The effect of flooding risk on residential property prices

First implications after the 2021 floods in The Netherlands

July 1, 2022

Niek Eghuizen

“Master theses are preliminary materials to stimulate discussion and critical comment. The analysis and conclusions set forth are those of the author and do not indicate concurrence by the supervisor or research staff.”

COLOFON

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ABSTRACT

Climate change is a growing global problem and has major effects on the built environment, spatial planning processes, and real estate markets. The topic of this research is to examine if flooding risk affects housing prices in The Netherlands and whether a flood event affects this effect. Different literature shows that housing prices drop in areas that are located in flood-prone areas. Depreciation is strengthened when the area has experienced a recent flood. This expectation is tested by performing a difference-in-difference hedonic regression for three case study areas in the Netherlands between 2020 and 2022. Regression results show that before the flood transaction prices for residential properties with a high probability of flooding were sold for 9.5% more than for properties in safe areas. After the flood, no significant price effects were found for the sample as a whole. It was found that regional differences occur, based on the magnitude of the impact of the flood. These results could help local governments in decision-making for assigning construction sites and help banks, appraisers, and investors to better value residential properties in flood-prone areas.

Keywords: Climate change, residential real estate markets, asset prices, flood risk, natural hazards

PREFACE

Dear reader,

Before you lies the master thesis “The effect of flooding risk on residential property prices” as my graduate document for the Master of Science Real Estate Studies at the University of Groningen. I was engaged in researching and writing this thesis from February to July 2022. My purpose of this study is to add knowledge about the urgent consequences of climate change and which implications this has on the real estate market.

I was not able to finish this thesis without the help of others. First of all, I would like to thank Deloitte, and especially director Wilfrid Donkers for helping me to obtain the transaction data. Without the commitment of his network, I would not have come into contact with Calcasa. At Calcasa special I would like to thank director Bob Dankbaar, who took the time to explain the database to me and how to interpret this. I could not have obtained this data without their help. Furthermore, great thanks to my supervisor Efstathios Margaritis for his pleasant cooperation and his flexibility. Although the subject was not directly associated with his research field, he was always very interested and keen to help to guide me to finish my thesis successfully. Also thanks to Mark van Duijn for replying quickly to my questions about thesis writing. Another person who should not be forgotten is my fellow student Cedric Jansen, whom I could always ask questions about running correct and clear GIS maps.

Last but not least, a special thanks to all my family members, friends and colleagues whom I bored with for a long time with my thesis topic. Their understanding of my state of mind when the writing process did not immediately go the way I wanted should not be mentioned unnoticed. They always kept me motivated for making progress.

I hope you enjoy reading.

Niek Eghuizen

Amsterdam, July 1, 2022

TABLE OF CONTENT

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

1.1 Motivation

Climate change is a growing problem and has major effects on the living environment of the world population. Hurricanes, tornadoes, and rainfall causes extensive damage to the built environment and have a great impact on the lives of people. In 2021, global damage from natural disasters amounted to approximately 250 billion euros (Munich RE, 2022). The occurrence and consequences of these natural disasters receive increasing media coverage worldwide compared with the last century. This is partly because of the improved technology in communication and broadcasting infrastructure but is also a result of a higher incidence of natural disasters. The Intergovernmental Panel on Climate Change (2022) warns of an existential threat in the next century, as the survival of European coastal towns, their inhabitants, and their cultural heritage is seriously threatened by rising sea levels. It assumes a maximum global sea rise of 1 meter in 2100. Flood damage to Europe's coasts could increase tenfold by the end of this century, scientists estimate. Besides rising sea levels, also the probability of extreme weather conditions and additional damage is rising. For example, in July 2021 the Benelux region experienced a major flood due to the extreme rainfall. Locally more than 160 millimeters of precipitation fell in 48 hours (Bruijn & Slager, 2022). The probability of occurrence is much smaller than can be directly derived from observations of past events, but model simulations indicate that the probability of this amount of rainfall is on the order of 1/100 to 1/1000 per year. Climate change has contributed to an increased likelihood of this event to a 9-fold probability increase relative to the preindustrial state of the climate (Task Force Fact Finding Hoogwater 2021, 2021). The exceptional rainfall led to major flooding in the area, resulting in 46 billion euros of damage and losses of life. One of the Benelux countries is the Netherlands, which is highly affected by the consequences of climate change. 26 percent of its surface is located below sea level and 59 percent of the Netherlands is prone to flooding (Pieterse, et al., 2010). As sea levels are rising and the summer showers are becoming more extreme, the Netherlands is therefore taking various measures to protect the country against high water, such as the Room for the River program and the Delta Programme. This should result in a climate-proof and water-robust design of the country.

The Netherlands has experienced inland flooding before in 1993 and 1995, where also several Limburg villages flooded. Research shows that had hardly any effect on the local housing market (Hegger, 2021). Properties in a location with the greatest flood risk have been sold for a higher average price over the past ten years than those in the rest of Limburg. In a report of the Atlas voor gemeenten, researchers Marlet, Woerkens, & Berg (2016) also claim that the proximity of water outweighs the potential risk of flooding in pricing. Living on or near water is so popular that the prices of houses are higher. In 2020, valuation company Calcasa calculated what a natural disaster, or the fear of it, could affect housing prices (Hegger, 2021). They state that because the Netherlands lies very low on the North Sea and is crossed by several large rivers, the risk of flooding is always latent. However, that chance is currently very small due to all the water protection measures. Hence, there is hardly any effect on house prices. But if climate change leads to local floods or 'near-floods', the housing market will start to calculate flooding as a greater risk. According to Calcasa, the total home value could then fall by 44 to no less than 174 billion euros.

The topic of this research is to investigate if the flooding risk affects housing prices, resulting in deepening our knowledge on this topic. As previous research focuses on events when climate change awareness was not as high as nowadays, it is interesting to investigate if the effect of this event on the residential market can be perceived. For instance, in Belgium after the 2021 flood, prices of houses that are located in a flood risk area were sold 4 percent less compared with similar houses that are in an area classified as less risky (HLN, 2022).

1.2 Academic relevance

In a meta-analysis, Daniel, Florax, and Rietveld (2009) find that an increase in the probability of flood risk of 0.01 in a year is associated with a difference in the transaction price of an otherwise similar house of –0.6%. The marginal willingness to pay for reduced risk exposure has increased over time, and it is slightly lower for areas with a higher per capita income. According to these researchers, amenity effects and risk exposure associated with proximity to water causes systematic bias in the implicit price of flood risk and result in obfuscated observations. The analysis mainly focuses on studies on the 90's US real estate market. However, a recent study performed in the US suggests that homes exposed to sea-level rise sell for approximately 7% less than observably equivalent unexposed properties equidistant from the beach (Bernstein, et al., 2019).

A study on housing prices and flooding risk in Finland addresses the importance of information gaps and asymmetries in assessing risks (Votsis & Perrels, 2016). According to the researchers, flooding probabilities indicate a significant price drop after the information disclosure for properties located in flood-prone areas as indicated by the maps. The identified effect is spatially selective; it caused a short-term localized shock in market prices in conjunction with some reorientation of demand from risky coastal properties towards ones that represent a similar level of coastal amenity but are less risky in terms of flooding. The timing of information on the nature of the flood risk is crucial. Another study found that disclosure laws, which require information earlier in the home search process, reduce housing values in flood-prone areas (Pope, 2008). Actual flood events also reduce prices as Bin and Polasky (2004) show in their study on the effects of hurricane Floyd in 1999. They find that a house located within a floodplain has a lower market value than an equivalent house located outside the floodplain. The drop is often transitory, however, with prices rebounding within a decade, sometimes sooner (Atreya, et al., 2013)

Already some research has been performed into the effect of flooding risk on housing prices. However, there is a difference between areas that have experienced a flooding event and those that have not. Also, most of the research has been done in the United States or Asian countries, in which city designs are in a way different compared to European ones. Furthermore, lots of research mostly focuses on events of 20 years ago, in a time when climate change was not as urgent as it is today. It is useful to investigate if flooding risk does impact the residential property value and contribute new knowledge to the current literature.

1.3 Research problem statement

This study aims to investigate if there is a relationship between the assessment of flooding risk into housing prices in the Netherlands before and after a flooding event. In this study residential property transaction data, nine months before and after the flood is combined with data on flooding risks in the Netherlands. For three different case study areas, selected by the magnitude of impact, the effect of inundation on housing prices is examined. Within this consideration, results could help local governments in making their choice for assigning construction sites and help appraisers to better value residential properties. Therefore, the main research question is formulated as follows: *To what extent does a flooding event affects residential property pricing in a flood-prone area?* In the direction of the needs for this study, four major research sub-questions are determined to be answered:

RQ1: *What is the relationship between flooding risk and flood events on residential property prices based on literature?*
RQ2: *What is the quantitative empirical pricing effect for a residential property located in a flood-prone area?*
RQ3: *What is the quantitative empirical pricing effect after flooding for a residential property located in a flood-prone area?*
RQ4: *What are the regional differences in the pricing effect for a residential property located in a flood-prone area after flooding?*

1.4 Research method and data

In this study, residential property transaction data between the beginning of October 2020 and the end of March 2022 is combined with data about flooding probability in the Netherlands, the timing of the flooding, and other characteristics affecting housing values. Three different areas are examined that are selected based on the economic impact that the flooding in 2021 had on the area, varying from no economic impact to significant economic impact. Based on the hedonic pricing method a difference-in-difference regression analysis is performed in which is controlled for other external effects.

1.5 Conceptual model

Based on theory about flooding risk affecting property prices a conceptual model is constructed as seen in Figure 1. The aim is to find a quantitative relationship between the probability of flooding and housing prices, moderated by a flood event.

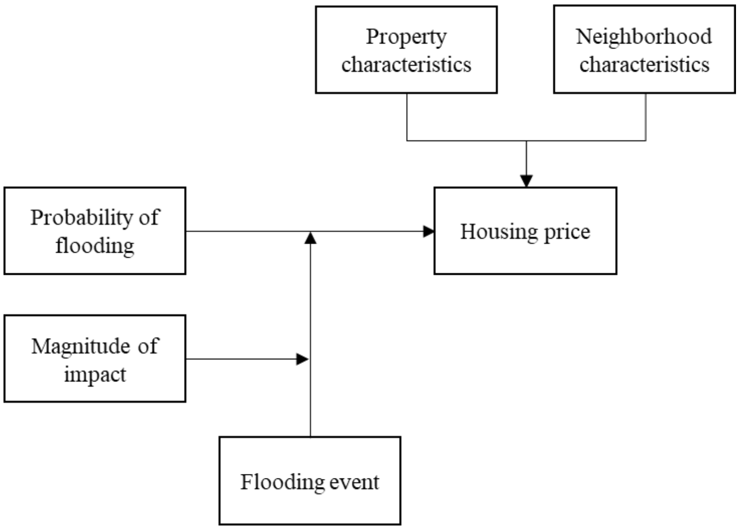

FIGURE 1: Conceptual model explaining the effect of flooding probability on residential property prices
Note: The effect flood probability has on housing prices is moderated by the event of flooding. The extent to which this affects housing prices depends on the impact of damage the flooding caused. Furthermore, based on the hedonic pricing model property characteristics and neighborhood characteristics are taken into account as independent variables.

1.6 Outline

The remainder of this thesis is organized as follows. In chapter 2, the relevant literature about the impact of flooding risk and flood events on housing prices is reviewed. A more detailed explanation of the case study region, data, and methods of the regression analysis is described in the methodology section in chapter 3. In chapter 4, the results and findings are presented and discussed. In chapter 5 the main conclusions and limitations of this research are mentioned, whereafter some suggestions for further research and policy implications are pointed out.

2. THEORETICAL FRAMEWORK

2.1 Hedonic price effect

The hedonic price model is based on the consumer behavior theory of Lancaster. In this theory, he argues that individual characteristics create utility and not the good itself (Lancaster, 1966). By considering the revealed preferences, the demand for a certain good can be estimated. This theory also applies to the real estate market, as this market is considered a multidimensional heterogeneous good with different characteristics (Bourne, 1986). By decomposing property values into different components, it is possible to measure the marginal effects of individual characteristics affecting housing prices (Rosen, 1974). A differentiated good can be defined as a vector of its characteristics, $C = (c_{1,}\, c_2, \dots, c_n)$. In the case of a house, these characteristics may include and are often categorized into location, structural- and neighborhood factors. It assumes that each property's attributes can be evaluated using the market price because consumers make choices to maximize the expected utility of the property. The hedonic pricing model is a revealed and proven method that estimates the market value of diverse non-market aspects of houses from the transactions observed (Pryce, et al., 2011; Tian, et al., 2017; Yoo & Frederick, 2017; Yoo & Wagner, 2016). Although the ease of applying the hedonic pricing models in valuing properties, the utilization of the hedonic pricing method relies on various key assumptions (Wing & Chin, 2003). For instance, the model does not require segmentation of real estate markets (Feitelson, et al., 1996). However, individual country markets are not uniform caused of their unique laws and regulations and so market segmentation will always exist (Fletcher, et al., 2000). Therefore, it is not reasonable to treat real estate markets in any geographical location as one. Another issue that needs to be considered in applying the hedonic pricing method is the misspecification of variables (Wing & Chin, 2003). If relevant independent variables are left out or irrelevant variables are included in the model, misspecification occurs. Over-specification results in unbiased and consistent coefficients, although it would be inefficient and result in a lower R-squared value. On the other hand, under-specification leads to biased and inconsistent coefficients. As misspecification of variables is argued as unavoidable, Butler (1982) and Mok et al. (1995) argue that it is sufficient to consider a low number of variables as biases due to missing variables are often limited and have no significant predicting and explanatory power.

2.2 Effect of flood hazards on property values

The main finding in studies that investigate the effects of flooding risk is that the event of a large flood increases the perceived risk (Atreya & Ferreira, 2015), which can be explained by the availability heuristic. Individuals assess the probability that an event will occur by how easily examples or information about these events come to their attention (Tversky & Kahneman, 1973). Hazard mapping and the disclosure of hazard information to the public are considered to be essential strategies that can increase risk awareness of citizens and can help local governments in assessing land-use policies (Grothmann & Reusswig, 2006). These maps can also strengthen the ability to respond to natural disasters and increase the self-protective behavior of citizens. However, when it comes to mitigation techniques, is necessary to understand the link between risk discounts and the availability of hazard information, as 'information asymmetry' could affect the impact on housing prices (Akerlof, 1970). If information asymmetry exists, and if a buyer cannot obtain all the required information, the buyer cannot determine if the asking price for a house is in proportion to its quality. This uncertainty can make properties undervalued and eventually cause market failure. A seller has more information about possible flood risks and previous experiences than buyers (Pope, 2008). However, when hazard information is publicly available, it is likely that the flooding risk discount is reflected in the prices of properties in hazardous zones and improves market efficiency. Researchers conducted empirical studies to analyze the result of publishing hazard information on property values and argue that perceived risk can have a significant impact on housing prices. For example, in a study about the influence of media, Koo and Lee (2015) find that frequent exposure through television or newspapers diminished property values more than the damage itself. In another research, Votsis and Perrels (2016) discovered that flood risk discounts for vulnerable properties became significantly larger than the effects of water-related amenities after the disclosure of flood risk maps. In contrast, Samarasinghe and Sharp (2010) show that the disclosure of a flood risk map increased residential property values in flood hazard zones. Walsh and Mui (2017) find that imparting information did not affect housing prices in areas where disaster risk is already well-known, but reduced prices in places where it is not. In conclusion, consumers are pricing their perceived risk into the valuation of a specific property based on previous experiences.

In an efficient housing market, property values in vulnerable areas are lower than those in safer areas because both sellers and buyers recognize hazard information which affects the acceptance of a lower price for a property (Beltrán, et al., 2018). Many researchers recognize that flood hazards negatively impact housing prices by using hedonic pricing models. For example, Bin et al. (2008) find that flood risk discounts were larger in higher-risk areas (7.8%) than those in lower-risk areas (6.2%). In another paper, Bin and Polasky (2004) find that flood risk discounts were 3.8% in vulnerable areas. After the flooding caused by Hurricane Floyd in 1999, the average value of property decreased additionally by 4.5%. Belanger and Bourdeau-Brien (2017) conducted the same research in Canada and also find a price decrease of 4.1% for houses in vulnerable areas. After the flood in the spring of 2017, they find that the level of risk awareness affected the magnitude of flood risk discounts. In non-flooded areas prices dropped by 1.6%, whereas in flooded regions prices dropped by 6%. Another research about flood incidents in England between 1995 and 2014 shows that immediately after an inland flood inundated properties are on average 24.9% lower than non-flooded properties (Beltrán, et al., 2019). For properties inundated by coastal flooding, the price reduction is 21.1%. These researchers also found that the origin of flooding and the magnitude of the impact affect the extent of price discounts. Inconsistencies created by the variable magnitude cause that hedonic property coefficients are not consistence across different studies (Sirmans, et al., 2005). The effect of flood risk on the real estate market varies spatially and temporarily. To summarize, risk discounts change over time whether an area has experienced a flood or not and varies between regions depending on the amount of damage it caused.

As discussed thus far, only negative pricing effects of flood risk are considered. However, as properties with significant flood risk are located near coastlines or major rivers and lakes, flood risk discounts often co-exist with amenities from those bodies of water (Bin & Kruse, 2006). Home owners are willing to pay for flood insurance to enjoy living near water and will take flooding hazards into account in the valuation of their property (Atreya & Czajkowski, 2014; Bin, et al., 2008; Kim, et al., 2017). As such, natural amenities can create a price premium so that property values in hazardous zones can be valued higher than in a safe space (Rajapaksa, et al., 2017). The natural amenity value of living close to a river can outweigh the associated risks. Daniel et al. (2009) address their concern that many previous-flood studies fail to adequately take into account the positive effect of a location close to water bodies. Therefore, when investigating flood risk effects on property values positive effects of proximity to water could dominate the negative effect of living in a flood-prone area.

Major cities are situated across river systems and on coastlines, that are likely to be threatened by rising sea levels or extreme weather conditions due to climate change (Neumann, et al., 2015). Housing globally is likely to be affected by floods from sea level rise and increased periodic inundation from storm events (Beltrán, et al., 2018). The effects this will have on properties are substantially underestimated, due to modeling expectations that focus only on direct sea-level rise, assuming flat water and little or no consideration of wave heights, tides, and storms (Fuerst & Warren-Myers, 2021). Warren-Myers et al. (2018) for instance found that for a municipality located on the coast of Australia, at 0.8 meters sea-level rise, only 0.24 percent of properties would be affected. When modeling a conservative storm wave of 0.5 meters with high tide consideration the number of affected properties increased to 40 percent. As public awareness grows Bernstein et al. (2019) found that the pricing discount for these properties has increased. However, flooding discounts for flood-prone properties are likely to be underestimated, as research by Ortega and Taspinar (2018) shows. They suggest that price subsequent risk to coastal properties concerning sea level rise implications will likely be felt initially through increased periodic flooding. Other evidence identified that homes exposed to sea-level rise are selling presently at 7% less than comparable dwellings of the same distance from the beach. Properties that are anticipated to be inundated by the end of the century are only sold for 4 percent less (Bernstein, et al., 2019). As such, future risks are not always included in the financial valuation of properties and can therefore distort the extent to which future potential depreciation is taken into account.

Based on the above literature review, the first research question (RQ1) could be answered: *"What is the relationship between flooding risk and flood events on residential property prices based on literature?"*. Research shows that consumers are pricing their perceived risk into the valuation of a specific property. Properties located in a flood-prone area are valued lower than those that are likely to remain unaffected. Flood events impact the way consumers assess associated risks by the magnitude of their impact, which thereafter is reflected in property valuation. However, price premiums could occur caused by the amenity of living near coastlines or rivers. In addition, risks are assessed more strongly based on historical events than based on future flood models.

3.3 Hypothesis

Based on this literature it is possible to specify hypotheses to answer the composing research questions. Prior literature found that housing prices in hazardous zones are valued lower than those in safe areas. However, as properties with high risk are often localized near bodies of water, this could cause consumers to be willing to pay a premium for this amenity. To answer RQ2, the following hypothesis is tested to assess if a price discount is taken into account for residential properties in a high-risk area or not:

H1: *"Residential property prices in an area with high flood risk significantly differ from those in a low-risk area."*

In addition, as research suggests that flood hazards affect housing prices negatively and floods strengthen the awareness of flooding risk, it is expected that residential property prices in a flood-prone area have decreased after a flood. Therefore, for answering RQ3 the main hypothesis is formulated as follows:

H2: *"A flood has a significant effect on housing prices in a high flood risk area."*

To deepen our knowledge, an additional hypothesis will be tested. As literature shows empirical studies found that the magnitude of impact has a moderating effect on the pricing effect that is caused by flooding. Hence, regional differences occur which makes it interesting to investigate them separately. The hypothesis aiming to answer RQ4 is as follows:

H3: *"The effect of a flood on housing prices is stronger for properties in highly affected regions than for those that are not impacted."*

3. METHODOLOGY

The empirical analysis of this research is focused on answering three quantitative research questions; RQ2 aims to find if for residential properties in high flood risk areas a significant premium or discount is paid. RQ3 aims to find the willingness to pay for a house in a flood-prone area after a flooding event. RQ4 one aims to find if regional differences occur in risk assessment. For answering the research questions, a difference-in-difference approach is used. The difference-in-difference analysis allows the researcher to compare a selected target group with a control group before and after a specific treatment (Zhang, et al., 2020). It is frequently used to assess the external impact of an event on the dependent variable. This analysis only can be performed if the target group and control group are comparable, except for the event. First, a description of the three selected case study areas is given, whereafter the data selection process is explained. Hereafter, all associated variables for constructing the regression model are introduced and descriptive statistics are given. Subsequently, for answering research questions, the regression equation for hypothesis testing is constructed.

3.2 Case study area

As mentioned in the introduction chapter, the majority of Dutch land area is located in flood-prone areas. At the time of writing, no insurer in the Netherlands offers insurance against flooding from sea and rivers. If a flood does occur, the Disaster Compensation Act can be declared applicable by the government. Private individuals and companies may be eligible for (partial) compensation for the damage suffered. This act does not apply to areas outside the dykes. The risk of damage in the event of flooding in areas outside the dikes lies with the property owner.

In 2021 the province of Limburg was affected by extreme rainfall causing floods in various regions. One of the most severely impacted is the municipality of Valkenburg a/d Geul, which serves as the first case study area. The municipality of Valkenburg a/d Geul is located in the south of Limburg and has 16,167 inhabitants (Central Bureau for Statistics, 2022). It is located in a valley formed by the river Geul and was impacted by the flooding. In Appendix I, the affected area in the city of Valkenburg due to the flooding is shown. The river flows through the historic center of Valkenburg, as well as many other built-up areas in South Limburg. The province of Limburg accepts the calculated risk of flooding as it is not cost-effective to invest in more defense systems compared to the estimated potential damage. Around 1,000 citizens were trapped by the flooding, others managed to escape in time. A total of 2,300 houses were damaged, 700 of which were seriously damaged (NOS, 2021). It is estimated that there are 200 million euros in material damage and 200 million euros in business losses due to lost income. Figure 2 shows the risk of flooding for the municipality of Valkenburg a/d Geul.

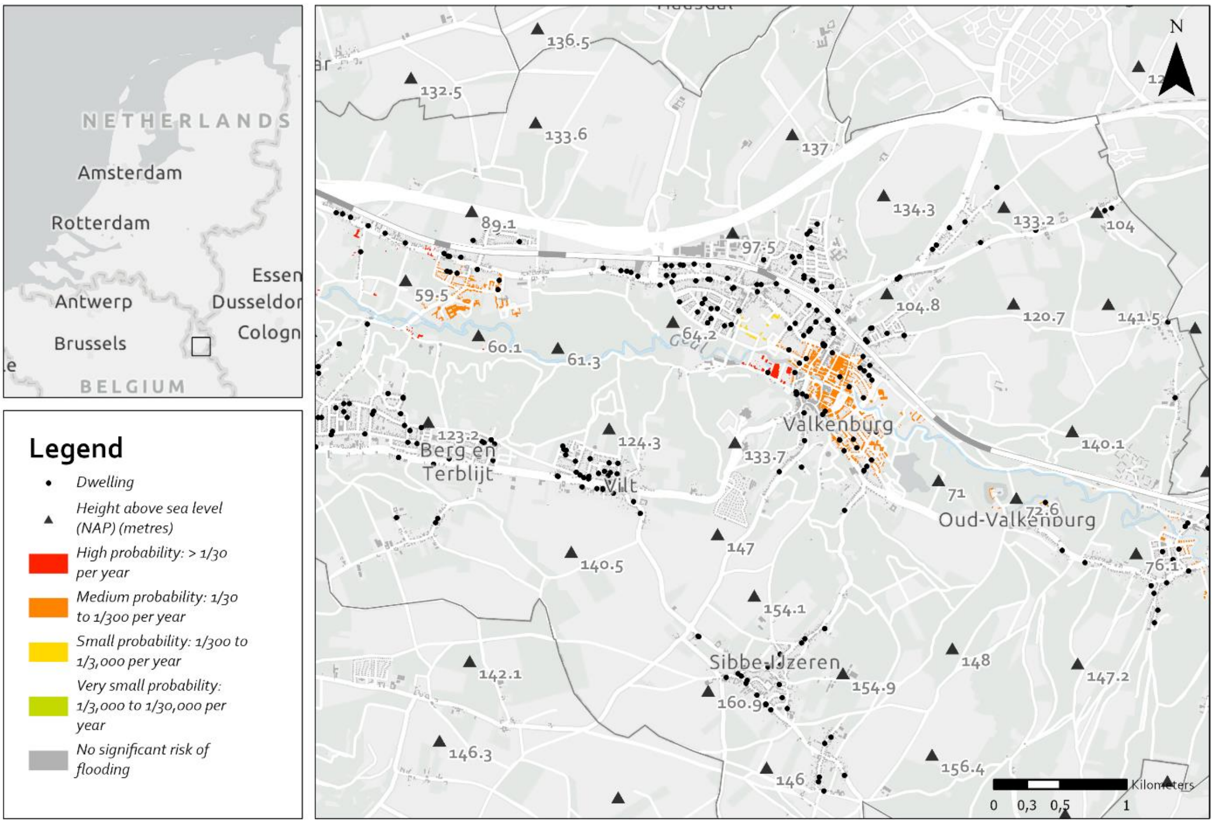

FIGURE 2: Map of flooding risk in Valkenburg a/d Geul

Note: This map shows the flood risk at the property level for the municipality of Valkenburg a/d Geul based on the standard in 2050. Black dots represent the individual observations included in this research (N = 275). Grey triangles represent the height above sea level measured in meters.

The second case study area is the municipality of Maastricht, which is another affected area by the flood. It is located in the south of the province of Limburg, right next to the river Meuse. Maastricht is the capital of the province of Limburg and has a population of 121,151 inhabitants. Due to the flooding 10,000 citizens were evacuated in the neighborhoods of Heugem and Randwyck, located in the south of Maastricht. In front of the hospital, sandbags were filled as a preventive measure for protection against the rising water. The municipality narrowly escaped a potential flood, causing no major economic damage to infrastructure or properties. The probability of flooding for Maastricht is shown in Figure 3.

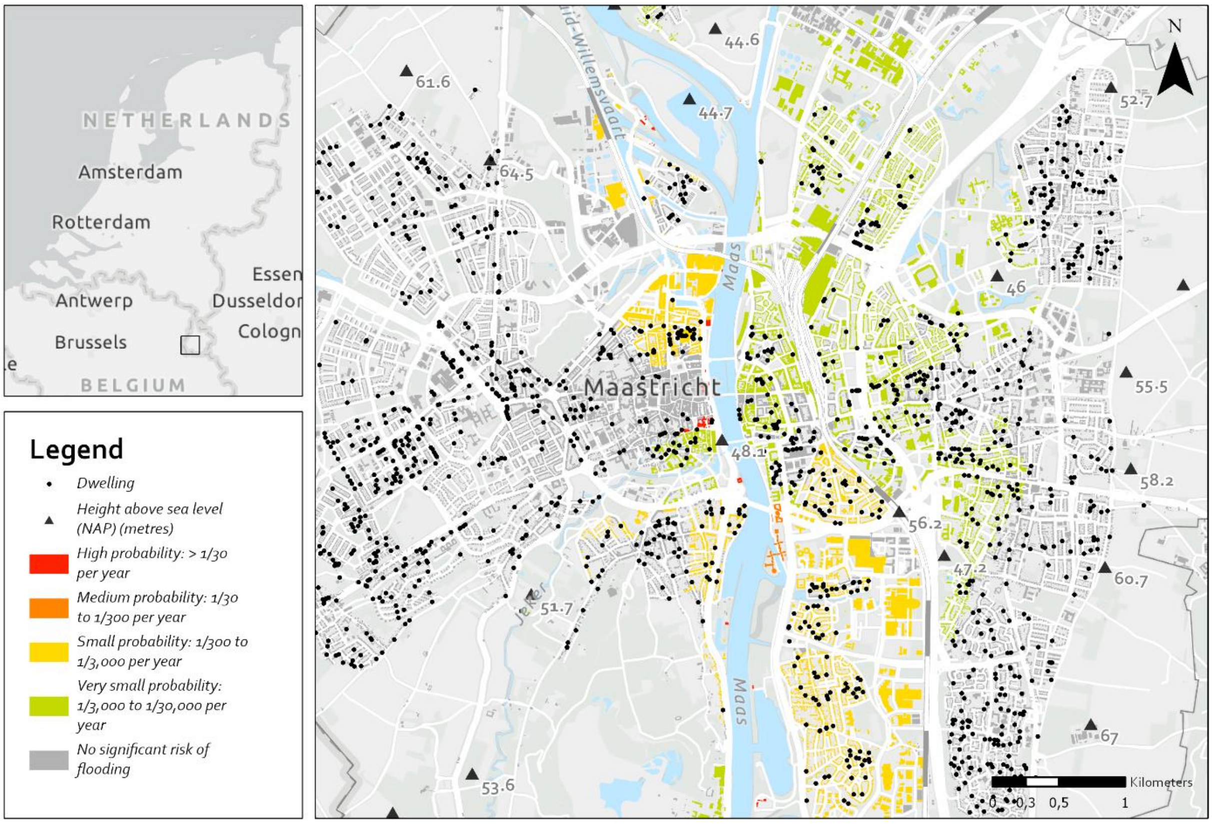

FIGURE 3: Map of flooding risk in Maastricht

Note: This map shows the flood risk at the property level for the municipality of Maastricht based on the standard in 2050. Black dots represent the individual observations included in this research (N = 1,707). Grey triangles represent the height above sea level measured in meters.

The third case study area is the municipality of Dordrecht, which is located in the south of the province of South Holland. Three rivers converge at the center of Dordrecht: the Beneden-Merwede, the North, and the Old Meuse. Parts of Dordrecht are located outside the dykes and sometimes suffer from flooding when the water level is too high. For Dordrecht and the surrounding area, the danger of flooding comes from both sea and river sides. On the one hand, the water will be pushed up from the rivers if all the barriers that hold back the sea during heavy storms are closed for a long time. On the other hand, despite fully opened sea defenses, the river water cannot be discharged quickly enough to the sea but is pushed up by the tide. However, in recent years no events of large flooding or water damage have occurred and so was not affected by the floods in 2021. A flooding probability map for Dordrecht is visualized in Figure 4.

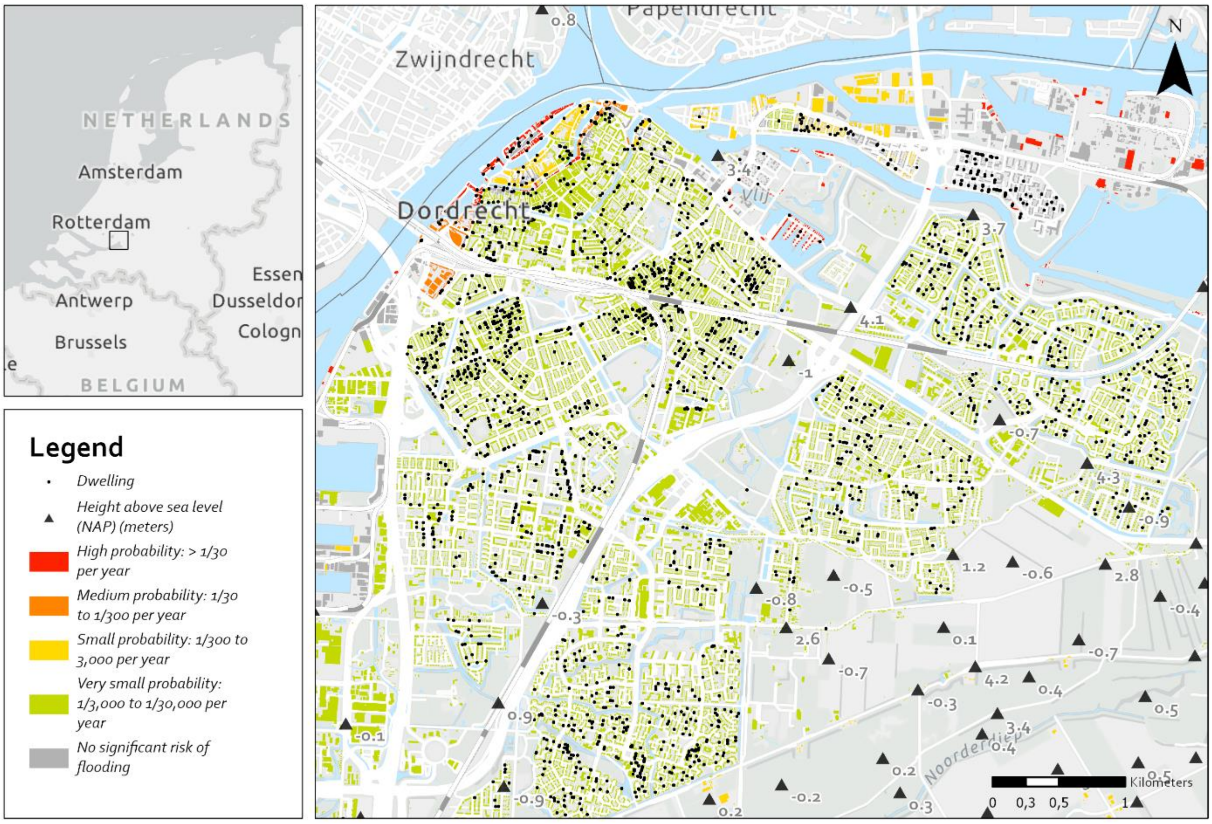

FIGURE 4: Map of flooding risk in Dordrecht

Note: This map shows the flood risk at the property level for the municipality of Dordrecht based on the standard in 2050. Black dots represent the individual observations included in this research (N = 2,283). Grey triangles represent the height above sea level measured in meters.

The case study areas are selected based on the magnitude of impact the flood of 2021 had on the different regions. Valkenburg was highly impacted by the flood on both economic and sociological levels, as hundreds of houses were damaged severely. In Maastricht in some districts, thousands of inhabitants were evacuated for preventive measures, but no properties were significantly affected. Therefore this municipality can be defined as impacted moderately. Dordrecht was not affected by the flood and serves as a not impacted region. The aim to include this region as a case study area is to control if, despite not being affected, it still increased the amount of awareness and so is reflected in transaction prices.

3.2 Data collection

The time scope of this study is October 2020 – March 2022, exactly nine months before and after the flooding in Limburg. The residential transaction dataset is obtained from Calcasa Residential Analyzer. Access to this database is granted by Deloitte. Only transactions in municipalities Valkenburg a/d Geul, Maastricht, and Dordrecht between October 2020 and March 2022 are selected. Transactions, of which building age or housing type is unknown, are excluded from this selection. All transactions are fully screened by Calcasa, which guarantees the integrity of the delivered data.

The flood risk map is obtained by the Landelijke Informatiesysteem Water en Overstromingen (LIWO, 2022). The LIWO is an information system that makes flood simulations available for crisis management and spatial adaptation. In the preparation and at the time of a flood, basic information can be viewed and a threat assessment can be compiled from the flood simulations with relevant information for water authorities and Rijkswaterstaat. The map is publicly available for citizens of the Netherlands where they can check if they are living in a flood-prone area. The map shows the likelihood that a person in a specific location will have to deal with a flooding event per year. For this research, the scenario with the maximum permissible flood probability that primary flood defenses must meet by law at 2050 at the latest, with a flooding depth higher than 20 centimeters is used. Furthermore, the cadastral data was obtained from the Basisregistratie Adressen en Gebouwen. Public available information about district characteristics comes from the Central Bureau of Statistics. These datasets are combined by using ArcGis for creating the maps as seen in Figures 1-3 and calculation purposes.

The selection leads to a total of 4,401 individual residential transaction observations between the beginning of October 2020 to the end of March 2022. No missing values that could disturb the results of this research are found in this dataset. To correct for outliers, all observations of the dependent variable that are lower than the 1st and larger than the 99th percentile are excluded, as is done in research by Zhang et al. (2020). These observations do not represent the population and could lead to troubling results. All transactions with a transaction price below 126,600 euros (44) or above 920,000 euros (44) are removed. After this selection, 4,313 transaction prices are left in the sample. Furthermore, the variables floor area and parcel size are also non-normally distributed and are rightly skewed. Therefore, observations with a floor area above 350 sq. meters (29) are removed from the sample. For the variable parcel size, the highest 0.5% (> 1835 sq. meters) (19) are excluded from the selection. In conclusion, this results in 4,265 observations that are included within the hedonic regression analysis. A visualization of the distribution of the transaction price is shown in Figure 5.

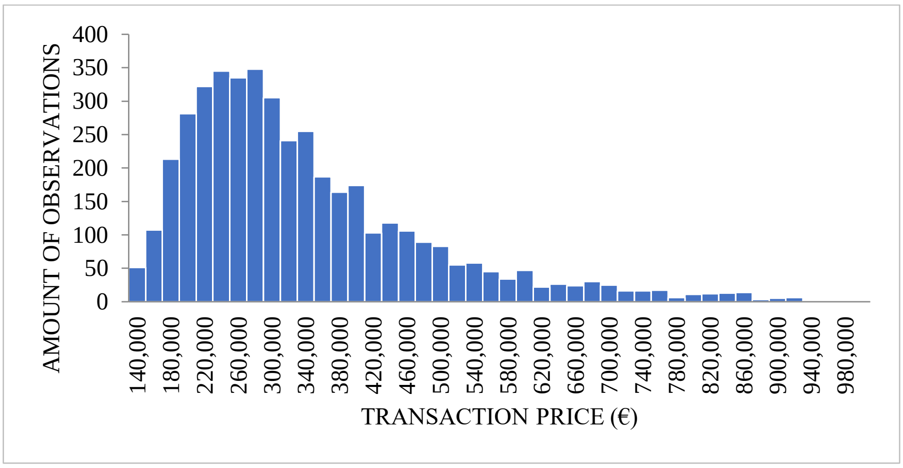

FIGURE 5: Distribution of amount of observations by the transaction price

Note: Histogram of the dependent variable *transaction price* in euros after the data selection process. The transaction prices are not normally distributed but are skewed to the right.

3.3 Descriptive statistics

In Table 1 a summary of descriptive statistics is shown for variables that are included in building the regression model.

TABLE 1: Summary of descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Transaction price	324,556.46	138,342.58	126,600	920,000
Property characteristics				
Floor area	120.253	48.372	24	347
Parcel size	154.375	189.166	0	1810
Construction period < 1940 (1 = yes)	.261	.439	0	1
Construction period 1940-1959 (1 = yes)	.09	.286	0	1
Construction period 1960-1969 (1 = yes)	.158	.365	0	1
Construction period 1970-1979 (1 = yes)	.174	.379	0	1
Construction period 1980-1989 (1 = yes)	.106	.308	0	1
Construction period 1990-1999 (1 = yes)	.122	.327	0	1
Construction period >2000 (1 = yes)	.089	.285	0	1
Type Apartment (1 = yes)	.315	.465	0	1
Type Semidetached (1 = yes)	.072	.258	0	1
Type Terraced (1 = yes)	.431	.495	0	1
Type Detached (1 = yes)	.041	.199	0	1
Type Corner (1 = yes)	.141	.348	0	1
Flood probability				
No risk (1 = yes)	.376	.485	0	1
Very small risk (1 = yes)	.548	.498	0	1
Small risk (1 = yes)	.055	.228	0	1
Medium risk (1 = yes)	.012	.109	0	1
High risk (1 = yes)	.008	.091	0	1
Number of obs.	**4,265**			

Note: This table denotes the descriptive statistics of the dependent variable *transaction price*, independent variables *property characteristics*, and *flood probability*. Other variables are not presented. For all dummy variables, the number represents the percentage relative to 1.0. *Mean*: Average value; *St. Dev.:* Standard deviation; *Min.:* Minimum value; *Max.:* Maximum value.

The dependent variable is *transaction price* and covers the transaction price for an individual unit. *Transaction price* is a continuous variable, measured in euros and collected from the dataset delivered by Calcasa. To correct for time fixed effects, the control variable *sales date* is added in the regression model, which is formatted on the year-quarter level. The independent variable *probability of flooding* is categorized into five different categories: *no risk*, *very small risk*, *small risk*, *medium risk*, and *high risk*. By using the software of ArcGis, for every individual observation is calculated to which category it belongs. For example, if an observation is in a medium risk area, the dummy *medium risk* equals 1. The next independent variable is *floor size*, which compromises the actual living area of a residential unit. The continuous variable is measured in square meters and is one of the property characteristics. The average floor size is 120,3 sqm, which is close to the average living area of 120 sqm. in the Netherlands (CBS, 2022). The variable *parcel size* is also one of the property characteristics and entails the size of the ground surface of an individual unit. It is a continuous variable, measured in square meters. The average parcel size of the sample data is 154 sqm. *Housing type* compromises the residential property category and is a categorical independent variable. In this research, five categories are made based on the dataset by Calcasa: *Apartment*, *Corner house*, *Detached house*, *Semidetached house*, and *Terraced house*. For every category a dummy variable is generated, which only can be equal to 0 or 1. As seen in Table 1 the majority of the units is either an apartment or terraced house, which represent 31.5 percent and 43.1 percent of the total sample size. The variable *building year* is based on the year of construction of an individual unit. As *building year* is not suitable to use within a regression analysis, this is transformed into the categorical variable construction period. The variable *building year* is divided into the variable *construction period* which contains seven category dummies: *<1940*, *1941-1960*, *1960-1969*, *1970-1979*, *1980-1989*, *1990-1999*, *>2000*. For the neighborhood characteristic, the categorical variable *municipality* is included, which entails three different municipalities. By incorporating this variable, location-fixed effects are controlled.

However, before continuing computing a regression analysis another difference needs to be considered. This study aims to compare houses with different flooding probabilities to each other, controlling for property characteristics and neighborhood effects. Despite this method being widely used in the literature on this subject, a recent study shows that it is likely to suffer from omitted variable bias. This effect occurs when a statistical model leaves out one or more relevant variables that are correlated with both flooding risk and transaction price (Beltrán, et al., 2018). If values that correlate are omitted, the estimates of the value of risk are expected to be biased. This research focuses on three different regions all of which have their unique characteristics. For instance, the proximity to local amenities, like supermarkets, schools, or restaurants in inner cities is likely to be lower than in rural areas. When only taking neighborhood characteristics into account at the municipality level, differences between different neighborhoods would not be observed. Therefore, similar houses would not be compared with each other and an omitted variable bias would occur. To deal with this, the location-fixed effects need to be on a more local level than on the municipality level. A categorical dummy variable *neighborhood* is added to the regression formula, where the value equals 1 if the residential unit is located in a specific neighborhood.

When looking at the flood risk maps, a difference between the three regions can be distinguished in the degree of risk probability. This is supported by Table 2, in which a distinction is made between the number of observations per region per flood probability. As seen the observations in the sample are not divided proportionally the same for the different regions. Because of this, it would not be correct if a regression analysis is run over the sample as a whole. One way to solve this is to recompose the risk variables into new categories that are more suitable for calculation purposes. The five probability categories are recomposed in the binary dummy variable *high probability*. If the variable *small risk, medium risk,* or *high risk* equals 1, the variable *high probability* also equals 1. For the other variables *very small risk* and *no risk,* the variable *high probability* equals 0 if one of those variables equals 1. It is assumed that the flooding probability associated with variable *very small risk,* so lower than 1/3,000 per year, is neglectable. This recategorization leads to a better distribution of probabilities per region, which makes it useable for modeling purposes.

TABLE 2: Distribution of observations per region by the probability of flooding

	VALKENBURG A/D GEUL		MAASTRICHT		DORDRECHT	
No risk of flooding	251	91.3%	1,211	70.9%	143	6.3%
Very small risk of flooding	0	0.0%	310	18.2%	2,028	89.0%
Small risk of flooding	0	0.0%	184	10.8%	51	2.1%
Medium risk of flooding	22	8.0%	0	0.0%	29	1.3%
High risk of flooding	2	0.7%	2	0.1%	32	1.4%
Total	275		1,707		2,283	

Note: This table denotes the distribution of observations per municipality categorized by the risk of flooding. As seen flood probabilities are not equally distributed when comparing the case study areas.

So far, all relevant variables are discussed that are used in building the regression model. This research aims to investigate if there is a difference in consumers' willingness to pay for a house that is located in an area that has a probability of flooding after a flood occurrence. This effect can be measured by performing a difference-in-difference regression analysis. All individual transaction units that are located in a significant flood-prone area are allocated to the target group (*high probability* = 1). The control group contains all individual units that belong outside the target group and are not located in a flood-prone area (*high probability* = 0*)*. This manner of allocating groups has been proven to be correct and has been performed in previous studies about flood effects (Dube, et al., 2021). Table 3 visualizes a summary of descriptive statistics for both groups. One condition for performing a correct difference-in-difference regression is that both groups must be identical to each other, except for the treatment. Comparing columns shows that there are differences between both groups. The average value of *transaction price* is higher in the target area than in the control area. Furthermore, the average *parcel size* of properties located in the target area is smaller than for the control area.

TABLE 3: Descriptive statistics: treatment area versus control area

	TARGET AREA (HIGH PROBABILITY = 1)				CONTROL AREA (HIGH PROBABILITY = 0)			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Transaction price	365,393	159,327	126,600	902,000	321,221	135,968	127,000	920,000
<u>Property characteristics</u>								
Floor area	125.562	54.490	39	346	119.819	47.819	24	347
Parcel size	122.615	156.124	0	1,490	156.969	191.397	0	1,810
Construction period < 1940 (1 = yes)	.329	0.471	0	1	.256	0.436	0	1
Construction period 1940-1959 (1 = yes)	.099	0.300	0	1	.089	0.285	0	1
Construction period 1960-1969 (1 = yes)	.062	0.242	0	1	.166	0.372	0	1
Construction period 1970-1979 (1 = yes)	.102	0.304	0	1	.18	0.384	0	1
Construction period 1980-1989 (1 = yes)	.155	0.363	0	1	.102	0.302	0	1
Construction period 1990-1999 (1 = yes)	.127	0.334	0	1	.121	0.327	0	1
Construction period >2000 (1 = yes)	.124	0.330	0	1	.086	0.281	0	1
Type Apartment (1 = yes)	.391	0.489	0	1	.309	0.462	0	1
Type Semidetached (1 = yes)	.062	0.242	0	1	.073	0.260	0	1
Type Terraced (1 = yes)	.41	0.493	0	1	.432	0.495	0	1
Type Detached (1 = yes)	.019	0.135	0	1	.043	0.203	0	1
Type Corner (1 = yes)	.118	0.323	0	1	.143	0.350	0	1
Number of obs.	**322**				**3,942**			

Note: This table denotes the descriptive statistics for both the target area and control area of the dependent variable *transaction price,* independent variables *property characteristics,* and *flood probability.* Other variables are not presented. For all dummy variables, the number represents the percentage relative to 1.0. *Mean*: Average value; *St. Dev.:* Standard deviation; *Min.:* Minimum value; *Max.:* Maximum value.

For answering RQ4, the research sample will be diverted into three subsamples per municipality. In Tables 4 and 5, the summary statistics per region are given. What stands out is the difference in average *transaction price* between different municipalities, where in Valkenburg a/d Geul the highest average *transaction price* is noted. This can be explained by a higher value for both *floor area* as *parcel size,* and also a higher proportion of semidetached and detached houses. As Valkenburg a/d Geul is in a more rural area compared with Maastricht and Dordrecht, this is not a surprising observation. Other negative external effects that are distinctive for urban areas, such as air pollution or noise disturbance could also affect the transaction price. This possibility must be taken into consideration when comparing these municipalities. Furthermore, the municipality of Dordrecht stands out, with a difference of 50,000 for transaction value between the means of the control and target group. This could be explained by the high share of apartment types in the target group compared with the control group. Besides this, 60.7 percent of the target group observations are built before 1940, compared with 30.5 percent in the control group. When looking at the map, it is observed that the majority of observations are located in the old town district which could have a great attraction to consumers. It is good to bear this in mind when concluding the results. In Appendix II visualizations of average transaction prices over time per region are presented.

TABLE 4: Descriptive statistics of the target group (high probability = 1)

	VALKENBURG A/D GEUL				MAASTRICHT				DORDRECHT			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Transaction price	370,563.13	152852.969	130,000	717,500	372,290.73	152,382.393	145,000	902,000	352,831.74	172,117.811	126,600	880,000
Property characteristics												
Floor area	165.292	61.821	54	335	129.355	53.288	40	346	110.75	49.752	39	283
Parcel size	276.958	296.507	0	1,490	144.882	149.273	0	940	52.563	64.822	0	287
Construction period < 1940 (1 = yes)	.25	0.442	0	1	.172	0.378	0	1	.607	0.491	0	1
Construction period 1940-1959 (1 = yes)	.25	0.442	0	1	.14	0.348	0	1	0	0.000	0	0
Construction period 1960-1969 (1 = yes)	.208	0.415	0	1	.059	0.237	0	1	.036	0.186	0	1
Construction period 1970-1979 (1 = yes)	.083	0.282	0	1	.124	0.330	0	1	.071	0.259	0	1
Construction period 1980-1989 (1 = yes)	.042	0.204	0	1	.231	0.423	0	1	.054	0.226	0	1
Construction period 1990-1999 (1 = yes)	.042	0.204	0	1	.172	0.378	0	1	.071	0.259	0	1
Construction period >2000 (1 = yes)	.125	0.338	0	1	.102	0.304	0	1	.161	0.369	0	1
Type Apartment (1 = yes)	.167	0.381	0	1	.333	0.473	0	1	.536	0.501	0	1
Type Semidetached (1 = yes)	.208	0.415	0	1	.07	0.256	0	1	.018	0.133	0	1
Type Terraced (1 = yes)	.333	0.482	0	1	.457	0.499	0	1	.348	0.479	0	1
Type Detached (1 = yes)	.167	0.381	0	1	.011	0.103	0	1	0	0.000	0	0
Type Corner (1 = yes)	.125	0.338	0	1	.129	0.336	0	1	.098	0.299	0	1
Number of obs.	**24**				**186**				**112**			

Note: This table denotes the descriptive statistics for the target group per municipality of the dependent variable *transaction price*, independent variables *property characteristics*, and *flood probability*. Other variables are not presented. For all dummy variables, the number represents the percentage relative to 1.0. *Mean*: Average value; *St. Dev.:* Standard deviation; *Min.:* Minimum value; *Max.:* Maximum value.

TABLE 5: Descriptive statistics of the control group (high probability = 0)

	VALKENBURG A/D GEUL				MAASTRICHT				DORDRECHT			
Variable	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Transaction price	356,609.2	127,364.366	145,000	895,000	343,589.84	143,956.995	127,000	908,000	301,458.99	127,722.415	128,000	920,000
Property characteristics												
Floor area	155.988	57.282	59	332	127.595	51.173	24	345	110.19	40.684	31	347
Parcel size	427.02	368.640	0	1,740	166.838	193.136	0	1,810	118.833	121.672	0	1,447
Construction period < 1940 (1 = yes)	.215	0.412	0	1	.192	0.394	0	1	.305	0.460	0	1
Construction period 1940-1959 (1 = yes)	.187	0.391	0	1	.104	0.305	0	1	.067	0.251	0	1
Construction period 1960-1969 (1 = yes)	.155	0.363	0	1	.197	0.398	0	1	.145	0.352	0	1
Construction period 1970-1979 (1 = yes)	.175	0.381	0	1	.199	0.400	0	1	.167	0.373	0	1
Construction period 1980-1989 (1 = yes)	.108	0.310	0	1	.103	0.303	0	1	.1	0.301	0	1
Construction period 1990-1999 (1 = yes)	.068	0.252	0	1	.134	0.341	0	1	.119	0.324	0	1
Construction period >2000 (1 = yes)	.092	0.289	0	1	.071	0.257	0	1	.096	0.295	0	1
Type Apartment (1 = yes)	.179	0.384	0	1	.343	0.475	0	1	.3	0.458	0	1
Type Semidetached (1 = yes)	.271	0.445	0	1	.081	0.273	0	1	.044	0.206	0	1
Type Terraced (1 = yes)	.179	0.384	0	1	.394	0.489	0	1	.489	0.500	0	1
Type Detached (1 = yes)	.255	0.437	0	1	.036	0.187	0	1	.023	0.151	0	1
Type Corner (1 = yes)	.116	0.320	0	1	.146	0.353	0	1	.144	0.351	0	1
Number of obs.	**251**				**1,521**				**2,171**			

Note: This table denotes the descriptive statistics for the control group per municipality of the dependent variable *transaction price*, independent variables *property characteristics*, and *flood probability*. Other variables are not presented. For all dummy variables, the number represents the percentage relative to 1.0. *Mean*: Average value; *St. Dev.:* Standard deviation; *Min.:* Minimum value; *Max.:* Maximum value.

3.4 Methodology

To perform a regression analysis correctly, all variables must be distributed in their best way. As seen in Figure 5, this does not count for the dependent variable *transaction prices* as the variables are highly right-skewed. This causes a non-linear relationship between the independent and dependent variables. Therefore, this variable is transformed into a logarithmic function, which is a common practice in housing market research (Zhang, et al., 2020). In Appendix III the normal distribution of the logarithmic function per municipality is visualized.

To determine the effect of flooding on housing prices, a difference-in-difference hedonic price model is composed. The general log-linear formula (1) can be formulated as

$$\log(P_{itn}) = \beta_0 + \beta_1 Target_i + \beta_2 Post_i + \beta_3 Target_i \times Post_i + \delta X_i + \alpha_t + \gamma_n + \epsilon_{itn} \qquad (1)$$

Where $\log(P_{itn})$ is the log of the transaction price of property i, at time t in neighborhood n. $Target_i$ is a dummy that reflects whether property i is in the target area (with a high probability) or not. $Target_i$ equals 1 if property i is in the target area, if not it equals 0. It captures the difference between transaction prices between properties located in the target area and those in the control area. $Post_i$ is a dummy variable indicating whether property i is sold after the flooding event or not. $Post_i$ equals 1 if property i is sold after the flooding, 0 otherwise. $Target_i \times Post_i$ is of main interest as it represents the interaction between $Target_i$ and $Post_i$. It equals 1 if property i is located in the target area and is sold after the flooding event, and 0 if it is located in the control area and sold before the flooding. For property characteristics are accounted in δX_i, where X_i is a vector of property characteristics: *floor area, parcel size, construction period,* and *housing type*. δ is the coefficient of this vector variable. α_t is a fixed effect for the month of sale to account for seasonal market changes, and γ_d is a fixed effect for each neighborhood that absorbs regional differences. ϵ_{itd} is the error term of the regression model. The coefficient measures the external effect of the flooding event on transaction prices in the target area. β_{1-3} are the estimated coefficients.

Multiple models are used to search for the existence of external impacts of flood risk on housing prices. In Table 6, different applied models are shown and are constructed by adding variables that increase the explanatory effect on the transaction price. Model 0 is there to control for all other effects except for risk probability. In Model 1 only the key variable *high probability* is included in the model. In Model 2 only all property characteristics are added and in Model 3 location and time fixed effects are included. In Model 4 the covariances are clustered to prevent any heteroscedastic errors due to non-constant standard deviations of independent variables.

TABLE 6: Overview of difference-in-difference regression model

Variable	Model 0	Model 1	Model 2	Model 3	Model 4
Target	No	Yes	Yes	Yes	Yes
Post	No	Yes	Yes	Yes	Yes
Target × Post	No	Yes	Yes	Yes	Yes
Covariance type	Nonrobust	Nonrobust	Nonrobust	Nonrobust	Cluster
Property characteristics	Yes	No	Yes	Yes	Yes
Location fixed effect	Yes	No	No	Yes	Yes
Time fixed effect	Yes	No	No	Yes	Yes

Note: This table denotes the variables that are included in models 0-4. The final Model 4 corresponds with the log-linear equation and represents key results.

4. RESULTS AND DISCUSSION

In this chapter, the regression results of the difference-in-difference hedonic pricing model are presented. The model investigates whether the probability of flooding affects housing prices before and after a flood. First, the results for testing the first and second hypotheses (H1, H2) are discussed, whereafter the subsamples per region are interpreted to test for the third hypothesis (H3). The target area entails all residential properties with a flooding probability greater than 1/3,000, the control area covers all properties with a probability smaller than 1/3,000. For finding an answer to the research questions, a comparison between literature and empirical results of this is made.

4.1 Effect of flooding risk on residential property prices

In Table 7 the regression results are shown. Column (4) reports the results from the most complete and preferred specification, which includes all relevant variables and is controlled for time- and location-fixed effects. To conclude whether H1 can be justified, it is necessary to look at key variable $Target_i$. This shows that transaction prices for properties in the target area before the flood were 9.5% ($= (exp^{(0.091} - 1) \times 100\%)$) higher than those in the control area. As these are significant at a 5% level, this means that there is a significant price difference measurable between the target area and the control area before the flood. In other words, residential properties in a flood-prone area were sold with a higher value on average than those in a safe area. Subsequently, as the adjusted R^2 indicates the explanatory power of the model this value should be as close as possible to 1. Model 4 reports an adjusted R^2 of 75.8%. This suggests that regardless of the probability of inundation in the future, consumers are willing to buy a premium for such properties. However, other relevant variables that are currently excluded could be added to maximize this value.

This result allows formulating an answer on RQ2: *“What is the quantitative empirical pricing effect for a residential property located in a flood-prone area?”* The result from the regression model is contrary to what previous literature about flooding risks has found because instead of a premium a discount would be expected (Beltrán, et al., 2018; Bin, et al., 2008). An explanation of this effect could be in line with what Rajapaksa et al. (2017) found in their study. Because properties in a flood-prone area are located close to the water, the price premium that consumers are willing to pay outweighs the associated risk.

As this study not is corrected for proximity to water but only for neighborhood-specific variables, the regression results of this study cannot provide a definitive answer to this suggestion. Future research is needed to investigate what causes this effect.

TABLE 7: Difference-in-difference regression results

Variable	(1)	(2)	(3)	(4)
Target	0.137***	0.0924***	0.0910***	0.0910**
	(0.0299)	(0.0173)	(0.0156)	(0.0358)
Post	0.0997***	0.112***	0.195***	0.195***
	(0.0122)	(0.00705)	(0.0105)	(0.0101)
Target × Post	-0.0400	-0.0333	-0.0526**	-0.0526
	(0.0447)	(0.0257)	(0.0224)	(0.0394)
Constant	12.56***	11.85***	12.17***	12.17***
	(0.00824)	(0.0134)	(0.0202)	(0.0357)
Covariance type	nonrobust	nonrobust	nonrobust	cluster
Property characteristics	NO	YES	YES	YES
Location FE	NO	NO	YES	YES
Time FE	NO	NO	YES	YES
Adjusted R-squared	0.021	0.677	0.758	0.758

Note: This table denotes the results of the difference-in-difference regression model. The dependent variable is the logarithm of the *transaction price.* Property characteristics include *floor area, parcel size, construction period,* and *housing type.* Location fixed-effects (FE) are based on a neighborhood level. Time fixed effects (FE) include *sales date* on the year-quarter level. The standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.2 Effect of a flood event on residential property prices

To justify if H2 is based on significant results, the interaction variable $Target_i \times Post_i$ is of interest. $Target_i \times Post_i$ represents the external effect if property i is located in the target area and is sold after the flooding event. Results show that the flood caused on average a -5.4% decrease in residential property prices when comparing those properties to properties in the control area, but it is non-significant. This indicates that properties sold after the flood and located in a high-risk zone are valued lower than those with a low flood probability, but it cannot be concluded whether this is due to the event itself or pure coincidence.

This result enables to answer RQ3: *"What is the quantitative empirical pricing effect after flooding for a residential property located in a flood-prone area?".* The difference-in-difference model shows that housing prices in an area with a high flood probability are sold for less than properties with a low flood probability. The depreciation of value is in line with what theory suggests, as average prices in other studies are proven to have declined after inundation (Bin & Polasky, 2004; Belanger & Bourdeau-Brien, 2017). However, because significance cannot be determined no firm conclusions can be drawn.

4.3 Effect of a flood event on residential property prices between regions

As literature proves that the magnitude of impact is of high influence to the extent that depreciation occurs, regional differences must be considered. Table 8 shows the regression results for three subsamples separately. When distinguishing municipalities, some interesting results emerge regarding Model 4. Whereas in the overall regression model variable $Target_i$ showed a significant effect, this is not the case for the regions individually. In Dordrecht, transaction prices for properties in a flood-prone area before the inundation were 13.1% higher compared with those in a low-risk area. For the other two regions, no significant effect is observed.

The main variable of interest $Target_i \times Post_i$ shows that for Valkenburg a/d Geul, properties with the same characteristics were sold for -12.4% less after the flood, but show no significant results. For Valkenburg a/d Geul, the regression analysis reports an R^2 of 63.3%, which makes it questionable if the model fits the data well. This could be explained by the low amount of transactions (24) in the target area, whereof only 45,8% (11) occurred after the flood. As the subsample size is too small, the measured effect is underpowered and therefore cannot be rejected. Maastricht reports significant results at a 5% level. In Maastricht after the flood transaction prices in flood-prone areas have dropped by -9.4% compared with properties with a low probability of flooding, reported with an explanatory power of 73.3%. On the other hand, in Dordrecht after the flood in Limburg, a significant positive effect of 4.4% is reported for properties that have a high likelihood of possible inundation. When looking into the R^2 the model fits best for Dordrecht, which explains 80.7% of the dependent variable.

The results enable to formulate an answer to RQ3: *"What are the regional differences in the pricing effect for a residential property located in a flood-prone area after a flooding?"* As regions were selected by the magnitude of the impact of the flood, it was expected that this had a moderating effect on the manner consumers assess their perceived risk (Beltrán, et al., 2019). Results show great variations between case study areas, whereas Dordrecht – which was not affected – reported no pricing discount in property valuations, but even a slight price increase. On the other hand, residential property prices in Maastricht – a region in a critical situation during the flood – dropped for houses in a flood-prone areas after the flood. For the heavily impacted region Valkenburg, no significant results were found, but the possibility of effect must be retained as not enough observations were included. For properties in regions that experienced or were near a flood, like the Limburg municipalities, a depreciation of housing prices has been observed. Properties in the region of Dordrecht, which has the same probability of flooding, but was not affected or near the flood, reported no discount but even a premium instead. The magnitude of impact has a moderating effect on the extent to which a value is attached to flood probability and therefore is essential when investigating flood risk effects. This corresponds to literature that found that the pricing effect is highly location-specific due to the extent the flood-impacted the region (Sirmans, et al., 2005).

TABLE 8: Difference-in-difference regression results per region

Region	Variable	(1)	(2)	(3)	(4)
	Target	0.159	0.0903	0.101	0.101
		(0.0987)	(0.0639)	(0.0653)	(0.0841)
	Post	0.201***	0.142***	0.251***	0.251**
		(0.0431)	(0.0284)	(0.0485)	(0.0657)
	Target × Post	-0.320**	-0.117	-0.132	-0.132
		(0.146)	(0.0957)	(0.0962)	(0.188)
Valkenburg	Constant	12.63***	11.93***	11.86***	11.86***
		(0.0292)	(0.0625)	(0.0724)	(0.0507)
	Covariance type	nonrobust	nonrobust	nonrobust	cluster
	Property characteristics	NO	YES	YES	YES
	Location FE	NO	NO	YES	YES
	Time FE	NO	NO	YES	YES
	Adjusted R-squared	0.067	0.623	0.633	0.633
	Target	0.108***	0.0812***	0.0795***	0.0795
		(0.0398)	(0.0244)	(0.0215)	(0.0531)
	Post	0.0966***	0.104***	0.173***	0.173***
		(0.0199)	(0.0121)	(0.0173)	(0.0143)
	Target × Post	-0.0488	-0.0527	-0.0894***	-0.0894**
		(0.0606)	(0.0367)	(0.0314)	(0.0301)
Maastricht	Constant	12.63***	11.97***	12.23***	12.23***
		(0.0133)	(0.0279)	(0.0294)	(0.0440)
	Covariance type	nonrobust	nonrobust	nonrobust	cluster
	Property characteristics	NO	YES	YES	YES
	Location FE	NO	NO	YES	YES
	Time FE	NO	NO	YES	YES
	Adjusted R-squared	0.004	0.626	0.737	0.737
	Target	0.104**	0.137***	0.123***	0.123**
		(0.0500)	(0.0251)	(0.0235)	(0.0460)
	Post	0.0973***	0.122***	0.211***	0.211***
		(0.0161)	(0.00800)	(0.0127)	(0.0117)
	Target × Post	0.0302	0.0313	0.0435	0.0435***
		(0.0727)	(0.0361)	(0.0328)	(0.0111)
Dordrecht	Constant	12.50***	11.74***	11.86***	11.86***
		(0.0111)	(0.0154)	(0.0209)	(0.0344)
	Covariance type	nonrobust	nonrobust	nonrobust	cluster
	Property characteristics	NO	YES	YES	YES
	Location FE	NO	NO	YES	YES
	Time FE	NO	NO	YES	YES
	Adjusted R-squared	0.020	0.759	0.807	0.807

Note: This table denotes the results of the difference-in-difference regression model per municipality. The dependent variable is the logarithm of the *transaction price.* Property characteristics include *floor area, parcel size, construction period,* and *housing type.* Location fixed-effects (FE) are based on a neighborhood level. Time fixed effects (FE) include *sales date* on the year-quarter level. The standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.4 Sensitivity analysis

When constructing regression models, it is important to test the validity of the identifying assumptions made and therefore verify the robustness of the baseline model. A problem that could occur is multicollinearity, in which the independent variables are found to be correlated. This can lead to skewed or misleading results and therefore the regression results would not be accurate. Therefore for every independent variable included in the regression model the variance inflation factor (VIF) is calculated and is presented in Table 9. From this, no variables are found that are highly correlated and therefore no multicollinearity is observed.

TABLE 9: Variance inflation factor

	VIF	1/VIF
Target	1.993	.502
Post	3.248	.308
Target × Post	1.921	.521
Living area	1.978	.506
Lot size	3.041	.329
Type Apartment	1.867	.536
Type Corner	1.195	.837
Type Detached	1.65	.606
Type Semidetached	1.321	.757
Construction period 1940-1959	1.462	.684
Construction period 1960-1969	2.077	.482
Construction period 1970-1979	2.155	.464
Construction period 1980-1989	1.871	.535
Construction period 1990-1999	1.806	.554
Construction period >2000	1.408	.71
Mean VIF	1.865	.

Note: This table denotes the variance inflation factor per independent variable. The variables *construction period <1940* and *Terraced house* are used as reference variables and therefore not included. A VIF value of 1 indicates that two variables are not correlated, a value between 1 and 5 indicates a moderate correlation and a value above 5 indicates a high correlation.

Another robustness check is to reassess the assumption on which the target area is specified. In the baseline model, the assumption was made that a flood probability larger than 1/3,000 years was neglectable. However, this probability could have an effect that would not be measured in the baseline model. Therefore, all properties with a probability of flooding between 1/3,000 and 1/30,000 (*very small risk* = 1) are included in the new specification of the variable *high probability*. In other words, the target area is enlarged to check if this assumption is neglectable or not. Shifting the target area enables to determine if the baseline model is robust. Table 10 shows the regression results of the alternative target area per region.

TABLE 10: Difference-in-difference regression results of the alternative specification

Variable	VALKENBURG A/D GEUL	MAASTRICHT	DORDRECHT
Target	0.101	0.00348	-0.0626**
	(0.0841)	(0.0493)	(0.0252)
Post	0.251**	0.174***	0.221***
	(0.0657)	(0.0189)	(0.0329)
Target × Post	-0.132	-0.0369	-0.00767
	(0.188)	(0.0256)	(0.0311)
Constant	11.86***	12.24***	11.96***
	(0.0507)	(0.0428)	(0.0280)
Covariance type	cluster	cluster	cluster
Property characteristics	YES	YES	YES
Location FE	YES	YES	YES
Time FE	YES	YES	YES
Adjusted R-squared	0.633	0.737	0.802
Observations	275	1,707	2,283

Note: This table denotes the results of the difference-in-difference regression model for the alternative specified target area. The dependent variable is the logarithm of the *transaction price.* Property characteristics include *floor area, parcel size, construction period,* and *housing type.* Location fixed-effects (FE) are based on a neighborhood level. Time fixed effects (FE) include *sales date* on the year-quarter level. The standard errors are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

As observed the key variable $Target_i \times Post_i$ shows no significant results for every individual case study area. For Valkenburg a/d Geul the results are the same as for the baseline model because no transaction observations fall in the category of *very small risk* as seen in Table 2. For Maastricht and Dordrecht a depreciation of -3.6% and -0.8% respectively is found, but it is not a significant effect. It can be concluded that for the redefined target area, property prices in a flood-prone area do not significantly differ from properties in safe areas after a flood. Based on this sensitivity analysis suggests that the regression results from the baseline model are quite robust.

5. CONCLUSION

5.1 Main results

This study examines the pricing effect of flooding risk on property values after a flood. Due to climate change awareness around this subject is rising. It has impacts on the current built environment, future spatial planning processes, and real estate markets. Therefore, the main research question is as follows:
"To what extent does a flooding event affects residential property pricing in a flood-prone area?"

Floods cause major damage to affected properties and as such are valued lower. This research argues that the growing probability of these events has an effect on where people are willing to live and it is reflected in the transaction price. Based on literature it is expected that a recent flood strengthens awareness and accelerates depreciation. By analyzing transaction prices in three high-risk areas in the Netherlands between 2020 and 2022 the empirical effect is tested. A difference-in-difference hedonic price model is proposed to compare residential property prices between target and control areas before and after a flood. Contrary to what is expected houses in flood-prone areas sold for higher sales prices than those in safe zones before the flood. Furthermore, the magnitude of flood impact has a moderating effect on the extent to the strength of house pricing discounts after this event. For properties in a non-affected region, no depreciation was found. Properties in a flood-prone area where the situation was critical, but no economic damage occurred, were valued at 9.4% less compared with the period before the flood. Due to a small number of observations, no significant effect could be found for the highly affected region.

5.2 Limitations & further research

This study encountered multiple constraints that affected the process of investigating the subject. The first one is the short investigated period. The flood only had taken place recently, which resulted in transaction prices being limited available. This had mainly consequences for the regression analysis of the municipality of Valkenburg a/d Geul. As this is a municipality in a rural area already a lower amount of observations was obtained compared to the urban areas of Maastricht and Dordrecht. When selecting the transaction units that are entailed in the target group only 24 observations remained. This had a major impact on the explanatory power of the regression analysis which caused no significant conclusions could be drawn. Further research could be suggested to broaden the investigated period. When examining a larger period this offers the opportunity to investigate if trend effects occur. It could be assumed that potential pricing discounts are greater directly after a flood than five years later. To broaden knowledge about the financial consequences of climate change it is interesting to study if depreciation still occurs after a longer period. Furthermore, enlargement of the case study area is an opportunity to check whether the results can be generalized to other areas. Based on this study it cannot be concluded that the same effect also occurs for regions with the same characteristics. This is related to the consideration of attaching a value for the magnitude of impact. In this study, case study areas are subjectively selected based on historical events and supporting reports. However, as found that the degree of impact had a moderating effect, there is no quantitative value defined for this variable. Future research could investigate what the exact moderating effect is by for instance incorporating the amount of damage per region. Only including economic damage would not be sufficient. Inhabitants also could suffer emotional damage as a result of experiencing a (near) flood which is hard to express in euros.

Second, must be noted that this research and risk assessment is based on flood probability models provided and used by the government. With current predictions or worsening future scenarios, flood prediction models are subject to change. Climate-change effects estimations are highly unpredictable and are based on different scenarios. Flood hazard mapping only provides a snapshot at a given point in time. Therefore it is likely that the pricing effects found in this research are underestimated, as research previous literature found (Ortega & Taspinar, 2018). It is highly recommended to perform this research more often as flood probabilities will change.

Finally, what has not been mentioned before is the constraint of using a difference-in-difference approach. The main challenge when identifying causation is to make the right comparison. By using this method, only transaction prices of a property with a given probability are observed. It is unknown what the price of this property would have been if the risk of flooding had been different. That is one of the major disadvantages of using this method, as no correct counterfactual is used. By incorporating property and neighborhood characteristics for the target group and comparing those to properties with similar characteristics in the control group an attempt is made to get the estimated value as close as possible to its true value. This study aimed to make the right distinction but improvement of the regression model is possible. The explanatory power of the model, the value of R^2 is sufficient, but might be better to increase it. Future research could explore if other unobserved variables are needed to add for constructing a better equation. Another way to encounter this problem is to perform a repeat sales analysis to check for the robustness of the model. It assesses the way housing prices change over time for one individual unit. The short period and a low number of observations made it unable to include this analysis in this study.

5.3 Policy implications

The effects of climate change are only recently visible resulting in a lack of large-scale studies. Even though it is hard to generalize study results for other regions in the Netherlands, it gives first insights into the way climate risks are priced into property values. The likelihood that countries will face extreme weather conditions and rising sea levels is rising and therefore affects spatial planning decision-making. It is important to start the debate about climate adaptation and the way countries organize their public housing. Governments could draw attention to the risks of living in a flood-prone area and should adapt their planning processes accordingly. Houses are built to accommodate residents for several decades and that is why it is wise to investigate if this is still feasible in the future. Based on this study questions could be raised about whether building permits for real estate development in attractive floodplain areas still should be issued. To illustrate, the Netherlands is currently planning to construct 800,000 newly build houses in areas subject to flooding or on wet and soft soil (Havermans, 2021).

Flood risk is also important for an investor with a mortgage portfolio because the value of the collateral could decrease and thus the chance of non-repayment of a residual debt could increase. The estimate of flood risks from an investor’s perspective contains a lot of uncertainty due to the lack of large-scale historical evidence. It could be argued that based on this research investors need to allocate a risk premium for properties with a significantly high flood probability. Another suggestion is to give residents of affected homes space to repair their damaged homes to recover. Mortgage lenders can help residents who find themselves in financial difficulties as a result of the damage, for example by offering a payment break.

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7. APPENDICES

7.1 Appendix I

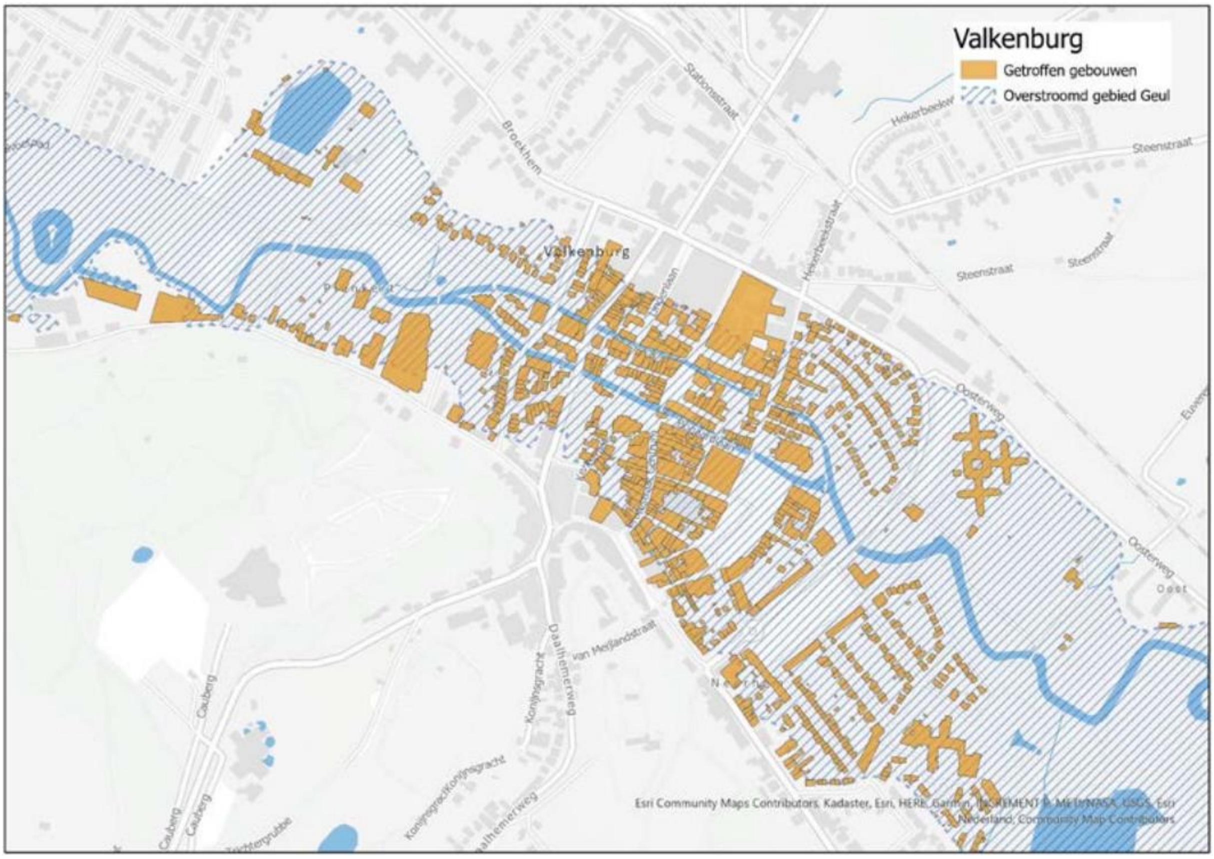

FIGURE 6: Affected and Flooded Areas in Valkenburg from the River Geul

Note: Adapted from *Hoogwater 2021 Feiten en Duiding*, by Task Force Fact-finding hoogwater 2021, 2021.

7.2 Appendix II

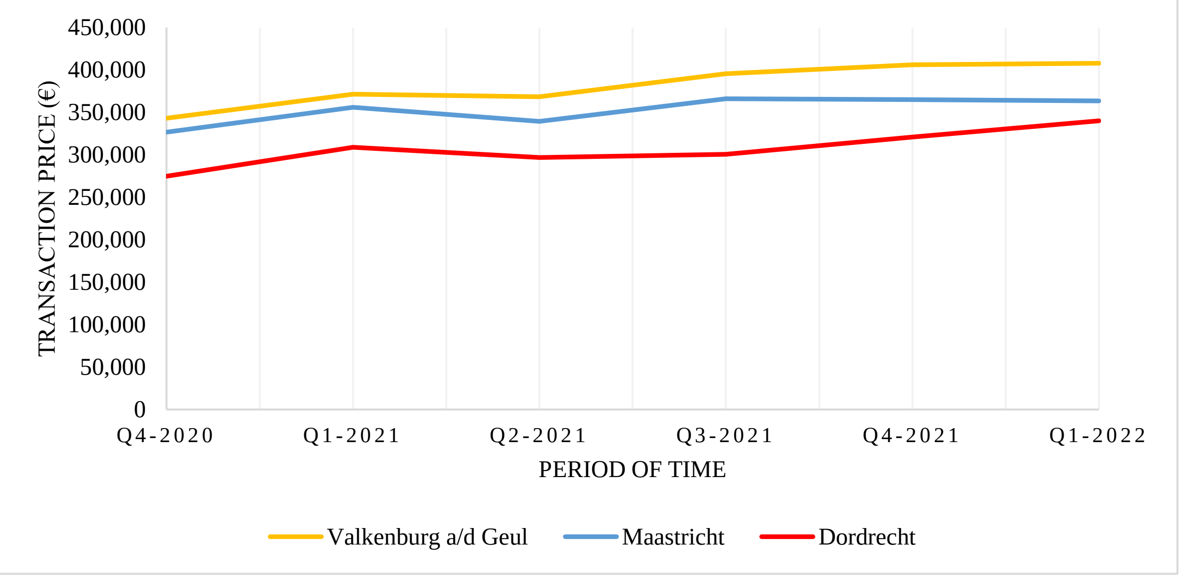

FIGURE 7: Development of average transaction price per quarter per region

Note: Graph denotes that the average transaction price follows the same trend for the three different regions, where the overall average transaction price in Valkenburg a/d Geul is 60,000 euros higher than in Dordrecht.

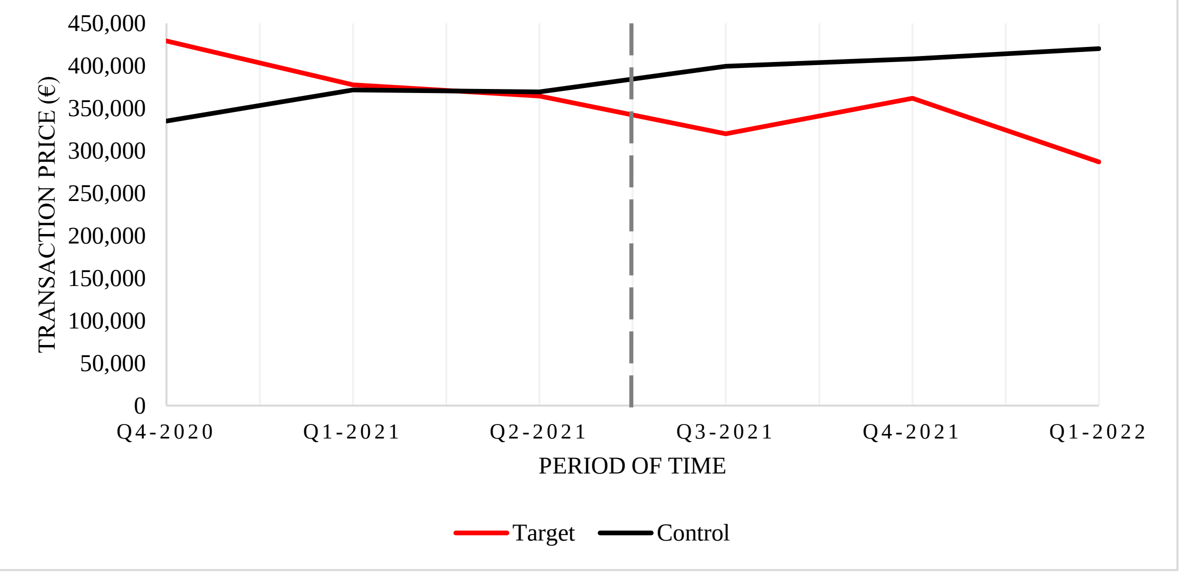

FIGURE 8: Development of average transaction price per quarter in Valkenburg a/d Geul

Note: The grey dashed line indicated the time of flooding. Graph denotes that the average transaction price for the target area follows a down-sloping trend before the flooding in Valkenburg a/d Geul, whereas the prices of the control group are rising. After the flooding, the average transaction price for the target group drops further, whereas the price for the control group continues to follow the upward trend. Due to a small number of observations, the target area line is more erratic.

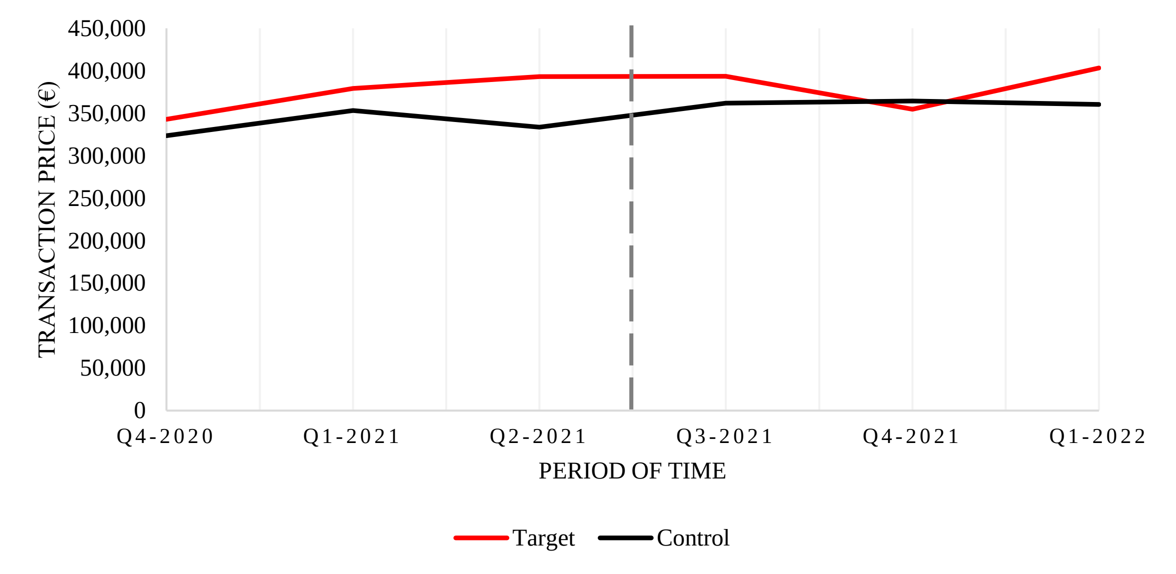

FIGURE 9: Development of average transaction price per quarter in Maastricht

Note: The grey dashed line indicated the time of flooding. Graph denotes that the average transaction price for the target area is higher than for the control area in Maastricht before the flooding. After the flooding, the average transaction price for the target group slightly drops, whereas the price for the control group stabilizes.

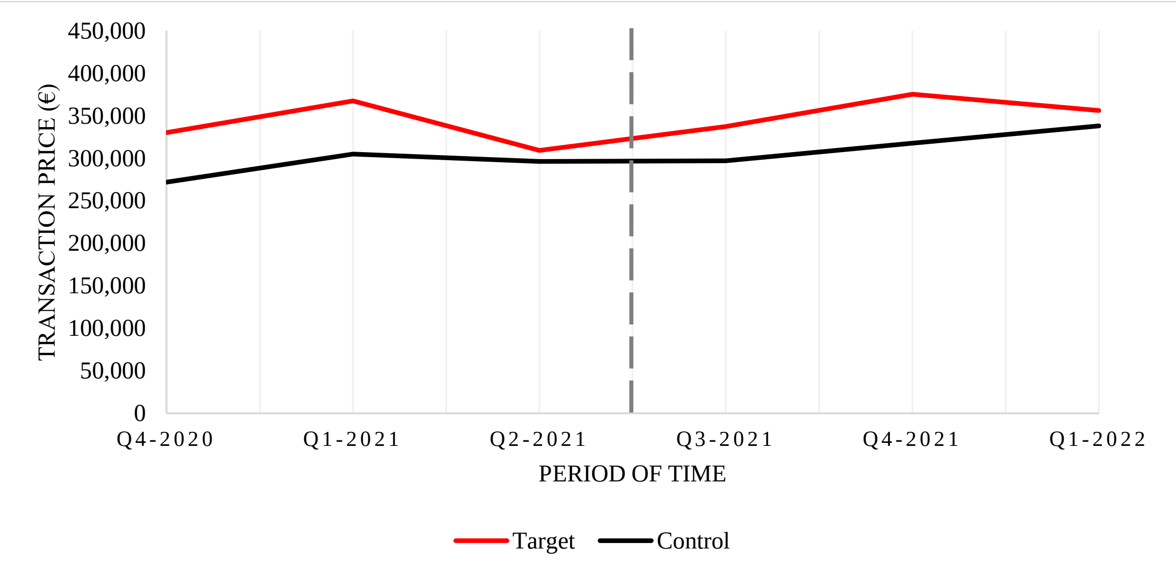

FIGURE 10: Development of average transaction price per quarter in Dordrecht

Note: The grey dashed line indicated the time of flooding. Graph denotes that the average transaction price for the target area is higher than for the control area in Dordrecht. Both lines follow the same trend over time.

7.3 Appendix III

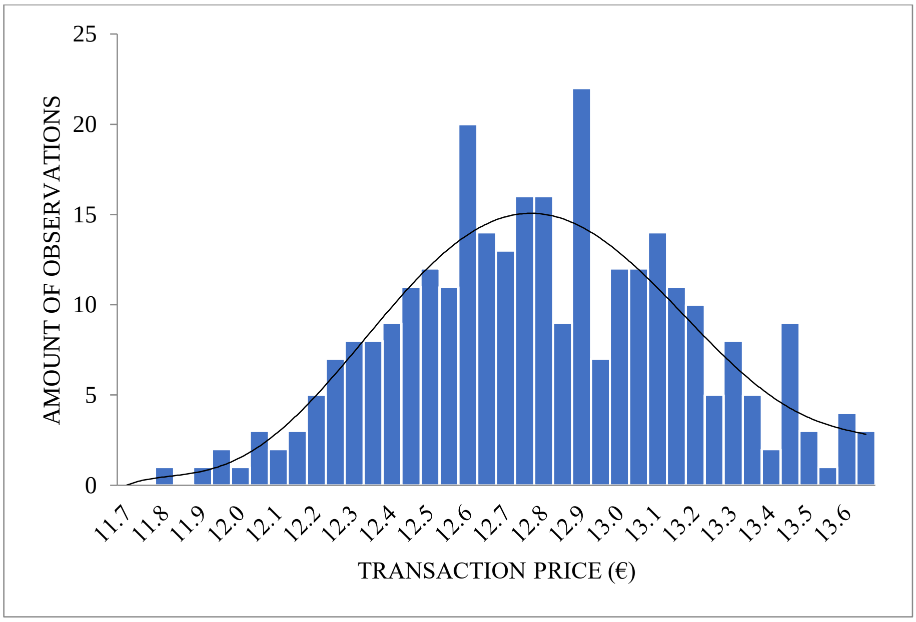

FIGURE 11: Logarithmic distribution of the number of observations by transaction price for Valkenburg a/d Geul
Note: Histogram of the logarithm of dependent variable *transaction price* in euros for Valkenburg a/d Geul. The transaction prices are close to normal distribution.

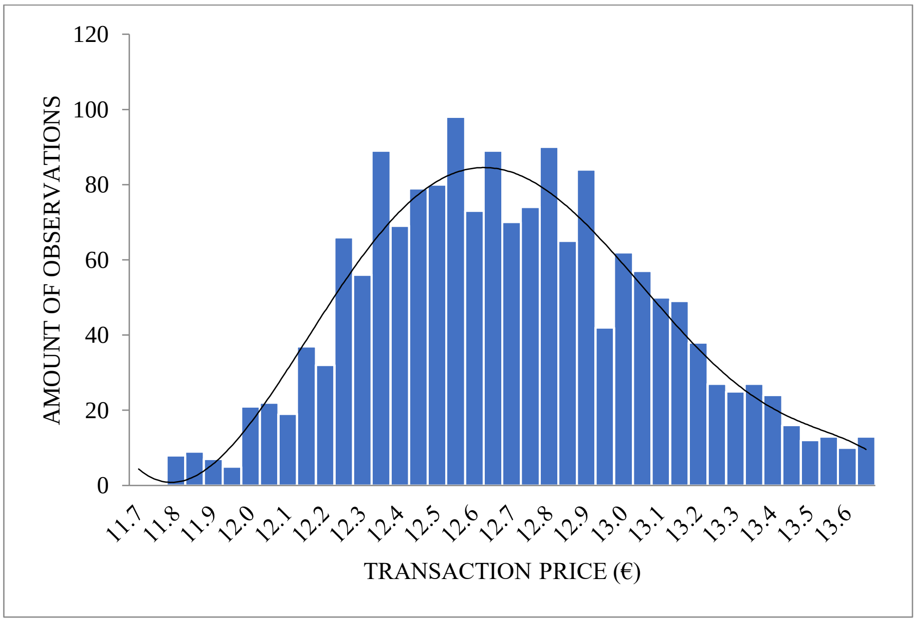

FIGURE 12: Logarithmic distribution of the number of observations by transaction price for Maastricht
Note: Histogram of the logarithm of dependent variable *transaction price* in euros for Maastricht. The transaction prices are close to normal distribution.

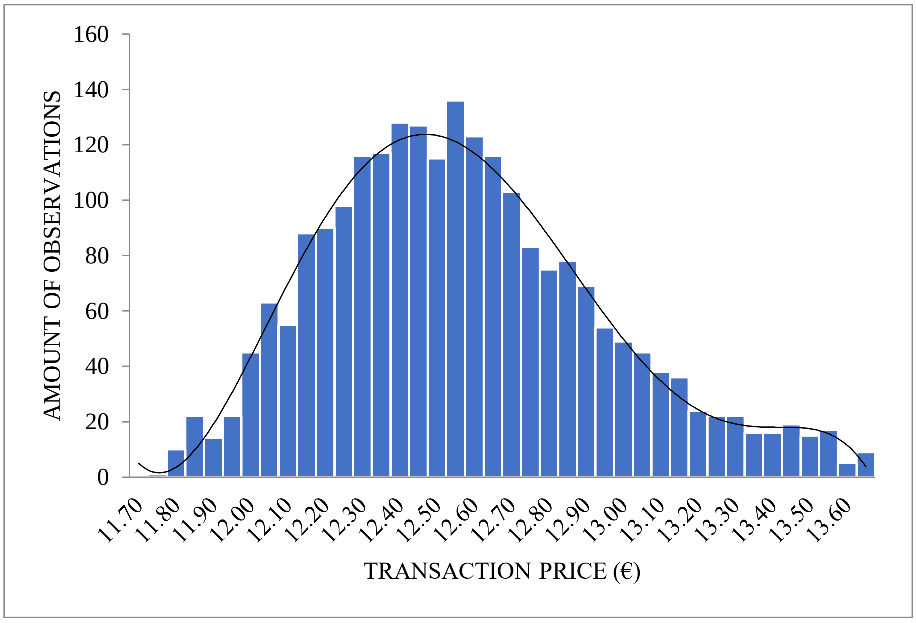

FIGURE 13: Logarithmic distribution of the number of observations by transaction price for Dordrecht

Note: Histogram of the logarithm of dependent variable *transaction price* in euros for Dordrecht. The transaction prices are close to normal distribution.