The impact of crime on housing prices; a case study of the municipality of Groningen

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Abstract

This thesis provides causal estimates for the impact of crime on housing value for the municipality of Groningen using panel data for the period 2015 – 2017. Hedonic pricing is utilized through a multilinear regression model. The panel data analysed is sourced via governmental and municipal statistics including average neighbourhood housing prices, reported crime statistics, and additional neighbourhood attributes. Results indicate that there is a statistically significant negative relationship concerning reported neighbourhood crime in conjunction with the average housing price. Average housing value is estimated to drop 0.0115% per reported crime per 1000 inhabitants. Further results illustrate that crime is not indiscriminate, criminal activity can be classified into several categories, each with their own set of implications. Therefore, next to the total crime, the separate forms are tested for their specific impact on neighbourhood housing value. Associated regression results reveal vandalism and assault are estimated to have the biggest effect with a 0.0317% and 0.0816% decline in housing value respectively.

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1.0 Introduction

Criminal behaviour has a notable impact on communities and the space they inhabit. Hence, the impact of crime on communities has been studied extensively. Societies, cities, and individuals have to cope with the physical and psychological impact every day. Criminal behaviour has an inherently negative effect on the economy. This is illustrated by the fact that the prevalence of criminality in a neighbourhood has been observed to compromise housing prices (Gibbons, 2004; Ceccato & Wilhelmson, 2019; oryś & Putek-Szelag, 2017; Ihlanfeldt & Maycock, 2010). Individuals want to live in a safe environment when circumstances impede on this safety, their valuation of the location will be affected. Consequently, prospective home-buyers prioritize safe neighbourhoods, which inevitably impacts the valuation of certain areas. In the age of connectivity, criminal activity is highlighted more than ever. Through the use of social media the dissemination of information regarding the prevalence of crime is accelerated (Intravia et al., 2017). Nevertheless, this image presented by social media diverges from reality in the case of the Netherlands, seeing as the actual crime rates have shown an overall decrease since 2005 (CBS, 2018).

The devaluation of housing prices due to crime has been observed throughout the world. An estimated 75% of the research conducted on the topic points toward a significant relationship between crime and housing value (Olijade & Lizam 2017). Exploring the existence and the magnitude of the effect will indicate the economic value lost due to criminal activity. Global real estate provides a veritable source of investment. This process is, however, heavily influenced by risks. Subsequently, lower risk through security produces a safe climate that attracts and enhances investment (Olajide et al., 2013). Beck & Goldstein (2018) conclude that places that are reliant on housing price growth and mortgage investment as a result exhibit greater local law enforcement through an increase in spending. Groningen, an expanding student city, itself subject to a housing shortage and accompanying speculation, could be subject to these same mechanisms.

1.1 Research problem

Even though the relation between crime and property valuation has been studied extensively in many international contexts there is still a gap in the literature regarding the crime to housing price relation in the Dutch urban landscape. This research aims to add to the academic debate through deductively using the existing theories and inductively analysing observations in the context of the Northern-Dutch city of Groningen. To achieve a more comprehensive understanding of whether actual crime rates impact the valuation of properties on a neighbourhood level, Finding out which concrete effects different forms of crime exhibit is done through applying separate regression models for different types of delinquencies. While the effects of total crime on housing value have been studied to a great extent, distinguishing between different forms of crime has gotten scarcer academic attention. Providing answers to these questions will illuminate the position of the Netherlands in the greater scientific debate regarding the effects of crime on housing value.

The results of this research regarding the causal effect of crime on property values can serve as valuable assets to governmental agencies, businesses, NGO's and individuals to decide on prevention and the undermining of crime. Besides this, the value of education and rehabilitation incentives can be partly demonstrated through this ‘’hidden’’ cost of crime. Moreover, the diminishing of real estate prices induced by crime results in a decline in property tax revenue for the municipality. The crime levels in Groningen are declining (CBS, 2018). Still, The municipality of Groningen is the least safe municipality of the northern Netherlands (Dagblad van het Noorden, 2019).

Via a hedonic pricing model, which controls for additional neighbourhood attributes that influence housing value, the specific effect of crime can be determined and quantified.

The following research question will precede this endeavour:

- *To what extent does crime impact neighbourhood housing prices in the municipality of Groningen?*

In order to discover the effect of different types of delinquency on property value the subsequent secondary research question is devised:

- *To what extent do separate forms of criminal activity impact the neighbourhood housing prices in the municipality of Groningen?*

In the subsequent section, preceding research and theory regarding the topic will be set out. After that, the methods used to construct an answer to this question are explained. The next section will display and discuss the findings. Lastly, the discussion and conclusion will strive to provide an elaborate and balanced answer to the research problem.

2.0 Theoretical framework

Every individual wants to feel safe in their place of dwelling. Safety is a basic need that has to be met in order to achieve wellbeing (Maslow, 1943). Criminality undermines the impression of safety for homeowners, tenants, and the communities they live in. To attract potential prospective home-buyers, neighbourhood amenity provision is important, especially in the Dutch context of a highly urbanized landscape (Garretsen & Marlet, 2017). Pope & Pope (2012) identify criminal activity to be a dis-amenity, an antonym, indicating its repelling nature. Therefore, crime can be at the root of a lower housing demand, resulting in a dwindling of the local property prices. Concluding an extensive literature review on the topic, Olajide & Lizam (2017) state that residents experience a negative economic impact due to crime hampering local housing value thereby impeding on the important role the property market plays as a generator of wealth. On The contrary, Some international studies describe a positive correlation between housing value and crime. Song et al. (2019) use panel models to conclude that even though housing prices are rising, crime is rising as well. Nevertheless, China, which was the focus of the said study is subject to special conditions unseen in the rest of the world.

Some particular places, however, are impacted more than others. The law of concentration of crime at place constitutes that crime tends to concentrate in specific spatial areas within a broader region (Weisburd & Anram, 2014). Moreover, crime, and the degeneration of neighbourhoods, has the tendency to further induce crime, this phenomenon is often referred to as the “broken windows” theory (Wilson & Kelling, 1982). Consequently, crime could impact the valuation of property exponentially. The impact of such crime hotspots is regarded by the literature as a particularly negative influence on housing value (Ceccato & Wilhelmsson, 2019).

Furthermore, Wong et al. (2019) conducted a hedonic pricing study in Malaysia’s districts and conclude that crime has a negative impact on housing value, additionally, they find evidence that a higher crime occurrence causes inhabitants to be more willing to pay for crime reduction. This corroborates with the findings of Beck & Goldstein (2018) who use a similar method comprising 171 cities in the United States concluding that places relying on housing price appreciation will spend more on local law enforcement.

Additionally, crime is not indiscriminate, several forms of crime can have distinct impacts on the dependent variable. Gibbons (2004) tests the impact of various types of crime on housing values in London in his paper which describes the cost of urban property crime. His analysis finds evidence that vandalism exhibits a significant impact while burglary does not.

The psychological impact of the perceived neighbourhood deterioration due to vandalization is considered to be at the roots of this relationship. Vandalization can induce a perception of unsafety in a neighbourhood. Where vandalism in the form of for instance demolished public infrastructure tends to be long-lasting and in the public domain, burglary Is often an isolated case intended to be furtive without the broader public noticing it. This corroborates with, the broken windows theory suggesting that vandalization leads to the physical deterioration of a place and the attraction of more criminal activity (Wilson & Kelling, 1982). The findings of Buonanno et al. (2013) who conducted a hedonic pricing study for the years 2004 through 2006 using a victimization survey in the city of Barcelona support this theory. They found that neighbourhoods that are perceived to be unsafe have highly discounted housing values reaching a loss of 1,27%. Ceccato & Wilhelmson (2012) describe a similar result in their hedonic analysis of the interplay between vandalism and fear influencing housing value in Stockholm. Using a different method, Doran & Burgess (2011) mapped the spatial distribution of safety perception in Wollongong, Australia, using Geographical information systems (GIS). Social disorder analysis showed that vandalization in the form of graffiti and overall litter in the streets contributed to these feelings of unsafety. Often, these crimes were located economically underprivileged neighbourhoods.

Besides vandalism, violent crimes are also observed to have considerable detrimental effects on neighbourhood housing prices. This is demonstrated by another study that looks into the separate impact of different types of crime conducted by Ihlanfeldt & Maycock (2010). In their paper, they estimate the effect of different types of crime using panel data for Miami-Dade County, Florida. The impact of violent crimes like aggravated assault and robbery is shown to have a significant effect on property prices while crimes like burglary are relatively unimportant. Pope & Pope (2012) obtain similar results analysing the effect of nation-wide crime in the United States during the crime drop of 1990. Where property theft is shown to have a significant negative effect on property value, violent crimes prove to be more detrimental with a nearly double effect of a 0.55% decrease in housing value per crime per 1000 inhabitants. Following these findings, Kim & Lee (2018) describe the significant negative impact of sex offences on nation-wide property prices in the neighbourhoods of South Korea. The same result was published by Pope (2008) in an identical study of Hillsborough County, Florida. Results indicate a decline in housing value of 2.3% whenever a sex offender moves into a neighbourhood. In light of this, the distinction between forms of crime is proven to be an important measure to infer the real source of an eventual decline in property value.

Neighbourhood housing prices are not solely determined by delinquency. Numerous attributes contribute to the property valuation in a residential location. Academics have attempted to detect these factors. Firstly, demographic characteristics are important since these can influence the property value. For instance, average age and income form important controls influencing property prices (Goodman, 1988). Immigration can also boost housing prices through an increase in demand (González & Ortega, 2009). Secondly, neighbourhood housing characteristics are important price-determining attributes. In their case study of Utrecht Permentier et al. (2011) identify the housing characteristics to be of key importance to neighbourhood satisfaction. Thirdly, physical attributes of the neighbourhood like surface area and the presence of water are shown to impact a neighbourhoods valuation. For instance, Chen et al. (2020) indicate that prospective home-buyers are willing to pay a premium for the presence of surface water. Lastly, the proximity of amenities is essential, as having a variety of urban amenities is found to be important in the Dutch highly urbanized landscape (Garretsen & Marlet, 2017). Schools, supermarkets, transportation, and health care are important attributes that determine property value.

2.1 Hypotheses

Based on previous research results and the theories discussed the following hypotheses are tested in this thesis:

H1. *In the municipality of Groningen, neighbourhood crime reports exhibit a negative relationship in conjunction with neighbourhood housing prices.*

H2. *In the municipality of Groningen, vandalism and violent crimes have a more profound impact on neighbourhood housing prices than property theft.*

Linking the research aim with the described literature provides a clear basis for research. Combined, this theoretical basis is visually represented in Figure 1. The conceptual model shows the relationships between the various concepts and factors that are under examination. Neighbourhood crime is made up of the prevalence of crime in absolute numbers and the sum of the types of crime conducted. The neighbourhood crime prevalence will also indicate the presence of a crime hotspot. Total neighbourhood crime is represented as a key independent variable which will partly explain the dependent variable housing prices. The crime categories as described by the literature can each influence the housing value inversely, therefore they are represented as independent variables individually influencing neighbourhood housing value as well as combined via total neighbourhood crime. Other independent variables that can impact housing prices are indicated as neighbourhood characteristics. These covariates are based upon previous literature reviewed. Lastly, since evidence suggests that neighbourhood characteristics could accelerate neighbourhood crime prevalence this is represented in the model as well. With all the factors in place, the model can be tested using regression analysis.

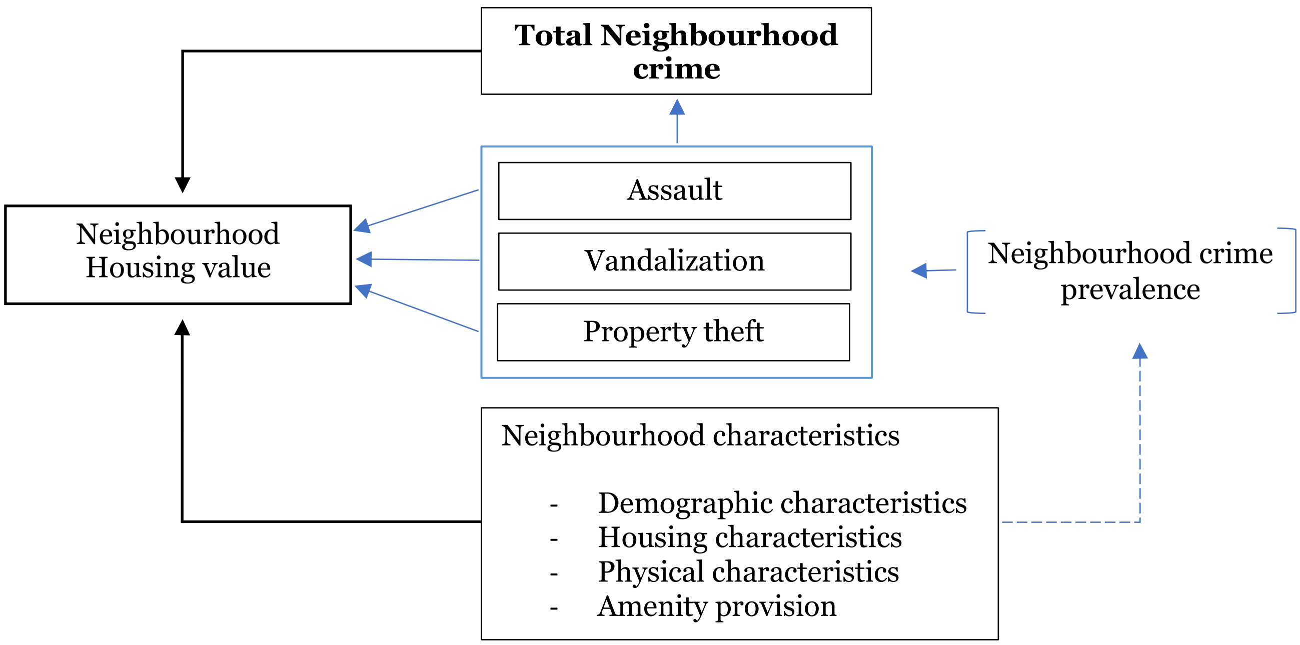

Figure 1- Conceptual model

3.0 Methodology

To explore the eventual relationship between crime and housing prices the method of hedonic pricing models will be applied employing multilinear regression. As a proxy for neighbourhood crime, statistics on reported crime per neighbourhood are used provided by the municipality of Groningen (OIS, 2020). It is known that reported crime can diverge from actual crime statistics since not every violation committed gets reported. Besides this, some reports might not be due to an actual crime. Nevertheless, since the actual crimes committed are not available, reported crime will form the best proxy. There are several types of crime on which statistics are published that is: Burglary, car theft, bike theft, theft from a business, theft from a car, vandalism, and assault. The first five are theft-related crimes, Therefore in the context of this study, these statistics are combined into the property theft category and will be referred to as such. Moreover, the sum of all these eight aforementioned categories will be used as the total crime metric. Hence, four different models are created to discover their independent impact on neighbourhood housing value.

Average neighbourhood housing prices will form the dependent variable. These statistics are published by the municipality of Groningen (IOS, 2020). It has to be noted that this metric is also proxy-based sourced from the Wet waardering onroerende zaken (WOZ) value. This is a valuation of real estate property conducted by the municipality based upon recent local property sales. The average of all the WOZ values in a neighbourhood will be utilized as the dependent variable in this study. Since the absolute average housing value will render results that are impractical to interpret the logarithm of housing value will be employed. This transformation will create results that can be interpreted in percentages which facilitates equal comparison.

To control for other price-determining factors, several independent variables will be added to make the model to limit omitted variable bias. In accordance with previous literature discussed, neighbourhood demographics, housing characteristics, physical neighbourhood characteristics, and neighbourhood amenity provision will form the control variables. To facilitate an equal comparison between the neighbourhoods all the variables should be comparable no matter the size or population of the area. Absolute numbers are therefore recalculated into statistics per 1000 inhabitants to relativize them. Categorizing the control variables will allow the illustration of the effect of each cluster of neighbourhood attributes on the model. In addition to these control variables, fixed effects of each neighbourhood are accounted for as well. This is done due to the eventual time-fixed unmeasured characteristics of the neighbourhood present in the data. Using fixed-effects creates a dummy variable for each of the neighbourhoods cleaning up the estimates in the output.

Hedonic pricing as a research method has been used widely in multiple disciplines first being employed by Waugh (1929) to study the factors influencing vegetable prices in Boston. The earliest appliance of the method to explore the impact of crime on a community was conducted by Thaler (1978), who looked into the effect and the willingness to provide crime control in Rochester New York. Goods that are consumed are often not homogeneous and valued through their different attributes. The valuation of these attributes can be revealed via price differences (Rosen, 1974). In the case of real estate, housing preferences can be uncovered through the price one pays for these attributes (Ceccato & Wilhelmsson, 2012). Therefore, hedonic pricing would be the logical way of modelling the impact of crime on housing value. The multilinear regression method facilitates the quantitative identification of the estimated impact of crime in its different forms. Pope & Pope (2012) describe economic actors making various trade-offs between the characteristics of a place, its amenities, and dis-amenities, such as crime.

This can be expressed as:

$$y = \beta x + \varepsilon$$

Where y represents a vector of the observed housing values, x is a matrix containing the attributes of a place, β stands for the vector of regression coefficients which indicate the estimated price of each attribute and ε is the vector of the random error term.

The data analysis is enabled by SPSS (IBM SPSS Statistics 25.0). The software enables the testing of the various models needed. To generate the effect of crime in total and the different types of crime, four separate regression models are conducted which are illustrated in Table 1. Determining the overall impact of crime on housing prices will be done through employing the sum of all the crime categories rendering total crime as the key independent variable for model one. Likewise, to reveal the effects of different types of crimes models two, three, and four will provide an estimation of the impact of property theft, vandalization, and violent crimes respectively. The null-hypothesis for the regression models is formulated as follows*: in the population, there Is no linear relation between the key independent variable and housing prices.*

Table 1 – regression models

Model	Key independent variable
1	Total reported crime
2	Reported property theft
3	Reported vandalization
4	Reported violent crimes

The following regression formulae will facilitate the testing;

$$price_i = \beta_1 + \beta_2 crime_i + \cdots + \sum_{\theta} a_\theta \, Neighbourhood_{\theta,i} + \varepsilon_i$$

Logarithm variant;

$$\log(price_i) = \beta_1 + \beta_2 crime_i + \cdots + \sum_{\theta} a_\theta \, Neighbourhood_{\theta,i} + \varepsilon_i$$

Where price_i is the dependent variable consisting of neighbourhood housing value, β_1 stands for the coefficient of the intercept, $\beta_2 crime_i$ stands for the key independent variable, in this case being the number of reported crimes per 1000 inhabitants with β_2 exemplifying its regression coefficient. The dots added (...) are representing the other independent control variables added into the model that are added in identical fashion. $\sum_\theta a_\theta \, Neighbourhood_{\theta,i}$ represents the dummy variables for the neighbourhoods fixed effects where alpha stands for the coefficient, $Neighbourhood_{\theta,i}$ is equal to 1 if the observation describes neighbourhood θ with θ representing any of the 70 neighbourhoods transformed into dummies. ε_i signifies the residual term.

In the logarithm variant, the percentage influence of an attribute on neighbourhood housing price coefficients equals $\beta \times 100$.

3.1 Data characteristics & ethical considerations

Secondary data will be utilized for the data analysis. This data is provided by the Centraal bureau voor de statistiek (CBS), the official statistical agency of the Netherlands, as well as by the Onderzoek informatie en Statistiek Groningen (OIS), the official statistical agency of the municipality of Groningen. The datasets utilized in this research contain numerous statistics on neighbourhoods all over the Netherlands. Using these sources an extensive dataset is formed with data describing different neighbourhood attributes that could influence the average property value. Appendix A contains a table with all the variables used and their respective sources.

The data employed is obtained in a qualified way by the CBS (2017) and the OIS (2020). The statistics are sourced from open data which is public and accessible for everyone. The objective of these datasets is to facilitate the comparison between regions. Analysing this data will, therefore, bring limited ethical problems. To briefly reflect on the positionality of this research as author. I live in one of the neighbourhoods that are included in this research. However, since I do not own any property myself this renders me an outsider in most respects. No ethical issues surfaced during the research. Through thoughtfully using public data this research aspires to be as objective and precise as possible within is. limitations. The privacy of participants is respected since averages are employed which will result in no individuals being referenced.

Several neighbourhoods of Groningen are subtracted from the sample. This is mainly done to exclude non-residential areas for instance business parks and green spaces. After their deletion, only neighbourhoods with a residential function are left. Moreover, some neighbourhood data was incomplete leading to the removal of these areas from the sample as well. These were often small neighbourhoods comprising of a single street. With this in mind, the distribution of the neighbourhoods utilized can be seen in Figure 2 where the blank areas indicate the excluded neighbourhoods and the blue ones the incorporated spatial units. The data trimming produced a final sample of 70 neighbourhoods which can be seen listwise in appendix B.

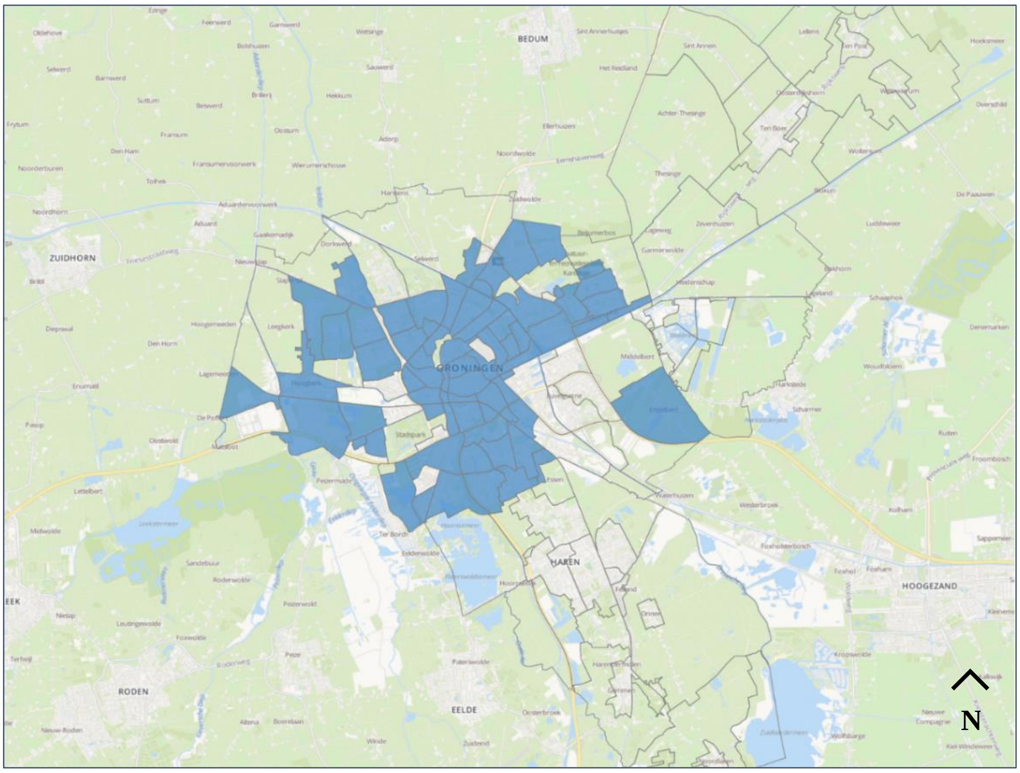

Figure 2 – map illustrating the spatial distribution of sample (OIS, 2020)

The sample is increased by adding several years to the analysis. Data gaps and municipal restructuration Has limited the scope of the research to only including the years 2015, 2016, and 2017 in the panel. These years are used to test both the impact of total crime on property prices and the impact of different types of crimes resulting in a total sample of 210. The 70 neighbourhoods utilized have a total population of approximately 200.000 inhabitants, all 3 years combined this exact number totals 595.455 inhabitants. To minimize the problems of multicollinearity and omitted variable bias, careful examination of the data has been conducted. The variables utilized in the regression, the categories they are divided up in, and their descriptive statistics can be seen in Table 2. Through the division of covariates in categories, the data can be analysed adding one group of control variables at a time. This is done to reveal their independent impact on the models.

Table 2 – Descriptive statistics

	Metric	N	Minimum	Maximum	Mean	Std. Deviation
Dependent variable						
Log Housing value	Log(€) × 1000	209	4,69	6,24	5,15	,36
Neighbourhood demographics						
Men	Per 1000 inhabitants	209	459,20	792,20	505,47	40,35
Women	Per 1000 inhabitants	209	207,79	540,79	493,75	40,30
Age 0 – 15	Per 1000 inhabitants	209	0	328,26	131,63	69,60
Age 15 – 25	Per 1000 inhabitants	209	49,18	545,45	206,65	126,03
age 25 – 45	Per 1000 inhabitants	209	90,91	454,55	290,05	84,85
Age 45 – 65	Per 1000 inhabitants	209	86,57	456,52	243,49	87,70
Age 65+	Per 1000 inhabitants	209	20,83	400	124,42	75,83
Western migrants	Per 1000 inhabitants	209	21,74	428,57	111,26	48,60
Non – western migrants	Per 1000 inhabitants	209	0	257,16	94,53	58,21
Population density	Residents per km^2	209	305,62	17349,33	3454,71	3601,17
amount of income receivers	Per 1000 inhabitants	209	256,41	1000	785,62	96,65
Average income	€×1000	209	15,20	63,90	30,11	9,97
Housing characteristics						
Uninhabited	%	209	0	19	3,95	3,14
After 2000	%	209	0	100	20,17	29,84
Physical neighbourhood characteristics						
Surface land	m^2	209	6,0	336,0	58,72	51,19
Surface water	m^2	209	,0	78,0	3,79	7,57
Neighbourhood amenity provision						
Distance hospital	Meter	208	,50	6,90	2,77	1,56
Distance general practitioner	Meter	208	,20	4,20	,94	,68
Distance ramp	Meter	208	,30	2,80	1,13	,54
Distance train	Meter	208	,20	5,90	2,62	1,60
Distance day-care	Meter	208	,20	1,90	,53	,30
Distance supermarket	Meter	208	,20	4,10	,79	,65
Distance primary school	Meter	207	,00	2,20	,81	,48
Distance secondary school	Meter	209	,30	5,50	1,36	,97
Reported crime and crime perception (key independent variables)						
Property theft total	Reported	209	0	359,26	29,32	46,46
Vandalization	Reported	209	0	176,92	10,40	20,98
Assault	Reported	209	0	66,67	4,76	8,87
Total crime	Reported	209	0	553,70	44,48	72,24

Note. numbers are rounded to 2 decimals

4.0 Results

Operating the regression analysis yields several interesting insights. The results are subsequently illustrated using four identical tables displaying the results for each of the four variables of interest. Four hedonic price equations are ran using the logarithm of average neighbourhood housing price is used as dependent variable. The tables show the regression results focusing on one key independent variable at a time. The impact of the covariate categories can be observed via six sub-models each adding a new category to the regression indicated by an X in the columns below. These separate covariates are presented in Table 2. Additionally, the sample size (N) and the adjusted R squared for each model are signified in the bottom rows.

The adjusted R squared indicates the explanatory power of the model. As can be seen in Tables 1, 2 3 & 4. Around 99,6% of the variation can be explained through the model. This is exceptionally high. The source of this high R squared is revealed to be the fixed effects which independently caused the R squared to be around 99.2%. Due to the large quantity of dummies, this is only to be expected.

In Table 3, the first regression model is displayed with the sum of the reported crime being the proxy for total neighbourhood crime.

Table 3 – Regression results total crime

	Regression coefficient					
Model	1**	2***	3***	4***	5***	6***
Total crime[1]	,000746**	-,000107**	-,000111***	-,000122***	-,000125***	-,000115***
Fixed effects		X	X	X	X	X
Demographic characteristics			X	X	X	X
Housing characteristics				X	X	X
Physical characteristics					X	X
Amenity provision						X
N	209	209	209	209	209	206
Adjusted R Squared[1]	,018	,992	,995	,995	,995	,996

Note. Significance level: *P <0.10 **P <0.5 ***P <0.01

[1] Dependent variable: Logarithm of neighbourhood housing value

All of the regression sub-models represented in Table 3 are shown to be significant. Hence we can reject the null hypothesis of no relation and conclude that in the years 2015 until 2018 there was a significant effect of criminal activity on housing prices in the municipality of Groningen. Adding fixed neighbourhood effects changes the coefficient into a negative number, this is observed in every regression model. Subsequent control variables affect the coefficient in both ways. With the fixed effects and all the control variables added the logarithm of housing price coefficient associated this relation is minus 0,000115. This relationship exhibits a significance level of less than 1%, meaning that the coefficient estimate has a certainty of 99%. To transform the logarithm value into a percentage we have to multiply it by 100. Thus, we can assume with 99% confidence that every reported crime per 1000 inhabitants in the municipality of Groningen, no matter the type, is estimated to cause a decline in housing value equal to 0.0115%.

Having established this, we can assume the initial hypothesis to be defendable. Consequently, we can presuppose that crime does retain a negative relationship in conjunction with housing value in the municipality of Groningen.

Table 4 – Regression results property theft

	Regression coefficient					
Model	1*	2***	3***	4***	5***	6***
Total property theft[1]	,001197**	-,000210***	-,000189***	-,000208***	-,000209***	-,000188***
Fixed effects		X	X	X	X	X
Demographic characteristics			X	X	X	X
Housing characteristics				X	X	X
Physical characteristics					X	X
Amenity provision						X
N	209	209	209	209	209	206
Adjusted R Squared[1]	,019	,992	,995	,995	,995	,996

Note. Significance level: *P <0.10 **P <0.5 ***P <0.01
[1] Dependent variable: Logarithm of neighbourhood housing value

Table 4 reveals the estimated effect of reported property theft on housing value. In this context property theft is the sum of several crimes including burglary, car theft, bike theft, theft from a business, and theft from a car. The effect of property theft on housing value is observed to be more profound than the effect of the indiscriminate total. With the fixed effects and control variables added to the model, a logarithm housing price coefficient of -,000188 surfaces with a significance level of less than 5%. Consequently, transforming the results into a percentage shows a decline in neighbourhood housing value of 0,0188% per reported case of property theft. These results indicate the existence of a negative relationship between neighbourhood housing value and property theft which is stronger than the relationship of the total crime regardless of the nature.

Table 5 – Regression results vandalization

	Regression coefficient					
Model	1*	2***	3***	4***	5***	6***
Vandalization[1]	,00229*	-.000151	-,000263*	-,000281*	-,000298**	-,000317**
Fixed effects		X	X	X	X	X
Demographic characteristics			X	X	X	X
Housing characteristics				X	X	X
Physical characteristics					X	X
Amenity provision						X
N	209	209	209	209	209	206
Adjusted R Squared[1]	,013	.991	,995	,995	,995	,996

Note. Significance level: *P <0.10 **P <0.5 ***P <0.01
[1] Dependent variable: Logarithm of neighbourhood housing value

Expectedly the results with vandalization as the key independent variable, illustrated in Table 5, show a significant negative relation in conjunction with housing value as well. With the fixed effects and the control variables added the accompanying logarithm of housing price regression coefficient is -,000317 with a significance level of under the 5% threshold. Converting this into a percentage facilitates the following result: every reported vandalization in a neighbourhood has the estimated degenerating effect of 0,0317% on average neighbourhood housing prices. These results showcase the consequence of vandalization to be more severe than the effect of reported property theft or the combined reported crimes as was theorized in hypothesis 2.

Table 6 – Regression results assault

	Regression coefficient					
Model	1	2***	3***	4***	5***	6***
Assault[1]	,00383	-,00073*	-,000722**	-,000812**	-,000901**	-,000816**
Fixed effects		X	X	X	X	X
Demographic characteristics			X	X	X	X
Housing characteristics				X	X	X
Physical characteristics					X	X
Amenity provision						X
N	209	209	209	209	209	206
Adjusted R Squared[1]	,004	,992	,995	,995	,995	,996

Note. Significance level: *P <0.10 **P <0.5 ***P <0.01

[1] Dependent variable: Logarithm of neighbourhood housing value

To conclude the analysis, Table 6 exemplifies the effect of reported assault on neighbourhood housing value. Adding control variables has increasingly led to a higher significance level. With the fixed effects as well as the control variables included the model exhibits a significant relationship. Accompanying estimates show that a reported assault leads to the average neighbourhood housing value falling by a coefficient of -,000816. This estimate indicates a devaluation of 0,0816% per case of reported assault with a significance level of 95%. This negative relationship is the most prominent observed among the different crime categories.

The results portrayed in Tables 5 and 6 show that vandalism and violent crimes have the most detrimental effect on housing value. This upholds hypothesis 2 predicting that the impact of vandalism and violent crimes would be more profound than the effect of property theft.

5.0 Discussion

Given the results, it can be deduced that crime does have a negative relation in conjunction with neighbourhood housing prices in the municipality of Groningen. Therefore, the initial hypothesis can be validated. The coefficients produced by the total reported crime model indicate a decline in neighbourhood housing value of 0,0115% per reported crime per 1000 inhabitants. This result is similar to previous studies. Such as Ceccato & Wilhelmson (2011) estimating that 1 extra crime on 1000 inhabitants results in a 0.004% drop in housing value.

Property theft also exhibits a significant negative relationship with neighbourhood housing value. The coefficients presented by the total amount of crime and property theft models are comparable in magnitude, this can be explained due to the latter being the most extensive category making up total crime. Tita et al, (2006) explore the impact of crime on housing prices in Ohio using hedonic pricing and obtain similar results that indicate the effect of total crime and property crime to be nearly identical. The property theft analysis results corroborate with the findings of Pope & Pope (2012) who show that during a big crime drop in the 1990's united states a decline in theft significantly increased housing value. Ceccato & Wilhelmson (2011) achieve the same result conducting a hedonic pricing model in Stockholm, Sweden estimating that 1 extra property theft per 1000 inhabitants induces a drop in apartment prices of 0,0021% which is comparable to the 0,00188% found in Groningen. Nevertheless, this result is at odds with Gibbons (2004) who concludes that burglary does not significantly affect housing value.

The prevalence of vandalization over theft and total crime is in line with the results of similar international studies conducted for instance the cases of vandalism in London (Gibbons, 2004) and Stockholm (Ceccato & Wilhelmsson, 2012). The latter applies a similar hedonic pricing model obtaining a fall in apartment prices due to vandalism equalling 0.034%. This result supports the findings in Groningen which exhibits a similar estimate of housing price decline of 0.0317%. The visual degeneration of a neighbourhood can be detrimental to its future. Socialists have described this phenomenon through the broken window theory (Wilson & Kelling, 1982). They describe that evidence of decay, such as broken windows, trash, and graffiti coincides with increasing crime. Using visual element detectors, Arietta et al. (2014) were able to test this notion of visual elements inducing a neighbourhoods degeneration. They conclude that there is indeed a predictive relationship between visual elements and housing prices. This forms a credible explanation for the higher impact of vandalization relative to property theft since this form of criminal activity often leaves its marks on the neighbourhood. Where theft is often conducted swiftly and secretly without leaving a mark, vandalization has a long-lasting effect that is noticed by more individuals. Gibbons (2004) describes it as follows in his paper on the cost of urban property crime in London. It is hard to hide vandalism from prospective new residents of a neighbourhood. The information regarding different crimes is often not readily available to buyers, therefore, the neighbourhoods first impression is important in determining the value of a property. Vandalism can greatly influence this impression and contribute to the formation of a negative neighbourhood image. This would also explain the smaller effect observed for the impact of property theft as discussed above.

Violent crimes are shown to have the most prominent impact on property value with a decrease of 0,0816% per reported assault crime per 1000 inhabitants. This result corroborates earlier findings of Tita et al. (2006) who estimate the drop in housing value due to violent crime to be 0.05% Furthermore, Pope & Pope (2012) who use nationwide data from the United States during the crime drop of 1990 to indicate the value loss crime has on property. Showing a decrease in housing value of 0,55% per violent crime 1000 inhabitants. Ihlanfeldt & Maycock (2010) produced similar results performing a hedonic pricing model using panel data for Miami-Dade County in Florida with an estimated coefficient of -0.151%. Some coefficients might substantially differ from the results yielded in Groningen yet this can be ascribed to the different scope and situation of the study. The American suburban landscapes often studied differs significantly from the Dutch urban fabric used in this study. Nevertheless, previous studies describe a similar effect of property theft being less detrimental to housing value than violent crimes. A potential explanation of the differences between theft, vandalization, and assault can be the prevention measures that can be taken. Ihlanfeldt & Maycock (2010) suggest that since property crimes like theft can be countered by alarm systems and professional locks which mitigate their impact. The same applies to vandalization albeit to a lesser extent. To counter violent crimes, however, these concrete measures have less effect. Furthermore, Miller et al. (1995) state that since property theft and vandalism cause no physical harm to victims their impact is perceived differently. Violent crimes are paired with a different set of implications often being perceived as more severe. Lasting individual harm and more pronounced media coverage are more likely to occur, resulting in the deterioration of a neighbourhood's image.

5.1 Limitations

This thesis is not without limits and restrictions. The research presented tries to get a grasp of reality and bring forth a better understanding of the real estate market while fully acknowledging that procuring the full truth is improbable. The sample size utilized in the analysis is rather conservative, therefore the findings might not be as robust as other studies. Moreover, an always-present risk is the eventual existence of hidden variables not caught in the models. For example, the proximity to green spaces could not be obtained and thus is not included in the analysis. Additionally, notions like the tendency of criminals to target high-end households could significantly influence the statistics. These can impede on the reliability of the findings. Furthermore, errors in the data collection could be inherent to the dataset since the statistics are derived from secondary sources. Although these are highly credible institutions, data errors such as human error could occur. Lastly, the metric used as a key independent variable is reported crime. Tita et al. (2006) discuss the tendency that less severe crimes are underreported therefore the reported crime statistic could be biased. Using proxies might result in statistics diverging from the actual number.

6.0 Conclusion

A negative relationship between property value and crime has been observed internationally in numerous studies. This thesis adds the Netherlands to this list with a focus on the city of Groningen, thereby contributing to the ongoing debate surrounding the economic impact of crime on neighbourhoods. The estimated effect of total crime on housing value in the municipality of Groningen is a fall in neighbourhood housing prices of 0.0115% per reported crime per 1000 inhabitants. Consequently, this answers the research question, since we can conclude that criminal activity negatively influences housing prices in the municipality of Groningen. Modelling the effect of different types of crime has yielded results that are in line with previous studies with property being the least, and violent crime being the most detrimental in regards to neighbourhood housing prices. These findings provide an answer to the secondary research question. Accompanying estimated coefficients range from -,0188% for theft, -,0317% for vandalism, and -,0816% for assault per reported crime per 1000 inhabitants.

A potential explanation of declining housing prices due to crime would be the physical and psychological impact it has on individuals and their place of residence. The discrepancy between the extent of the housing value decline caused by the different crime categories could also rely on these notions. Property theft for instance potentially generates less awareness and lasting harm then vandalism and violent crimes.

6.1 Implications & recommendations

The findings discussed help to quantify the effect criminal activity has on neighbourhoods. Knowing the economic cost of a crime can be used to comprehend the value of undermining delinquency. Furthermore, the findings can help to strike an adequate financial balance, for instance, the estimated loss in property tax revenue can be appraised. This thesis goes in-depth about the economic costs of criminal activity. For future research, a suggestion would be to look into the social cost of crime and the different forms it exhibits. Establishing social costs could be done through broader census data and the use of qualitative methods. Furthermore, the panel scale of the research method applied could be increased to establish nation-wide effects of criminality on housing value.

7.0 References

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Appendix A – data sources

Variable	Source	Link
Dependent variables		
Log Housing value	Own calculations	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83765NED/table?ts=1592516067873
Housing value (×1000)	CBS kerncijfers wijken en buurten	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83765NED/table?ts=1592516067873
Neighbourhood demographics		
Men (per 1000 inhabitants)	CBS kerncijfers wijken en buurten	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83765NED/table?ts=1592516067873
Women (per 1000 inhabitants)	CBS kerncijfers wijken en buurten	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83765NED/table?ts=1592516067873
Age 0 – 15 (per 1000 inhabitants)	CBS kerncijfers wijken en buurten	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83765NED/table?ts=1592516067873
Age 15 – 25 (per 1000 inhabitants)	CBS kerncijfers wijken en buurten	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83765NED/table?ts=1592516067873
age 25 – 45 (per 1000 inhabitants)	CBS kerncijfers wijken en buurten	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83765NED/table?ts=1592516067873
Age 45 – 65 (per 1000 inhabitants)	CBS kerncijfers wijken en buurten	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83765NED/table?ts=1592516067873
Age 65+ (per 1000 inhabitants)	CBS kerncijfers wijken en buurten	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83765NED/table?ts=1592516067873
Western migrants (per 1000 inhabitants)	CBS kerncijfers wijken en buurten	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83765NED/table?ts=1592516067873
Non – western migrants (per 1000 inhabitants)	CBS kerncijfers wijken en buurten	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83765NED/table?ts=1592516067873
Population density	CBS kerncijfers wijken en buurten	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83765NED/table?ts=1592516067873
amount of income receivers (per 1000 inhabitants)	CBS kerncijfers wijken en buurten	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83765NED/table?ts=1592516067873
Average income (×1000)	CBS kerncijfers wijken en buurten	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83765NED/table?ts=1592516067873
Housing characteristics		
Uninhabited (%)	CBS kerncijfers wijken en buurten	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83765NED/table?ts=1592516067873
After 2000 (%)	CBS kerncijfers wijken en buurten	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83765NED/table?ts=1592516067873
Physical neighbourhood characteristics		

Surface land (m2)	CBS kerncijfers wijken en buurten	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83765NED/table?ts=1592516067873
oppervlakte water (m2)	CBS kerncijfers wijken en buurten	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/83765NED/table?ts=1592516067873
Amenity provision		
Distance GP (m)	CBS Nabijheid voorzieningen; afstand locatie, wijk- en buurtcijfers	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/84334NED/table?ts=1592516000416
Distance ramp (m)	CBS Nabijheid voorzieningen; afstand locatie, wijk- en buurtcijfers	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/84334NED/table?ts=1592516000416
Distance train (m)	CBS Nabijheid voorzieningen; afstand locatie, wijk- en buurtcijfers	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/84334NED/table?ts=1592516000416
Distance day-care (m)	CBS Nabijheid voorzieningen; afstand locatie, wijk- en buurtcijfers	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/84334NED/table?ts=1592516000416
Distance supermarket (m)	CBS Nabijheid voorzieningen; afstand locatie, wijk- en buurtcijfers	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/84334NED/table?ts=1592516000416
Distance primary school (m)	CBS Nabijheid voorzieningen; afstand locatie, wijk- en buurtcijfers	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/84334NED/table?ts=1592516000416
Distance secondary school (m)	CBS Nabijheid voorzieningen; afstand locatie, wijk- en buurtcijfers	https://opendata.cbs.nl/statline/#/CBS/nl/dataset/84334NED/table?ts=1592516000416
Reported and perceived crime		
Theft total (reported)	OIS GemeenteGroningen_aangiftenpolitie_perbuurt	https://groningen.dataplatform.nl/#/data/7498165c-c40d-459e-9f75-df5eb28c30d3?totalViews=41
Vandalization (reported)	OIS GemeenteGroningen_aangiftenpolitie_perbuurt	https://groningen.dataplatform.nl/#/data/7498165c-c40d-459e-9f75-df5eb28c30d3?totalViews=41
Assault (reported)	OIS GemeenteGroningen_aangiftenpolitie_perbuurt	https://groningen.dataplatform.nl/#/data/7498165c-c40d-459e-9f75-df5eb28c30d3?totalViews=41
Total crime (reported)	OIS GemeenteGroningen_aangiftenpolitie_perbuurt	https://groningen.dataplatform.nl/#/data/7498165c-c40d-459e-9f75-df5eb28c30d3?totalViews=41

Appendix B – list of neighbourhoods included in the analysis.

Neighbourhood name	Municipal neighbourhood code
Badstratenbuurt	BU00140105
Bangeweer	BU00140809
Beijum-Oost	BU00141101
Beijum-West	BU00141100
Binnenstad-Noord	BU00140000
Binnenstad-Oost	BU00140002
Binnenstad-West	BU00140003
Binnenstad-Zuid	BU00140001

Bloemenbuurt	BU00140402
Coendersborg	BU00140601
Corpus den Hoorn	BU00140700
Damsterbuurt	BU00140404
De Buitenhof	BU00140810
De Held	BU00140906
De Hoogte	BU00140300
De Hunze	BU00141102
De Kring	BU00140812
De Linie	BU00140500
De Meeuwen	BU00140100
De Wijert	BU00140605
De Wijert-Zuid	BU00140606
Drielanden	BU00141208
Engelbert	BU00141301
Europapark	BU00140501
Florabuurt	BU00140403
Gorechtbuurt	BU00140400
Gravenburg	BU00140806
Grunobuurt	BU00140104
Helpman	BU00140604
Herewegbuurt	BU00140102
Hoogkerk Dorp	BU00140800
Hoogkerk-Zuid	BU00140801
Hoornse Meer	BU00140701
Hoornse Park	BU00140702
Hortusbuurt-Ebbingekwartier	BU00140005
Indische buurt	BU00140301
Klein Martijn	BU00140602
Kop van Oost	BU00140503
Kostverloren	BU00140203
Laanhuizen	BU00140107
Lewenborg-Noord	BU00141200
Lewenborg-West	BU00141202
Lewenborg-Zuid	BU00141201
Noorderhoogebrug	BU00141104
Noorderplantsoenbuurt	BU00140201
Oosterhoogebrug	BU00141203
Oosterpoort	BU00140101
Oranjebuurt	BU00140200
Paddepoel-Noord	BU00141002
Paddepoel-Zuid	BU00141001
Piccardthof	BU00140704
Professorenbuurt	BU00140302
Reitdiep	BU00140904
Rivierenbuurt	BU00140103
Ruischerbrug	BU00141210
Ruischerwaard	BU00141211
Schildersbuurt	BU00140202
Selwerd	BU00141000
Stationsgebied	BU00140008
Sterrebosbuurt	BU00140600
Tuinwijk	BU00141005

Ulgersmaborg	BU00141204
Van Starkenborgh	BU00141103
Vierverlaten	BU00140803
Villabuurt	BU00140603
Vinkhuizen-Noord	BU00140900
Vinkhuizen-Zuid	BU00140901
Vogelbuurt	BU00140401
Zeeheldenbuurt	BU00140106
Zilvermeer	BU00141206