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The effect of crime on housing values in Rotterdam – A hedonic price model

Master thesis

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Abstract

Purpose: The purpose of this study is to test the effect of crime on housing values in Rotterdam and to consider how this effect varies for different types of houses in different neighborhoods.

Methodology: A hedonic price model is applied in this study. Regarding the statistical tests, one null single level model and five multilevel models have been performed in STATA. To accomplish this, housing data of Rotterdam in 2012 is used. The statistical test is based on a sample of 265.650 houses, which are dispersed over 68 neighborhoods.

Results: If the SafetyIndex decreases with 1 point, then the housing value decreases with €9.926, which confirms that crime indeed has a negative effect on housing values. Furthermore, it is found that crime not only has a larger negative effect on the value of big houses compared to small houses, but also on owner-occupied houses compared to rental houses. All of these findings are in line with the expectations created in advance.

Limitations: There was no data available for house characteristics such as number of bathrooms and garage, which are likely to have a statistically significant effect on housing prices. In addition, there is a high probability that the dataset still contains exceptions, as it has a large number of observations. Furthermore, this study did not focus on spatial effects, which may affect to some extent the results.

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The copyright of the master thesis rests with the author. I am responsible for the content.

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1. Introduction

By nature, all human beings desire to live in an affordable and a nice house that is located in an attractive neighborhood. The affordability of houses and the attractiveness of neighborhoods depend upon different factors (i.e. physical house characteristics and neighborhood characteristics). Therefore, people should consider these factors when they decide to purchase a house in a certain neighborhood. Neighborhood characteristics can be divided into two categories; neighborhood amenities and neighborhood disamenities. Neighborhood amenities such as parks, family doctors, train stations and supermarkets are considered as positive because they are likely to increase housing values. Neighborhood disamenities are considered as negative. Examples of neighborhood disamenities are noise pollution and crime. It appears from the existing literature that crime is a significant neighborhood disamenity. For example, Buonanno et al., (2013) indicate in their study that crime is negatively related to neighborhood quality. They found that the value of houses in less safe neighborhoods was on average 1.27% lower. It becomes noticeable that crime negatively influences the housing values. Crime can be considered, in almost all cases, as an act that is not in line with the law determined by the government. Naturally, each person differently perceives the seriousness of criminal offenses. People who try to live fairly will feel more disturbed when they are confronted with crime than people who are less sensitive for crime. This, in turn, may affect the way people deal with the effects of crime in their daily life, as people take into account, for example, the newspapers and interpersonal conversations (victimization) when they decide to move from neighborhood A to neighborhood B.

In addition to Buonanno et al., (2013), various articles can be used as a support for conducting this study. A study conducted by Pope (2008) indicates that when someone, who has been convicted of a sex crime, moves into a neighborhood (hence less safe neighborhood), the value of houses decrease with 2.3%. Furthermore, a review of 18 studies by Ihlanfeldt & Mayock (2009) indicates that 14 studies found that crime negatively affects the housing values. By considering this kind of studies, the expectation is that feeling less safe and experiencing more crime has a negative effect on the housing values. Therefore, *the first focus* of this study is to investigate whether crime has an effect on housing values in the neighborhoods of Rotterdam. Most of these studies that looked at the effect of crime on housing values were conducted in United States. In this manner, it will be investigated whether the findings in previous studies are also applicable to a European city.

However, in order to contribute to and not only to re-examine the existing literature, it is essential to investigate how the effect of crime varies for different types of houses in different neighborhoods of Rotterdam. Therefore, the concentration on different housing submarkets will be *the second focus* of this study. Depending on the number of rooms, a house can be classified as small, medium or big. It is plausible to expect that a big house will be more sensitive for crime compared to a medium or a small house, as it probably contains more valuable goods. So, bigger houses may be more attractive for burglars. With this in mind, it expected that crime has a larger negative effect on bigger houses than on medium and smaller houses. In fact, the preferred option was to exactly know the resident of a certain house. However, there is no data available to pursue this option. Therefore, this assumption relies on proxy measures. Another interesting housing submarket is the ownership of houses. The expectation is that crime will have a larger negative effect on privately owned houses compared to rental houses, as buying a house is a long-term investment. By taking the aforementioned arguments together, the research question of this study is as follows:

Does crime negatively affect the housing values in Rotterdam and does this vary for different types of houses in different neighborhoods?

The following two sub-questions will allow this study to draw up a structure and will also enable this study to answer the main research question:

- To what extent does crime affect the housing values in Rotterdam?
- To what extent does crime affect the value of different types of houses differently?

Given that houses substantially vary in their features, are considered as heterogeneous and are located in neighborhoods with varying features, the hedonic price model is an appropriate method to assess their value (Herath & Maier, 2010). Regarding the statistical test, STATA will use Multilevel Analysis to answer the research question. The dataset contains 68 neighborhoods with 265.650 houses and amenities and disamenities, which is partly provided by the municipality of Rotterdam and partly retrieved from the website of Statistics Netherlands. Neighborhood crime will be measured by using the *SafetyIndex* of each neighborhood, which is broadly discussed in section 3.

The remainder of this report is structured as follows. The next section provides a broad review of the literature. In section 3, the variables used in the statistical test are discussed. Section 4 outlines the methodology of the statistical test. In the subsequent section, the results of the statistical tests are presented. Finally, the last two sections contain the conclusion and limitations of this study.

2. Literature Review

This section broadly discusses the focus of this study based on empirical studies and consists of three sub-sections.

2.1. House and neighborhood characteristics

When a person decides to purchase a house in a certain residential area, he or she should consider different factors that may influence his or her choice. Undoubtedly, housing prices are one of the influencing factors. It is, in turn, interesting to clarify what factors determine the housing prices. According to previous empirical studies (e.g. Grether & Mieszkowski, 1974; Lang & Jones, 1979) housing prices are determined by physical house characteristics (e.g. type, year of construction, number of bedrooms) as well as neighborhood characteristics. However, it is difficult for households to exactly know what the positive features of a neighborhood are due to limited information. Atkinson & Crocker (1987) indicate that it is important to include a wide set of house characteristics in order to deal with omitted variable bias. However, Nguyen-Hoang & Yinger (2011) argue that researchers are dependent on the availability of data in terms of house characteristics. Therefore, the number of house characteristics used differs largely from one study to another.

2.1.1. Amenities

In addition to the physical house characteristics, the characteristics of a neighborhood in which a house is located require great attention. In other words, there are neighborhood amenities and disamenities. Given the fact that buying a house is a long-term investment and that houses are immobile, it is crucial to carefully consider these neighborhood amenities and disamenities. Nevertheless, the way in which the amenities are identified differs from one study to another. One study may concern the availability of amenities and the other one may concern the accessibility (distance) of amenities. Positive amenities are likely to increase the quality of life and hence the residential values (Huang, Leung, & Qu, 2015; McDonald, 2012). A lot of studies (e.g. Bolitzer & Netusil, 2000; Anderson & West, 2006) have examined the effect of positive characteristics of residential areas on housing prices. A common weakness of these studies is that they focused only on a limited number of neighborhood characteristics (e.g. green, water, open spaces). When this happen, the effect of one or a limited number amenities will be overestimated since there is an omitted variable bias. So, contrary to expectations, studies that simply take a wide set of neighborhood characteristics into consideration are scarce (e.g. Tse, 2002; Benefield, 2009). By taking this kind of studies into account, Visser, van Dam, & Hooimeijer (2008) came up with three categories, which consist of different neighborhood characteristics. These three categories are labeled as physical, social and functional characteristics of residential areas.

Regarding neighborhood characteristics, Lutzenhiser & Netusil (2001) found that the effect of open spaces on housing prices is positive and statistically significant. This effect is different for each type of open spaces and it changes when the distance between houses and open spaces changes as well. Another studies such as Anderson & West (2006) and Luttik (2000) provide support for this finding. In addition to open spaces, Cho, Bowker, & Park (2006) confirm the findings of previous studies by showing that other amenities such as water and green spaces also positively affect housing prices. With regards to social characteristics (for example income and racial background), it is revealed that also these characteristics have an effect on the housing prices because they may influence the choice an individual makes. Li & Brown (1980) conducted a study in which they estimated three models. In the first model, median income had a positive significant effect on housing prices. After adding micro-neighborhood variables (e.g. distance to non-residential activities) in the second and third model, the effect of median income on housing prices became statistically insignificant. They explain this by arguing that median income proxies for omitted variables that are highly correlated with income. Furthermore, Holly & Jones (1997) found in their study that income is one of the most important determinants of real housing prices. This study has used a dataset from 1934 to 1994 in order to look at the behavior of housing prices in United Kingdom. They found that real income increased with 312% since 1934 whereas real housing prices increased with 278%. It is reasonable to say that if people have a higher income, than they will live in neighborhoods consisting of mainly big houses with higher values. Another important social characteristic is the racial composition of neighborhoods. In this respect, the study of Harris (1999) found that the housing values decreases with at least 16% in neighborhoods that consists of 10% or more black people. This study has shown that this lower value is not mainly caused by an aversion to black people. Instead, residents prefer to have neighbors that are well-educated and affluent. These features are more common among white people than black people. Another research that deals with race and housing prices is conducted by Myers (2004).

This study found that there is no difference between the prices paid by black and white owners or renters. But they found that if there is an increase in the percent of black people, then the housing prices and rents will decrease in some neighborhoods. However, Visser, van Dam & Hooimeijer (2008) argue that there is a scarcity of studies that take care of this effect. This can be explained by the fact that there is not always data available and hence exploring the relationship between the housing prices and the resident characteristics becomes complicated. Lastly, concerning functional characteristics (i.e. the proximity to schools, family doctor, hospitals, shopping areas and the accessibility of public transport and job opportunities), different interpretations exist. To be more specific, the basic assumption is that when the accessibility to these amenities increase, the value of houses will increase as well. This assumption is supported by different studies. For example, Owusu-Edusei, Espey, & Lin (2007) found that short distances between houses and schools positively affect the housing prices regardless of the school levels (elementary, middle and high schools). On the other hand, distances between houses and schools that is above the average distance result in significantly negative housing values. Besides that, it is repeatedly proven that the quality of schools has an effect on the housing prices. Although different research methodologies have been used by studies, Nguyen-Hoang & Yinger (2011) found in their review that one additional standard deviation in student test scores leads to an increase of 1-4% in housing prices. Furthermore, Hui, Chau, Pun, & Law (2006) has confirmed the earlier findings by suggesting that the longer one travels from his house to the central business district (i.e. traveling for work), the lower the housing prices will be. However, it should be recognized that there are households who choose to live in expensive houses located far from the central business district because they are well educated and have higher income (Wilkinson, 1973). A possible explanation might be that green spaces are lacking in neighborhoods located close to the central business district and that high-density neighborhoods cause noise pollution. It appears that houses benefiting from a more accessible public transport have a higher value than houses with a poorer access, while both houses possess comparable physical characteristics (Agostini & Palmucci, 2008). Debrezion, Pels, & Rietveld (2006) conducted a study to explore the impact of the accessibility of Dutch railways stations on housing prices. Their findings also point out that the value of houses decreases when the distance between a house and a station increases. A possible explanation for these findings is that, in case of better access, a resident probably pays less for distance travelled. Accordingly, the costs for making the public transport more accessible (i.e. building new stations, introducing new lines) are incorporated in housing prices. In order to relate these amenities to the whole Dutch housing market, a report written by Visser & Vam (2006) will be discussed. Their findings confirm the findings of previous studies by arguing that amenities in the vicinity of houses positively affect the housing prices. To give an example, neighborhoods with low-density and green spaces are associated with higher housing prices, while neighborhoods with high-density and without open spaces are associated with lower housing prices.

2.1.2. Disamenities

Logically, there are also neighborhood disamenities that negatively affect housing prices. This means that neighborhoods suffer from negative characteristics that, in turn, negatively influence one's willingness to pay (WTP). Specifically, people tend to consider a neighborhood as less attractive when the abovementioned (positive) amenities are absent. The absence of some positive amenities can be described as the availability of disamenities (e.g. good schools). However, there are also disamenities that cannot be expressed in terms of positive amenities (e.g. whether a house is located close to industrial areas). Different studies have explored the effect of disamenities on housing prices. For example, Wilhelmson (2000) found that noise pollution in Sweden has a negative and significant effect on single-family houses. If a single-family house is located close to a road known for noise pollution, the value of this house will decrease with approximately 30%, from 975.000 to 650.000 Swedish Krona. The article of Iman et al., (2009) also provides support for this finding. Furthermore, Farber (1998) have summarized empirical studies about the relationship between undesirable facilities (e.g. waste sites and industrial facilities) and housing values. Although being located near industrial facilities enhance employment, undesirable facilities negatively affect housing prices. Support for these disamenities (industrial areas & highway proximity) can also be found in the report of Visser & van Dam (2006). Furthermore, a shorter distance between coffee shops/nightclubs and houses decreases the housing values. This can be explained by the fact that such places result in more noise pollution and criminal activities (Hughes et al., 2008). Another disamenty that plays a crucial role in determining the housing prices is crime. Buonanno et al., (2013) indicate in their study that crime is negatively related with neighborhood quality. They found that the value of houses in less safe neighborhoods is on average 1.27% lower. The effects of crime on housing prices are thoroughly discussed in sub-section 2.3. The aforementioned house and neighborhood characteristics can be used to create a hedonic housing price model (Monson, 2009). In the next sub-section, the hedonic housing prices model is discussed.

2.2. Hedonic price model

Given that houses and other real estate properties substantially vary in their features and are considered as heterogeneous, the HPM is an appropriate method to assess their value (Herath & Maier, 2010).

2.2.1. A brief historical overview

Despite the disagreements among researchers about who firstly introduced the hedonic price model (henceforth HPM), a considerable number of researches have accepted Court (1939) as the first user of this model. The study of Court (1939) was about passenger cars and it argued that an objective composite measure for price comparisons might be constructed by combining car specifications (e.g. horsepower and tire size). In this manner, a hedonic price index can take into account the desires of a buyer and production cost that are reflected in the prices and car specifications. As the years have passed, different studies (e.g. Griliches, 1961) have contributed to the HPM. An important study with respect to this model is conducted by Rosen (1974), which has analyzed purchaser and seller decisions and market equilibrium. By relying on the assumption that differentiated products are prized on the basis of their utility-bearing characteristics, he developed a hedonic model. According to him, the model defines the price of a product (in this instance the housing prices) as a dependent variable and the certain number of characteristics that are associated with this product as the independent variables. In this study, the physical house characteristics and neighborhood characteristics discussed in previous section are defined as independent variables. The idea behind this can be explained by the fact that it is not possible to sell these characteristics individually, because there is no market available for them. Therefore, all of these characteristics are incorporated in the housing prices. By doing so, the HPM aims to estimate the WTP for both the characteristics of a house and its location (Haan & Diewert, 2013; Linneman, 1981). So, there are different factors (e.g. affluence, racial composition, safety, proximity to positive amenities) that can be included in this model in order to assess whether people are ready to pay more for a house located in a certain neighborhood. Accordingly, this model explains the equilibrium estimations of the characteristics that are (economically) related to a product.

2.2.2. Estimation method and the model description

A hedonic housing price model is a regression of housing value on house and neighborhood characteristics. The use of regression as an estimation method has become very prevalent among the researchers. This approach attempts to detect a vector of parameters that optimally explains the relationship between independent variables (characteristics) and the corresponding value (housing price). The usual hedonic regression can be represented as follows:

$$P = f(H, N)$$

Where

P = the value, rent or sales price of the house

H = a vector of physical house characteristics

N = a vector of neighborhood characteristics

As discussed in sub-section 2.1, data availability is an important determinant of what variables should be included in the hedonic regression applied in housing markers. Based on earlier studies, Malpezzi (2003) identified the following independent variables that are relevant for and frequently used in the HPMs: room specifications, floor area, type of house, year of construction, other house specifications (e.g. availability of garage), socioeconomic numbers of the neighborhood, distance to amenities (e.g. CBD, train stations, schools). In broad terms, the variables on this list are in line with the characteristics discussed in previous sub-section. However, the way in which these variables are defined differs per study. To be more specific, some studies have defined bedrooms in terms of certain numbers, while other studies have used a series of dummy variables to specify 1, 2 and 3 bedrooms (Sirmans et al., 2005). The use of different variable definitions and functional forms (i.e. linear, log-log and semi-log specifications (Halvorsen & Pollakowski, 1981)) makes a comparison of hedonic pricing studies tricky (Sirmans et al., 2005). Lastly, regarding dependent variable, in case of housing market, rents or sales prices are used. When we compare these two types of dependent variables, it appears that in practice sales prices are much more used compared to rents. Different types of rents are used, which can be categorized as net rents (e.g. Brunauer et al., 2010) and gross rents (e.g. Filippini et al., 2007). Naturally, some researchers did not clarify whether their study uses net or gross rents (see Gelfand et al., 2005). A rent does not reflect the real value of a house because of two reasons. Firstly, rents depend on demand and supply conditions (Herath & Maier, 2010). Secondly, rents rely mainly on rental contracts that vary for different types of houses. For these reasons, using sales prices (i.e. determined through actual transactions) as dependent variables are more suitable. A possible explanation is that actual transaction data may result in less biased valuation compared to owner's self-assessment (Sirmans et al., 2005; Malpezzi, 2003). With regard to the functional forms, Sirmans et al., 2005 argued that the semi-log form has been preferred by myriad studies over the past decades. In this case, the dependent variable is transformed in log, whereas the independent variables remain unlogged. An advantage of this specification is that it deals with changes in characteristic prices across various price categories within the dataset. This is supported by (Follain & Malpezzi, 1980).

2.2.3. Disadvantages of hedonic regressions

Haan & Diewert (2013) enumerated the main disadvantages of hedonic regressions. First, it requires micro-level data about relevant product characteristics that probably affect its value. Nevertheless, such a dataset is not always available or easily accessible. Second, researchers have different opinions about the selection and specification of variables and the appropriateness of functional forms (O'Sullivan & Gibb, 2003). Therefore, different estimates and interpretations will be the result. Another risk of hedonic regressions, as denoted by So et al., (1997), is the existence of multicollinearity between characteristics and the following instability of estimates.

2.2.4. HPM and housing market

Sheppard (1997) indicates that economists would pay great attention to comprehend the demand for houses and the equilibrium in the housing markets. There are different conceivable explanations for this expectation. First, a house is one of the most precious assets of individuals. This, in turn, determines the level of welfare and hence is highly related to the economic health and wealth of our society (Chin & Chau, 2003). Also, individuals spend a large portion of their income to afford a house. Another arguable explanation, as previously stated, is that houses are heterogeneous in terms of structural and locational characteristics. With all of these arguments in mind, the HPMs have been widely applied in real estate and housing market research in order to determine the price that must be paid for a house. Especially, compared to the Eastern part of the world, a major part of these studies have concentrated on the investigation of housing markets in

US and Europe (Chin & Chau, 2003). Based on the existing literature, Can (1992) has distinguished different contexts in which this model is applied. Firstly, it estimates demand for several house and neighborhood characteristics (e.g. Ohsfeldt, 1988; Blomquist & Worley, 1981) and demand for houses in general. Secondly, this model is extended to the construction of housing price indices (e.g. Goodman, 1978) and corrects for quality changes (Sheppard, 1997). Furthermore, it analyzes the effect of negative neighborhood attributes on housing prices (see Mingche & Brown, 1980). In addition to the real estate and housing markets, these models are applied to agricultural land values (e.g. Maddison, 2000; Bastian et al., 2002), automobile markets (see Matas & Raymond, 2009; Griliches, 1961), labor markets (see Hwang et al., 1998) and markets for other differentiated goods such as personal computers (e.g. Berndt et al., 1995).

2.3. Crime as disamenity

In sub-section 2.1.2 different neighborhood disamenities are mentioned and briefly discussed. One of the most interesting neighborhood disamenities is crime. Crime can be considered, in almost all cases, as an act that is not in line with the law determined by the government (Wilson, 1998). There are different reasons for selecting crime as a neighborhood disamenity in the present study. Firstly, despite the fact that there are myriad studies that evaluate housing prices by using different neighborhood characteristics, the number of studies that take care of crime is limited. Secondly, it appears from the existing literature that in general crime has a negative effect on housing prices. However, some surprising findings indicate that crime has a positive effect on housing prices. Therefore, it is quite interesting to investigate in which cases there will be a positive effect. Lastly, most of these studies are conducted in United States. Therefore, a study that focuses on European housing market is not only interesting but also indispensable. The following sub-sections provide an overview of previous empirical findings about crime and its impact on housing prices.

2.3.1. Causes of crime

It is quite interesting to be aware of the fact that crime does not arise spontaneously. It is not reasonable to only consider the effect of crime on housing values, but also to gain insight into risk factors of crime. This sub-section is therefore meant to identify what factors increase or decrease the chance of criminal behavior of an individual. Criminologists argue that factors or situations associated with crime not necessarily result in criminal behavior (Weatherburn, 2001). In its place, these factors or situations raise the risk of criminal behavior. In other words, when a citizen has to deal intensively with these factors or situations, the risk of his or her involvement in crime will be higher. Naturally, numerous criminological studies (e.g. Tanner-Smith et al., 2013; van der Laan et al., 2009) have tried to detect whether a specific factor raise the risk of criminal behavior by keeping other pertinent factors constant. However, the findings do not imply with absolute certainty that a particular factor leads to crime. Therefore, the determination of the causes of crime is not simple and is subject to uncertainty. The term 'crime' is possibly giving a wrong idea or impression. This is because there are different types of crime, varying from unpaid traffic fines to homicides. Prior to the identification of the causes, a couple of fundamental evidences regarding crime should be clarified.

Firstly, age and gender are very relevant in the discussion of crime. According to Steffensmeier & Allan (1996), females are less likely to commit criminal acts than males, especially in the case of serious crime, regardless the situation and its location. In addition, Farrington (1986) has discussed a well-known age-crime curve. Despite the fact that this curve has considered different characteristics, (i.e. UK and US, men and women, period, types of crime), the age-crime pattern was almost similar. Specifically, it appears that involvement in crime starts at younger ages (12 years) and increases to a peak in the late teenage years (18 years), independently of gender and types of crime. From that point, the curve declines quickly until approximately 24 years and after that it declines gradually. Secondly, criminal career of offenders is relevant as well. Coumarelos (1994) indicated that a large proportion of teenagers who were involved in crime stop committing offences in a short period of time. However, the remaining proportion of teenagers continue with committing crime well into their 40s. In addition to the fact that adult offenders account for a large part of all crime (Wolfgang et al., 1972), there is also evidence that the older they become, the more serious criminal acts they commit (Farrington, et al., 1990).

With regards to the causes of crime, Weatherburn (2001) presented two categories consisting of factors that make persons and locations more crime-prone than others. These two categories are discussed one by one. Considering crime-prone persons, their involvement in crime is primarily attributed to *family* (parents) *factors*. A meta-analysis by Hoeve et al., (2009) has demonstrated that bad parental mentoring has a positive significant effect on crime. This study has also showed that positive features of parental support (e.g. acceptance or love) negatively affects crime, whereas negative features of parental support (e.g. rejection or neglect) are positively related to crime. Another factors that are associated with crime are *intelligence* and *education success*. Hirschi & Hindelang (1977) showed that a low IQ negatively affects school performance. Being less succesful in education, in turn, increases the probability of committing crime (Maguin & Loeber, 1996). In addition, *poverty* and *unemployment* are unpleasant conditions that can be linked to crime. Despite the fact that different studies (e.g. Thornberry & Farnworth, 1982; Raphael & Winter-Ebmer, 2001) have found support for the assumption that poverty and unemployment lead to crime, it is also reasonable to presume that crime leads to unemployment and poverty. For example, after being convicted of crime, it becomes harder to find a job. Therefore, the direction of this relationship is somewhat discussableMoreover, it is proven that *alcohol consumption* raises the risk of criminal behavior (see for example Greenfeld, 1998).

Within the context of crime-prone neighborhoods, the first relevant factor is *criminal opportunity*. There are a various neighborhood features that trigger offenders to commit crime. Some examples are attractive commercial targets or higher income households (see Eck & Weisburd, 1995; Smith & Jarjoura, 1989) and the absence of police (Sherman & Eck, 2003). The basic idea is that higher income households are more likely to have high value products (e.g. computer) which logically becomes an attractive target. The absence of police decreases the risk of being arrested and hence increases criminal offences. Furthermore, *economic and social disadvantages* (e.g. income inequality) are also relevant in making a neighboorhood crime-prone (Heller et al., 2010). Kawachi et al., (1999) found that *income inequality* was exteremely correlated with violent crime rates (i.e. murder, assault and robbery). When the inequality increases, these crime increases as well. Income inequality was also highly correlated with burglary rates.

2.3.2. Perception of crime

Almost all people have had to deal with crime at least once in his or her live. In other words, they have become a victim of crime, have committed crime or have been a witness of an offence. Regardless the manners in which people have experienced crime, media plays an important role in influencing people's perceptions of crime (Dowler, 2003). According to Chiricos et al., (2000), there is a relationship between both local and national TV news and fear of crime. It appears that local TV news have stronger impact on people who live in cities with high crime rates or who have victimization experience. The finding that watching local news increases concerns about crime is supported by Romer et al., (2003). Furthermore, Heath (1984) conducted a study to examine the effect of newspapers on fear of crime. These newspapers contained local, sensational and random crime news. Sensational crimes in this study refer to extremely violent crime. It appeared from 335 telephone interviews that participants who read local crime news, which contains sensational and randomly chosen crime, experienced more fear of crime. Participants who read nonlocal crime news, which also contains sensational and randomly chosen crime, experienced lower fare of crime. Based on these findings, it can be concluded that when people are confronted with crime news from other neighborhood, they feel safer in their own neighborhood. In addition to the content of a message conveyed through a newspaper or television, the receivers of this message are also important for determining fear of crime (Skogan & Maxfield, 1981). Skogan & Maxfield (1981) have defined interpersonal communication (especially conversations with victims) as a more important factor than media. This is because the media present crime news which are more abstract and less directly linked to the receivers. Personal conversations, however, are more likely to infleunce perceptions and behavior due to close ties between people in question and, for example, victims, especially when crime information concerns own neighborhood.

Another important finding by a fairly recent study (Jackson, 2009) is that women have, on average, significantly more concerns about all forms of crime than men. This can be explained by the fact that women have the feeling that they are less able to protect themselves against danger caused by an offender. Moreover, this study found that gender predicts fear of personal crime but does not predicts fear of property crime. The latter finding is especially interesting because there are studies (e.g. Skogan & Maxfield, 1981; Box et al., 1988) which argued that the risk is greater for males to become a victim of crime.

2.3.3. Crime and housing prices

Sirmans et al., (2005) provided a review of studies that applied HPM to evaluate the housing prices. They argued that in these studies crime (neighborhood disamenity) has usually a negative effect on housing prices. One of the first published article that investigated the effect of crime on housing values is Kain & Quigley (1970). They found a small effect on individual house values. Ihlanfeldt & Mayock (2009) came up with a review of existing 18 studies that estimated the effect of crime on housing prices. These studies have used neighborhood crime as independent variable to estimate its effect on housing prices. Studies that estimate the effect of crime on housing prices use aggregated data, which reduce neighborhood-level variation in crime and housing transactions ((Boggess et al., 2013). It appears from the review that 14 studies found that crime has a negative significant effect on housing prices. A striking finding was that one (Case & Mayer, 1996) of the remaining four studies found a positive significant effect of crime on housing prices and other three studies had insignificant results. There are two possible explanations for the positive significant effect. First, people who live in high quality neighborhoods have greater tendency to report more petty crimes compared to people who live in low quality neighborhoods. Second, an affluent neighborhood has probably more valuable objects that become attractive for offenders (Gibbons, 2002). This, in turn, leads to positive correlation between housing prices and the number of property crimes (Lynch & Rasmussen, 2001). Nevertheless, given the fact that approximately 78% of these studies found a negative significant effect of neighborhood crime on housing prices, it is reasonable to assume that crime is an important neighborhood disamenity and hence people are ready to pay more for houses located in safer neighborhoods. Some of these studies that found a negative significant effect are discussed.

Firstly, Thaler (1978) have estimated the effect of property crime on the selling prices of 398 single-family houses. This study has used property crimes rates because of the assumption that they more accurately reported. A possible explanation, in case of property crime, is that it is required to report this to the police in order to get paid by an insurance firm. The finding suggests that 1 standarddeviation increase in property crime results in a decrease of 430 dollar per house. This amount is approximately 3% of the average value of per house. Secondly, Dubin & Goodman (1982) have investigated the effect of 12 types of neighborhood crime on housing prices. They came up with principical components for property crime, violent crime and shopping center crime. It appears from the results that crime has a negative significant effect. Specifically, 1 unit increase in property crime, violent crime and shopping center crime results in respectively a decrease of 795, 3143 and 3721 dollar in housing values. Furthermore, Schwartz et al., (2003) have investigated the effect of property crime and personal crime on housing prices. They have used a dataset with sales transaction prices for apartments, single-family houses and tenant-owned apartments between 1975-1988. personal crime rates, in this case, aggregated rates of homicide, rape, robbery and assault. Property crime rates, on the other hand, aggregated the rates of burglary, automobile theft and other thefts. The results of repeat-sales regression indicate that personal crime rate is negative significant whereas property crime is positive but insignificant. This means that 1 unit increase in personal crime rate results in a decrease of 12% in housing value. Another study by Tita et al., (2006) related 43.000 individual house sales between 1995 and 1998 to crime rates at the tract level. They took total crime rates, property crime rates and personal crime rates. The findings of these study also indicate that crime negatively affects housing prices. Another finding of this study is that total crime rates have a negligible impact on housing prices. This study did not provide any clarification for the specific pattern of significant against insignificant observations across the neighbhoor categories and between levels and changes in crime rates. Despite the fact that there are some expections, the general findings indicate that crime has a negative effect on housing values. Accordingly, the first hypothesis is:

H1:

Neighborhood crime has a statistically significant negative effect on housing values.

With regards to crime measurement, it is important to be aware that the use of some forms of crime variable has limitations. For example, when one only considers crime based on registered numbers, different types of crime will get the same weight. In United States there are crime indexes used, which consist of murder, assault, burglary and automobile theft. Given that assault is more severe than burglary, it is not reasonable to treat them equally. Another problem is the use of only one type of crime because of the omitted variable bias.

In general, empirical studies agree on the finding that crime has a negative effect on housing values. Suprisingly, as mentioned earlier, in some studies it appeared that crime has a positive effect on housing prices, which is actually difficult to explain. A possible explanation for this could be the existence of submarkets. There is more study needed to identify how crime is related to submarkets. Therefore, the contribution of the present study is to identify and hence fill this knowledge gap. This is discussed in the next sub-section.

2.3.4. Housing submarkets

There are various reasons why people may react differently on crime, which in turn may affect the value of houses differently. Not only people living in neighborhoods are diverse, but also the houses located in these neighborhoods (Wu & Sharma, 2012). Among the researchers, there is an agreement that the housing market is not an identical entity and that it consists of a set of idiosyncratic submarkets (Aidar et al., 1996). Bourassa et al., (1999) describe a housing submarket as a set of houses that may be an alternative for one another, but are not be an ideal alternative for houses in other submarkets. In this context, different proxies are possible. Firstly, the study of Tita et al., (2006), which was discussed shortly in previous sub-section, will be related to housing submarkets. Their regression is for housing values regarding crime rates (level of crime) and the changes in crime rates. For each of these crime rates, they used separate regressions on logged sales prices. They have estimated 4 equitions, namely one for full sample and three for income catergory, consisting of low-income, medium-income and high-income neighborhoods. The key findings indicate that when the personal crime rate decreases, the housing prices in both low-income and high-income neighborhoods will increase. Furthermore, when the level of both personal and property crime rates negatively changes, the housing prices in high-income neighborhood will increase. In addition to different income groups, housing submarkets can also be characterized by means of the physical house characteristics. In this respect, Scharne & Struyk (1976) have used the number of rooms. Depending on the number of rooms, a house can be classified as small or big. For instance, a bigger house will probably be more sensitive for crime compared to a medium or a smaller house because it is more attractive for burglars as it probably contains more valuable goods. This could mean that people who live in a small house are less affected by crime because there is not much to steal. So, number of rooms may be used as an indicator of what kind of people is living in a house. With this in mind, it is interesting to determine whether crime has a larger impact on bigger houses than on smaller houses. In fact, the preferred option was to exactly know the resident of a certain house and his or her features. However, there is no data available to pursue this option and hence this assumption relies on proxy measures. Accordingly, the second hypothesis is:

H2:

Neighborhood crime has a larger negative effect on the value of bigger houses than on the value of smaller houses.

According to Harris (1999), both owners and renters of houses have varying and unequal stakes in their residential areas. Therefore, type of house is another submarket. An owner, for example, considers a house not only as an asset to live but also as a long-term investment. The latter is closely related to the fact that a house is immobile, which forces people to make a good decision. A renter, however, uses a house mainly to live in. With this difference in mind, the most logical assumption is that an owner pays greater attention to neighborhood (dis)amenities. To be more specific, it is easier for a renter, compared with an owner, to move from his or her neighborhood when it becomes unsafe. Given that an owner probably buys a house to stay permanently in a neighborhood and spends many years in it together with his or her children, he or she may have more difficulty accepting unsafety. Therefore, the assumption is that the value of owner-occupied houses will be lower than rental houses when the residents experience the same neighborhood crime. Accordinlgy, the third hypothesis is as follows;

H3:

Neighborhood crime has a larger negative effect on the value of owner-occupied houses than the value of rental houses.

Jaccard & Turrisi (2003) mentioned that there are different forms of relationships that may occur within causal models. These models identify the impact of at least one independent variable on the dependent variable. With regards to the last two hypotheses, the *moderated* causal relationship is relevant in the present study. This means that the relationship between the variable of interest and the dependent variable is moderated by another independent variable (i.e. type of house & number of rooms). These relationships are also known as interaction effects. Interaction effects will be used in the models in order to test the last two hypotheses. In this case, the variable of interest will be multiplied with the moderator variable, which is also called the interaction variable. To give an example from the book of Jaccard & Turrisi (2003) about the interaction effect, the impact of education (i.e. variable of interest) may be larger on income (i.e. dependent variable) for some racial groups than for other racial groups (i.e. the moderator variable). So, this interaction effect will be applied in this present study.

3. Data

Based on the existing literature, this section defines the variables that are relevant in the present study. The previous section has provided a general overview of the effect of crime on housing prices. This study aims to reinvestigate the findings of the literature review and contribute to the existing literature. To accomplish this, housing data of Rotterdam in 2012 is used. The statistical test is based on a sample of 265.650 houses, which are dispersed over 68 neighborhoods. These neighborhoods are listed in the appendix. The dataset contains both the physical characteristics and the (tax)value of each house in these neighborhoods. It also contains the related neighborhood amenities and characteristics. More specifically, two datasets (i.e. an existing dataset and collected data) are combined in STATA by using the option 'merge two datasets'. The municipality of Rotterdam has provided the existing dataset (house characteristics).

With regards to outliers and exceptions, different changes have been made in the dataset. Firstly, houses with a value that is lower than €40.000 are dropped from the dataset. The idea behind this is that on the website Funda.nl, which is the most visited Dutch house supply website, there are parking garages with a value ranging from €16.000 to €39.000 (Funda, 2015). After evaluating the dataset, it became clear that indeed a large part of houses with a value between €1.000 and €39.000 had a type that was unclassified and contained 1 room. This observation is in line with the search results of Funda.nl. This also applies to a house located in Groot IJsselmond, which had a value of €8.401.000. This house had a type that is unclassified and contained 2 rooms. It is reasonable to conclude that this house is not a residential building. Therefore, this house is dropped from the dataset. Furthermore, the oldest building (1678) is dropped from the dataset, which had a type that was unclassified. After a research on the Internet, it became clear that this building is a church. Secondly, some neighborhoods are dropped from the dataset. The idea behind this is that some neighborhoods consist of houses that are not equal to houses located in other neighborhoods, which could mean that they represent other housing markets. Therefore, this kind of neighborhoods is not relevant for this study. For example, the neighborhood Noord Kethel consists of only 22 houses with an average value of €425.318, which is quite high. According to a report published by the municipality Rotterdam (Rotterdam, 2008), the neighborhood Noord Kethel contains five farmhouses. This study, however, focuses on residential neighborhoods that consist of hundreds or thousands of houses. Lastly, for some neighborhoods there were no safety indexes available. All the neighborhoods dropped from the dataset are listed in the appendix.

3.1. The dependent variable

Housing values is the dependent variable. The name of this variable is ***TaxValue*** and is labeled as *Registered tax value of dwellings in 1000's of Euros.* Every year, the municipality of Rotterdam determines the value of properties based on the Property Valuation Act (called WOZ in Dutch). Therefore, the municipality and people often talk about the WOZ-value. The WOZ-value refers to the value of a house that is assigned by the municipality in order to determine how much municipal tax charges a resident must pay. The municipalities determine the WOZ-value on the basis of taxation. Appraisers visit the houses in the municipality that represent a particular category. These houses are randomly selected or have been sold around the value reference date (1 January of the previous year) (WOZ-waarde, 2015). As mentioned earlier, this way of valuation of houses may be less biased compared to owner's self-assessment. It should be noticed that there is a difference between the selling price and the WOZ-value of a house. For example, when an occupant is forced to sell his or her house in a short period of time due to personal circumstances, the selling price of this house will decrease enormously. However, this does not by definition mean that the original value is also decreasing. The consequence is that selling prices become to some extent unstable, while WOZ-values do not fluctuate regularly. Moreover, the WOZ value is applied to all houses included in the housing market (i.e. rental & owner-occupied) (CBS, WOZ-waarde gedaald tot onder het niveau van 2007, 2014). In order to say more about the reliability of WOZ-value, the way in which it is calculated should be discussed. For the calculation of the WOZ-value, the location, year of construction and size of the house are also taken into account. Given the fact that these house characteristics are considered and this calculation is done every year, the WOZ-value of all types of houses is up-to-date. Furthermore, an independent administrative body, which is called the *Waarderingskamer*, checks whether the municipalities properly estimate the WOZ-values. According to this party, Rotterdam properly estimates the WOZ-value (Waarderingskamer, 2015). More specifically, the WOZ-value of 97.9% of the total number of houses was estimated correctly. Accordingly, the probability of underestimating or overestimating the housing values is reduced (hence less biased). Therefore, the data is quite reliable and provides a large number of observations.

3.2. The independent variables

Crime is the first independent variable. It is defined as the ***SafetyIndex*** and is used for testing all the hypotheses. The safety index reflects the social safety conditions in the neighborhoods, the sub-municipalities and the city as a whole. All neighborhoods in Rotterdam got a score, which ranges from 1 (unsafe) to 10 (safe) (Veiligheidsindex, 2012). From 2002 to 2010, the safety index is published every year. From 2010, however, the frequency is reduced to every two year. So, the safety index of 2009 is determined in 2010 and the safety index of 2011 is determined in 2012. This means that there is no safety index available for 2012. Therefore, this study uses the safety index of 2011 because this is most relevant for the housing data of 2012. In 2011, Bloemhof has the lowest safety index (4.5) and nine neighborhoods (e.g. Terbregge) have the highest safety index (10.0). As described in section 2, some studies have used objective crime data and other studies have argued that perception of crime (i.e. subjective data) is also important. The uniqueness of the safety index of Rotterdam is that a large of amount of data – both objective and subjective – are combined into a single number representing the safety conditions. Therefore, this makes the safety index a useful instrument to apply in this study. There are eight safety elements that build on objective and subjective data and that have different weighting factors. These safety elements are theft (2.0), drug-related nuisance (1.75), violence (2.0), burglary (1.0), vandalism (1.0), nuisance (1.75), a public space that is clean and undamaged (1.5), and road safety (1.0) (i.e. traffic incidents). It is argued in the documents that homicides are not captured in the safety index because these incidents often have little relationship with the actual safety conditions in respective neighborhoods. Homicides occur almost always in the criminal contexts and hence can happen in any neighborhood. These eight elements are determined on the basis of safety priorities of Rotterdam. A research commissioned by Association of Dutch Municipalities has investigated safety policies of municipalities and the priorities they set (Gaalen & Atalay, 2013). The top five priorities of Rotterdam are nuisance caused by youth, unsafety feelings of citizens, residential and commercial burglary, nuisance in a living area, and drug and alcohol use. The objective data refers to registered data and is derived from the police, the fire brigade and other municipal institutions. This data builds on reported crime and police calls. The subjective data is derived from questionnaires completed by the residents. These questionnaires contain questions that ask for perception of safety, experienced safety problems in the neighborhood and victimization. So, it is likely that the answers of residents on these questions reflect their opinion formed beforehand about their neighbhorhoods through local news, personal conversations or victimization. For the safety index of Rotterdam in 2011, 60.000 residents were invited to participate in this survey. Finally, approximately 16.000 residents have completed the questionnaires through Internet (51%), phone (35%) and paper (14%) (Veiligheidsindex, 2012). Lastly, this index contains also contextual data because it is known that the composition of the population is related to crime/safety. These contextual features are age, ethnicity, unemployment and income, which are not separately included in the models. This might lead to multicollinearity. In order to be sure that *SafetyIndex* does not highly correlate with the control variables (these control variables are explained in following sub-sections), the correlation test has been performed in advance. It appeared that there was no strong or very strong correlation between the *SafetyIndex* and the control variables. Based on this, it can be concluded that the contextual data in the *SafetyIndex* does not cause problems in the analysis. The opinion of residents (i.e. subjective data) plays the major role in the calculation of the safety index because two of the three components are derived from survey (i.e. victimization and experienced safety problems on one side and objective data on the other). The safety index of the neighborhoods is retrieved from the documents posted on the website of Rotterdam (Gemeente Rotterdam, 2012). It is expected that the lower the safety index of a neighborhood, the lower the housing values will be.

A room is an indispensable variable. The dataset contains houses that have more than 8 rooms and is expressed by the variable ***Rooms.*** The variable *Rooms* is kept as a continuous variable, as there are too many rooms to create (generate in STATA) dummy variables. A new variable is created instead of *Rooms*. The new variable is called ***RoomsCente****r*. *RoomsCenter* reflects the number of rooms in the house, centered on the average house size in rooms. The variable *Rooms* is centered on 3 rooms (to be precise, the mean value is 3.544012). The idea behind centering on 3 rooms is that it enables a researcher to get more meaningful coefficients. In this manner, models can show how much a house with 3 rooms increase in its value when the number of rooms rises by one. For answering the second hypothesis, the variable *RoomsCenter* plays a crucial role. It is expected that bigger houses (i.e. more rooms), compared to smaller houses (i.e. less rooms), would have a lower value when a neighborhood is less safe. This is explained by an interaction variable, which is created by multiplying *RoomsCenter* with *SafetyIndex* (see section 4).

In order to test the third hypothesis, another independent variable is defined that specifies whether a house is privately owned or is rental. The name of this variable is ***PrivOwn*** and this dummy variable takes the value 0 when a house is rental and 1 when a house is privately owned. It is expected that privately owned houses, compared to rental houses, would have a lower value when the residents experience the same neighborhood crime. This is explained by an interaction variable, which is created by multiplying *PrivOwn* with *SafetyIndex* (see section 4).

3.3. Control variables

Housing prices are influenced by a number of physical house characteristics and neighborhood characteristics, which were discussed in the literature section. Based on their availability, data for the determinants of housing prices are included in the analysis as control variables. House-level variables (i.e. composition effects) and neighborhood-level variables (i.e. contextual effects) are distinguished and discussed shortly.

3.3.1. House-level (level-1) variables

First of all, *Rooms* is one of the most important house characteristics. This variable is already discussed in previous sub-section and centered on 3 rooms. The general expectation is that more rooms will result in higher house values. In addition, ***PrivOwn*** is another house-level variable, which is also discussed in previous sub-section. Moreover, the variable *Consyr* reflects the year of construction. The oldest house has been built in 1738 and the newest house in 2011. Dummy variables for *Consyr* are created in order to get more meaningful interpretations. Houses that were built before 1920 are expressed as **_pre1920**, between 1920 and 1945 as ***_1920to1945***, between 1945 and 1970 as ***_1945to1970***, between 1970 and 1990 as ***_1970to1990***, and after 1990 as ***_post1990***. Based on Funda.nl and the website welke.nl (Welke-Redactie, 2011), the following arguments will explain why these categories are chosen and why *_1945to1970* is used as the reference category. The houses belonging to the category *_pre1920* are already quite old and may therefore cause high maintenance costs for elements such as walls and roofs. Obviously, the state of maintenance plays a crucial role in determining the current market value. The style and quality of these houses are more or less similar to each other (i.e. middle-class houses, porch). Furthermore, *_1920to1945* refers to houses that were built between the First and the Second World War. These houses have generally a better quality compared to houses belonging to *_pre1920*, as the cavity wall was introduced in the twenties. Nowadays, the cavity wall is still used to build new houses. Generally, these houses can be considered as big and they have a large garden. Surprisingly, after the Second World War, the main focus was on building large numbers of houses (i.e. flats) instead of building houses with high quality, as there was a huge housing shortage (*_1945to1970*). From this period up to the present day, these houses face problems with respect to maintenance and moisture. In the past, especially between 1955 and 1970, asbestos has been used to build houses. Over the years, it became clear that this material causes health issues. Accordingly, houses belonging to this category are lower in quality and have less attractive design compared to houses belonging to the previous two categories. In the course of the seventies (*_1970to1990*), there was more attention paid to the design of houses (i.e. low-rise houses). Their quality was also improved, as better techniques and materials were used. Lastly, the category *_post1990* refers to houses with much higher quality and lower heating costs compared to the previous four categories. These houses face barely maintenance problems, as all the houses have been built by using low-maintenance materials. So, on the basis of quality, materials, design and costs, it can be concluded that the variable *_1945to1970* should be the reference category. It is expected that houses belonging to the reference category have a lower value compared to houses belonging to other categories. Finally, *Type* is a categorical variable and it classifies houses based on their type. There are 5 categories, which are as follows; single-family houses (***T2_SingleFamily***), high-rise houses with an elevator (***T3_HighRiseElevator***), high-rise houses without an elevator (***T4_HighRiseNoElevator***), low-rise multi-family houses (***T5_LowRiseMultiFamily***) and houses that are unclassified (***T1_Unclassified***). These categories are created on the basis of certain characteristic. It is, for example, not reasonable to assume that high-rise houses with an elevator are equal to high-rise houses without an elevator. An elevator is an important house characteristic, as it provides more comfort for residents. According to Bouwbesluit, it is mandatory that high-rise houses with five or more floors contain an elevator. However, houses consisting of only two floors are also considered as high-rise, while most of them do not contain an elevator. Therefore, the expectation is that high-rise houses with an elevator will have a higher value than high-rise houses without an elevator, which is mainly supported by Funda.nl. The variable *T2_SingleFamily* is the reference category, as single-family houses have more space and freedom than other type of houses. Therefore, it is expected that residents are willing to pay more for single-family houses than for all the other houses.

3.3.2. Neighborhood-level (level-2) variables

With regards to neighborhood amenities and disamenities, different control variables are needed. In addition to the variable of interest (i.e. *SafetyIndex*), the literature review has identified other amenities and disamenities. The data is retrieved from and explained by the documents (i.e. Excel and PDF) that were published on the website of Statistics Netherlands (CBS in Dutch) (CBS, 2012). This study has taken into account (for some amenities/variables) the availability of an amenity in a neighborhood by using the average number of it within 1 kilometer, which is expressed as '*AV1*'. All houses located in neighborhood *j* have the same value for the neighborhood-level variable, as the average distances and numbers are used. All these variables will be discussed shortly.

Firstly, variables that are considered as neighborhood amenities will be discussed. The following variables can be interpreted as the average distance between all houses in a neighborhood to the nearest amenity. All the distances between houses and amenities are measured in kilometers and are expressed as '*Dist*'. ***DistHospital*** is used for the nearest *hospital*. ***DistSchool*** specifies the nearest *elementary schools*. However, special elementary schools are not included. Furthermore, ***DistLargeSuper*** refers to the nearest *large supermarket*. ***DistTrainStat*** specifies the nearest *Dutch Railway stations*. ***DistGreen*** refers to a space that is used as a park for daily recreation, nature or forest. So, it specifies the *green space*. In addition, ***DistSport*** stands for the nearest *sports grounds*. These sports grounds are used for different sport activities such as gyms, swimming pool and sports field, including related parking and bleachers. ***DistLibrary*** refers to *libraries*. ***DistFamDoc*** is used for the nearest *family doctor*. ***DistCinema*** defines the nearest *cinema.* Finally, ***AV1_Restaurant*** is used for the average number of *restaurants* within 1 kilometer. The expectation is that an increase in the distance between a house and these amenities will result in lower housing values. This applies also to the average number of amenities.

Now, variables that are considered as neighborhood disamenities will be discussed. ***DistHighway*** specifies the average distance of all houses in the neighborhood to the nearest *highway access*. This variable is likely to have two directions (i.e. positive effect or negative effect on housing values). The first assumption indicates that when a house is located near to the highway access, the accessibility of a highway from a certain neighborhood increases, which is generally considered as positive. To be more specific, a resident does not have to travel long distances (through narrow roads) to access a highway. In this case, however, the noise pollution is ignored. The second assumption indicates that when a house is located near to the highway access, this house is also located close to the highway. In this case, the value of this house will be lower, as the existing literature has found that a highway causes noise pollution. However, the latter assumption is a proxy measure. It should be noticed that there might be a large distance between a house and the nearest highway access, while in fact this house is located right next to a (certain part of a) highway. The present study upholds the second assumption (i.e. negative effect on housing values). Another variable is ***DistCafe***, which refers to the nearest cafes, coffee houses, coffee shops, discos, sex/night clubs and party centers. The expectation is that an increase in the distance between a house and these places will result in higher housing values

Last but not least, the dataset includes an important level-2 variable. Firstly, the variable ***North*** is a dummy variable and is labeled as *Indicator North of the River* (i.e. Nieuwe Maas). This dummy variable takes the value 0 when a house is located in the south of the Nieuwe Maas and 1 when a house is located in the north of the Nieuwe Maas. This variable is especially important because it can be related to commuting distance (both in kilometers and in minutes). To be more specific, a lot of citizens of Rotterdam are working or studying in cities situated in north of Rotterdam (e.g. Den Haag, Amsterdam, Leiden, Utrecht, Delft, Gouda). The citizens living in neighborhoods that are located in the south of the Nieuwe Maas, compared to the north of the Nieuwe Maas, travel longer distances to get to these cities (i.e. crossing bridges or driving through a tunnel) (Google maps is used). Therefore, traveling from a neighborhood in the north of the Nieuwe Maas to one of these cities is shorter and cheaper. On the contrary, the housing values in the north of the Nieuwe Maas might be higher than in the south of the Nieuwe Maas because the costs of being closer to jobs and universities are incorporated in housing values. So, the expectation is that houses located in the north of the river will have a higher value.

4. Methodology

The present study intends to investigate the effect of crime on housing values in Rotterdam by using Multilevel Analysis. This technique is useful for studying clustered data (e.g. houses in neighborhoods, students in classrooms). Clustering refers to time or group dependence. Given that this study has to deal with multilevel data, there is group dependence. Furthermore, this technique is efficient because it uses both within and between dimensions. Accordingly, there are no different models needed for each group (i.e. houses in neighborhood X; houses in neighborhood Y) and it is not needed to aggregate the data to compare neighborhood mean of housing prices. Moreover, it allows a researcher to investigate neighborhood effects without using lots of dummies (i.e. no OLS with a dummy for every neighborhood). Therefore, a multilevel model is needed instead of OLS model. So, the multilevel version of an OLS regression model does not look much different, but it should be noticed that there is a difference in the estimation technique. Regarding estimation technique, multilevel analysis uses maximum-likelihood estimation (=mle). On the basis of this, STATA estimates the most suitable model for the available data. The basic multilevel model has the following expression (LEMMA, 2011):

$$\boldsymbol{y}_{\mathbf{ij}} = \boldsymbol{\beta}_{\mathbf{0}} + \boldsymbol{u}_{\mathbf{j}} + \boldsymbol{\varepsilon}_{\mathbf{ij}}$$

where y_{ij} is the independent variable and the value of y for ith house in jth neighborhood, β_0 is the overall mean of y, u_j is the neighborhood residual, and ε is the error term. The neighborhood residual shows the estimate of the value of an average house in neighborhood$_j$ (i.e. neighborhood X, neighborhood Y, etc.). The neighborhood residual u_j is determined by composition effects (level-1; house-level characteristics) and contextual effects (level-2; neighborhood-level characteristic). The first step for building a multilevel model is to add all relevant level-1 variables to the model. When there is a model with sufficient level-1 variables, the researcher get close to the 'pure' neighborhood effect u_j. In the second step, level-2 variables can be added to explain this neighborhood effect.

A researcher should consider the var(_cons) and var(Residual) in order to evaluate the variance in housing values that is explained by the neighborhood in which a house is located. The var(_cons) clarifies the variance in housing values that is explained by the neighborhood on the basis of the housing value average of different neighborhoods deviating from the housing value average of Rotterdam. Furthermore, the var(Residual) clarifies the variance in housing values that is attributable to differences between individual houses. This variance includes the deviations of house *i* from the mean neighborhood *j*. In order to determine how much the variance is at the neighborhood level, Variance Partitioning Coefficient (henceforth VPC) should be calculated. In this study, the VPC determines the portion of the total variance in housing values in Rotterdam that is caused by the differences between neighborhoods. The outcomes of the VPC calculation and its meaning are discussed for each model in the next section. The VPC is calculated by using the following equation.

$$\frac{\mathrm{var(\_cons)}}{\mathrm{var(\_cons)} + \mathrm{var(Residual)}} \text{ x } 100\%$$

In order to answer the first hypothesis, three models are created. Model 1 contains all relevant level-1 variables. Model 2 contains both level-1 and level-2 variables. Model 3 contains the variables included in model 2 and the variable of interest (*SafetyIndex*). Before the creation of the definite model 1 and model 2, a couple of regression are performed. The control variables on both levels are added one by one in order to check whether the model is significantly improved or not. To do this, the likelihood-ratio test has been performed. The H0 of the likelihood-ratio test assumes that there is no difference between two models.

The definite **model 1** is expressed below:

$$\mathit{TaxValue}_{ij} = \beta_{0j} + \beta_1 * \mathit{RoomsCenter}_{ij} + \beta_2 * \mathit{T1\_Unclassified}_{ij} + \beta_3 * \mathit{T3\_HighRiseElevator}_{ij} + \beta_4 * \mathit{T4\_HighRiseNoElevator}_{ij} + \beta_5 * \mathit{T5LowRiseMultiFamily}_{ij} + \beta_6 * \mathit{PrivOwn}_{ij} + \beta_7 * \mathit{\_pre1920}_{ij} + \beta_8 * \mathit{\_1920to1945}_{ij} + \beta_9 * \mathit{\_1970to1990}_{ij} + \beta_{10} * \mathit{\_post1990}_{ij} + u_j + \varepsilon_{ij}$$

As it can be seen in model 1, the variables *T2_SingleFamily* and *_1945to1970* are not included. These variables are omitted because of perfect multicollinearity. This means that at least one of the categories should be excluded. These omitted variables became the reference category (as described in sub-section 3.3.1.). The results are interpreted in terms of the difference between each category and these omitted categories. The next step in this study is creating a model 2 by adding level-2 variables.

The definite **model 2** is expressed below:

$$TaxValue_{ij} = \beta_{0j} + \beta_1 * RoomsCenter_{ij} + \beta_2 * T1\_Unclassified_{ij} + \beta_3 * T3\_HighRiseElevator_{ij} + \beta_4 * T4\_HighRiseNoElevator_{ij} + \beta_5 * T5LowRiseMultiFamily_{ij} + \beta_6 * PrivOwn_{ij} + \beta_7 * \_pre1920_{ij} + \beta_8 * \_1920to1945_{ij} + \beta_9 * \_1970to1990_{ij} + \beta_{10} * \_post1990_{ij} + \beta_{11} * North_{ij} + \beta_{12} * DistFamDoc_{ij} + \beta_{13} * DistTrainStat_{ij} + \beta_{14} * DistHighway_{ij} + \beta_{15} * DistCafe_{ij} + \beta_{16} * DistSchool_{ij} + \varepsilon_{ij}$$

As it can be seen in model 2, variables *T2_SingleFamily* and *_1945to1970* are still not included. It is important to see whether a variable significantly improves the model or not. The likelihood-ratio test has compared the log-likelihood (i.e. badness of fit) of the models after adding one more level-2 variable. Based on that, it can be concluded that these level-2 variables has significantly improved the model. Therefore, these variables are included in the definite model 2. Given that model 2 contains variables on both levels and is quite complete, the variable of interest can be added in the next model.

The definite **model 3** is expressed below:

$$TaxValue_{ij} = \beta_{0j} + \beta_1 * RoomsCenter_{ij} + \beta_2 * T1\_Unclassified_{ij} + \beta_3 * T3\_HighRiseElevator_{ij} + \beta_4 * T4\_HighRiseNoElevator_{ij} + \beta_5 * T5LowRiseMultiFamily_{ij} + \beta_6 * PrivOwn_{ij} + \beta_7 * \_pre1920_{ij} + \beta_8 * \_1920to1945_{ij} + \beta_9 * \_1970to1990_{ij} + \beta_{10} * \_post1990_{ij} + \beta_{11} * North_{ij} + \beta_{12} * DistFamDoc_{ij} + \beta_{13} * DistTrainStat_{ij} + \beta_{14} * DistHighway_{ij} + \beta_{15} * DistCafe_{ij} + \beta_{16} * DistSchool_{ij} + \beta_{17} * SafetyIndex_{ij} + \varepsilon_{ij}$$

As described earlier, this model is created in order to answer the first hypothesis. So, with this model the first focus of the present study is considered. However, the remaining two hypotheses concentrate on the second focus of this study. In order to answer the second and third hypothesis, model 4 and 5 are created. Each of these models contains an interaction variable, which is created by multiplying the variable *SafetyIndex* with two other variables of interest. Model 4 contains the interaction variable ***safetyXrooms*** and is used to answer the second hypothesis.

The definite **model 4** is expressed below:

$$TaxValue_{ij} = \beta_{0j} + \beta_1 * RoomsCenter_{ij} + \beta_2 * T1\_Unclassified_{ij} + \beta_3 * T3\_HighRiseElevator_{ij} + \beta_4 * T4\_HighRiseNoElevator_{ij} + \beta_5 * T5LowRiseMultiFamily_{ij} + \beta_6 * PrivOwn_{ij} + \beta_7 * \_pre1920_{ij} + \beta_8 * \_1920to1945_{ij} + \beta_9 * \_1970to1990_{ij} + \beta_{10} * \_post1990_{ij} + \beta_{11} * North_{ij} + \beta_{12} * DistFamDoc_{ij} + \beta_{13} * DistTrainStat_{ij} + \beta_{14} * DistHighway_{ij} + \beta_{15} * DistCafe_{ij} + \beta_{16} * DistSchool_{ij} + \beta_{17} * SafetyIndex_{ij} + \beta_{18} * safetyXrooms_{ij} + \varepsilon_{ij}$$

Model 5 includes the interaction variable ***safetyXprivown*** and is used to answer the third hypothesis.

The definite **model 5** is expressed below:

$$TaxValue_{ij} = \beta_{0j} + \beta_1 * RoomsCenter_{ij} + \beta_2 * T1\_Unclassified_{ij} + \beta_3 * T3\_HighRiseElevator_{ij} + \beta_4 * T4\_HighRiseNoElevator_{ij} + \beta_5 * T5LowRiseMultiFamily_{ij} + \beta_6 * PrivOwn_{ij} + \beta_7 * \_pre1920_{ij} + \beta_8 * \_1920to1945_{ij} + \beta_9 * \_1970to1990_{ij} + \beta_{10} * \_post1990_{ij} + \beta_{11} * North_{ij} + \beta_{12} * DistFamDoc_{ij} + \beta_{13} * DistTrainStat_{ij} + \beta_{14} * DistHighway_{ij} + \beta_{15} * DistCafe_{ij} + \beta_{16} * DistSchool_{ij} + \beta_{17} * SafetyIndex_{ij} + \beta_{18} * safetyXprivown_{ij} + \varepsilon_{ij}$$

Both interactions in model 4 and 5 are cross-level interactions. A cross-level interaction is an interaction between a variable measured at level-1 (i.e. *PrivOwn* & *RoomsCenter*) and one measured at level 2 (i.e. *SafetyIndex*).

5. Results

This section discusses the regression outputs of STATA based on the models that were formulated in section 4. The results of regression outputs are showed in table 1.

Table 1. Regression outputs of random intercept models

DV: *TaxValue*	**Model 0**	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Level-1 variables:						
RoomsCenter		32.364***	32.364***	32.364***	-47.456***	32.085***
T1_Unclassified		-20.310***	-20.311***	-20.307***	-11.884***	-16.177***
T3_HighRiseElevator		-47.732***	-47.730***	-47.726***	-37.618***	-43.542***
T4_HighRiseNoElevator		-69.974***	-69.969***	-69.964***	-61.682***	-67.271***
T5_LowRiseMultiFamily		-65.188***	-65.182***	-65.177***	-55.715***	-62.029***
PrivOwn		29.131***	29.128***	29.127***	27.353***	-69.131***
_pre1920		38.890***	38.887***	38.892***	36.392***	35.779***
_1920to1945		25.514***	25.524***	25.525***	20.497***	22.446***
_1970to1990		22.668***	22.663***	22.666***	21.810***	20.538***
_post1990		59.325***	59.321***	59.320***	58.839***	57.706***
Level-2 variables:						
North			58.489***	53.868***	51.880***	53.470***
DistFamDoc			-53.059**	-45.097**	-37.719*	-42.903**
DistTrainStat			-15.591**	-16.271***	-15.263**	-15.919**
DistHighway			22.407***	26.615***	24.722***	26.672***
DistCafe			71.248***	59.815***	52.314***	57.855***
DistSchool			71.549***	58.183**	55.181**	55.604**
Variable of interest:						
SafetyIndex				9.926**	3.390	4.626
Interaction variables:						
safetyXrooms					10.924***	
safetyXprivown						13.421***
_cons	180.236***	167.477***	73.113**	3.593	53.131	39.723
Neighborhood: Identity						
var(_cons)	8316.852	5609.925	3155.971	2978.371	2744.929	2986.558
var(Residual)	10779.39	7304.356	7304.395	7304.399	6598.203	6937.987

N=68 neighborhoods
*** Significance at 1%
** Significance at 5%
* Significance at 10%

Model 0

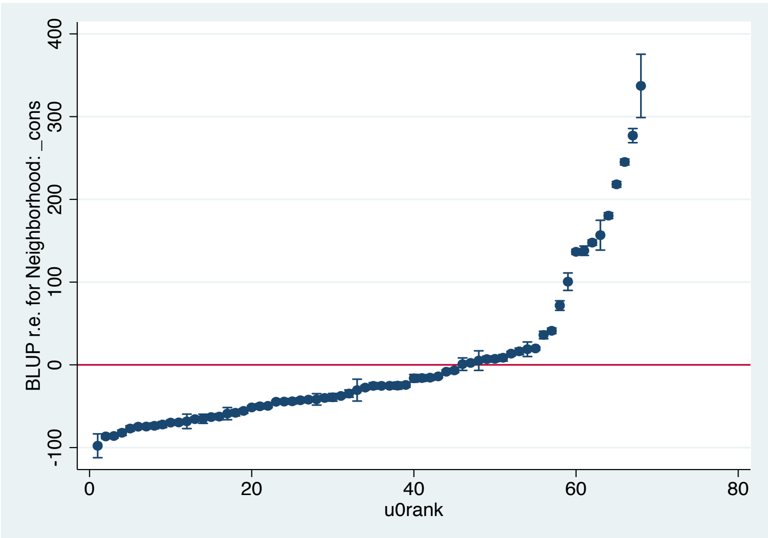
First of all, an empty multilevel model (model 0) is estimated, with only the dependent variable *TaxValue*. In this model, ***Neighborhood*** is properly specified as the grouping variable. It can be seen in table 1 that mean house value (i.e. anywhere in Rotterdam) is

€180.236. This constant term is significant at the 1% level. Based on the var(_cons) and var(Residual) estimates, it is possible to compute the VPC. In this case, the following equation is generated:

$$\mathrm{VPC} = \frac{8316.852}{8316.852 + 10779.39} \text{ x } 100\% = 43.55\%$$

The outcome of this calculation is 43.55 percent, which indicates that around 44 percent of the variance in housing values in Rotterdam is explained by the neighborhood in which a house is located. Another explanation of this outcome is that any pair of houses selected randomly from the same neighborhood is expected to be 43.55% similar in value. Furthermore, the neighborhood-level variance is significantly different from zero (at the 1% significance level), as the 95% confidence interval does not cross zero (5921.761 to 11680.65). A caterpillar plot is created and is exhibited in figure 1 to visually inspect the neighborhood effects.

Figure 1. The neighborhood effects



The dots are estimates of neighborhood effects, with their confidence intervals. It should be noticed that some dots have a wider confidence interval. This can be explained by the fact that certain neighborhoods have a smaller sample size (less houses) compared to other neighborhoods. These neighborhood effects can be described as unobserved characteristics that are related to neighborhood quality. In order to determine the neighborhood quality, level-2 variables are added to the multilevel model. However, the composition effects also play a role. To be more specific, some neighborhoods contain mainly big houses (thus higher average value), while some neighborhoods contain mainly small houses (thus lower average value). In order to reduce this composition effect, level-1 variables are added to the multilevel model.

Model 1

In the next step, the following level-1 variables are added to the multilevel model: *RoomsCenter*, the *Type* dummies, *PrivOwn* and the *Consyr* dummies (see table 1). The coefficients of model 1 inform us about the value of a specific house anywhere in Rotterdam and are interpreted as follows:

- The **constant term** implies that the average value of a rental 3-room single-family house anywhere in Rotterdam that has been built between 1945 and 1970 is €167.477, ceteris paribus. This is significant at the 1% level.
- The coefficient of **RoomsCenter** has a large and positive (32.364) effect on housing value. One additional room anywhere in Rotterdam increases, on average, the housing value with €32.364, ceteris paribus. This coefficient is significant at the 1% level.
- The coefficient of **T1_Unclassified** is negative (-20.310) and is significant at the 1% level. A house whose type is unclassified has, on average, a value that is €20.310 lower than a single-family house, ceteris paribus.
- The coefficient of **T3_HighRiseElevator** is negative (-47.732) and is significant at the 1% level. A high-rise house with an elevator has, on average, a value that is €47.732 lower than a single-family house, ceteris paribus.
- The coefficient of **T4_HighRiseNoElevator** is negative (-69.974) and is significant at the 1% level. A high-rise house without an elevator has, on average, a value that is €69.974 lower than a single-family house, ceteris paribus.
- The coefficient of **T5_LowRiseMultiFamily** is negative (-65.188) and is significant at the 1% level. A low-rise multi-family house has, on average, a value that is €65.188 lower than a single-family house, ceteris paribus.

The findings with regards to different house types are quite reasonable, as it was expected that residents are almost always willing to pay more for more space and freedom around their house. Given the fact that a single-family house is a freestanding residential building, it is fairly logical that its average value is higher than other house types.

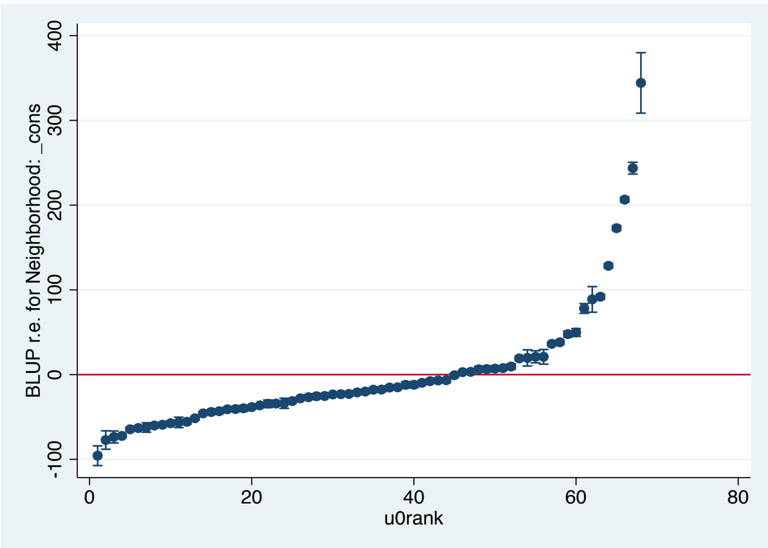
- The coefficient of **PrivOwn** is positive (29.131) and significant at the 1% level. A house that is privately owned has, on average, a value that is €29.131 higher compared to a rental house, ceteris paribus.
- The coefficient of **_pre1920** is positive (38.890) and is significant at the 1% level. A house that has been built before 1920 has, on average, a value that is €38.890 higher than a house that has been built between 1945 and 1970, ceteris paribus.
- The coefficient of **_1920to1945** is positive (25.514) and is significant at the 1% level. A house that has been built between 1920 and 1945 has, on average, a value that is €25.514 higher than a house that has been built between 1945 and 1970, ceteris paribus.
- The coefficient of **_1970to1990** is positive (22.668) and is significant at the 1% level. A house that has been built between 1970 and 1990 has, on average, a value that is €22.668 higher than a house that has been built between 1945 and 1970, ceteris paribus.
- The coefficient of **_post1990** is positive (59.325) and is significant at the 1% level. A house that has been built after 1990 has, on average, a value that is €59.325 higher than a house that has been built between 1945 and 1970, ceteris paribus.

Regarding the house-level variance, var(Residual) in model 0 was 10779.39. This variance is now 7304.356 (model 1). So within neighborhood variance decreased massively in the new model. This can be explained by the fact that house characteristics such as rooms, type, ownership and year of construction are important predictors of housing values in Rotterdam. By accounting for these predictors, a large part of within neighborhood (between houses) differences can be explained. With regards to the neighborhood-level variance, var(_cons) in model 0 was 8316.852. This variance is now 5609.925 (model 1). This means that between neighborhood variance also decreased massively in the new model. A precise explanation for this is that the composition effect is a part of the neighborhood residual. The neighborhood residual refers to the deviation of the neighborhood average housing value from the average housing value of Rotterdam. As mentioned before, for example, some neighborhoods have higher average housing values because they contain more big houses. By adding different house characteristics to the model, this potential composition effect has been accounted for. The neighborhood differences caused by the composition effect are (to some extent) taken into account, which means that the total neighborhood-level variance is reduced. On the basis of these variances, the VPC is calculated once more:

$$\text{VPC} = \frac{5609.925}{5609.925 + 7304.356} \text{ x } 100\% = 43.44\%$$

The outcome of this calculation is 43.44 percent, which indicates that around 44 percent of the variance in housing values in Rotterdam is explained by the neighborhood in which a house is located. Lastly, the likelihood-ratio test has been performed to compare model 0 with model 1. The H0 of the likelihood-ratio test is rejected at 1% significance level. It appeared that the model 1 had a significantly lower log-likelihood. The "badness of fit" became lower after adding level-1 variables. So, model 1 is significantly improved. A new caterpillar plot is created and is exhibited in figure 2 to visually inspect the 'pure neighborhood effects' after mostly taking out the composition effects.

Figure 2. Close to 'pure neighborhood effects'



Model 2

The next step in building a multilevel model is to add the neighborhood-level (level-2 variables) to the model. Accordingly, the level-2 variables *North*, *DistFamDoc*, *DistTrainStat*, *DistHighway*, *DistCafe* and *DistSchool* are added to model 2. It is important to notice that the coefficients for the level-1 variables hardly changed and they are still significant at the 1% level. Therefore, these coefficients will not be interpreted again, except the constant term. The new variables are interpreted as follows:

- The **constant term** implies that the average value of a rental 3-room single-family house located in the south of the Nieuwe Maas that has been built between 1945 and 1970 is €73.113, ceteris paribus. This is significant at the 5% level.
- The coefficient of **North** is positive (58.489) and significant at the 1% level. A house that is located in the north of the Nieuwe Maas has, on average, a value that is €58.489 higher than a house that is located in the south of the Nieuwe Maas, ceteris paribus.
- The coefficient of **DistFamDoc** is negative (-53.059) and significant at the 5% level. When the average distance between the nearest family doctor and a house increases with 1 kilometer, the value of this house decreases, on average, with €53.059, ceteris paribus.
- The coefficient of **DistTrainStat** is negative (-15.591) and significant at the 5% level. When the average distance between the nearest Dutch Railway station and a house increases with 1 kilometer, the value of this house decreases, on average, with €15.591, ceteris paribus.
- The coefficient of **DistHighway** is positive (22.407) and significant at the 1% level. When the average distance between the access of the nearest highway and a house increases with 1 kilometer, the value of this house increases, on average, with €22.407, ceteris paribus.
- The coefficient of **DistCafe** is positive (71.248) and significant at the 1% level. When the average distance between the nearest cafes, coffee shops, sex/night clubs and/or discos and a house increases with 1 kilometer, the value of this house increases, on average, with €71.248, ceteris paribus.
- The coefficient of **DistSchool** is positive (71.549) and significant at the 1% level. When the average distance between the nearest elementary school and a house increases with 1 kilometer, the value of this house increases, on average, with €71.549, ceteris paribus.

All of these outcomes, except DistSchool, are in line with the expectations that were created beforehand (on the basis of empirical findings). There are two possible explanations for this surprising result. Firstly, the expectation is that in high-density neighborhoods, the average distance between a house and the nearest elementary school will be shorter. In general, the assumption is that high-density can be considered as negative in residential areas (i.e. overcrowding), which is supported by Mitrany (2005). However, the present study did not consider the population density. Accordingly, this might have caused the omitted variable bias. Secondly, it is quite reasonable to say that elementary schools cause noise pollution, as children are screaming and playing in the schoolyards. There are various municipalities that can be used as an example to support this idea. For example, in the municipality of Alpen aan den Rijn, the administrative court has decided to close all the schoolyards after school hours due to noise pollution that is caused by children (Binnenlandsbestuur, 2010). Accordingly, a house will have a higher value when it is located far away from an elementary school. Therefore, it seems that the second explanation is most reasonable. With the likelihood-ratio test, all level-2 variables described in section 3 were tested one by one. The variables *DistHospital*, *DistLargeSuper*, *DistRestaurant*, *DistCinema*, *DistLibrary*, *DistSport*, *DistGreen* and *AV1_Restaurant* did not improve the model significantly. Therefore, they were not included in the definite model 2. In this model, the neighborhood-level variance has also decreased massively. It dropped from 5609.925 to 3155.971. The house-level variance, however, is hardly changed (i.e. from 7304.356 to 7304.395).

Model 3

After completing and interpreting model 1 and model 2, the variable of interest is added to model 3. This model is used to test the hypothesis that less safe neighborhoods/more neighborhood crime leads to a statistically significant lower housing value. As it can be seen in table 1, after adding *SafetyIndex* to the model, the coefficients of level-1 variables are hardly changed and they are still significant at the 1% level. However, the coefficients of level-2 variables have noticeably changed. The coefficients of *DistTrainStat* and *DistHighway* have increased from -15.591 and 22.407 to -16.271 and 26.615, respectively. The coefficients of *North*, *DistFamDoc*, *DistCafe* and *DistSchool* are dropped respectively to 53.868, -45.097, 59.815 and 58.183. All of these coefficients are still significant at the 1%, 5% and 10% level. These coefficients will not be interpreted again, as their sign did not change. The difference in the coefficients of level-2 variables in two models might be the effect of imperfect multicollinearity. A Pearson's correlation technique is used in order to evaluate the strength of the relationship between the control variables (level-2 variables) and the variable of interest. By analyzing the correlation values (see table 2) and following the suggestions of Evans (1996) for the absolute value of *r*, different conclusion can be drawn. It appears from the correlation test that there is one very weak positive correlation, one weak positive relationship, one moderate negative relationship and three moderate positive relationships between the SafetyIndex and the level-2 variables. In other words, model 2 suffers from the omitted variable bias, as the coefficients of the control variables have changed, which is caused by the variable of interest.

Table 2. Pearson's correlation

	SafetyIndex	North	DistFamDoc	DistTrainStat	DistHighway	DistCafe	DistSchool
SafetyIndex	**1.0000**						
North	**0.3822***	1.000					
DistFamDoc	**0.4296***	0.0210*	1.0000				
DistTrainStat	**0.0541***	-0.3315*	0.3743*	1.0000			
DistHighway	**-0.4103***	-0.5019*	-0.0837*	0.2355*	1.0000		
DistCafe	**0.5814***	0.0362*	0.7247*	0.3362*	-0.2138*	1.0000	
DistSchool	**0.5155***	0.1006*	0.5153*	0.0993*	-0.1849*	0.4313*	1.0000
*Significance at 1%							

- The coefficient of **SafetyIndex** is positive (9.926) and significant at the 5% level. If the SafetyIndex increases with 1 point, then the value of a house increases, on average, with €9.926, ceteris paribus. This means also that if the SafetyIndex decreases with 1 point, then the value of a house decreases, on average, with €9.926, ceteris paribus. This finding is in line with the expectations formulated beforehand.

The first focus of this study was to reinvestigate and to confirm the findings of previous studies that crime leads to lower housing values. The outcome of model 3 does not reject the first hypothesis. In this manner, this study has confirmed previous empirical findings. Neighborhood crime (lower safety in neighborhoods) has indeed a statistically significant negative effect on housing values. Again, the neighborhood-level variance has dropped massively from 3155.971 to 2978.371. The house-level variance in model 3 did not change compared with the house-level variance in model 2. According to the outcome of the likelihood-ratio test, it appeared that model 2 and model 3 are significantly different and that the model fit has significantly improved.

Model 4

Given that the second focus of this study is to contribute to the existing literature by testing whether crime affect the value of different types of houses differently, model 4 and 5 are estimated. To remember, the second hypothesis assumes that neighborhood crime has a larger negative effect on the value of bigger houses than on the value of smaller houses.

After adding the interaction variable ***safetyXrooms*** to the model, the coefficients of both level-1 and level-2 variables have dropped or increased in comparison to model 3 (see table 1). These changes mean that model 3 suffered from the omitted variable bias, which is now accounted for in model 4. The coefficient of *SafetyIndex* became insignificant at the 10% level, while all other coefficients remained significant at the 1%, 5% and 10% level. Actually, it is not meaningful to say that the effect of *SafetyIndex* became insignificant, as this coefficient cannot be compared with the coefficient from model 3. The constant term (53.131) remained insignificant at the 10% level. The sign of *RoomsCenter* has changed in negative (-47.456), while the sign of other variables (on both levels) remained the same. The coefficient of *RoomsCenter* is significant at the 1% level. The interaction variable *safetyXrooms* drastically changes the interpretation of the coefficients of *RoomsCenter* and *SafetyIndex*. Without an interaction variable, the coefficients of *SafetyIndex* and *RoomsCenter* were interpreted as unique effects on the housing value. In order to facilitate the interpretation of the interaction between those two continuous variables, the following equation is formulated:

$$TaxValue_{ij} = \beta_{0j} + \beta_1 * RoomsCenter_{ij} + \beta_2 * SafetyIndex_{ij} + \beta_3 * safetyXrooms_{ij} + \varepsilon_{ij}$$

The interaction variable *safetyXrooms* allows this study to calculate safety effect for different number of rooms, and room effect for different numbers of safetyindex. The coefficient of *safetyXrooms* is positive (10.924) and significant at the 1% level. A positive coefficient implies that more safety leads to higher housing values if houses also have more rooms. Using the equation below (i.e. taking the partial derivative regarding the variable *SafetyIndex*), the interpretation of *safetyXrooms* will be done.

$$\partial \text{TaxValue}/\partial \text{SafetyIndex} = \beta_2 + \beta_3 * \text{safetyXrooms}$$

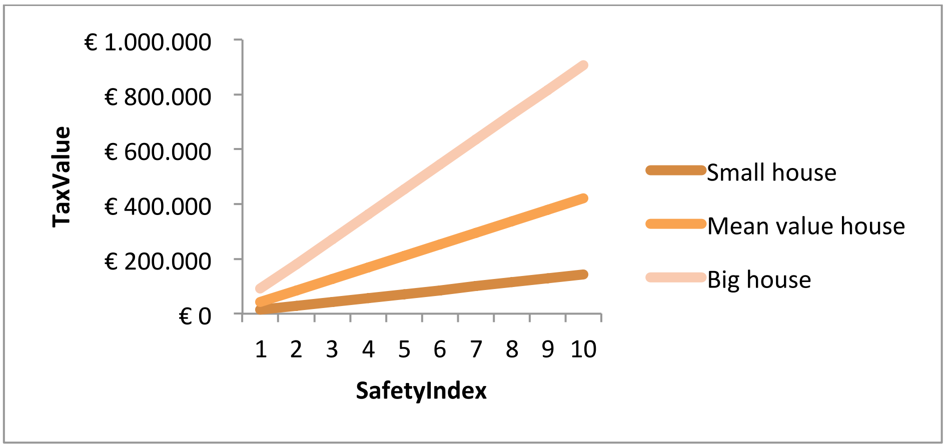
Change in the housing value for **1 point** change in SafetyIndex:

- If RoomsCenter=1 → ∂TaxValue = β_2 * (1) + β_3 * (1)
  = 3.390 + (10.924 * 1) = €14.314
- If RoomsCenter=3.544012 → ∂TaxValue = β_2 * (1) + β_3 * (3.544012)
  = 3.390 + (10.924 * 3,544012) = €41.105
- If RoomsCenter=8 → ∂TaxValue = β_2 * (1) + β_3 * (8)
  = 3.390 + (10.924 * 8) = €90.782

Based on the calculation above, different conclusions can be drawn. The first step was to use the values 1, 3.544012 and 8 for the RoomsCenter, which range from small to big houses, respectively. The second step was to calculate to what extent the housing values changes when the SafetyIndex changes with 1 point if the RoomsCenter is 1, 3.544012 and 8. The idea behind this is to see what happens with the housing value when a neighborhood becomes safer at different numbers of rooms (i.e. min, mean value, max). In the first calculation, the housing value changes with €14.314 when the SafetyIndex changes with 1 point and the variable RoomsCenter is 1, ceteris paribus. In the second calculation, the housing value changes with €41.105 when the SafetyIndex changes with 1 point and the variable RoomsCenter is 3.544012, ceteris paribus. In the third calculation, the housing value changes with €90.782 when the SafetyIndex changes with 1 point and the variable RoomsCenter is 8, ceteris paribus.

By comparing the outcomes of the calculations, it becomes clear that when the SafetyIndex of a neighborhood increases with 1 point (hence less crime), the value of big houses increases with €90.782, while the value of small houses increases with €14.314. Another interpretation is that when the SafetyIndex of a neighborhood decreases with 1 point (hence more crime), the value of big houses decreases with €90.782, while the value of small houses decreases with €14.131. So, this model provides support for accepting the second hypothesis. Neighborhood crime has indeed a larger negative effect on the value of bigger houses than on the value of smaller houses. An interaction plot is created and is exhibited in figure 3 to show this effect. According to the outcome of the likelihood-ratio test, it appeared that model 3 and model 4 are significantly different and that the model fit has significantly improved.

Figure 3. Interaction between crime and house sizes.



Model 5

In order to answer the third hypothesis, the results of model 5 will be discussed. This hypothesis is also meant for the second focus of this study. To remember, the third hypothesis assumes that neighborhood crime has a larger negative effect on the value of owner-occupied houses than the value of rental houses. After adding the interaction variable ***safetyXprivown***, the coefficients of both level-1 and level-2 variables have dropped or increased in comparison to model 3 (see table 1). These changes mean that model 3 suffered from the omitted variable bias, which is now accounted for in model 4. The coefficient of *SafetyIndex* became insignificant at the 10% level, while all other coefficients remained significant at the 1%, 5% and 10% level. Actually, it is not meaningful to say that the effect of *SafetyIndex* became insignificant, as this coefficient cannot be compared with the coefficient from model 3. The constant term (39.723) remained insignificant at the 10% level. The sign of *PrivOwn* has changed in negative (-69.131), while the sign of other variables (on both levels) remained the same. The coefficient of *PrivOwn* is significant at the 1% level. The interaction variable *safetyXprivown* drastically changes the interpretation of the coefficients of *PrivOwn* and *SafetyIndex*. Without an interaction variable, the coefficients of *SafetyIndex* and *PrivOwn* were interpreted as unique effects on the housing value. In order to facilitate the interpretation of the interaction between those dummy and continuous variables, the following equation is formulated:

$$TaxValue_{ij} = \beta_{0j} + \beta_1 * PrivOwn_{ij} + \beta_2 * SafetyIndex_{ij} + \beta_3 * safetyXprivown_{ij} + \varepsilon_{ij}$$

Estimating a potential difference in the effect of *SafetyIndex* between rental and owner-occupied houses requires taking the partial derivative with respect to the variable *SafetyIndex*. The interaction variable *safetyXprivown* allows this study to calculate safety effect for owner-occupied houses. The coefficient of *safetyXrooms* is positive (13.429) and is significant at the 1% level.

$$\partial \text{TaxValue}/\partial \text{SafetyIndex} = \beta_2 + \beta_3 * \text{safetyXprivown}$$

This equation implies that the difference in the value between an owner-occupied house and a rental house will be increasing as the SafetyIndex for owner-occupied houses is increasing. When a house is privately owned (i.e. PrivOwn=1) and the SafetyIndex changes with 1 point, the calculation is as follows:

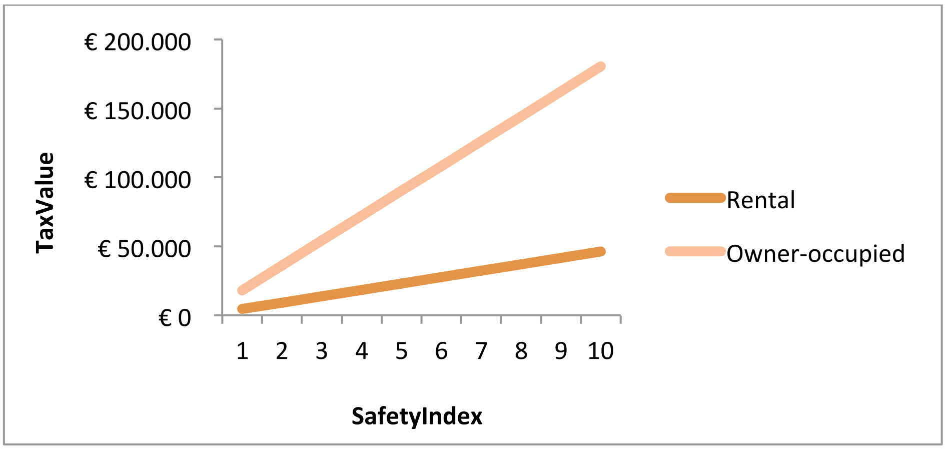
$$\partial \text{TaxValue} = 4.626 + (13.429 * 1) = €18.047$$

When a house is rental (i.e. PrivOwn=0) and the SafetyIndex changes with 1, the calculation is as follows:

$$\partial \text{TaxValue} = 4.626 + (13.429 * 0) = €4.626$$

The interpretation is that when the SafetyIndex of a neighborhood decreases with 1 point (hence more crime), the value of owner-occupied houses decreases with €18.047, while the value of rental houses decreases with €4.626. So, based on the calculations, it can be concluded that SafetyIndex has not the same effect on the value of owner-occupied houses and rental houses. This provides support for the third hypothesis. Neighborhood crime has a larger negative effect on the value of owner-occupied houses than on the value of rental houses. An interaction plot is created and is exhibited in figure 4 to show this effect. Lastly, the outcome of the likelihood-ratio test indicates that model 3 and model 5 are significantly different and that the model fit has significantly improved.

Figure 4. Interaction between crime and ownership.



6. Conclusion

In this concluding section, the sub-questions and the research question are answered. The main objective of this research was to investigate the effect of crime on housing values in Rotterdam and to see how this effect varies for different types of houses in different neighborhoods. After having created a model with all relevant house characteristics and neighborhood (dis)amenities, the variable of interest (the *SafetyIndex*) was added to the model. The results of the statistical tests have succeeded in accepting the first hypothesis that more neighborhood crime has a statistically significant negative effect on housing values. The answer of the first sub-question is that 1 point lower SafetyIndex results in a housing value that is €9.926 lower, ceteris paribus. So, the safer the neighborhood, the higher the housing value in that neighborhood. In this dataset, neighborhood with the lowest SafetyIndex is 4.5 and neighborhood with the highest SafetyIndex is 10. By multiplying 9.926 with 5.5 (=10-4.5), it can be argued that moving a house from the least to the most safe neighborhood of Rotterdam will increase the value of this house with €54.593, which increases considerably. Furthermore, all control variables were significant and all coefficients had the expected sign, except *DistSchool*. So, the findings outlined from previous studies are fairly supported by this study. In this manner, this study strengthens the existing literature.

In order to answer the second sub-question, two different housing submarkets were considered. It was expected that lower neighborhood safety not only has a larger negative effect on the value of big houses than on the value of small houses, but also on the value owner-occupied houses than on the value of rental houses. The statistical test found also support for these hypotheses. The first answer on the second sub-question is that if the SafetyIndex decreases with 1 point and a house contains 8 rooms (big house), then the value of this house will decrease with €90.782 (small houses with 14.314). The second answer on this sub-question is that if the SafetyIndex decreases with 1 point and a house is privately owned, then the value of this house decreases with €18.047 (rental houses with €4.626). Such a decrease in housing values is quite substantial and confirms the expectations. With these statistically significant results, this study has not only re-investigated previous findings but also contributed to the existing literature.

7. Limitations

This study has, like many other studies, some limitations. The limitations of this study are related to future researches, as scientist may be provided with an opportunity to consider these limitations in their studies. However, these limitations are also related to previous studies. As mentioned earlier, the house-level variance in model 1 was 7304.356. This variance has very slightly changed after having added level-2 variables, the variable of interest and the interaction variables to the model. This indicates that more house characteristics (level-1 variables) should be added to the model to explain why the housing values differ within certain neighborhoods. More specifically, some level-1 variables (i.e. physical house characteristics) in previous studies (e.g. Malpezzi (2003); Goodman & Thibodeau (1998)) had a statistically significant effect on housing prices, while in the present study there was no data available for these characteristics. Examples of these physical house characteristics are the number of bathrooms, garage, aircoditioning and garden. Accordingly, the *first limitation* is that the effect of some variables may be (to some extent) over- or underestimated since there is an omitted variable bias.

Despite the fact that different changes have been made in the dataset, it is difficult to control for all exceptions, as it contains a large number of observations. For example, there are still a lot of houses with a type that is unclassified. It is virtually impossible to specify whether each house of this type is a residential building or not. A possible consequence is that they do not represent the same housing markets. This in turn causes biased results and is therefore the *second limitation.*

In sub-section 2.3.2, it was stated that when people are confronted with crime news from other neighborhoods, they feel safer in their own neighborhood. This finding suggests that there are spatial effects. To be more specific, when a value observed in one neighborhood depends on the values observed in surrounding neighborhoods, one can speak about spatial dependence. However, the present study did not focus on these spatial effects. A possible consequence could be that the spatial effects may affect to some extent the findings of this study. In that case, this may cause the *third limitation*. Therefore, scientists can focus on the spatial effects in their future researches.

8. Bibliography

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9. Appendix

1. List of neighborhoods

District	District	District	District
Charlois	Delfshaven	Feijenoord	Hillegersberg-Schiebroek
Neighborhoods (South)	**Neighborhoods**	**Neighborhoods (South)**	**Neighborhoods**
Carnisse	Bospolder	Afrikaanderwijk	Hillegersberg-Noord
Heijplaat	Delfshaven	Bloemhof	Hillegersberg-Zuid
Oud-Charlois	Middelland	Feijenoord	Molenlaankwartier
Pendrecht	Nieuwe Westen	Hillesluis	Schiebroek
Tarwewijk	Oud-Mathenesse	Katendrecht	Terbregge
Wielewaal	Schiemond	Kop v. Zuid	
Zuidplein	Spangen	Kop v. Zuid-Entrepot	
Zuidwijk	Tussendijken	Noordereiland	
	Witte Dorp	Vreewijk	

District	District	District	District
IJsselmonde	Kralingen-Crooswijk	Noord	Overschie
Neighborhoods (South)	**Neighborhoods**	**Neighborhoods**	**Neighborhoods**
Beverwaard	De Esch	Agniesebuurt	Kleinpolder
Groot IJsselmonde	Kralingen-Oost	Bergpolder	Landzicht
Lombardijen	Kralingen-West	Blijdorp	Overschie
Oud IJsselmonde	Kralingse Bos	Liskwartier	Schieveen
	Nieuw Crooswijk	Oude Noorden	Zestienhoven
	Oud Crooswijk	Provenierswijk	
	Rubroek		
	Struisenburg		

District	District
Prins Alexander	Rotterdam Centrum
Neighborhoods	**Neighborhoods**
‘s-Gravenland	C.S. Kwartier
Het Lage Land	Cool
Kralingseveer	Dijkzigt
Nesselande	Nieuwe Werk
Ommoord	Oude Westen
Oosterflank	Stadsdriehoek
Prinsenland	
Zevenkamp	

2. Dropped neighborhoods

Neighborhoods	Reason
Noord Kethel	Different house types/buildings/unclassified
Charlois Zuidrand	No safety index
Zuiderpark	No safety index
Haven- en industriegebieden	Different house types/buildings/unclassified & No safety index
Blijdorpsepolder	No safety index & limited observations
Rozenburg	No safety index