The relationship between physical climate risks and real estate values

A study on physical climate risks and real estate rents in the Netherlands

Abstract

The climate around the world is changing. Climate change and the associated risks are increasing for real estate. Therefore, the following research question is examined: *"To what extent can a relationship be observed between physical climate risks and the value of real estate?"*. This study uses a unique dataset of 12.213 commercial real estate properties in different segments in the Netherlands, provided by ING Real Estate Finance and Bluelabel. Using a hedonic model, the main findings show that properties with higher rents per square meter are located in areas in high risk areas in terms of drought, heat stress, and pluvial floods are positively correlated with higher rents per square meter. The difference between low and high risks areas for drought is 6.54%, heat stress is 5.02%, and pluvial flood is 7.86%. Fluvial flood has a significant negative correlation with the rent per square meter. A property in an area with high risk has, on average, 7.21% lower rents per square meter in comparison to a property in a low risk area. In addition, using a Chow test, the findings in this paper reveal that the residential and non-residential properties have a significantly different correlation with the physical climate risks. This paper creates the foundation for research into these physical climate risks that increasingly impact the way of living and the value of real estate in the Netherlands. Therefore, this paper should be used as a first start in examining these climate risks and their influence on rent per square meter.

Key words: Physical climate risks, drought, fluvial flood, heat stress, pluvial flood

Colophon

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1. Introduction

1.1 Societal relevance

In the sustainability development goals report of 2022, the United Nations (UN) calls for action. The UN's agenda is in danger, along with humanity's survival itself (UN, 2022). To support the agenda of the UN, the Netherlands aims to reduce greenhouse gas emissions by 80 to 95% compared with 1990 (PBL, 2021). In the Netherlands, the consequences of climate change are becoming more visible and tangible. Recently, the years 2018, 2019, 2020, and 2022 were in the top 5% of most dry years ever recorded. In addition, the recent drought in the Rhine in 2022 and floodings in Limburg in 2021 are examples of these risks. Real estate causes 40% of greenhouse gas emissions (UN environment, 2018), indicating the necessity for increasing action regarding sustainability of the real estate market.

Investors in international real estate markets are increasingly concerned with sustainable investments and the physical climate risks[1] of their real estate portfolio. Physical climate risks can negatively impact the value of real estate. The negative consequences of climate risks for real estate include problems with the foundation, water damage, and increased property deterioration (KNMI, 2022; Financieel Dagblad, 2022). Because of these implications, the question arises whether resilience against physical climate risks can influence the value of real estate. The addition of physical climate risks in the investment decision is needed.

1.2 Academic relevance

Earlier studies examined the influence of climate risks on the value of real estate. The climate risks that these studies cover include drought (Li et al., 2019; Farzanegan, 2020), earthquakes (Keskin et al., 2017), fluvial floods (Bernstein et al., 2019; Miller & Pinter, 2021; Addoum et al., 2021), heat stress (Gabriel & Endlicher, 2011; Chiang & Feng, 2022), hurricanes (Ortega & Taspunar, 2018; Fisher & Rutledge, 2021), landslides (Vranken et al., 2013), pluvial floods (Xue et al., 2016; Mobini et al., 2021), sinkholes (Dumm et al., 2020), and wildfires (Donovan et al., 2007). Climate risks can be divided into severity and probability aspects. The combination is the actual risk related to one of the climate risks. This indicates that physical climate risks have different effects on rent as the impact of an occurrence and the frequency differs per climate risk. Different physical climate risks are relevant to different countries and cities. The physical climate risks of the Netherlands are drought, fluvial floods, heat stress, and pluvial floods (KAN, 2022).

Most of these studies focus on the impact or relationship between one climate risk and the value of real estate in one country or city (Turnbull et al., 2013; Keskin et al., 2017; Ortega & Taspinar, 2018). Few studies focus on multiple physical climate risks, but some studies consider two or more climate risks

[1] Physical climate risks are defined as the physical consequences of a changing climate (Hultman et al., 2010).

(Bunten & Kahn, 2014; Boustan & Kahn, 2020). Additionally, most of the literature focuses on the residential property market. The residential market is partly representative of the whole real estate property market (Clayton et al., 2021; Hirsch & Hahn, 2017; Stanley et al., 2015). Other real estate property market segments should be examined more intensively. The most common segments are logistics, office, residential, and retail. Exceptions that examine the relationship between climate risks and the value of commercial real estate are Addoum et al. (2021), Chiang & Feng (2022), and Sayce et al. (2022). The gap in the literature this research addresses is the lack of research in commercial real estate markets while investigating multiple physical climate risks. This research examines this gap while using data from one of the largest real estate lenders in the Netherlands and the physical climate risks related to their portfolio. This has not been done before in academic literature. The Netherlands specifically is examined because it has a history of being vulnerable to physical climate change such as floodings and the expectation is that these problems caused by climate change will increase (KNMI, 2022).

1.3 Research problem statement

This study aims to analyze the relationship between multiple climate risks and the value of real estate. This research focuses on the gaps by focusing on commercial and separating real estate markets and the relationship with multiple physical climate risks. The central research question is:

"To what extent can a relationship be observed between physical climate risks and the value of real estate?"

To address the main research question, three sub-questions are formulated. First, the literature on physical climate risks will be examined to answer the first sub-question: *"What does theory say about the relationship between physical climate risks and the rental income of real estate?"* Earlier research will be examined, and a framework will be formed to derive a theoretical prediction focusing on the relation between physical climate risks and the value of real estate.

The second sub-question examines the relationship between physical climate risks and the value of real estate in 2020 in the Netherlands. The second sub-question is formulated as follows: *"To what extent can a relationship be observed between the physical climate risks and the rental income of real estate using a cross-section of 2020 bank-lending data for the Netherlands?".* To answer this question, the outcomes of sub-question one will be combined with the data collection of exact locational data and property aspects of the ING database on property level. Next, the dataset of ING REF, in collaboration with Bluelabel will be analyzed using quantitative analysis in the software program Stata. This dataset includes exact locational data from different asset classes in the Netherlands in 2020. Some of the properties are combined in an apartment building. Next to that, part of the portfolio has buildings with different extensions. These factors combined cause these buildings to have the same physical climate risks. The sample of 12,213 properties represents the ING portfolio of 40,000 with a 99% confidence interval in terms of number of loans. The accuracy is higher as the addresses occasionally represent a complex of multiple properties. This dataset contains multiple characteristics of the properties that are examined. The characteristics include postal code, property value, rental income, quality of the tenant, object condition, and climate risk scores for drought, fluvial flood, heat stress, and pluvial flood. The sample used in this research contains data from one point in time, which means the research will focus on cross-sectional analysis.

The third sub-question aims to explore the heterogeneity between different asset classes. The third sub-question is formulated as *"To what extent can a difference be observed between segments in the real estate market and the relationship of physical climate risk and the rental income of real estate in a lender's portfolio in the Netherlands?"* The second sub-question's outcome will be used to answer this question. The relationship is examined by segmenting the dataset using property segments in different categories. The properties are divided into 9,358 residential, 2,096 retail/leisure, 430 offices, 304 industrial, 15 logistics, and 10 hotels. This property data is from 2022.

This thesis consists of five chapters. The next chapter outlines the existing literature to give an overview of the physical climate risks. In the third chapter, the data collection and the descriptive statistics are presented, and the methodology for the quantitative analysis is outlined. The fourth chapter provides the results of the data analysis, the additional analysis, and discusses these findings. The last chapter concludes the research.

2. Theoretical framework

2.1 Property value

The definition of the value of a real estate property is "the estimated amount for which an asset or liability should exchange on the valuation date between a willing buyer and a willing seller in an arm's length transaction after proper marketing where the parties had each acted knowledgeably, prudently and without compulsion" (RICS[2]). In commercial real estate there are multiple ways to value a property, one of the options is discounting the future cash flow to the present value (Brueggeman, 2010). A discount factor is used throughout the years to discount the future cash flow and calculate the present value (Clayton et al., 2009). The rent and the corresponding present value depend on the locational and object-specific characteristics. The income from a property exists of direct and indirect returns. The direct return is the rent. The indirect return is the possible value appreciation during the holding period (Christersson et al., 2015). The appraisal value is not an exact estimation of the value of a property. In fact, the appraisal value can be more than 10% of the transaction value in commercial real estate (Cannon & Cole, 2011). Next to this, the appraisal value is a theoretical valuation, and the rent is a component that is the actual price paid for the use of a property and is a real-life indication of the value (Taipalus, 2006).

The information available for buyers and sellers is an essential indicator of the ability to value the property properly (Harvey & Jowsey, 2004). On the one hand, a seller or landlord has better access to information about possible climate risks from previous experience than buyers or tenants (Pope, 2008). On the other hand, the occurrence of events related to climate risks increases the perceived risk (Atreya & Ferreira, 2015). The perceived probability of an event increases with the availability of information regarding these events (Tversky & Kahneman, 1973). The unavailability of information regarding climate risks causes the real estate market to be inefficient. Next to the unavailability, a reason for information asymmetry could be the heterogeneity in belief in climate change because there is no unanimous consensus over the implications of climate change (Baldauf et al., 2020; Javadi & Masum, 2021).

For investors and tenants the physical climate risks can influence their decisions differently. A different time horizon or the problem with split incentives, which is the difference between the landlord who invests in improving the property and the tenant who benefits from these improvements without increasing the rent (Melvin, 2018). Physical climate risks are interesting for the landlord as it possibly influences future values and rents (Miller & Pinter, 2021; Bernstein et al., 2019; Addoum et al., 2021). Physical climate risks are an important part of the decision for tenants because of a lower energy bill and less convenience, or even damage the health of tenants (Chang & Yi, 2015).

[2] RICS is the Royal Institute for Chartered Surveyors.

2.2 Determinants

Real estate objects have unique characteristics due to the fixed location of the object and the internal characteristics (Wilkinson, 1973). The specific object characteristics are capitalized in the price of an object. The unique internal characteristics of the construction year and the size, combined with the unique locational characteristics, cause the prediction of object prices to be more complex than in homogeneous markets.

The determinants of the price are, in essence, supply and demand. The demand for real estate consists of locational and property characteristics, and the determinants differ for every real estate segment (Ricardo, 1817; Alonso, 1960). The different market segments are competing for the same fixed supply of land. The main segments in the real estate market are offices, logistics, residential, and retail. Offices and retail are expected to be located near the Central Business District (CBD) because these firms need the accessibility to generate a high turnover per square meter. The main drivers of the office market are the availability of jobs, and this market uses agglomeration effects (van der Vlist et al., 2021). Research finds an increased capitalization rate for offices exposed to climate risks (Addoum et al., 2021). For the retail market, footfall is the primary driver, where an increase in the number of potential customers passing the retail property increases the rent. The climate risk, heat stress can impact the footfall commuting to the retail shops and thus impact the rental income of the real estate negatively. Residential occupants make a trade-off between low transportation costs, accessibility, and cheaper land. Homes exposed to climate risks can trade at a discount (Bernstein et al., 2019). However, the research is inconclusive as some studies do not find a significant price difference. For logistics, the distance to the CBD is less important, rather the location in the supply chain and the distance to multiple CBDs are critical (Lockwood & Rutherford, 1996). Next to these determinants, the demand for real estate is uncertain due to climate risks and the potential impact of climate change on the value and desirability of real estate properties. Overall, climate risks can significantly impact the uncertainty in the market and thus influencing the demand for real estate (Bunten & Kahn, 2014; Giglio et al., 2021)

Real estate supply is generally considered to be fixed in the short term, since it takes time and resources to develop new properties and increase the supply. However, in the long term, the supply of real estate can be increased by developing new properties (Evans, 2008). The demand for real estate consists of multiple aspects. The first aspect is economic, meaning that income levels, and employment rates affect the demand for real estate. With higher and more stable incomes and employment rates, households are more likely to have the financial resources to buy a home, leading to increased demand for real estate (Evans, 2008). Secondly, population growth has an impact on the demand for real estate, this means that an increase in the number of people living in an area can lead to an increased demand for housing (Aizenman & Jinjarak, 2009). Thirdly, government policies, such as tax incentives for home ownership, investments or restrictions on development, can influence the demand for real estate (DiPasquale, 1999). The fourth aspect is the interest rates. These affect the demand for real estate by influencing the cost of borrowing. In case of low interest rates, it may be more affordable for investors to borrow money to buy properties, increasing demand for real estate (Geltner et al., 2001). The last aspect is demographics, such as the age of the population. For example, young families with children may have a higher demand for homes with more bedrooms, while retirees may have a higher demand for smaller, more easily maintained homes (Bujang et al., 2010).

2.3 Physical climate risks

Considering the increased climate change and its effect. The research on the impact and the implications for real estate has increased. In case of drought, the groundwater level decreases substantially. This decrease can damage the foundation of old and new properties and thus lower the values (Li et al., 2019). Drought is defined as an abnormal water shortage because of evaporation and a lack of rainfall (Dai et al., 2004). Drought across the world has increased in previous decades, and the prediction is that drought will increase in the future (Sheffield et al., 2012). The increase of hardened surfaces is one of the reasons for the occurrence of drought, which can be a characteristic of urban areas. In reaction to the increase of drought, multiple solutions have surfaced. The amount of water the soil is able to take in has decreased because of the increase in the surface of hardened surfaces. To increase the ability to retain the water on the remaining surface, the preservation of water during periods of rain is essential. Increasing the amount of green improves the soil and decreases water evaporation and the amount of water directed to the sewer (Allen et al., 2020). In cases of drought, the vegetation is negatively impacted by drought and increases tree mortality rates and regrowth patterns (Miller et al., 2020). Literature that measures the impact of drought on the value of real estate has yet to be made available. However, many studies find damage to real estate because of drought and indicate that damaged buildings trade at a discount compared to undamaged buildings.

Previous research shows positive and negative effects of flooding on the price of residential real estate (Miller & Pinter, 2021; Bernstein et al., 2019; Addoum et al., 2021). A fluvial flood is defined as a flood that is caused by rising sea or river levels which causes the water to overflow in neighboring land (Neri-Flores et al., 2019). The number of floodings has more than doubled from 1980 to 2013, with the forecast that this increasing trend is continuing in the future (Hirsch et al., 2015). The relationships found between flooding and the value of real estate are not only positive. The properties exposed to fluvial flooding risk are subject to this risk because of the location near a river, lake, or coastal area, which are favorable amenities. The price premium for the water amenity can be higher than the flood risk discount for properties near water. This imbalance possibly causes studies to fail in examining the climate risk discount (Daniel et al., 2009). This is a heuristic approach for a country, where the coastline, rivers, and lakes must be taken into account. This is mainly the adaptability to react to storms and rising water. Multiple studies find lower values for properties vulnerable to floodings, ranging from 3.8% to 21.1% after a flooding (Bin & Polasky, 2004; Sirmans et al., 2005; Bin et al., 2008; Belanger & Bourdeau-Brien, 2017; Beltran et al., 2018).

The return of real estate has a negative relationship with the climate risk heat stress (Chiang & Feng, 2022). Heat stress is defined as the discomfort occurring because of more and more prolonged heat (Chang & Yi, 2015). The number of days with heat has increased in the last decade, and heat waves are estimated to be common in the summer in the 2040s (Taylor et al., 2015). Heat stress is more common in urban areas, where the effect of urban heat islands occurs, exacerbating the temperatures (Gabriel & Endlicher, 2011). Next, heat stress occurs more often in locations with increased sun days and a warmer climate throughout the year. This can be perceived as a premium for the weather aspect and can be seen as an amenity. To tackle heat stress, objects to cool the environment are needed, locations with a lot of hardened surfaces can be cooled with the addition of green. Green is cooling because of shade and less evaporation. Tools such as urban forests and parks score among the highest in fighting heat stress in cities (Pearlmutter et al., 2017). The discount because of heat stress is not measured in previous research, where the negative aspects mainly are discomfort, cooling costs, depreciation of the exterior, and the exact impact has not been found in previous literature.

In areas influenced by pluvial floods, damage occurs to real estate properties, which decreases the value after such an event (Mobini et al., 2021). A pluvial flood is defined as a rainstorm causing waterlogging, where the amount of rain surpasses the capacity of the drainage system (Xue et al., 2016). The rainfall events are increasing in frequency and intensity (Mobini et al., 2021). One of the ways to improve resilience against pluvial floods is increasing vegetation, such as green parks and urban forests. This causes the peak of rainfall to slowly drain to the system instead of entering the sewer directly and thus relieving the high stress on the capacity of the drainage systems. More urban areas have less vegetation and inner cities tend to have fewer parks and more hardened surfaces, which decreases the ability to drain the water slowly. The discount for pluvial flood risk is theoretical and has not yet been examined in previous literature.

The literature above addresses the first sub-question: *"What does theory say about the relationship between physical climate risks and the value of real estate?"* Previous research shows that the physical climate risks negatively affect real estate value. However, some climate risks have a positive relationship with the value of real estate as there is a price premium for the amenities for living in the city center or near water bodies. The risks of the four climate risks examined in this research are experienced as more impactful based on the past rather than the risk in the future.

2.4 Hypotheses

This study aims to examine the relationship between physical climate risks and the value of real estate properties. This research focuses on the gaps in prior literature. Prior literature focused mainly on the residential real estate market, while this thesis examines commercial real estate. This means that next to the first hypothesis, in this research a separate hypothesis and analysis are performed on commercial real estate. These three hypotheses are stated below.

Hypothesis 1: *"physical climate risks have a negative relationship with the rental income of real estate"*

Hypothesis 2: *"The relationship between physical climate risks and the rental income of real estate varies with the type of physical climate risk"*

To address the third sub-question, the dataset is divided into multiple real estate market segments. These segments are used to identify if the relationship between the physical climate risks and the value of real estate properties are different across the segments. To answer this question, the following hypothesis is formulated:

Hypothesis 3: *"The relationship between physical climate risks with the rental income of real estate varies per segment"*

3. Data & Methodology

3.1 Context

As discussed in previous chapters, the Netherlands is facing increasing climate risks in the form of drought, fluvial floods, heat stress, and pluvial floods (KAN, 2022). According to prior literature, this leads to lower values for real estate. Some risks are longer prevalent in the Netherlands, where 26% of the Netherlands is below sea level, and 59% of the Netherlands is vulnerable to high water levels and storms while the sea level is rising. The number of tropical days increased from 1 to 5 per year compared to 1900. The warm days increased from 10 to 25 (KNMI, 2022). The amount of rain increased from 750mm to 900mm per year (KNMI, 2022), and the number of extreme rainfall events has increased from 5 to 10 (KNMI, 2022). The frequency of climate risks is increasing, and this trend is expected to continue in the future. Currently, there is no legislation for mapping or mitigating physical climate risks. For different sustainability aspects of real estate in the Netherlands, legislation is currently in development or is set in motion[3]. Regarding the future, possible legislation could become prevalent in case of the increasing climate risks and the impact this has on real estate in the Netherlands.

3.2 Data

To analyze the relationship between physical climate risks and the rental income of investors in the Netherlands, the lend portfolio dataset of ING Real Estate Finance is used in combination with the physical climate risks dataset from Bluelabel[4]. This merged dataset combines the property and locational characteristics from the portfolio of ING and the climate risk score of these properties. The rent data from ING consists of high-quality rent data because the net rent information is collected from investors. The net rent includes the rent incentives given by landlords to tenants, such as rent discounts or rent-free months. The clients of ING are professional investors with no owner-occupant constructions and corporations where the majority of income is from real estate. This research is the first quantitative analysis of this dataset. ING grants permission to access this dataset. Ethical and privacy issues for investors are considered by anonymizing the dataset. To use this data, a non-disclosure agreement (NDA) was signed which prohibits the sharing of data. In addition, the data was only accessible on a ING laptop using a secure virtual private network (VPN).

The starting dataset consists of 7,546 6-digit postal codes with corresponding data for every climate risk. By connecting the dataset of the ING properties with these postal codes, a total of 14,967 properties have attributed physical climate risks. Combining this dataset with the data from ING provides a suitable dataset for this thesis. The observations are spread across the Netherlands with the majority in the Randstad and the cities in more rural areas. Next to that, the majority of the properties can be categorized as residential, a significant amount is retail/leisure and a small portion is industrial. This

[3] From January the 1st 2023, an office property must have an energy label C or higher.
[4] Bluelabel is a joint venture between Achmea, Royal Haskoning DHV, and Nelen & Schuurmans.

dataset represents the portfolio of one of the largest lenders in the Netherlands. The data available from ING is split up into three datasets. The first dataset contains information regarding the properties. The second dataset contains anonymous information regarding the tenants. The last dataset contains information regarding the BAG ID. These datasets are merged using the internally used object ID by ING to create the dataset used in this research. After dropping missing values for all the variables, a dataset of 12,213 properties remains.

3.3 Dependent variable

The operationalization of the dependent variable, real estate rent, is the gross rental income per year (GRI) per square meter. Research aims to explain the dependent variable using independent variables (Brooks & Tsolacos, 2010). This is the monthly payment the occupant pays the owner for the use of the property. This dataset shows the gross rental income (GRI) per property per year. This is the gross rent collected by the owner and depends on the contract's start date for the property. The rent increase per annum is maximized[5], in contrast, if a new contract is initiated the landlord freely sets the rent (DiPasquale, 1999). This indicates that the starting date of the contract must be included in this regression. In this research, the net GRI per m^2 is used as the dependent variable, which includes discounts or perks given by landlords. The appraisal value is a theoretical value of a property. In contrast, the rent is the actual transferred amount of money for the use of a property. The documentation for loans at ING Real Estate Finance is structured the same for every loan, where the same documents are needed. The rental contract for the tenants can differ slightly, but in the Netherlands the residential tenants are protected by law, which sets the standard for rental contracts. These reasons causes the contracts to be fairly similar and the net rental income used in this research to be calculated in the same way.

3.4 Independent variables

The climate risks are the variables of interest in this research. Each climate risk has a label from a low risk score to a high risk score, respectively A to E[6]. The climate risks are presented on the map of the Netherlands in figure 3.1 to figure 3.4

An overview of the labels is provided in table 3.1. Drought is the depth of the water level around the property in the summer. Where label A is the depth less than 1 meter, label B is between 1 and 2 meters, label C is between 2 and 4 meters, label D is between 4 and 8 meters and label E the water level is higher than 8 meters. Fluvial flood is the height of the water at the house in case of flooding. Label A is less than 20 centimeters, label B is between 20 and 50 centimeters, label C is between 50 and 200 centimeters, label D is between 200 and 500 cm, and label E is higher than 500 centimeters. Heat stress

[5] This is linked to the inflation.
[6] See Appendix B for the division per risk per label.

is the wind chill temperature at a property measured on a day where the average temperature was above 25 degrees Celsius. Label A is less than 38 degrees, label B is between 38 and 40 degrees, label C is between 40 and 42 degrees, label D is between 42 and 44 degrees, label E is higher than 44 degrees. Pluvial flood is the difference between the water level and the threshold height in case of heavy rainfall of 93 millimeters per 70 minutes. Label A is no water, label B is less than 5 centimeters, label C is between 5 and 10 centimeters, label D is between 10 and 23 centimeters, and label E is more than 23 centimeters.

Table 3.1: Overview of the definition of the labels per risk

Label	Drought	Fluvial flood	Heat stress	Pluvial flood
A	No water	<38	< 1m	< 20 cm
B	< 5 cm	38 – 40	1 -2 m	20 – 50 cm
C	5 – 10 cm	40 – 42	2 – 4m	50 – 200 cm
D	10 – 23 cm	42 – 44	4 – 8 m	200 – 500 cm
E	> 23 cm	> 44	> 8 m	> 500 cm

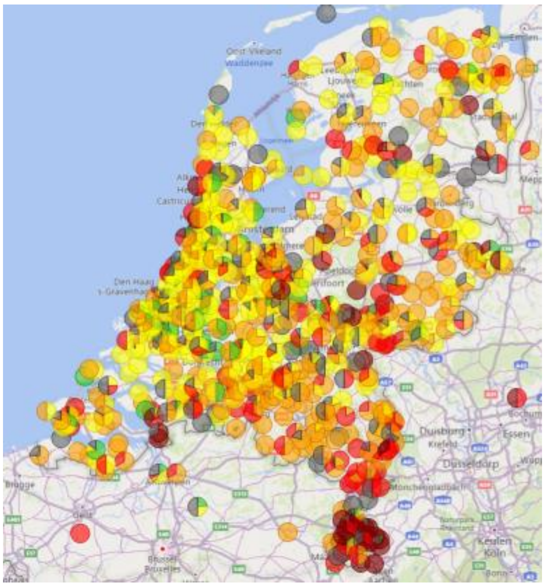

Figure 3.1: Drought in the Netherlands

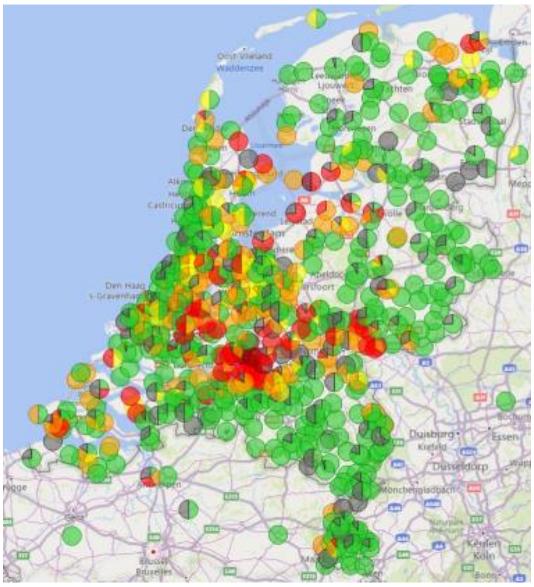

Figure 3.2: Fluvial flood in the Netherlands

Figure 3.3: Heat stress in the Netherlands

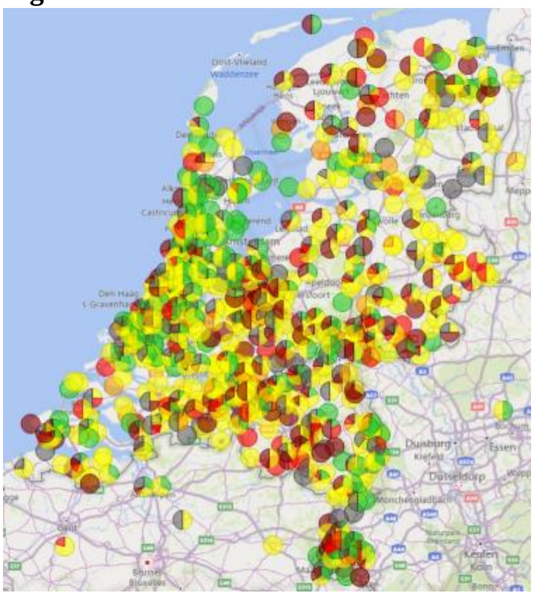

Figure 3.4 Pluvial flood in the Netherlands

Figures 3.5 to 3.8 show the dataset's physical climate risk labels plotted on the city center of Amsterdam. The figures show that some areas of climate risks contain multiple properties and the properties' locations can be near each other in the dataset. In addition, observing the plots, it is remarkable that some low risk (green) areas can be next to high risk (red) areas. For example, the pluvial flood risk label plot in figure 3.8 shows that in some areas properties in the same street can have labels ranging from A to E. This implies that a property can have the same locational amenities, but different physical climate risks. Indicating that a hedonic model is appropriate in this research to determine the differences between the different levels of physical climate risks. The large differences in physical climate risks are examined and explanations can be downward sloping streets or areas with inadequate water drainage.

Not every physical climate risk is fairly distributed in Amsterdam. The overview in table 3.2 presents the labels per physical climate risk in Amsterdam. It is noteworthy that some labels are not well divided and are not evenly distributed. Next to that, in the city center of Amsterdam, the physical climate risks drought and fluvial flood range from label A to C. Combining table 3.2 and figure 3.5 to 3.8, the assumption can be made that it is interesting to analyze the data in Amsterdam.

Table 3.2: Overview labels per physical climate risk in Amsterdam

Label	Drought	Fluvial flood	Heat stress	Pluvial flood	Total
A	120	1,435	72	444	2,071
B	744	74	223	876	1,917
C	764	75	544	45	1,428
D	4	47	445	150	646
E	0	0	347	116	463

Figure 3.5 Drought labels + objects in the city center of Amsterdam

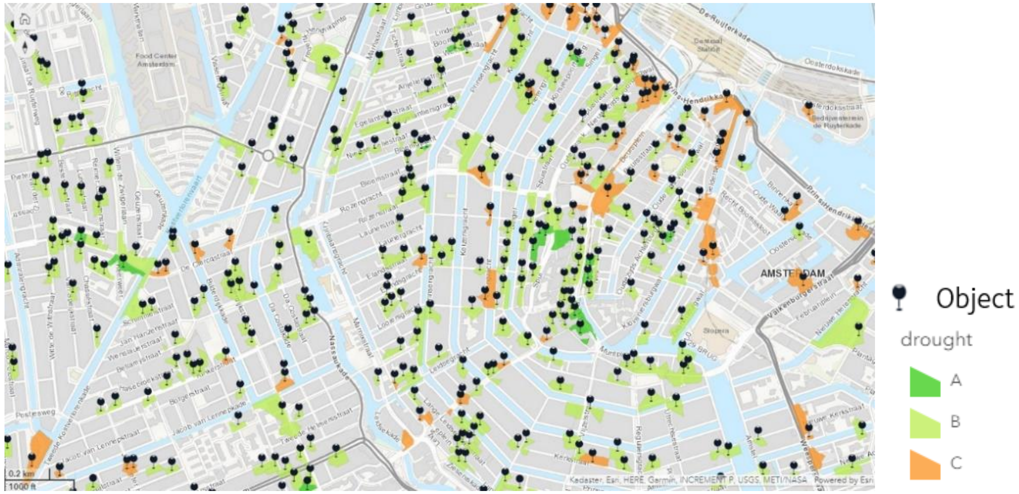

Figure 3.6 Fluvial flood labels + objects in the city center of Amsterdam

Figure 3.7 Heat stress risks labels + objects in the city center of Amsterdam

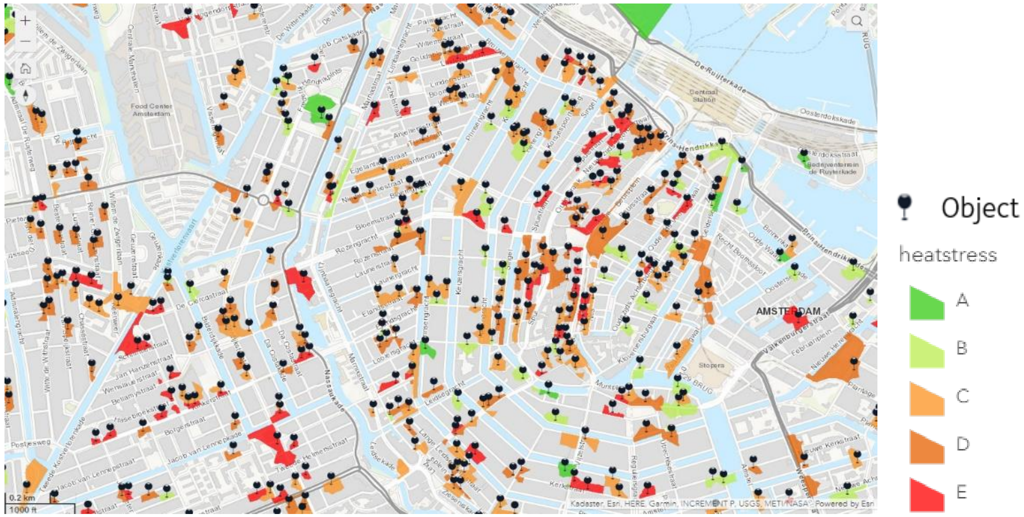

Figure 3.8: Pluvial flood risks labels + objects in the city center of Amsterdam

As discussed before, these variables are not the only factors explaining the value of real estate. The model's explanatory power increases with the addition of additional explaining factors, the control variables. For real estate properties, the control variables consist mainly of locational and individual property characteristics. The property characteristic control variables consist of the age of the building[7], the size, object condition, segments, energy label, tenant quality, and the age of the rental contract, as these are well-known price-determining factors of real estate.

The build year is included as the first control variable in the model. This controls for the effect of the age of a property and helps to isolate the effects of the physical climate risks on the value of real estate. Depreciation of a building is higher in younger buildings and lower in cities with supply constraints (Bokhari & Geltner, 2018). Older properties can be more valuable because of the added value in aesthetics. There are dummies for different building periods, as the influence of the age of a building is a non-linear relationship (RICS, 2020).

The second control variable is the size of the property. The variable size for real estate properties is measured using the usable square meters. The size of a property influences the rent per square meter because the rent per square meter varies with the total surface of a property (Li et al., 2015).

The third control variable is the object condition. The object condition is a combination of multiple aspects where a certified surveyor indicates the condition of an object on a scale from 1 to 7, where 1 is very bad and 7 is very good. The object is ranked on the aspects, structural state, indoor maintenance, outdoor maintenance, parking possibilities on own property, and functionality (RICS, 2020).

The fourth control variable is the zip code. The zip code available in this dataset is specified using six characters. However, for this research, the zip code will be used as a control variable, starting with zip level 1 and increasingly zooming in on the dataset. This thesis uses the zip codes for 1, 2, 3, and 4 numbers. This locational control variable is added to control for the differences between locations and the effect on the rent per square meter. If the properties are closer, the difference in locational effect is less important (Evans, 2008).

The fifth control variable is the segments. The retail and leisure properties are bundled because some properties (retail or leisure) in this dataset were labeled as residential. This problem occurs because a whole building is financed, including retail, or leisure and residential, which causes the software to occasionally label the whole building as residential, retail or leisure. This is solved by looking at the type of tenant. If the tenant is a 'private person', the specific property is residential. If the tenant is a 'non-private person' (a company), this indicates that the property is not residential but retail or leisure.

[7] Age of the building = current year – construction year.

The sixth control variable is the energy label of an object. Due to legislation, a decrease in service charges such as electricity, and an increase in living comfort, the rent per square meter increases with a better energy label (Brounen & Kok, 2011).

The seventh control variable is the quality of the tenant. A tenant's quality impacts the risk for the investor and an increased risk increases the return for the investor to justify the risk. The quality of the tenant is available for non-residential properties as the tenant quality for residential properties is not available and is labeled as 'private person'.

The last control variable is the start year of the rental contract. In the Netherlands, the increase in rent for an existing contract is subject to political decisions (Haffner et al., 2008). However, in case of a new contract in the free rental market in the Netherlands, the landlord can set the rent to market levels. This means that the longer a tenant has a contract, the chance of the rent being below market levels is increased (Haffner et al., 2008).

3.5 Descriptive statistics

Table 3.3 presents an overview of the statistics for the sample in this research. The number of properties used in this research is 12,213. The lowest rental income is 42.55 euros per square meter per year and the highest is 591.41 euros per year. The smallest property in this dataset is 28 square meters and the largest property is 2,569 square meters and is an industrial property. The mean appraisal value is 709,365 euros, the lowest appraised value is 106,737 and the highest is 8,406,928 euros. Remarkably, the oldest building included in this dataset is from 1800. In general, as mentioned before, the value of a building decreases with the age of the building. However, in cases where the property becomes a monument, the age of the building can become a premium instead of a discount. For example, most of the inner city of Amsterdam is included on the list of UNESCO[8] monuments and this is one of the reasons that the value of real estate is higher in the city center of Amsterdam.

Approximately 77% of the dataset is in the residential sector. This indicates that the research is able to focus on the difference between residential and non-residential. However, investigating the difference between multiple segments is impossible as the non-residential properties consist primarily of retail. The other segments have a small sample, complicating the analysis between multiple segments and the generalization of the outcomes.

The distribution of the climate risks in the Netherlands is shown in figures 3.1 to 3.4. The percentage per physical climate risk is presented in table 3.3. Drought and heat stress have a higher mean score,

[8] The canals of Amsterdam were placed on the UNESCO monumental list in 2010.

confirming the ‘red’ impressions from the map of the Netherlands. In contrast, the fluvial and pluvial flood risk have a lower mean, which is represented in a ‘greener’ map of the Netherlands.

The in-depth descriptive statistics per physical climate risks are divided and presented in table 3.3. Drought, fluvial flood, and pluvial flood have the majority of the observations in the high risk category. Heat stress has the majority of the observations in the low risk category. The GRI per year per square meter and the contract age are close to the mean of the whole dataset. The difference in appraisal value between the low- and high risk properties for every physical climate risk is high. The percentage of retail/leisure is higher at the high risk subsamples for drought, heat stress, and pluvial flood. The share of residential is very high for the high risk subsample of fluvial flood.

Remarkable is the high percentage of properties recently built in high risk fluvial flood areas and the low percentage built in high risk fluvial flood areas in earlier days. This could be an explanation for the low number of bad energy labels in the fluvial flood areas with high risk. It is important to note that the physical climate risks are not correlated. The correlation matrix is presented in appendix G.

Table 3.3 Descriptive statistics

	Parameter	Mean	Std. dev.	min	max
GRI per year per m2	€	157.786	985.000	42.546	591.411
Appraisalvaluetotal	€	709,365	1,282,700	106,737	8,406,928
SQM2	m2	190.372	37.140	28	2,569
Contract age	years	9.018	7.334	1	38
Buildyear	years	1958.214	48.908	1800	2018
Segments					
Residential	1 = yes	0.766	0.423	0	1
Retail / Leisure	1 = yes	0.172	0.377	0	1
Office	1 = yes	0.035	0.184	0	1
Industrial	1 = yes	0.025	0.156	0	1
Logistic	1 = yes	0.001	0.035	0	1
Hotel	1 = yes	0.001	0.029	0	1
Tenant quality					
Average	1 = yes	0.035	0.183	0	1
Bad	1 = yes	0.044	0.206	0	1
Good	1 = yes	0.047	0.211	0	1
Private	1 = yes	0.751	0.432	0	1
Vacant	1 = yes	0.025	0.155	0	1
Unknown	1 = yes	0.099	0.298	0	1
Object condition					
Renovation necessary	1 = yes	0.001	0.024	0	1
Very bad	1 = yes	0.000	0.018	0	1
Bad	1 = yes	0.008	0.088	0	1
Moderate	1 = yes	0.330	0.470	0	1
Good	1 = yes	0.613	0.487	0	1
Very good	1 = yes	0.020	0.142	0	1
Without defaults	1 = yes	0.027	0.163	0	1
Energy label					
A	1 = yes	0.216	0.412	0	1
B	1 = yes	0.082	0.274	0	1
C	1 = yes	0.215	0.411	0	1
D	1 = yes	0.132	0.339	0	1
E	1 = yes	0.074	0.262	0	1
F	1 = yes	0.045	0.208	0	1
G	1 = yes	0.234	0.424	0	1
Buildperiod					
Before 1900	1 = yes	0.104	0.305	0	1
1900 to 1945	1 = yes	0.198	0.399	0	1
1945 to 1970	1 = yes	0.165	0.371	0	1
1970 to 1985	1 = yes	0.188	0.390	0	1
1985 to 2000	1 = yes	0.178	0.383	0	1
2000 to 2022	1 = yes	0.167	0.373	0	1
Physical climate risk labels					
Drought low	1 = yes	0.519	0.500	0	1
Drought medium	1 = yes	0.336	0.472	0	1
Drought high	1 = yes	0.145	0.352	0	1
Fluvial flood low	1 = yes	0.744	0.436	0	1
Fluvial flood medium	1 = yes	0.160	0.367	0	1
Fluvial flood high	1 = yes	0.096	0.294	0	1
Heat stress low	1 = yes	0.175	0.380	0	1
Heat stress medium	1 = yes	0.263	0.440	0	1
Heat stress high	1 = yes	0.562	0.496	0	1
Pluvial flood low	1 = yes	0.751	0.432	0	1
Pluvial flood medium	1 = yes	0.052	0.221	0	1
Pluvial flood high	1 = yes	0.197	0.398	0	1

Note: This table summarizes the data used in this thesis. GRI per year per m2 is the dependent variable, the property characcteristics and the physical climate risks are the independent variables. The mean of the dummy variables represents the percentage relative to 1.0. Mean = average value, Std Dev. = Standard deviation, min. = minimum, max. = maximum. Outliers are prevented in the gross rental income per m2, appraisal value, sqm2, and the age contract by winsorizing these variables at 1% on each side. Number of observations = 12,213

Table 3.4: Descriptive statistics, means per variable per climate risk high and low risk

	All	Drought		Fluvial flood		Heat stress		Pluvial flood	
Variable		Low risk	High risk	Low risk	High risk	Low risk	High risk	Low risk	High risk
GRI per year per m2	157.786	150.285	158.965	170.210	114.513	140.416	166.661	153.145	176.988
Appraisal value	709,365	645,994	730,806	767,538	500,456	505,201	831,116	694,983	824,214
SQM2	190.372	173.223	213.394	192.464	187.29	137.093	227.328	190.223	207.91
Contract age	9.017	9.099	8.933	9.066	9.235	8.842	9.012	9.253	8.086
Buildyear	1958.214	1962.723	1950.242	1950.577	1984.315	1962.477	1957.784	1959.462	1952.478
Segment									
Residential	0.766	.813	.69	.736	.88	.866	.701	.779	.69
Retail/Leisure	0.172	.129	.25	.201	.056	.099	.221	.16	.235
Office	0.035	.03	.049	.038	.03	.026	.04	.034	.044
Industrial	0.025	.027	.008	.023	.032	.009	.035	.025	.029
Logistic	0.001	.001	.001	.001	.002	0	.002	.001	.001
Hotel	0.001	0	.003	.001	0	0	.001	.001	0
Tenant quality									
Average	0.035	.026	.045	.039	.031	.018	.044	.034	.041
Bad	0.044	.035	.063	.051	.019	.025	.057	.041	.06
Good	0.047	.038	.059	.052	.027	.021	.062	.045	.056
Private	0.751	.8	.68	.719	.872	.85	.685	.763	.674
Vacant	0.025	.02	.026	.026	.015	.022	.029	.024	.034
Unknown	0.099	.081	.127	.114	.036	.064	.122	.093	.135
Energy label									
A	0.001	.217	.229	.197	.286	.196	.241	.204	.263
B	0.0003	.095	.089	.08	.086	.063	.097	.081	.079
C	0.008	.231	.173	.194	.281	.225	.201	.222	.176
D	0.330	.139	.1	.122	.181	.18	.118	.142	.114
E	0.613	.075	.077	.075	.068	.095	.066	.077	.065
F	0.020	.042	.049	.05	.016	.048	.039	.049	.033
G	0.027	.201	.284	.281	.08	.192	.239	.226	.27
Object condition									
Renovation necessary	0.216	0	0	.001	0	0	0	.001	0
Very bad	0.082	0	.001	0	.002	0	0	0	0
Bad	0.215	.008	.005	.01	.002	.006	.008	.009	.005
Moderate	0.132	.342	.341	.333	.326	.364	.327	.337	.303
Good	0.074	.609	.607	.602	.632	.576	.607	.602	.65
Very good	0.045	.013	.038	.025	.013	.034	.023	.022	.019
Without defaults	0.234	.027	.008	.03	.026	.019	.034	.029	.021
Build period									
Before 1900	0.104	.071	.189	.132	.013	.06	.114	.092	.159
1900 to 1945	0.198	.187	.144	.248	.038	.184	.203	.195	.21
1945 to 1970	0.165	.179	.152	.175	.109	.245	.13	.174	.108
1970 to 1985	0.188	.228	.116	.144	.358	.256	.156	.211	.111
1985 to 2000	0.178	.181	.194	.159	.19	.099	.207	.181	.172
2000 to 2022	0.167	.155	.205	.143	.292	.155	.19	.147	.24
Drought low	0.519	1	0	.445	.753	.592	.465	.539	.417
Drought medium	0.336	0	0	.371	.224	.335	.345	.332	.381
Drought high	0.145	0	1	.184	.023	.073	.189	.129	.201
Fluvial flood low	0.744	.638	.947	1	0	.695	.759	.747	.771
Fluvial flood medium	0.160	.223	.038	0	0	.208	.149	.165	.127
Fluvial flood high	0.096	.139	.015	0	1	.098	.092	.088	.102
Heat stress low	0.175	.199	.088	.163	.178	1	0	.188	.123
Heat stress medium	0.263	.296	.176	.264	.279	0	0	.275	.218
Heat stress high	0.562	.504	.736	.573	.543	0	1	.537	.659
Pluvial flood low	0.751	.78	.672	.755	.686	.807	.718	1	0
Pluvial flood medium	0.052	.062	.053	.041	.103	.054	.051	0	0
Pluvial flood high	0.197	.158	.274	.204	.21	.139	.231	0	1
Observations	12,213	6,338	1,767	9,088	1,170	2,133	6,866	9,175	2,407

Note: This table summarizes the means per variable for every extreme physical climate risks. The mean of the dummy variables represents the percentage relative to 1. Low risk is label A or B, high risk is label D or E. The medium risk, C, is not presented.

3.6 Empirical model

To test the hypothesis of this thesis, a cross-sectional quantitative analysis is performed on the previously described dataset to analyze the relationship between physical climate risks and real estate rents. By decomposing the characteristics in variables, parts and the marginal effect of unique characteristics influencing rental prices can be distinguished (Rosen, 1974). The hedonic pricing model is used to take all the characteristics into account. This method is widely used in science for real estate and is a method to explain rental price variation between properties (Herath & Maier, 2010).

The natural logarithm of the dependent variable is used to transform the left-skewed sample for rental income to a normally distributed variable, shown in appendix G. This transformation ensures that reliable generalization is possible when interpreting the outcomes of this research (Brooks & Tsolacos, 2010). A hedonic model, displayed in formula 1 is introduced to perform this analysis.

The rental function of the log of gross rental income of property i is a function of locational, property, rental contract, and physical climate risks characteristics, or:

$$\begin{aligned}\ln(GRI) = \beta_0 + \beta_1 \ln SQM_i i + \beta_2 Age_i + \beta_3 Segment_i + \beta_4 Energy\ label_i \\ + \beta_5 Object\ condition_i + \beta_6 Tenant\ quality + \beta_6 Drought_i \\ + \beta_7 Fluvial\ flood_i + \beta_8 Heat\ stress_i + \beta_9 Pluvial\ flood_i \\ + \alpha_1 Rent\ year_i + \gamma_1 Zip\ code_i + \varepsilon_i\end{aligned} \quad (1)$$

Where ln(GRI) is the natural log of the gross rental income per year; β_0 is the constant; $\ln SQM_i$ is the natural log of the rentable square meters; Age_i is the age of the property, age is a continuous variable; Segment is a categorical variable for the different segments; Object $condition_i$ is the state that the building is in; Tenant quality is the quality of non-residential tenants based on size and default risk; $Drought_i$, Fluvial $flood_i$, Heat $stress_i$, and Pluvial $flood_i$ are the independent variables of interest. ε_i is the error term of the regression model. The parameters β_6 to β_9 give information on the correlation between the physical climate risks and the GRI. This indicates the direction, positive or negative, and the significance of the relationship.

Multiple models are used to examine the relationship between physical climate risks and the rent of properties. In table 4.1, the models are shown with increasing variables to increase the explanatory effect of the models on the rental income. In model 1, only the four physical climate risks are used to explain the rental income of a real estate property. In model 2, the property characteristics are included in the regression model. In model 3, the locational effects are included by controlling for the zip code and comparing all observations with the same starting number of the zip code. By comparing the objects with identical first 2 number zip code in model 4. The area of comparison for objects is further decreased in model 5. In model 5, the properties with the same first 3 digits of the zip code are compared to each other. At last, the first 4 digits of the zip code are used in model 6.

In the analysis, we address robustness and look for a possible structural break in the dataset. For this, we will perform a Chow test to determine if the difference between residential and non-residential commercial properties is significantly different. The Chow test hypothesizes that no difference between the residential and non-residential subsamples can be obtained. To test this hypothesis, the following formula is used.

$$F = \frac{R\ RSS - (RSS1 + RSS2)}{(RSS1 + RSS2)}\, x\, \frac{(n-2k)}{(2k-k)} \qquad (2)$$

Where R RSS is the residual sum of squares for the whole sample. RSS1 is the residual sum of squares of the residential subsample. RSS2 is the residual sum of squares of the non-residential subsample. The number of observations is n, k is the number of regressors including the constant (Chow, 1960; Burt et al., 2009; Brooks & Toscalos, 2010).

4. Results

This section presents the results on the relation between the rental income per square meter and the physical climate risks on part of the ING Real Estate Finance portfolio. Firstly, the results of the basic model will be presented. Secondly, the robustness of the model will be tested. Lastly, the results will be discussed.

4.1 Main results

The results of the models in table 4.1 include the explanatory variables, the dependent, and the control variables. The explanatory power of the analysis, measured by the R-squared, increases from 6.7% in the first model to 67.7% in the last model. The property and locational characteristics explain a substantial part of the difference in the rent per square meter. However, due to the increasing locational effects, the regression becomes less significant because the ability to compare properties within this dataset on the locational level decreases. In this research, model (4) is the best fit, and the R-squared (51%) is the highest while accounting for the significance of the results.

In model (4), the properties with the physical climate risk drought with low risk have a 3.25% lower rent per square meter than properties with medium risk and 6.54% lower than properties with high risk. These coefficients are significant (0.1%). For properties with low risk labels for the physical climate risk fluvial flood, the rent per square meter is higher than in areas with labels medium or high risk. These coefficients are significantly different from zero (0.1%).

Properties with heat stress low risk have a higher rent per square meter in comparison to properties with heat stress medium risk. However, this coefficient is not significant from zero. The rent for properties with high risk is 5.08% higher than properties with low risk. This coefficient is significantly different from zero (0.1%).

For the last physical climate risk, pluvial floods, the higher rents per square meter are found in locations with medium and high risk compared to low risk. Properties in areas with high risk have 3.69% higher rents per square meter in comparison to properties in areas in low risk areas. Properties with medium risk for pluvial flood have 7.86% higher rents per square meter compared to properties in low risk areas. These coefficients differ significantly from zero (5% and 0.1%).

Table 4.1 Main results regression analysis, dependent variable (log) rent per square meter

	(1)	(2)	(3)	(4)	(5)	(6)
Drought label C	0.0325**	0.00697	0.0552***	0.0325***	0.00996	0.0230
	(0.0100)	(0.00794)	(0.00810)	(0.00841)	(0.0100)	(0.0131)
Drought label D or E	-0.0595***	-0.0592***	0.0436***	0.0654***	0.00493	0.0117
	(0.0137)	(0.0110)	(0.0122)	(0.0137)	(0.0174)	(0.0251)
Fluvial flood label C	-0.219***	-0.0619***	-0.0689***	-0.0528***	-0.0494**	0.0186
	(0.0125)	(0.0102)	(0.0100)	(0.0118)	(0.0151)	(0.0190)
Fluvial flood label D or E	-0.307***	-0.110***	-0.0611***	-0.0721***	0.0829***	0.0233
	(0.0155)	(0.0127)	(0.0128)	(0.0161)	(0.0225)	(0.0353)
Heat stress label C	0.0504***	0.0256*	-0.00615	-0.0106	0.000276	-0.00612
	(0.0137)	(0.0108)	(0.0107)	(0.0114)	(0.0120)	(0.0129)
Heat stress label D or E	0.123***	0.0654***	0.0608***	0.0502***	0.0601***	0.0374**
	(0.0122)	(0.00986)	(0.0103)	(0.0113)	(0.0120)	(0.0131)
Pluvial flood label C	0.0449*	0.0224	0.0513***	0.0369*	0.0372*	0.0292
	(0.0202)	(0.0160)	(0.0155)	(0.0155)	(0.0159)	(0.0164)
Pluvial flood label D or E	0.117***	0.0458***	0.0794***	0.0786***	0.0505***	0.0351***
	(0.0113)	(0.00899)	(0.00890)	(0.00909)	(0.00956)	(0.0105)
Constant	4.875***	6.661***	6.582***	6.575***	6.559***	6.343***
Physical climate risks	Yes	Yes	Yes	Yes	Yes	Yes
Property specific (6)		Yes	Yes	Yes	Yes	Yes
Building period dummies (6)		Yes	Yes	Yes	Yes	Yes
Zip level			Zip-1	Zip-2	Zip-3	Zip-4
Observations	12,213	12,213	12,213	12,213	12,213	12,213
R-squared	0.071	0.428	0.467	0.510	0.576	0.672

Note: The dependent variable is the natural log of the rent per square meter. The explanatory variables are the physical climate risks. The reference category is the group of label A and B. The property specific control characteristics are the surface, the contract age, the quality of the tenant, the energy label, and the object condition. The building period dummies are before 1900, from 1900 to 1945, 1945 to 1970, from 1970 to 1985, from 1985 to 2000, and from 2000 to 2022. Standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.5

4.2 Robustness of the model

Testing the robustness of the models is an essential part of validating the assumptions and the findings. The model used in this research will be tested on the assumptions of the ordinary least square (OLS) method. The tests are for linearity, independence of errors, homoscedasticity, normality of errors, and the absence of multicollinearity. Additionally, the correlation between the physical climate risk is tested and presented in appendix G.

One of the possible problems is multicollinearity, the correlation between independent variables, which can lead to inaccurate regression results. To check for multicollinearity, the variance inflation factor (VIF) is calculated for every independent variable and is presented in Appendix G. The VIF values of the independent variable ‘segments’ are above 5, which indicates a high correlation. The high correlation between the segment and the quality of the tenant occurs because, as mentioned before, a residential property always indicates a private person as tenant and more than 75% of the dataset is residential. When the segments are excluded from the model, no VIF values are above 5, which means multicollinearity is not observed in this model. The normality of the errors is tested using the Jarque-

Bera test. The Breusch-Pagan test is performed in Stata. These results show that the assumptions of the OLS are met in this research, as can be seen in appendix G.

4.3 Additional analysis

Different segments require unique approaches to maximize the rent, as mentioned before. Therefore, separating the main sample and performing multiple regressions on the different subindustries is valuable. The model using the residential properties (7) is very similar to the main model (4) because the main model consists of 77% of residential properties.

The results of the models (7-11) using the subindustries as samples are presented in table 4.2. Noteworthy is the decrease in the number of coefficients significantly different from zero. The models using the office (10) and the industrial (11) samples only have one significant correlation between the physical climate risks and the rent per square meter. This is due to the low number of observations.

Retail and leisure properties have a significantly (10%) lower rent in low risk places compared to medium risk ones. In the retail and leisure model, the risk of a property with high risk in the fluvial flood risk has a lower rent per square meter than a property with low risk. This correlation is significantly different from zero (5%). The retail and leisure properties have a significantly higher rent in areas with high risk for heat stress and pluvial flood compared to low risk. The office model (10) finds that a property with high risk on heat stress negatively correlates with the rent per square meter compared to an office in an area with low risk. The R-squared of the models ranges from 0.323 to 0.512, slightly lower for the non-residential properties compared to the 0.497 of the main model.

Due to the low number of observations, there are few significant findings for the separate real estate segments. Next to that, the regression only provides significant results when comparing properties on the zip 1 level. However, table 4.2 provides insight into the differences between subindustries and the correlation between physical climate risks and the rent per square meter.

Table 4.2 Additional regression results dividing sample in subindustries

	(4) Main model	(7) Residential	(8) Non-residential	(9) Retail	(10) Office	(11) Industrial
Drought label C	0.0552***	0.0644***	0.0349	0.0368	-0.0250	-0.0579
	(0.00810)	(0.00804)	(0.0216)	(0.0245)	(0.0470)	(0.0478)
Drought label D or E	0.0436***	0.0390***	0.0395	0.0333	-0.0695	-0.282**
	(0.0122)	(0.0123)	(0.0310)	(0.0355)	(0.0624)	(0.117)
Fluvial flood label C	-0.0689***	-0.0738***	-0.0708**	-0.0424	-0.0342	-0.0943*
	(0.0100)	(0.00959)	(0.0311)	(0.0372)	(0.0638)	(0.0563)
Fluvial flood label D or E	-0.0611***	-0.0451***	-0.137***	-0.128**	-0.105	-0.114*
	(0.0128)	(0.0119)	(0.0447)	(0.0612)	(0.0784)	(0.0685)
Heat stress label C	-0.00615	-0.0123	0.00817	0.0192	-0.0459	0.0633
	(0.0107)	(0.00998)	(0.0364)	(0.0415)	(0.0673)	(0.103)
Heat stress label D or E	0.0608***	0.0587***	0.0380	0.0829**	-0.128**	0.00596
	(0.0103)	(0.00991)	(0.0321)	(0.0362)	(0.0630)	(0.0888)
Pluvial flood label C	0.0513***	0.0646***	-0.0374	-0.0408	-0.0144	-0.515
	(0.0155)	(0.0143)	(0.0568)	(0.0597)	(0.132)	(0.345)
Pluvial flood label D or E	0.0794***	0.0886***	0.0495**	0.0752***	-0.00819	-0.00248
	(0.00890)	(0.00919)	(0.0217)	(0.0243)	(0.0478)	(0.0507)
Constant	6.582***	6.480***	6.096***	6.097***	5.505***	5.538***
	(0.0453)	(0.0477)	(0.0903)	(0.106)	(0.198)	(0.206)
Physical climate risks	Yes	Yes	Yes	Yes	Yes	Yes
Property specific (6)	Yes	Yes	Yes	Yes	Yes	Yes
Building period dummies (6)	Yes	Yes	Yes	Yes	Yes	Yes
Zip level	Zip-1	Zip-1	Zip-1	Zip-1	Zip-1	Zip-1
Observations	12,213	9,358	2,855	2,096	430	304
R-squared	0.467	0.466	0.416	0.327	0.446	0.450

Note: The dependent variable is the natural log of the rent per square meter. The explanatory variables are the physical climate risks. The reference category is the group of label A and B. The property specific control characteristics are the surface, the contract age, the quality of the tenant, the energy label, and the object condition. The building period dummies are before 1900, from 1900 to 1945, 1945 to 1970, from 1970 to 1985, from 1985 to 2000, and from 2000 to 2022. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The relationship between the physical climate risks and the rent per square meter is explored on the subindustry level. A Chow test is performed between the residential and non-residential properties to examine whether the true coefficients are equal across these two groups. The outcome of the chow test is shown in table 4.3. The tenant quality is private for the residential model and the not-private options for the non-residential group. The following F-statistic results from the insertion of the residuals for the pooled, residential, and non-residential samples.

The critical F-value on a 5% significance level is 1.4591[9]. The F-value from the chow test is higher than the critical F-value, 14.98[10] is higher than 1.4591. This means that the earlier stated null hypothesis: 'no difference can be obtained between the residential subsample and non-residential subsample', can be rejected. There is no parameter stability throughout the samples of the residential and non-residential properties. A possible explanation is the use of the properties and the different determinants for the rent, resulting in other influences on the rent per square meter.

Table 4.4 – Regression chow test, whole dataset

	Pooled		Residential		Non-residential	
log_SQM2	-0.290***	(0.00601)	-0.385***	(0.00945)	-0.246***	(0.00986)
log_Age_contract	-0.0670***	(0.00464)	-0.0924***	(0.00478)	0.0192*	(0.0115)
Tenant quality average	0.110***	(0.0249)			0.0867***	(0.0321)
Tenant quality bad	0.149***	(0.0248)			0.112***	(0.0320)
Tenant quality good	-0.610***	(0.0209)			-0.116**	(0.0534)
Tenant quality Private	-0.388***	(0.0298)	0.0921***	(0.0254)		
Tenant quality vacant	-0.157***	(0.0220)			-0.124***	(0.0285)
Buildperiod_before 1900	0.505***	(0.0175)	0.486***	(0.0194)	0.531***	(0.0394)
Buildperiod 1900 to 1945	0.348***	(0.0156)	0.331***	(0.0168)	0.381***	(0.0375)
Buildperiod 1945 to 1970	0.0502***	(0.0152)	0.0161	(0.0161)	0.176***	(0.0400)
Buildperiod 1970 to 1985	0.00754	(0.0153)	-0.00522	(0.0161)	0.0720*	(0.0406)
Buildperiod 1985 to 2000	-0.00925	(0.0136)	0.00401	(0.0142)	-0.0187	(0.0357)
Energy label A	0.0772***	(0.0148)	0.0965***	(0.0154)	-0.000139	(0.0430)
Energylabel B	0.0335**	(0.0164)	0.0337**	(0.0158)	-0.0142	(0.0523)
Energylabel C	0.0183	(0.0125)	0.0210*	(0.0117)	-0.0127	(0.0475)
Energylabel E	-0.0434***	(0.0160)	-0.0422***	(0.0153)	-0.0311	(0.0528)
Energylabel F	-0.0805***	(0.0192)	-0.0958***	(0.0190)	-0.0527	(0.0566)
Energylabel G	-0.122***	(0.0138)	-0.164***	(0.0139)	-0.0882**	(0.0418)
Objectcondition renovation necessary	-0.375***	(0.145)	-0.275**	(0.137)	-0.786	(0.492)
Objectcondition very bad	-0.414**	(0.192)	-0.151	(0.336)	-0.493*	(0.286)
Objectcondition bad	-0.0698*	(0.0400)	-0.0824**	(0.0416)	-0.0122	(0.0945)
Objectcondition good	0.120***	(0.00813)	0.0714***	(0.00843)	0.244***	(0.0200)
Objectcondition very good	0.383***	(0.0267)	0.310***	(0.0251)	0.467***	(0.0998)
Objectcondition without defaults	0.0258	(0.0221)	-0.00326	(0.0207)	0.185**	(0.0801)
Drought medium risk	0.00697	(0.00794)	0.00614	(0.00794)	0.00443	(0.0211)
Drought high risk	-0.0592***	(0.0110)	-0.0744***	(0.0114)	-0.0358	(0.0266)
Fluvial flood medium risk	-0.0619***	(0.0102)	-0.0530***	(0.00986)	-0.100***	(0.0309)
Fluvial flood high risk	-0.110***	(0.0127)	-0.0995***	(0.0120)	-0.164***	(0.0447)
Heat stress medium risk	0.0256**	(0.0108)	0.0198*	(0.0103)	0.0314	(0.0365)
Heat stress high risk	0.0654***	(0.00986)	0.0602***	(0.00952)	0.0374	(0.0315)
Pluvial flood medium risk	0.0224	(0.0160)	0.0360**	(0.0149)	-0.0813	(0.0574)
Pluvial flood high risk	0.0458***	(0.00899)	0.0555***	(0.00943)	0.00714	(0.0213)
Constant	6.661***	(0.0465)	6.568***	(0.0497)	6.178***	(0.0902)
Residual sum of squares	1,791.98		1,042.21		681.74	
k	32		32		32	
Observations	12,213		9,358		2,855	
R-squared	0.428		0.405		0.396	

Note**:** reference category is tenant quality unknown, buildperiod 2000 to 2022, objectcondition moderate, and low risk for every physical climate risk. Standard errors in parentheses with *** p<0.01, ** p<0.05, * p<0.1.

[9] The F-value is obtained in the F-value statistics table F(32,12213-2*32) = F(32,12149) = 1.4591

[10] $F = \frac{1{,}791.98389-(1{,}042.20595+681{,}73732)}{(1{,}042.20595+681{,}73732)} \times \frac{(12{,}213-2*32)}{(2*32-32)} = 14.98$

Until this point in the research, the whole dataset is investigated. However, this paragraph focuses on the city with the highest density of data points, Amsterdam. One of the benefits is the decrease in heterogeneity between the properties used in the regression. The data of every property in the city of Amsterdam is presented in table 4.6.

The mean of the GRI of properties in Amsterdam is 252,74 euros per square meter per year. This is 60.18% higher than the average of the initial dataset. The mean of the surface is lower in Amsterdam compared to the whole dataset, 190 square meters versus 144 square meters. Remarkable is that the average build year in Amsterdam is 1921, whereas the average build year for the whole dataset is 1958. This is emphasized in the build period cohorts, 22.1% of the properties are constructed before 1900 and 53.2% of the properties is constructed between 1900 and 1945. The properties in Amsterdam are less energy efficient. Most of the properties have energy labels D (34.4%) or E (59.8%). Only 2.4% of the properties have a ‘green’ label[11], compared to 51.33% ‘green’ labels in the initial dataset.

Looking at the physical climate risks in Amsterdam, a clear division of the climate risk in the city can be observed. The risk of drought and fluvial flood is not influencing the dataset, where 0.2% of the properties have a high risk of drought and 2.9% of the properties have a high risk of fluvial flood. Amsterdam has the highest risk score on heat stress, 48.6% of the dataset has a high risk of heat stress. The majority of the properties has a low risk for pluvial flood (80.9%), while 16.3% of the properties are subject to high risk of pluvial floods.

The property division across the segments is more evenly distributed. In this subsample, 67.2% of the properties are residential in comparison to 76.6% in the whole sample. The retail/leisure segment is 25.3% of Amsterdam and 17.2% of the whole sample. To check for a structural break between the residential and the non-residential properties, a Chow test is performed by dividing this subsample into smaller subsamples. The critical F-value is 1.57. The F-value from the Chow test is 6.21[12]. The F-value from the Chow test is higher than the critical F-value, indicating that the hypothesis ‘No difference can be obtained between the residential and the non-residential properties in Amsterdam’ can be rejected.

The subsample of Amsterdam is divided into smaller subsamples categorized per segment. The analysis of these subsamples is presented in appendix E, where the residential subsample in Amsterdam has some significant results. The non-residential and separate segments only give one significant result, the offices in Amsterdam are negatively correlated with the physical climate risks. Next to this correlation, no other result is significant for the subsample regression per segment in Amsterdam.

[11] A green energy label is label A, B, or C

[12] $\frac{348.48277-(209.76929+99.5045684)}{(209.76929+99.5045684)} \times \frac{(1631-2*32)}{(2*32-32)} = 6.21$

Table 4.6 - Descriptive statistics Amsterdam

	Parameter	Mean	Std. dev.	min	max
GRI per year per m2	€	252.743	135.341	42.546	591.411
Appraisalvaluetotal	€	1,188,147.3	1,664,540.7	106,737	8,406,927.7
SQM2	m2	143.853	272.268	28	2569
Contract age	years	9.985	8.465	1	38
Buildyear	years	1921.074	48.52	1800	2018
Segments					
Residential	1 = yes	.672	.47	0	1
Retail / Leisure	1 = yes	.253	.435	0	1
Office	1 = yes	.051	.22	0	1
Industrial	1 = yes	.023	.151	0	1
Logistic	1 = yes	0	0	0	0
Hotel	1 = yes	.001	.025	0	1
Tenant quality					
Average	1 = yes	.049	.216	0	1
Bad	1 = yes	.056	.231	0	1
Good	1 = yes	.055	.227	0	1
Private	1 = yes	.641	.48	0	1
Vacant	1 = yes	.037	.188	0	1
Unknown	1 = yes	.162	.368	0	1
Object condition					
Renovation necessary	1 = yes	.137	.344	0	1
Very bad	1 = yes	.048	.215	0	1
Bad	1 = yes	.131	.338	0	1
Moderate	1 = yes	.097	.297	0	1
Good	1 = yes	.046	.21	0	1
Very good	1 = yes	.042	.201	0	1
Without defaults	1 = yes	.497	.5	0	1
Energy label					
A	1 = yes	.004	.061	0	1
B	1 = yes	0	0	0	0
C	1 = yes	.02	.141	0	1
D	1 = yes	.344	.475	0	1
E	1 = yes	.598	.49	0	1
F	1 = yes	.007	.082	0	1
G	1 = yes	.028	.164	0	1
Buildperiod					
Before 1900	1 = yes	.221	.415	0	1
1900 to 1945	1 = yes	.532	.499	0	1
1945 to 1970	1 = yes	.094	.293	0	1
1970 to 1985	1 = yes	.025	.157	0	1
1985 to 2000	1 = yes	.086	.281	0	1
2000 to 2022	1 = yes	.042	.2	0	1
Physical climate risk labels					
Drought low risk	1 = yes	.53	.499	0	1
Drought medium risk	1 = yes	.468	.499	0	1
Drought high risk	1 = yes	.002	.049	0	1
Fluvial flood low risk	1 = yes	.925	.263	0	1
Fluvial flood medium risk	1 = yes	.046	.21	0	1
Fluvial flood high risk	1 = yes	.029	.167	0	1
Heat stress low risk	1 = yes	.181	.385	0	1
Heat stress medium risk	1 = yes	.334	.472	0	1
Heat stress high risk	1 = yes	.486	.5	0	1
Pluvial flood low risk	1 = yes	.809	.393	0	1
Pluvial flood medium risk	1 = yes	.028	.164	0	1
Pluvial flood high risk	1 = yes	.163	.37	0	1

Note: This table summarizes the 1,631 objects in Amsterdam. The mean of the dummy variables represents the percentage relative to 1.0. Mean = average value, Std. dev. = standard deviation, min. = minimum, max. = maximum. Outliers are prevented in the GRI, appraisal value, surface, and the age contract by winsorizing these variables at 1% on each side.

Table 4.7 Regression results subsample Amsterdam

	(12)	(13)	(14)	(15)	(16)	(17)
	Physical climate risks	Including property characteristics	Zip 1 level	Zip 2 level	Zip 3 level	Zip 4 level
Drought medium risk	-0.00808	0.0246	0.0246	0.0247	-0.0411	0.0311
	(0.0297)	(0.0244)	(0.0244)	(0.0244)	(0.0306)	(0.0367)
Drought label high risk	0.271	-0.106	-0.106	-0.111	-0.258	-0.194
	(0.292)	(0.249)	(0.249)	(0.249)	(0.241)	(0.287)
Fluvial flood medium risk	-0.233***	0.209***	0.209***	0.229***	0.107	0.193*
	(0.0704)	(0.0668)	(0.0668)	(0.0674)	(0.0856)	(0.101)
Fluvial flood high risk	-0.421***	-0.0795	-0.0795	-0.0796	-0.0378	0.0332
	(0.101)	(0.0846)	(0.0846)	(0.0845)	(0.0967)	(0.327)
Heat stress medium risk	0.137***	0.0665*	0.0665*	0.0679*	0.0806**	0.0602
	(0.0425)	(0.0356)	(0.0356)	(0.0355)	(0.0348)	(0.0370)
Heat stress high risk	0.236***	0.107***	0.107***	0.108***	0.0931***	0.0648*
	(0.0405)	(0.0342)	(0.0342)	(0.0341)	(0.0333)	(0.0363)
Pluvial flood medium risk	0.226**	0.217***	0.217***	0.215***	0.156**	0.136*
	(0.101)	(0.0823)	(0.0823)	(0.0822)	(0.0786)	(0.0790)
Pluvial flood high risk	0.159***	0.0783**	0.0783**	0.0780**	0.0457	0.0423
	(0.0393)	(0.0326)	(0.0326)	(0.0326)	(0.0312)	(0.0323)
Constant	5.206***	6.707***	6.707***	6.705***	6.834***	6.670***
	(0.0381)	(0.154)	(0.154)	(0.154)	(0.152)	(0.161)
Physical climate risks	Yes	Yes	Yes	Yes	Yes	Yes
Property specific (6)		Yes	Yes	Yes	Yes	Yes
Building period dummies (6)		Yes	Yes	Yes	Yes	Yes
Zip level			Zip-1	Zip-2	Zip-3	Zip-4
Observations	1,631	1,631	1,631	1,631	1,631	1,631
R-squared	0.053	0.398	0.398	0.400	0.464	0.517

Note: Low risk is the comparison category. Standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

4.4 Discussion

This chapter provides the discussion and interpretation of the results from the regression analyses. Despite the significant coefficients found using the regression model, it is essential to note that the model finds correlations. Lower or higher rents in areas with low or high risks can be correlated, but this does not mean that causation can be concluded from this model.

The results for fluvial flood risks align with the research by Bin and Polasky (2004), who find a 3.8% discount in areas vulnerable to fluvial floods. Most research finds a negative relationship between fluvial flood risks and real estate value (Belanger & Bourdeau-Brien, 2017; Beltran et al., 2019; Bin et al., 2008). This implies that the risk of a flood is higher than the premium of the amenity of living close to water bodies.

The results for drought, heat stress, and pluvial floods indicate that the physical climate risks do not decrease the rent per square meter in the Netherlands. For heat stress, the findings are not in line with the expectations from the research by Bunten and Kahn (2014), which expects the value of real estate to decrease because of increasing heat stress. A reason for this correlation could be urban heat islands and increased heat stress in central places in the city (Gabriel & Endlicher, 2011). The premium of living in a location where heat stress occurs outweighs, possibly, the discount of heat stress. The higher rents for properties with a high risk for drought are not in line with the expectations that properties subject to the possible damages from drought have a lower value. In areas with higher risks this research finds higher rents, where the literature suggests that the rents in these areas are expected to be lower.

In this research, the factual risk labels used can be different from the perceived risk by investors and tenants. The difference occurs because the perceived risk increases as a physical climate risk event are observed, while the measured risk increases due to the changing climate (KNMI, 2022). As mentioned in chapter 1, the physical climate risks are increasing. However, investors and tenants do not anticipate risk but on perceived risk. The availability of information regarding physical climate risk can impact the perceived risk for properties in zones exposed to climate risks. It could be interesting to look into the perceived risk for investors and tenants and the contribution to the contract negotiation between the two.

Next to that, physical climate risks have different frequencies and severity. Fluvial floods can have a high impact, the examples of flooding are more prevalent than the consequences of drought or heat stress. The lack of knowledge on the impact of heat stress and drought limits the ability of real estate investors to price in the climate risks.

One of the more straightforward problems is the obstacles in the main regression and the additional regressions, which is the need for more data. At this moment, the main regression is able to provide significant results. However, when increasing the dataset, the regression is able to run using zip-3 and zip-4 comparisons. Looking at the figures of the climate risks across Amsterdam, there is room for data improvement. For testing different segments and the correlation between physical climate risks and these segments, an increase in the number of non-residential properties is necessary to provide valid significant results. This research uses data from one moment in time, whereas a panel dataset through the years could be an addition to the research.

Next to this, the physical climate risks are a new phenomenon in a conservative market and one of the reasons could be the lack of knowledge on this topic. The risk of fluvial floods is more prevalent in the Netherlands as this is a risk that has affected this country. On the contrary, heat stress, drought, and pluvial floods are relatively new risks that will increasingly impact the Netherlands' population and will get more attention. Therefore, this research is a starting point for future research on this topic and the impact on the value of real estate.

5. Conclusion

This paper investigated the correlation between physical climate risks and real estate value in the Netherlands. Physical climate risks are increasing, and, in the future, the risks are predicted to increase. This indicates that physical climate risks impact the current and future built environment and influence the real estate markets. Therefore, the main research question is: *"To what extent can a relationship be observed between physical climate risks and the value of real estate?"*

In this research, the value of real estate is measured as the rent per square meter. The association between physical climate risks and real estate value is examined using a unique dataset provided by ING and a hedonic model. The findings are different from the expectations set by the literature. For drought, heat stress, and pluvial flood risk this research finds higher rent per square meter in areas with higher risk. In comparison to low risk areas, we find that properties in high risk areas for drought have 6.54% higher rents per square meter. For heat stress and pluvial, we find 5.02% and 7.86% higher rents per square meter. For fluvial flood risk, this research finds 7.21% lower rent per square meter in areas with high risk compared to areas with low risk. In addition, this paper finds differences between residential and non-residential properties using a Chow test. This research finds the same direction of correlations for the segments residential and leisure/retail. For other segments, the results are not significant. Zooming into Amsterdam, the same relations are found for heat stress and pluvial flood. For drought and fluvial flood the results are not significant. Using a Chow test, this thesis showed that there is a structural difference between the relationship between physical climate risk and residential or non-residential real estate in Amsterdam. The sample is subdivided into segments in Amsterdam. However, the results from performing regressions on these subsamples are not significant. One of the possibilities is to add a qualitative part to this research by contacting professional real estate investors or by examining the impact of occurrences of physical climate risks and the impact on real estate. Ideally, the analysis to examine this relationship is performed on a dataset where the physical climate risk differences can be isolated from differences in property or locational characteristics. With properties in close proximity and different physical climate risks while having all the property data available. However, this research will have limitations due to the lack of availability of property characteristics data and the number of observations. This thesis is the first step in researching physical climate risks and the value of real estate in the Netherlands. Because of this research, the need for attention for these physical climate risk has increased at ING Real Estate Finance and more research into this field will be initiated. There is more attention needed for the contribution of physical climate risks on the thoughts and actions of investors and tenants. In the future, these risks will have more impact on the lives of every human being. This paper is a step in addressing humanity's biggest challenge, which is living sustainable and preserving the planet for future generations.

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Appendix A Overview segments

Table A1: Overview segments whole dataset

Object type	Frequency	Percent	Cumulative
Residential	9.358	76,62%	76.62%
Leisure/Retail	2.096	17,16%	93.79%
Office	430	3,52%	97.31%
Industrial	304	2,49%	99.80%
Logistic	15	0,12%	99.92%
Hotel	10	0,08%	100%
	12.213	100,00%	

Table A2: Overview segments dataset Amsterdam

Object type	Frequency	Percent	Cumulative
Residential	1,096	67.20%	67.20%
Leisure/Retail	413	25.32%	92.52%
Office	83	5.09%	97.61%
Industrial	38	2.33%	99.94%
Logistic	0	0,00%	99.94%
Hotel	1	0,06%	100%
	12.213	100,00%	

Appendix B Chow test

Table B1: Chow test outcomes, whole dataset

Chow test	Pooled model	Residential	Non-residential
Residual sum of squares	1,791.98	1,042.21	681.74
Observations	12,213	9,358	2,855
F-value	(32,12180) = 284.58	(32,9329) = 227.13	(32,2823) = 59.73
Critical F value (2,5% significance level)	1.57	1.57	1.57
Chow F statistics	14.98	14.98	14.98

Note: The degrees of freedom vary because the tenant quality is one of the variables. The tenant quality for residential is always 'private' and for non-residential the tenant quality will not be 'private'.

Appendix C Frequency tables

Table C1: Drought frequency

Drought	Frequency	Percent	Cumulative
A	870	7,12%	7,12%
B	5.468	44,77%	51,90%
C	4.108	33,64%	85,53%
D	1.200	9,83%	95,36%
E	567	4,64%	100,00%
	12213	100,00%	

Table C2: Fluvial flood frequency

Fluvial flood	**Frequency**	**Percent**	**Cumulative**
A	8.518	69,75%	69,75%
B	570	4,67%	74,41%
C	1.955	16,01%	90,42%
D	1.159	9,49%	99,91%
E	11	0,09%	100,00%
	12213	100,00%	

Table C3: Heat stress frequency

Heat stress	**Frequency**	**Percent**	**Cumulative**
A	772	6,32%	6,32%
B	1.361	11,14%	17,46%
C	3.214	26,32%	43,78%
D	3.171	25,96%	69,75%
E	3.695	30,25%	100,00%
	12213	100,00%	

Table C4: Pluvial flood frequency

Pluvial flood	**Frequency**	**Percent**	**Cumulative**
A	3.252	26,63%	26,63%
B	5.923	48,50%	75,12%
C	631	5,17%	80,29%
D	830	6,80%	87,09%
E	1.577	12,91%	100,00%
	12.213	100,00%	

Table C5: Overview labels per physical climate risk

	Drought	**Fluvial flood**	**Heat stress**	**Pluvial flood**	**Total**
A	870	8.518	772	3.252	13.412
B	5.468	570	1.361	5.923	13.322
C	4.108	1.955	3.214	631	9.908
D	1.200	1.159	3.171	830	6.360
E	567	11	3.695	1.577	5.850

Appendix D Scatterplots

Figure D1 – Scaterplot rent per square meter x Appraisal value in millions (per drought label)

Figure D2 – Scaterplot rent per square meter x Appraisal value in millions (per fluvial flood label)

Figure D3 – Scaterplot rent per square meter x Appraisal value in millions (per heat stress label)

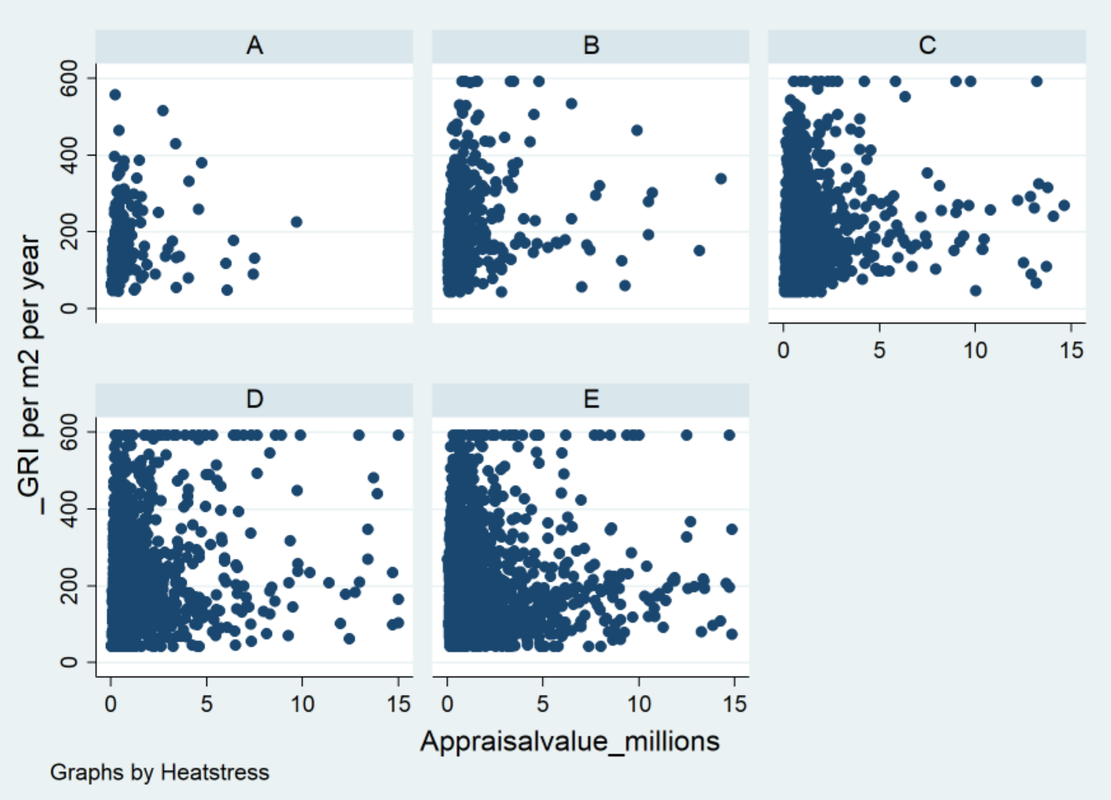
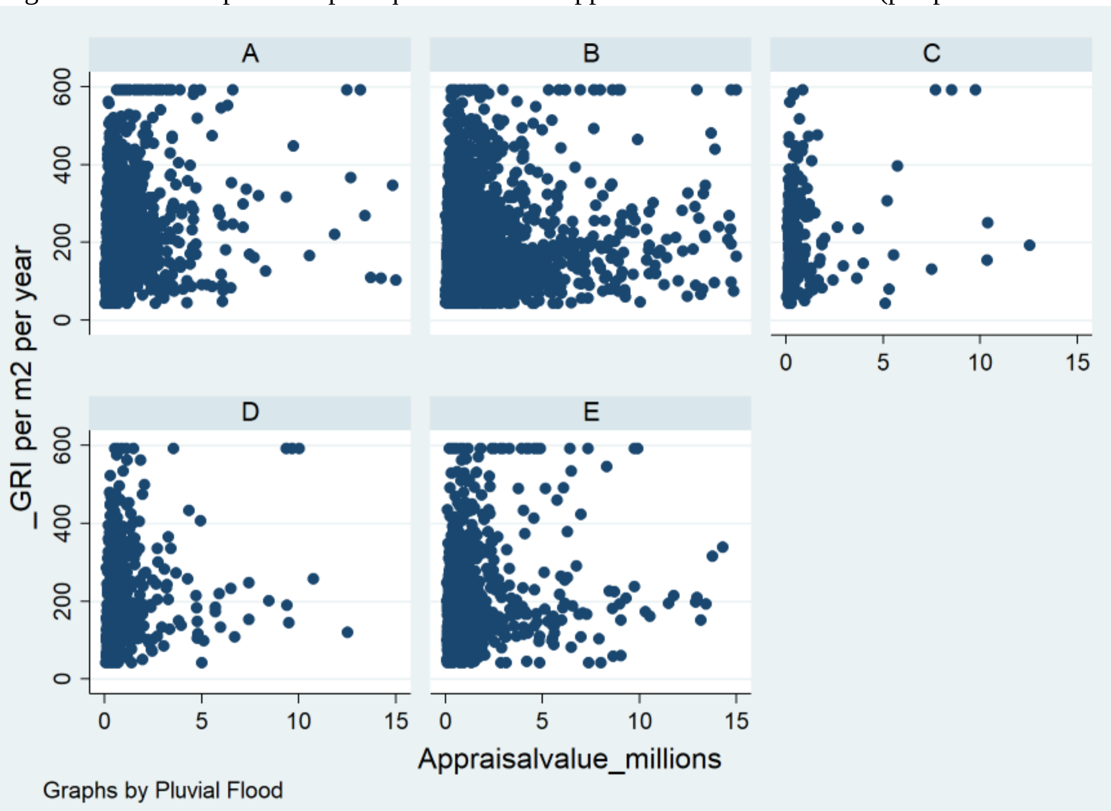


Figure D4 – Scaterplot rent per square meter x Appraisal value in millions (per pluvial flood label)



Appendix E Regression models extended

	(1) Physical climate risks	(2) Including property characteristics	(3) Zip 1 level	(4) Zip 2 level	(5) Zip 3 level	(6) Zip 4 level
log_SQM2		-0.290***	-0.278***	-0.266***	-0.249***	-0.208***
		(0.00601)	(0.00583)	(0.00568)	(0.00576)	(0.00615)
log_Age_contract		-0.0670***	-0.0717***	-0.0750***	0.0873***	0.0934***
		(0.00464)	(0.00451)	(0.00448)	(0.00464)	(0.00488)
Tenant quality average		0.110***	0.104***	0.105***	0.0973***	0.0913***
		(0.0249)	(0.0241)	(0.0233)	(0.0228)	(0.0226)
Tenant quality bad		0.149***	0.155***	0.158***	0.139***	0.109***
		(0.0248)	(0.0239)	(0.0231)	(0.0230)	(0.0229)
Tenant quality good		-0.610***	-0.585***	-0.563***	-0.553***	-0.465***
		(0.0209)	(0.0202)	(0.0196)	(0.0194)	(0.0196)
Tenant quality Private		-0.388***	-0.379***	-0.368***	-0.395***	-0.367***
		(0.0298)	(0.0288)	(0.0279)	(0.0273)	(0.0270)
Tenant quality vacant		-0.157***	-0.154***	-0.147***	-0.153***	-0.141***
		(0.0220)	(0.0212)	(0.0205)	(0.0200)	(0.0197)
Buildperiod_before 1900		0.505***	0.445***	0.364***	0.251***	0.122***
		(0.0175)	(0.0172)	(0.0179)	(0.0196)	(0.0232)
Buildperiod 1900 to 1945		0.348***	0.274***	0.178***	0.133***	0.0794***
		(0.0156)	(0.0154)	(0.0162)	(0.0180)	(0.0214)
Buildperiod 1945 to 1970		0.0502***	0.0481**	0.00836	0.00959	0.0147
		(0.0152)	(0.0148)	(0.0154)	(0.0169)	(0.0217)
Buildperiod 1970 to 1985		0.00754	0.0336*	0.00578	-0.000996	-0.00946
		(0.0153)	(0.0149)	(0.0152)	(0.0171)	(0.0219)
Buildperiod 1985 to 2000		-0.00925	-0.0134	-0.0403**	0.0778***	0.0877***
		(0.0136)	(0.0132)	(0.0136)	(0.0156)	(0.0205)
Energy label A		0.0772***	0.0702***	0.0706***	0.0739***	0.0655***
		(0.0148)	(0.0144)	(0.0143)	(0.0145)	(0.0150)
Energylabel B		0.0335*	0.0417**	0.0504**	0.0643***	0.0470**
		(0.0164)	(0.0159)	(0.0158)	(0.0161)	(0.0164)
Energylabel C		0.0183	0.0201	0.0265*	0.0282*	0.0177
		(0.0125)	(0.0121)	(0.0120)	(0.0122)	(0.0125)
Energylabel E		-0.0434**	-0.0461**	-0.0541***	-0.0488**	-0.528***
		(0.0160)	(0.0155)	(0.0152)	(0.0152)	(0.0151)
Energylabel F		-0.0805***	-0.0857***	-0.0864***	-0.100***	-0.132***
		(0.0192)	(0.0186)	(0.0181)	(0.0178)	(0.0178)
Energylabel G		-0.122***	-0.130***	-0.137***	-0.148***	-0.157***
		(0.0138)	(0.0133)	(0.0130)	(0.0129)	(0.0131)
Objectcondition renovation necessary		-0.375**	-0.431**	-0.480***	-0.423***	-0.463***
		(0.145)	(0.140)	(0.135)	(0.128)	(0.119)
Objectcondition very bad		-0.414*	-0.324	-0.297	-0.338	-0.431
		(0.192)	(0.186)	(0.179)	(0.209)	(0.243)
Objectcondition bad		-0.0698	-0.126**	-0.0879*	-0.106**	-0.0478
		(0.0400)	(0.0387)	(0.0378)	(0.0371)	(0.0394)
Objectcondition good		0.120***	0.122***	0.112***	0.103***	0.0993***
		(0.00813)	(0.00788)	(0.00789)	(0.00830)	(0.00915)
Objectcondition very good		0.383***	0.334***	0.345***	0.342***	0.309***
		(0.0267)	(0.0259)	(0.0267)	(0.0286)	(0.0363)

Objectcondition without defaults		0.0258	-0.00688	-0.0176	-0.0133	-0.0166
		(0.0221)	(0.0214)	(0.0211)	(0.0212)	(0.0233)
Drought label C	0.0325**	0.00697	0.0552***	0.0325***	0.00996	0.0230
	(0.0100)	(0.00794)	(0.00810)	(0.00841)	(0.0100)	(0.0131)
Drought label D or E	-0.0595***	-0.0592***	0.0436***	0.0654***	0.00493	0.0117
	(0.0137)	(0.0110)	(0.0122)	(0.0137)	(0.0174)	(0.0251)
Fluvial flood label C	-0.219***	-0.0619***	-0.0689***	-0.0528***	-0.0494**	0.0186
	(0.0125)	(0.0102)	(0.0100)	(0.0118)	(0.0151)	(0.0190)
Fluvial flood label D or E	-0.307***	-0.110***	-0.0611***	-0.0721***	0.0829***	0.0233
	(0.0155)	(0.0127)	(0.0128)	(0.0161)	(0.0225)	(0.0353)
Heat stress label C	0.0504***	0.0256*	-0.00615	-0.0106	0.000276	-0.00612
	(0.0137)	(0.0108)	(0.0107)	(0.0114)	(0.0120)	(0.0129)
Heat stress label D or E	0.123***	0.0654***	0.0608***	0.0502***	0.0601***	0.0374**
	(0.0122)	(0.00986)	(0.0103)	(0.0113)	(0.0120)	(0.0131)
Pluvial flood label C	0.0449*	0.0224	0.0513***	0.0369*	0.0372*	0.0292
	(0.0202)	(0.0160)	(0.0155)	(0.0155)	(0.0159)	(0.0164)
Pluvial flood label D or E	0.117***	0.0458***	0.0794***	0.0786***	0.0505***	0.0351***
	(0.0113)	(0.00899)	(0.00890)	(0.00909)	(0.00956)	(0.0105)
Constant	4.875***	6.661***	6.582***	6.575***	6.559***	6.343***
	(0.0120)	(0.0465)	(0.0453)	(0.0447)	(0.0452)	(0.0484)
Observations	12,213	12,213	12,213	12,213	12,213	12,213
R-squared	0.071	0.428	0.467	0.510	0.576	0.672

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Appendix F Additional regression results dividing sample in subindustries in Amsterdam

	(18) Main model	(19) Residential	(20) Non-residential	(21) Retail leisure	(22) Office	(23) Industrial
Drought label C	0.0246	0.0961***	-0.0638	-0.0603	-0.0823	-0.225
	(0.0244)	(0.0294)	(0.0411)	(0.0450)	(0.0999)	(0.284)
Drought label D or E	-0.106	-0.718	0.0432	0.0319		
	(0.249)	(0.453)	(0.297)	(0.292)		
Fluvial flood label C	0.209***	0.345***	0.0927	0.0478	0.0548	0.248
	(0.0668)	(0.0805)	(0.129)	(0.170)	(0.284)	(0.496)
Fluvial flood label D or E	-0.0795	-0.0100	-0.114	-0.0675	-0.430*	-0.481
	(0.0846)	(0.0959)	(0.170)	(0.269)	(0.228)	(0.665)
Heat stress label C	0.0665*	0.0959**	0.0101	0.0237	-0.0858	0.674
	(0.0356)	(0.0398)	(0.0693)	(0.0831)	(0.121)	(0.784)
Heat stress label D or E	0.107***	0.117***	0.0743	0.111	-0.279**	0.732
	(0.0342)	(0.0394)	(0.0650)	(0.0782)	(0.118)	(0.855)
Pluvial flood label C	0.217***	0.207**	0.0159	0.0213		
	(0.0823)	(0.0938)	(0.165)	(0.163)		
Pluvial flood label D or E	0.0783**	0.0467	0.0337	0.0928	0.0694	-0.433
	(0.0326)	(0.0392)	(0.0530)	(0.0576)	(0.133)	(0.409)
Constant	6.707***	6.819***	5.967***	6.015***	5.870***	6.000***
	(0.154)	(0.204)	(0.214)	(0.260)	(0.532)	(0.746)
Physical climate risks	Yes	Yes	Yes	Yes	Yes	Yes
Property specific (6)	Yes	Yes	Yes	Yes	Yes	Yes
Building period dummies (6)	Yes	Yes	Yes	Yes	Yes	Yes
Amsterdam	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,631	1,096	535	413	83	38
R-squared	0.398	0.443	0.365	0.252	0.434	0.843

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

Appendix G Assumption testing

Correlation:

	Drough~s	Fluvia~s	Heats~rs	Pluvia~s
Drought_nu~s	1.0000			
Fluvialflo~s	-0.2530	1.0000		
	0.0000			
Heatstress~s	0.1454	-0.0384	1.0000	
	0.0000	0.0000		
Pluvialflo~s	0.0995	0.0092	0.0942	1.0000
	0.0000	0.3106	0.0000	

VIF

Variable	VIF	1/VIF
log_SQM2_w	1.90	0.527042
log_Age_co~w	1.14	0.875494
Tenant_qua~y		
1	1.34	0.747552
2	1.45	0.688870
3	1.53	0.652375
4	2.72	0.367384
5	1.26	0.792694
Buildpe~1900	2.38	0.420757
Buildpe~1945	3.23	0.309980
Buildpe~1970	2.66	0.376033
Buildpe~1985	2.97	0.336854
Buildpe~2000	2.26	0.443108
Energylabe~s		
1	3.08	0.324821
2	1.67	0.597155
3	2.21	0.452694
5	1.47	0.681806
6	1.33	0.749488
7	2.82	0.354195
Objectcond~r		
1	1.01	0.993673
2	1.01	0.994181
3	1.02	0.977167
5	1.30	0.767887
6	1.18	0.844888
7	1.07	0.932995
Drought_nu~s		
2	1.17	0.856353
3	1.23	0.811143
Fluvialflo~s		
2	1.16	0.863536
3	1.16	0.865173
Heatstress~s		
2	1.89	0.530036
3	1.98	0.503858
Pluvialflo~s		
2	1.04	0.962422
3	1.06	0.941088
Mean VIF	1.71	

Normality of errors

```
. jb resid1
Jarque-Bera normality test:  934.7 Chi(2)  1.e-203
Jarque-Bera test for Ho: normality:

. jb resid2
Jarque-Bera normality test:   1282 Chi(2)  4.e-279
Jarque-Bera test for Ho: normality:

. jb resid3
Jarque-Bera normality test:   1266 Chi(2)  1.e-275
Jarque-Bera test for Ho: normality:

. jb resid4
Jarque-Bera normality test:   1249 Chi(2)  7.e-272
Jarque-Bera test for Ho: normality:

. jb resid5
Jarque-Bera normality test:   1160 Chi(2)  1.e-252
Jarque-Bera test for Ho: normality:

. jb resid6
Jarque-Bera normality test:  816.3 Chi(2)  6.e-178
Jarque-Bera test for Ho: normality:
```

Appendix H Histogram of rent per square meter