Effect of Crime on House Price

"Impact of crime on local urban housing prices in Rotterdam, Utrecht, the Hague, and Eindhoven"

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1. Introduction

1.1 Background and problem statement

In 2011, Rotterdam was proclaimed to be the most dangerous city of the Netherlands. This is for the fifth time in ten years that Rotterdam is the most dangerous city of the Netherlands (Deira, 2011). Falling crime rates are beneficial for people living in the city, but also causes an increase of tourism and hotel occupancy, increasing property prices, and increasing application to local colleges (Schwarz et al., 2003). Therefore falling crime rates are beneficial for the city as a whole, being the most unsafe city in the country is not beneficial for the image of Rotterdam. This research will focus on how crime levels affect the development of residential areas, mainly housing prices. How strong do housing prices react to crime rates going up or down in districts of urbanized areas in the Netherlands. Will property prices go up elsewhere, or will people move away, and therefore leaving a lot of vacancy in the real estate market? But is this a significant effect due to (fear for) crime, or are other variables influencing housing prices more strongly?

A lot of research has not been done in this field in the Netherlands, making it an interesting topic to discuss. Mainly Rotterdam being the most dangerous city again, will this affect the future negatively for population numbers in deprived districts of the city? Parts of the city, like the south of Rotterdam, suffer from a negative image. Would removing the threat of crime flourish the district and make the housing prices go up? Understanding the relationship between property prices and the exposure to crime is useful for measuring the willingness of individuals to pay to reduce the exposure to crime risk (Linden et al., 2008). This research might also be useful for urban planners, police, property owners, and insurance companies on how much it is worthwhile to spend on safety (Ceccato et al., 2011). This research field brings up the following research question:

> *"How strong is the effect of crime on the local real estate market in the cities of Rotterdam, Utrecht, the Hague, and Eindhoven?"*

The focus of this research will be the city of Rotterdam, because Rotterdam is perceived to be the most dangerous city in the Netherlands. Also Rotterdam is the city of interest because it is the base of the research. To estimate an effect of crime on housing prices, three extra cities will be taken into account to get more observations. Therefore I have chosen the biggest cities in the Netherlands, these are Rotterdam, Utrecht, The Hague, and Eindhoven. The exception in this case is Amsterdam. Reason for leaving Amsterdam out of this research is the statistical bureau of the municipality of Amsterdam does not provide a dataset of crime records on neighbourhood level. Estimating the effect of crime on housing prices on city level does not provide accurate information on the local effects of crime. Therefore the biggest municipalities providing the data on neighbourhood level are included in this research.

1.2 Approach and method

Goal of the research is to investigate the effects of crime related activities on local urbanized areas, with a focus on housing prices and population in districts of the four big cities in the Netherlands. In foreign countries the effect of crime on housing price has been investigated, for example New York and Ohio. Though the impact of crime on housing prices may differ across countries, because of the contextualization in different forms of capitalism. The literature leaned strongly on research in the North America and the UK, with cities of over a million citizens (Ceccato et al., 2011). The combination of the four cities in the dataset generates enough observations of neighbourhoods to estimate the effect of crime in the urbanized areas on housing prices, like done in similar research abroad.

The first step is to analyse the literature available in this field to give insight in current state of affairs. The available literature will be assessed to create a clear overview of the previously done research, including the effects of crime on housing prices found by these authors. The second step is to create a database with the estimated tax value of houses, crime rates, and control variables influencing housing prices. Using the literature overview helps in setting up the dataset with relevant variables important for this research. The third step is to create (a) regression model(s) to estimate the effect of crime on the fluctuations in housing prices. This will give the research an empirical body of the effect of crime rather than a descriptive analysis of the current situation.

Eventually this approach would lead towards the effects of crime on the urban development in the cities of Rotterdam, Utrecht, The Hague, and Eindhoven. Resulting in whether crime levels do influence the housing prices significantly and to show which neighbourhoods suffer from high crime levels.

1.3 Composition research

The research will start by analysing current literature in a descriptive overview to investigate the important determinants influencing housing price in chapter 2. Predominately to find attributes which are influencing housing prices, besides crime, to eventually create a dataset in chapter 3 containing all the important attributes. After completing the dataset, two models will be set up to measure the effects of crime on housing price in chapter 4. The reason for creating two regression models is to compare both outcomes, to check for any differences in the estimation results. The two models will be created according to the linear regression method, with the Ordinary Least Square (OLS) estimation method, to find the best fit of the regression line. The assumptions of OLS are discussed and the regression models will be tested to check whether the assumptions hold. If the model is the Best Linear Unbiased Estimator (BLUE) the results will be analysed and discussed in chapter 5. After the assessment of the results, the conclusion and answering of the research question follows in chapter 6. The used references are summed up in chapter 7, and for easy reading the figures and output tables have been put in chapter 8.

2. Literature review

Many studies in the past have examined the impact of crime on housing prices, and changes in housing prices due to crime. Particularly relevant for this research are the papers based on a neighbourhood level analysis in big cities abroad, like New York City. A brief overview of the existing literature will give insight in the field of crime and the correlated effects on the housing prices. This leads towards a framework to estimate the effects of crime and as to how strong residents in heavy crime areas react to different levels of crime. In this chapter the different aspects of crime are described and the effects found in previous literature will be discussed. From there on the existing literature will be used to create a dataset and to add relevant variables to the regression model(s).

2.1 Effects of crime

Crime affects people's quality of life everywhere, feeling safe and happy in your own home is the most important determinant to stay in the neighbourhood. High crime rates lead to less life satisfaction in a city district, and lower crime rates towards more life satisfaction. Although real crime rates do not affect the life satisfaction that much, it is the perceived risk of facing criminal activities that affects life satisfaction in the city neighbourhoods. The feeling of being unsafe is more important than the actual criminal statistics of the neighbourhood (Cohen, 2008).

But people actually make a well thought choice to live in a district that is perceived to be more dangerous. Higher perceived risk is compensated in the lower housing prices and rental prices. Individuals are willing to accept the higher risk for lower housing prices and rental prices. It is likely that crime rates selects individuals in neighbourhoods according to their preferences and financial constraints. If someone can afford to move to a low crime neighbourhood one would do so, as safety is an important factor for the quality of life. Crime would then have smaller effect on people's perceived safety. Living close to the city centre has the advantage of more amenities, but suffers from higher crime rates. The perceived feeling of being safe is changeable by installing burglary alarms for example. The perceived risk of being exposed to crime is therefore very personal and changeable (Cohen, 2008).

Important for measuring the effect of crime are the differences between sorts and types of crime. A high murder rate is perceived different then a car mobile theft, which victim's just notice after the crime has been committed. Different types of crimes have different influences on people's feeling of being safe in a neighbourhood, and even on housing prices. Levels of crime in a neighbourhood are an important catalyst for change in the socio-economic composition of communities. Changes in the communities occur slowly, but crime levels are adjusted quickly in the housing prices, and therefore a first sign of a changing community (Tita et al., 2006).

Many literature in this field used city level crime indexes, resulting in a distorted picture because crime has a local effect. Different types of crime influence individual behavior in different ways. Housing markets react very local and therefore crime rates influence the housing markets local too. For convenience and accuracy, housing price should be analysed as local as possible with matching crime rates. Resulting in more accurate and local influences of crime on the particular housing price in the neighbourhood (Tita et al., 2006).

Like done in other literature (Tita et al., 2006; Schwartz et al., 2003), total crime can be divided into two composite crime categories: violent crime and property crime. Violent crime includes murder, rape, robbery, and assault. Property crime includes burglary, larceny, automobile theft and other similar type of felonies. This distinction between the composite crime categories gives a clear insight as to why housing prices decline or rise. Violent crime influences the perceived risk stronger, because people are being attacked in person in their own environment. For property crime, direct interaction with the suspect is not necessary, influencing the perceived risk of crime less. Creating a distinction in violent crime and property crime also creates the opportunity to statistically address and measure the (if existing) effect of both on housing prices.

2.2 Effects on mobility

This research builds on earlier work that examines the impact of crime on local residential choices of citizens. Urban areas with low housing prices are typically described as districts with high criminal rates. In previous literature, victimization is proven to change the daily life of the residents. Residents of burglarised households are more likely to behave cautiously, by remaining home more often, installing burglary alarms, locking doors and other crime prevention activities. But an underestimated effect is the increase of the probability for individuals to move to a new residence (Dugan, 1999).

This research is aiming to estimate the effect that crime has on housing prices, and could be an important reason for citizens of the four cities to move elsewhere. After a household has been a victim of a violent and/or property crime, they may decide to move to another neighbourhood. If the perceived risk and fear of repeat is higher than the benefits of the city and its amenities, households might leave the city as well. Panel studies in the past have shown that if urban crime increases more people tend to leave the city. Cullen and Levitt (1997) have shown that family households tend to leave the city faster. The authors used a panel of 137 cities in a time spawn of 17 years. Concluding that if robbery rates increase, the white population significantly decreases in the suburbs.

Problem with this type of aggregate research is that it shows overall increase in crime rates and migration. Not taken into consideration is the movement of the specific victims of property and violent crime. An assessment at neighbourhood level may not give insight into these mobility effects of crime on residential location choice, but it is definitely more localized than a study at city level. More individual based investigation on the movement of victims may be needed to provide real insight in the effect of crime on mobility of victims. Though it can be concluded that high crime rates creates vacancy, as households tend to leave these particular neighbourhoods or even the city as a whole.

2.3 Aspects influencing housing price

Crime is not the only factor influencing a housing price. Controlling for other variables influencing housing prices needs to be done in order to gain the unbiased estimation effect. As described crime can affect individuals' decision to move and subsequently sell their house, selling a house can take months or years (in current homeownership crisis). Neighbourhood changes take even longer to occur in a housing price. To collect the neighbourhood characteristics and also the crime rates, the relevant variables need to be clear and what kinds of various attributes (other than crime) are influencing the housing price. Therefore other similar research will be analysed to create categories of variables influencing the housing prices. In chapter 3 the main variables of crime and housing price will be addressed, what kinds of variables are specifically added in other research and useful for the regression model(s) created in chapter 4. The other relevant categories of variables from the literature will be examined in the appendix, used as control variables for the regression model. The analysis of the literature will be used to add relevant control variables from the dataset in the regression model(s).

Schwartz et al. (2003) have done similar research in New York City, measuring if falling crime rates influenced a real estate boom. This research was done with great availability of detailed data on neighbourhood conditions and public services. Housing prices were address-specific, meaning that data could be matched to an address. Having address-specific data would be ideal to control for structural attributes of a house, like the number of windows, and floors. Adding attributes in the category property characteristics in the dataset would be important, to at least account for available property determinants on neighbourhood level. Unfortunately the available data does not provide address-specific data to research on structural house specific characteristics.

The other important variables added in the model created by the authors are individual school performance, student characteristics, and housing production, renovation, and investment. Defining the relevancy of education as an important attribute influencing the housing price and/or place people want to live. The availability and proximity to different types of school is beneficial for the future of the children in family households. Remarkable in this research is the addition of an extra category of crime variable, namely misdemeanor arrest rate. Around 1994 the local police introduced a 'zero-tolerance' or 'broken windows' policy. From 1994 until 1998 reported misdemeanor crime increased with 68%. Therefore including misdemeanor crime as a category reflects the change of policy rather than a change in criminal activity. Adding this category would only be needed if some kind of new policies were implemented, which in this case were no signs of.

In contrary to address-specific, research also has been done on a neighbourhood level measuring crime impact on housing prices (Tita et al., 2006). The characteristics of place play an undeniable important role in determining levels and patterns of crime. Factors like poverty, racial composition, residential instability and percentage of home ownership are some of the factors correlated with crime. As crime induces neighbourhood changes and mobility, this may start a difficult and vicious cycle leading towards even more crime. In comparison to Schwartz, this research is broader and adds more factors like locational and neighbourhood characteristics to the model. Including demographics of people living in the neighbourhood, like Black and Hispanic population in the neighbourhood. Other important attributes are income levels and unemployment rates in the neighbourhood. Neighbourhoods with high levels of unemployment may be the poorer areas of the city, and could therefore be a reason of deprivation of property. Therefore people who do have an (certainty of) income might want to avoid living in the deprived areas. This is correlated with the income of people living in the neighbourhood. Earning a higher income gives incentives for people to move to better areas in town, especially with children involved (Tita et al., 2006). Opposed to this statement, I would argue it is rather about opportunities than incentives. The demand in the housing market is latent (induced) demand, consumers are unable to satisfy their wants or desire in the housing market, because there is a lack of money.

2.4 Statistical effects of crime on housing price

No one wants to live in neighbourhoods with a perceived high crime risk, leaving more vacancy in the market in neighbourhoods with high crime rates. Both violent crime and property crime influence the perceived risk of being affected to crime. So overall, people tend to leave as the perceived risk becomes too high and want to live in more peaceful neighbourhoods. Though people live in neighbourhoods with higher crime rates, according to latent demand theory they do have the willingness to live in better neighbourhoods. But they are forced to live in neighbourhoods with higher crime rates due to financial constraints. Buyers are willing to pay more to live in neighbourhoods with lower prices or, alternatively, buyers expect a discount when buying a housing in a neighbourhood with high crime levels (Ceccato et al., 2011). So does crime influence the housing prices significantly in these areas and how strong is the effect? In this paragraph the statistical effect of crime on housing prices from previous research will be assessed in order to compare results against the results of the model(s) created in this research.

Tita et al. (2006) did a neighbourhood analysis of the impact of crime on housing prices in Columbus and Ohio (USA). In this research a distinction between low, middle and high income is made; the lowest 25% and the highest 25% represent the low and high category. This is done because of the underreporting problem, since the authors expect that underreporting of crime may vary across neighbourhoods. The authors emphasized that housing prices are likely to differ upon characteristics of the community the property is in. Testing with a distinction in income levels, tests whether results indeed are sensitive to the underreporting problem and different characteristics among the communities. Also this adds structure to the research and eliminates the most likely source of unequal variances.[1] Regression of the logarithm of the sales prices resulted in a positive non-significant estimation. The authors found the estimate by using the lagged crime levels for the previous year. The change in crime levels was significant and showed the expected (negative) influence on housing prices. Both measurements were done on all income categories combined. Separating the categories for income showed that impact of crime levels across different neighbourhoods differ significantly. The hedonic regression showed a negative influence of violent crime for the medium-income and the high-income group, but positive estimation for the low-income group. The property crime showed the same pattern as the total crime coefficients, the medium-income group had significant negative influence on housing prices. Both in the low-income and high-income group, property crime had a significant positive influence on housing prices. Because of the peculiar findings and the expectations of systematically varying underreporting in neighbourhoods, the author used an instrumental variable as the standard economic solution for the measurement error problem. The homicide rate was used as instrumental variable because of its correlation with the crime indexes but unlikely to be correlated to the error due to reliable reporting of a homicide. The coefficients have the expected (negative) influence on housing prices for all combined income groups, but still only the violent crime is significant. As discussed by the author, underreporting and the negligible influence leads to biased estimations. Underlying effects are failed to be distinguished, therefore making it hard to estimate the impact of crime levels on people decisions (Tita et al., 2006).

During the final decade of the last century New York experienced a drop in violent and property crime with over 50%. But were the falling crime rates responsible for the increase or decline of housing prices? Schwartz et al. (2003) examined if the falling

[1] One of the assumptions in OLS is equal variance, more in chapter 4: methodology.

crime levels influenced the housing prices. From 1994 until 1998 the property prices increased with 17.5%, but the violent and property crime decreased with 48.6% and 54.6% respectively. Using a cross-section hedonic regression model, the coefficient for the logarithm of violent crime in 1990 was -.185 and in 1995 -.137. These coefficients indicated a magnitude of crime drop on housing prices of roughly 7 to 9 percent.[2] For property crime a panel hedonic regression from 1988 until 1998 generates a non-significant estimation of -.0097, meaning that property crime has a effect of 0.46% on housing prices. Violent crime has a coefficient estimation of -.1300 in the panel hedonic regression, having an influence of 6.5% on the housing prices. Both property crime and violent crime are showing the expected (negative) influence on housing prices. Including the misdemeanor arrests to the panel hedonic regression model; falling crime levels are explaining 6 percent of the increasing housing prices (from the total of 17.5%).
Schwarz et al. (2003) also denoted a repeat-sales regression, first model had only the crime variables added and in the second model the control variables were added, to control for additional neighbourhood characteristics. In the last model violent crime estimated a coefficient of -.1200, a magnitude similar to the effect in the panel hedonic regression. The coefficient of property crime had a smaller magnitude, .0324, but is still not significant. Including the misdemeanor arrest, this model explained roughly 6 percent of the total increase of 17.5% in housing prices. The effect is mainly due to violent crime, it caused an 8% rise in property price, and property crime had a small non-significant positive influence on the housing prices in New York from 1988 until 1998.

The two previous articles showed a negative effect of violent crime and mostly negative effect of property crime on housing prices. Though the last paper discussed, examined a positive and sometimes significant influence of property crime on housing prices. Case and Mayer (1996) found a positive effect of crime on housing prices using citywide available statistics in the state Massachusetts on the housing prices in Boston area. No distinction between different types of crime is made, though crime had a positive significant influence. Other authors seem to find signs of crime influencing housing prices positively. Could it be that property crime indeed has a positive effect? Properties with higher value tend to attract more burglary, as valuable property is affordable for

[2] As violent crime rates dropped around 50%, dividing the coefficient by half generates the magnitude.

the high-income group. In this case higher housing prices are influencing the increase of either violent and/or property crime levels (reverse causality).

Evidence of a causal relationship in both directions has been analysed in a research about the impact of crime on apartment prices in Stockholm. Property crime is directly related to the houses, endogenous. High valued areas attract burglars and these areas could suffer from high number of burglaries. In estimating a hedonic pricing model, like done by the authors, the endogenous crime variable could be a problem. The exogenous crime variables, like violence and vandalism, are less of a problem (exogenous crime are not directly related to the houses). Using endogenous variables in a hedonic pricing model could generate biased estimation(s) because of the reverse causality. Ceccato et al. (2011) found a positive effect of crime on prices of apartments. The authors controlled for the endogeneity bias by using an instrumental variable and lagged variables. Using murder rates as an instrumental variable, like done in Tita et al. (2006), captures unobservable influences on apartment prices, using variables that are correlated with crime but not with apartment prices. The reason for using lagged variables is that crime in one neighbourhood could influence housing prices in another neighbourhood. Crime goes beyond a specific area, because offenders and victims are mobile. Rising crime levels in one neighbourhood might predict an increased likelihood of the same type of crime in a neighbourhood close by. The simple OLS estimation of the influence of crime showed indeed a positive influence of crime on apartment prices. After using the instrumental variable and a spatial lag model, crime negative influences the apartment prices. The total crime variable has a negative influence of 0.04 percent on apartment prices, if crime rates go up by one percent. After separating crime into categories, the burglary coefficient (property crime) has the strongest effect on apartment prices (Ceccato et al., 2011).

The cross-sectional analysis and the panel hedonic regression of the impact of violent crime are significantly negative according to Tita et al. (2006) and Schwarz et al. (2003). After adjusting for time in a panel hedonic regression, violent crime still seems to negatively influence the housing prices. On the other hand property crime shows signs of a positive influence on housing prices in cross-sectional analysis. After adjusting for time in a panel hedonic regression, property crime becomes the expected (negative) influence on housing prices. Ceccato et al. (2011) analysed the endogeneity bias and the importance of the relation between close by neighbourhoods. After adjusting for the bias from the reverse causality and spill over effects from close by neighbourhoods, property crime has a significant negative effect on housing prices. This effect is even stronger than the assault and vandalism coefficient, which is similar to the violent crime coefficient found in Tita et al. (2006).

Obviously, different research and authors found different effects of crime on housing prices. Crime was added as an endogenous in the models in the latest papers, similar to the research of Tita et al. (2006) as described. Ihlanfeldt and Mayock (2010) examined six of these studies where crime has been added as an endogenous variable, and concludes these models suffer from specification errors and questionable instrumentation strategy.

Three reasons for finding a positive influence of property crime and using it as endogenous variable are mentioned. First, the expected payoffs of the market value of stolen goods are higher in more expensive homes. Second, the crime statistics are limited to the crimes reported to the police. Better neighbourhoods have significantly higher reporting rates than deprived neighbourhoods. Finally, unobservable factors could increase the attractiveness of property as a target of crime, for example a secluded house or a lot of big windows.

The authors used a nine-year panel of crime rates in Miami at neighbourhood level, with crime as endogenous variable. The estimation showed an elasticity of housing value to aggravated assault and robbery crime as -.152 and -.111, respectively. So people are willing to pay more to live in a neighbourhood with less assault and robbery crime. The authors explain the stronger influence of violent crime, as this category causes far more physical harm to victims in comparison to property crime. In particular, self-protection provides an effective protection to burglary and car thieves. There are far less self-protection options, to prevent one from being victimized to a violent crime.

The latest literature available in this field adds the crime factors as endogenous variables in the models. According to the literature examined of estimating a regression model using OLS, a positive property crime and a negative violent crime effect can be expected. Whether higher property crime does influence housing prices positively, can be further examined like done in the described literature.

3. Dataset and variables

3.1 Dataset: housing price & crime variables[3]

Crime can have severe effects on people's life, and can have great impact on the place you either want to live or currently living. The investigation of the impact of crime rates on housing prices is particularly interesting on neighbourhood level. With the availability of detailed data on neighbourhood level, neighbourhoods are an interesting field to study, giving a local estimation effect of crime rates in different areas in the Netherlands.

To the best of the authors' knowledge a neighbourhood level analysis has never been conducted in the Netherlands. A neighbourhood level analysis gives insight as to how strong people react towards crime. In previous research big cities have been investigated, these cities were a lot bigger than the existing cities in the Netherlands. Therefore I chose to investigate the four biggest cities in the Netherlands with available crime rates on neighbourhood level. These cities are: Rotterdam, Den Haag, Utrecht and Eindhoven. The statistical bureaus of the municipalities of these four cities provide data of crime levels in the neighbourhoods, all other data is provided by the Central Bureau of Statistics (CBS). These four cities will provide enough observations to draw a conclusion of the impact of crime on housing prices.

The data sources include all information about a neighbourhood's location and important determinants like crime, characteristics of the area, income and population in the particular area. The main variables will be discussed per category in this chapter, housing price and crime variables. From the full dataset, relevant variables will be used to create (a) regression model(s). Meaning that not the whole dataset will be used to estimate the effect on housing prices. The housing price and crime determinants are discussed next, the other determinants can be found in the appendix 8.1.

[3] Dataset link in chapter 7: Literature list.

Housing Price[4]

To find the effect of crime on housing prices, data of the value of the housing is needed. In this case the average estimated tax value per neighbourhood would be useful as housing price. The estimated tax value is the worth of property according to the Dutch law, the valuation of immovable property. The law was created in 1994 for tax payment on immovable property, before 1994 every property owner was allowed to determine the value of its own property. The taxation method used to determine the value is the comparison-method. Unknown prices of houses are compared to houses in close proximity, which have been sold recently, to determine the estimated tax value. This "price" is used as the value of the property and this value will also be used as the price of housing in this research (Wet Onroerende Zaken, 2012).

Crime determinants[5]

The main goal of this research is to investigate the effect of crime on housing prices. Like done in previous research and mentioned in the literature overview, crime will be split into two categories, property crime and violent crime. Mainly because property crime and violent crime differ in the effect it has on people, (strong) different effects will be expected. Before estimating the effect of both categories, I will discuss what felonies fall in which category of crime. Examples of both types are given:

> <u>Property Crime</u>: havoc, nuisance from drugs and alcohol, pickpocket, theft automobile, shoplifting and other related criminal activities (crime influencing property).
>
> <u>Violent Crime</u>: murder, immoral offence, rape, threatening, mistreatment, mugging and other related criminal activities (crime influencing people directly).

The distinction between these two categories is made, because violent crime has a direct effect on the victim. Victims are threatened by crime on the street in their

[4] Estimated tax value data of housing available from CBS, Central Organization of Statistics in The Netherlands.
[5] Crime data available from safety index on neigboorhood level from respective municipality.

neighbourhood. As to property crime, which mostly goes unnoticed or is discovered after the crime has been committed. The available data for all four cities will be categorised according to this distinction. Some cities have broader data available to investigate the effect of specific kinds of crime deeper, but this research is based on the distinction between property crime and violent crime.

The control variables of the dataset are denoted in the appendix 8.1. This paragraph also contains the variables used to filter the dataset to keep the urbanized neighbourhoods of the four cities and drop the industrial areas, which do not contain that many residents. The variables upon which the dataset is filtered, and the observations kept, are: neighbourhoods with at least a population bigger than 1000 people, neighbourhoods with at least a population of 750 per square kilometre, and a housing stock per neighbourhood of at least 100. These restrictions eliminated 120 observations and the available number of observations for research is 290.

3.2 Limitations of the dataset

Every house in a neighbourhood can differ in its composition, size, rooms, and number of floors and other specific house characteristics. Ideal would be to collect the estimated tax value of every single property in the neighbourhood and the property characteristics. This would further specify the crime effect on housing price, because in this research average characteristics of the neighbourhood are used as data. This would enable the research to control for address-specific house characteristics, like number of windows. Then effects like why people choose a certain neighbourhood to live in (or not), and as to how much people are willing to pay to live in a safer environment. Does crime prevent people from moving into property, which complies with all other requirements, but suffers from a negative image due high crime rates?

The dataset is limited due to the lack of time needed to collect individual structural housing characteristics, noting that estimated tax value per address is not publicly available.

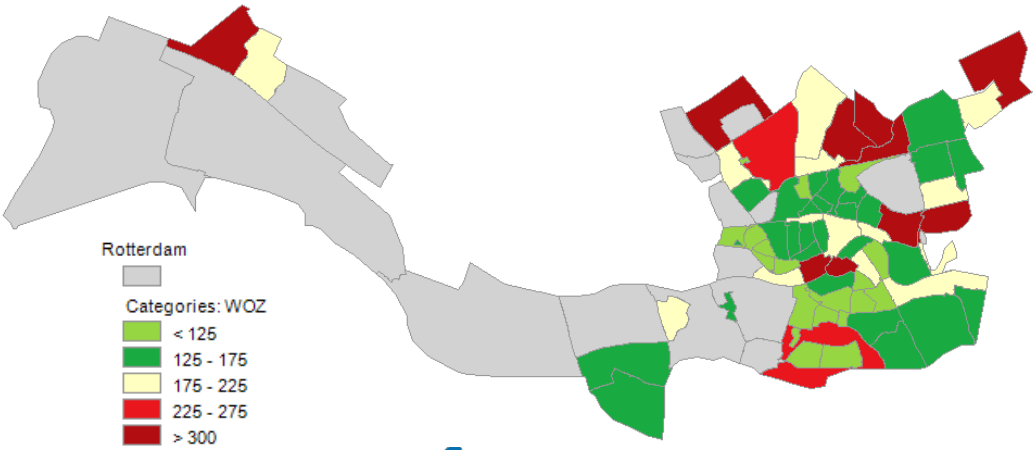
3.3 Pre-analysis: housing prices, crime, and income

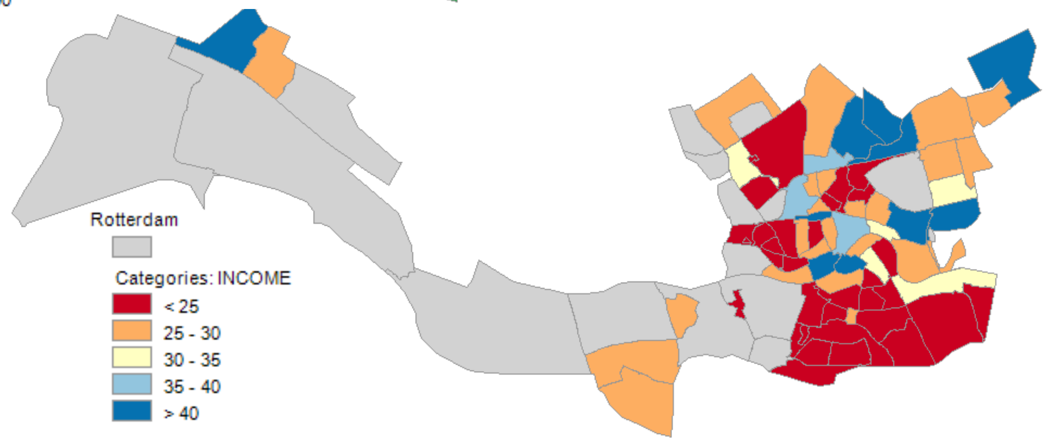
Before analysing the estimation results generated by the two models created in chapter 4, the crime variables, housing price and income will be visually represented on the next four pages. This makes it convenient to look up your own neighbourhood in the maps and to compare them against other neighbourhoods of the city. The two crime variables violent crime and property crime are included to show if there exists a (logical) relationship. The last variable mapped is income, because a higher income creates the opportunity to pay for a 'better' neighbourhood.

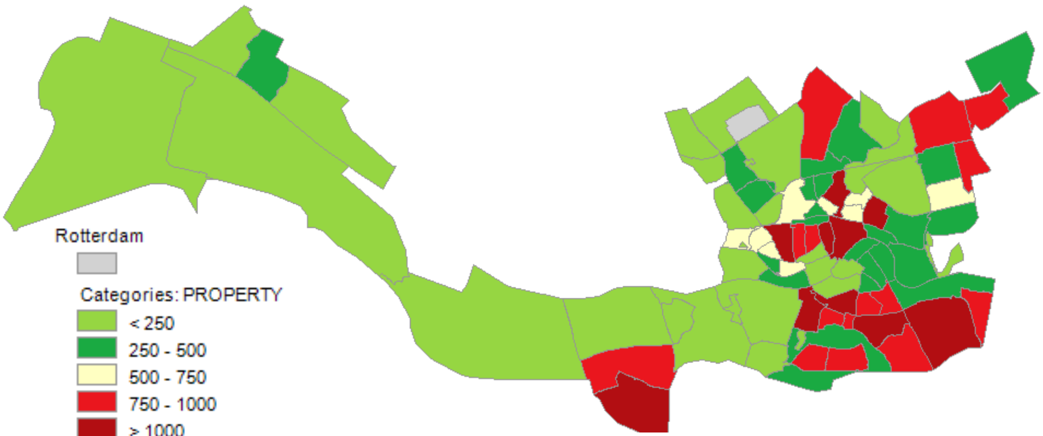
The higher the housing price, the more one must earn in order to pay for it. These patterns are seen in the geological maps, the higher the estimated tax value of the property, the higher the average income is. For example in south of Rotterdam the average income is the lowest compared to the rest of the city, only a few neighbourhoods in this region contradict the pattern and have a (somewhat) higher estimated tax value. In this region the crime levels are also high compared to the rest of the city. So it seems that high crime levels could influence the housing prices, as people do not want to live in an unsecure neighbourhood. The high density and the close proximity to amenities of the city centre could explain the high crime level of both property crime and violent crime in the city centre of Rotterdam. But housing prices and income seems to be higher too; people might want to pay more to live in the city centre, despite the higher crime rates.

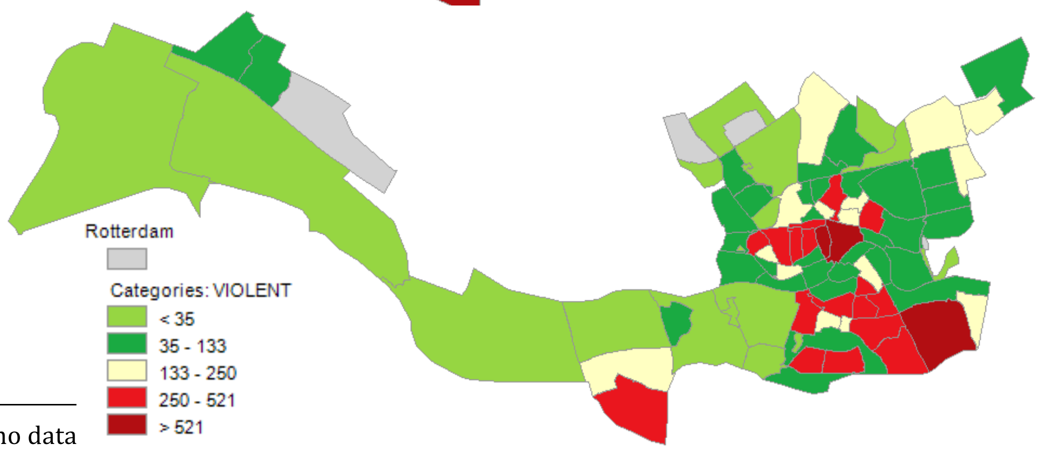
In The Hague the pattern is more clear than in Rotterdam but overall similar. Property crime and violent crime are related, as each neighbourhood that has a high level of property crime suffers from a high level violent crime also, logically. The same can be said for the relationship between average income and housing prices, where housing prices are in the low(est) category, income is in the low(est) category too. Though property crime levels seem to be somewhat higher than violent crime levels in areas with higher housing prices in all four cities. Noticeable is that the available data in Eindhoven is less than in the three other cities. Although nothing statistically can be said about the relationship between the four variables, however it shows visually similar patterns exists between the four variables in the four cities.

Rotterdam[6]



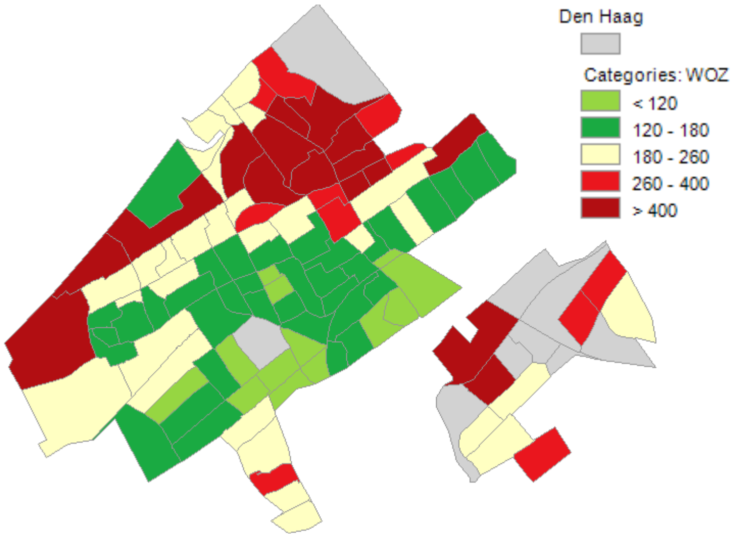


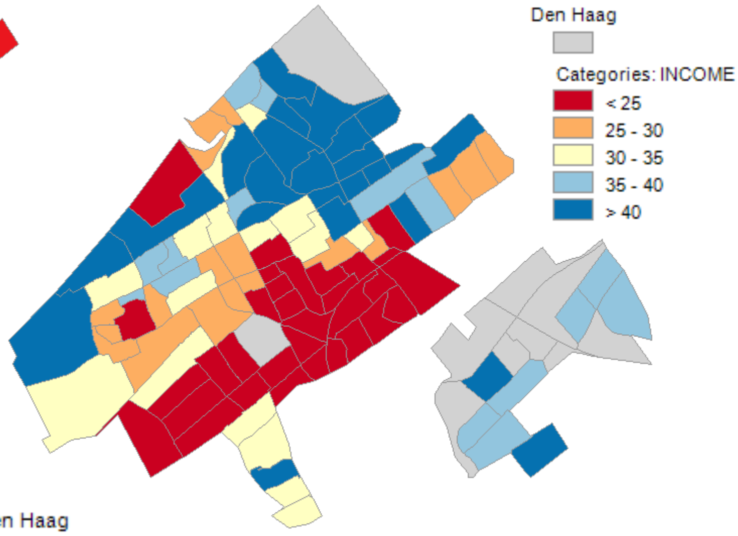


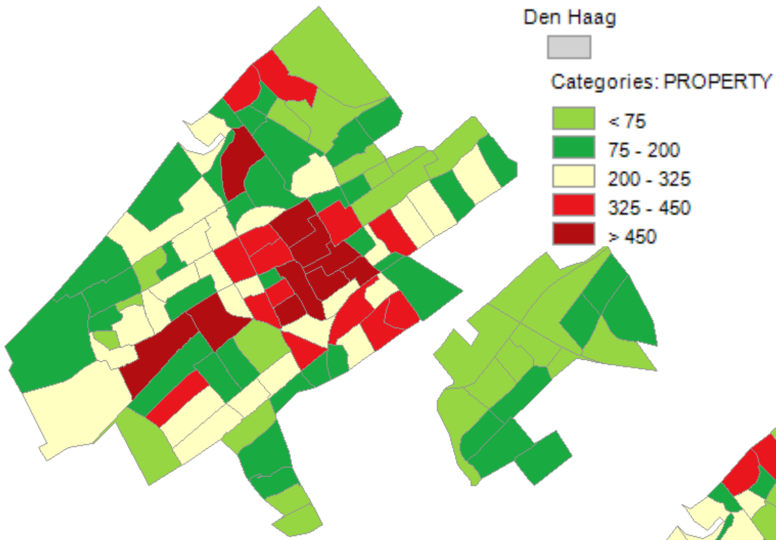


[6] Grey represents no data available

The Hague[6]


Den Haag
Categories: WOZ
< 120
120 - 180
180 - 260
260 - 400
> 400


Den Haag
Categories: INCOME
< 25
25 - 30
30 - 35
35 - 40
> 40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< 75
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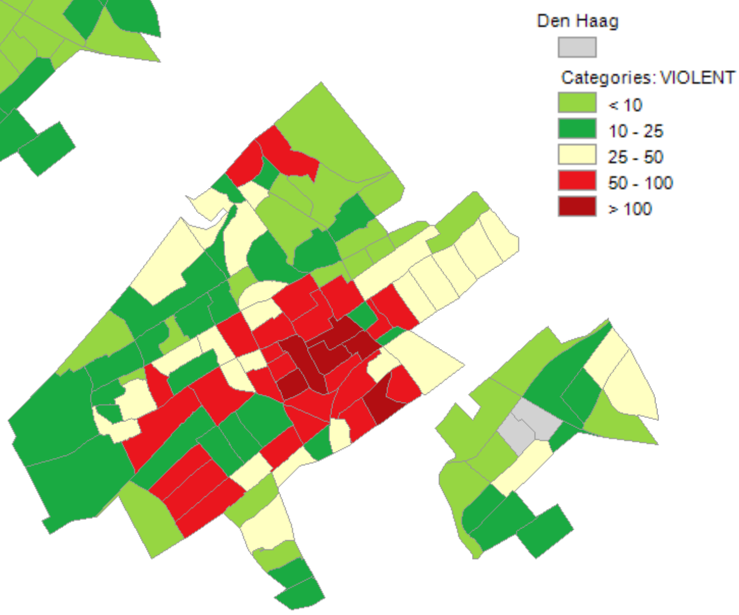
200 - 325
325 - 450
> 450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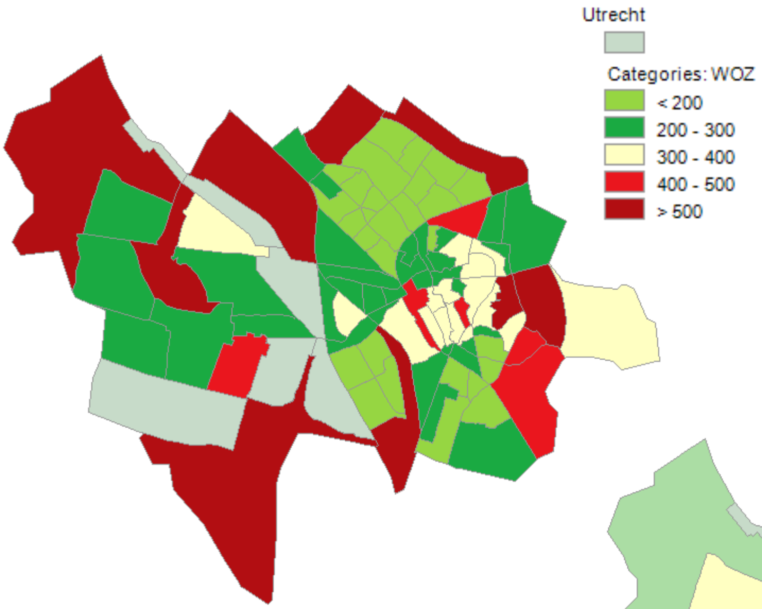
Categories: VIOLENT
< 10
10 - 25
25 - 50
50 - 100
> 100

Utrecht[6]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Categories: WOZ
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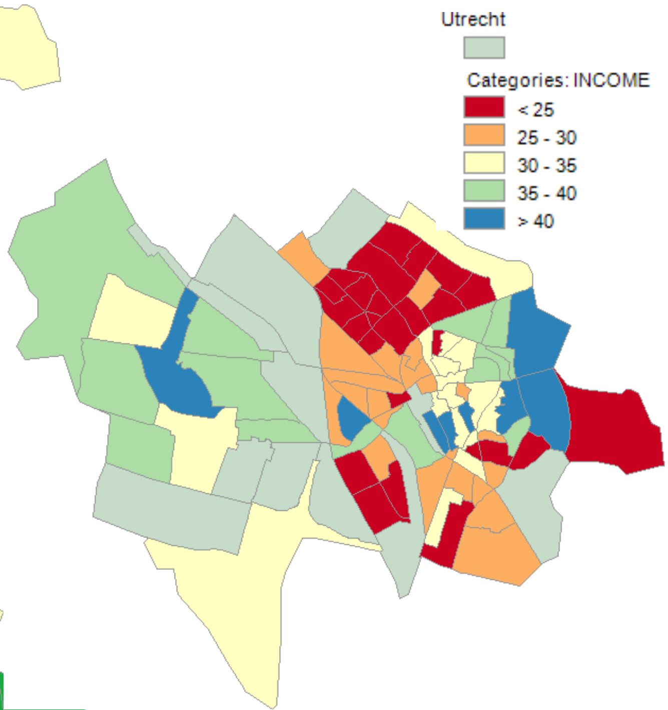
300 - 400
400 - 500
> 500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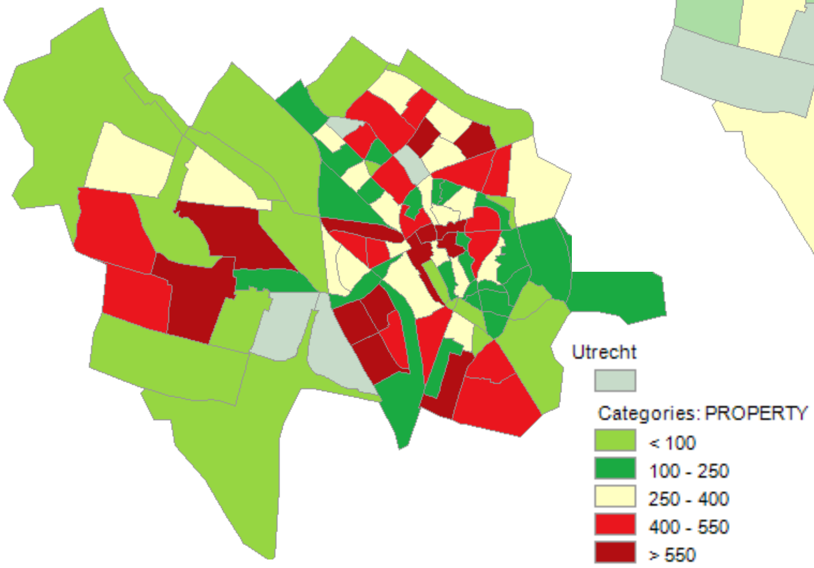
30 - 35
35 - 40
> 40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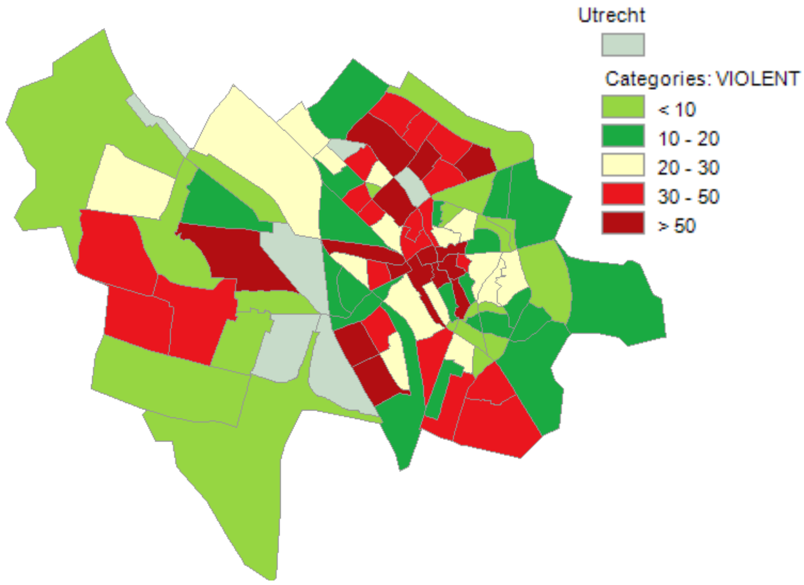
250 - 400
400 - 550
> 550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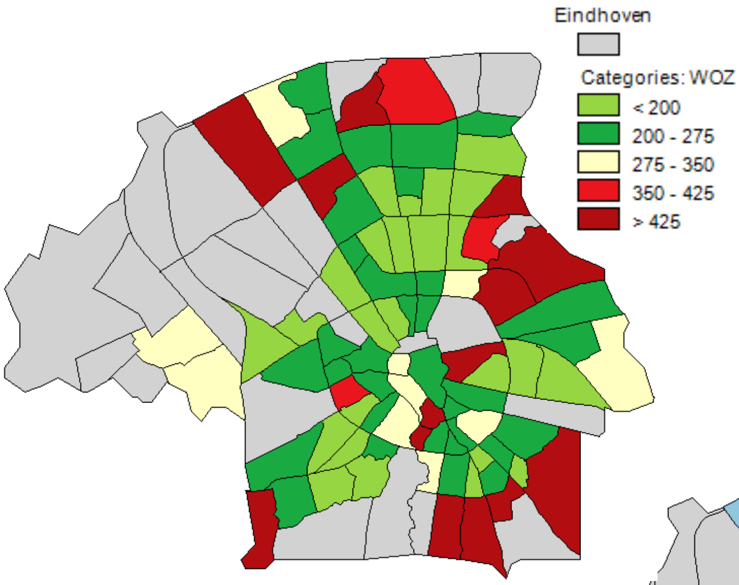
Categories: VIOLENT
< 10
10 - 20
20 - 30
30 - 50
> 50

Eindhoven[6]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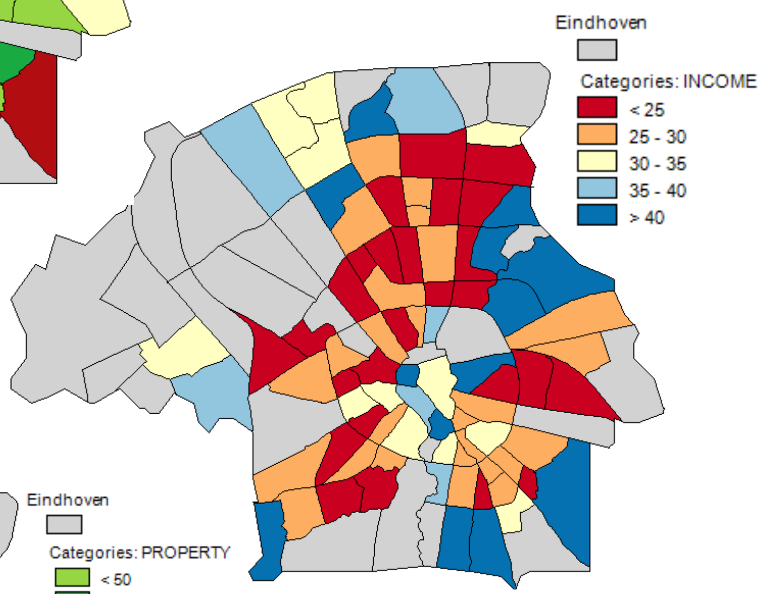
200 - 275
275 - 350
350 - 425
> 425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Categories: INCOME
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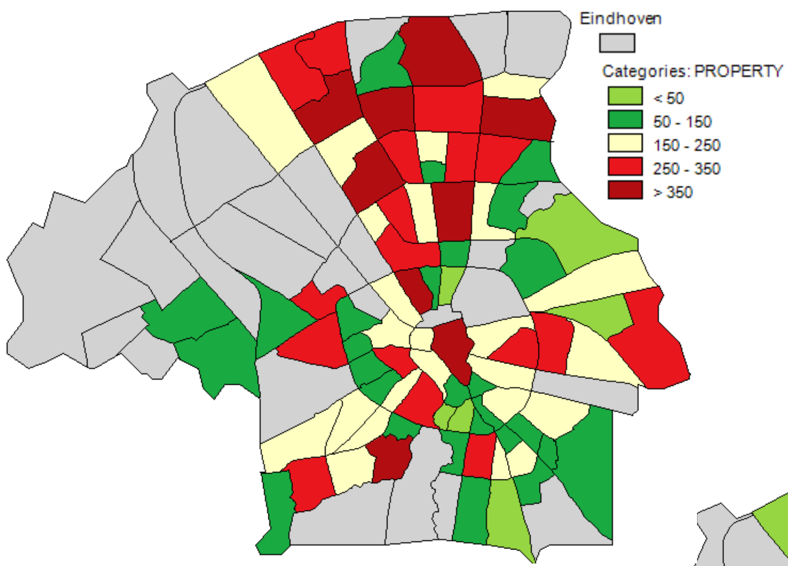
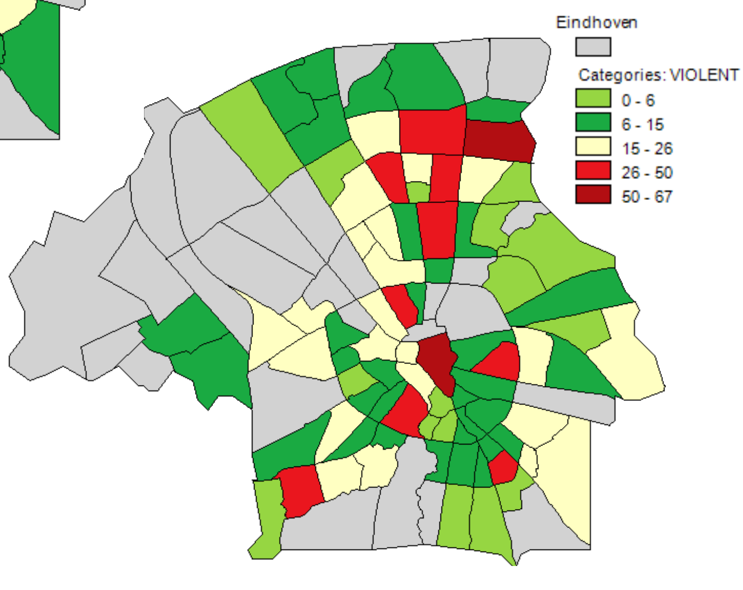
25 - 30
30 - 35
35 - 40
> 40


Eindhoven
Categories: PROPERTY
< 50
50 - 150
150 - 250
250 - 350
> 350


Eindhoven
Categories: VIOLENT
0 - 6
6 - 15
15 - 26
26 - 50
50 - 67

4. Methodology

In this chapter the model and methodology will be discussed in order to obtain the results relevant for the research. First step will be describing the technique, Ordinary Least Square (OLS), used here. Including the assumptions needed to estimate a BLUE regression model and if the assumptions are satisfied or not. After the general theory behind the regression analysis, the explanation of the used variables follows. Last step would be to examine whether variations in housing prices can be (partially) explained by levels of crime rates.

4.1 The method of Ordinary Least Square (regression)

A linear regression model describes the relationship between one or more than one interval predictor variable $x_1, x_2, \ldots, x_k$ and an interval outcome variable y. Here, the $f(x_1, x_2, \ldots, x_k)$ is described as a "systematic" component of y. In the case of a linear regression model, f is specified as a linear function. The "non-systematic" component describes the behavior of the error, which is the divergence of the unobservable true function from the sample function. The error component is not necessarily a linear function. The unknown weight of the parameters can be determined using the Ordinary Least Square (OLS) method.

In the case of only one variable x describing the outcome variable y (simple linear regression), the linear specification would be: $y = \alpha + \beta * x$. The α and β are the unknown parameters, with α being the constant term. An important aspect of the regression analysis is the error component. With α, β as parameters we can also write: $y = \alpha + \beta x + e(\alpha,\beta)$. The last component in this formula, $e(\alpha,\beta) = y - \alpha - \beta x$, denotes the error term form this specification in the simple regression model. Important to note is that for every different parameter values, the errors differ too. Some variables may be a function of some other variables, for example when $x = c^2$. Then the formula becomes $y = \alpha + \beta c^2 + e(\alpha,\beta)$. This is not a linear regression as c^2 gives the formula a nonlinear shape, but the function is still linear in x (in the parameter). Then $x = log\ c$ and then the parameter is still linear. Such specification can than be used in a linear regression model, which this research will also need (Kuan, 2004; Koning, 2011).

After the simple regression, which briefly explains the model, comes the multiple regression model used for this research. In this model more than one independent variable specifies a linear function of the behaviour of *y.* As said with the simple regression model, the formula becomes now: $y = \alpha + \beta x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + e(\beta_1, \ldots, \beta_k)$. Again the component $e(\beta_1, \ldots, \beta_k)$ denotes the error of this specification. With a sample of n observations, the formula can also be expressed as: $y = \alpha + X\beta + e(\beta)$. Here the β is the vector of unknown parameters, and y and X contain all the n observations of the dependent and independent variable(s). Again the $e(\beta)$ is the vector of all the error terms of the n observations (Kuan, 2004; Koning, 2011).

The method of Ordinary Least Square (OLS) is a method that estimates the unknown parameters in a regression model. In a simple and multiple regression model OLS tries to find the 'best fit' of the sum of squared distances between the observed and the predicted outcomes. With the results, the estimator can be expressed in a simple formula even when there are more then one independent variables.

4.2 Assumption Ordinary Least Square (OLS)

The models in the next paragraphs need to be validated according to the assumptions of OLS. When the assumption(s) are not met, the model simply does not generate the effect it computes. Therefore the main assumptions for a BLUE model, Best Linear Unbiased Estimator, are essential in this research. The created models will be tested against the assumptions with mainly Stata, and SPSS. The model is BLUE when all the four assumptions are validated. The regression lines drawn, uses the estimates so that the error is minimized (OLS). The main four assumptions are:

1 – The relationship is linear in X and Y. This seems to be the most obvious assumptions, as OLS calculates the best fit of the regression line in the observations. In order to create a model, there needs to be a relationship between X and Y which is linear. If the model includes terms like c^2 the regression line will not be linear, violating the first assumption already (Kuan, 2004).

2 – The errors have the same variance (errors are homogenous). Also known as the variance of the error term is homoscedasticity. Homoscedasticity is an important assumption for OLS as it causes the Linear Unbiased Estimator to be 'Best'. When the errors are heteroskedasticity OLS does no longer provide the estimate with the smaller variance, or best fit. The observations with larger errors tend to get more weight, therefore giving less information about where the true regression lines lies, as OLS gives equal weight to all observations. Heteroskedasticity leads to biased standard errors and bias also in the confidence intervals and test statistics.
To detect if the errors have the same variance (are homoscedastic) we have two options. First option is visual inspection through the plot of the errors along the horizontal *y-line = 0*, generating a plot of all the residuals. The ideal situation would be an equal width of all observations of errors around the y-line. The second option is the Breusch-Pagan test for heteroskedasticity. The command *hettest* will test the null hypothesis that the error variances are all equal (Williams[1], 2011).

3 – Errors are independent of each other; there is no autocorrelation in the errors. Cases have not been selected independently from each other, for example if percentages of buy houses and rent houses are included as separate variables. Both are related, as the total is the 100%, so including both (might) lead(s) to misspecification of the model (Williams[2], 2011).

4 – Errors are normally distributed. When a model has a lot of outliers the error distribution can be skewed. When the parameters are estimated using the minimization of the squared error, the outliers can influence the regression line disproportionately. Confidence intervals, significance tests, and parameter estimation are based on the assumption that errors are normally distributed. Therefore the model might be biased and does not necessarily provide the true information, as the OLS is no longer BLUE. To check if the errors are normally distributed, a normal probability plot of the residuals can be created. If the plot shows a close pattern to the diagonal line, the errors are normal distributed (Koning, 2010).

Other tests will also be used to test if the model provides the true effects for interpreting the effect of crime on housing prices and the usefulness of the two created models.

– Case of multicollinearity. This is not an assumption in order for OLS to be unbiased and BLUE, even extreme multicollinearity does not violate the assumptions as long it is not perfect. Still I test for multicollinearity, because high multicollinearity leads to greater standard errors and wider confidence intervals for coefficients. In order for these coefficients to be statically significant they have to be larger, so it is harder to reject the null hypothesis (though large standard errors may also be caused for other reasons besides multicollinearity). Used for testing will be the Variance Inflation Factor, this shows how strong the variance of the estimation of the coefficient is being inflated by multicollinearity. In this research the Variation Inflation Factor above 10 will be seen as a reason to suspect multicollinearity (Williams[3], 2011).

- Stata can detect a specification error with the commands *linktest* and *ovtest*. The *linktest* expresses if a regression is properly specified, one should not be able to find any additional independent variables that are significant except by chance. The test generates two new variables of prediction, the *_hat* and squared prediction, *_hatsq*. The model is then refit using these two variables as predictors. The squared prediction *_hatsq* should not be significant, because if the models are specified correctly, the squared predictions should not have much explanatory power. So we will be looking at the p-value for *_hatsq* (Chen, 2012).
The second test is the omitted variable test (*ovtest*), which is very similar to the *linktest* and test for a regression specification error. It tests whether excluded variables significantly influence the dependent variable and should be in the model. Meaning that the unexplained part of the dependent variable becomes larger, so more biased. The Ramsey Reset test tests whether there are omitted variables, using the null hypothesis of no omitted variables (Chen, 2012; O'Halloran, 2005).

In the next two paragraphs two models will be addressed, trying to estimate the effect of crime on housing prices. The reason for estimating two models is to compare both estimated outcomes for a significant effect and to spot any similarities defining a similar positive or negative effect of crime on the housing price.

4.3 Model 1: dependent variable ln(housing price)

Model 1 is the examining the logarithm of housing price. Choosing this as the first model tries to estimate the influence of the control variables and the crime variables on the logarithm of housing price. To compare the results gained from model 1, I decided to create a second model[7], to compare parameter signs and estimation. But first, the model gives direct insight into what and how much the effect of the chosen variables is on the logarithm of housing price. Of course the main interest is the effect of crime on housing price, but before adding crime variables, a basic model explaining housing prices is needed. After that the crime variables can be added, to check for the effect of crime in comparison to other variables.

The dependent variable, the logarithm of housing price, is influenced by some control variables. The first control variable added is the logarithm of income. As explained in chapter 8.1, income is a very important determinant for explaining housing prices. People buy homes, which they can afford, or matches their income groups. People tend to live next to people from the same income categories. Important to notice here is that both housing prices and income are not linear, but transforming income and housing prices in logarithm makes them linear and useful for our linear regression model.

Opposed to income characteristics, also neighbourhood characteristics are important to control for. Education is important in the development of children, being close to a school might be a factor for housing prices to go up or down. Therefore the distance to closest Vmbo/Havo/Vwo School will be added to the model to control for influencing the housing price. Another area characteristic is the distance to a local supermarket, which is might also a factor to choose for a specific house.

The limitation to this research is the lack of individual housing characteristics in the dataset. But we can control for the number of housing stock in the neighbourhoods relevant for this research. Therefore the number of houses available is added in the model also. Though needs to be mentioned that the dataset is filtered on number of house stock bigger than 100 in a particular neighbourhood. Reasoning behind keeping observations with house stock bigger than 100 in the neighbourhoods is that it eliminates business districts with almost no residents.

[7] Section 4.4

The control variables added from demographics of a neighbourhood, is the number of people from Moroccan ethnicity living in the neighbourhood. Research has shown that number of different ethnicities influences housing price, as listed in the literature review. To research the different cities, as mentioned in the research question, the last variables added are the dummy variables of the three cities: The Hague, Utrecht, and Eindhoven. Rotterdam was the base city, leaving this out of as a dummy variable.
Finally, to estimate the effect of interest, the crime variables are added to the model. These are the violent and property crime per person living in a neighbourhood.

To conclude, model 1 is:

*ln(housing price) = α + b1 * Dummy Utrecht + b2 * Dummy Eindhoven + b3 * Dummy The Hague + b4 * ln(income) + b5 * Distance to Havo/Vwo School + b6 * Distance to Vmbo School + b7 * Distance to Shop + b8 * Housing Stock + b9 * Number of Moroccan people + b10 * Violent crime per person + b11 * Property crime per person*

Here, the b stands for all the estimated effects of the bèta. In the results the estimated effects will be shown plus if the assumptions of OLS hold, indicating a BLUE model.

4.4 Model 2: dependent variable ln(housing price/income)

Model 2 is examining the logarithm of the ratio of housing price and income. The variable *ln_ratio_hpink*, the dependent variable, is the logarithm of the housing divided by average income. The ratio gives insight as to how much people are willing to spend for (housing) property. The higher ones income is, the higher the chance one would spend more on a valuable house. Adding this extra model creates the estimation of the effect of crime on the ratio citizens are willing to spend on housing.
Included will be the following control variables to attain the effect of crime on the ratio of housing prices and income. All city dummies will be included again to create a possibility to attain the effect per city. Rotterdam is the base of this research; therefore this city will be left out. From the base model the other effects per city are measureable. Population proximity has an effect on housing prices; people wanting to live in the city

centre are in most cases willing to pay more. Therefore controlling for population per square kilometre, because in Rotterdam the number of people per square kilometre is higher opposed to the other three cities. Also what might bias the model is the fact that high incomers are willing to pay more to live in the quiet parts of the city. As a control variable for housing characteristics will be used the percentage of buy houses. Most housing prices in the dataset are based on property bought by the people who live there. Those people are more interested to invest in their own neighbourhood, because they stay for a longer term than people renting a house, rental house are more easy to leave. When a neighbourhood does not meet your wants or needs, having a rental house makes the intent to move quicker. The last two control variables will be the distance to a train station and the distance to a VMBO-school. Both influence the location preference for housing property, and can be important determinant for people to move into a neighbourhood.

This research is mainly interest in the effect of crime on housing price, therefore the two crime variables of violent and property crime per person will be added to estimate the effect of both types of crime.

The results of model 2 will be analysed in chapter 5 under paragraph 2. To give an overview, model 2 consists of the following dependent and independent variables.

> *ln(housing price/average income) = α + b1*Dummy Utrecht + b2*Dummy Eindhoven + b3*Dummy The Hague + b4*Population per km2 + b5*Percentage Buy House + b6* Distance to train station + b7*Distance to VMBO-school + b8*Violent crime per person + b9*Property crime per person*

Here, the b stands for all the estimated effect of the bèta. In the results the estimated effects will be shown plus if the assumptions of OLS hold, indicating a BLUE model.

5. Results

5.1 Results model 1: dependent variable ln(housing price)

The first model is explaining the logarithm of housing price in comparison within the four cities, and tries to estimate the effect of crime on the logarithm of housing prices. The estimation formula consists of the following variables:

*ln(housing prices) = α + b1 * Dummy Utrecht + b2 * Dummy Eindhoven + b3 * Dummy The Hague + b4 * ln(income) + b5 * Distance to Havo/Vwo School + b6 * Distance to Vmbo School + b7 * Distance to Shop + b8 * Housing Stock + b9 * Number of Moroccan people + b10 * Violent crime per person + b11 * Property crime per person*

In paragraph 2 of the appendix is the output collected for this model. With the restrictions described in chapter 3, I only kept the observations with more than 100 as housing stock, population bigger than 1000, and the density per square kilometre bigger than 750. Therefore 120 neighbourhoods are filtered out, keeping 291 observations. The model has an explanation power (R-squared) of 90,76%, meaning that 90,76% of the dependent variable is explained by the independent variables used in this model. Looking at the independent variables, all are significant after using the robust function in Stata with a significance level of 5%. Number of housing stock is not strongly significant, but also has a weak effect on the logarithm of housing price. Adding all the estimations of the bèta's, leads towards the following formula:

*ln(housing price) = .79004 + .24596 * Dummy Utrecht + .31072 * Dummy Eindhoven + .071056 * Dummy The Hague + 1.28514 * ln(income) - .03178 * Distance to Havo/Vwo School + .03978 * Distance to Vmbo School + .08088 * Distance to Shop - .00001 * Housing Stock + .00004 * Number of Moroccan people – 1.34579 * Violent crime per person + .64969 * Property crime per person*

First step is to check whether this model follows all the assumptions in order for the regression model to be BLUE. The generated tables performing the needed tests are in chapter 8.2. The most important assumption is that the errors are homoscedastic, meaning that the errors have same variance. The Breusch-Pagan test produces a p-value of .1073. So the null hypothesis of constant variance is not rejected, so the variance of the errors is the same for all values of the independent variables. Even visually the plot of the residuals along the horizontal *y-line = 0,* show a similar pattern on both sides of the line. From both the Breusch-Pagan test and the visual plot of the residual, one can assume the errors have the same variance for all values of the independent variable. Second is the test for multicollinearity in the model, meaning that variables are influencing each other and causing the estimation(s) to be biased. The variation inflation factor produces a value 2.18, which does not exceed the value of 10 used as the critical value for multicollinearity. So the independent variable does not significantly influence each other to be a problem for this model. Lastly the Ramsey Reset test and the *linktest*, the first checks for omitted variables and the linktest test for variables, which the model misses but could logically be added. Both show no signs of a problem; the reset test for omitted variables produces a p-value of .248. The second the *linktest* generates a p-value .884. Model 1, which explains the logarithm of housing price, is therefore according to the assumptions BLUE.

The research is estimating the effect of crime on housing prices. The parameter of violent crime is the biggest influence of the independent variables on the logarithm of housing price; even the logical variable income has a less strong influence on the logarithm of housing price. On the other hand property crime has a positive influence on housing price and less strong of an influence. Partly a reason for this is that people do not immediately see a reason to move out of a neighbourhood after being victimized by a property crime. Opposed to victims of a violent crime, which are often confronted personally, and could potentially not feel safe anymore in their own neighbourhood. Interpersonal effects play a role, as emotions of people living in the neighbourhood are influence by the environment. The surrounding neighbourhood influences someone's daily life and adopt habits of the people they are related to.

In comparison to other variables, crime is an important factor in housing prices. Only income has a strong influence, the other variables like housing stock and distance to school are much less influential, though significant. Remarkable also is the fact that Rotterdam is the 'cheapest' city. All dummy variables for the three other cities, Utrecht, The Hague and Eindhoven, have positive signs. Meaning that when choosing for one of the three cities, the logarithm of the housing price rises.

5.2 Results model 2: dependent variable ln(housing price/income)

Model 1 had some different outcomes than logically expected, reason to add another model for comparison. Mainly to check for errors in model 1, and whether the unexpected outcomes come forth in the second model. For recap, model 2 consists of the following dependent and independent variables.

> *ln(housing price/average income) = α + b1 * Dummy Utrecht + b2 * Dummy Eindhoven + b3 * Dummy The Hague + b4 * Population per km2 + b5 * Percentage Buy House + b6 * Distance to train station + b7 * Distance to VMBO-school + b8 * Violent crime per person + b9 * Property crime per person*

Using Stata to estimate the linear regression, the following estimations are generated (output tables and figures in paragraph 8.3). With the restrictions described in chapter 3, the numbers of observations kept are 291. The model is explaining 60,93% of the total variation of the housing prices, the dependent variable (R-squared). Using the robust option in Stata generates all significant variables, using a barrier of 5%. Adding all the estimations of the bèta's from the output, leads towards the following formula:

> *ln(housing price/average income) = 1.5127 + .0904 * Dummy Utrecht + .1170 * Dummy Eindhoven + .0241 * Dummy The Hague + .00002 * Population per km2 - .0008 * Percentage Buy House + .0054 * Distance to train station + .0099 * Distance to VMBO-school - .3705 * Violent crime per person + .1973 * Property crime per person*

First needs to be checked if this model does not violate the assumptions of OLS in order to perform a regression analysis. The output of the tests for the second model is in paragraph 3 in the appendix. To check for signs of multicollinearity the variation inflation factor will be used, which generates 1.87, not exceeding the limitation of 10. So, there are no signs of variables being correlated to each other. The most important test to do is to check whether the variances of the errors are equal. Figure 15 in the output is showing a similar pattern across the *y-line = o,* and the Breusch-Pagan test with the null hypothesis of homoscedasticity is not rejected (p-value 0.7314). Both visually and statistically there are no signs of violating the assumption of homoscedasticity. Lastly I am checking for any omitted variables and if any logical variables are missing, with the Ramsey RESET test and the *linktest*. Both are showing non-significance, concluding that there are no omitted variables and no variables, which logically could be added to create a better model without chance. Therefore all assumptions seem to have been met, even the normal probability plot of the residuals is showing a (roughly) straight line, concluding that the model seems to be BLUE.

Immediately is noticeable in the parameter estimations that both violent and property crime have a big influence on the housing price/income ratio. Though it is remarkable that property crime has a positive sign also in this model, meaning that if property crime would rise, the ratio would also rise. In this case either the housing price becomes higher or average income might decline. Therefore in this model it cannot be said that property crime eventually raises the housing price. Is the model therefore estimating the true effect the research is interested in? The model has been tested against the assumptions and there were no signs of bias. But in comparison to the first model, there was also a positive influence of property crime on the housing price. Therefore the influence of property crime on people in the neighbourhood might not be that strong in comparison to violent crime, which people victimize personally. In the second model, the total explanation of the variation on the dependent variable is less strong, looking at the lower R-squared (model 1: 90,76%, model 2: 60,93%). Property crime and violent crime both influence the ratio of housing price divided by income the strongest of the variables.

The second model shows the same pattern as the first model considering the dummy variables of the cities. The included cities of Utrecht, The Hague and Eindhoven have all positive signs and therefore influence the ratio stronger than Rotterdam. Meaning that people in the other three cities than Rotterdam are more willing to spend income on bigger property and housing. Showing that the housing price in Rotterdam is the lowest of these four cities and less influenced by the variables used in these two models. But these unstandardized coefficient effects are not comparable.

5.3 Comparison of the two models

The parameter estimation in OLS generates unstandardized coefficients, because the parameter coefficient is mainly based on the means and variances of the independent variables. The independent variables may strongly differ in the range of intervals, leading to non-comparable coefficients. In some cases the coefficient estimations are directly comparable, like comparing one extra year of education to one year of experience. Though in most cases standardizing is necessary. The table on the next page shows the standardized estimations in the bèta column. In model 1 for example, can be said that increasing the logarithm of the income by 1 standard deviation, the logarithm of the housing price will increase with .8657 standard deviations. In model 2 for example, can be said that an increasing number of property crime per person has 1.41778 times more effect than an increasing density of people per square kilometre on the ratio of housing prices divided by income[8].

The positive effect of property crime on housing price is in both models striking. In model 1 an increase of property crime with one standard deviation has 1.61185 times more effect than a decrease of one standard deviation of violent crime, on the logarithm of housing prices[9]. The same effect estimation can be done for model 2. Here an increase of one standard deviation of property crime has 1.7781 times more affect than a decrease of one standard deviation of violent crime on the logarithm of housing prices[10]. Estimating the effects of the reciprocal variables offers policymakers to choose the right policy. Depending on the costs, policymakers can consider whether to increase the income of the neighbourhood or decrease the number of property crime, to increase the housing prices in a neighbourhood. Other variables used in these models can be used for policymaking too. According to model 2 a decrease of the percentage of buy houses in the neighbourhood in comparison to an increase of the proximity per square kilometre of one standard deviation, has 2,045999 more effect on the ratio of housing price divided by income.[11] So decreasing the percentage of buying houses leads towards lower housing prices or increasing income (as the ratio as a whole is decreasing).

[8] (0.1793862 / 0.1265257 = 1.41778)
[9] (.0916053 / .0568323 = 1.611853)
[10] (.1793862 / .1008886 = 1.77806214)
[11] (.2588714 / .1265257 = 2.04599856)

Not only crime rates affect the housing prices, therefore implementing the right policy for not too high or too low housing prices is important. The estimate results of the standardized bèta's generated in these two models, creates the opportunity to compare costs and effects to improve upon the current situation (University At Albany, 2004).

Model 1				**Model 2**			
Ln_house_price	*Coef.*	*Std. Err.*	*Beta*	*Ln_ratio_hpink*	*Coef.*	*Std. Err.*	*Beta*
DumUtrecht	.245964	.0304558	.2547668	*DumUtrecht*	.0903521	.0090887	.6034939
DumEind	.3107223	.031424	.3187163	*DumEind*	.1170342	.0084961	.7741195
DumDenHaag	.0710563	.0255193	.0789595	*DumDenHaag*	.0241331	.007448	.1729328
Ln_income	1,285142	.0366036	.8657215	*PercBuyHouse*	-.0008101	.0001308	-.2588714
DistHavoVwo	-.0317783	.0116873	-.069107	*DistVMBO*	.0099196	.0031609	.1253247
DistVMBO	.0397845	.0125624	.0779456	*DistTrainStat~n*	.0053696	.0017301	.1324573
DistShop	.0808768	.0303151	.0569337	*Populationkm2*	1.74e-06	5.97e-07	.1265257
HouseStock	-.0000107	5.53e-06	-.0494037	*Violent_pp*	-.3704756	.2108338	-.1008886
AllochMarok	.0000361	.0000185	.0462418	*Property_pp*	.1972929	.0633611	.1793862
Violent_pp	-1,345785	.2006507	-.0568323	*_cons*	1,512726	.0126151	.
Property_pp	.6496905	.6589288	.0916053				
_cons	.7900399	.1347171	.				

6. Conclusion

Crime serves as one of the most important influences for change in structure of a particular community. A change in crime levels is a first indicator of a changing neighbourhood, because the housing price adjusts quickly to changing crime levels in a slowly transitioning community. The question addressed in this thesis is:

> *"How strong is the effect of crime on the local real estate market in the cities of Rotterdam, Utrecht, the Hague, and Eindhoven?"*

The question is addressed by using publicly available data and by using two regression house price models, which allowed controlling for different characteristics of a neighbourhood influencing housing prices. The effect of crime is divided into two categories, namely violent crime and property crime. The literature found in this field expected a negative influence of violent crime and mainly negative influence of property crime on housing price. Cross-sectional research showed a positive influence of property crime on housing prices. This could be because of high valued neighbourhoods attracting more burglary than low valued neighbourhoods. The causality may work in both directions; therefore it is difficult to estimate the unbiased effect of property crime on housing prices. In the literature review some research adjusted for time, endogeneity bias, and spill over bias of neighbourhoods in close proximity. Eventually explaining an expected negative influence of property crime on housing prices.

Though results showed strong negative influence of violent crime on the logarithm of housing prices and the ratio of housing price divided by income. Indicating that the number of violent crimes per person in the neighbourhood significantly influences housing prices. Property crime on the other hand had a significant positive influence in both models. Indicating that if the number of property crimes per person in a neighbourhood would rise, the housing price would rise along. One reason for the positive influence of property crime could be that high valued property attracts crime. In a deprived neighbourhood is less valuable property than in a rich neighbourhood, meaning that housing prices influence the level of property crime. Further research would be needed in this case, as this finding would be contrary against literatures done in this field. Required would be to further analyse the effect of crime over time and to control for whether neighbourhoods influence the likelihood of crime in other close by neighbourhoods (spill over effects). This could tackle the positive estimated influence of property crime on housing prices in the Netherlands.

The control variables added have a less strong effect on housing prices than violent crime and property crime. Comparing the four cities included in this research concludes that Rotterdam provides the cheapest housing compared to the other cities. Decreasing the violent crimes per person is most beneficial for the image of Rotterdam and housing prices in the city. The comparison of the two models concluded that policymakers and police should focus on crime, as these two variable have the strongest impact on housing prices compared to the other included variables.

For further research, address-specific structural characteristics would enrich data for the regression model and could specify the positive property crime effects found in this research. Other interesting aspect would be to research the movement of victims of both violent and property crime.

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8. Appendix

8.1 Dataset: control variables

This paragraph contains the control variable categories obtained from the statistical bureau of statistics in the Netherlands. From these categories control variables will be added to the models to estimate the effect of crime on housing prices. Each category is briefly explained and all included variables are denoted in the dataset.
In order to gain the unbiased effect of crime on housing price, control variables need to be included to be able control for influences of other variables on the dependent variable. The control variables will be discussed per block of similar control variables. Not all variables will be included in the model due to time restrictions, but the full dataset with all mentioned variables is available for further research.

Population characteristics[12]

Population determinants consist of control variables considering the population demographics. These are the number of people living in the neighbourhood and number of people per square kilometre. Adding population variables will control for the fact that the biggest city in this research of the Netherlands, Rotterdam, has a more dense population than the three other cities. Taking the number of people living in the neighbourhood into account is important, because cities attract crime. When there more people living in a neighbourhood, there are more potential victims for criminal activities. Cities also attract more crime because of the high dense population citizens can act more anonymous (Bluestone, 2008).
Important aspect of the population characteristics is that it enables the dataset to be filtered. Using the variable population and population per square kilometre, the dataset will be filtered. This needs to be done to filter out particular areas of the neighbourhood like industrial areas, which do not have many residents. These areas are not a part of this research, which investigates the effect of crime on housing price in four urbanized cities in the Netherlands. Therefore neighbourhoods with less than 1000 population and less than 750 citizens per square kilometre will be filtered out of the dataset.

[12] Population data available from CBS, Central Organization of Statistics in The Netherlands.

A common assumption is that neighbourhoods with a lot of different ethnical groups, cause low housing prices and high crime levels. Therefore included in the population determinants is the composition of the ethnicity in the neighbourhood, to tackle the racial bias. In this research can be controlled for the most common origins living in the Dutch cities, these are: Moroccans, Netherlands Antilles, Surinamese, and Turks.

Property Characteristics[13]

Opposed to population determinants, it is important to control for housing determinants. Different aspects of houses might bias the effect, on a neighbourhood level. Therefore variables will be added like housing stock in the neighbourhood, which contains the number of housing available in the neighbourhood.
To filter the least urbanized areas from the cities from the database, neighbourhoods with less than 100 housing stock will be filter out of the variables. Just like with population and population per square kilometre, this also needed to be done to filter out the "outliers". These are mainly the high valued houses, which cause the linear effect to distort. This will cause the model to follow the assumptions needed according to the Ordinary Least Square (OLS) model (chapter 4: Methodology).
Other available variables from the dataset in this section are the owner(s) of the property. In the case of the four cities in the Netherlands this could be: the residents itself (buy-house), rented from housing corporation or other (rental-house). This could be important for the model because logically households who bought the house, are more interested to invest in there own neighbourhood. Buying a house automatically commits the buyers to a long-term relationship to the neighbourhood opposed to rental house residents, whom are less involved and more likely to move on a short term basis.

Income[14]

As mentioned in the literature review and logically, income is an important factor for a housing price. When people decide they want to move, a house has to meet their wants and needs and fit in their budget. The rent or mortgage cannot exceed the owners'

13 Property data available from CBS, Central Organization of Statistics in The Netherlands.
14 Income data available from CBS, Central Organization of Statistics in The Netherlands.

income systematically. The lower the mortgage income ratio is, the less a household can afford on other expenditures. It also works the other way around, the higher the mortgage income ratio the more they can afford to buy other goods. Therefore to control with variables for income seems almost a must, so data is included to control for different levels of income. These are the main income per person and average income per liver in a property, this is corrected for the number of people earning an income and living in the same property.

Neighbourhood facilities[15]

The research is built upon statistics on neighbourhood level in the cities of Rotterdam, The Hague, Utrecht and Eindhoven. Unfortunately the available data was not available to control for address-specific, to match structural housing attributes, therefore adding some specific neighbourhood facilities could compensate for the lack of specific property determinants. Some neighbourhoods have better connections to a train station and/or highway roads, important transportation hubs. For citizens who need to travel to work, this might be important factor for choosing a house, therefore influencing the housing price. So including the distance to the closest train station and highway are included in the dataset.

Other aspects for choosing a particular neighbourhood might be the available amenities. What makes a neighbourhood more 'liveable' compared to others? Having a swimming pool, cinema and big shops close by, could be the final factor for people to actually buy a house or give a price boost to the property.

Completing this category with the number and distance to education, from primary school to high schools and all coherent facilities like a library. Education is the way to a higher income. Households with children could benefit from living close to a good school, for a better future outside a deprived neighbourhood.

[15] Neighbourhood facilities data available from CBS, Central Organization of Statistics in The Netherlands.

Area Characteristics[16]

The last category of the data set is the area characteristics. These are the dummies for controlling per city, so at the end we can derive crime levels and influence on housing prices per city. Noting that the base city of this research is Rotterdam, meaning that the other cities in this research are added as dummy variable.

Also added in this category is the size of the area in hectare, to be able to divide variables in size. The total hectare is divided into 2 variables, land and water. The more water available in an area means it is less crowded for city principles and the availability of recreational facilities. Property could benefit from a less crowded area of the city, but still have the proximity to the city centre and its amenities.

8.2 Model 1: output

Source	SS	df	MS
Model	45.4104246	11	4.12822042
Residual	4.62127369	279	.016563705
Total	50.0316983	290	.172523098

Number of obs =	291
F(11, 279) =	249.23
Prob > F =	0.0000
R-squared =	0.9076
Adj R-squared =	0.9040
Root MSE =	.1287

Ln_house_p~e	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
DumUtrecht	.245964	.0304558	8.08	0.000	.1860116	.3059164
DumEind	.3107223	.031424	9.89	0.000	.248864	.3725806
DumDenHaag	.0710563	.0255193	2.78	0.006	.0208215	.1212911
Ln_income	1.285142	.0366036	35.11	0.000	1.213087	1.357196
DistHavoVwo	-.0317783	.0116873	-2.72	0.007	-.0547847	-.0087719
DistVMBO	.0397845	.0125624	3.17	0.002	.0150553	.0645136
DistShop	.0808768	.0303151	2.67	0.008	.0212015	.1405521
HouseStock	-.0000107	5.53e-06	-1.94	0.054	-.0000216	1.70e-07
AllochMarok	.0000361	.0000185	1.95	0.052	-3.71e-07	.0000726
Property_pp	.6496905	.2006507	3.24	0.001	.254709	1.044672
Violent_pp	-1.345785	.6589288	-2.04	0.042	-2.642888	-.0486812
_cons	.7900399	.1347171	5.86	0.000	.5248488	1.055231

Figure 1: Regression model (not robust)

[16] Area data available from CBS, Central Organization of Statistics in The Netherlands.

```
Linear regression                                  Number of obs =       291
                                                   F( 11,    279) =    224.77
                                                   Prob > F      =    0.0000
                                                   R-squared     =    0.9076
                                                   Root MSE      =     .1287
```

Ln_house_p~e	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
DumUtrecht	.245964	.0280943	8.75	0.000	.1906602	.3012677
DumEind	.3107223	.0257737	12.06	0.000	.2599866	.361458
DumDenHaag	.0710563	.0219044	3.24	0.001	.0279374	.1141752
Ln_income	1.285142	.0393597	32.65	0.000	1.207662	1.362621
DistHavoVwo	-.0317783	.0119177	-2.67	0.008	-.0552384	-.0083182
DistVMBO	.0397845	.0120311	3.31	0.001	.0161012	.0634677
DistShop	.0808768	.0300377	2.69	0.008	.0217476	.140006
HouseStock	-.0000107	5.42e-06	-1.98	0.049	-.0000214	-5.17e-08
AllochMarok	.0000361	.0000148	2.45	0.015	7.09e-06	.0000652
Property_pp	.6496905	.1591113	4.08	0.000	.3364794	.9629015
Violent_pp	-1.345785	.3678325	-3.66	0.000	-2.069864	-.6217052
_cons	.7900399	.1430968	5.52	0.000	.5083533	1.071726

Figure 2: Regression model 1 (robust)

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of Ln_house_price

         chi2(1)      =     2.65
         Prob > chi2  =   0.1039
```

Figure 3: Heteroskedasticity test model

Source	SS	df	MS
Model	45.4107668	2	22.7053834
Residual	4.62093154	288	.016044901
Total	50.0316983	290	.172523098

```
Number of obs =      291
F(  2,    288) =  1415.12
Prob > F      =   0.0000
R-squared     =   0.9076
Adj R-squared =   0.9070
Root MSE      =   .12667
```

Ln_house_p~e	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
_hat	1.063329	.4339181	2.45	0.015	.2092765	1.917382
_hatsq	-.0058254	.0398768	-0.15	0.884	-.0843124	.0726616
_cons	-.1711637	1.176	-0.15	0.884	-2.485809	2.143482

Figure 4: Linktest model 1

```
Ramsey RESET test using powers of the fitted values of Ln_house_price
       Ho:  model has no omitted variables
                 F(3, 276) =      1.38
                  Prob > F =      0.2484
```

Figure 5: Ramsey Reset test for omitted variable(s) model 1

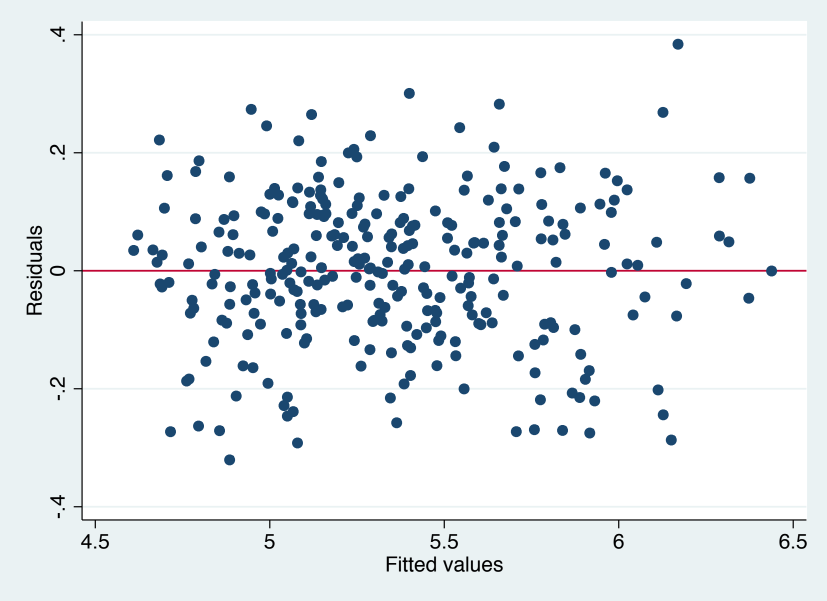

Figure 6: Residual plot against yline(0) model 1

Variable	VIF	1/VIF
DumEind	3.14	0.318658
DumUtrecht	3.01	0.332681
DumDenHaag	2.43	0.411691
Property_pp	2.42	0.413621
Violent_pp	2.34	0.427560
HouseStock	1.96	0.509286
DistHavoVwo	1.95	0.512512
Ln_income	1.84	0.544515
DistVMBO	1.83	0.546525
AllochMarok	1.70	0.587821
DistShop	1.38	0.726949
Mean VIF	2.18	

Figure 7: Variation inflation factor test model 1

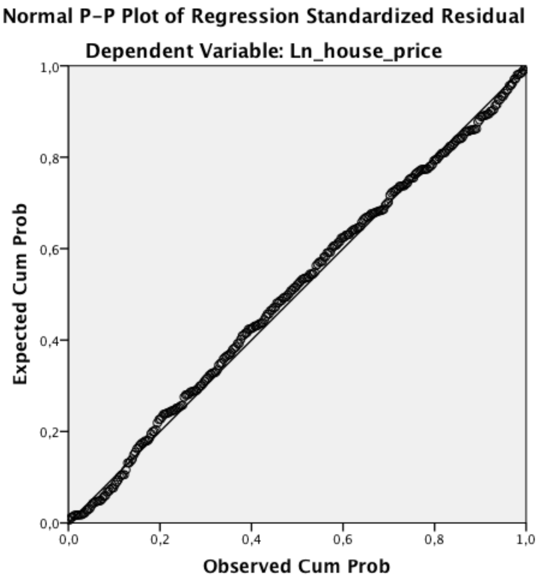

Figure 8: Normal probability plot model 1

8.3 Model 2: output

Source	SS	df	MS
Model	.733054799	9	.081450533
Residual	.470092563	281	.001672927
Total	1.20314736	290	.004148784

Number of obs =	291
F(9, 281) =	48.69
Prob > F =	0.0000
R-squared =	0.6093
Adj R-squared =	0.5968
Root MSE =	.0409

Ln_ratio_hpink	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
DumUtrecht	.0903521	.0090887	9.94	0.000	.0724615	.1082427
DumEind	.1170342	.0084961	13.78	0.000	.1003102	.1337582
DumDenHaag	.0241331	.007448	3.24	0.001	.0094721	.038794
PercBuyHouse	-.0008101	.0001308	-6.19	0.000	-.0010676	-.0005525
DistVMBO	.0099196	.0031609	3.14	0.002	.0036975	.0161417
DistTrainStat~n	.0053696	.0017301	3.10	0.002	.0019639	.0087752
Populationkm2	1.74e-06	5.97e-07	2.92	0.004	5.66e-07	2.92e-06
Violent_pp	-.3704756	.2108338	-1.76	0.080	-.7854897	.0445386
Property_pp	.1972929	.0633611	3.11	0.002	.0725703	.3220156
_cons	1.512726	.0126151	119.91	0.000	1.487894	1.537558

Figure 9: Regression model 2 (not robust)

```
Linear regression                               Number of obs =        291
                                                F(  9,    281) =     57.94
                                                Prob > F       =    0.0000
                                                R-squared      =    0.6093
                                                Root MSE       =     .0409
```

Ln_ratio_hpink	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
DumUtrecht	.0903521	.0088262	10.24	0.000	.0729782	.107726
DumEind	.1170342	.0076793	15.24	0.000	.1019181	.1321504
DumDenHaag	.0241331	.0073568	3.28	0.001	.0096516	.0386146
PercBuyHouse	-.0008101	.0001501	-5.40	0.000	-.0011056	-.0005145
DistVMBO	.0099196	.0031626	3.14	0.002	.0036942	.0161451
DistTrainStat~n	.0053696	.0017006	3.16	0.002	.002022	.0087171
Populationkm2	1.74e-06	6.44e-07	2.70	0.007	4.74e-07	3.01e-06
Violent_pp	-.3704756	.1220881	-3.03	0.003	-.6107989	-.1301523
Property_pp	.1972929	.0494139	3.99	0.000	.1000246	.2945613
_cons	1.512726	.0132982	113.75	0.000	1.486549	1.538903

Figure 10: Regression model 2 (robust)

Variable	VIF	1/VIF
DumUtrecht	2.65	0.377296
Property_pp	2.39	0.418946
Violent_pp	2.37	0.421806
DumEind	2.27	0.440284
DumDenHaag	2.05	0.488144
Population~2	1.35	0.739170
DistTrainS~n	1.31	0.763342
PercBuyHouse	1.26	0.795361
DistVMBO	1.15	0.871862
Mean VIF	1.87	

Figure 11: Variation Inflation Factor test model 2

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: fitted values of Ln_ratio_hpink

         chi2(1)      =     0.12
         Prob > chi2  =   0.7314
```

Figure 12: Heteroskedasticity test model 2

```
Ramsey RESET test using powers of the fitted values of Ln_ratio_hpink
       Ho:  model has no omitted variables
                  F(3, 278) =      0.70
                  Prob > F =      0.5541
```

Figure 13: Ramsey Reset test for omitterd variable(s) model 2

Source	SS	df	MS
Model	.735349259	2	.36767463
Residual	.467798103	288	.001624299
Total	1.20314736	290	.004148784

Number of obs	=	291
F(2, 288)	=	226.36
Prob > F	=	0.0000
R-squared	=	0.6112
Adj R-squared	=	0.6085
Root MSE	=	.0403

Ln_ratio_h~k	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
_hat	-3.204651	3.538023	-0.91	0.366	-10.16831	3.759011
_hatsq	1.323008	1.113153	1.19	0.236	-.8679383	3.513954
_cons	3.337363	2.808986	1.19	0.236	-2.191382	8.866108

Figure 14: Linktest model 2

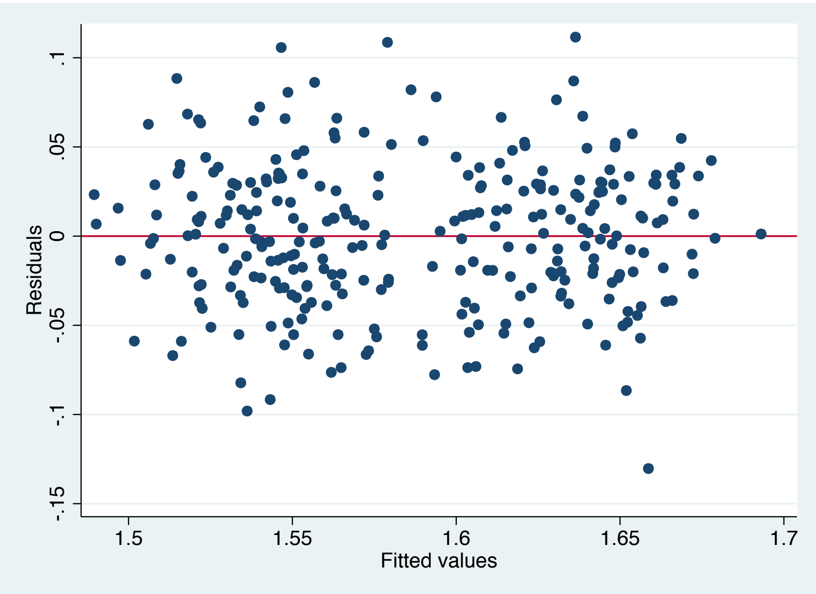

Figure 15: Residual plot model 2

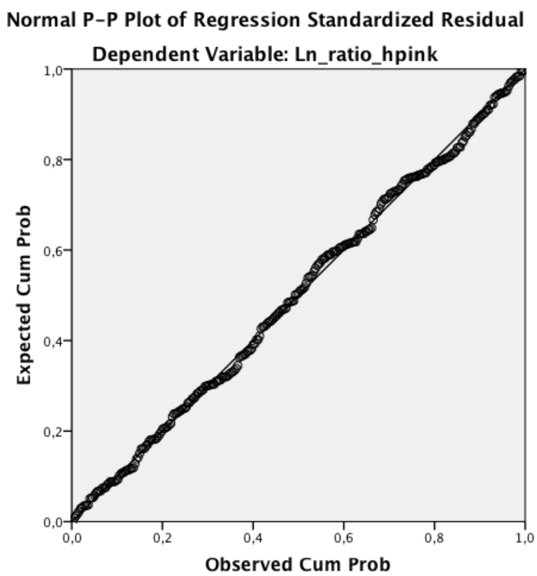

Figure 16: Normal probability plot model 2

Effect of Crime on House Price

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