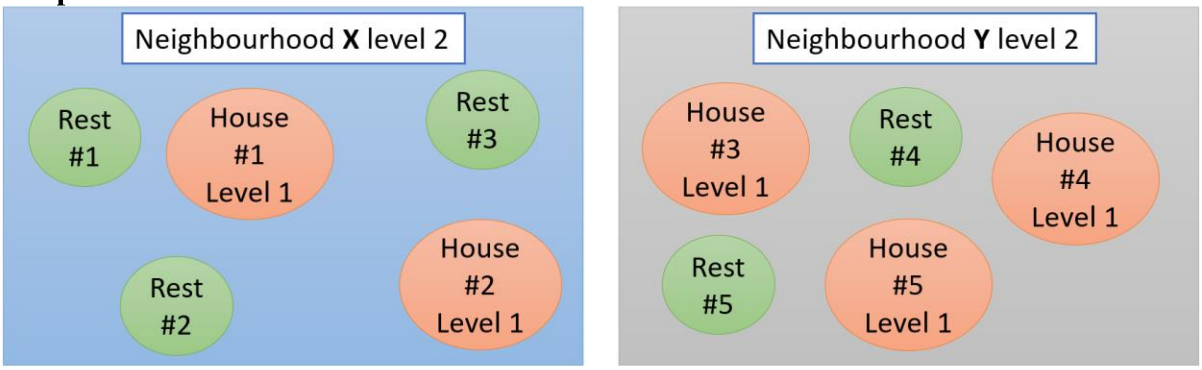
- ❖ *Hypothesis 3: Restaurants have a significant different effect (slope) per neighbourhood on the house transaction prices.*

The third hypothesis is the first step in the spatial analysis via multi-level modelling in this research. This will be explained visually. Graph 1 displays two neighbourhoods (X and Y), each neighbourhood has its own characteristics. In those neighbourhoods, there are different houses and restaurants, with their own characteristics. No two neighbourhoods, houses or restaurants are identical. Therefore, there is reason to

[1] This will be explained in section 1.3 (third hypothesis)

assume and to test that in different neighbourhoods the effects of restaurants is different on the house transaction prices.

Graph 1. Multi-level model



- ❖ *Hypothesis 4: There is a significant difference in the effect of restaurants inside and outside of the city centre of Rotterdam.*

With this hypothesis, a closer look will be taken to the lay-out of cities, as it could reveal insights to the dynamic of amenities of neighbourhoods inside the city centre and neighbourhoods outside the city centre (agglomerations).

- ❖ *Hypothesis 5: There is a significant difference in the effect of restaurants between in neighbourhoods with newer built houses and restaurants with older houses.*

The fifth hypothesis is an extension of the fourth hypothesis. As newly constructed houses do not only reside outside the city centre, but also within the city centre. As is planned with developments in Rotterdam.

There are countless aspects that can researched and this research is a proxy for further research in the spatial analysis via multi-level modelling.

2. Literature review

This chapter discusses the relevant literature surrounding the topics of consumer amenities, location effects and other factors that affect house prices. These will be a base for this research in the hedonic pricing method and multi-level modelling in which a spatial analysis will be performed.

2.1 Consumer city

The growth of cities have been spurred on by trade, finance, manufacturing and industrialsm. In the past, people did not have much of a choice in terms of residence and employment. However, the overall increase in wealth of the population has opened up more oppurtunities and the desire to recreate. These aspects have attraced people to work and/or settle in cities as there is a wider diversity in choice of jobs, consumption and/or other possibilities. However, big cities have also shown decline. In order for cities to sustain their growth, a strong and diversified economy is required (Kim & Short, 2007). Cities are no longer just centres of production and employment, but they are (also) more and more becoming a place in which there will be an emphasis on the consumption of goods and services (Glaeser, Kolko, & Saiz, 2001).

There are four important types of amenities that cities have in order to attract people to live in a dense urban area and for cities to thrive. These are (1) a large variety of consumer goods and services, whereas restaurants are described as non-tradable and highly localized amenities. (2) The aesthetics and physical setting of a city, such as monuments and the architecture of a city. (3) The quality of public services, such as the availability of good schools to educate the (future) workforce and a low crime rate upheld by these services. (4) Speed and mobility. Time is becoming an increasingly important aspect and a lot of effort is made to decrease the transportation and commuting times, which offers more choices due to the access of goods, services and other aspects that contribute to the quality of life.

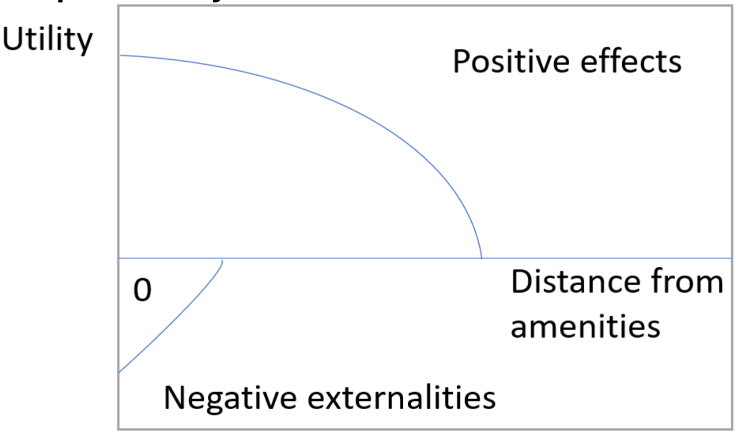
2.2 Neighbourhood factors

One of the earlier studies in these fields was conducted by Li and Brown (1980). In which they have tested micro-neighbourhood effects on the attributes affecting house prices. They have made a distinction between (I) aesthetic features, (II) pollution levels and (III) proximity to amenities. The first factor, aesthetic features, is measured by rating the visual quality of neighbourhoods. However, aesthetic features does not only relate to the physical setting, but also the perceived attractiveness of a neighbourhood. There are multiple (abstract) factors which contribute to the perceived attractiveness (reputation) of a neighbourhood. Koopman (2012) describes this feature as the (social) affinity a person has towards a neighbourhood and its residents. Which is based on the (dis)similarities between income, education, ethnicity, lifestage and lifestyle. The reputation of a neighbourhood leads to a (biased) sorting of households, which can influence the choice of residency. This results in a self-fulfilling prophecy in which people will settle in neighbourhoods with households similar to themselves. This is reason to assume that there are differences between neighbourhoods as well and it is worth investigating whether there are effects of income, education, ethnicity, lifestage and lifestyle on the house prices.

2.3 Utility and distance

Li and Brown (1980) have described their third factor (proximity to amenities) as a function of utility over distance, which is displayed in graph 2 here blow.

Graph 2. Utility over distance[2]



The closer a household is to the amenity (with 0 being to the center to the amenity), the higher the utility. This is due to positive effects such as accessibility to transportation infrastructure, goods and services. There are diminishing returns of the positive the longer the distance to the amenities, which can be explained by time and transportation costs. On the other hand there are negative externalities, such as noise, pollution and congestion. These effects are stronger near the center of the amenity.

An interesting thought is to assume that neighbourhoods outside the city centre are more attractive due to lower negative externalities compared to the city centre as the central point of amenities. Some people prefer the density of cities, due to the abundant availabilty of goods and services, which meets their need. This urban attractiveness could outweigh the higher rents in the city centre, commuting time and higher crime rates. Which seems to be reflected in a faster growth of cities with more amenities (Glaeser, Kolko, & Saiz, 2001). In general, the negative effects diminishes faster over distance than the positive effects, which is why most people prefer to live in areas with acces to amenities. This preference leads to a higher willingness to pay, which can be illustrated with the following formula:

Urban rent premium = urban wage premium + urban amenity premium.

An important part of this research is to investigate whether this utility is capitalized in the house transaction prices.

[2] This figure is based on the model of Li & Brown (1980)

2.4 Restaurants

Restaurants are key consumer amenities and will be the focal point in this research. There are hundreds of restaurants in Rotterdam, which differ in type, cuisine, rating and price levels. More densely populated cities have a higher chance of having an uncommon cuisine (Schiff, 2014). It is possible that this diversity in restaurants could have an effect on the house prices. Hence, it is possible that the effect of restaurants on the house prices could differ per neighbourhood.

Kuang (2017) has done research by focusing on the three following aspects of restaurants: Quality, quantity and price levels. The results are as follows. (1) The quantity of restaurants in an area positively effects the house prices. (2) A larger number of highly rated/perceived restaurants have a positive effect on the house prices. (3) There is no statistical proof that more expensive restaurants effect the local house prices positively. A possible explanation for this is that people are willing to travel (further) to visit a high rated restaurant. Which could mean that the sphere of influence is greater than that of lower rated restaurants. Kuang has tested a reverse causation and that he has found no statistical evidence that high rated restaurants locate in rich neighbourhoods. These findings are especially interesting for the scope of this report. As it implies that restaurants have spatially heterogeneous effects. Furthermore, this research will delve deeper in the quantity aspect of restaurants.

2.5 Earlier study

This research follows up on an earlier study conducted by Van Haaren, Van Oort, and Wildeboer (2017). They have expanded on traditional hedonic pricing models on house prices by adding a spatial analysis of the effect of restaurants in the region of Amsterdam. Via multi-level modelling, they have tested for the effects of consumption amenities with the following variables: availability, diversity and quality of restaurants. This is done on a structural level (level one) and on a neighbourhood level (level two). This report elaborates on this approach by emperically extending the geography and controlling for restaurant specific effects.

3. Data and methodology

In this chapter, there will be a description of the dataset, summary statistics and the methodology.

3.1 Dataset

The dataset in this research consists of three sources. Data of house prices and other structural variables are provided by the Dutch Association of Real Estate Agents (NVM); Neighbourhood statistics are retrieved from Statistics Netherlands (CBS) and a dataset of restaurants in Rotterdam has been created for this research, based on the findings of iens.nl.

The dataset has been geocoded and restricted to the area of Rotterdam. Geocoding allows for the data to be merged based on location, which allows for multi-level analysis.

3.2 Hedonic pricing method

Pagourtzi et al. (2003) described twelve methods, whereas the hedonic pricing method is the best fit for this research for several reasons. The first reason is that this method fits with the available resources to find an answer to the first hypothesis in this report. Malpezzi (2003) states that a fundamental hedonic equation consists of the following characteristics: Structural, neighbourhood, location, contract/market and the time of observation, which we will go into more detail in 3.3. The second reason is that the hedonic pricing method can derrive the monetary value of characteristics through the house prices, which is a key point in this research, because this method is capable of measuring the value of restaurants in neighbourhoods. The third reason is that restaurants are heterogeneous, which can be difficult to implement in other models mentioned by Pagourtzi et al. (2003).

3.3 Selection of relevant variables

A hedonic pricing method is in essence a large regression model. The studies of Sirmans, Macpherson and Zietz (2005) and Sirmans et al. (2006) are used to determine which variables should be incorporated in the hedonic pricing method. These studies have delved into the literature for the most common used variables to estimate the effects on the house prices while controlling for geographical location, time, type of data and model specification. After reviewing the literature and the variables relevant and available in this research, the following selection of variables has been made for the hedonic pricing method[3].

$$\begin{aligned}(log)price = \ & \beta_0 + \beta_1 * size + \beta_2 * sizesquare + \beta_3 * rooms + \beta_4 * housetype + \beta_5 \\ & * cohort + \beta_6 * floors + \beta_7 * condition + \beta_8 * parking + \beta_9 * busy \\ & + \beta_{10} * density + \beta_{11} * demography + \beta_{12} * NRestaurant + \varepsilon_i\end{aligned}$$

In this research two dependent variables have been created. The first dependent variable in our research is called '*logprice*'. This variable consists of the logarithmic values derived from the transaction prices of the houses. The reason for choosing the transaction value is because the real estate market is a platform with imperfect

[3] See appendix B

information, fluctuations, outliers and many other factors that influence the appraisal of house prices (Quan & Quigley, 1991). The transaction prices can be viewed as the market value in that specific point in time. The most conventional method for transforming data on house prices is the utilization of logarithms. This could be deemed to be the best method, because this retains all the data without cropping or merging. However, this also means that outliers could influence the results.

The second dependent variable in this research is called ‘price’. These are the winsorized transaction prices at a 0.02 fraction. Winsorization is a process in which the ends of the data points are capped at a minimum and a maximum. This reduces the negative effects of outliers on statistical analysis, which can be helpful in the real estate market because of the large variances between houses. It could be argued that this method could be more valuable than using the logarithmic values in this research, because the average house price differs a lot with the highest transaction price[4].

To decide which transformation with the original transaction prices would be the best fit (winsorized transaction prices or the logarithms of the transaction prices), several tests were conducted. After testing for the normal distribution[5], statistical significance, and interpretation of the results[6] (Altman & Bland, 1995; Box, Hunter, & Hunter, 1978), it has been decided to use both logarithmic and winsorized values. This is as a robustness test and if the results would differ, it would imply that there should be a closer look to the method in which transaction prices are transformed.

Basic structural attributes

To create a hedonic pricing model that is fit for research, it is important to incorporate certain basic structural attributes. The attributes incorporated in this model are: the surface area of the house (*size*), the number of rooms (*rooms*), the type of house (*housetype*), the period in which the house is constructed (*cohort*), the number of floors (*floors*), the sold condition (*condition*), and parking facilities (*parking*).

Locational attributes

The following locational attributes have been used in the model: vicinity to a busy road (*busy*), the number of adresses in a square kilometre (*density*), the demographic[7] outside the western hemisphere) and the number of restaurants in the neighbourhood (*NRestaurant*). In the multi-level model analyses the neighbourhoods themselves will be a focal point in the research as these and other location attributes are incorporated.

[4] The average transaction price is 210,508.10 and the highest transaction price is 6,250,000.

[5] Comparing histograms of the data distribution. See appendix D.

[6] Section 4.1: Winsorization changes the interpretation of certain variables

[7] Percentage of immigrants outside the western hemisphere

3.4 Summary statistics

There will be three types of summary statistics. The first type is to display the trend of the average house transaction prices of Rotterdam in the period 2008-2017. The second type is an overview of the nominal variables with the number of observations, mean, standard deviation, minimum and maximum. The third type is in the form of frequency tables, which shows insight in the general constitution of houses.

In the dataset of the NVM, the dates of the transaction prices are given. The period between 2008 and 2017 will be observed as a reference for the peculiar fluctuation of the housing market these past few years. Therefore, a categorical variable will be created that indicates the average transaction price per year. This variable accounts for trends, inflation, unemployment rates and other omitted variable bias. The results are displayed here below and are in line with the findings of the CBS.

Table 1 & graph 3. Trend average transaction prices 2008-2017

Year	Average transaction price
2008	191,556.10
2009	195,203.70
2010	197,817.80
2011	200,459.20
2012	202,038.70
2013	202,792.30
2014	202,984.70
2015	205,043.60
2016	223,447.60
2017	262,429.70

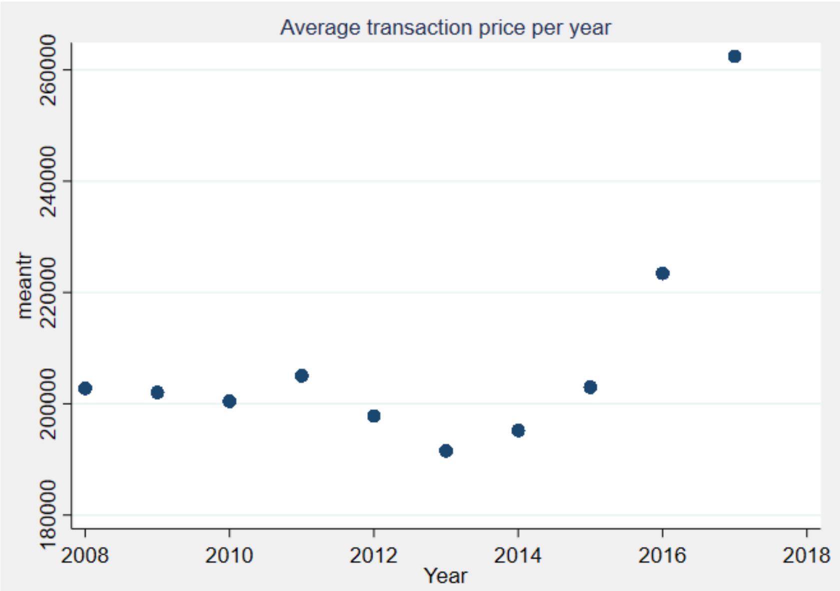


Table 2. Summary statistics nominal variables

Variable	Obs.	Mean	Std. dev.	Min	Max
logprice	40,294	12.07	0.59	4.79	15.65
price*	40,294	204,617.10	129,640.30	60,000	690,000
size	39,701	102.05	42.54	26	532
density	40,392	3,994.75	1,902.17	57	8,208
demography	40,392	32.76	16.35	2	80
NRestaurant	39,641	20.51	39.01	1	178
Original transaction prices	40,294	211,014.80	180,122.8	120	6,250,000
Original number of rooms	40,111	3.89	1.46	1	44
Original number of floors	40,111	1.82	0.93	1	8

The original variable of the transaction prices has coding errors and in some cases peculiar values, such as very low transaction prices. Therefore, this variable has been transformed by using a 0.02 fraction winsorization (*price*) and transforming the data to logarithms (*logprice*).

Table 3. Frequency table of rooms winsorized at 0.03

Number of rooms	Frequency	Percentage
2	4,257	10.61
3	14,859	37.04
4	9,879	24.63
5	6,593	16.44
6	2,836	7.07
7	1,687	4.21
Total	40,111	100.00

The original variable of the number of rooms has a range between 1 and 44 rooms. This has been winsorized to a minimum of 2 rooms and a maximum of 7 rooms in order to create a categorical variable with more (statistical) meaning. As this range is closer to the mean and its confidence intervals. One room houses only consists of 0.71% of all observations and houses with more than 7 rooms only consist of 1.19% of all observations.

Table 4. Frequency table floors winsorized at 0.01

Number of floors	Frequency	Percentage
1	19,309	48.14
2	10,363	25.84
3	8,880	22.14
4	1,559	3.89
Total	40,111	100.00

The original variable of the number of floors has a range of 1 to 8 floors. Houses with more than 4 floors only consist of 0.05% of all observations. Therefore, this variable has been winsorized. Note that this range is closer to the mean and its confidence intervals.

Table 5. Frequency table parking

Parking facility	Frequency	Percentage
None	33,593	83.75
Parking lot	2,667	6.65
Carport without garage	1,229	3.06
Garage without carport	2,033	5.07
Garage & carport	131	0.33
Big garage	458	1.14
Total	40,111	100.00

3.5 Multi-level modelling

The goal of this research is to observe the effects of restaurants in different neighbourhoods in Rotterdam. Therefore, there is a need to group houses by neighbourhoods and restaurants by neighbourhoods. Multi-level modelling is a statistical method that can structure and operate grouped/ clustered data.

In these mixed models, the coefficients consist of a mix of fixed parameters and random variables. Fixed coefficients are (unknown) constants, whereas random coefficients can vary per sample group. In this research, the fixed parameters are the neighbourhoods and the random coefficients are the other variables (StataCorp LP, 2013).

A multi-level model consists of two or more levels. The first level is on a structural level, which is almost equivalent to the hedonic pricing model in 3.3. The second level is on neighbourhood level in which the houses are grouped by their respective neighbourhood. Each neighbourhood has its own features (employment rate, number of schools, variety of amenities et cetera) which leads to the belief that houses in the same neighbourhood share these features. Thus, by implementing dummy variables for neighbourhoods, we can improve the accuracy of the model by assigning different intercepts for each neighbourhood on the Y-axis. This also helps to reduce the endogenity in the model as it accounts for omitted variable bias.

There are different types of mixed models, which can show different insights between the relationships of the variables. With a random slopes model it is possible to measure the effect restaurants have in different neighbourhoods. In this model, neighbourhoods will have a different base value (intercept) and it allows us to observe whether the effect of restaurants have significant different effects per neighbourhood (slope).

Lastly, multi-level modelling will be applied for two more facets. First, to observe the effects of restaurants inside the city centre and outside the city centre. Second, to observe the effects of restaurants in newer built and older built neighbourhoods.

4. Results

4.1 Hedonic pricing method models

In section 3.3 is described which variables are selected for the hedonic pricing method. Which has led to the following model:

$$(log)price = \beta_0 + \beta_1 * size + \beta_2 * sizesquare + \beta_3 * rooms + \beta_4 * housetype + \beta_5 * cohort + \beta_6 * floors + \beta_7 * condition + \beta_8 * parking + \beta_9 * busy + \beta_{10} * density + \beta_{11} * demography + \beta_{12} * NRestaurant + \varepsilon_i$$

Most variables are conformed to the expectations found in the literature (Sirmans, Macpherson, & Zietz, The composition of hedonic pricing models, 2005), meaning that the coefficients have the expected signs. Some variables will be elaborated on for more in depth analysis.

The variable '*size*' has the highest T-value of all the variables, meaning that this variable explains a lot of the variation in the model. For every square meter of a house, the transaction price increases by a set amount. The variable '*sizesquare'* is the square function of the previous variable. The sign of this effect is negative value, meaning that there is a decrease in value per square meter. This means that there are diminishing returns for every additional square meter.

The variable '*rooms'* has been winsorized at a 0.03 fraction to a minimum of two rooms and a maximum of seven rooms. The reason for adjusting this variable is to improve the statistical analysis. In some occasions, houses with one room are used as a parking facility[8]. Therefore, houses with one rooms are lumped together with houses with two rooms. Houses with seven or more rooms only consist of 2.09% of the total observations. Additionally, there is a wide range of rooms (ranging between 7 and 44 rooms), which would skew this variable, making the interpretation less valuable.

From the 5th room onwards this variable seems logical, because houses with more rooms are usually bigger (and therefore have a higher value) than houses with fewer rooms. However, there is a decreased effect of adding an additional room if the total number of rooms is between 3 and 4 rooms. An interpretation of this can be illustrated with the following example: There are two near identical houses with the same number of square meters. House A has 3 rooms and house B has 4 rooms. House A will have bigger rooms than house B. It can be speculated that a house with bigger rooms is preferred over a house with smaller rooms (i.e. such houses have a higher value).

The next variable *housetype'* is categorical and indicates the type of house. 'There are 18 types of houses defined by the NVM[9]. The base value is the single-family home (*eengezinswoning*). Some types were not significant due to the low volume of that type of house. This variable has led to the decision to use logarithms instead of winsorization for the transaction prices. The winsorized cap at a 2% level[10] is 690,000. This would negatively influence the data on houses with a higher value, such as villas and country houses.

[8] Manual checks
[9] See appendix C table 7
[10] A 2% winsorization level was chosen to attain a normal distribution

The variable named ‘*cohort*‘ indicates the building period in which houses are constructed. The base value is the period 1500-1905 to keep a chronological order. The results can be explained by history and policymaking at those times. Our base value is 1500-1905, which means that in many cases this kind of houses have historical value. The similar could be said for the period 1906-1930. The First World War took part during this period, but the Netherlands were not at war. It did affect the country economically, but not as drastic as the Second World War did. The period 1931-1944 was a period in which there was a worldwide financial crisis, which started in 1929 in the United States and spread to Europe. The period 1945-1959 was the period in which cities were rebuilt. Rotterdam is a special case, because despite the overall growth of economy in the Netherlands, Rotterdam was bombed in the Second World War. This meant that the houses that were built had to be constructed quicker and cheaper than it would have been in other areas (Andere tijden, 2010). The period between 1971-1980 and 1981-1990 were marked by economic recessions. The period 1950-1970 was a period filled with optimism, abundance of resources and wealth. Unfortunately, this could not be sustained and the government had to cut back in government spending. This affected the population (and the real estate) heavily. Due to high unemployment rates and decreased wealth, it is quite likely that the houses built (such as flats) in this period were built quicker and cheaper to be affordable. The period 1981-1990 shows a growth, the economic situation was improving, however real estate can be perceived as a reactive market (Catte, Girouard, Price, & André, 2004). Even though people have increased wealth, this does not mean that they will immediately purchase a new house. The period 1991-2000 shows a further improvement. The period after 2001 shows a positive effect on the transaction prices.

The variable ‘*floors*’ is the number of floors of a house. This variable has been winsorized[11] to a minimum of one floor and a maximum of four floors. The base value (omitted dummy variable) are houses with one floor. The effects of adding a second-floor cannot be derived from the results, but adding a third and a fourth-floor results in a significant decrease. These results seem counter-intuitive. Therefore, the results will be dissected for interpretation.

Most one-floor houses are apartments, which have a generally lower value as can be derived from the ‘*soortwon*’ variable. Bungalows are expensive one-floor houses, but there are only 109 Bungalows of the 19,309 one-floor houses. This indicates two possibilities that are not mutually exclusive. First, the model is lacking information, i.e. there is omitted variable bias or an endogeneity problem. The second possibility is that there is a similar effect as with the variable ‘*rooms’*. In this case that would be that adding an additional floor decreases the value of the house, because it would split the surface of the house. It is preferable to have a large surface (one floor) than to split that surface area in two or more floors. Due to the variance in floors and winsorization it is hard to tell if there is a non-linear relationship.

The variable *‘condition’* contains information about the house’s selling condition, which are ‘kosten koper’, ‘vrij op naam’ and ‘geveild’. The first and base value in our model is ‘kosten koper’, which means the costs for the transfer of the house are paid by the buyer. This is the most common condition and makes up for 98.20% of our observations. This occurs when a house already has an occupant and sells it to

[11] A 1% winsorization level was chosen to set the maximum at four floors.

another person. The second condition is 'vrij op naam', which means that the costs for the transfer of the house are paid by the seller. This situation occurs when new built houses are sold, as there are no occupants yet. The third condition is 'geveild', which means auctioned. This occurs when a house is force sold, because the occupant could not pay off the mortgage. This part of the variable has the largest T-value of the entire model[12] and has a significant negative effect.

The variable *'demography'* displays the effect of an additional percentage point of non-western immigrants of the neighbourhood. This variable has a significant negative effect and one the largest T-value in the model. There are multiple explanations for this effect. Non-western immigrants generally have a lower income and education. Therefore, they cannot afford houses with a high transaction price. Immigrants also tend to live in areas with people of the same background. Hence, neighbourhoods with a high percentage of non-western immigrants are generally neighbourhoods with lower house values. Additionally, Sá (2014) found statistical evidence that there is a mobility response of the native people. They move to other neighbourhoods, which are generally neighbourhoods with better/more expensive housing. These findings correspond with the research of Koopman (2012) in section 2.2.

The last variable in the model is '*NRestaurant'*. This displays the number of restaurants in a neighbourhood. This variable is created after geocoding and merging the data sets (of houses, neighbourhoods and restaurants). An additional restaurant adds a significant positive effect and ranges from one to 178 restaurants in a neighbourhood. This variable alongside the dependent variables (*price* & *logprice*) are central in this research. The results of the hedonic pricing method is an important finding for our first hypothesis, as it confirms that: *Restaurants have a significant positive effect on the house prices*. However, it is important to realize that the hedonic pricing method aggregates all variables. There could be relationships between variables that are not directly visible on aggregate. In the next sections, the results of the mixed models will be displayed which reveal new insights to the variables in this research.

The constants are not zero in both models. Therefore, the intercept has no intrinsic meaning. Further explanation of the variables can be found in Appendix A

[12] Except for the constant

4.2 Mixed models

In this section, the results of the mixed models will be displayed and interpreted. The goal is to acquire more in depth analysis about the relationship between neighbourhoods and restaurants and which other factors effect this.

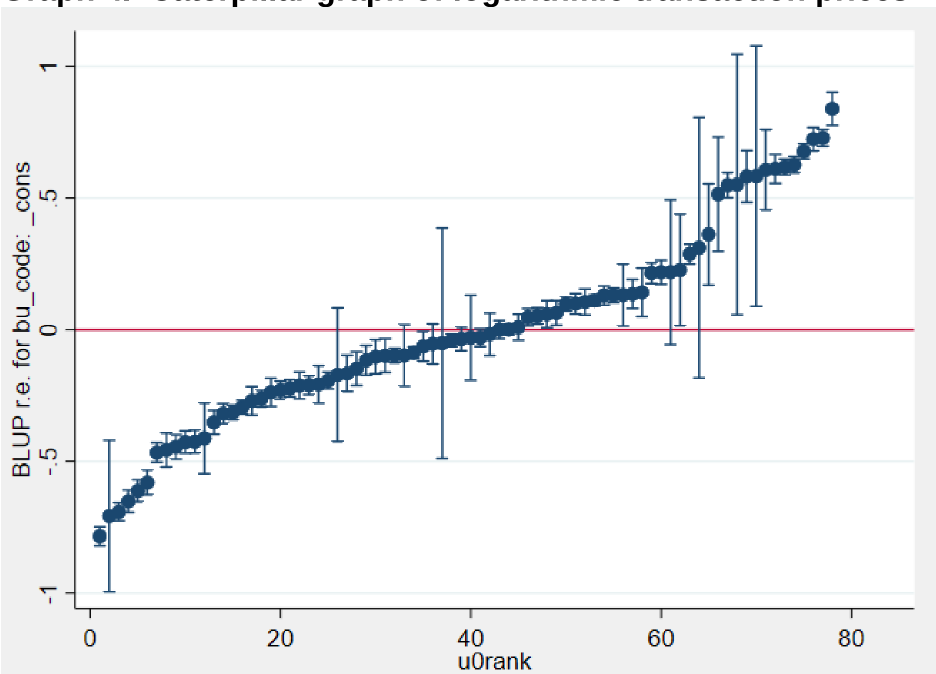
4.2.1 Random intercepts model

The first mixed models are random intercepts models. These models indicate whether the dependent variables (*logprice*[13] and *price*[14]) are significantly different per neighbourhood, which both are on a 0.00% significance level. However, it is yet unclear how these neighbourhoods are different from one another. Therefore, caterpillar graphs will be created in order to display the difference in average house transaction prices per neighbourhood visually.

4.2.2 Caterpillar graph

The goal in this section is to find an answer to the second hypothesis: *There is a significant difference in transaction prices between neighbourhoods.* This can be displayed via a caterpillar graph. A caterpillar graph is a graph in which the grouped variables (neighbourhoods) are displayed with their respective means and confidence intervals. When the confidence intervals intersect with average 0 line[15], there is no statistical evidence to state that that neighbourhood deviates from the average. In this case, it would mean that the neighbourhood does not have higher/lower transaction prices than the average. The caterpillar figure will be displayed below with the average house transaction prices of the neighbourhoods in ascending order.

Graph 4. Caterpillar graph of logarithmic transaction prices



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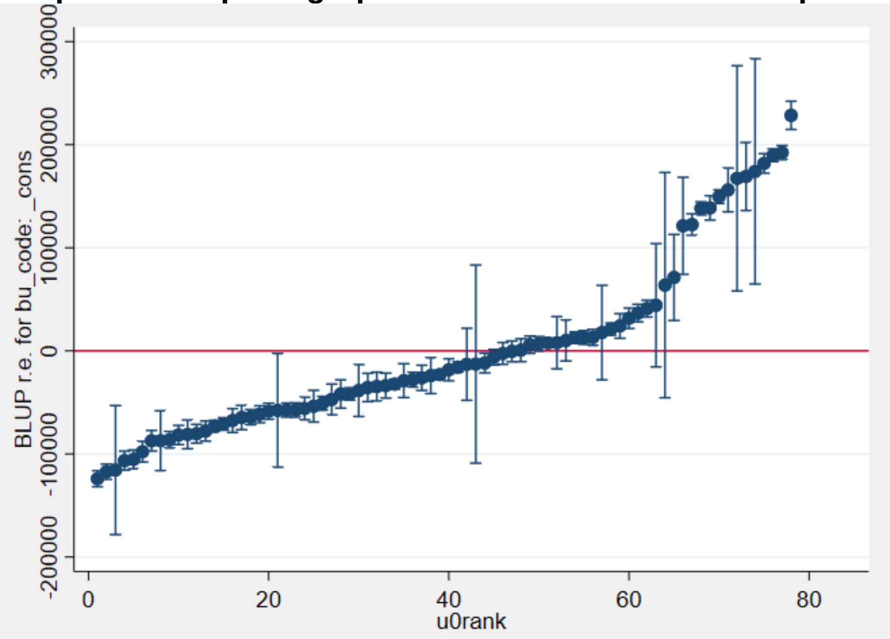
[13] xtmixed logprice || bu_code:, mle
[14] xtmixed price || bu_code:, mle
[15] The red line in graph 2

Graph 5. Caterpillar graph of winsorized transaction prices



According to the model the neighbourhoods with the lowest average transaction prices are Carnisse (ranked lowest), Tarwewijk (2nd), Zuidplein (3th), Oud-Mathense (4th). The neighbourhoods with the highest average transaction prices are mostly industrial areas. This seems to be (coding) errors as those neighbourhoods[16] are without confidence intervals. The highest ranked neighbourhoods that are with confidence intervals are Niewe Werk (78th), 's-Gravenland (77th), Kralingen-Oost (76th), Molenlaankwartier (75th).

Carnisse, Tarwewijk, Zuidplein and Oud-Mathenese are known to be some of the poorer neighbourhoods in Rotterdam. Nieuwe werk is the neighbourhood centrally located next to the Erasmusbrug and with accommodations such as Euromast, Het Park, many restaurants and a view over the harbour. Kralingen Oost has traditionally been a neighbourhood for people who are well-off. Molenlaankwartier and 's-Gravenland are neighbourhoods in the east of Rotterdam surrounded by green and are even called the tuinsteden (garden cities). Apart from the errors, the found results are intuitively correct, therefore this graph is deemed to be accurate. Hence, the second hypothesis can be accepted: "*There is a significant difference in transaction prices between neighbourhoods*."

4.2.3 Variance partitioning coefficient

The caterpillar graph and (unrestricted maximum) likelihood test derived from the mixed model can indicate that the average transaction price differs significantly between neighbourhoods, but a multi-level model has the potential for more in-depth analysis. The variance partitioning coefficient (vpc) can be used to calculate what proportion of the variance the second level variable(s) has (/have) on the total variance (Goldstein, Browne, & Rasbash). The vpc can be derived from the residuals of the

[16] Botlek, Waalhaven-Zuid, Kralingse Bos, Eemhaven, Bedrijventerrein Rotterdam Noord-West.

mixed models[17]. residuals of the second command We take the standard deviation of the random-effects parameters and use the following formula:

$$vpc = \frac{\sigma_{constant}}{(\sigma_{constant} + \sigma_{residual})}$$

With *logprice* as the dependent variable this yields a fraction of 0.4430[18], thus 44.30% of the variance is in level 2, which is a large fraction and could indicate a multi-level problem. With price as the dependent variable this yields a fraction of .4565[19], thus 45.65% of the variance is in level 2. Next, the variables of the hedonic pricing method will be added to the mixed model[20]. This yields a vpc of 0.4395[21] (*logprice*) and a vpc of 0.4021[22] (*price*). This is already an improvement, but this does not explain the heterogeneity in the second level itself. A random slopes model will be created to find such a relationship.

4.2.4 Random slopes model

As seen by the previous models, the second level of the multilevel is a part of the variation that is still underexplored. There are numerous factors that could have an effect and in this research, the focus is on which role the restaurants play. The goal is to analyse whether neighbourhoods also have different slopes, which would indicate that neighbourhoods have differing effects with regards to restaurants and house prices. This will help us to find an answer to the third hypothesis: *Restaurants have a significant different effect (slope) per neighbourhood on the transaction prices.*

The model can be illustrated with the following formula.

$$\begin{aligned} Y_{ij} = \beta_0 + \big(&\beta_1 * size + \beta_2 * sizesquare + \beta_3 * rooms + \beta_4 * housetype + \beta_5 \\ &* cohort + \beta_6 * floors + \beta_7 * condition + \beta_8 * parking + \beta_9 * busy \\ &+ \beta_{10} * density + \beta_{11} * demography + \beta_{12} * NRestaurant\big) * \chi_{ij} \\ &+ \mathrm{u}_{1\mathrm{j}} * \mathrm{\chi}_{\mathrm{ij}} + \epsilon_{ij} \end{aligned}$$

The Y_{ij} represents the average transaction prices per neighbourhood. The *i* represents the house. The *j* represents the neighbourhood. β_0 represents the constant. $\beta_{1\rightarrow 12}$ represents the average slope of the explanatory variables. The χ_{ij} represents the the winsorized transaction prices derived from the houses and neighbourhoods. u_{0j} represents the intercept of the number of restaurants in a neighbourhood (*NRestaurant*). $u_{1j} * \chi_{ij}$ represents the slope based on the

[17] xtmixed logprice || bu_code:, mle xtmixed price || bu_code:, mle
[18] .3796342/(.3796342 + .4772611)
[19] 86554/(86554+103060.4)
[20] xtmixed logprice ib2013.year size sizesquare i.rooms ib5.housetype i.cohort i.floors i.condition i.parking i.busy density demography || bu_code:
xtmixed price ib2013.year size sizesquare i.rooms ib5.housetype i.cohort i.floors i.condition i.parking i.busy density demography || bu_code:
[21] .1902682/(.1902682+.2426302)
[22] 34758.38/(34758.38+51683.81)

neighbourhood, *NRestaurant* and the corresponding houses. The ε_{ij} represents the error terms.

Now, there are two variables on the second level[23]. The random-effects parameters, are split in two parts: standard deviation of *NRestaurant* and the standard deviation of the constant. *NRestaurant* is only a tiny fraction in explaining the variance when the dependent variable is the logarithm of the transaction prices 0.00188[24]. When the winsorized transaction prices are taken as the dependent variable, the fraction of the variance yields 0.022[25]. This means that *NRestaurant* explains 2.2% of the variance in neighbourhoods. Both models[26] indicate random slopes by the spatial heterogeneity with respect to restaurants. Which model to take is dependent on the research, which in this case is to create a model which can explain the effect of restaurants on transaction prices for the ordinary citizen[27].

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[23] Command used: xtmixed logprice ib2013.year size sizesquare i.rooms ib5.housetype i.cohort i.floors i.condition i.parking i.busy density demography || bu_code: NRestaurant

[24] .0002911/.1547

[25] 679.047/30811.06

[26] Displayed in appendix E

[27] This will be elaborated on in the discussion

4.3 Neighbourhoods

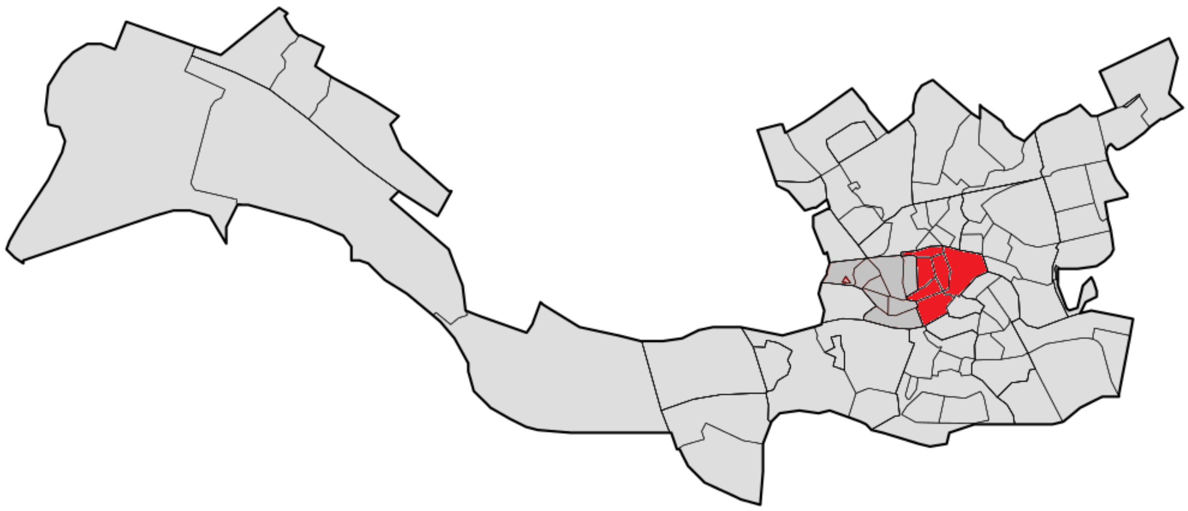
In 4.3 we did find different slopes for neighbourhoods, however the effect of *NRestaurant* is still unclear. So far, we know that *NRestaurant* explain 2.2% of the variance of the neighbourhoods. In this section, we will sort neighbourhoods by type and observe whether restaurants have a different effect for the different types of neighbourhoods.

4.3.1 Inside and outside the city centre

In this section, the goal is to answer the fourth hypothesis: "*There is a significant difference in the effect of restaurants inside and outside of the city centre of Rotterdam.*" The reason for researching this hypothesis is to examine the centrality effects of the neighbourhoods. Inside the city centre are all kinds of amenities in abundance, which are less abundant outside the neighbourhood. Therefore, it is interesting to observe the effect of restaurants in and outside the city centre.

For this purpose, a dummy variable has been created to indicate whether the neighbourhood is either inside or outside the city centre. According to Gemeente Rotterdam (2019) the neighbourhoods inside the city centre are: Stadsdriehoek, Oude Westen, Cool, C.S. kwartier, Nieuwe Werk, Dijkzigt, which are displayed in the graph 6 below.

Graph 6. Map of city centre neighbourhoods of Rotterdam[28]



The models show that restaurants outside the city centre have significant positive results[29]. Restaurants inside the city centre do not have significant results. This can be interpreted as follows: a restaurant in a neighbourhood outside the city centre has added value to the transaction prices in that neighbourhood. Whereas, there is not enough statistical support to claim the same for restaurants in neighbourhoods inside the city centre.

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[28] Source: © 2008, Centraal Bureau voor de Statistiek / Topografische Dienst Kadaster

[29] Displayed in appendix F

This heterogeneity in how restaurants (and other amenities) have different effects in neighbourhoods inside and outside the city centre raises the question: how should we appraise amenities? It is often assumed that more amenities (restaurants) have a positive significant effect on the house prices, which is supported by hedonic pricing methods. However, the mixed models in this research indicate that there is a spatial difference in how restaurants (amenities) effect the house transaction prices in different kinds of neighbourhoods. The first possible explanation are the negative externalities near the amenities of the city centre (as described in graph 2) offsetting the positive effects of restaurants. The second explanation could be due to the abundance of amenities inside the city centre. An additional restaurant in neighbourhoods inside the city centre does not have the same value, as an additional restaurant in neighbourhoods outside the city centre with fewer amenities. Therefore, it could me a matter of scarcity.

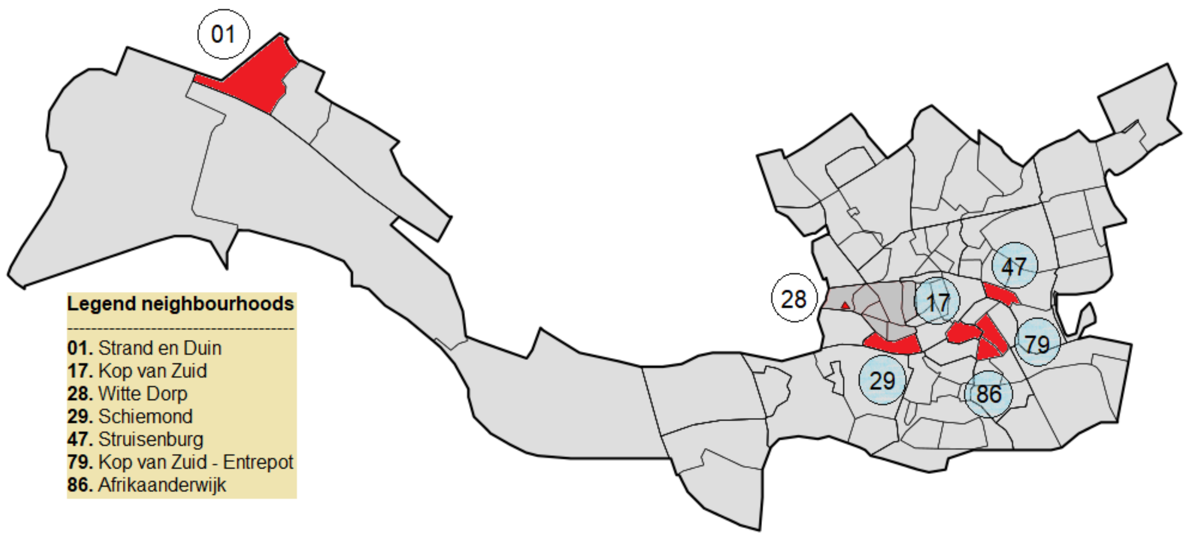
4.3.2 New and old neighbourhoods

In this section, the goal is to answer the fifth hypothesis: "*There is a significant difference in the effect of restaurants between in neighbourhoods with newer built houses and restaurants with older houses.*" There are two concepts that need to be addressed before answering this hypothesis.

First, there is a need to define which houses are newly developed and why. In this research, the houses built in the cohorts 1991-2000 and after 2001 are chosen to be defined as newer built houses. This definition is based on the historical findings in section 4.1, where not only the building year is accounted for, but also the economic and real estate situation in those time periods. Second, new houses could (in theory) be built anywhere, which could make the effect of restaurants ambiguous[30]. Therefore, a dummy variable will be created that indicates whether the average building year (cohort) of the houses in the neighbourhoods are roughly around 1990. This is done on a neighbour level, because the variable *NRestaurant* is also on a neighbourhood level and not on structural level.

Several tests were conducted with variations in the choice of defining 'new houses', the inclusion and exclusion of the historical buildings of the cohort 1500-1905. This has yielded the same type of results. Namely, that (1) restaurants in old neighbourhoods have a positive significant effect and (2) there is no statistical evidence to state that there is a significant effect of restaurants in new neighbourhoods. The location of the 'old neighbourhoods' are displayed in the following graph.

Graph 7. Map of old neighbourhoods in Rotterdam[31] (CBS)



These neighbourhoods are Strand en Duin, Kop van Zuid, Witte Dorp, Schiemond, Struisenburg, Kop van Zuid – Entrepot and Afrikaanderwijk.

[31] Source: © 2008, Centraal Bureau voor de Statistiek / Topografische Dienst Kadaster

In section 4.3.1 the results showed that restaurants in neighbourhoods outside the city centre have a significant positive effect. The addition of this section is that restaurants have a significant positive effect in the ‘older’ neighbourhoods and that there is no statistical evidence to state the same effect for ‘newer’ neighbourhoods.

Table 6 displays the average property valuation and average annual income level of these neighbourhoods of the period (2013-2018) to give additional details of the old neighbourhoods.

Table 6. Average property valuation and average annual income level of old neighbourhoods 2013-2018[32]

Neighbourhoods	2013	2014	2015	2016	2017	2018	Average annual income level
Strand en Duin	366,000	344,000	333,000	335,000	353,000	352,000	32,700
Kop van Zuid	229,000	207,000	241,000	242,000	254,000	284,000	42,300
Witte Dorp	137,000	135,000	137,000	142,000	146,000	155,000	16,200
Schiemond	187,000	174,000	170,000	170,000	172,000	186,000	26,400
Struisenburg	192,000	184,000	179,000	183,000	170,000	136,000	29,500
Kop van Zuid – Entrepot	178,000	170,000	166,000	169,000	177,000	196,000	26,600
Afrikaanderwijk	95,000	91,000	90,000	92,000	100,000	114,000	14,100

The average property valuation and annual income levels of the old neighbourhoods are rather diverse. Strand en Duin can be perceived as an outlier, because it is far away from the city centre and it does not show similarities with the other neighbourhoods. The other neighbourhoods are located close to the city centre and have several similar features. (1) a low average property valuation, a relatively high density level, a high percentage of immigrants and low income levels (except for Kop van Zuid) (AlleCijfers.nl, sd). There is not yet a clear explanation as to why restaurants have a significant positive effect for these type of neighbourhoods.

A possible link could be that different demographic groups have different customs related to restaurants. The study of Moschis, Curasi and Bellenger (2003) suggests that mature consumers (people over the age of 55) have certain dining characteristics that set them apart from other demographic groups. They are wealthier and can have a higher expenditure on restaurants and they have a certain loyalty to particular restaurants. This loyalty can be explained by the following factors. Mature consumers can benefit more from the catering services, because they visit the restaurants on off-peak times presumably more often than other groups. This could imply a higher service level, more attention, social contact and the more the visit the same restaurant, the more they will make acquintances with the staff.

While these neighbourhoods are generally poor, some factors such as the social aspect and loyalty might still apply.

[32] Source: https://allecijfers.nl/

5. Conclusion

To answer the research question of this report: *What are the effects of restaurants in different neighbourhoods of Rotterdam on the house prices?* Several hypotheses have been created to research different aspects of neighbourhoods and restaurants.

- *Hypothesis 1: Restaurants have a significant positive effect on the house transaction prices.*
- *Hypothesis 2: There is a significant difference in transaction prices between neighbourhoods.*
- *Hypothesis 3: Restaurants have a significant different effect (slope) per neighbourhood on the house transaction prices.*
- *Hypothesis 4: There is a significant difference in the effect of restaurants inside and outside of the city centre of Rotterdam.*
- *Hypothesis 5: There is a significant difference in the effect of restaurants between in neighbourhoods with newer built houses and restaurants with older houses.*

The first hypothesis would be accepted based on the hedonic pricing method. However, multi-level modelling implicates that there is a spatial layer that has not been accounted for. Thus, the first hypothesis is rejected, which is contrary to the literature. The second hypothesis is accepted at a 0.00% significance level (4.2.1) and is visually represented by the caterpillar graphs (4.2.2). The third hypothesis is accepted, as the results of the random intercepts random slopes model supports the spatial heterogeneity with respect to restaurants. Therefore, restaurants have a significant different effect per neighbourhood on the transaction prices. However, the effect of restaurants on the house transaction prices is marginal in the random intercepts random slopes model. The fourth hypothesis should be split in two parts. As multi-level modelling indicates that there is no statistical support that restaurants inside the city centre have a positive significant effect on the house transaction prices. On the other hand, restaurants outside the city centre do have a significant positive effect on the house transaction prices. This could be due to negative externalities of (amenities in) the city centre offsetting the positive effects or due to restaurants being valued outside the city centre due the scarcity of restaurants compared to the abundance of amenities in the city centre. The results for the fifth hypothesis is that restaurants have a positive significant effect in neighbourhoods with older built houses, but there is no statistical evidence to state an effect of restaurants on neighbourhoods with newer built houses. There is not yet a clear explanation for this finding. Presumably, factors such as age, demographics, income levels, preferences play a role.

These hypotheses yield different insights to the research question. The hedonic pricing method shows that on aggregate restaurants have a significant positive on the transaction prices. Via multi-level modelling, analyses of the spatial structure of Rotterdam have been made. These results show that restaurants have a positive significant effect on the house transaction prices in neighbourhoods outside the city centre of Rotterdam, but there is no statistical evidence to state that restaurants have a positive significant effect on the house transaction prices inside the city centre. This finding questions how the effect of consumer amenities should be perceived. As the effect of restaurants of the house transaction prices does not solely depend on the quantity of restaurants, but more importantly *where* the restaurants are situated.

6. Discussion

This research explored the possibilities with multi-level modelling and spatial analysis, which can serve as a base for future analysis. There are many facets in which this paper can be expanded on, such as researching more amenities, broadening the scope from a city to a larger region and researching which other aspects effect the variance in multi-level modelling.

Ideally in order to improve this research, the endogeneity for restaurant location behaviour could have been taken into account. Which could be a hint to find an answer to the fifth hypothesis.

What effects this choice has not yet been examined and can be interesting, as it is expected that there will be 20 to 30 new agglomerations and new residential area inside centres. Which changes will this bring in future (spatial) analysis of the effect of restaurants on house prices and does it differ per city?

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7. Appendix

Appendix A – Variable lists

A.1 – List of variables of the NVM dataset

Name	Type	Description
buurt_ID	Text	ID of the neighbourhood
bwper	Ordinal variable	Period in which the house is constructed
categorie	Categorical variable	Indicates the type of house
DAT_AANM	Date	Date of entry in database NVM
DAT_AFMEL	Date	Date of withdrawal out of database NVM
LVRGPRIJS	Nominal Variable	Last asking price
ERFPACHT	Dummy variable	Leasehold property
GARAGE	Categorical variable	Type of garage
VERHUURD	Dummy variable	Rented (partly) or not
MEUBELS	Dummy variable	Furnished
HUISNR	Nominal variable	House number
HUISNRTOE	Text/nominal variable	House number addition
INHOUD	Nominal variable	Volume in cubic metres
INPANDIG	Categorical variable	Indicates whether the building is/has indoor parking
INVEST	Dummy variable	Indicates whether the house is bought as an investment
NIEUWBOUW	Dummy variable	New construction
ISOL	Ordinal variable	Isolation level
KELDER	Categorical variable	Type of basement
KOOPCOND	Categorical variable	Selling condition
KWALITEIT	Ordinal variable	Quality of the apartment
HUURPIJS	Nominal variable	Rent price
VRGPRIJS	Nominal Variable	Last asking price
VRGM2	Nominal variable	Last asking price per square meter
LIFT	Dummy variable	Indicates whether the building has a lift or not
LIGCENTR	Categorical variable	Position relative to centre of the city
LIGMOOI	Categorical variable	Position of house as to a (nice) location
LIGDRUKW	Categorical variable	Indicator of a busy road
LOOPT	Nominal variable	Indicates how many days the house is registered
M2HUIS	Nominal variable	Total surface of house in square meters
MONUMENT	Dummy variable	Indicates whether it is a monument or not
MONUMENTA	Dummy variable	Indicates whether it is monumental or not
NBALKON	Nominal variable	Number of balconies
NKAMERS	Nominal variable	Number of rooms
NVERDIEP	Nominal variable	Number of floors
NVMCIJFER	Categorical variable	Type of house
NWC	Nominal variable	Number of toilets
ONBI	Ordinal variable	Maintenance state of interior
ONBU	Ordinal variable	Maintenance state of exterior
OVRGPRIJS	Nominal variable	Original asking price
OVRGM2	Nominal variable	Original asking price per square meter
OPENH	Categorical variable	Indicates whether it can have/has a fireplace
PARKEER	Categorical variable	Parking facilities
PERCEEL	Nominal variable	Indicates the number of parcels of a lot
PC4	Nominal variable	4-digit zipcode

PC6	Nominal variable	8-digit ID code
POSTCODE	Text	4-digit zipcode and 2 letters
PROVERSCH	Nominal variable	Difference between asking price and transaction price in percentages
SCHUUR	Categorical variable	Type of shack
SOORTAPP	Categorical variable	Type of apartment
SOORTHUIS	Categorical variable	Type of house
SOORTWON	Categorical variable	Type of house
SOORTDAK	Categorical variable	Type of roof
STATUS	Categorical variable	Status
STRNAAM	Text	Street address
TRPRIJS	Nominal variable	Transaction price of the house
TRPRIJSM2	Nominal variable	Transaction price per square meter
TUIN_OPP	Nominal variable	Surface area of the garden in square meters
TUINLIGG	Categorical variable	Position of the garden
TYPE	Categorical variable	Type of house
VERKPCOND	Categorical variable	Selling condition
VERW	Categorical variable	Heating facilities
VLIER	Dummy variable	Indicates whether it has an attic or not
WIJK	Nominal variable	Neighbourhood code
WOONKA	Categorical variable	Type of living room
WOONOPP	Nominal variable	Total surface of house in square meters
WOONPLA	Text	Residence
ZOLDER	Dummy variable	Whether it has a loft (larger than attic) or not

A.2 – List of variables of the CBS dataset neighbourhood level

Name	Type	Description	Value
bu_code	Text	ID of the neighbourhood. Consisting of the municipality (4), district (2) and neighbourhood (2) codes	BU 8-digit code
bu_naam	Text	Name of the neighbourhood	
wk_code	Text	ID of the district. Consisting of the municipality (4) and district (2) codes	WK 6-digit code
gm_code	Text	ID of the municipality	GM 4-digit code
gm_naam	Text	Name of the municipality	
ind_wbi	Categorical variable	Indicator per neighbourhood that shows whether the values have changed compared to the year before.	1 (unadjusted), 2 (code has changed, but the statistics remained the same), 3 (the demarcation has changed compared to the previous year, therefore statistics will differ from the year before)
water	Dummy variable	Indicates if the area is water/sea	JA (yes), NEE (no)
postcode_2	Text	Most frequent zip code	4-digits
dek_perc	Categorical variable	Indicates the percentage levels of the most frequent zip code	1 (>90% same zip code), 2 (81-90% same zip code), 3 (71-80% same zip code), 4 (61-70% same zip code), 5 (51-60% same zip code), 6 (50% or less same zip code)
oad	Nominal variable	Average number of addresses in a square kilometre	
sted	Categorical variable	Urbanity level based on addresses per square kilometre (oad)	1 (≥2500), 2 (1500-2500), 3 (1000-1500), 4 (500-1000), 5 (<500)
aant_inw	Nominal variable	Number of inhabitants	
aant_man	Nominal variable	Number of male inhabitants	
aant_vrouw	Nominal variable	Number of female inhabitants	
p_00_14_jr	Nominal variable	Percentage of people between age 0-15	

p_15_24_jr	Nominal variable	Percentage of people between age 15-25	
p_25_44_jr	Nominal variable	Percentage of people between age 25-45	
p_45_64_jr	Nominal variable	Percentage of people between age 45-65	
p_65_eo_jr	Nominal variable	Percentage of people of age 65 and beyond	
p_ongehuwd	Nominal variable	Percentage of people never being married	
p_gehuwd	Nominal variable	Percentage of people that have married	
p_gescheid	Nominal variable	Percentage of people that have divorced	
p_verweduw	Nominal variable	Percentage of people that have been widowed	
geboo_tot	Nominal variable	Total number of births	
p_geboo	Nominal variable	Number of births per 1000 inhabitants	
sterft_tot	Nominal variable	Total number of deaths	
p_sterft	Nominal variable	Number of deaths per 1000 inhabitants	
bev_dichth	Nominal variable	Number of inhabitants per square kilometre	
aantal_hh	Nominal variable	Total number of households	
p_eenp_hh	Nominal variable	Percentage of one-person households (at least older than 14)	
p_hh_z_k	Nominal variable	Percentage of households without children	
p_hh_m_k	Nominal variable	Percentage of households with children	
gem_hh_gr	Nominal variable	Average number of people per household	
p_west_al	Nominal variable	Percentage of western immigrants (European, North-American,	

		Oceanian, Indonesian and Japanese)	
p_n_w_al	Nominal variable	Percentage not western immigrants	
p_marokko	Nominal variable	Percentage of immigrants that are Moroccan	
p_ant_aru	Nominal variable	Percentage of immigrants that are from the Netherlands Antilles and Aruba	
p_surinam	Nominal variable	Percentage of immigrants that are from Suriname	
p_turkije	Nominal variable	Percentage of immigrants that are from Turkey	
p_over_nw	Nominal variable	Percentage of immigrants that are from other countries	
opp_tot	Nominal variable	Total surface of the sum of water and land in hectares	
opp_land	Nominal variable	Total surface of land in hectares	
opp_water	Nominal variable	Total surface of water in hectares	

A.3 – List of variables of the CBS dataset municipality level

Name	Type	Description	Value
gm_code_2	Text	ID of the municipality	GM 4-digit code
gm_naam_2	Text	Name of the municipality	
water_2	Dummy variable	Indicates if the area is water/sea	JA (yes), NEE (no)
oad_2	Nominal variable	Average number of addresses in a square kilometre	
sted_2	Categorical variable	Urbanity level based on addresses per square kilometre (oad)	1 (≥2500), 2 (1500-2500), 3 (1000-1500), 4 (500-1000), 5 (<500)
aant_inw_2	Nominal variable	Number of inhabitants	
aant_man_2	Nominal variable	Number of male inhabitants	
aant_vrouw_2	Nominal variable	Number of female inhabitants	

p_00_14__2	Nominal variable	Percentage of people between age 0-15	
p_15_24__2	Nominal variable	Percentage of people between age 15-25	
p_25_44__2	Nominal variable	Percentage of people between age 25-45	
p_45_64__2	Nominal variable	Percentage of people between age 45-65	
p_65_eo__2	Nominal variable	Percentage of people of age 65 and beyond	
p_ongehu_2	Nominal variable	Percentage of people never being married	
p_gehuwd_2	Nominal variable	Percentage of people that have married	
p_gesche_2	Nominal variable	Percentage of people that have divorced	
p_verwed_2	Nominal variable	Percentage of people that have been widowed	
bev_dich_2	Nominal variable	Number of inhabitants per square kilometre	
aantal_h_2	Nominal variable	Total number of households	
p_eenp_h_2	Nominal variable	Percentage of one-person households (at least older than 14)	
p_hh_z_k_2	Nominal variable	Percentage of households without children	
p_hh_m_k_2	Nominal variable	Percentage of households with children	
gem_hh_g_2	Nominal variable	Average number of people per household	
p_west_a_2	Nominal variable	Percentage of western immigrants (European, North-American, Oceanian, Indonesian and Japanese)	
p_n_w_al_2	Nominal variable	Percentage not western immigrants	

p_marokko_2	Nominal variable	Percentage of immigrants that are Moroccan	
p_ant_ar_2	Nominal variable	Percentage of immigrants that are from the Netherlands Antilles and Aruba	
p_surina_2	Nominal variable	Percentage of immigrants that are from Suriname	
p_turkij_2	Nominal variable	Percentage of immigrants that are from Turkey	
p_over_n_2	Nominal variable	Percentage of immigrants that are from other countries	
opp_tot_2	Nominal variable	Total surface of the sum of water and land in hectares	
opp_land_2	Nominal variable	Total surface of land in hectares	
opp_wate_2	Nominal variable	Total surface of water in hectares	
woz2018	Nominal variable	Average house value 2018 per municipality	
crime2017	Nominal variable	Total number of registered crimes per municipality	

Appendix B – Hedonic pricing method

B.1 - Transaction prices

VARIABLES	(1) logprice	(2) winsorized prices	(3) Original transaction prices
2008.year	0.135***	21,454.760***	23,589.309***
	(0.007)	(1,425.253)	(1,921.218)
2009.year	0.108***	16,733.257***	19,008.455***
	(0.007)	(1,498.948)	(2,020.558)
2010.year	0.095***	16,210.589***	16,631.863***
	(0.007)	(1,507.276)	(2,031.783)
2011.year	0.087***	15,432.584***	18,290.392***
	(0.007)	(1,537.072)	(2,071.948)
2012.year	0.052***	6,895.660***	7,215.395***
	(0.007)	(1,553.839)	(2,094.549)
2014.year	0.030***	3,517.164**	3,187.571
	(0.007)	(1,461.938)	(1,970.669)
2015.year	0.066***	12,310.528***	14,232.192***
	(0.007)	(1,406.503)	(1,895.943)
2016.year	0.166***	34,018.504***	36,814.321***
	(0.006)	(1,377.448)	(1,856.777)
2017.year	0.315***	65,588.138***	70,860.849***
	(0.007)	(1,414.321)	(1,906.481)
size	0.015***	2,922.705***	1,630.260***
	(0.000)	(31.217)	(42.079)
sizesquare	-0.000***	-3.631***	2.313***
	(0.000)	(0.089)	(0.120)
3.rooms	0.024***	-8,542.086***	-3,269.895**
	(0.005)	(1,080.794)	(1,456.893)
4.rooms	0.019***	-12,375.928***	-5,098.414***
	(0.006)	(1,298.143)	(1,749.876)
5.rooms	0.019**	-11,105.141***	-5,397.121**
	(0.008)	(1,618.712)	(2,181.997)
6.rooms	0.027***	2,240.369	3,869.391
	(0.009)	(1,965.281)	(2,649.167)
7.rooms	0.035***	12,529.729***	18,123.037***
	(0.012)	(2,579.087)	(3,476.567)
sta caravan.housetype	-0.195	-55,999.254	-51,010.118
	(0.270)	(57,854.752)	(77,987.263)
eenvoudig.housetype	-0.114***	-23,636.264***	-21,700.884***
	(0.010)	(2,222.188)	(2,995.473)
woonboot.housetype	-0.059	-2,880.232	-8,438.191
	(0.061)	(13,043.898)	(17,582.962)
recreatiewoning.housetype	-0.594***	-618.317	-17,418.595
	(0.156)	(33,396.727)	(45,018.243)
grachtenpand.housetype	0.229**	68,506.659***	15,701.854
	(0.110)	(23,666.077)	(31,901.486)
herenhuis.housetype	0.081***	65,994.891***	43,390.153***
	(0.008)	(1,803.300)	(2,430.818)
woonboerderij.housetype	-0.002	58,785.992***	-54,092.116***
	(0.064)	(13,797.622)	(18,598.970)

bungalow.housetype	0.198***	86,517.614***	101,519.836***
	(0.030)	(6,381.675)	(8,602.394)
villa.housetype	0.274***	133,641.009***	246,758.443***
	(0.015)	(3,143.828)	(4,237.829)
landhuis.housetype	0.467***	99,552.538***	340,516.165***
	(0.063)	(13,510.702)	(18,212.206)
benedenwoning.housetype	-0.072***	-13,350.869***	-15,103.291***
	(0.007)	(1,528.891)	(2,060.920)
bovenwoning.housetype	-0.133***	-27,904.050***	-28,066.310***
	(0.006)	(1,314.448)	(1,771.855)
maisonnette.housetype	-0.125***	-22,297.395***	-19,806.812***
	(0.008)	(1,648.318)	(2,221.906)
portiekflat.housetype	-0.127***	-20,793.122***	-21,043.085***
	(0.007)	(1,437.408)	(1,937.602)
galerijflat.housetype	-0.117***	-26,487.380***	-26,264.408***
	(0.008)	(1,623.632)	(2,188.630)
verzorgingsflat.housetype	-0.127	-11,801.077	-15,470.739
	(0.082)	(17,498.362)	(23,587.506)
beneden-en bovenwoning.housetype	-0.027*	-981.408	-1,652.623
	(0.014)	(3,039.772)	(4,097.563)
1906-1930.cohort	-0.045***	-5,311.355***	1,256.805
	(0.008)	(1,716.332)	(2,313.588)
1931-1944.cohort	-0.119***	-20,576.682***	-15,543.892***
	(0.008)	(1,723.430)	(2,323.156)
1945-1959.cohort	-0.086***	-15,341.590***	-13,273.021***
	(0.009)	(1,835.825)	(2,474.662)
1960-1970.cohort	-0.177***	-41,154.022***	-38,436.083***
	(0.009)	(1,935.840)	(2,609.481)
1971-1980.cohort	-0.198***	-56,576.553***	-50,203.723***
	(0.009)	(1,988.976)	(2,681.107)
1981-1990.cohort	-0.079***	-26,867.929***	-22,094.564***
	(0.009)	(1,825.913)	(2,461.301)
1991-2000.cohort	0.086***	401.085	4,978.508**
	(0.009)	(1,861.179)	(2,508.840)
>2001.cohort	0.102***	4,986.126***	6,958.578***
	(0.009)	(1,899.516)	(2,560.517)
2.floors	-0.053***	-23,832.551***	-22,799.140***
	(0.005)	(1,084.438)	(1,461.804)
3.floors	-0.113***	-39,803.076***	-40,210.010***
	(0.007)	(1,538.522)	(2,073.903)
4.floors	-0.109***	-35,926.725***	-49,002.050***
	(0.011)	(2,357.998)	(3,178.543)
vrij op naam.condition	0.051***	9,179.091***	5,082.005
	(0.013)	(2,819.925)	(3,801.212)
geveild.condition	-0.447***	-32,077.337***	-27,319.443***
	(0.024)	(5,150.548)	(6,942.854)
parkeerplaats.parking	0.123***	27,506.034***	30,578.730***
	(0.006)	(1,313.238)	(1,770.224)
carpoort.parking	0.150***	35,702.755***	39,870.683***
	(0.009)	(1,838.292)	(2,477.988)
garage.parking	0.140***	45,876.084***	39,973.561***
	(0.007)	(1,490.421)	(2,009.063)
garage & carpoort.parking	0.261***	67,683.529***	80,181.001***

	(0.024)	(5,187.899)	(6,993.204)
garage+.parking	0.249***	68,480.653***	115,370.798***
	(0.015)	(3,159.638)	(4,259.141)
onbekend.busy	-0.006*	-1,609.567**	-1,038.650
	(0.003)	(662.870)	(893.538)
druk.busy	-0.071***	-17,281.540***	-18,416.536***
	(0.008)	(1,629.504)	(2,196.544)
density	0.000***	2.546***	1.878***
	(0.000)	(0.239)	(0.322)
demography	-0.009***	-1,558.424***	-1,713.504***
	(0.000)	(22.647)	(30.527)
NRestaurant	0.001***	207.900***	223.561***
	(0.000)	(9.152)	(12.337)
Constant	11.043***	12,829.898***	72,392.024***
	(0.015)	(3,255.853)	(4,388.837)
Observations	38,848	38,848	38,848
R-squared	0.767	0.789	0.750

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix C – Frequency tables of categorical variables

Table 7. Frequency table housetype

House type	Frequency	Percentage
Sta caravan	1	0.00
Eenvoudig	853	2.13
Woonboot	24	0.06
Recreatiewoning	7	0.02
Eengezins	8,749	21.81
Grachtenpand	7	0.02
Herenhuis	1,872	4.67
Woonboerderij	26	0.06
Bungalow	103	0.26
Villa	523	1.30
Landhuis	21	0.05
Benedenwoning	4,147	10.34
Bovenwoning	8,877	22.13
Maisonnette	2,072	5.17
Portiekflat	8,910	22.21
Galerijflat	3,478	8.67
Verzorgingsflat	12	0.03
Beneden-en bovenwoning	429	1.07
Totaal	40,111	100.00

Table 8. Frequency table cohorts

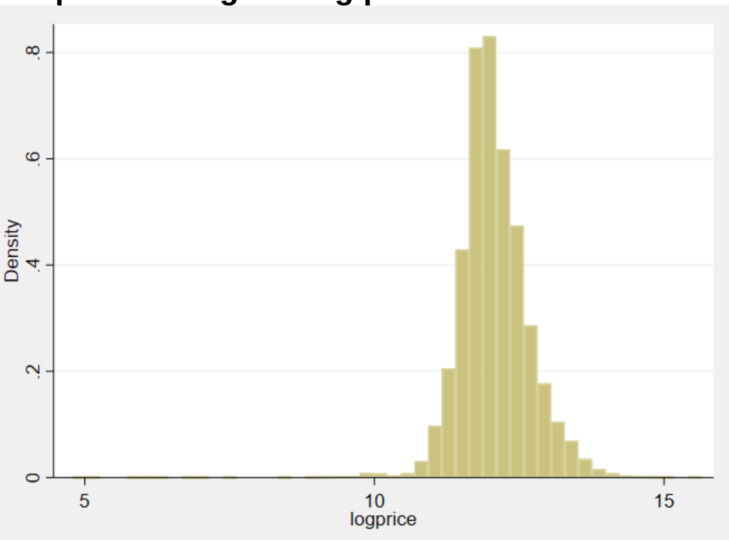
Cohort	Frequency	Percentage
1500-1905	1,684	4.20
1906-1930	5,142	12.82
1931-1944	7,240	18.05
1945-1959	5,202	12.97
1960-1970	4,294	10.71
1971-1980	2,816	7.02
1981-1990	4,901	12.22
1991-2000	4,042	10.08
>2001	4,781	11.92
Total	40,102	100.00

Table 9. Frequency table selling condition

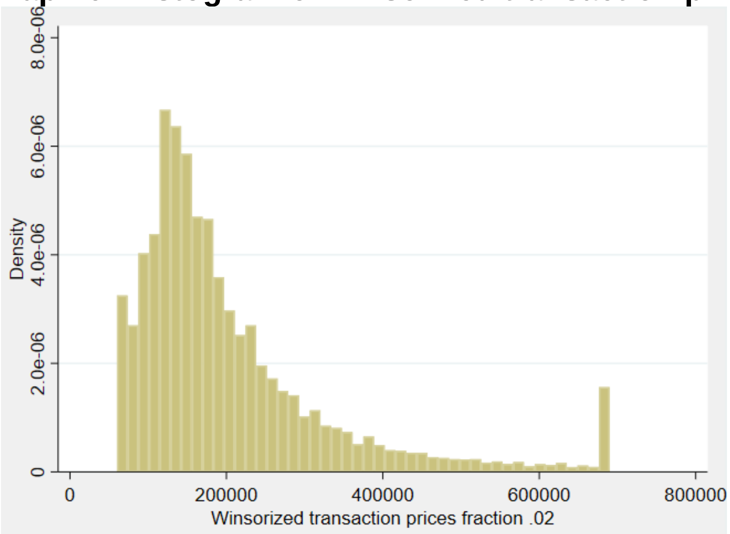
Condition	Frequency	Percent
Kosten koper	39,391	98.20
Vrij op naam	499	1.24
Geveild	221	0.55
Total	40,111	100,00

Appendix D – Data distribution

Graph 8. Histogram log price



Graph 9. Histogram of winsorized transaction prices



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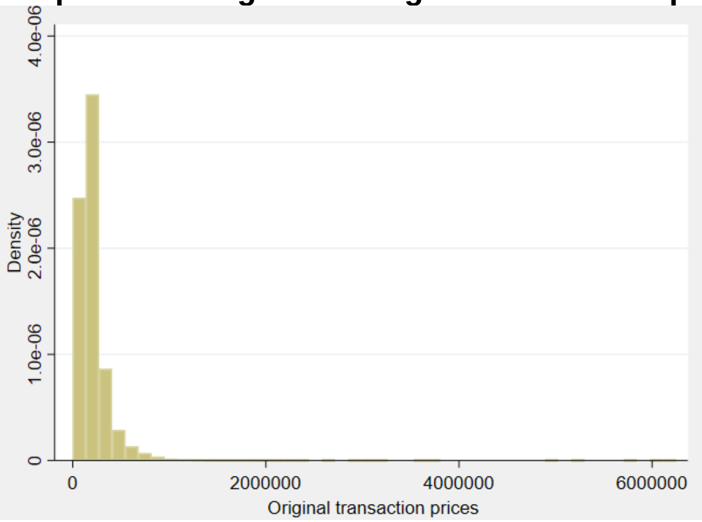
Graph 10. Histogram of original transaction prices



Appendix E – Mixed models, random slopes model

VARIABLES	(1) logprice	(2) winsorized transaction prices
2008.year	0.147***	24,004.350***
	(0.006)	(1,277.667)
2009.year	0.113***	18,252.902***
	(0.006)	(1,343.561)
2010.year	0.091***	15,994.205***
	(0.006)	(1,350.470)
2011.year	0.091***	16,030.865***
	(0.006)	(1,377.467)
2012.year	0.054***	7,855.660***
	(0.006)	(1,391.193)
2014.year	0.032***	4,183.231***
	(0.006)	(1,309.076)
2015.year	0.067***	13,222.040***
	(0.006)	(1,261.301)
2016.year	0.176***	36,204.101***
	(0.006)	(1,236.719)
2017.year	0.335***	69,194.430***
	(0.006)	(1,269.678)
size	0.012***	2,546.722***
	(0.000)	(28.919)
sizesquare	-0.000***	-3.042***
	(0.000)	(0.081)
3.rooms	0.048***	-2,858.377***
	(0.005)	(984.638)
4.rooms	0.065***	-2,184.133*
	(0.006)	(1,187.185)
5.rooms	0.059***	-2,849.835*
	(0.007)	(1,473.529)
6.rooms	0.054***	6,759.289***
	(0.008)	(1,785.777)
7.rooms	0.067***	17,689.552***
	(0.011)	(2,331.770)
sta caravan.housetype	-0.170	-33,040.199
	(0.242)	(51,831.793)
eenvoudig.housetype	-0.099***	-18,270.612***
	(0.009)	(2,004.569)
woonboot.housetype	-0.086	-3,395.537
	(0.057)	(12,257.635)
recreatiewoning.housetype	-0.637***	652.000
	(0.139)	(29,886.922)
grachtenpand.housetype	0.193*	71,217.804***
	(0.099)	(21,266.478)
herenhuis.housetype	0.053***	56,559.941***
	(0.008)	(1,635.162)
woonboerderij.housetype	0.098*	91,402.648***
	(0.058)	(12,470.886)

bungalow.housetype	0.199***	78,005.480***
	(0.027)	(5,724.887)
villa.housetype	0.259***	121,289.556***
	(0.013)	(2,878.379)
landhuis.housetype	0.432***	97,616.156***
	(0.056)	(12,095.387)
benedenwoning.housetype	-0.103***	-20,417.218***
	(0.007)	(1,440.201)
bovenwoning.housetype	-0.186***	-37,934.452***
	(0.006)	(1,256.430)
maisonnette.housetype	-0.186***	-36,260.359***
	(0.007)	(1,536.712)
portiekflat.housetype	-0.182***	-33,156.454***
	(0.006)	(1,361.722)
galerijflat.housetype	-0.176***	-37,000.758***
	(0.007)	(1,514.781)
verzorgingsflat.housetype	-0.238***	-36,448.795**
	(0.073)	(15,689.108)
beneden-en bovenwoning.housetype	-0.074***	-11,351.281***
	(0.013)	(2,753.808)
1906-1930.cohort	-0.006	487.499
	(0.008)	(1,641.572)
1931-1944.cohort	-0.027***	-4,103.497**
	(0.008)	(1,697.832)
1945-1959.cohort	-0.057***	-13,054.676***
	(0.008)	(1,750.441)
1960-1970.cohort	-0.129***	-24,890.053***
	(0.009)	(1,941.226)
1971-1980.cohort	-0.094***	-25,166.644***
	(0.009)	(2,032.078)
1981-1990.cohort	-0.065***	-18,217.245***
	(0.008)	(1,743.986)
1991-2000.cohort	0.086***	3,694.906**
	(0.008)	(1,777.715)
>2001.cohort	0.137***	12,965.715***
	(0.009)	(1,828.544)
2.floors	-0.028***	-18,403.379***
	(0.005)	(987.226)
3.floors	-0.058***	-28,679.839***
	(0.007)	(1,405.708)
4.floors	-0.098***	-32,600.236***
	(0.010)	(2,144.542)
vrij op naam.condition	0.014	-144.471
	(0.012)	(2,572.738)
geveild.condition	-0.363***	-22,518.046***
	(0.022)	(4,617.542)
parkeerplaats.parking	0.113***	24,210.488***
	(0.006)	(1,205.287)

carpoort.parking	0.145***	33,929.975***
	(0.008)	(1,669.050)
garage.parking	0.122***	38,992.899***
	(0.006)	(1,347.789)
garage & carpoort.parking	0.211***	54,491.368***
	(0.022)	(4,660.440)
garage+.parking	0.209***	56,868.007***
	(0.013)	(2,847.903)
onbekend.busy	-0.012***	-2,148.321***
	(0.003)	(601.013)
druk.busy	-0.049***	-13,496.017***
	(0.007)	(1,473.792)
density	0.000***	4.917**
	(0.000)	(2.418)
demography	-0.008***	-1,417.880***
	(0.001)	(258.249)
Constant	11.112***	18,827.712*
	(0.051)	(10,439.139)
Observations	38,848	38,848
Number of groups	69	69

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix F – Inside and outside the city centre

F.1 – Outside the city centre

VARIABLES	(1) logprice	(2) winsorized transaction prices
2008.year	0.153***	24,855.419***
	(0.006)	(1,298.271)
2009.year	0.117***	18,634.694***
	(0.007)	(1,367.595)
2010.year	0.097***	16,876.480***
	(0.007)	(1,377.337)
2011.year	0.098***	17,274.234***
	(0.007)	(1,407.031)
2012.year	0.059***	8,556.611***
	(0.007)	(1,416.322)
2014.year	0.032***	4,505.436***
	(0.006)	(1,335.409)
2015.year	0.066***	13,310.529***
	(0.006)	(1,288.358)
2016.year	0.170***	34,577.249***
	(0.006)	(1,256.721)
2017.year	0.323***	65,168.377***
	(0.006)	(1,290.901)
size	0.012***	2,415.117***
	(0.000)	(29.447)
sizesquare	-0.000***	-2.883***
	(0.000)	(0.081)
3.rooms	0.056***	-2,170.996**
	(0.005)	(1,027.187)
4.rooms	0.073***	-1,916.529
	(0.006)	(1,223.939)
5.rooms	0.068***	-1,640.533
	(0.007)	(1,508.042)
6.rooms	0.064***	8,873.217***
	(0.009)	(1,808.339)
7.rooms	0.079***	21,582.669***
	(0.011)	(2,344.895)
sta caravan.housetype	-0.172	-36,166.705
	(0.243)	(50,676.245)
eenvoudig.housetype	-0.103***	-19,975.609***
	(0.009)	(1,961.488)
woonboot.housetype	-0.017	7,186.972
	(0.059)	(12,382.676)
recreatiewoning.housetype	-0.641***	-3,007.932
	(0.140)	(29,218.093)
grachtenpand.housetype	0.187*	70,880.919***
	(0.100)	(20,793.928)
herenhuis.housetype	0.061***	60,059.525***
	(0.008)	(1,614.301)
woonboerderij.housetype	0.103*	96,940.056***
	(0.059)	(12,207.902)

bungalow.housetype	0.203***	81,152.320***
	(0.027)	(5,604.297)
villa.housetype	0.270***	127,169.889***
	(0.014)	(2,835.441)
landhuis.housetype	0.441***	103,343.027***
	(0.057)	(11,835.516)
benedenwoning.housetype	-0.102***	-21,436.289***
	(0.007)	(1,431.148)
bovenwoning.housetype	-0.190***	-39,452.794***
	(0.006)	(1,250.817)
maisonnette.housetype	-0.180***	-35,693.768***
	(0.008)	(1,577.439)
portiekflat.housetype	-0.187***	-35,090.493***
	(0.007)	(1,371.537)
galerijflat.housetype	-0.173***	-36,387.956***
	(0.007)	(1,540.515)
verzorgingsflat.housetype	-0.241***	-38,858.597**
	(0.074)	(15,341.072)
beneden-en bovenwoning.housetype	-0.071***	-11,060.768***
	(0.013)	(2,742.399)
1906-1930.cohort	-0.015*	-1,303.979
	(0.008)	(1,660.221)
1931-1944.cohort	-0.042***	-6,436.663***
	(0.008)	(1,730.493)
1945-1959.cohort	-0.061***	-12,117.119***
	(0.009)	(1,803.795)
1960-1970.cohort	-0.137***	-26,423.796***
	(0.009)	(1,954.345)
1971-1980.cohort	-0.098***	-24,647.591***
	(0.010)	(2,103.970)
1981-1990.cohort	-0.064***	-17,022.416***
	(0.009)	(1,804.804)
1991-2000.cohort	0.077***	2,229.994
	(0.009)	(1,830.559)
>2001.cohort	0.122***	7,508.045***
	(0.009)	(1,901.513)
2.floors	-0.025***	-16,569.785***
	(0.005)	(1,002.814)
3.floors	-0.050***	-25,264.935***
	(0.007)	(1,417.415)
4.floors	-0.082***	-27,255.585***
	(0.010)	(2,162.068)
vrij op naam.condition	0.000	-6,902.653**
	(0.014)	(2,856.952)
geveild.condition	-0.369***	-25,395.378***
	(0.022)	(4,625.582)
parkeerplaats.parking	0.117***	25,285.068***
	(0.006)	(1,299.574)

carpoort.parking	0.142***	31,190.811***
	(0.009)	(1,925.395)
garage.parking	0.123***	40,126.569***
	(0.007)	(1,367.018)
garage & carpoort.parking	0.207***	53,096.839***
	(0.025)	(5,147.207)
garage+.parking	0.203***	53,269.608***
	(0.014)	(2,978.278)
onbekend.busy	-0.015***	-2,446.021***
	(0.003)	(602.101)
druk.busy	-0.052***	-13,468.237***
	(0.007)	(1,557.403)
density	0.000**	2.195
	(0.000)	(2.657)
demography	-0.007***	-1,257.741***
	(0.001)	(270.103)
NRestaurant	0.003***	930.525***
	(0.001)	(214.277)
Constant	11.117***	26,497.729**
	(0.051)	(10,729.210)
Observations	35,522	35,522
Number of groups	64	64

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

F.2 – Inside the city centre

VARIABLES	(1) logprice	(2) winsorized transaction prices
2008.year	0.091***	19,868.328***
	(0.018)	(4,838.239)
2009.year	0.088***	21,825.694***
	(0.019)	(4,970.485)
2010.year	0.047**	16,226.412***
	(0.018)	(4,896.742)
2011.year	0.041**	13,384.246***
	(0.018)	(4,922.520)
2012.year	0.006	6,265.003
	(0.019)	(5,110.389)
2014.year	0.036**	7,537.843
	(0.018)	(4,714.045)
2015.year	0.096***	20,685.436***
	(0.017)	(4,530.246)
2016.year	0.250***	59,364.274***
	(0.017)	(4,667.690)
2017.year	0.472***	115,127.550***
	(0.018)	(4,752.128)
size	0.012***	2,771.669***
	(0.000)	(124.904)
sizesquare	-0.000***	-0.358
	(0.000)	(0.435)
3.rooms	0.005	-8,140.530***
	(0.011)	(2,928.305)
4.rooms	0.007	-4,088.020
	(0.015)	(3,977.037)
5.rooms	-0.009	-17,268.429***
	(0.021)	(5,567.971)
6.rooms	0.051	3,076.443
	(0.035)	(9,445.752)
7.rooms	-0.057	-55,816.331***
	(0.049)	(13,139.144)
woonboot.housetype	-0.738***	39,814.166
	(0.205)	(55,134.991)
herenhuis.housetype	-0.074	-34,285.487**
	(0.056)	(14,943.562)
villa.housetype	0.540***	283,024.711***
	(0.205)	(55,097.132)
benedenwoning.housetype	0.193***	71,508.731***
	(0.052)	(13,828.619)
bovenwoning.housetype	0.170***	66,039.986***
	(0.049)	(13,178.549)
maisonnette.housetype	0.129**	57,004.622***
	(0.050)	(13,477.823)
portiekflat.housetype	0.175***	69,181.099***
	(0.049)	(13,222.613)

galerijflat.housetype	0.156***	58,860.263***
	(0.050)	(13,448.397)
beneden- en bovenwoning.housetype	0.222***	87,707.482***
	(0.068)	(18,353.278)
1906-1930.cohort	0.045	13,524.822
	(0.034)	(9,124.661)
1931-1944.cohort	0.156***	14,177.707**
	(0.027)	(7,168.482)
1945-1959.cohort	-0.096***	-8,455.654
	(0.024)	(6,550.792)
1960-1970.cohort	-0.030	-7,510.365
	(0.066)	(17,786.734)
1971-1980.cohort	-0.102***	-18,528.951***
	(0.026)	(7,068.897)
1981-1990.cohort	-0.093***	-13,740.123**
	(0.023)	(6,272.623)
1991-2000.cohort	0.063***	8,066.984
	(0.024)	(6,529.202)
>2001.cohort	0.145***	37,970.227***
	(0.024)	(6,363.778)
2.floors	-0.037**	-22,456.979***
	(0.015)	(4,076.778)
3.floors	-0.085***	-36,956.678***
	(0.027)	(7,225.283)
4.floors	-0.024	-13,307.942
	(0.043)	(11,528.719)
vrij op naam.condition	0.083***	33,731.991***
	(0.023)	(6,180.603)
geveild.condition	-0.211***	38,335.150*
	(0.080)	(21,527.180)
parkeerplaats.parking	0.077***	16,800.963***
	(0.011)	(3,048.955)
carpoort.parking	0.127***	31,351.993***
	(0.013)	(3,389.727)
garage.parking	0.078***	16,825.879***
	(0.020)	(5,339.621)
garage & carpoort.parking	0.148***	41,764.778***
	(0.039)	(10,444.904)
garage+.parking	0.204***	58,188.600***
	(0.032)	(8,682.703)
onbekend.busy	0.043***	5,584.568*
	(0.011)	(2,892.406)
druk.busy	-0.011	-9,550.534**
	(0.017)	(4,489.408)
density	0.000**	4.990
	(0.000)	(8.099)
demography	-0.011***	-2,258.056**
	(0.002)	(942.008)

NRestaurant	0.000	173.043
	(0.000)	(184.630)
Constant	10.895***	-99,204.445**
	(0.118)	(43,051.432)
Observations	3,326	3,326
Number of groups	9	9

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix G – New and old neighbourhoods

G.1 – Old neighbourhoods (average building period before ~1985[33])

	(1)	(2)
VARIABLES	logprice	winsorized transaction prices
2008.year	0.150***	23,558.546***
	(0.006)	(1,288.917)
2009.year	0.117***	18,571.856***
	(0.007)	(1,356.205)
2010.year	0.091***	15,336.025***
	(0.007)	(1,363.752)
2011.year	0.092***	15,783.054***
	(0.007)	(1,388.385)
2012.year	0.055***	7,816.610***
	(0.007)	(1,406.963)
2014.year	0.033***	4,371.921***
	(0.006)	(1,327.284)
2015.year	0.073***	14,049.428***
	(0.006)	(1,281.289)
2016.year	0.179***	35,554.060***
	(0.006)	(1,257.133)
2017.year	0.342***	68,531.275***
	(0.006)	(1,291.587)
size	0.012***	2,457.541***
	(0.000)	(29.564)
sizesquare	-0.000***	-2.934***
	(0.000)	(0.083)
3.rooms	0.055***	-2,048.948**
	(0.005)	(997.339)
4.rooms	0.073***	-843.324
	(0.006)	(1,204.217)
5.rooms	0.069***	-1,422.357
	(0.007)	(1,495.386)
6.rooms	0.065***	8,179.901***
	(0.009)	(1,834.581)
7.rooms	0.074***	20,925.186***
	(0.011)	(2,384.406)
sta caravan.housetype	-0.167	-31,909.597
	(0.244)	(50,803.999)
eenvoudig.housetype	-0.107***	-19,512.878***
	(0.010)	(1,981.566)
woonboot.housetype	-0.074	2,871.954
	(0.058)	(12,070.685)
recreatiewoning.housetype	-0.644***	-1,028.440
	(0.140)	(29,293.201)
grachtenpand.housetype	0.199**	74,219.733***
	(0.100)	(20,847.918)
herenhuis.housetype	0.062***	60,837.671***

[33] The dummy variable 'new' assigned numbers to the cohorts. A value of 7.5 was chosen (between 1981-1990 and 1991-2000) due to the frequency and margins of the cohort variable.

	(0.008)	(1,741.523)
woonboerderij.housetype	0.123**	98,898.199***
	(0.059)	(12,246.818)
bungalow.housetype	0.201***	81,274.204***
	(0.029)	(5,969.376)
villa.housetype	0.325***	124,332.103***
	(0.017)	(3,496.854)
landhuis.housetype	0.507***	100,410.089***
	(0.062)	(12,950.512)
benedenwoning.housetype	-0.099***	-18,834.835***
	(0.007)	(1,444.901)
bovenwoning.housetype	-0.189***	-37,502.458***
	(0.006)	(1,259.998)
maisonnette.housetype	-0.192***	-35,696.996***
	(0.007)	(1,563.396)
portiekflat.housetype	-0.190***	-33,321.232***
	(0.007)	(1,372.827)
galerijflat.housetype	-0.179***	-35,156.178***
	(0.007)	(1,534.612)
verzorgingsflat.housetype	-0.234***	-35,787.517**
	(0.074)	(15,380.021)
beneden-en bovenwoning.housetype	-0.073***	-9,585.122***
	(0.013)	(2,742.513)
1906-1930.cohort	-0.003	707.172
	(0.008)	(1,633.776)
1931-1944.cohort	-0.021**	-4,366.020***
	(0.008)	(1,689.292)
1945-1959.cohort	-0.048***	-13,080.581***
	(0.008)	(1,745.834)
1960-1970.cohort	-0.116***	-24,294.273***
	(0.009)	(1,936.074)
1971-1980.cohort	-0.081***	-24,264.822***
	(0.010)	(2,022.583)
1981-1990.cohort	-0.047***	-16,388.243***
	(0.008)	(1,745.790)
1991-2000.cohort	0.102***	6,996.258***
	(0.009)	(1,812.739)
>2001.cohort	0.154***	16,863.434***
	(0.009)	(1,869.115)
2.floors	-0.025***	-17,066.365***
	(0.005)	(990.650)
3.floors	-0.051***	-25,732.979***
	(0.007)	(1,423.831)
4.floors	-0.087***	-29,292.435***
	(0.011)	(2,215.397)
vrij op naam.condition	-0.018	-11,530.896***
	(0.014)	(2,973.476)
geveild.condition	-0.368***	-22,840.684***
	(0.022)	(4,562.861)
parkeerplaats.parking	0.116***	25,645.552***
	(0.006)	(1,335.105)
carpoort.parking	0.125***	27,798.954***
	(0.009)	(1,798.000)

garage.parking	0.128***	39,376.922***
	(0.007)	(1,431.108)
garage & carpoort.parking	0.189***	47,947.080***
	(0.024)	(5,088.130)
garage+.parking	0.181***	49,594.471***
	(0.015)	(3,089.528)
onbekend.busy	-0.010***	-1,520.124**
	(0.003)	(610.282)
druk.busy	-0.040***	-10,381.416***
	(0.007)	(1,481.499)
density	0.000***	4.762*
	(0.000)	(2.641)
demography	-0.009***	-1,558.518***
	(0.001)	(283.255)
NRestaurant	0.002***	368.398**
	(0.001)	(158.199)
Constant	11.088***	22,262.850**
	(0.050)	(11,132.291)
Observations	36,067	36,067
Number of groups	62	62

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

G.2 – New neighbourhoods (average building period after ~1985)

VARIABLES	(1) logprice	(2) winsorized transaction prices
2008.year	0.106***	33,292.173***
	(0.019)	(5,971.354)
2009.year	0.051**	17,256.122***
	(0.020)	(6,192.547)
2010.year	0.094***	28,484.389***
	(0.020)	(6,191.237)
2011.year	0.082***	23,825.139***
	(0.021)	(6,532.251)
2012.year	0.036*	12,171.116**
	(0.020)	(6,202.245)
2014.year	-0.004	4,123.326
	(0.018)	(5,662.589)
2015.year	0.004	9,971.072*
	(0.017)	(5,392.781)
2016.year	0.124***	42,729.135***
	(0.017)	(5,248.505)
2017.year	0.250***	81,131.082***
	(0.017)	(5,350.547)
size	0.012***	3,390.756***
	(0.000)	(126.939)
sizesquare	-0.000***	-3.864***
	(0.000)	(0.349)
3.rooms	-0.008	-3,487.145
	(0.015)	(4,566.314)
4.rooms	-0.005	-5,825.288
	(0.017)	(5,399.164)
5.rooms	0.021	3,289.127
	(0.022)	(6,749.518)
6.rooms	0.043*	14,255.843*
	(0.024)	(7,445.488)
7.rooms	0.008	3,080.055
	(0.032)	(9,779.682)
eenvoudig.housetype	0.170***	73,810.195***
	(0.060)	(18,667.354)
herenhuis.housetype	0.034**	25,718.535***
	(0.015)	(4,746.012)
bungalow.housetype	0.402***	65,307.820***
	(0.063)	(19,511.568)
villa.housetype	0.135***	81,357.238***
	(0.019)	(5,869.087)
landhuis.housetype	-0.075	2,703.528
	(0.110)	(33,955.973)
benedenwoning.housetype	-0.159***	-29,239.827***
	(0.027)	(8,292.528)
bovenwoning.housetype	-0.047*	-12,735.482
	(0.027)	(8,243.330)
maisonnette.housetype	-0.130***	-31,482.721***
	(0.022)	(6,878.074)
portiekflat.housetype	-0.046*	-10,952.001

	(0.025)	(7,604.692)
galerijflat.housetype	-0.115***	-24,626.570***
	(0.026)	(8,096.470)
beneden-en bovenwoning.housetype	-0.091	-23,871.751
	(0.060)	(18,537.655)
1906-1930.cohort	0.014	15,572.968
	(0.038)	(11,835.878)
1931-1944.cohort	0.348***	163,738.847***
	(0.070)	(21,549.934)
1945-1959.cohort	0.019	-6,612.024
	(0.056)	(17,266.103)
1960-1970.cohort	-0.206***	-2,754.905
	(0.062)	(18,967.667)
1971-1980.cohort	0.099	79,641.039***
	(0.082)	(25,248.198)
1981-1990.cohort	-0.500***	-53,949.914***
	(0.038)	(11,750.549)
1991-2000.cohort	-0.097***	-23,237.231***
	(0.028)	(8,775.248)
>2001.cohort	-0.037	-15,551.718
	(0.031)	(9,462.715)
2.floors	0.004	-3,968.718
	(0.019)	(6,007.668)
3.floors	-0.071***	-31,791.982***
	(0.023)	(7,219.381)
4.floors	-0.091***	-43,893.390***
	(0.029)	(9,042.722)
vrij op naam.condition	0.059***	28,540.807***
	(0.018)	(5,498.734)
geveild.condition	0.086	40,006.699
	(0.131)	(40,404.156)
parkeerplaats.parking	0.062***	17,436.768***
	(0.010)	(2,974.683)
carpoort.parking	0.202***	61,787.539***
	(0.015)	(4,620.345)
garage.parking	0.078***	28,536.295***
	(0.013)	(3,968.285)
garage & carpoort.parking	0.250***	73,436.769***
	(0.038)	(11,737.116)
garage+.parking	0.268***	79,416.193***
	(0.025)	(7,776.083)
onbekend.busy	-0.015*	-6,030.622**
	(0.008)	(2,578.890)
druk.busy	-0.161***	-56,074.647***
	(0.024)	(7,423.233)
density	-0.000	-1.361
	(0.000)	(7.345)
demography	-0.005**	-1,212.790**
	(0.002)	(482.278)
NRestaurant	0.004	1,388.393
	(0.006)	(1,214.473)
Constant	11.472***	-29,147.620
	(0.092)	(21,772.448)

Observations	2,781	2,781
Number of groups	7	7

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1