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Pricing Climate Risk: Evidence from Housing Markets in Sweden

Svante Forsmark & Simon Fast

Abstract:

This thesis investigates the relationship between climate risk, both theoretical and perceived, and property price levels and property price growth in the Swedish single-family housing market from 2015 to 2023. The topic is highly relevant in light of alarming reports highlighting areas at risk of becoming uninhabitable due to climate threats, as well as the rising frequency of extreme weather events in recent years. By using panel data covering Sweden's 290 municipalities, the study incorporates a forward-looking theoretical climate risk indicator, based on The Swedish Civil Contingency Agency's (MSB) climate risk index and two perception-based measures through insurance claims and damage costs from Insurance Sweden. Contrary to expectations, the results show no consistent negative relationship between any measures of climate risk and property prices. Theoretical climate risk showed no significant impact on property price levels. However, in certain years, the perceived risk variables, damage costs and insurance claims, had a significant positive contribution to the price level in that year. These findings may reflect reverse causality or mitigating effects from Sweden's robust insurance system. Furthermore, no significant relationship was found between any measure of climate risk and property price growth. The study contributes to the literature by providing empirical evidence on the effect of multiple climate risk dimensions in a Swedish context, offering insights for policymakers and market participants about the complex interplay between climate risk perception and real estate valuation.

Keywords: Climate Risk, Real Estate, Sweden, Property Price, Single Family Houses

Supervisor: Laszlo Sajtos, Konjunkturinstitutet, Mistra Center For Sustainable Markets

Authors: Svante Forsmark (42644) and Simon Fast (50640)

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1. Introduction

“Climate change is estimated to potentially wipe out nearly ten percent of global real estate values” - Swiss Re Institute (2021)

Climate change was first predicted over 120 years ago by Swedish scientist Svante Arrhenius. Since then, it has gained exponential importance, becoming a global priority for politicians, governments, the private sector, and individuals alike. Despite cultural and national differences, climate change is one of the few challenges that unites people worldwide.

An increasingly important concept in the context of climate change is climate risk. Climate risk is defined through two categories. Transition risks, which are the risks related to the transition to a lower-carbon economy, and physical risks, which are the risks related to the physical impacts of climate change (EPA, 2025). This paper will focus on the latter.

In today's world, much of our wealth is tied to real estate. In 2022, global real estate values reached $379,7 trillion, almost four times the world's GDP, demonstrating the fact that real estate is the world's most significant store of wealth (Savills, 2023). Of all the segments, residential is by far the largest, accounting for 76% of the total value. The same is true for many other countries, one of which is Sweden. In 2025, real estate values in Sweden are expected to reach $4.14 trillion, with more than 75% contributed by the residential segment (Statista, 2024b).

At the same time, recent turmoil in several countries has highlighted the impact that climate change and climate risk can have on properties. During the California wildfires in early 2025, property damages were estimated at between $28 billion and $53.8 billion, with many affected properties lacking insurance due to insurers having identified and withdrawn from high-risk areas in advance (Horton et.al., 2025). Historical international research has shown that real estate markets often fail to price in climate risks (Hino and Burke, 2021; Dong, 2024; Gourevitch et al., 2023), leaving market participants vulnerable to significant future losses. Moreover, as insurance companies increasingly refuse to cover high-risk properties, values on these properties will most likely decline in the future. Without insurance, buyers often cannot secure mortgage financing, since banks generally require insurance as a condition for lending, which reduces the overall purchasing power and demand for such properties (Mäklarsamfundet, 2024). This combination of unpriced risk, rising damage costs, and weakening future market activity presents a potentially hazardous dynamic that could lead to significant economic losses for today's property owners.

Meanwhile, real estate price levels and growth already vary significantly across Sweden. While many factors influence housing market dynamics, there is both a research gap and a growing interest in examining whether Swedish housing markets stand out and have begun to price climate risks. Heightened media attention, such as reports highlighting areas that may become uninhabitable in the future due to climate threats and more frequent extreme weather events in varying parts of the country, has further amplified the relevance of this issue (Mäklarsamfundet, 2024; SGI and MSB, 2021).

In this paper, we examine whether there exists a relationship between climate risk and single-family house values in Sweden, both in terms of price levels and price growth. The distinction between these two measures is important because Sweden exhibits significant variability in price levels, with values concentrated in metropolitan areas, while growth in recent years has been more prominent in municipalities with relatively lower price levels (Svensk Mäklarstatistik n.d.; SCB, 2024). Our goal is to explore whether any of these pricing patterns in the Swedish housing market are influenced by increased climate risks.

An important distinction lies between the theoretical climate risk, which we refer to as the probability of future damages due to climate change and its consequences, and the perception of climate risk, which reflects the actual damages recognized by market participants today, and is what makes the effects of climate change tangible in economic terms. This paper includes both of these dimensions. The time period under focus is 2015-2023, which is due to the lack of key datasets with tangible data prior to 2015. The tangible data make our study, to the best of our knowledge, one of the first to attempt an analysis of the impact of climate risk in Sweden using several dimensions.

Our empirical findings provide little evidence that increased climate risk, or the perception of it, is negatively associated with single-family house price levels or price growth. This is in line with previous research in other countries. However, a significant positive relationship was found in some years. This is counterintuitive, but could be due to reverse causality. Nevertheless, this suggests that, at the aggregate municipal level, market participants, also in Sweden, ultimately fail to incorporate climate risks into property pricing.

2. Literature review

Climate risk's effect on property values is a well-documented international research area within academia. Previous studies have tried to explain and prove the correlation between increased climate risk and decreased property values with regard to climate change.

In typical asset market theory, an asset featuring uninsurable idiosyncratic risk must offer a higher rate of return to compensate risk-averse investors. This has been hard to prove in some residential real estate markets, especially when the population in cities is heterogeneous (Bunten and Khan, 2014). In many cases, it seems to be crucial to take into consideration a population's perception together with the overall risk assessment to better understand the pricing dynamics in the residential real estate market.

Baldauf et.al. (2020) investigated in their study whether house prices in the USA reflect differences in beliefs about climate change. The study ultimately found that in an equilibrium model of housing choice in which agents derive utility from ownership in a neighborhood of similar agents, prices exhibit different elasticities to climate risk. Houses projected to be underwater in believer neighborhoods sell at a discount compared to houses in denier neighborhoods. This finding suggests that trust in governmental institutions and science plays an important role in shaping the perception of climate risk, which consequently influences house prices. Climate risk is, therefore, only another example of how the general public's own beliefs and perceptions affect the ultimate result in property valuation.

Numerous event studies have been carried out to see if recent disasters affect how properties in affected areas are priced. Dong (2024) examined how the major wildfires in California from 2016 to 2021 influenced home values. The study, conducted using regression analysis, found that the price effect in areas directly affected by fire, compared to unaffected areas, was not statistically significant. However, a greater extent of land burned was associated with a stronger negative impact on property prices. The study also found that major wildfires had a significant impact on surrounding neighborhoods, leading to an average property price decline of 2.2%. This suggests that there could be a spillover effect where homeowners and buyers fear that what happened in the other neighbourhood could happen in theirs as well. Of particular interest is that actual fire-touched areas showed non-significant results, indicating that the theoretical risk of wildfires might have already been priced in these neighbourhoods, but in the surrounding neighbourhoods, knowledge struck as they perceived it. Information, therefore, seems to be locally based, but as disasters and other events strike, information quickly spreads and causes price drops.

Whether information and risk are, in fact, already priced or not is another area of interest. Previous studies have shown that climate risk may not always be priced even in high-risk areas. Hino and Burke (2021) examined how areas exposed to floods in the USA are priced and whether this reflects overvaluation compared to what they should be worth, considering the climate risk. They found little evidence that housing markets fully price information about flood risk in aggregate. However, the price penalty is larger in markets where buyers are more risk aware, suggesting that policies to improve risk communication could influence market outcomes. Findings indicate that houses in flood zones in the United States are currently overvalued by a total of $43.8 billion based on the information in publicly available flood hazard maps alone and by using a national efficient flood zone discount rate of 5%. This finding again suggests that real estate markets in general fail to incorporate theoretical climate risk based on publicly available information, indicating that people's experience and perception play a vital role, but that governmental risk communication to some extent also plays a role. This finding was confirmed by Gourevitch et.al. (2023), who found that, in general, highly overvalued properties are concentrated in counties along the coast with no flood risk disclosure laws and where there is less concern about climate change.

3. Theoretical framework and hypothesis development

3.1 Economic channels that affect housing prices

Housing prices are influenced by a range of economic channels that jointly shape both demand and supply dynamics in the real estate market. Understanding these mechanisms is essential to analyzing spatial and temporal variations in housing price levels and price growth. Usual variables that are brought up are interest rates, inflation, price expectations, government policy, tax incentives, and external shocks (Case and Shiller, 2003). These factors are all, to varying degrees, influenced by national economic conditions and subject to temporal fluctuations. The actual impact of each variable could also differ between economies, where more leveraged households are more affected by interest rates.

The analysis of price differences between regions within the same economy is a different matter, many times influenced by factors beyond those related to the national economic activity. Historical research has found a wide range of economic, financial, demographic, and structural factors that affect housing prices across regions, both in the short term and in the long term.

Short-term determinants:

Mortgage credit growth (Maher, 2017), after-tax mortgage interest rates (Maher, 2017), population density (Wilhelmsson 2008), wealth (Yang and Turner, 2016), GDP (Cohen, 2017), unemployment rate (Cohen, 2017), macroprudential policy (Cohen, 2017) and price level in the previous period (Cohen, 2017).

Long-term determinants:
Disposable income (Maher 2017; Claussen 2012; Sutton 2002; Bjellerup and Majtorp 2019), mortgage regulations (Bjellerup and Majtorp 2019), housing supply (Claussen, 2012), and mortgage rates (Claussen, 2012).

3.2 Hypothesis

Sweden is currently undergoing strong urbanization trends, with population growth and economic activity increasingly concentrated in major metropolitan areas (Statista, 2024a). Despite the strong urbanisation trend, the relationship between traditional determinants and housing price disparities has become increasingly complex and challenged by what it looks like, new dynamics during the last decade (Svensk Mäklarstatistik, n.d.; SCB, 2024). A closer look at housing data reveals certain anomalies and spatial patterns in differences in both price levels and price growth that are not fully explained by traditional factors such as income levels, population density, or employment opportunities at first sight. At the same time, climate risks across Sweden's municipalities are gaining more and more attention (SGI and MSB, 2021). From 2015 to 2023, more than 146,000 natural hazard-related insurance claims were reported in Sweden, and approximately 8.8 billion SEK were paid out in coverage (Svensk försäkring, 2024). At the same time, the risk of experiencing a climate-related loss is currently thought to be twice as high as it was 30 years ago (Folksam, 2023). This is thought to significantly shape and affect the Swedish housing market, if not now, at least in the future (Mäklarsamfundet, 2024).

Climate-related risks and the potential for future damages represent characteristics that, from the perspective of a property owner, can be viewed as inherently undesirable. Unlike amenities or location-based advantages, these factors do not offer any utility or positive value—rather, they pose a threat to the physical integrity of the asset and, more importantly, to its long-term financial viability. According to standard market theory, any increase in ownership costs, whether direct, such as repairs, insurance premiums, or mitigation investments, or indirect, such as heightened risk perception should be reflected in a lower market valuation of the asset. This is because such costs reduce the expected net present value of future cash flows or utility derived from the asset (Morgan Stanley, 2022).

Considering historical literature, climate risk can be viewed from different perspectives. The Taskforce on Climate-Related Financial Disclosures (TCFD) defines physical climate risk as either "acute", which is a short-term, event-driven risk, or "chronic," referring to longer-term shifts associated with climate change (DNA Economics and Vivid Economics, 2021). To illustrate this distinction in practice, one can consider the example of precipitation. Over a given period (e.g., monthly totals over a decade), precipitation follows a distribution, with most observations clustering around the mean and rarer events occurring in the tails (Pindyck, 2011). Acute climate risk refers to the probability of experiencing one of these extreme outcomes — a tail event — under the current climate distribution. However, climate change is expected to alter this distribution itself, typically by shifting the mean and fattening the tails (Seneviratne et.al. 2012). As a result, extreme events that once were rare are projected to become more frequent and more intense. This shift exemplifies chronic climate risk, which is the evolving, structural change in the probability of extreme events under future climate conditions.

An important distinction also exists between the theoretical climate risk associated with a geographical location and the perception of climate risk. The two don't necessarily align, as pointed out in previous studies (Baldauf et al., 2020). Since previous findings pointed out that one can expect different results in different housing markets (Bunten and Khan, 2014), it is debatable which of these measures should have the greatest influence on current property prices. Perceptions of climate risk are inherently subjective and cannot be universally defined. Nevertheless, one way individuals form such perceptions is through direct experience. Therefore, analyzing past and ongoing climate-related events, the "acute climate risk", can serve as a meaningful proxy for how rational actors across regions might perceive overall climate risk. To capture the full behavioural response and the different perspectives of climate risk, one therefore benefits from including variables that state the publicly available theoretical, or "chronic" climate risk, as well as other variables that affect the perception of it, like damage costs and insurance claims assignable to natural damages. Including both damage costs and insurance claims is relevant because they don't necessarily align. Municipalities can experience many claims at a lower cost, as well as the opposite, and they can both affect the perception. Households and investors may act differently on these types of information, but they are all aspects of climate risk.

The most effective way to capture the price effect from an external risk is to analyze a market where the owner bears the most risk and therefore the most economic consequence. The object must also be liquid with a big enough transaction market. One such market is the one for single-family houses, where the owner owns the land and is responsible for all damages that may be incurred on the specific property. In 2024, single-family houses represented 41% of the total Swedish housing stock (SCB, 2025).

With regards to the above, two hypotheses have been established. Our focus is on the long-term, future, or theoretical climate risk and how it affects the different housing markets for single-family houses in Sweden's municipalities. This is because real estate is usually a long-term investment for households and investors, and climate risk may have a long-term effect on the housing market that is relevant for policymakers and inhabitants. However, the short-term, or "acute", climate risk can shape how climate risk is perceived, which makes it interesting to include as well.

H1: Theoretical and perceived climate risk are expected to separately help explain variation in single-family house price levels across Sweden's municipalities between 2015 and 2023, with higher risk associated with lower prices.

We expect municipalities with more historical claims, higher damage costs, and with a higher theoretical climate risk to experience relatively lower price levels on single-family houses for permanent residence between 2015 and 2023.

H2: Theoretical and perceived climate risk are expected to separately help explain variation in price growth of single-family houses across Sweden's municipalities, with higher risk associated with slower growth.

Secondly, we expect municipalities with more historical claims, higher damage costs, and with a higher theoretical climate risk to experience relatively lower price growth on single-family houses for permanent residence throughout the time period 2015-2023.

3.3 Modelling framework

3.3.1 Hedonic pricing theory

Hedonic pricing theory emerged during the late 1960s and 1970s, building upon the characteristics theory of value developed by Lancaster in 1966, Griliches in 1971, and further formalized by Rosen in 1974 (Chin and Chau, 2003). The central idea behind the theory is that the price of a good is determined not simply by the good itself, but by the bundle of characteristics or attributes it embodies (Monson, 2009).

In the context of real estate, hedonic pricing models assume that a property's value is derived from both internal characteristics, such as size, architectural style, age, construction materials, number of rooms, and energy efficiency, and external characteristics that relate to its surrounding environment. These may include proximity to amenities like water bodies, parks, public transportation, good schools, and shopping areas, as well as disamenities such as high crime rates, pollution, noise, and environmental risks like flooding or landslides (Monson, 2009)

In practical terms, homeowners and other market participants should rationally assign a negative value, or a discount, to properties exposed to climate risk. This discount reflects the anticipated increase in the cost of ownership due to potential damages, higher insurance costs, regulatory requirements, or depreciation in resale value (Schuetz and Devens, 2024).

Hedonic pricing models are particularly well-suited to capturing and quantifying such effects. By analyzing a large number of property transactions across different time periods and geographic areas, these models can isolate the marginal impact of specific risk-related attributes such as flood exposure, erosion risk, or proximity to areas identified as climate-vulnerable, on property prices (Rehdanz, 2002).

One key challenge with the theory is its ability to only capture effects from what market participants perceive as an environmental difference between goods (Chin and Chau, 2003). For example, if a homeowner is not aware of a potential danger in the area, the model won't capture the effect of that danger in a proper way. This is especially relevant regarding environmental and climate characteristics as found by Baldauf et.al. (2020), Hino and Burke (2021), and Gourevitch et al. (2023) in their research. By incorporating perception-based measures and tangible data into the hedonic pricing model, however, the model's limitations regarding awareness might be smaller than by just using theoretical climate risk, which in many cases depends on the individual's climate literacy (OECD, 2024).

To be able to test a version of the hedonic model given its limitations, one must also find a market with a relatively homogeneous population with regard to beliefs (Rosen, 1974). Sweden has a position as a climate risk-aware nation (Naturvårdsverket, 2018) and has been a leading figure in addressing climate change challenges for a long time (Government Offices of Sweden, 2023). An aware and constructive market should, all else equal, be better at pricing climate risk (Krueger et.al., 2020). Climate change is also intensifying the frequency and severity of natural hazards in Sweden, with significant implications for public safety, infrastructure, and the economy. Studies indicate that the increasing occurrence of extreme weather events, such as heatwaves, droughts, flooding, and wildfires, is driving a rise in multi-hazard risks. For instance, Ducros et al. (2024) highlight the 2018 summer heatwave and drought, which led to devastating wildfires across Scandinavia. These events caused a GDP drop in the region and a dramatic drop in exports. This underscores the economic vulnerabilities associated with climate risks in Sweden and the urgent need for adaptation measures and improved disaster risk management and understanding.

Summarized, applying a hedonic pricing framework can help explain regional differences in property prices that might otherwise be overlooked, while also offering valuable insights into how well the Swedish housing market is internalizing emerging climate risks. Sweden is a suitable market given its position as a climate risk-aware nation, and perception-based measures might capture awareness and restrict the theory's limitations.

4. Data description

4.1 Data collection

To be able to construct the models, data have been collected from several different sources and structured into a panel data set. The main source for the majority of the data has been Statistics Sweden (SCB), which collects and publishes statistics largely based on information submitted to them in various surveys from enterprises, government agencies, and private persons. Other sources have been the Swedish Civil Contingency Agency (MSB), which publishes risk and emergency reports; the private company Hemnet, which, through their platform, advertise and save data on sales of single-family houses; Insurance Sweden (Sw: *Svensk Försäkring*), which provide data on insurance claims and damages; and Swedish Real Estate Statistics (Sw: *Svensk Mäklarstatistik*), which together with SCB, highlights and structures data about the Swedish housing market.

The final dataset is a panel of 287[1] Swedish municipalities observed annually over the period 2015 to 2023. Each observation corresponds to a specific municipality in a given year, resulting in a municipality-year panel structure. The panel includes variables related to property prices, insurance claims, and damage costs, a theoretical climate risk indicator, as well as control variables. The panel is balanced, capturing both cross-sectional and temporal

[1] Sweden consists of 290 municipalities but the municipalities Nybro, Perstorp, and Uppvidinge are excluded from this study because they have not received a theoretical climate risk point by MSB and SGI.

variation across municipalities and over time. In some tests, the final sample of 287 municipalities is trimmed due to insufficient transaction data (see section 4.2.3).

The period 2015–2023 was selected primarily due to data limitations before 2015 and after 2023. To ensure the ability to draw meaningful conclusions, the longest possible time span with consistent and reliable data was chosen.

4.2 Key datasets

In this chapter, we describe in detail the key datasets employed to construct our dependent and explanatory variables.

4.2.1 MSB and SGI climate risk study (Theoretical Climate Risk Indicator)

In 2019, the Swedish government commissioned the Swedish Geotechnical Institute (SGI) and MSB to identify specific risk areas for landslides, slope collapse, erosion, and flooding in Sweden that are climate-related. The assignment included describing the socio-economic consequences of the climate-related risks and ranking the risk areas (SGI and MSB, 2021).

In the 2017 national strategy for climate adaptation and in the assignment given to SGI and MSB, the government highlights that risks associated with landslides, slope collapse, erosion, and flooding can have very significant consequences for people's lives and health, for ecosystems, and for infrastructure, buildings, and cultural heritage. The government, therefore, concluded that there was a need to identify specific risk areas in Sweden regarding landslides, slope collapse, erosion, and flooding, and to rank them based on probability, potential consequences, and specific problems. The assignment was carried out in close collaboration with the county administrative boards, the Swedish Environmental Protection Agency (Sw: *Naturvårdsverket*), The Geological Survey of Sweden (SGU), and Swedish Meteorological and Hydrological Institute (SMHI).

The objective of the analysis was to assign a certain climate risk point to every affected area and the consequences it would bear to the businesses and activities in that area. The activities included in the study were those deemed most vulnerable. If these activities were impacted, the consequences would be particularly severe for the residents in the affected area. The activities included in the assignment to assess potential societal consequences of landslides, slope collapse, erosion, and flooding are presented in **Table 1**.

Table 1: *Main activities and sub-activities for assessing the potential societal consequences of landslides, slope collapse, erosion, and flooding.*

Human Health	Environment – Protected Areas	Environment – Facilities	Economic Activity	Cultural Heritage
Number of residents	National parks	Environmentally hazardous activities	Number of employees	World heritage sites
Hospitals	Nature reserves	Contaminated areas	Buildings	Cultural reserves
Health centers	Natural monuments	Seveso activities	National interest – railway	National interest – cultural environment
Fire stations	Natura 2000 areas	Sewage treatment plants	National interest – railway stations	Listed buildings
Emergency call centers	Conservation areas		National interest – airport	State-owned listed buildings
Communication masts	Water protection areas		National interest – port	National archives
Police stations			Transformer stations	Ancient monuments
National interest – road			Distribution buildings	Churches
Waterworks			Hydropower plants	Museums
Schools			Heating plants	
Preschools			Dams	
Sveriges Radio			Agricultural land	
SVT (Swedish Television)			Animal production sites	

The economic activities in **Table 1** have varying levels of impact on society if they are damaged during an event. Activities that maintain and ensure critical societal functions have been given particular attention in the analyses to identify risk areas. All sub-activities in **Table 1** have been assessed relative to one another (weighted against each other) based on the potential consequences for economic, social, and ecological values in the event of landslides, slope collapse, erosion, or flooding. The assessment assumed that the activity is damaged to the extent that it can no longer maintain its function or poses a risk of contaminating other areas. The activities have been assigned scores according to the scale described in **Table 2.**

Table 2: *Assessment basis for developing the weighting of activities.*

Impact	Economic	Social	Ecological	Score
Low	Costs that can be managed within the existing budget framework of the activity.	Disruptions affecting a few individuals.	Minor and temporary damage to ecosystem capacity and recovery ability.	1
Medium	Costs requiring reallocation of priorities within the activity.	Health effects for people or animals or serious disruptions affecting more individuals.	Moderate damage to ecosystem capacity and recovery ability.	2
High	Costs that are difficult for the activity to bear.	Significant health effects for people or animals or serious disruptions affecting many individuals.	Serious and long-term damage to ecosystem capacity and recovery ability, or damage to areas of national interest.	3
Very High	Costs that are difficult for society to bear.	Threats to human life and health or extensive damage to socially critical activities.	Severe and irreversible damage to ecosystem capacity and recovery ability, or extensive damage to areas of national interest.	4

The total score assigned to each sub-activity was then used to group these into three weighting classes. The results are presented in **Table 3.**

Table 3: *Results after weighting of activities.*

Human Health	Environment - Protected Areas	Environment - Facilities	Economic Activity	Cultural Heritage	Weighting Score
Housing Hospitals Waterworks Fire Stations	Water protection area	Seveso activities Environmentally hazardous activities Water treatment plants Contaminated areas	Employees Hydropower plants Dams Buildings	World Heritage	3
National interest roads Police stations Health centers Schools Preschools Emergency call centers	National park Natura 2000 area Nature reserve		Heating plants National interest ports National interest railways National interest airports National interest railway stations Animal production sites Farmland	National Archives Cultural reserves National interest cultural heritage Museums	2
Masts Swedish Radio SVT	Conservation area Natural monument		Transformer station Distribution building	Churches State-owned historic buildings Listed buildings Ancient monuments	1

The fact that an activity is located in a threatened area does not mean that damage will occur in the event of an incident. Local conditions are of great importance for the consequences of an incident, but these were not analyzed within the MSB and SGI assignment.

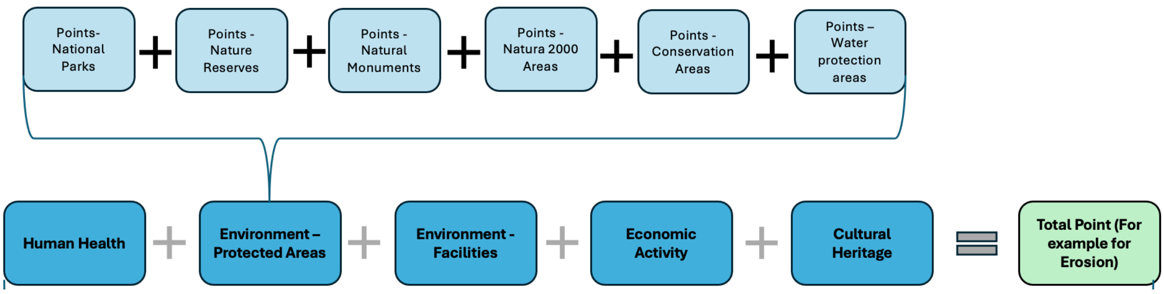
The risk of landslides, slope collapse, erosion, and flooding affects Swedish municipalities to varying extents. In some municipalities, large areas may be threatened, while in others, only smaller areas are at risk. To facilitate comparisons between Sweden's municipalities, an analysis was conducted that shows, for each municipality, the number of businesses located in areas at risk. Each business has also been assigned a weight score according to the distribution shown in **Table 3**. This score was used to calculate the total score for each business within each municipality. The total score consists of a sum of scores based on how various sectors (human health, environment, economic activity, and cultural heritage) are affected within the municipality and their importance. In some sectors, a large number of objects may be affected, for example, the number of cultural heritage sites, while in other sectors, only a small number of objects are affected, but these may be of critical societal importance, such as hospitals. MSB continued with creating histograms for each sector. These histograms showed the frequency of values within a dataset. It visualizes, for example, whether 150 threatened objects in a municipality are a large or small number in relation to the number of affected objects within that sector compared to other municipalities. Based on the histograms, a distribution of scores was made. Municipalities with a high number of affected businesses in relation to other municipalities within threatened areas were assigned 3 points. Municipalities with a medium-high number of affected businesses were assigned 2 points, and municipalities with a low number of affected businesses were assigned 1 point. This scoring system allowed for an effective comparison of risk across municipalities. See an example of this calculation in **Table 4.**

Table 4: *Example of climate point calculation for the sub-activities natural reserves and natural conservation areas.*

Municipality	Number of natural reserves inside threatened area	Point from number of natural reserves (1-3)	Weight point for natural reserves (1-3)	Number of natural conservation areas within threatend areas	Point from number of natural conservation areas (1-3)	Weight point for natural conservation areas (1-3)	Total point
A	1	1	2	41	3	1	1x2+3x1=5
B	3	1	2	22	2	1	1x2+2x1=4
C	11	3	2	12	1	1	3x2+1x1=7

To relate back to **Table 1,** the above example is for erosion risk, for natural reserves and conservation areas in municipalities A, B, and C. For example, municipality A has few natural reserves within a threatened area compared to municipality B and C, and therefore gets 1 point. The weight point from **Table 3** indicates that natural reserves are worth 2 points. The same thing is then done for natural conservation areas and all the other sub-activities under "Environment - Protective areas". The points for all sub-activities under "Environment - Protective areas", with regard to, for example, erosion, are then summed, and one can conclude the total risk point for each municipality concerning erosion and the effect on "Environment - Protective areas".

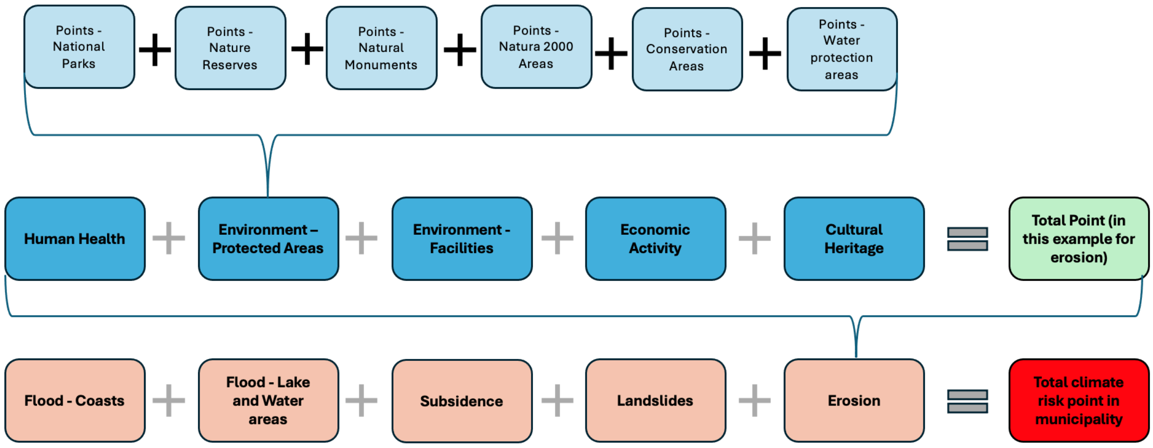
Figure 1: *Visualization of climate risk point calculation as done by MSB and SGI.*



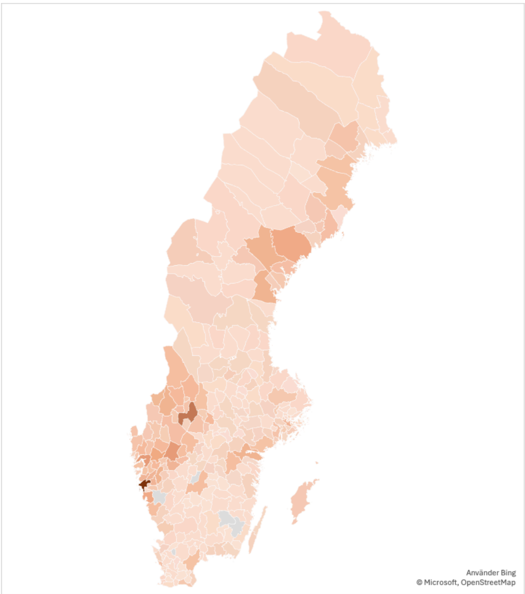
Later on, the same thing was done for landslides, slope collapse, erosion, and flooding, for all the other main activities in **Table 1** and its sub-activities, for each municipality. Ending up with a total risk point per climate risk category, per main activity, per municipality.

This concludes the summary of the MSB and SGI study. In our new study, the climate risk scores discussed are processed and aggregated for each category, activity, and municipality, forming a variable in our panel dataset that represents the overall climate risk per municipality. A visualization of this is available in **Figure 2.**

Figure 2: *Visualization of the total municipality risk point calculation done in this study.*



Heatmap 1: *Total municipality climate risk points based on MSB and SGI report.*[2,3]



Dark brown = Highest total risk point in all categories
Light brown = Lowest total risk point in all categories

4.2.2 Insurance Sweden: Insurance claims and damage costs

For nearly 40 years, Insurance Sweden has collected and published statistics on insurance claims related to natural and weather-related damages. The data includes storm-related damages since 1985, water-related damages (such as flooding) since 2011, and other natural

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[2] The municipalities with the highest total climate risk points is: Göteborg (1,053), Karlstad (736), Uddevalla (577), Lidköping (577), Vänersborg (514), Kungsbacka (509), Örnsköldsvik (499), Mark (454), Norrköping (438), Alingsås (429).
The municipalities with the lowest total climate risk points is: Bjuv (4), Lessebo (7), Hörby (7), Kumla (9), Gnosjö (10), Örkelljunga (12), Staffanstorp (14), Svedala (14), Emmaboda (14), Vaggeryd (16).
The average total risk point in all municipalities is 142,17.

[3] Nybro, Perstorp, and Uppvidinge have all received 0 points in all categories and are excluded from this study because this could either mean an actual risk of zero or that MSB and SGIs study was not conducted in these municipalities. These municipalities are visible in light grey in the heatmap.

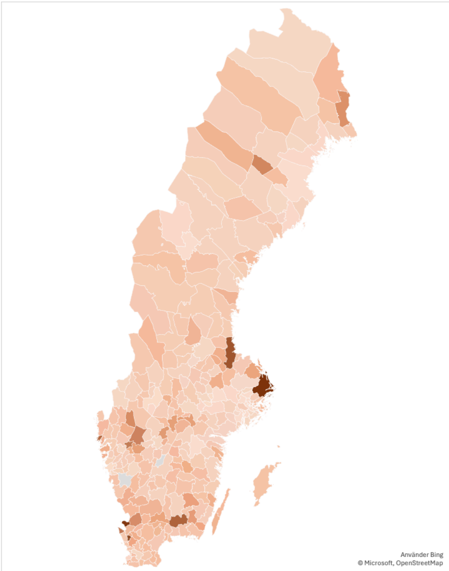
and weather-related damages since 2015. The statistics cover both the number of claims and the compensation paid out by insurance companies. The latest dataset covers 2023 and includes updated figures for the period 2015 to 2023 (Svensk försäkring, 2024).

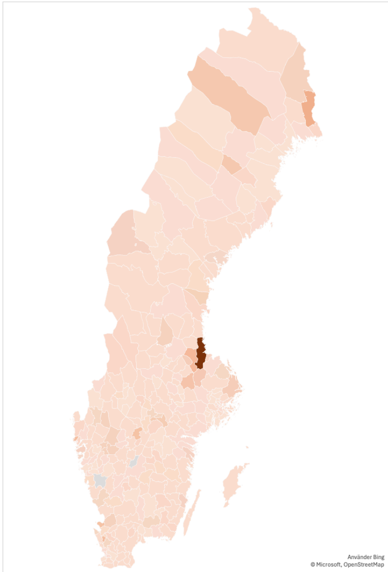
The dataset covers the number of natural disaster-related insurance claims and the total compensation paid, broken down by insurance type, type of natural damage, and municipality. The number of claims for each year represents only those that resulted in payouts; claims that did not lead to compensation are excluded. The compensation amounts include reserves for known claims but exclude reserves for unknown claims. Additionally, the deductible paid by the policyholder is not included in the reported compensation amounts. Payments that insurance companies may receive from municipalities due to inadequate drainage capacity are also excluded.

The dataset only includes damages covered by insurance at the time of the event, which means the actual societal cost of natural damages is likely higher. Natural damages include those caused by water, storms, and other weather- and nature-related events. Certain damages related to forestry and agriculture, such as crop damage, are included when covered by these insurance policies. However, land damages are generally not covered. Forest insurance data is included where applicable. Damages caused by lightning and wildfires are not included in these statistics because it was not part of the government assignment in 2021.

Furthermore, the data cover damages related to home and villa insurance, vacation home insurance, boat insurance, corporate and property insurance, and other property-related insurance policies. However, they do not include damages covered by traffic and motor vehicle insurance. Insurance for state and municipal properties and infrastructure is included only if reported by participating insurance companies. Some public assets and infrastructure are typically not insured. Participation in the reporting process has been voluntary. However, all members of Insurance Sweden with significant insurance operations in Sweden have submitted data. The coverage rate for property insurance, including home and villa, vacation home, boat, corporate, and property insurance, was 87% for 2023. The data is presented in an aggregated format for the entire industry, which means that company-specific information is not published (Svensk försäkring, 2024).

Heatmap 2 and 3: *Accumulated claims of damages[4] (left) and accumulated damage costs[5] (right) caused by natural reasons per 1,000 inhabitants in Sweden's municipalities 2015-2023.*





Dark brown = Most claims and higher damage costs[6]
Light brown = Fewest claims and lower damage costs

4.2.3 Svensk mäklarstatistik K/T index (Estimate for price growth)

Swedish Real Estate Statistics is a database provider that, since 2005, has collected data from the Swedish residential real estate market. The original data comes from real estate broker reports, and the data is later structured and validated by Statistics Sweden (SCB) before Swedish Real Estate Statistics publishes the end product (Svensk Mäklarstatistik, n.d).

To follow the price trend on the housing market, Swedish Real Estate Statistics uses the K/T method. This method determines a quota between the final sales price (K) and tax assessment value (T), which can be followed and analysed over time. By considering the property's location, size, age, and standard, the calculations become more reliable than using other methods like price per square meter over time, which is a much rougher metric.

[4] The municipalities with the highest accumulated claims of damages caused by natural reasons per 1,000 inhabitants was: Norrtälje (70.6), Båstad (69.8), Bjuv (64.3), Gävle (61), Tingsryd (56.7), Sotenäs (55), Höganäs (50.2), Grästorp (49.8), Lidköping (47.3), Malå (46.2).
The municipalities with the lowest accumulated claims of damages caused by natural reasons per 1,000 inhabitants was: Sundbyberg (2.7), Solna (3.1), Botkyrka (4.8), Sigtuna (5.1), Östersund (5.1), Järfälla (5.2), Stockholm (5.4), Upplands-Bro (5.9), Södertälje (6.2), Skellefteå (6.3).
[5] The municipalities with the highest accumulated damage costs caused by natural reasons per 1,000 inhabitants was: Gävle (16,974,000), Övertorneå (7,519,000), Sandviken (5,718,000), Bjuv (5,397,000), Sotenäs (5,226,000), Båstad (4,814,000), Töreboda (4,688,000), Sala (4,463,000), Malå (4,082,000), and Jokkmokk (3,925,000).
The municipalities with the lowest accumulated damage costs caused by natural reasons per 1,000 inhabitants was: Sundbyberg (77,000), Kungsör (143,000), Salem (156,000), Hammarö (160,000), Håbo (177,000), Solna (189,000), Sigtuna (191,000), Munkfors (196,000), Ljusnarsberg (196,000), and Malmö (217,000).
[6] Gävle, which stands out in the statistics, is heavily affected by the torrential rain in 2021 which caused floods and damages of 1.65 billion SEK, which is almost 25% of the total damage costs due to natural reasons in Sweden during 2015-2023.

Consider a basic example: In Year 1, the average house in a municipality sells for 50,000 SEK per square meter. In Year 2, the average price rose to 60,000 SEK per square meter, indicating a 20% increase. However, this ratio doesn't account for the fact that in Year 2, a luxury villa was sold, while only standard homes were sold in Year 1. In contrast, the K/T ratio compares the sale price of a house to its tax assessment value, which is set by the Swedish Tax Agency every three years and is intended to reflect around 75% of the market value (Skatteverket, n.d). Even if a luxury villa is sold in Year 2, the tax assessment value (T) will capture this, and the K/T ratio will indicate that in Year 1, the ratio was 1.25, and in Year 2, it remained at 1.25, showing no real price increase.

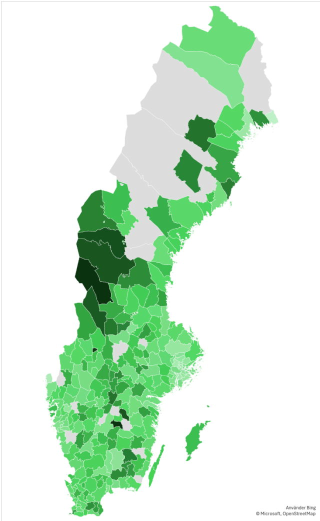
Tax assessment values typically increase when they are updated, as they are determined based on the average price change (usually an increase) in each respective area. At the same time, the valuation level is measured at the municipal level. Given this increase, if no adjustments were made, the K/T ratio curve would show a downward shift every third year. Therefore, each time the assessed tax values are updated, all historical curves are recalculated based on the new valuation level, most recently when the 2024 assessed values were finalized. As a result, the figures in the entire data series from 2005 onward reflect the latest 2024 tax assessment value, and in that way, you can calculate year-over-year average price growth in each municipality.

If the number of transactions during any of the relevant comparison periods falls below 25, Swedish Real Estate Statistics considers it too few to have statistical relevance for the given municipality. Because of this, 29 municipalities fall short in some or all periods from 2015 to 2023, and a general K/T quota can't be determined. These municipalities have been omitted from the dataset when analyzing price growth, as discussed in section 5.5 (Svensk Mäklarstatistik, n.d.).

The data reveals that between 2015 and 2023, prices on single-family houses in Sweden grew at an average annual rate of 4.0%. However, there were large differences across municipalities. The fastest-growing municipalities between 2015 and 2023 include Aneby and Älvdalen, both with an annual growth rate of 8.9%, followed by Munkfors (8.8%), Berg (8.2%), and Härjedalen (8.0%). All of these exceeded the national average by a wide margin. In contrast, the slowest-growing municipalities were Haparanda (0.8%), Strömstad and Salem (both 1.3%), Järfälla (1.5%), Uppsala (2.1%), and Luleå (2.0%).

The data shows that some smaller or more rural municipalities have seen much faster property price growth than larger urban areas. See **Appendix 1a** for the complete table.

Heatmap 4: *Single-family house CAGR between 2015 and 2023 in Sweden's municipalities.*[7][8]



Dark green = highest growth
Light green = lowest growth

4.2.4 SCB average house prices (Estimate for price level)

Statistics Sweden (SCB) calculates the average purchase price of sold single-family houses for permanent residence per municipality by compiling sales data from the Swedish Land Registry (Sw: *Lantmäteriet*). The dataset includes information on purchase prices for properties classified under property type code 220 (single-family housing units). Permanent residence refers to properties where someone has been registered as a resident on the property during any of the last three quarters, as well as the current quarter of the transfer. Additionally, single-family houses on land leasehold are excluded from the data (SCB, 2024).

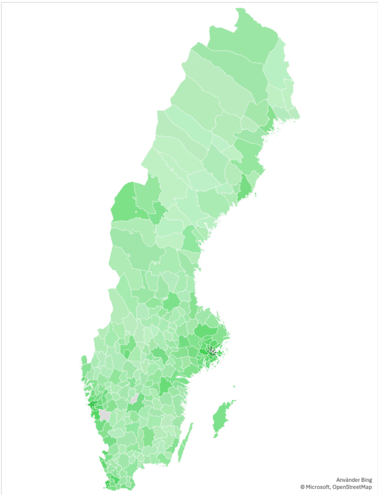
The timing of the transactions on which the statistics are based is determined by the date on the bill of sale, which is the day the buyer becomes the new formal owner of the acquired property. To calculate the average, the total purchase price of all sold single-family houses within a specific municipality during a given year is summed and then divided by the number of sales to obtain an average sales price. The data is presented in units of 1,000.

It is important to note that SCB applies certain limitations and criterias when compiling this statistic. For example, properties with exceptionally high or low purchase prices may be excluded or capped to prevent the average from being disproportionately affected by atypical sales. For single-family houses, the maximum allowed purchase amount is 20,000,000 SEK; this means that purchases above this amount are capped.

7 Similar results were found when excluding 2023, a year marked by elevated interest rates. This suggests robustness in the results.
8 Note that 29 municipalities were excluded because too few transactions occurred in either 2015 or 2023. These are visible in light grey in the heatmap.

In 2023, the average price for a single-family house in Sweden was 2,670,000 SEK. The most expensive municipalities were located near Stockholm or in desirable coastal areas. Lidingö had the highest average price at 12.8 million SEK, followed by Danderyd at 12.6 million SEK. Other highly priced municipalities included Solna, Nacka, and Sundbyberg, all above 9.3 million SEK. Stockholm itself had an average of 8.3 million SEK. Dorotea had the lowest average price at just 398,000 SEK, followed by Sorsele at 435,000 SEK and Åsele at 452,000 SEK. All bottom ten municipalities had average house prices well below 650,000 SEK, more than 80% lower than the national average (SCB, 2024). See **Appendix 1b** for the complete table.

Heatmap 5: *Average single-family house price levels 2023 in Sweden's municipalities.*



Dark green = highest average price level
Light green = lowest average price level

5. Methodology

In this section, the research methodology is presented. We will begin by presenting the overall research design. We then describe all variables included in the study and the descriptive statistics for each variable. Afterwards, we will discuss the estimation techniques and describe the statistical models. Finally, we will discuss important limitations with regard to our research methodology.

5.1 Research design

Hedonic pricing theory explains that a property's value is derived from its characteristics. A quantitative regression analysis is a key tool to estimate the individual contribution of a characteristic to the overall price, making it an appropriate method for testing and applying hedonic pricing theory. Consequently, our research design, with the link to the hedonic pricing model, allows us to estimate whether, and to what extent, climate risk is reflected in housing prices and their development.

Our research design involves a deductive approach (Bell et al., 2019), where theory derives hypotheses that are later tested and either confirmed or rejected. To reflect the fact that climate risk as a concept is multi-dimensional, our research design makes use of multiple-indicator measures that consider different aspects of the concept (Bell et al., 2022).

To capture multiple aspects of climate risk's influence on the housing market, we estimate two complementary models, one examining its year-by-year effect on property price levels and another assessing the average impact on price growth over time.

5.2 Description of Variables

5.2.1 Dependent variables

- ***Average property price per municipality per year:***

To measure the explanatory variables' effect on the single-family house price level for our first hypothesis, we use the average transaction value of single-family houses per municipality from SCB in every year from 2015 to 2023. Extreme transaction values are capped at 20 MSEK, and extreme outliers in each municipality are therefore excluded from the data. This represents the most accurate way of estimating the average price level per municipality (SCB, 2024).

$$\text{Average Property Price}_{i,t} = \frac{1}{n_{i,t}} \sum_{j=1}^{n_{i,t}} \min(\text{Transaction Value}_{i,t,j},\ 20{,}000{,}000)$$

Where i denotes municipality, t the year, and j the individual transaction. $n_{i,t}$ represents the number of single-family house transactions in municipality i at year t.

- ***Average price growth per municipality between years***

To measure the explanatory variables' effect on single-family house price growth for our second hypothesis, we use the growth rate in the K/T number for single-family houses per municipality in every year from 2015 to 2023.

$$\frac{\left(\frac{K}{T}\right)_{\text{Municipality},\,t} - \left(\frac{K}{T}\right)_{\text{Municipality},\,t-1}}{\left(\frac{K}{T}\right)_{\text{Municipality},\,t-1}}$$

5.2.2 Explanatory variables

The key explanatory variables in both models are the following, and each represents a dimension of climate risk.

- ***Climate risk points per municipality***

As a proxy for theoretical climate risk, we use the climate risk points calculated in the study conducted by MSB and SGI. The climate risk points are time-invariant and assumed to be constant, as discussed in section 5.5.

- ***Insurance claims per 100,000 inhabitants per municipality per year***

As a proxy for the perception of climate risk, we use aggregated insurance claims per municipality per year. These are then normalized with the population per municipality per year, multiplied by 100,000. This is done to exclude the effect that municipalities with bigger populations also tend to have more claims. By normalizing the variable, municipalities can be compared against each other.

$$\left(\frac{\sum \text{Insurance Claims}_{\text{Municipality},\, t}}{\text{Population}_{\text{Municipality},\, t}}\right) \times 100{,}000$$

- ***Damage costs per 100,000 inhabitants per municipality per year***

As another proxy for the perception of climate risk, we use aggregated damage costs per municipality per year. These are then normalized with the population per municipality per year, multiplied by 100,000. This is done to exclude the effect that municipalities with bigger populations also tend to have higher aggregated damage costs. By normalizing the variable, municipalities can be compared against each other.

$$\left(\frac{\sum \text{Damage Costs}_{\text{Municipality},\, t}}{\text{Population}_{\text{Municipality},\, t}}\right) \times 100{,}000$$

5.2.3 Control variables

Model 1 - Price level (Hypothesis 1)

With regards to previous literature on price level determinants as outlined in section 3.1, the following variables have been selected as control variables in the model construction: *Population Density, Disposable Income per household, Unemployment Rate, and Total Single-family Houses per 1,000 inhabitants.*

Additionally, *Reported Crimes per 100,000 inhabitants, Average Age, Municipality Size (KM²), Near Major City (dummy), Near Airport (dummy), Has Coastline (dummy)* have been included as control variables as they are believed to have a specific strong effect in Sweden because most of them reflect the urbanization trend as well as infrastructure differences between municipalities. Reported crimes are included because previous research has found it to be an important variable (Lynch and Rasmussen, 2001).

Model 2 - Price growth (Hypothesis 2)

With regards to previous literature on price growth determinants as outlined in section 3.1, the following variables have been selected as control variables in the model construction: *Population Density Growth, Disposable Income per household Growth, Unemployment Rate*, and *New Single-family Houses per 100,000 inhabitants.*

Additionally*, Reported Crimes per 100,000 inhabitants Growth, Average Age, Municipality Size (KM²)*, *Near Major City (dummy), Near Airport (dummy)*, and *Has Coastline (dummy)* have been included for the same reasons as in model 1.

Dummy explanation:

➔ *Near Major City (0-1)* are defined as a maximum of 1 hour by car from the municipality's county town to either Stockholm, Gothenburg, or Malmö.

➔ *Near Airport (0-1)* is defined as a maximum of 1 hour by car from the municipality's county town to one of the state-owned Swedavia airports.

➔ *Has Coastline (0-1)* is defined as if the municipality has a coast to either the Baltic Sea or the North Sea.

5.2.4 Data transformations

All data was compiled into a panel data structure in Excel, and all further data transformations and tests were performed using the statistical software RStudio.

5.2.4.1 Data inspection and logarithmic transformations

As one of our initial steps, we visualised all data and checked descriptive statistics on all variables. We noted that a few variables had extensive ranges and also showed signs of skewness and kurtosis. To address non-normal distributions and reduce the influence of outliers, we applied logarithmic transformations (Wooldridge, 2013) to the following variables: *Damage Costs per 100K*[9], *Insurance Claims per 100K*, *Population Density*,

[9] For the remainder of this report, "per 100,000 inhabitants" is referred to as "per 100K".

Disposable Income, and *Reported Crimes per 100K.* All of these were transformed in both models, and before the growth rate transformations in the property price growth model. In the model analyzing property price levels, we applied an additional logarithmic transformation to the *Property Price* variable, which is based on the average property price data from SCB. In contrast, the *Property Price Growth* variable, used in the model analyzing property price growth and based on the K/T number provided by Swedish Real Estate Statistics, was not transformed, as its distribution was already appropriate.

5.2.4.2 Growth rate transformations

Given that our dependent variable in the property price growth model is expressed as a growth rate, we decided to transform some of our control variables into growth rates as well. The rationale is that the growth rate of these variables, rather than their absolute levels, is more appropriate for explaining variation in the property price growth. However, this does not apply to our explanatory variables *Climate risk, Damage Costs per 100K, and Insurance Claims per 100K*. These variables intend to capture the theoretical and perceived climate risk, where the level of these variables, rather than their change, is more relevant to our research question. The following variables were transformed into growth rates: *Population Density Growth*, *Disposable Income Growth*, and *Reported Crimes per 100K Growth*. Since *Unemployment Rate* was already expressed as a rate, *Average Age* and *Municipality Size (KM^2)* had very small or no fluctuations between years, and *New Single-family Houses per 100K* were already a growth term, those were kept as they were. Similarly, the dummy variables *Has Coastline*, *Near Airport*, and *Near Major City* were all kept binary.

5.2.4.3 Construction and use of interaction terms

In the first panel regression model, connected to hypothesis 1, we estimated the yearly effect of each explanatory variable on the property price level. This reflects our interest in whether climate risk has a persistent effect on the price level, not only between municipalities, but also across time. In contrast, the second panel regression, connected to hypothesis 2, estimated the average effect of our explanatory variables on the property price growth. By focusing on long-term dynamic trends rather than year-specific fluctuations, this allows us to assess whether higher climate risk is associated with lower appreciation in value over time.

Rather than running separate yearly cross-sectional regressions to estimate how *Climate Risk*, *Damage Costs per 100K*, and *Insurance Claims per 100K* affect property price levels in a given year, we chose to estimate a single fixed-effects panel regression in the first model. This approach allows for more precise estimates of our control variables (Wooldridge, 2013; Hoechle, 2007). To be able to capture the year-specific effects of the explanatory variables, we constructed time dummies for each year from 2015 to 2023 and interacted them with *Climate Risk*, *Damage Costs per 100K*, and *Insurance Claims per 100K*. These interaction terms enabled us to estimate how the impact of each variable evolves over time, even for the climate risk variable, which is otherwise time-invariant.

5.2.4.4 Construction of lagged variables

Previous research indicates that the effect of changes in economic variables is often realized with a delay rather than instantaneously (Mankiw, 2016; Wooldridge, 2013; Friedman, 1957). For that reason, we anticipated a delayed effect in our models for both property price levels and property price growth. We therefore proceeded by constructing 1-year lagged variables for *Damage Costs per 100K*, *Insurance Claims per 100K*, *Population Density*, *Disposable Income*, *Reported Crimes per 100K*, *Single-family Houses per 1,000*, and *Unemployment Rate*. Variables that were transformed into growth rates for our model on property price growth were treated in a similar manner. The 1-year lagged regression models are reported together with the non-lagged models in the regression tables. We also constructed 2-year lagged variables and estimated 2-year lagged regression models. These results are not reported in the result section, as these models reduced the sample size significantly by removing two out of nine years of data. In addition, it was challenging to include multiple lags simultaneously due to multicollinearity, and the 2-year lagged models on their own did not offer additional insights beyond the 1-year lag specifications. The results of the 2-year lagged regression models are presented in **Appendices 2a, 2b, 2c, and 2d**.

5.2.5 Descriptive statistics

The descriptive statistics for the dependent variable, independent variables, and control variables in the property price level model are presented in **Table 5a**[10]. The descriptive statistics of the original variables prior to any transformation can be found in **Appendix 3a**. The mean value of the theoretical *Climate Risk* variable is 142.17, and it exhibits high variation as indicated by the standard deviation of 136.49. The range of the *Climate Risk* variable is also quite substantial, ranging from 4 in the municipality with the lowest theoretical climate risk to 1,053 in the municipality with the highest theoretical climate risk.

[10] Note that the dependent variable and several other independent variables are logarithmic transformed to deal with different types of non-normality as described in section 5.2.4.1.

The minimum values of the variables *Damage Costs per 100K* and *Insurance Claims per 100K* are 0, which reflects that certain municipalities in certain years didn't see any claims or insurance payouts related to natural or weather-related damages. The average municipality has 289.87 *Single-family Houses per 1,000*, with a standard deviation of 75.92 among the 287 different municipalities. Naturally, there are quite noticeable differences, which are highly dependent on the municipality's housing type mix. The control variables, *Has Coastline*, *Near Airport*, and *Near Major City* are all binary, where 1 equals yes and 0 equals no.

Table 5a: *Descriptive statistics (Property Price Level model).*

Variable	N	Mean	Median	St. Dev.	Min	Max
Average Property Price (log)	2,583	7.53	7.50	0.69	5.58	9.52
Climate Risk	2,583	142.17	93.00	136.49	4.00	1,053.00
Damage Costs per 100K (log)	2,583	15.14	15.16	1.65	0.00	21.22
Insurance Claims per 100K (log)	2,583	4.87	4.81	0.95	0.00	8.61
Population Density (log)	2,583	3.50	3.38	1.56	0.18	8.77
Disposable Income (log)	2,583	6.10	6.07	0.15	5.82	6.77
Reported Crimes per 100K (log)	2,583	9.11	9.13	0.28	8.04	10.09
Single-family Houses per 1,000	2,583	289.87	296.50	75.92	6.70	533.80
Unemployment Rate	2,583	0.13	0.12	0.04	0.05	0.24
Average Age	2,583	43.57	43.80	2.72	36.30	52.40
Has Coastline (1 = Yes)	2,583	0.28	0.00	0.45	0.00	1.00
Near Airport (1 = Yes)	2,583	0.31	0.00	0.46	0.00	1.00
Near Major City (1 = Yes)	2,583	0.25	0.00	0.43	0.00	1.00
Municipality Size (KM^2)	2,583	1,413.98	667.34	2,410.90	8.73	18,685.00

Note: The full sample consists of 2583 observations from 287 unique municipalities across 9 years during the period 2015–2023. Where indicated, variables are log-transformed and normalized per 1,000 or 100,000 inhabitants.

The descriptive statistics for the dependent variable, independent variables, and control variables for the property price growth model are presented in **Table 5b**[11]. The descriptive statistics of the original variables prior to any transformation can be found in **Appendix 3b**. Compared to the variables presented in **Table 5a**, the dependent variable and several other control variables presented in **Table 5b** have negative minimum values, which reflects

[11] Note that several independent variables are logarithmic transformed, to deal with different types of non-normality as described earlier in section 5.2.4.1.

negative growth. On average, there were 172.66 *New Single-family Houses per 100K* over the period, with a standard deviation of 328.18. The minimum value was -2,811.75, which reflects an observation where demolitions and transformations to other property types exceeded the number of new productions.

Table 5b: *Descriptive statistics (Property Price Growth model).*

Variable	N	Mean	Median	St. Dev.	Min	Max
Average Property Price Growth	2,277	0.06	0.06	0.09	-0.21	0.37
Climate Risk	2,277	148.70	95.00	141.79	4.00	1,053.00
Damage Costs per 100K (log)	2,277	15.21	15.18	1.36	0.00	21.22
Insurance Claims per 100K (log)	2,277	4.88	4.79	0.90	0.00	8.61
Population Density Growth (log)	2,024	0.01	0.005	0.01	-0.05	0.04
Disposable Income Growth (log)	2,024	0.0004	0.003	0.02	-0.06	0.06
Reported Crimes per 100K Growth (log)	2,024	-0.005	-0.005	0.13	-0.74	0.53
New Single-family Houses per 100K	2,277	172.66	120.88	328.18	-2,811.75	7,210.33
Unemployment Rate	2,277	0.13	0.12	0.04	0.05	0.24
Average Age	2,277	43.19	43.40	2.59	36.30	52.40
Has Coastline (1 = Yes)	2,277	0.32	0.00	0.47	0.00	1.00
Near Airport (1 = Yes)	2,277	0.33	0.00	0.47	0.00	1.00
Near Major City (1 = Yes)	2,277	0.28	0.00	0.45	0.00	1.00
Municipality Size (KM²)	2,277	1,126.65	608.63	1,959.46	8.73	18,685.00

Note: The full sample consists of 2277 (2024 for variables that were transformed into growth rates) observations from 253 unique municipalities across 9 years during the period 2015-2023. Where indicated, variables are log transformed, growth transformed, and normalized per 100,000 inhabitants.

5.3 Estimation techniques

In this section, we present and discuss a series of diagnostic checks and estimation techniques, together with the interpretation of statistical significance. To ensure the validity and reliability of our empirical analysis, we address econometric issues connected to multicollinearity, heteroskedasticity, and autocorrelation.

5.3.1 Multicollinearity, Heteroskedasticity, and Autocorrelation

Important concerns for our different regression models are the degree of multicollinearity between our independent variables and the presence of heteroskedasticity and autocorrelation in our dataset. Multicollinearity can result in inflated standard errors for our coefficients, and heteroskedasticity and autocorrelation can even invalidate the standard errors. This will lower the significance levels, or invalidate the hypothesis testing (Wooldridge, 2013; Greene, 2003)

To check for correlations and multicollinearity, we constructed a correlation matrix for each regression and performed VIF tests. Variance inflation factor (VIF) measures the increase in variance as a result of multicollinearity, and the threshold value to deviate from small to large is generally a VIF value of 10 (Alin, 2010). The results of our VIF tests are reported in **Appendices 4a, 4b, 4c, and 4d**. The highest value observed was 12.9 and 2.6, respectively. The VIF of 12.9, in the model on property price levels, is associated with the constructed interaction terms (see section 5.2.4.3). This is expected by construction, and since the standard errors remain low and coefficients are relatively stable, the multicollinearity is not considered problematic. Our correlation matrices indicated high correlation between our explanatory variables *Damage Costs per 100K* and *Insurance Claims per 100K*, which is why we throughout the empirical analysis estimated these separately together with *Climate Risk* and all other control variables. The correlation between *Climate Risk* and the other two explanatory variables was not high enough to create any potential issues.

The Breusch-Pagan (BP) tests indicated the presence of heteroskedasticity in all of our regression models. To correct for the heteroskedasticity, we used different types of robust standard errors, as described in section 5.3.2. The results of the Breusch-Pagan tests are reported in **Appendices 5a and 5b**.

The Wooldridge test for autocorrelation in panel models indicated that there was autocorrelation in all of our regression models. To correct for the autocorrelation, we used different types of robust standard errors, as described in section 5.3.2. The results of Wooldridge tests are reported in **Appendices 6a and 6b**.

5.3.2 Robust Standard Errors

To correct for the presence of heteroskedasticity and autocorrelation as indicated by the BP test and the Wooldridge test for autocorrelation in section 5.3.1, we applied a combination of different robust standard errors. For each regression model, we used (1) heteroskedasticity robust standard errors - HC1, and (2) Driscoll and Kraay (DK) standard errors. Heteroskedasticity robust standard errors (HC1) have been shown to be heteroskedasticity consistent (MacKinnon and White, 1985). Driscoll and Kraay standard errors, in addition to being heteroskedasticity consistent, have also been shown to be robust to general forms of cross-sectional and temporal dependence (Hoechle, 2007). Since real estate prices have been found to exhibit positive serial correlation at one year intervals (Case and Shiller, 1989;

Titman et al., 2014), with subsequent reversals of price changes over longer periods (Titman et al., 2014), we use a lag of 1 in the Driscoll and Kraay standard errors.

It's important to note that since the Driscoll and Kraay estimator is based on asymptotic theory, one should be somewhat cautious with its application to panels that contain a large cross-section but only a short time dimension (Hoechle, 2007), which is applicable to our panel data with only 9 time dimensions. To be robust and conservative in our hypothesis testing and ensure the validity and reliability of our findings, we therefore compared the different alternatives and picked the alternative that gave the highest standard errors on average. Both alternatives are discussed and reported in all regression tables, but only the most conservative are analysed and used for our conclusion.

5.3.3 Interpretation of Statistical Significance

Given the relatively large sample size in our study, parameters can be estimated very precisely. Furthermore, standard errors are often quite small, which usually results in statistical significance (Wooldridge, 2013). This requires caution when interpreting statistical significance to reduce the risk of committing a Type I error. For this reason, we consider a result to be statistically significant only if it achieves a p-value below 1%. This stricter threshold reduces the risk of incorrectly claiming that an effect exists when it does not, which otherwise could arise with the common significance levels of 10% and 5%, due to the large number of observations.

5.4 Statistical models

To test the hypotheses outlined in section 3.2, we established two different panel regression models. Even though the hypotheses are directional, we decided to use two-sided hypothesis tests to allow for effects in both directions, which is also more conservative. The panel data structure makes it possible to analyze dynamic effects, which is particularly relevant when studying delayed impacts of economic variables (Wooldridge, 2013). For Hypothesis 1, where we test the relationship between climate risk and property price level, we used a fixed-effects (FE) model with explanatory and control variables expressed in numbers. For Hypothesis 2, where we instead want to test the relationship between climate risk and property price growth, we used a fixed-effects (FE) model with explanatory variables expressed in numbers, and some control variables expressed in rates, while others are kept in numbers (see section 5.2.4.2). In both models, we use year fixed effects to control for macroeconomic trends across time (Greene, 2003). Key for our model selection process is that one of our most important explanatory variables, *Climate Risk*, as well as several other control variables, are time-invariant within a given municipality. Municipality fixed effects was therefore never an alternative since municipality fixed effects would absorb all time-invariant differences between municipalities (Wooldridge, 2013). Thus, we wouldn't be able to utilize those variables, nor would we be able to compare differences between municipalities, which is central to our research question.

5.4.1 Climate risk's effect on the property price level

The first panel regression model estimates the year-specific effect of climate risk on property price levels by interacting the explanatory variables with time dummies. This approach reflects our interest in whether cross-sectional differences in climate risk are consistently associated with lower property price levels across municipalities and over time. Since our correlation matrices indicated a high correlation between two of our explanatory variables, *Damage Costs per 100K* and *Insurance Claims per 100K* (see section 5.3.1), we estimated the effect of these variables separately, each one together with *Climate Risk* and all other control variables. In our first hypothesis, we test the continuous dependent variable *Average Property Price* with two different FE panel regression specifications, thus testing the following:

$$Average\ Property\ Price_{i,t} = \beta_t * (Climate\ Risk_{i,t}\ x\ Year_t) + \lambda_t * (Damage\ Costs_{i,t}\ x\ Year_t) + Controls_{i,t} + fe_t + \epsilon_{i,t} \quad [1]$$

$$Average\ Property\ Price_{i,t} = \beta_t * (Climate\ Risk_{i,t}\ x\ Year_t) + \lambda_t * (Insurance\ Claims_{i,t}\ x\ Year_t) + Controls_{i,t} + fe_t + \epsilon_{i,t} \quad [2]$$

Where the dependent variable is *Average Property Price,* and the explanatory variables are *Climate Risk* and *Damage Costs per 100K* for regression 1 and *Climate Risk* and *Insurance Claims per 100K* for regression 2. To get a yearly estimate of the effect of our explanatory variables on each year's property price level, the explanatory variables were interacted with year dummies (see section 5.2.4.3). Both regressions include the control variables *Population Density, Disposable Income*, *Reported Crimes per 100K*, *Single-family Houses per 1,000, Unemployment Rate*, *Average Age*, *Municipality Size (KM²)*, and the binary control variables *Has Coastline*, *Near Airport*, and *Near Major City*. To account for heteroskedasticity and autocorrelation due to temporal dependence in the panel, as described in section 5.3.2, each regression was estimated using two different types of robust standard errors, heteroskedasticity robust standard errors (HC1) and Driscoll and Kraay standard errors. We also estimate each regression with lagged variables, to capture any delayed effects as described in section 5.2.4.4. Finally, we include time (*t)* fixed effects in both equations.

5.4.2 Climate risk's effect on the property price growth

The second panel regression model estimates the average effect of climate risk on property price growth over the full period. This allows us to assess whether higher climate risk is associated with lower appreciation in housing values over time. Since our correlation matrices indicated a high correlation between two of our explanatory variables, *Damage Costs per 100K* and *Insurance Claims per 100K* (see section 5.3.1), we estimated the effect of these variables separately, each one together with *Climate Risk* and all other control variables. In our second hypothesis, we test the continuous dependent variable *Average Property Price Growth* with two different FE panel regression specifications, thus testing the following:

$$Average\ Property\ Price\ Growth_{i,t} = \beta_1 Climate\ Risk_{i,t} + \beta_2 Damage\ Costs_{i,t} + Controls_{i,t} + fe_t + \epsilon_{i,t} \quad [3]$$

$$Average\ Property\ Price\ Growth_{i,t} = \beta_1 Climate\ Risk_{i,t} + \beta_2 Insurance\ Claims_{i,t} + Controls_{i,t} + fe_t + \epsilon_{i,t} \quad [4]$$

Where the dependent variable is *Average Property Price Growth*, the explanatory variable is *Climate Risk* and *Damage Costs per 100K* for regression 3 and *Climate Risk* and *Insurance Claims per 100K* for regression 4. Both regressions includes the control variables *Population Density Growth, Disposable Income Growth*, *Reported Crimes per 100K Growth*, *New Single-family Houses per 100K, Unemployment Rate*, *Average Age*, *Municipality Size (KM²)*, and the binary control variables *Has Coastline*, *Near Airport*, and *Near Major City*. Each regression was, similar to 5.4.1, estimated using two different types of robust standard errors, heteroskedasticity robust standard errors (HC1) and Driscoll and Kraay standard errors. Like in the previous 2 regressions, we also estimate each regression with lagged variables and we include time (*t)* fixed effects in both equations.

5.5 Limitations

This study is subject to several limitations that should be considered when interpreting the results. A detailed account of these limitations is provided in this section.

Data availability

This study is limited by data availability in several instances.

Mortgage rates and credit availability are factors believed to vary across municipalities and influence property price disparities. Even in aggregated form, banks were unwilling to provide such data and it could therefore not be obtained. As an alternative, supervisory agencies such as the Swedish Financial Supervisory Authority (FI) and SCB were contacted, but they do not collect this type of data at the municipal level.

Climate adaptation measures per municipality are not included in this study because no suitable proxy for this was found. This limitation is worth considering since municipalities with high climate adaptation measures limit the risk, even if they are exposed to significant theoretical climate risk.

Timing and time period of variables

The study's explanatory variables are limited to the time period 2015-2023. This is due to the fact that Insurance Sweden started their relevant data collection from 2015 onwards, and hence, no data regarding insurance claims and damage costs from natural damages is available before this point in time. This restricts the entire study to the time period, as those are key explanatory variables. The reason for the limitation to 2023 is that official data for 2024 was not yet compiled for any of the control variables at the point of this study.

MSB and SGI Climate risk points: The climate risk assessments by MSB and SGI were conducted between 2020 and 2021, but this paper assumes that the findings are relevant for the entire time period and therefore that the risks have been constant through this time. There is a possibility that the municipality-specific risk was higher or lower before 2020-2021, specifically because the climate risk points are based upon how many services and inhabitants that may be affected by any climate-related incident. Of course, both services and inhabitants fluctuated over this time, but assumptions have been made that the fluctuations were too minor to have any impact on the significance of the results, and therefore that the climate risk points should have been fairly constant throughout this time. Nevertheless, one must be aware of this limitation.

Data collection: Human error and missing data

Data has mainly been collected from SCB's website and their tool "find statistics" as well as a story map on MSB's website (ArcGIS StoryMaps, n.d.). The process of data handling involves downloading the data, formatting the data in Excel, and combining it into the main panel data sheet. This process involves several manual steps, and one can't exclude that minor errors can occur. To limit the possibility of errors, several controls have been conducted, both visually and computationally, but there could be data issues as a result of human error. The same goes for the insurance data from Insurance Sweden.

The municipalities Nybro, Perstorp, and Uppvidinge are excluded from all models since they did not receive a theoretical climate risk point by MSB and SGI. For the price growth model, K/T quotas on the municipality level have been used to measure price development. If the number of transactions in a municipality, in any of the years between 2015 and 2023, falls below 25, it is considered too few to have statistical relevance for the given municipality. Where this has been the case, the municipality has been omitted, and therefore the dataset in the price growth model only includes 253 municipalities, instead of 287 in the other model.[12]

6. Result

This section presents our tests and results for the hypotheses outlined in section 3.2. First, a visualization of top and bottom municipalities from sections 4.2.3 and 4.2.4 and their corresponding theoretical climate risk is presented together with accumulated insurance claims and damage costs from 2015 to 2023. Afterwards, we present the tests and results from the regression models described in section 5.4.

6.1 Top and bottom municipalities in price growth and price level, and their climate risk

In this section, a first indication can be found regarding whether climate risk, and how it is perceived, can explain differences between municipalities with the lowest vs the highest price levels on single-family houses in 2023. This comparison is presented in **Table 6**. The same

[12] The omitted municipalities include: Solna, Ödeshög, Ydre, Boxholm, Högsby, Torsås, Dals-Ed, Färgelanda, Grästorp, Essunga, Hällefors, Ljusnarsberg, Norberg, Vansbro, Älvdalen, Ånge, Ragunda, Bräcke, Strömsund, Berg, Bjurholm, Vindeln, Norsjö, Malå, Storuman, Sorsele, Dorotea, Vilhelmina, Åsele, Arjeplog, Jokkmokk, Överkalix, Övertorneå, and Pajala.

comparison between the municipalities that have experienced the lowest vs highest property price growth on single-family houses between 2015 and 2023 is presented in **Table 7**.

In **Table 6**, the results indicate that the municipalities with the highest price level in 2023 have somewhat higher climate risk points but substantially lower outcomes on the perception variables insurance claims and damage costs. This suggests that the municipalities with the lowest price level in 2023 also experience relatively more climate-related incidents.

In **Table 7**, the results indicate otherwise. There is no apparent relationship between price growth and theoretical climate risk or the perception variables that can help explain why some municipalities have experienced lower price growth between 2015 and 2023. Those with the lowest growth have somewhat higher climate risk points, but the perception variables, insurance claims and damage costs, are actually higher in the municipalities with the highest growth.

Table 6: *Top and bottom average single-family house price levels in Sweden's municipalities in 2023 and corresponding climate risk.*

Municipality	Price level 2023	Theoretical climate risk (MSB & SGI risk point)	Insurance claims 2015-2023 per 1,000	Damage costs 2015-2023 per 1,000 (kSEK)
Lidingö	12 779	94	14,3	685
Danderyd	12 597	104	18,4	906
Solna	9 954	169	3,1	189
Nacka	9 530	109	9,6	360
Sundbyberg	9 382	48	2,7	77
Vaxholm	8 434	33	25,4	1 209
Stockholm	8 285	409	5,4	492
Täby	8 158	65	11,1	443
Sollentuna	7 774	84	7,9	260
Vellinge	7 046	77	22,3	664
Average	9 394	119	12,0	529

Municipality	Price level 2023	Theoretical climate risk (MSB & SGI risk point)	Insurance claims 2015-2023 per 1,000	Damage costs 2015-2023 per 1 000 (kSEK)
Dorotea	398	33	12,5	297
Sorsele	435	54	31	1 133
Åsele	452	51	20,7	470
Ragunda	510	214	12,1	258
Malå	545	22	46,2	4 082
Övertorneå	581	33	43,2	7 519
Storfors	582	203	29,7	1 340
Ljusnarsberg	617	41	10,2	196
Överkalix	629	66	21,9	934
Norsjö	630	60	23,2	1 218
Average	538	78	25	1 745

Table 7: *Top and bottom municipalities in single-family house CAGR between 2015 and 2023 in Sweden's municipalities and corresponding climate risk.*

Municipality	CAGR	Theoretical climate risk (MSB & SGI risk point)	Insurance claims 2015-2023 per 1,000	Damage costs 2015-2023 per 1,000 (kSEK)	Municipality	CAGR	Theoretical climate risk (MSB & SGI risk point)	Insurance claims 2015-2023 per 1,000	Damage costs 2015-2023 per 1 000 (kSEK)
Aneby	8,9%	19	26,1	945	Haparanda	0,8%	42	17,5	1 415
Älvdalen	8,9%	71	16,5	706	Strömstad	1,3%	269	17	858
Munkfors	8,8%	236	14,8	196	Salem	1,3%	113	6,8	156
Berg	8,2%	49	21,4	937	Järfälla	1,5%	109	5,2	303
Härjedalen	8,0%	125	15,6	999	Upplands-Bro	1,7%	41	5,9	229
Boxholm	8,0%	96	12,1	1 269	Botkyrka	1,7%	210	4,8	259
Malung	7,9%	105	26,8	1 250	Upplands-Väsby	1,8%	33	6,5	278
Arvidsjaur	7,3%	56	11,2	457	Sollentuna	2,0%	84	7,9	260
Karlsborg	7,2%	43	17	767	Luleå	2,0%	152	8,3	376
Vansbro	7,2%	96	18,7	850	Uppsala	2,1%	230	8,7	722
Average	8,0%	90	18,0	838	**Average**	1,6%	128	8,9	486

6.2 Regression results

6.2.1 Hypothesis 1 - Climate risk's effect on property price level

In this section, we apply the year fixed-effects (FE) model described in section 5.4.1 to test if there exists a statistically significant negative relationship between our explanatory variables and the price level in Sweden's municipalities between 2015 and 2023, as outlined in hypothesis 1. We separate insurance claims and damage costs into different versions of the model to eliminate any multicollinearity between the two. We use four different regression models for each version of insurance claims and damage costs: one with robust standard errors and non-lagged variables, one with Driscoll and Kraay standard errors and non-lagged variables, one with robust standard errors and one-year lagged variables and one model with Driscoll and Kraay standard errors with one-year lagged variables. We conclude each section by presenting the most conservative standard error specification and the explanatory power of our models.

6.2.1.1 Damage Cost

We first test the relationship between damage cost, climate risk (two out of the three variables of interest), and property price level in every year between 2015 and 2023. We include the following control variables: *Population Density, Disposable Income, Reported Crimes per 100K, Single-family Houses per 1,000, Unemployment Rate, Average Age, Municipality Size*

(KM²), as well as the dummy variables *Has Coastline, Near Airport, and Near Major City.* The results are presented in **Table 8**, showing only the explanatory variables of interest. Control variables are included in the estimation but omitted from the table. The complete regression output can be found in **Appendix 7a**.

The results present different outcomes across the four regression models. In the first model, the theoretical climate risk is not significant in any of the years, and damage costs is not significant in any of the years except for 2021, where it is positive and significant. This means that the damage costs in 2021 have a positive contribution to the 2021 average property price level. When using the Driscoll and Kraay standard errors in model 2 theoretical climate risk in 2015, 2016, 2017, and 2023 becomes significant with a positive relationship to price levels in these years. Furthermore, damage costs in all years from 2015 to 2023 are significant, with a positive relationship to price levels in these years. When we introduce lagged effects in model 3, we see that the lagged climate risk becomes insignificant in all years, which is in line with regression 1 and expected, given that it is time invariant. Furthermore, lagged damage costs in 2021 and 2022 become significant with a positive relationship[13]. This means that the damage costs in 2020 have a positive contribution to the average property price level in 2021. Similarly, damage costs in 2021 have a positive relationship to price levels in 2022. When using lagged effects and Driscoll and Kraay standard errors in model 4, lagged climate risk in 2016 and 2017 becomes positive with a significant relationship to price levels in these years. Furthermore, the lagged damage costs from 2016 to 2023 have a significant positive contribution to price levels in every year. The results do not provide strong support for Hypothesis 1; on the contrary, all of these results indicate a positive relationship between damage costs and the dependent variable property price level.

The different specification of robust standard errors was compared as described in section 5.3.2, and heteroskedasticity robust standard errors (HC1) have the highest average SEs across estimates. Thus, it is the more conservative option for our hypothesis testing. The results of the comparison of average standard errors can be found in **Appendix 9a.**

When we compare the 4 regression models, we can see that they all have quite high explanatory power with an adjusted R2 around 0.9, indicating that our control variables help in explaining the variability in price levels. *Disposable Income, Population Density,*

[13] Note that the 1-year lagged damage costs in 2022 represents damage costs in 2021, as indicated by the note under table 8.

Single-family Houses per 1,000, and *Unemployment Rate* are all significant, which is in line with previous research and further strengthens the validity of our results.

Table 8: *Regression results for Price Levels - Damage costs.*

	Robust SE (HC1)	Driscoll-Kraay (DK)	1Y Lagged Robust SE (HC1)	1Y Lagged DK
Climate Risk 2015	1.30e-04	1.30e-04***		
	(7.93e-05)	(1.59e-05)		
Climate Risk 2016	8.60e-05	8.60e-05***	1.18e-04	1.18e-04***
	(7.91e-05)	(1.70e-05)	(8.06e-05)	(1.98e-05)
Climate Risk 2017	9.41e-05	9.41e-05***	1.15e-04	1.15e-04***
	(7.80e-05)	(1.63e-05)	(7.85e-05)	(2.11e-05)
Climate Risk 2018	1.82e-05	1.82e-05	2.16e-05	2.16e-05
	(7.86e-05)	(1.53e-05)	(7.97e-05)	(1.95e-05)
Climate Risk 2019	-1.13e-06	-1.13e-06	8.55e-06	8.55e-06
	(7.88e-05)	(1.50e-05)	(7.76e-05)	(1.90e-05)
Climate Risk 2020	4.49e-05	4.49e-05*	-3.47e-06	-3.47e-06
	(8.41e-05)	(1.55e-05)	(8.12e-05)	(1.82e-05)
Climate Risk 2021	-8.56e-06	-8.56e-06	-3.08e-05	-3.08e-05+
	(8.19e-05)	(1.50e-05)	(8.23e-05)	(1.60e-05)
Climate Risk 2022	-2.31e-05	-2.31e-05	2.47e-05	2.47e-05
	(8.10e-05)	(1.58e-05)	(8.12e-05)	(1.73e-05)
Climate Risk 2023	5.07e-05	5.07e-05**	5.06e-05	5.06e-05*
	(8.33e-05)	(1.35e-05)	(8.27e-05)	(1.83e-05)
Damage Costs per 100K 2015 (log)	0.007	0.007***		
	(0.009)	(9.64e-04)		
Damage Costs per 100K 2016 (log)	0.015	0.015***	0.014	0.014***
	(0.009)	(3.46e-04)	(0.010)	(6.12e-04)
Damage Costs per 100K 2017 (log)	0.009	0.009***	0.011	0.011***
	(0.007)	(2.31e-04)	(0.008)	(1.81e-04)
Damage Costs per 100K 2018 (log)	0.011	0.011***	0.012	0.012***
	(0.011)	(0.001)	(0.011)	(0.002)
Damage Costs per 100K 2019 (log)	0.008	0.008***	0.007	0.007***
	(0.010)	(9.72e-04)	(0.010)	(7.99e-04)
Damage Costs per 100K 2020 (log)	0.037*	0.037***	0.037*	0.037***
	(0.017)	(0.002)	(0.016)	(0.002)
Damage Costs per 100K 2021 (log)	0.032***	0.032***	0.032***	0.032***
	(0.008)	(1.14e-04)	(0.008)	(2.80e-04)
Damage Costs per 100K 2022 (log)	0.029*	0.029***	0.033**	0.033***
	(0.013)	(3.91e-04)	(0.012)	(4.41e-04)
Damage Costs per 100K 2023 (log)	0.020*	0.020***	0.019*	0.019***
	(0.010)	(7.06e-04)	(0.009)	(7.56e-04)
Num.Obs.	2583	2583	2296	2296

Cont. Table 8: *Regression results for Price Levels - Damage costs.*

R2	0.889	0.889	0.887	0.887
R2 Adj.	0.887	0.887	0.885	0.885
R2 Within	0.883	0.883	0.882	0.882
R2 Within Adj.	0.881	0.881	0.881	0.881
AIC	-158.5	-158.5	-139.3	-139.3
BIC	58.2	58.2	55.8	55.8
RMSE	0.23	0.23	0.23	0.23
Std.Errors	Heteroskedasticity-robust	Driscoll-Kraay (L=1)	Heteroskedasticity-robust	Driscoll-Kraay (L=1)
Year Fixed Effects	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Dependent variable = *Average Property Price (log)*

Robust standard errors (HC1) and Driscoll-Kraay (DK) standard errors (Lag = 1) are reported. Lagged models use one-year lags for all independent variables, except for the control variables *Average Age*, *Municipality Size*, and the control dummies *Has Coastline (1 = Yes)*, *Near Airport (1 = Yes)*, and *Near Major City (1 = Yes)*, which are not lagged in any of the models.

Control variables are included in all models but omitted from the table; the full regression outputs are reported in the appendix.

Where indicated, variables are log-transformed and normalized per 1,000 or 100,000 inhabitants.

6.2.1.2 Insurance Claims

Secondly, we test the relationship between insurance claims, climate risk (two out of the three variables of interest), and average property price level in every year between 2015 and 2023. We include the same control variables as in section 6.2.1.1, that is, *Population Density, Disposable Income, Reported Crimes per 100K, Single-family Houses per 1,000, Unemployment Rate, Average Age, Municipality Size (KM²),* as well as the dummy variables *Has Coastline, Near Airport,* and *Near Major City.* The results are presented in **Table 9,** showing only the independent variables of interest. Control variables are included in the estimation but omitted from the table. The complete regression output can be found in **Appendix 7b**.

The results yield different outcomes across all four regression models. In the first model, theoretical climate risk is insignificant in all years, and insurance claims has a significant and positive coefficient in 2021. In the second model, when using the DK standard errors, theoretical climate risk becomes significant in 2015, 2016, 2017, 2020, and 2023, all with a positive relationship to the price level. Insurance claims are significant from 2017 to 2023, also with a positive relationship to the price level. When introducing lags in model 3, lagged theoretical climate risk is still insignificant, which is expected given that it is time invariant. Lagged insurance claims are only significant in 2021, with a positive relationship to price level, meaning that insurance claims in 2020 affect price levels in 2021 positively. In model 4, when using lags and DK standard errors, lagged climate risk is significant in 2016, 2017, and 2022, indicating that the climate risk in the previous year has a positive effect on the average property price level in those years. The lagged insurance claims become significant every year between 2017 and 2023. The relationship is still positive, which means that the insurance claims in the previous year had a positive effect on price levels in 2017-2023. Similarly to the regression in section 6.2.1.1, the results do not provide any strong support for Hypothesis 1.

The different specification of robust standard errors was compared as described in section 5.3.2, and heteroskedasticity robust standard errors (HC1) have the highest average SEs across estimates. Thus, it is the more conservative option for our hypothesis testing. The results of the comparison of average standard errors can be found in **Appendix 9b**.

When we compare the 4 regression models, we can see that they all have quite high explanatory power with an adjusted R2 around 0.9, which again indicates that our control variables help in explaining the variability in price levels. Most control variables are significant, which is in line with previous research and strengthens the validity of our results.

Table 9: *Regression results for Price Levels - Insurance claims.*

	Robust SE (HC1)	Driscoll-Kraay (DK)	1Y Lagged Robust SE (HC1)	1Y Lagged DK
Climate Risk 2015	1.26e-04	1.26e-04***		
	(8.02e-05)	(1.41e-05)		
Climate Risk 2016	8.36e-05	8.36e-05***	1.12e-04	1.12e-04***
	(7.78e-05)	(1.46e-05)	(7.98e-05)	(1.65e-05)
Climate Risk 2017	9.41e-05	9.41e-05***	1.15e-04	1.15e-04***
	(7.92e-05)	(1.46e-05)	(7.99e-05)	(1.91e-05)
Climate Risk 2018	1.88e-05	1.88e-05	2.13e-05	2.13e-05
	(7.86e-05)	(1.45e-05)	(7.95e-05)	(1.83e-05)
Climate Risk 2019	9.94e-06	9.94e-06	1.58e-05	1.58e-05
	(8.03e-05)	(1.19e-05)	(7.90e-05)	(1.63e-05)
Climate Risk 2020	5.44e-05	5.44e-05**	4.27e-06	4.27e-06
	(8.34e-05)	(1.34e-05)	(8.03e-05)	(1.60e-05)
Climate Risk 2021	1.70e-05	1.70e-05	-5.65e-06	-5.65e-06
	(8.34e-05)	(1.38e-05)	(8.36e-05)	(1.50e-05)
Climate Risk 2022	1.27e-05	1.27e-05	5.94e-05	5.94e-05**
	(8.39e-05)	(1.23e-05)	(8.49e-05)	(1.37e-05)
Climate Risk 2023	4.94e-05	4.94e-05**	5.01e-05	5.01e-05*
	(8.08e-05)	(1.09e-05)	(8.03e-05)	(1.58e-05)
Insurance Claims per 100K 2015 (log)	7.89e-04	7.89e-04		
	(0.013)	(0.002)		

Cont. Table 9: *Regression results for Price Level - Insurance claims.*

Insurance Claims per 100K 2016 (log)	5.61e-04	5.61e-04	-0.004	-0.004
	(0.017)	(0.001)	(0.018)	(0.003)
Insurance Claims per 100K 2017 (log)	0.013	0.013***	0.015	0.015***
	(0.018)	(0.001)	(0.019)	(0.002)
Insurance Claims per 100K 2018 (log)	0.032+	0.032***	0.036+	0.036***
	(0.019)	(0.003)	(0.020)	(0.004)
Insurance Claims per 100K 2019 (log)	0.022	0.022***	0.018	0.018***
	(0.016)	(0.002)	(0.016)	(0.002)
Insurance Claims per 100K 2020 (log)	0.024	0.024***	0.031	0.031***
	(0.022)	(0.005)	(0.021)	(0.005)
Insurance Claims per 100K 2021 (log)	0.053**	0.053***	0.054**	0.054***
	(0.020)	(0.001)	(0.020)	(0.002)
Insurance Claims per 100K 2022 (log)	0.050*	0.050***	0.051*	0.051***
	(0.021)	(0.002)	(0.021)	(0.002)
Insurance Claims per 100K 2023 (log)	0.022	0.022***	0.024	0.024***
	(0.020)	(0.002)	(0.019)	(0.002)
Num.Obs.	2583	2583	2296	2296
R2	0.888	0.888	0.886	0.886
R2 Adj.	0.887	0.887	0.884	0.884
R2 Within	0.882	0.882	0.881	0.881
R2 Within Adj.	0.880	0.880	0.880	0.880
AIC	-136.9	-136.9	-117.3	-117.3
BIC	79.8	79.8	77.8	77.8
RMSE	0.23	0.23	0.23	0.23
Std.Errors	Heteroskedasticity-robust	Driscoll-Kraay (L=1)	Heteroskedasticity-robust	Driscoll-Kraay (L=1)
Year Fixed Effects	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Dependent variable = *Average Property Price (log)*

Robust standard errors (HC1) and Driscoll-Kraay (DK) standard errors (Lag = 1) are reported. Lagged models use one-year lags for all independent variables, except for the control variables *Average Age*, *Municipality Size*, and the control dummies *Has Coastline (1 = Yes)*, *Near Airport (1 = Yes)*, and *Near Major City (1 = Yes)*, which are not lagged in any of the models.

Control variables are included in all models but omitted from the table; the full regression outputs are reported in the appendix.

Where indicated, variables are log-transformed and normalized per 1,000 or 100,000 inhabitants.

6.2.2 Hypothesis 2 - Climate risks' effect on property price growth

In this section, we apply the year fixed-effects (FE) model described in section 5.4.2 to test if there exists any statistically significant negative relationship between the climate risk variables and price growth in Sweden's municipalities as outlined in hypothesis 2. We use the same methodology as in section 6.2.1, which means that we separate insurance claims and damage costs into different versions of the model to eliminate any multicollinearity between these two. We also use four different regression models for each version of insurance claims and damage costs: two regressions with non-lagged variables and two with one-year lagged variables, both versions with robust standard errors and Driscoll and Kraay standard errors. We conclude each section by presenting the most conservative standard error specification and the explanatory power of our models.

6.2.2.1 Damage Costs

We first test the relationship between damage costs, theoretical climate risk (two out of the three variables of interest), and single-family house price growth. We include the control variables *Population Density Growth, Disposable Income Growth, Reported Crimes per 100K Growth, New Single-family Houses per 100K, Unemployment Rate, Average Age*, *Municipality Size (KM²),* as well as the dummy variables *Has Coastline, Near Airport, and Near Major City.* The results are presented in **Table 10**, showing only the independent variables of interest. Control variables are included in the estimation but omitted from the table. The complete regression output can be found in **Appendix 8a**.

The results are very consistent across the four regression models. In none of the models theoretical climate risk or damage costs are statistically significant. The results do not indicate any support for Hypothesis 2.

The different specification of robust standard errors was compared as described in section 5.3.2, and Driscoll and Kraay standard errors have the highest average SEs across estimates. Thus, it is the more conservative option for our hypothesis testing. The results of the comparison of average standard errors can be found in **Appendix 9c**.

All 4 regression models have an adjusted R2 of around 0,7, indicating that our control variables help in improving the explanatory power of the models, but that there exists some effects that can not be explained by the model.

Table 10: *Regression results for Price Growth - Damage costs.*

	Robust SE (HC1)	Driscoll-Kraay (DK)	1Y Lagged Robust SE (HC1)	1Y Lagged DK
Climate Risk	-1.23e-05+	-1.23e-05	-8.76e-06	-8.76e-06
	(7.18e-06)	(8.88e-06)	(7.68e-06)	(1.11e-05)
Damage Costs per 100K (log)	-8.77e-04	-8.77e-04	8.54e-04	8.54e-04
	(9.76e-04)	(7.56e-04)	(0.001)	(7.73e-04)
Num.Obs.	2024	2024	1771	1771
R2	0.665	0.665	0.688	0.688
R2 Adj.	0.662	0.662	0.685	0.685

Cont. Table 10: *Regression results for Price Growth - Damage costs.*

R2 Within	0.030	0.030	0.050	0.050
R2 Within Adj.	0.024	0.024	0.044	0.044
AIC	-6131.2	-6131.2	-5428.5	-5428.5
BIC	-6019.0	-6019.0	-5324.4	-5324.4
RMSE	0.05	0.05	0.05	0.05
Std.Errors	Heteroskedasticity-robust	Driscoll-Kraay (L=1)	Heteroskedasticity-robust	Driscoll-Kraay (L=1)
Year Fixed Effects	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Dependent variable = *Average Property Price Growth (K/T)*

Robust standard errors (HC1) and Driscoll-Kraay (DK) standard errors (Lag = 1) are reported. Lagged models use one-year lags for all independent variables, except for the control variables *Average Age*, *Municipality Size*, and the control dummies *Has Coastline (1 = Yes)*, *Near Airport (1 = Yes)*, and *Near Major City (1 = Yes)*, which are not lagged in any of the models.

Control variables are included in all models but omitted from the table; the full regression outputs are reported in the appendix.

Where indicated, variables are log transformed and normalized per 100,000 inhabitants.

6.2.2.2 Insurance Claims

Secondly, we test the relationship between insurance claims, theoretical climate risk (two out of the three variables of interest), and single-family house price growth. We include the same control variables as in section 6.2.2.1, that is, *Population Density Growth, Disposable Income Growth, Reported Crimes per 100K Growth, New Single-family Houses per 100K, Unemployment Rate, Average Age. Municipality Size (KM²),* as well as the dummy variables, *Has Coastline, Near Airport, and Near Major City.* The results are presented in **Table 11**, showing only the independent variables of interest. Control variables are included in the estimation but omitted from the table. The complete regression output can be found in **Appendix 8b**.

The results are in line with the regression models in section 6.2.2.1. In none of the models theoretical climate risk nor insurance claims are statistically significant. The results do not indicate any support for Hypothesis 2.

The different specification of robust standard errors was compared as described in section 5.3.2, and Driscoll and Kraay standard errors have the highest average SEs across estimates. Thus, it is the more conservative option for our hypothesis testing. The results of the comparison of average standard errors can be found in **Appendix 9d**.

All 4 regression models have an adjusted R2 of around 0.7, indicating that our control variables help in improving the explanatory power of the models, but that there exists some effects that can not be explained by the model.

Table 11: *Regression results for Price Growth - Insurance claims.*

	Robust SE (HC1)	Driscoll-Kraay (DK)	1Y Lagged Robust SE (HC1)	1Y Lagged DK
Climate Risk	-1.27e-05+	-1.27e-05	-7.93e-06	-7.93e-06
	(7.20e-06)	(8.37e-06)	(7.71e-06)	(1.11e-05)
Insurance Claims per 100K (log)	-8.88e-04	-8.88e-04	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.001)
Num.Obs.	2024	2024	1771	1771
R2	0.665	0.665	0.688	0.688
R2 Adj.	0.662	0.662	0.685	0.685
R2 Within	0.030	0.030	0.051	0.051
R2 Within Adj.	0.024	0.024	0.044	0.044
AIC	-6130.7	-6130.7	-5429.5	-5429.5
BIC	-6018.4	-6018.4	-5325.4	-5325.4
RMSE	0.05	0.05	0.05	0.05
Std.Errors	Heteroskedasticity-robust	Driscoll-Kraay (L=1)	Heteroskedasticity-robust	Driscoll-Kraay (L=1)
Year Fixed Effects	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Dependent variable = *Average Property Price Growth (K/T)*

Robust standard errors (HC1) and Driscoll-Kraay (DK) standard errors (Lag = 1) are reported. Lagged models use one-year lags for all independent variables, except for the control variables *Average Age*, *Municipality Size*, and the control dummies *Has Coastline (1 = Yes)*, *Near Airport (1 = Yes)*, and *Near Major City (1 = Yes)*, which are not lagged in any of the models.

Control variables are included in all models but omitted from the table; the full regression outputs are reported in the appendix.

Where indicated, variables are log transformed and normalized per 100,000 inhabitants.

7. Analysis

7.1 Analysis of results and theoretical contributions

By studying the heatmap in section 4.2.4, it is clear that the highest price levels are found in rich suburbs of Stockholm, Gothenburg, and Malmö, with, in some cases, modest price growth. At the same time, the heatmaps in section 4.2.3 indicate that the highest annual price growth between 2015 and 2023 was centered around inland municipalities in northern Sweden with, on average, lower price levels. This conflicting indication means that the same explanatory variables are unlikely to explain both price levels and price growth equally well. Demonstrating both relationships using the same explanatory variables was therefore not entirely expected.

Our first hypothesis suggested that there should be a negative relationship between the long-term theoretical climate risk variable and the perception variables, historical insurance claims and historical damage costs, and property price levels between 2015 and 2023. The first indicative tables that visualized price levels together with theoretical climate risk, aggregated insurance claims, and aggregated damage costs between 2015 and 2023 showed that there might actually exist a relationship between some of the variables and price level. Despite showing contradicting results on theoretical climate risk, those municipalities with the highest price levels intuitively also had fewer claims and lower damage costs compared to those municipalities with the lowest price levels. This was later overthrown by the regression models. The regression concluded, given the most conservative standard errors, that for theoretical climate risk, no relationship could be estimated in any of the models. For damage costs, a statistically significant positive relationship was found in 2021. When lagging the variables to see if there were any delayed effects of high damage costs on price levels, lagged damage costs in 2021 and 2022 also became significant, with a positive relationship towards price levels in these years. For insurance claims, a significant positive relationship was found in 2021 when using the most conservative standard errors. In the lagged model, lagged claims in 2021 had a positive and significant effect on price levels in 2021.

Overall, neither the long-term theoretical climate risk nor the perception variables could explain lower price levels in some municipalities. However, the positive relationship between price levels and the significant damage costs and insurance claims variables are interesting. It indicates that municipalities with higher damage costs and claims actually have higher price levels, which is contradictory. When reading the results, it's important to note that the municipality of Gävle in 2021 experienced nearly 25% of all damage costs in Sweden between 2015 and 2023, as outlined in the footnote in section 4.2.2, due to heavy torrential rain and floods. This makes the results this year somewhat misleading because 2021 was also a year where prices on single-family houses stood at one of their highest levels. The regression estimates on damage costs and insurance claims might therefore capture other effects that are not included in our model. Nevertheless, the analysis from this finding is that damage costs and insurance claims seem to be ignored by market participants when determining their price willingness for single-family houses. This could possibly indicate that even when extreme climate-related incidents occur, there might not be a negative effect on the price level, which, intuitively, should have been the case. One could also argue that the market should incorporate higher damage costs and more claims in a delayed way because it's hard to build a perception about something in the moment, but the findings from the lagged models proved otherwise and still show a positive relationship in 2021 and 2022. This ultimately points to other factors being more important price determinants and that markets ultimately fail to incorporate climate risk on an aggregated level, which is also in line with previous literature (Bunten and Kahn, 2014).

Our second hypothesis suggested that there should also be a negative relationship between the long-term climate risk variable, theoretical climate risk, and the perception variables, insurance claims and damage cost, and price growth. The first indicative tables showed that theoretical climate risk might have an impact, but those with the lowest price growth had fewer claims and lower damage costs compared to those with the highest growth. The regression results found that no significance could be found between any of our explanatory variables and property price growth. This makes it difficult to draw any conclusions regarding the relationship between the variables, and we can't reject the null hypothesis that our explanatory variables have no effect on the property price growth. Once again, this finding is interesting, especially with regard to the big weather event in Gävle in 2021. Even after such significant damages, which should affect the perception of climate risk, no relationship with price growth can be observed in the result.

Ultimately, the only relationship that was significant proved to be the perception variables, which had a positive contribution to price levels in some years. One possible explanation for the positive relationship between damage costs and property price levels is reverse causality, more expensive properties naturally generate higher total claim amounts when disasters occur. Additionally, properties with high prices are often located in attractive but risk-prone locations, for example, waterfronts, where people are willing to pay premium prices despite known risks. However, the same reasoning cannot be applied to the significant lagged effects, as price levels in 2022 cannot influence damage costs in 2021 intuitively. Of course, one property that was expensive in 2021 will remain expensive in 2022, and it might therefore look like the high damage costs in 2021 affected the high price level in 2022, but there might also be some other factors that drive the contradictory results. One of these factors could be that well-functioning insurance markets may offset the financial impact of damage, allowing property values to remain high even in risk-exposed municipalities. Extreme trust in the ability to receive compensation following a disaster may be exceptionally strong among market participants.

However, the logic surrounding the possible correlation between expensive neighbourhoods, compensation amounts, and increased risk does not apply as clearly to the number of insurance claims, which has nothing to do with money amounts. Here, the positive association between claims and price levels may instead reflect another version of reverse causality, where wealthier municipalities with higher property values tend to file more claims due to better insurance coverage, greater awareness, or more frequent reporting, even for minor incidents.

These interpretations remain speculative, however, but the results suggest that there are underlying factors at play that the model does not fully capture. One possibility could just be that market participants in Sweden place strong trust in the insurance system, which may offset any negative effects from an increased perception of climate risk.

7.2 Practical implications

The practical implications of this study are in the context of how the Swedish housing market incorporates climate risk in pricing. The findings highlight the importance of continuously informing the Swedish public about the potential costs of climate-related incidents, enabling market participants to make more informed decisions. Additional practical implications of today's results are that many warning signs appear to be ignored, maybe consciously or unconsciously. Future years could bring significant events that might lead to damage costs whose effects could have been mitigated if market participants had acknowledged the signs and accounted for this in their pricing. The fact that the insurance market may mitigate the effects of increased costs today does not guarantee that this will continue in the future.

8. Conclusion

The purpose of this study is to quantitatively estimate whether there is a negative relationship between climate risk, including both theoretical and perceived, and property price levels and growth in the Swedish single-family house market. Through MSB's climate risk report on Sweden's 290 municipalities, as well as Insurance Sweden's statistics on insurance claims and damage costs associated with natural and weather-related incidents, we estimated two fixed-effects panel models to test whether climate risk may explain differences in property price levels and property price growth. Based on previous literature and the increased importance of climate risk, we anticipated that there would be a negative relationship between both the forward-looking theoretical climate risk variable, and the perception variables insurance claims and damage costs, and (1) the property price level of single-family houses, and (2) the property price growth of single-family houses, across Sweden's 290 municipalities.

Ultimately, for price levels, we could not reject the null-hypothesis that the theoretical climate risk has no effect on house price levels. For one of the perceived climate risk variables, damage costs, we can reject the null hypothesis in 2021, and we can also reject the null hypothesis in 2021 and 2022 with the lagged effects from damage costs in 2020 and 2021, respectively. For the other perception variable, insurance claims, we can reject the null hypothesis in 2021, both in relation to the actual claims in 2021, but also with the delayed effects from claims in 2020. For price growth, we fail to reject the null hypothesis that climate risk, including both theoretical and perceived, has no effect on property price growth in the Swedish single-family house market.

Our findings indicate no support for our first hypothesis; on the contrary, all significant relationships that exist in some years, between the perception variables and the property price level, are positive. We attribute these findings to a combination of reverse causality, where a higher property price level could imply both higher damage costs and an increase in the number of claims, and the influence of other factors, like Sweden's well-functioning insurance market.

We further find no statistically significant evidence of any relationship between climate risk and property price growth as outlined in the second hypothesis.

The study makes several contributions to both practice and existing literature. In terms of practice, it highlights the need to continuously inform the population about the potential cost of climate-related incidents, enabling market participants to make more informed decisions. The study further provides literature on the intersection of climate risk and property valuation with a new perspective on how climate risk affects property price levels and property price growth in a Swedish context. While previous studies have examined specific aspects of climate risk and its effect on property prices in an international context, no previous study has, to the best of our knowledge, studied the impact of climate risk in Sweden using several dimensions and with tangible data on actual damages.

8.1 Limitations to key assumptions

When interpreting the results in this study, it's important to have in mind the limitations of two key assumptions. The first one is the use of climate risk points from MSB and SGI as a proxy for theoretical climate risk. As outlined in section 4.2.1, each municipality receives points across five risk categories: coastal flooding, flooding from lakes and inland waters, slope collapse, landslides, and erosion. The scoring within each category is based on the number of businesses operating in identified risk zones and how this compares to other municipalities. These category-specific scores are then summed to produce a total climate risk score for each municipality.

However, several limitations affect the reliability and comparability of these scores. For starters, other risk categories like wildfires and extreme weather are excluded from the categorization of risky areas. Furthermore, not all municipalities receive points in every category. This may reflect either an actual absence of risk or simply the fact that the municipality was not assessed in that specific category. As a result, the total risk score may disproportionately reflect only those municipalities that were comprehensively studied, potentially excluding others entirely.

Additionally, the risk assessment is based on business activity within hazardous areas. Consequently, genuinely at-risk areas without significant business presence may be underrepresented, which means the total risk score might not capture the full extent of climate risk exposure.

According to MSB, the risk categories are not directly comparable either. For instance, a higher score in landslides than in erosion does not indicate a higher overall risk, as the scoring is relative to how many businesses are affected in each category across other municipalities.

Despite these shortcomings, the total climate risk points still offer a useful, albeit imperfect, proxy for identifying areas with relatively high climate exposure. Municipalities with higher scores are likely to face elevated risks. However, the points should only be seen as indicative, helping to highlight municipalities that may warrant closer scrutiny due to their relative exposure to climate-related hazards.

Another limitation lies in the use of average property price from SCB and average price growth per municipality from Swedish Real Estate Statistics as proxies for the overall municipality. These measures can be misleading, as both only reflect the properties that were actually sold. In municipalities with high-risk areas, it is possible that few or no transactions occurred in those vulnerable zones, with sales instead concentrated in lower-risk areas. As a result, the average price and the price growth may primarily reflect safer locations, potentially missing the true impact of climate risk on property values and price growth. It is important to recognize this limitation when interpreting the data.

8.2 Future research

While writing this thesis and researching climate risk connected to the housing markets, we identified several compelling areas suitable for future research. Previous literature has found mortgage rates and credit availability to be important drivers of property price developments, which is an important limitation in this study. Given that mortgage rates should reflect the risk of a loan, including the climate risk, it is possible that the relationship between climate risk and property prices could be better understood and distinguished via the mortgage rate.

In the analysis, we, among other things, attribute our findings of a positive relationship between the perception variables and property price level to the influence of other factors. One such factor is Sweden's well-functioning insurance market, which makes it yet another area for future research. Specifically, the insurance market's role in mitigating climate-related risks, and whether property insurance premiums appropriately reflect the climate risk associated with a geographical location. Insurance premiums should incorporate the probability of future damages and their financial consequence, and should therefore, similar to mortgage rates, reflect climate risk as well.

While this study aimed to quantitatively estimate whether there exists a relationship between climate risk and the property price level and/or property price growth, a qualitative approach could shed light on *why* climate risk might influence housing prices by examining individuals' perceptions, beliefs, and decision-making processes. Such research questions could provide additional insights into the importance of climate risk relative to other factors.

9. References

Alin, A., 2010, Multicollinearity, WIREs Computational Statistics 2(3), 370–374.

ArcGIS StoryMaps, n.d., Riskområden. Available at: https://storymaps.arcgis.com/collections/e842517ce39045a4a7603dba84281208 (Accessed: 2 May 2025).

Baldauf, M., Garlappi, L., and Yannelis, C., 2020, Does climate change affect real estate prices? Only if you believe in it, The Review of Financial Studies 33(3), 1256–1295.

Bjellerup, M., and Majtorp, L., 2019, Focus report: The Development of Swedish Housing Prices. Swedish National Debt Office, Stockholm.

Bell, E., Bryman, A., and Harley, B., 2019, Business Research Methods (5th ed.). Oxford University Press.

Bell, E., Bryman, A., and Harley, B., 2022, Business Research Methods (6th ed.). Oxford University Press.

Bunten, D. M., and Kahn, M. E., 2014, The impact of emerging climate risks on urban real estate price dynamics, NBER Working Paper No. 20018.

Case, K. E., and Shiller, R. J., 1989, The efficiency of the market for single-family homes, The American Economic Review 79(1), 125–137.

Case, K.E., and Shiller, R.J., 2003, Is there a bubble in the housing market? Brookings Institution, Brookings Papers on Economic Activity.

Chin, T. L., and Chau, K. W., 2003, A critical review of literature on the hedonic price model, International Journal for Housing and Its Applications 27(2), 145–165.

Claussen, C. A., 2012, Are Swedish houses overpriced? Sveriges Riksbank. Available at: https://www.riksbank.se/globalassets/media/forskning/medarbetare/2011/houseprices_dec_2011.pdf.

Cohen, V., and Karpavičiūtė, L., 2017, The analysis of the determinants of housing prices, Independent Journal of Management & Production 8(1).

DNA Economics and Vivid Economics, 2021, Physical Risk Assessment in TCFD Reporting.

Dong, H., 2024, Climate change and real estate markets: An empirical study of the impacts of wildfires on home values in California, Landscape and Urban Planning 247, 105062.

Ducros, G., Tiggeloven, T., Ma, L., Daloz, A. S., Schuhen, N., & de Ruiter, M. C., 2024, Multi-hazards in Scandinavia: Impacts and risks from compound heatwaves, droughts and wildfires, EGUsphere [preprint], 2024-3158.

Environmental Protection Agency (EPA), 2025, Climate risks and opportunities defined. Available at: https://www.epa.gov/climateleadership/climate-risks-and-opportunities-defined (Accessed: 3 May 2025).

Folksam, 2023, The risk of climate-related damage has doubled in 30 years. Available at: https://nyhetsrum.folksam.se/pressmeddelanden/risken-att-drabbas-av-klimatrelaterade-skador-har-fordubblats-pa-30-ar?id=4CCEED011C0E4E9A&d=2023-09-04 (Accessed: 5 May 2025).

Friedman, M., 1957, A Theory of the Consumption Function. Princeton University Press.

Government Offices of Sweden, 2023, Historic agreement at COP28. Available at: https://www.government.se/press-releases/2023/12/historic-agreement-at-cop28/ (Accessed: 2 May 2025).

Gourevitch, J. D., Kousky, C., Liao, Y., Nolte, C., Polack, A.B., Porter, J.R., Weill, J.A., 2023, Unpriced climate risk and the potential consequences of overvaluation in US housing markets, Nature Climate Change 13, 250–257.

Greene, W. H., 2003, Econometric Analysis (5th ed.). Pearson Education.

Hino, M., and Burke, M., 2021, The effect of information about climate risk on property values, Proceedings of the National Academy of Sciences USA 118(17).

Hoechle, D. (2007). Robust standard errors for panel regressions with cross-sectional dependence. The Stata Journal, 7(3), 281–312.

Horton, M., Sedgwick, S. M., Adams, J., Wei, D., and Skyberg, M., 2025, Impact of 2025 Los Angeles wildfires and comparative study, Institute for Applied Economics, Los Angeles County Economic Development Corporation.

Krueger, P., Sautner, Z., and Starks, L. T., 2020, The importance of climate risks for institutional investors, The Review of Financial Studies 33(3), 1067–1111.

Lynch, A. K., and Rasmussen, D. W., 2001, Measuring the impact of crime on house prices, Applied Economics 33(15), 1981–1989.

MacKinnon, J. G., and White, H., 1985, Some heteroskedasticity-consistent covariance matrix estimators with improved finite sample properties, Journal of Econometrics 29(3), 305–325.

Maher, A., 2017, Long-run drivers and short-term dynamics of Swedish real house prices, International Journal of Housing Markets and Analysis 11(1).

Mankiw, N. G., 2016, Macroeconomics (9th ed.). Worth Publishers.

Monson, M., 2009, Valuation using hedonic pricing models, Cornell Real Estate Review 7.

Morgan Stanley, 2022, Climate-related risk data for real assets: A framework for assessment. Available at: https://www.morganstanley.com/content/dam/msdotcom/en/assets/pdfs/3616169-21-07-15_Climate-related-risk-data-report_FINAL.pdf (Accessed: 2 May 2025).

Mäklarsamfundet, 2024, Om borgen brister: Är hemförsäkring redo för framtidens klimat?. Klimatrapporten.

Naturvårdsverket, 2018, The public’s views on climate. Available at: https://www.naturvardsverket.se/en/topics/climate-transition/sveriges-klimatarbete/the-publics-views-on-climate/ (Accessed: 2 May 2025).

OECD, 2024, Empowering young people through climate literacy, OECD Publishing, Paris.

Pindyck, R, 2011, Fat tails, thin tails, and climate change policy, *Review of Environmental Economics and Policy* 5(2), 275–292.

Rehdanz, K., 2002, Hedonic pricing of climate change impacts to households in Great Britain, Climatic Change 74, 413–434. Centre for Marine and Climate Research, Hamburg University

Rosen, S., 1974, Hedonic prices and implicit markets: Product differentiation in pure competition, Journal of Political Economy 82(1), 34–55.

Savills, 2023, Total global value of real estate estimated at $379.7 trillion – almost four times the value of global GDP, Savills News, 25 September. Available at: https://www.savills.com/insight-and-opinion/savills-news/352068 (Accessed: 3 May 2025).

Schuetz, J., and Devens, E., 2024, Homes and commercial buildings need substantial investments to become more resilient and sustainable. Brookings Institution.

Seneviratne, S.I., N. Nicholls, D. Easterling, C.M. Goodess, S. Kanae, J. Kossin, Y. Luo, J. Marengo, K. McInnes, M. Rahimi, M. Reichstein, A. Sorteberg, C. Vera, and X. Zhang, 2012, Changes in climate extremes and their impacts on the natural physical environment. In: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds.)]. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate

SGI and MSB, 2021, Riskområden för ras, skred, erosion och översvämning, Redovisning av regeringsuppdrag enligt regeringsbeslut M2019/0124/Kl, Statens geotekniska institut, SGI, Linköping och Myndigheten för samhällsskydd och beredskap, MSB, Karlstad.

Statista, 2024a, Sweden: Urbanization from 2013 to 2023. Available at: https://www.statista.com/statistics/455935/urbanization-in-sweden/ (Accessed: 2 May 2025).

Statista, 2024b, Real estate – Sweden. Available at: https://www.statista.com/outlook/fmo/real-estate/sweden (Accessed: 3 May 2025).

Statistics Sweden (SCB), 2025, Bostadsbeståndet 31 december 2024. Available at: https://www.scb.se/hitta-statistik/statistik-efter-amne/boende-bebyggelse-och-mark/bostader-och-boende/bostadsbestand/pong/statistiknyhet/bostadsbestandet-31-december-2024/ (Accessed: 3 May 2025)

Statistics Sweden (SCB), 2024, Försålda småhus efter region (kommun, län, riket) och fastighetstyp. År 1981–2023. Available at: https://www.statistikdatabasen.scb.se/pxweb/sv/ssd/START__BO__BO0501__BO0501B/FastprisSHRegionAr/table/tableViewLayout1/ (Accessed: 3 May 2025).

Sutton, G.D., 2002, Explaining changes in house prices. Bank for International Settlements, BIS Quarterly Review.

Swedish Tax Agency (Skatteverket), n.d., Tax assessment values for properties. Available at: https://www.skatteverket.se/foretag/skatterochavdrag/fastighet/fastighetstaxering/deklareralantbruk/taxeringsvarde.html (Accessed: 2 May 2025).

Svensk Försäkring, 2024, Natural hazard-related damages in Sweden 2015–2023. Available at: https://www.svenskforsakring.se/globalassets/rapporter/naturorsakade-skador-i-sverige/naturorsakade-skador-i-sverige-2015-2023.pdf/ (Accessed: 2 May 2025).

Svensk Mäklarstatistik, n.d., Om statistiken. Available at: https://www.maklarstatistik.se/om-statistiken/ (Accessed: 3 May 2025).

Swiss Re Institute, 2021, The Economics of Climate Change: No Action Not an Option. Zurich: Swiss Re.

Titman, S., Wang, K., and Yang, J., 2014, The dynamics of housing prices, NBER Working Paper No. 20418, National Bureau of Economic Research.

Wilhelmsson, M., 2008, Regional house prices: An application of a two-equation model to the Swedish housing market, International Journal of Housing Markets and Analysis 1(1), 33–51.

Wooldridge, J. M., 2013, Introductory Econometrics: A Modern Approach (5th ed.). South-Western Cengage Learning.

Yang, Z., and Turner, B., 2016, Shock hunting: Effects of regional-dependent, regional-specific shocks in the Swedish property market, Housing, Theory and Society 33(2), 178–194.

10. Appendix

Appendix 1a: *Top and bottom municipalities in single-family house CAGR between 2015 and 2023.*

Municipality	CAGR
Aneby	8,9%
Älvdalen	8,9%
Munkfors	8,8%
Berg	8,2%
Härjedalen	8,0%
Boxholm	8,0%
Malung	7,9%
Arvidsjaur	7,3%
Karlsborg	7,2%
Vansbro	7,2%

Municipality	CAGR
Haparanda	0,8%
Strömstad	1,3%
Salem	1,3%
Järfälla	1,5%
Upplands-Bro	1,7%
Botkyrka	1,7%
Upplands-Väsby	1,8%
Sollentuna	2,0%
Luleå	2,0%
Uppsala	2,1%

Sweden	4,0%

Appendix 1b: *Top and bottom average single-family house price levels in Sweden's municipalities 2023.*

Municipality	Average price (kSEK)
Lidingö	12 779
Danderyd	12 597
Solna	9 954
Nacka	9 530
Sundbyberg	9 382
Vaxholm	8 434
Stockholm	8 285
Täby	8 158
Sollentuna	7 774
Vellinge	7 046

Municipality	Average price (kSEK)
Dorotea	398
Sorsele	435
Åsele	452
Ragunda	510
Malå	545
Övertorneå	581
Storfors	582
Ljusnarsberg	617
Överkalix	629
Norsjö	630

Sweden	2 670

Appendix 2a: *Price Levels - Damage Costs. 2-Year lag full regression table including control variables.*

	2Y Lagged Robust SE (HC1)	2Y Lagged Driscoll-Kraay
Climate Risk 2017	1.55e-04+	1.55e-04***
	(8.01e-05)	(1.86e-05)
Climate Risk 2018	5.32e-05	5.32e-05*
	(8.00e-05)	(1.92e-05)
Climate Risk 2019	2.08e-05	2.08e-05
	(7.83e-05)	(1.80e-05)
Climate Risk 2020	1.75e-05	1.75e-05
	(8.03e-05)	(1.77e-05)
Climate Risk 2021	-6.95e-05	-6.95e-05**
	(7.84e-05)	(1.46e-05)
Climate Risk 2022	9.81e-06	9.81e-06
	(8.16e-05)	(1.42e-05)
Climate Risk 2023	1.04e-04	1.04e-04***
	(8.44e-05)	(1.62e-05)
Damage Costs per 100K 2017 (log)	0.010	0.010***
	(0.008)	(2.42e-04)
Damage Costs per 100K 2018 (log)	0.011	0.011***
	(0.011)	(0.002)
Damage Costs per 100K 2019 (log)	0.004	0.004***
	(0.010)	(5.35e-04)
Damage Costs per 100K 2020 (log)	0.031*	0.031***
	(0.015)	(0.001)
Damage Costs per 100K 2021 (log)	0.030***	0.030***
	(0.007)	(3.84e-04)
Damage Costs per 100K 2022 (log)	0.034**	0.034***
	(0.012)	(2.59e-04)
Damage Costs per 100K 2023 (log)	0.019+	0.019***
	(0.010)	(6.82e-04)

Cont. Appendix 2a: *Price Levels - Damage Costs. 2-Year lag full regression table including control variables.*

Population Density (log)	0.180***	0.180***
	(0.011)	(0.004)
Disposable Income (log)	1.084***	1.084***
	(0.080)	(0.044)
Reported Crimes per 100K (log)	0.025	0.025
	(0.028)	(0.047)
Single-family Houses per 1,000	-0.002***	-0.002***
	(2.05e-04)	(7.36e-05)
Unemployment Rate	-4.256***	-4.256***
	(0.249)	(0.275)
Average Age	-0.009+	-0.009***
	(0.005)	(0.001)
Has Coastline (1 = Yes)	0.172***	0.172***
	(0.012)	(0.005)
Near Airport (1 = Yes)	-0.054***	-0.054**
	(0.014)	(0.011)
Near Major City (1 = Yes)	0.030+	0.030***
	(0.018)	(0.004)
Municipality Size (KM^2)	2.60e-05***	2.60e-05***
	(3.87e-06)	(1.30e-06)
Num.Obs.	2009	2009
R2	0.885	0.885
R2 Adj.	0.884	0.884
R2 Within	0.882	0.882
R2 Within Adj.	0.880	0.880
AIC	-139.2	-139.2
BIC	34.6	34.6
RMSE	0.23	0.23
Std.Errors	Heteroskedasticity-robust	Driscoll-Kraay (L=1)
Year Fixed Effects	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Dependent variable = *Average Property Price (log)*

Robust standard errors (HC1) and Driscoll-Kraay (DK) standard errors (Lag = 1) are reported. The models use two-year lags for all independent variables, except for the variables *Average Age*, *Municipality Size*, and the control dummies *Has Coastline (1 = Yes)*, *Near Airport (1 = Yes)*, and *Near Major City (1 = Yes)*, which are not lagged in any of the models.

Where indicated, variables are log-transformed and normalized per 1,000 or 100,000 inhabitants.

Appendix 2b: *Price Levels - Insurance Claims. 2-Year lag full regression table including control variables.*

	2Y Lagged Robust SE (HC1)	2Y Lagged Driscoll-Kraay
Climate Risk 2017	1.53e-04+	1.53e-04***
	(8.11e-05)	(1.76e-05)
Climate Risk 2018	5.16e-05	5.16e-05*
	(7.99e-05)	(1.91e-05)
Climate Risk 2019	2.19e-05	2.19e-05
	(7.98e-05)	(1.60e-05)
Climate Risk 2020	2.21e-05	2.21e-05
	(7.97e-05)	(1.67e-05)
Climate Risk 2021	-4.79e-05	-4.79e-05*
	(7.99e-05)	(1.43e-05)
Climate Risk 2022	4.46e-05	4.46e-05**
	(8.58e-05)	(1.14e-05)
Climate Risk 2023	9.86e-05	9.86e-05***
	(8.21e-05)	(1.48e-05)
Insurance Claims per 100K 2017 (log)	0.009	0.009**
	(0.019)	(0.002)
Insurance Claims per 100K 2018 (log)	0.030	0.030***
	(0.019)	(0.004)
Insurance Claims per 100K 2019 (log)	0.012	0.012***
	(0.016)	(0.002)
Insurance Claims per 100K 2020 (log)	0.020	0.020**
	(0.021)	(0.004)
Insurance Claims per 100K 2021 (log)	0.054**	0.054***
	(0.018)	(0.001)
Insurance Claims per 100K 2022 (log)	0.052*	0.052***
	(0.021)	(0.002)
Insurance Claims per 100K 2023 (log)	0.019	0.019***
	(0.020)	(0.001)

Cont. Appendix 2b: *Price Level - Insurance Claims. 2-Year lag full regression table including control variables.*

Population Density (log)	0.180***	0.180***
	(0.012)	(0.003)
Disposable Income (log)	1.088***	1.088***
	(0.080)	(0.046)
Reported Crimes per 100K (log)	0.031	0.031
	(0.028)	(0.045)
Single-family Houses per 1,000	-0.002***	-0.002***
	(2.12e-04)	(5.78e-05)
Unemployment Rate	-4.300***	-4.300***
	(0.248)	(0.254)
Average Age	-0.009+	-0.009***
	(0.005)	(0.001)
Has Coastline (1 = Yes)	0.173***	0.173***
	(0.012)	(0.005)
Near Airport (1 = Yes)	-0.056***	-0.056**
	(0.015)	(0.010)
Near Major City (1 = Yes)	0.026	0.026**
	(0.018)	(0.005)
Municipality Size (KM^2)	2.66e-05***	2.66e-05***
	(3.85e-06)	(1.11e-06)
Num.Obs.	2009	2009
R2	0.884	0.884
R2 Adj.	0.883	0.883
R2 Within	0.881	0.881
R2 Within Adj.	0.879	0.879
AIC	-120.3	-120.3
BIC	53.4	53.4
RMSE	0.23	0.23
Std.Errors	Heteroskedasticity-robust	Driscoll-Kraay (L=1)
Year Fixed Effects	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Dependent variable = *Average Property Price (log)*

Robust standard errors (HC1) and Driscoll-Kraay (DK) standard errors (Lag = 1) are reported. The models use two-year lags for all independent variables, except for the variables *Average Age*, *Municipality Size*, and the control dummies *Has Coastline (1 = Yes)*, *Near Airport (1 = Yes)*, and *Near Major City (1 = Yes)*, which are not lagged in any of the models. Where indicated, variables are log-transformed and normalized per 1,000 or 100,000 inhabitants.

Appendix 2c: *Price Growth - Damage Costs. 2-Year lag full regression table including control variables.*

	2Y Lagged Robust SE (HC1)	2Y Lagged Driscoll-Kraay
Climate Risk	-1.06e-05	-1.06e-05
	(8.26e-06)	(1.46e-05)
Damage Costs per 100K (log)	-0.002	-0.002
	(0.001)	(8.86e-04)
Population Density Growth (log)	0.424*	0.424
	(0.198)	(0.275)
Disposable Income Growth (log)	0.180	0.180
	(0.153)	(0.182)
Reported Crimes per 100K Growth (log)	-0.032*	-0.032***
	(0.013)	(0.003)
New Single-family Houses per 100K	-2.10e-06	-2.10e-06
	(4.57e-06)	(2.15e-06)
Unemployment Rate	0.028	0.028
	(0.045)	(0.061)
Average Age	0.004***	0.004+
	(7.51e-04)	(0.002)
Has Coastline (1 = Yes)	-0.005+	-0.005
	(0.003)	(0.003)
Near Airport (1 = Yes)	0.005	0.005
	(0.004)	(0.005)
Near Major City (1 = Yes)	-0.006	-0.006
	(0.005)	(0.009)
Municipality Size (KM^2)	1.41e-06+	1.41e-06
	(8.53e-07)	(1.33e-06)
Num.Obs.	1518	1518
R2	0.710	0.710
R2 Adj.	0.707	0.707
R2 Within	0.047	0.047
R2 Within Adj.	0.039	0.039
AIC	-4655.0	-4655.0
BIC	-4559.1	-4559.1
RMSE	0.05	0.05
Std.Errors	Heteroskedasticity-robust	Driscoll-Kraay (L=1)
Year Fixed Effects	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Dependent variable = *Average Property Price Growth (K/T)*

Robust standard errors (HC1) and Driscoll-Kraay (DK) standard errors (Lag = 1) are reported. The models use two-year lags for all independent variables, except for the variables *Average Age*, *Municipality Size*, and the control dummies *Has Coastline (1 = Yes)*, *Near Airport (1 = Yes)*, and *Near Major City (1 = Yes)*, which are not lagged in any of the models.

Where indicated, variables are log transformed, growth transformed, and normalized per 100,000 inhabitants.

Appendix 2d: *Price Growth - Insurance Claims. 2-Year lag full regression table including control variables.*

	2Y Lagged Robust SE (HC1)	2Y Lagged Driscoll-Kraay
Climate Risk	-1.17e-05	-1.17e-05
	(8.26e-06)	(1.47e-05)
Insurance Claims per 100K (log)	-0.003	-0.003
	(0.002)	(0.003)
Population Density Growth (log)	0.424*	0.424
	(0.197)	(0.279)
Disposable Income Growth (log)	0.185	0.185
	(0.153)	(0.184)
Reported Crimes per 100K Growth (log)	-0.032*	-0.032***
	(0.013)	(0.003)
New Single-family Houses per 100K	-1.98e-06	-1.98e-06
	(4.60e-06)	(2.34e-06)
Unemployment Rate	0.026	0.026
	(0.045)	(0.063)
Average Age	0.004***	0.004*
	(7.61e-04)	(0.001)
Has Coastline (1 = Yes)	-0.005+	-0.005
	(0.003)	(0.003)
Near Airport (1 = Yes)	0.005	0.005
	(0.004)	(0.005)
Near Major City (1 = Yes)	-0.006	-0.006
	(0.005)	(0.009)
Municipality Size (KM^2)	1.34e-06	1.34e-06
	(8.53e-07)	(1.36e-06)
Num.Obs.	1518	1518
R2	0.710	0.710
R2 Adj.	0.707	0.707
R2 Within	0.047	0.047
R2 Within Adj.	0.039	0.039
AIC	-4654.8	-4654.8
BIC	-4559.0	-4559.0
RMSE	0.05	0.05
Std.Errors	Heteroskedasticity-robust	Driscoll-Kraay (L=1)
Year Fixed Effects	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Dependent variable = *Average Property Price Growth (K/T)*

Robust standard errors (HC1) and Driscoll-Kraay (DK) standard errors (Lag = 1) are reported. The models use two-year lags for all independent variables, except for the variables *Average Age*, *Municipality Size*, and the control dummies *Has Coastline (1 = Yes)*, *Near Airport (1 = Yes)*, and *Near Major City (1 = Yes)*, which are not lagged in any of the models.

Where indicated, variables are log transformed, growth transformed, and normalized per 100,000 inhabitants.

Appendix 3a: *Price Level. Descriptive Statistics of original variables.*

Variable	N	Mean	Median	St. Dev.	Min	Max
Average Property Price	2,583	2,376.52	1,801.00	1,824.49	265.00	13,609.00
Climate Risk	2,583	142.17	93.00	136.49	4.00	1,053.00
Damage Costs per 100K	2,583	11,124,980.62	3,855,361.00	44,531,196.07	0.00	1,649,185,872.00
Insurance Claims per 100K	2,583	211.86	121.40	337.67	0.00	5,511.80
Population Density	2,583	158.56	28.40	576.38	0.20	6,441.50
Disposable Income	2,583	450.92	430.00	77.51	337.40	873.00
Reported Crimes per 100K	2,583	9,434.52	9,250.00	2,600.16	3,107.00	24,021.00
Single-family Houses per 1,000	2,583	289.87	296.50	75.92	6.70	533.80
Unemployment Rate	2,583	0.13	0.12	0.04	0.05	0.24
Average Age	2,583	43.57	43.80	2.72	36.30	52.40
Has Coastline (1 = Yes)	2,583	0.28	0.00	0.45	0.00	1.00
Near Airport (1 = Yes)	2,583	0.31	0.00	0.46	0.00	1.00
Near Major City (1 = Yes)	2,583	0.25	0.00	0.43	0.00	1.00
Municipality Size (KM²)	2,583	1,413.98	667.34	2,410.90	8.73	18,685.00

Note: The full sample consists of 2583 observations from 287 unique municipalities across 9 years during the period 2015–2023.
Where indicated, variables are normalized per 1,000 or 100,000 inhabitants.

Appendix 3b: *Price Growth. Descriptive Statistics of original variables.*

Variable	N	Mean	Median	St. Dev.	Min	Max
Average Property Price Growth	2,277	0.06	0.06	0.09	-0.21	0.37
Climate Risk	2,277	148.70	95.00	141.79	4.00	1,053.00
Damage Costs per 100K	2,277	10,776,842.81	3,896,380.00	43,809,672.30	0.00	1,649,185,872.00
Insurance Claims per 100K	2,277	208.19	119.80	326.44	0.00	5,511.80
Population Density	2,277	162.42	33.70	554.82	0.90	6,441.50
Disposable Income	2,277	458.93	435.30	78.14	337.90	873.00
Reported Crimes per 100K	2,277	9,555.44	9,378.00	2,590.14	3,107.00	24,021.00
New Single-family Houses per 100K	2,277	172.66	120.88	328.18	-2,811.75	7,210.33
Unemployment Rate	2,277	0.13	0.12	0.04	0.05	0.24
Average Age	2,277	43.19	43.40	2.59	36.30	52.40
Has Coastline (1 = Yes)	2,277	0.32	0.00	0.47	0.00	1.00
Near Airport (1 = Yes)	2,277	0.33	0.00	0.47	0.00	1.00
Near Major City (1 = Yes)	2,277	0.28	0.00	0.45	0.00	1.00
Municipality Size (KM²)	2,277	1,126.65	608.63	1,959.46	8.73	18,685.00

Note: The full sample consists of 2277 observations from 253 unique municipalities across 9 years during the period 2015–2023.
Where indicated, variables are normalized per 100,000 inhabitants.

Appendix 4a: *Price Level - Damage Costs: Variance Inflation Factor (VIF) Test.*

Variable	Damage Costs	1Y Lagged Damage Costs
Climate Risk 2015	1.9735	NA
Climate Risk 2016	1.9780	1.9628
Climate Risk 2017	1.9661	1.9546
Climate Risk 2018	2.0276	2.0162
Climate Risk 2019	1.9748	1.9641
Climate Risk 2020	1.9979	1.9890
Climate Risk 2021	2.0030	1.9902
Climate Risk 2022	1.9597	1.9433
Climate Risk 2023	1.9489	1.9344
Damage Costs per 100K 2015 (log)	11.4437	NA
Damage Costs per 100K 2016 (log)	11.4428	12.4598
Damage Costs per 100K 2017 (log)	11.1884	12.1913
Damage Costs per 100K 2018 (log)	11.8053	12.8955
Damage Costs per 100K 2019 (log)	11.5182	12.5631
Damage Costs per 100K 2020 (log)	11.7854	12.7717
Damage Costs per 100K 2021 (log)	11.5494	12.6312
Damage Costs per 100K 2022 (log)	11.4527	12.4798
Damage Costs per 100K 2023 (log)	11.4874	12.3434
Population Density (log)	8.7463	8.6927
Disposable Income (log)	6.5329	6.5507
Reported Crimes per 100K (log)	1.9337	1.9251
Single-family Houses per 1,000	5.5529	5.4301
Unemployment Rate	2.7560	2.6789
Average Age	4.5038	4.4105
Has Coastline (1 = Yes)	1.4027	1.4055
Near Airport (1 = Yes)	1.9830	1.9837
Near Major City (1 = Yes)	3.0973	3.0994
Municipality Size (KM²)	2.0152	2.0339

Note: The Variance Inflation Factor (VIF) assesses multicollinearity among regressors. A VIF above 10 may indicate serious multicollinearity, while values between 5 and 10 suggest moderate concern. The 1Y Lagged model use one-year lags for all independent variables, except for the control variables *Average Age*, *Municipality Size*, and the control dummies *Has Coastline (1 = Yes)*, *Near Airport (1 = Yes)*, and *Near Major City (1 = Yes)*, which are not lagged in any of the models. Since the VIF test is independent of the standard error specification, the same result applies to both the Robust Standard Errors (HC1) and the Driscoll-Kraay (DK) Standard Errors. Where indicated, variables are log transformed and normalized per 1,000 or 100,000 inhabitants.

Appendix 4b: *Price Level - Insurance Claims: Variance Inflation Factor (VIF) Test.*

Variable	Insurance Claims	1Y Lagged Insurance Claims
Climate Risk 2015	1.8803	NA
Climate Risk 2016	1.8598	1.8494
Climate Risk 2017	1.8932	1.8841
Climate Risk 2018	1.9808	1.9706
Climate Risk 2019	1.8738	1.8654
Climate Risk 2020	1.9708	1.9641
Climate Risk 2021	1.9542	1.9428
Climate Risk 2022	1.8540	1.8375
Climate Risk 2023	1.8593	1.8465
Insurance Claims per 100K 2015 (log)	5.2383	NA
Insurance Claims per 100K 2016 (log)	5.1927	5.7307
Insurance Claims per 100K 2017 (log)	5.2778	5.8358
Insurance Claims per 100K 2018 (log)	5.6390	6.2718
Insurance Claims per 100K 2019 (log)	5.3003	5.8719
Insurance Claims per 100K 2020 (log)	5.7727	6.2881
Insurance Claims per 100K 2021 (log)	5.5828	6.2108
Insurance Claims per 100K 2022 (log)	5.2924	5.8919
Insurance Claims per 100K 2023 (log)	5.3774	5.8238
Population Density (log)	8.7561	8.6967
Disposable Income (log)	6.5208	6.5437
Reported Crimes per 100K (log)	1.9322	1.9237
Single-family Houses per 1,000	5.7871	5.5973
Unemployment Rate	2.7413	2.6892
Average Age	4.5072	4.4087
Has Coastline (1 = Yes)	1.4133	1.4159
Near Airport (1 = Yes)	1.9841	1.9848
Near Major City (1 = Yes)	3.0958	3.0981
Municipality Size (KM²)	2.0116	2.0297

Note: The Variance Inflation Factor (VIF) assesses multicollinearity among regressors. A VIF above 10 may indicate serious multicollinearity, while values between 5 and 10 suggest moderate concern. The 1Y Lagged model use one-year lags for all independent variables, except for the control variables *Average Age*, *Municipality Size*, and the control dummies *Has Coastline (1 = Yes)*, *Near Airport (1 = Yes)*, and *Near Major City (1 = Yes)*, which are not lagged in any of the models. Since the VIF test is independent of the standard error specification, the same result applies to both the Robust Standard Errors (HC1) and the Driscoll-Kraay (DK) Standard Errors. Where indicated, variables are log transformed and normalized per 1,000 or 100,000 inhabitants.

Appendix 4c: *Price Growth - Damage Costs: Variance Inflation Factor (VIF) Test.*

Variable	Damage Costs	1Y Lagged Damage Costs
Climate Risk	1.0448	1.0456
Damage Costs per 100K (log)	1.1053	1.0870
Population Density Growth (log)	1.7991	1.7537
Disposable Income Growth (log)	1.1597	1.0946
Reported Crimes per 100K Growth (log)	1.0302	1.0154
New Single-family Houses per 100K	1.1562	1.1334
Unemployment Rate	1.2290	1.2350
Average Age	1.9799	1.9617
Has Coastline (1 = Yes)	1.1433	1.1396
Near Airport (1 = Yes)	2.0836	2.0784
Near Major City (1 = Yes)	2.5650	2.5702
Municipality Size (KM^2)	1.1304	1.1399

Note: The Variance Inflation Factor (VIF) assesses multicollinearity among regressors. A VIF above 10 may indicate serious multicollinearity, while values between 5 and 10 suggest moderate concern. The 1Y Lagged model use one-year lags for all independent variables, except for the control variables *Average Age*, *Municipality Size*, and the control dummies *Has Coastline (1 = Yes)*, *Near Airport (1 = Yes)*, and *Near Major City (1 = Yes)*, which are not lagged in any of the models. Since the VIF test is independent of the standard error specification, the same result applies to both the Robust Standard Errors (HC1) and the Driscoll-Kraay (DK) Standard Errors. Where indicated, variables are log transformed, growth transformed, and normalized per 100,000 inhabitants.

Appendix 4d: *Price Growth - Insurance Claims: Variance Inflation Factor (VIF) Test.*

Variable	Insurance Claims	1Y Lagged Insurance Claims
Climate Risk	1.0514	1.0501
Insurance Claims per 100K (log)	1.1936	1.1735
Population Density Growth (log)	1.8173	1.7678
Disposable Income Growth (log)	1.1590	1.0946
Reported Crimes per 100K Growth (log)	1.0320	1.0176
New Single-family Houses per 100K	1.1563	1.1333
Unemployment Rate	1.2318	1.2379
Average Age	2.0281	2.0220
Has Coastline (1 = Yes)	1.1432	1.1396
Near Airport (1 = Yes)	2.0825	2.0782
Near Major City (1 = Yes)	2.5688	2.5720
Municipality Size (KM^2)	1.1336	1.1427

Note: The Variance Inflation Factor (VIF) assesses multicollinearity among regressors. A VIF above 10 may indicate serious multicollinearity, while values between 5 and 10 suggest moderate concern. The 1Y Lagged model use one-year lags for all independent variables, except for the control variables *Average Age*, *Municipality Size*, and the control dummies *Has Coastline (1 = Yes)*, *Near Airport (1 = Yes)*, and *Near Major City (1 = Yes)*, which are not lagged in any of the models. Since the VIF test is independent of the standard error specification, the same result applies to both the Robust Standard Errors (HC1) and the Driscoll-Kraay (DK) Standard Errors. Where indicated, variables are log transformed, growth transformed, and normalized per 100,000 inhabitants.

Appendix 5a: *Price Level: Breusch-Pagan test for Heteroskedasticity.*

Model	Statistic	DF	P-value
Damage Costs	340.234	28	2.28e-55
1Y Lagged Damage Costs	284.259	26	2.91e-45
Insurance Claims	333.885	28	4.28e-54
1Y Lagged Insurance Claims	280.620	26	1.54e-44

Note: The Breusch-Pagan (BP) test examines heteroskedasticity in the idiosyncratic error of each model. Since the BP test is independent of the standard error specification, the same result applies to both the Robust Standard Errors (HC1) and the Driscoll-Kraay (DK) Standard Errors. A low p-value (< 0.05) provides evidence of heteroskedasticity, suggesting that the null hypothesis of homoskedasticity should be rejected.

Appendix 5b: *Price Growth: Breusch-Pagan test for Heteroskedasticity.*

Model	Statistic	DF	P-value
Damage Costs	86.636	12	2.20e-13
1Y Lagged Damage Costs	105.107	12	5.53e-17
Insurance Claims	83.494	12	8.86e-13
1Y Lagged Insurance Claims	121.374	12	3.29e-20

Note: The Breusch-Pagan (BP) test examines heteroskedasticity in the idiosyncratic error of each model. Since the BP test is independent of the standard error specification, the same result applies to both the Robust Standard Errors (HC1) and the Driscoll-Kraay (DK) Standard Errors. A low p-value (< 0.05) provides evidence of heteroskedasticity, suggesting that the null hypothesis of homoskedasticity should be rejected.

Appendix 6a: *Price Level: Wooldridge Test for Autocorrelation (pwartest).*

Model	Statistic	DF 1	DF 2	P-value
Damage Costs	6812.109	1	2294	2.2e-16
1Y Lagged Damage Costs	7042.723	1	2007	2.2e-16
Insurance Claims	9176.377	1	2294	2.2e-16
1Y Lagged Insurance Claims	9780.687	1	2007	2.2e-16

Note: The Wooldridge test for autocorrelation (pwartest) examines whether there is first-order serial correlation in a panel model. Since the pwartest is independent of the standard error specification, the same result applies to both the Robust Standard Errors (HC1) and the Driscoll-Kraay (DK) Standard Errors. A low p-value (< 0.05) indicates the presence of autocorrelation, suggesting that the null hypothesis of no serial correlation should be rejected.

Appendix 6b: *Price Growth: Wooldridge Test for Autocorrelation (pwartest).*

Model	Statistic	DF 1	DF 2	P-value
Damage Costs	12.708343	1	1769	0.0004
1Y Lagged Damage Costs	8.427827	1	1516	0.0037
Insurance Claims	12.466354	1	1769	0.0004
1Y Lagged Insurance Claims	8.560321	1	1516	0.0035

Note: The Wooldridge test for autocorrelation (pwartest) examines whether there is first-order serial correlation in a panel model. Since the pwartest is independent of the standard error specification, the same result applies to both the Robust Standard Errors (HC1) and the Driscoll-Kraay (DK) Standard Errors. A low p-value (< 0.05) indicates the presence of autocorrelation, suggesting that the null hypothesis of no serial correlation should be rejected.

Appendix 7a: *Price Level - Damage Costs. Full regression table including control variables.*

	Robust SE (HC1)	Driscoll-Kraay (DK)	1Y Lagged Robust SE (HC1)	1Y Lagged DK
Climate Risk 2015	1.30e-04	1.30e-04***		
	(7.93e-05)	(1.59e-05)		
Climate Risk 2016	8.60e-05	8.60e-05***	1.18e-04	1.18e-04***
	(7.91e-05)	(1.70e-05)	(8.06e-05)	(1.98e-05)
Climate Risk 2017	9.41e-05	9.41e-05***	1.15e-04	1.15e-04***
	(7.80e-05)	(1.63e-05)	(7.85e-05)	(2.11e-05)
Climate Risk 2018	1.82e-05	1.82e-05	2.16e-05	2.16e-05
	(7.86e-05)	(1.53e-05)	(7.97e-05)	(1.95e-05)
Climate Risk 2019	-1.13e-06	-1.13e-06	8.55e-06	8.55e-06
	(7.88e-05)	(1.50e-05)	(7.76e-05)	(1.90e-05)
Climate Risk 2020	4.49e-05	4.49e-05*	-3.47e-06	-3.47e-06
	(8.41e-05)	(1.55e-05)	(8.12e-05)	(1.82e-05)
Climate Risk 2021	-8.56e-06	-8.56e-06	-3.08e-05	-3.08e-05+
	(8.19e-05)	(1.50e-05)	(8.23e-05)	(1.60e-05)
Climate Risk 2022	-2.31e-05	-2.31e-05	2.47e-05	2.47e-05
	(8.10e-05)	(1.58e-05)	(8.12e-05)	(1.73e-05)
Climate Risk 2023	5.07e-05	5.07e-05**	5.06e-05	5.06e-05*
	(8.33e-05)	(1.35e-05)	(8.27e-05)	(1.83e-05)
Damage Costs per 100K 2015 (log)	0.007	0.007***		
	(0.009)	(9.64e-04)		
Damage Costs per 100K 2016 (log)	0.015	0.015***	0.014	0.014***
	(0.009)	(3.46e-04)	(0.010)	(6.12e-04)
Damage Costs per 100K 2017 (log)	0.009	0.009***	0.011	0.011***
	(0.007)	(2.31e-04)	(0.008)	(1.81e-04)
Damage Costs per 100K 2018 (log)	0.011	0.011***	0.012	0.012***
	(0.011)	(0.001)	(0.011)	(0.002)
Damage Costs per 100K 2019 (log)	0.008	0.008***	0.007	0.007***
	(0.010)	(9.72e-04)	(0.010)	(7.99e-04)

Cont. Appendix 7a: *Price Level - Damage Costs. Full regression table including control variables.*

Damage Costs per 100K 2020 (log)	0.037*	0.037***	0.037*	0.037***
	(0.017)	(0.002)	(0.016)	(0.002)
Damage Costs per 100K 2021 (log)	0.032***	0.032***	0.032***	0.032***
	(0.008)	(1.14e-04)	(0.008)	(2.80e-04)
Damage Costs per 100K 2022 (log)	0.029*	0.029***	0.033**	0.033***
	(0.013)	(3.91e-04)	(0.012)	(4.41e-04)
Damage Costs per 100K 2023 (log)	0.020*	0.020***	0.019*	0.019***
	(0.010)	(7.06e-04)	(0.009)	(7.56e-04)
Population Density (log)	0.176***	0.176***	0.179***	0.179***
	(0.010)	(0.005)	(0.011)	(0.004)
Disposable Income (log)	1.198***	1.198***	1.125***	1.125***
	(0.073)	(0.043)	(0.076)	(0.047)
Reported Crimes per 100K (log)	0.047+	0.047	0.036	0.036
	(0.025)	(0.036)	(0.026)	(0.046)
Single-family Houses per 1,000	-0.003***	-0.003***	-0.002***	-0.002***
	(1.87e-04)	(1.49e-04)	(1.96e-04)	(1.07e-04)
Unemployment Rate	-4.166***	-4.166***	-4.297***	-4.297***
	(0.222)	(0.196)	(0.235)	(0.272)
Average Age	-0.007	-0.007*	-0.008+	-0.008**
	(0.005)	(0.003)	(0.005)	(0.002)
Has Coastline (1 = Yes)	0.171***	0.171***	0.171***	0.171***
	(0.011)	(0.004)	(0.011)	(0.005)
Near Airport (1 = Yes)	-0.057***	-0.057***	-0.057***	-0.057***
	(0.013)	(0.006)	(0.014)	(0.009)
Near Major City (1 = Yes)	0.030+	0.030***	0.032+	0.032***
	(0.016)	(0.006)	(0.017)	(0.004)
Municipality Size (KM^2)	2.51e-05***	2.51e-05***	2.55e-05***	2.55e-05***
	(3.46e-06)	(8.61e-07)	(3.69e-06)	(1.04e-06)

Cont. Appendix 7a: *Price Level - Damage Costs. Full regression table including control variables.*

Num.Obs.	2583	2583	2296	2296
R2	0.889	0.889	0.887	0.887
R2 Adj.	0.887	0.887	0.885	0.885
R2 Within	0.883	0.883	0.882	0.882
R2 Within Adj.	0.881	0.881	0.881	0.881
AIC	-158.5	-158.5	-139.3	-139.3
BIC	58.2	58.2	55.8	55.8
RMSE	0.23	0.23	0.23	0.23
Std.Errors	Heteroskedasticity-robust	Driscoll-Kraay (L=1)	Heteroskedasticity-robust	Driscoll-Kraay (L=1)
Year Fixed Effects	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Dependent variable = *Average Property Price (log)*

Robust standard errors (HC1) and Driscoll-Kraay (DK) standard errors (Lag = 1) are reported. Lagged models use one-year lags for all independent variables, except for the variables *Average Age*, *Municipality Size*, and the control dummies *Has Coastline (1 = Yes)*, *Near Airport (1 = Yes)*, and *Near Major City (1 = Yes)*, which are not lagged in any of the models.

Where indicated, variables are log-transformed and normalized per 1,000 or 100,000 inhabitants.

Appendix 7b: *Price Level - Insurance Claims. Full regression table including control variables.*

	Robust SE (HC1)	Driscoll-Kraay (DK)	1Y Lagged Robust SE (HC1)	1Y Lagged DK
Climate Risk 2015	1.26e-04	1.26e-04***		
	(8.02e-05)	(1.41e-05)		
Climate Risk 2016	8.36e-05	8.36e-05***	1.12e-04	1.12e-04***
	(7.78e-05)	(1.46e-05)	(7.98e-05)	(1.65e-05)
Climate Risk 2017	9.41e-05	9.41e-05***	1.15e-04	1.15e-04***
	(7.92e-05)	(1.46e-05)	(7.99e-05)	(1.91e-05)
Climate Risk 2018	1.88e-05	1.88e-05	2.13e-05	2.13e-05
	(7.86e-05)	(1.45e-05)	(7.95e-05)	(1.83e-05)
Climate Risk 2019	9.94e-06	9.94e-06	1.58e-05	1.58e-05
	(8.03e-05)	(1.19e-05)	(7.90e-05)	(1.63e-05)
Climate Risk 2020	5.44e-05	5.44e-05**	4.27e-06	4.27e-06
	(8.34e-05)	(1.34e-05)	(8.03e-05)	(1.60e-05)
Climate Risk 2021	1.70e-05	1.70e-05	-5.65e-06	-5.65e-06
	(8.34e-05)	(1.38e-05)	(8.36e-05)	(1.50e-05)
Climate Risk 2022	1.27e-05	1.27e-05	5.94e-05	5.94e-05**
	(8.39e-05)	(1.23e-05)	(8.49e-05)	(1.37e-05)
Climate Risk 2023	4.94e-05	4.94e-05**	5.01e-05	5.01e-05*
	(8.08e-05)	(1.09e-05)	(8.03e-05)	(1.58e-05)
Insurance Claims per 100K 2015 (log)	7.89e-04	7.89e-04		
	(0.013)	(0.002)		
Insurance Claims per 100K 2016 (log)	5.61e-04	5.61e-04	-0.004	-0.004
	(0.017)	(0.001)	(0.018)	(0.003)
Insurance Claims per 100K 2017 (log)	0.013	0.013***	0.015	0.015***
	(0.018)	(0.001)	(0.019)	(0.002)
Insurance Claims per 100K 2018 (log)	0.032+	0.032***	0.036+	0.036***
	(0.019)	(0.003)	(0.020)	(0.004)
Insurance Claims per 100K 2019 (log)	0.022	0.022***	0.018	0.018***
	(0.016)	(0.002)	(0.016)	(0.002)

Cont. Appendix 7b: *Price Level - Insurance Claims. Full regression table including control variables.*

Insurance Claims per 100K 2020 (log)	0.024	0.024***	0.031	0.031***
	(0.022)	(0.005)	(0.021)	(0.005)
Insurance Claims per 100K 2021 (log)	0.053**	0.053***	0.054**	0.054***
	(0.020)	(0.001)	(0.020)	(0.002)
Insurance Claims per 100K 2022 (log)	0.050*	0.050***	0.051*	0.051***
	(0.021)	(0.002)	(0.021)	(0.002)
Insurance Claims per 100K 2023 (log)	0.022	0.022***	0.024	0.024***
	(0.020)	(0.002)	(0.019)	(0.002)
Population Density (log)	0.177***	0.177***	0.179***	0.179***
	(0.010)	(0.004)	(0.011)	(0.004)
Disposable Income (log)	1.198***	1.198***	1.130***	1.130***
	(0.074)	(0.046)	(0.076)	(0.048)
Reported Crimes per 100K (log)	0.050*	0.050	0.038	0.038
	(0.025)	(0.036)	(0.027)	(0.045)
Single-family Houses per 1,000	-0.003***	-0.003***	-0.002***	-0.002***
	(1.93e-04)	(1.24e-04)	(2.01e-04)	(8.48e-05)
Unemployment Rate	-4.194***	-4.194***	-4.306***	-4.306***
	(0.223)	(0.186)	(0.236)	(0.252)
Average Age	-0.008	-0.008*	-0.009+	-0.009**
	(0.005)	(0.003)	(0.005)	(0.002)
Has Coastline (1 = Yes)	0.172***	0.172***	0.172***	0.172***
	(0.011)	(0.005)	(0.011)	(0.005)
Near Airport (1 = Yes)	-0.058***	-0.058***	-0.059***	-0.059***
	(0.013)	(0.005)	(0.014)	(0.008)
Near Major City (1 = Yes)	0.027+	0.027**	0.029+	0.029***
	(0.016)	(0.006)	(0.017)	(0.005)
Municipality Size (KM^2)	2.59e-05***	2.59e-05***	2.65e-05***	2.65e-05***
	(3.45e-06)	(8.53e-07)	(3.67e-06)	(9.27e-07)

Cont. Appendix 7b: *Price Level - Insurance Claims. Full regression table including control variables.*

Num.Obs.	2583	2583	2296	2296
R2	0.888	0.888	0.886	0.886
R2 Adj.	0.887	0.887	0.884	0.884
R2 Within	0.882	0.882	0.881	0.881
R2 Within Adj.	0.880	0.880	0.880	0.880
AIC	-136.9	-136.9	-117.3	-117.3
BIC	79.8	79.8	77.8	77.8
RMSE	0.23	0.23	0.23	0.23
Std.Errors	Heteroskedasticity-robust	Driscoll-Kraay (L=1)	Heteroskedasticity-robust	Driscoll-Kraay (L=1)
Year Fixed Effects	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Dependent variable = *Average Property Price (log)*

Robust standard errors (HC1) and Driscoll-Kraay (DK) standard errors (Lag = 1) are reported. Lagged models use one-year lags for all independent variables, except for the variables *Average Age*, *Municipality Size*, and the control dummies *Has Coastline (1 = Yes)*, *Near Airport (1 = Yes)*, and *Near Major City (1 = Yes)*, which are not lagged in any of the models.

Where indicated, variables are log-transformed and normalized per 1,000 or 100,000 inhabitants.

Appendix 8a: *Price Growth - Damage Costs. Full regression table including control variables.*

	Robust SE (HC1)	Driscoll-Kraay (DK)	1Y Lagged Robust SE (HC1)	1Y Lagged DK
Climate Risk	-1.23e-05+	-1.23e-05	-8.76e-06	-8.76e-06
	(7.18e-06)	(8.88e-06)	(7.68e-06)	(1.11e-05)
Damage Costs per 100K (log)	-8.77e-04	-8.77e-04	8.54e-04	8.54e-04
	(9.76e-04)	(7.56e-04)	(0.001)	(7.73e-04)
Population Density Growth (log)	-0.215	-0.215	0.520*	0.520+
	(0.172)	(0.149)	(0.202)	(0.259)
Disposable Income Growth (log)	0.223+	0.223	0.521***	0.521*
	(0.133)	(0.175)	(0.137)	(0.168)
Reported Crimes per 100K Growth (log)	-0.008	-0.008	0.023+	0.023**
	(0.011)	(0.019)	(0.012)	(0.004)
New Single-family Houses per 100K	-9.29e-07	-9.29e-07	4.08e-06	4.08e-06
	(5.90e-06)	(5.86e-06)	(9.75e-06)	(1.00e-05)
Unemployment Rate	-0.026	-0.026	0.041	0.041
	(0.039)	(0.057)	(0.043)	(0.067)
Average Age	0.003***	0.003*	0.004***	0.004*
	(6.65e-04)	(0.001)	(6.90e-04)	(0.001)
Has Coastline (1 = Yes)	-0.006*	-0.006*	-0.007**	-0.007*
	(0.002)	(0.002)	(0.003)	(0.002)
Near Airport (1 = Yes)	1.92e-04	1.92e-04	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Near Major City (1 = Yes)	-0.001	-0.001	-0.005	-0.005
	(0.004)	(0.007)	(0.004)	(0.007)
Municipality Size (KM^2)	3.75e-08	3.75e-08	6.15e-07	6.15e-07
	(7.53e-07)	(1.30e-06)	(7.62e-07)	(1.44e-06)
Num.Obs.	2024	2024	1771	1771
R2	0.665	0.665	0.688	0.688
R2 Adj.	0.662	0.662	0.685	0.685
R2 Within	0.030	0.030	0.050	0.050
R2 Within Adj.	0.024	0.024	0.044	0.044
AIC	-6131.2	-6131.2	-5428.5	-5428.5
BIC	-6019.0	-6019.0	-5324.4	-5324.4
RMSE	0.05	0.05	0.05	0.05
Std.Errors	Heteroskedasticity-robust	Driscoll-Kraay (L=1)	Heteroskedasticity-robust	Driscoll-Kraay (L=1)
Year Fixed Effects	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Dependent variable = *Average Property Price Growth (K/T)*

Robust standard errors (HC1) and Driscoll-Kraay (DK) standard errors (Lag = 1) are reported. Lagged models use one-year lags for all independent variables, except for the variables *Average Age*, *Municipality Size*, and the control dummies *Has Coastline (1 = Yes)*, *Near Airport (1 = Yes)*, and *Near Major City (1 = Yes)*, which are not lagged in any of the models.

Where indicated, variables are log transformed, growth transformed, and normalized per 100,000 inhabitants.

Appendix 8b: *Price Growth - Insurance Claims. Full regression table including control variables.*

	Robust SE (HC1)	Driscoll-Kraay (DK)	1Y Lagged Robust SE (HC1)	1Y Lagged DK
Climate Risk	-1.27e-05+	-1.27e-05	-7.93e-06	-7.93e-06
	(7.20e-06)	(8.37e-06)	(7.71e-06)	(1.11e-05)
Insurance Claims per 100K (log)	-8.88e-04	-8.88e-04	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.001)
Population Density Growth (log)	-0.213	-0.213	0.523**	0.523+
	(0.173)	(0.147)	(0.202)	(0.260)
Disposable Income Growth (log)	0.224+	0.224	0.518***	0.518*
	(0.133)	(0.176)	(0.137)	(0.169)
Reported Crimes per 100K Growth (log)	-0.008	-0.008	0.023+	0.023**
	(0.011)	(0.019)	(0.012)	(0.004)
New Single-family Houses per 100K	-9.72e-07	-9.72e-07	3.83e-06	3.83e-06
	(5.92e-06)	(5.86e-06)	(9.71e-06)	(1.00e-05)
Unemployment Rate	-0.026	-0.026	0.042	0.042
	(0.039)	(0.058)	(0.043)	(0.068)
Average Age	0.003***	0.003+	0.004***	0.004*
	(6.80e-04)	(0.001)	(7.05e-04)	(0.001)
Has Coastline (1 = Yes)	-0.006*	-0.006*	-0.007**	-0.007*
	(0.002)	(0.002)	(0.003)	(0.003)
Near Airport (1 = Yes)	2.58e-04	2.58e-04	0.003	0.003
	(0.004)	(0.004)	(0.004)	(0.004)
Near Major City (1 = Yes)	-0.001	-0.001	-0.005	-0.005
	(0.004)	(0.007)	(0.004)	(0.007)
Municipality Size (KM^2)	-1.12e-09	-1.12e-09	6.77e-07	6.77e-07
	(7.51e-07)	(1.28e-06)	(7.59e-07)	(1.48e-06)
Num.Obs.	2024	2024	1771	1771
R2	0.665	0.665	0.688	0.688
R2 Adj.	0.662	0.662	0.685	0.685
R2 Within	0.030	0.030	0.051	0.051
R2 Within Adj.	0.024	0.024	0.044	0.044
AIC	-6130.7	-6130.7	-5429.5	-5429.5
BIC	-6018.4	-6018.4	-5325.4	-5325.4
RMSE	0.05	0.05	0.05	0.05
Std.Errors	Heteroskedasticity-robust	Driscoll-Kraay (L=1)	Heteroskedasticity-robust	Driscoll-Kraay (L=1)
Year Fixed Effects	Yes	Yes	Yes	Yes

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Dependent variable = *Average Property Price Growth (K/T)*

Robust standard errors (HC1) and Driscoll-Kraay (DK) standard errors (Lag = 1) are reported. Lagged models use one-year lags for all independent variables, except for the variables *Average Age*, *Municipality Size*, and the control dummies *Has Coastline (1 = Yes)*, *Near Airport (1 = Yes)*, and *Near Major City (1 = Yes)*, which are not lagged in any of the models.

Where indicated, variables are log transformed, growth transformed, and normalized per 100,000 inhabitants.

Appendix 9a: *Price Level - Damage Costs. Average standard errors per standard error type.*

Model	Robust SE (HC1)	Driscoll-Kraay (DK)
Damage Costs	**0.0168**	0.0110
1Y Lagged Damage Costs	**0.0184**	0.0152

Note: The table presents the average standard error across coefficients for each regression model. The specification with the highest average standard error is indicated in bold.

Appendix 9b: *Price Level - Insurance Claims. Average standard errors per standard error type.*

Model	Robust SE (HC1)	Driscoll-Kraay (DK)
Insurance Claims	**0.0194**	0.0111
1Y Lagged Insurance Claims	**0.0211**	0.0150

Note: The table presents the average standard error across coefficients for each regression model. The specification with the highest average standard error is indicated in bold.

Appendix 9c: *Price Growth - Damage Costs. Average standard errors per standard error type.*

Model	Robust SE (HC1)	Driscoll-Kraay (DK)
Damage Costs	0.0306	**0.0347**
1Y Lagged Damage Costs	0.0339	**0.0428**

Note: The table presents the average standard error across coefficients for each regression model. The specification with the highest average standard error is indicated in bold.

Appendix 9d: *Price Growth - Insurance Claims. Average standard errors per standard error type.*

Model	Robust SE (HC1)	Driscoll-Kraay (DK)
Insurance Claims	0.0307	**0.0347**
1Y Lagged Insurance Claims	0.0340	**0.0431**

Note: The table presents the average standard error across coefficients for each regression model. The specification with the highest average standard error is indicated in bold.