

HOUSING LAB WORKING PAPER SERIES

2025 | 4

Climate Risks and Housing Markets.

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OSLOMET

Climate risks and housing markets*

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November 3, 2025

Abstract

Using different indices of climate related risk for damage at the housing unit and building unit level together with housing market transaction data, we investigate the relationship between these risks and house prices. This study analyzes sales from five different Norwegian cities from a dataset of almost 200,000 transactions from 2019 to 2024. In addition, three different indices are used to assess the risk of natural damage at the building level and the housing unit level, using both hazard zones and machine learning techniques. The risks analyzed in this study are mainly related to pluvial floods, landslides and avalanches, which are the dominant types of damage in Norway in terms of magnitude and dispersion. We also include the risk of damage related to floods, storms and storm surges in the analysis.

The findings of the study indicate that homebuyers take climate risk into account in their valuation processes. By using hedonic regression models and dynamic event analyses, we find that the risk of damage caused by climate-related natural disasters and water damages negatively affects house prices. The effect also appears to be greater after certain serious incidents related to some types of injuries, indicating behavioral effects. The negative risk premium is significant and robust across different model specifications and for different market segments, and also when we take into account various control variables and time- and area-fixed effects.

*We are grateful for comments from participants at conferences, seminars, and workshops, including the 12th Annual Conference of the French Association of Environmental and Resource Economists (FAERE). We are grateful to Eiendomsverdi AS for providing data.

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Keywords: Natural disasters, Extreme weather, Housing market, Risk
JEL classification: R21, R23, Q54

1 Introduction

Worldwide we see that the number of natural disasters increase due to global warming. Furthermore we expect higher frequency and intensity of extreme weather events. The «big five» hazards (floods, earthquakes, storms, drought and extreme heat) accounted in 2023 for direct economic costs of about 195.7 billion USD, or approximately 0.15% of global GDP. However, this number is without counting what is lost during and after a disaster, in livelihoods disrupted, degraded ecosystems or lives derailed by displacement or long-term health impacts. (United Nations Office for Disaster Risk Reduction, 2023)

Norwegian insurance claims data, available from Finance Norway, reveals that avalanches has been the most severe type of damage the past years, and that pluvial floods has been the most frequent type of weather related damage. Hence, these two types of damages are relevant to analyze separately in order to get a better view on how the housing market reacts to the risk of these types of damages. See Table ?? for details. Norway is also relevant to analyze in an international context because it is one of the countries with the highest homeownership share in Europe, and insurance premiums related to natural disasters are low and flat, and not adjusted for the risk for damages.

Flooding is the most frequent and costliest global natural hazards. Despite efforts to manage floods, the economic losses from flood events keep escalating (Anshuka et al., 2025; Smith, 2020). Urban flooding occurs predominantly during intense rainfall events in densely populated areas with inadequate drainage and sewer systems (Prokić et al., 2019; Palla et al., 2018). This phenomenon, also called pluvial flooding, differs from fluvial flooding, which is mainly caused by overflowing rivers. Despite the fact that pluvial floods often cause less damage per event than fluvial ones, their higher frequency can result in substantial cumulative losses (Tanaka et al., 2020; Moftakhari et al., 2017).

Pluvial flooding is one of the natural hazards which we look closer at in this study in addition to landslides and avalanches. There are particularly two reasons why these natural hazards are highlighted here. One is that they are the dominant damage types in Norway where the case areas are located, as mentioned above. Additionally, this is a type of natural hazard where local topography and land use have a large impact. This means that it is possible to calculate the risk for these hazards based on digital terrain data with high accuracy.

The impacts of climate change threaten the stability of the housing market world-wide. In response to growing concerns, there is a realization that increasing costs of for example flooding are not fully captured in property values (Valderrama et al., 2023; Urban Land Institute, 2020; Gourevitch et al., 2023). Hence, it constitutes a substantial financial risk for capital tied up in the housing market. This risk is mostly present for individuals and households, but it may also in the aggregate influence regional housing markets. Risk may thereby in turn affect financial stability and the real economy through e.g. the financial accelerators (Bernanke et al., 1999). In the US, 90 percent of natural disasters involve flooding, and the number is increasing due to both weather and demographic trends. More people are moving to flood-prone areas, and many of them do not know that their homeowners insurance does not cover flood damage (Dunsavage, 2022).

The literature on housing markets provides lots of evidence that flood risk impacts property prices. However, studies on the the direction and magnitude of this impact has yielded varied results (Belanger and Bourdeau-Brien, 2018). Skouralis et al. (2024) found that properties at risk for various climate effects in the UK are sold at an 8.14 percent discount compared to non-exposed properties, and the price discount increases to 32.2 percent for properties with very high flood risk. Furthermore, their empirical model suggested that a percentage point increase in the flood risk of properties is associated with a decrease of 0.07 to 0.11 percent in both sold and asking property prices. They also found that the impact was higher for properties of which flood risk was expected to increase or for regions that recently experienced a flood event.

Homebuyers who have access to flood risk information when searching for home

listings online are then more likely to view and make offers on homes with lower flood risk than those who do not have access. As more people become aware of climate risk, homes in endangered areas will most likely receive fewer offers, causing home values to fall. At the same time, it is expected that prices in lower-risk, inland areas rise as more Americans move there to avoid flooding (Gourevitch et al., 2023).

According to Urban Land Institute (2020) the real estate industry’s prioritization of climate risk has increased significantly in recent years, and is expected to accelerate further, focusing on market-level climate risk and resilience. Furthermore, the industry needs to be able to better measure the value impact, so it can base its future decision-making on a quantitative rather than qualitative understanding of the risks.

Natural disasters can lead to lower housing prices, but the effect may not be constant over time (Gallagher, 2014; Atreya and Ferreira, 2015). Other studies which explore how new environmental risk information affects housing prices, have found that the effect is large to begin with, but becomes less important over time. (Currie et al., 2015). Hence, it is relevant also to analyze these salience effects in how the price development is influenced by major floods and other events of natural hazards over time.

Our research question is then to investigate whether house prices in Norwegian cities are affected by climate risk. We combine risk indices for natural hazards at the building level with housing price development using housing transaction data. Sales from five Norwegian cities located all around the country with different risk profiles due to differing topography are analyzed, and the data set consists of in nearly 200 000 transactions from 2019-2024. We analyze two types of indices describing risk for pluvial floods, landslides and avalanches, and also an index which is a joint measure for many types of damages. Norway’s varied geography, with steep mountains and flat areas, means that different cities and areas are threatened by different natural hazards. Therefore, it is particularly interesting to distinguish between several types of risk indexes and to look at different areas.

Initially, in the theoretical section, we generalize approaches in developing risk index models and describe the three indices more detailed. Furthermore, the hedonic

house price function as the theoretical backdrop used for this study is presented. The next section describes an overview of the data sources which are applied, followed by the methodological framework used for the analysis. Finally in this study, the data is analyzed by estimating a hedonic model for the three types of indexes.

The price effect associated with climate risk in Norwegian cities may transferable to countries world wide, especially in the light of how the insurance system is in Norway compared to other countries (Monasterolo et al., 2025). The outcome of this study should be of interest for multiple stakeholders, mainly house owners, banks, insurance companies as well as neighborhoods at risk for natural hazards. Quantifying the effect will bring new information and can hopefully raise the attention to climate adaption and preventive measures

2 Assessing risk of natural hazards at building level

In this section three indices, all assessing risk for natural hazards, are described. We label these as 1) Physical Risk Score (PRS), 2) Pluvial Flood Index for buildings (PFIB), and 3) Avalanche Indicator for buildings (AIB).

While the pluvial flood index and avalanche indication are specifically constructed around the characteristics and location of each building, the physical risk score is derived by intersecting the building's location with broader caution zones and extracting the corresponding score from the underlying model. Later in this article they are all used for the analysis related to house price developments.

The PRS relies on general hazard zones created from aggregated terrain, hydrological, and climate datasets, which gives a broad risk estimate for each home, incorporating many types of potential damages. The PFIB and AIB are developed from machine learning techniques at the building level, and focus only on one general type of damage.

2.1 Physical Risk Score (PRS)

The Norwegian real-estate data provider Eiendomsverdi AS has conducted an extensive analysis to quantify and estimate to what extent homes are exposed to physical climate risks. Their analysis incorporates risk for most types of damages such as floods, quick clay landslides, small and large avalanches, coastal surges, tides, and pluvial floods. They use both publicly available data and private data to assess how prone a home is to various damages in the area it lies.

Beyond quantifying exposure, Eiendomsverdi’s methodology involves providing a risk score for each housing unit. Each dwelling is evaluated against various hazard indicators, and a score is assigned for each type of hazard. This yields the Physical Risk Score (PRS), which ranges from 0 (no hazard exposure) to 6 (maximum risk score for at least one type of damage). The measure thus captures all types of hazards, and provides a transparent, interpretable metric for stakeholders, including insurers, lenders, and urban planners, to assess and compare physical risk exposure across properties. The risk score also takes into account the floor number of apartments, since the distance above ground can impact the risk, especially for damages related to floods.

2.2 Pluvial Flood Index for Buildings (PFib)

The Pluvial Flood Index for buildings (PFib) represents another approach of data-centric risk modeling in the domain of urban flood exposure (Zolghadr-Asli et al., 2024). Developed and deployed through the InzureFlood pilot project, PFib harnesses the growing availability and resolution of geospatial and insurance data to provide a continuous, building-specific risk estimate (Svellingen and Torgersen, 2024). This approach differs from traditional hydrological models by using machine learning, particularly the random forest algorithm, to empirically discover relationships between diverse predictors and observed water damage outcomes. The PFib workflow begins with the systematic assembly of a comprehensive dataset for each building, which can include more than 250 quantifiable parameters: topographic elevation, slope, aspect, local roughness, distance to watercourses, surrounding land use and

infiltration potential, catchment characteristics, and building-specific information such as construction year or footprint (Svellingén and Torgersen, 2024). This richness in predictor variables enables the model to account for subtle but influential differences in flood susceptibility between buildings, even within the same neighborhood or municipality. Key strengths of the random forest algorithm for PFIB include:

- Accommodation of many predictor variables: The model can incorporate not only topography and land use, but also infrastructure, hydrological context, and fine-grained building attributes, without risk of multicollinearity or dimensionality overload (Rodríguez-Galiano et al., 2012; Elith et al., 2008).
- Variable importance analysis: The random forest provides direct, interpretable metrics of which factors are most influential for flood risk, offering insight for both researchers and practitioners as to which interventions may be most effective (Svellingén and Torgersen, 2024; Rodríguez-Galiano et al., 2012).
- Resilience to overfitting and robustness across spatial domains: Because each tree in the ensemble is trained on a random subset of data and predictors, the model is less likely to overfit to local idiosyncrasies, making it reliable for broad national applications as well as detailed urban studies (Elith, Leathwick, and Hastie 2008; Rodríguez-Galiano et al. 2012).

The PFIB model is trained on national insurance claims data, which has been systematically standardized and includes both flooded and non-flooded buildings. The result is a binary classification framework that, once trained, can assign a continuous risk score (0–1) for any structure (Svellingén and Torgersen, 2024).

Notably, the data-centric approach allows the model to be retrained or incrementally updated as new claims, improved DEMs, or revised land-use datasets become available, ensuring continued relevance in the context of rapid urban growth or shifting climate regimes (Zolghadr-Asli et al., 2024).

In its current operational form, PFIB reflects the risk of flooding under historical conditions, but the architecture is inherently extensible: scenario-based precipitation,

future land-use plans, or climate change projections can be incorporated for forward-looking risk assessment (Di Baldassarre and Uhlenbrook, 2012).

The methodology is also transferable to other regions, provided there is access to equivalent datasets for training and validation. By making flood risk quantifiable at the level of individual buildings, PFIB supports targeted mitigation, insurance pricing, and evidence-based policy decisions, helping cities and property owners adapt to intensifying rainfall extremes (Svellingen and Torgersen, 2024).

2.3 Avalanche Indication for Buildings (AIB)

Avalanche and landslide hazard mapping in Norway is guided by detailed technical protocols established by the Norwegian Water Resources and Energy Directorate (NVE), which set forth procedures for systematically identifying both release areas and runout zones for the main classes of avalanche and landslide processes (NVE, 2020).

Traditionally, implementation of these protocols involved a mixture of expert interpretation, semi-automated GIS overlays, and field validation. While effective in localized or high-stakes contexts, this approach posed limitations for national-scale mapping: manual processes were not scalable, updating was cumbersome, and reproducibility could be compromised by subjectivity or inconsistency (NVE, 2020; Zolghadr-Asli et al., 2024). To overcome these barriers, the Avalanche Indication for Buildings (AIB) is developed as a fully automated, data-centric workflow that embeds NVE’s protocols in a modular and reproducible spatial analysis pipeline. The AIB approach leverages harmonized, high-resolution DEMs, soil and landform data, and forest/vegetation cover to systematically operationalize each step in hazard mapping, eliminating reliance on field survey or subjective expert judgment for initial zoning (Woodrow et al., 2016; Callow et al., 2007).

In short, the AIB is generated through a fully automated process consisting of the following steps; Acquisition (1), Preparation (2), Enrichment (3), Processing (4) and Validation (5).

1. Acquisition: National repositories supply DEMs, land use, soil maps, and

surface roughness, continuously updated for relevance and accuracy (Zolghadr-Asli et al., 2024)

2. Preparation: Data is harmonized in terms of projection and resolution, with careful artifact correction and exclusion of built infrastructure so that only natural terrain is assessed (Woodrow et al., 2016)

3. Enrichment: Derived spatial layers (e.g., slope, aspect, geomorphons, forest type and density) are generated to serve as input for hazard logic. For example, concave landforms are identified for their potential to concentrate flood avalanches, while slope and roughness combinations are used for rockfall and snow avalanche zoning (Callow et al., 2007).

4. Processing: NVE thresholds for each process are algorithmically implemented—for instance, snow avalanches are mapped on slopes of 25–45°, rockfall sources above 45°, and soil/flood slides in areas with susceptible soils and slopes above 15–20°. Each identified release area triggers an automated runout simulation, using appropriate mass-flow or trajectory modeling, producing a continuous probability surface for runout impact (NVE, 2020).

5. Validation: Outputs are benchmarked against historical inventories and events, and quality is monitored through automated statistical checks and, where feasible, expert review (Troin et al., 2021).

A distinguishing feature of AIb is that, for every building, exposure is calculated for all four main avalanche/landslide types, snow avalanche, rockfall, soil slide, and flood avalanche. The final AIb value is conservatively set as the maximum risk from these four processes, ensuring that the most hazardous scenario governs the building’s risk indication (NVE, 2020). This strategy recognizes the potentially compounding and site-specific nature of avalanche risk in complex terrain and supports both conservative planning and transparent communication to stakeholders. The shift from manual, binary hazard zones to fully probabilistic, high-resolution building indicators marks a significant advance. AIb supports dynamic updating, objective benchmarking, and efficient nationwide scaling, features essential for proactive land use planning, insurance, and disaster risk reduction under evolving environmental conditions (NVE, 2020; Zolghadr-Asli et al., 2024).

3 Methodology

A hedonic house-price framework is augmented with three climate-risk measures, the model-based Physical Risk Score (PRS) and two building-level indices for pluvial flooding (PF_{Ib}) and avalanches (AI_b). Identification relies on dwelling controls and fixed effects (e.g area of dwelling; number of bedrooms) with indices scaled to $[0,1]$ and coefficients interpreted as percentage effects. Dynamic responses are probed via event-study and differences-in-differences designs around severe weather incidents, followed by checks to alternative specifications and sample restrictions.

3.1 Conceptual framework

The price of a house may be modeled by a standard hedonic house price function such as in Rosen (1974). House prices, P , will then be a function of its different internal and external amenities Z ,

$$P = P(Z)$$

where Z includes structural, neighborhood and environmental characteristics.

Beltrán et al. (2019) also adds flood risk to the hedonic house price model;

$$P = P(Z, r, p(i, r))$$

where r is the risk for damage and $p(i, r)$ is the subjective assessed probability of damage for a household, where i is household information. Hence, the both subjective and objective risk may impact the price.

We consider this to be a model for how risk for all climate related damages may impact house prices.

Households will maximize their expected utility

$$EU = p(i, r) \cdot U^F[Z, r, Q] + (1 - p(i, r)) \cdot U^{NF}[Z, r, Q]$$

where U^F (U^{NF}) is utility with the possibility of a natural disaster (or not), and Q

is level of consumption. Maximized subject to the budget constraint

$$M = P(Z, r, p(i, r)) + Q + L(r) + I(\pi(r), C) - C$$

where $L(r) = 0$ if there is no disaster, or $L(r) = \bar{S}$ is the loss function where $\bar{S}$ is the cost of structural replacement in the case of a disaster. $I(\pi(r), C)$ insurance premium where $\pi(r)$ is the objective probability of disaster and C is insurance cover.

Maximizing utility yields

$$\begin{aligned}\frac{\partial P}{\partial p} &< 0 \\ \frac{\partial P}{\partial i} &< 0 \\ \frac{\partial P}{\partial r} &< 0\end{aligned}$$

Hence, both objective and subjective probability of risk will have a negative impact on house prices

3.2 Estimating a hedonic model

We estimate a hedonic model which includes different housing attributes as explanatory variables, in addition to the risk measures presented in the previous section. The dependent variable is the logarithm of the sell price, including common debt for the units that also have that:

$$\begin{aligned}\ln P_{i,t} = & \beta_0 + \beta_1 risk_i + \beta_2 size_i + \beta_3 rooms_i + \beta_4 age_i \\ & + \sum_{j=1}^J \theta_j City_{j,i} + \sum_{k=1}^K \gamma_k Area_{k,i} + \sum_{m=1}^M \xi_m Month_{m,i} + \varepsilon_i\end{aligned}\quad (1)$$

Hence, $\hat{\beta}_1$ will be the estimate of the effect of risk on the price when controlling for the other regressors. $size_i$ is the size of dwelling i , $rooms_i$ the number of bedrooms and age_i the age of the dwelling in 2024. $City_{j,i}$ includes dummy variables

for four of the cities included in the dataset, and $Area_{k,i}$ dummy variables each of the 1440 areas. This enables us to control for area-fixed effects, by using one area or city as reference category. The 'grunnkrets' areas are constructed in order consist of a “geographically contiguous area”, and also be similar with respect to conditions related to nature and economy, communication and building types and composition (SSB, 2025). Controlling for these area fixed effect should thus enable the estimates of our risk measures on prices to reflect the effect of the risk of a particular home, since we control for the general risk in the area, as well other fixed effects over the period such as socioeconomic conditions, distance to city center, public transportation, school quality, access to kindergartens, etc.

It is important to ensure that the risk indicators do not contain the same housing characteristics used as control variables in the hedonic model, to avoid endogeneity. Only one indicator, the Physical Risk Score (PRS), includes a unit-specific characteristic, namely the property’s floor level which may be relevant for apartments. To prevent this variable from directly influencing both the risk index and the housing price, we have consistently excluded floor level as an independent variable in the regression models where the PRS index is included. The other risk indicators are based solely on geographical and natural conditions, and are therefore independent of the individual housing characteristics included in our models.

Finally, $Month_{m,i}$ includes month dummies for each month in the data set in order to control for time fixed effects such as the interest rate level, seasonal effects and other national economic conditions, and ε_i is an error term. A dwelling may have been sold multiple times in the data set, but we only have information about the lot number and not the building or apartment number for each dwelling such that we are unable to control for this for all units.

3.3 Salience effects from events

There have been certain notable events that have influenced many homes and/or caused large damages to houses. These have also gathered media attention and are thus known by the public. We include some of these events in the model by adding

dummy variables equal to one after the event took place, and interact them with the risk variable to investigate whether the event may impact homes with different risk profiles differently. Hence, we estimate the model

$$\begin{aligned} \ln P_{i,t} = & \beta_0 + \beta_1 risk_i + \beta_2 PostEvent_i + \beta_3 PostEvent_i \times risk_i \\ & + \beta_4 size_i + \beta_5 rooms_i + \beta_6 age_i \\ & + \sum_{j=1}^J \theta_j City_{j,i} + \sum_{k=1}^K \gamma_k Area_{k,i} + \sum_{m=1}^M \xi_m Month_{m,i} + \varepsilon_i \end{aligned} \quad (2)$$

From (2), we thus have that if β_3 is negative and significant, and β_1 is negative and significant, risk for damages has a higher negative impact on house prices after the event. β_2 measures whether the event effect may be influenced the entire population and not just those with high risk, or controlling for other events that may have occurred simultaneously such as e.g. changes housing market policy or other economic conditions. Such a finding may suggest that public awareness through large disasters adds to the subjective risk perception. We also use different event dummies with varying duration, in order to measure potential myopic behavior. We estimate

$$\begin{aligned} \ln P_{i,t} = & \beta_0 + \beta_1 risk_i \\ & + \beta_2 PostEvent3M_i \times risk_i + \beta_3 PostEvent36M_i \times risk_i \\ & + \beta_4 PostEvent612M_i \times risk_i + \beta_5 PostEvent12M_i \times risk_i \\ & + \beta_6 size_i + \beta_7 rooms_i + \beta_8 age_i \\ & + \sum_{j=1}^J \theta_j City_{j,i} + \sum_{k=1}^K \gamma_k Area_{k,i} + \sum_{m=1}^M \xi_m Month_{m,i} + \varepsilon_i \end{aligned} \quad (3)$$

where $PostEvent3M_i$ is a dummy variable equal to one the first three months after the event, $PostEvent36M_i$ from three to six months after the event, $PostEvent612M_i$ from six months to a year and $PostEvent12M_i$ a year after and more. We use these dummies in separate estimated models, to investigate dynamic effects of risk on house

prices. The estimated β_2 through β_5 in (3) thus measures whether and how the event may influence risk perception at different horizons after an event. If the event is important for risk assessment only shortly after the event, β_2 should be significantly negative, and β_3 through β_5 should not be significant, etc.

Ideally, an analysis of the effects of these events would be conducted using a “Differences-in-Differences” (DiD) approach. However, such a method requires precise data on which specific properties that were damaged after an event and which were not, in order to have both a treatment group and a control group. We do not have information on damages for all of the homes in the data set, rendering it impossible to perform such an analysis. Given these data limitations, our use of interaction terms represents an alternative method for examining changes in the pricing of risk before and after the events. This approach captures the market’s general response to risk changes, even without identifying individual damaged properties. There is a risk that the event may coincide with other changes that may have influenced the risk assessment, but the events should be considered the most probable cause. Future research, with access to damage data, could further elaborate on these findings and move closer to identifying causal effects.

4 Data and summary statistics

Transaction records (2019–2024) for five Norwegian cities are linked at address level to PFIB and AIB and at the dwelling level to PRS, alongside standard structural attributes (size, age, bedrooms, dwelling type). We thus combine building-level risk geo-spatially with each sale.

4.1 Data sources and overview

As outlined in Section 2, we have three different indices of risk or damage for natural hazards. The physical risk score (PRS) is at the dwelling level, while the pluvial flood index (PFIB) and the avalanche indicator (AIB) is at the building level.

We also have transaction data for the Norwegian housing market from Eien-

domsverdi AS. These data cover the five Norwegian cities Oslo, Fredrikstad, Stavanger, Bergen and Tromsø from 2019 to 2024. This consists of 195 214 transactions (sales) of apartments, detached houses, townhouses and duplexes. The sell price of each transaction is included as variables, in addition to the sell date, the size and lot size of the dwelling, number of bedrooms, floor number, and its age. The physical risk score is included directly in this data set. It also includes the specific address of each sold unit, such that we can connect it to the pluvial flood index and the avalanche indicator.

4.2 Summary statistics

House prices has in general increased over the sample, with seasonal patterns and some different patterns across cities, as shown in Figure 1. House price growth has also in general dampened after the high-inflationary period starting in 2022 in most cities, while there has also been some decline in the average square meter price for homes sold in some cities after 2022.

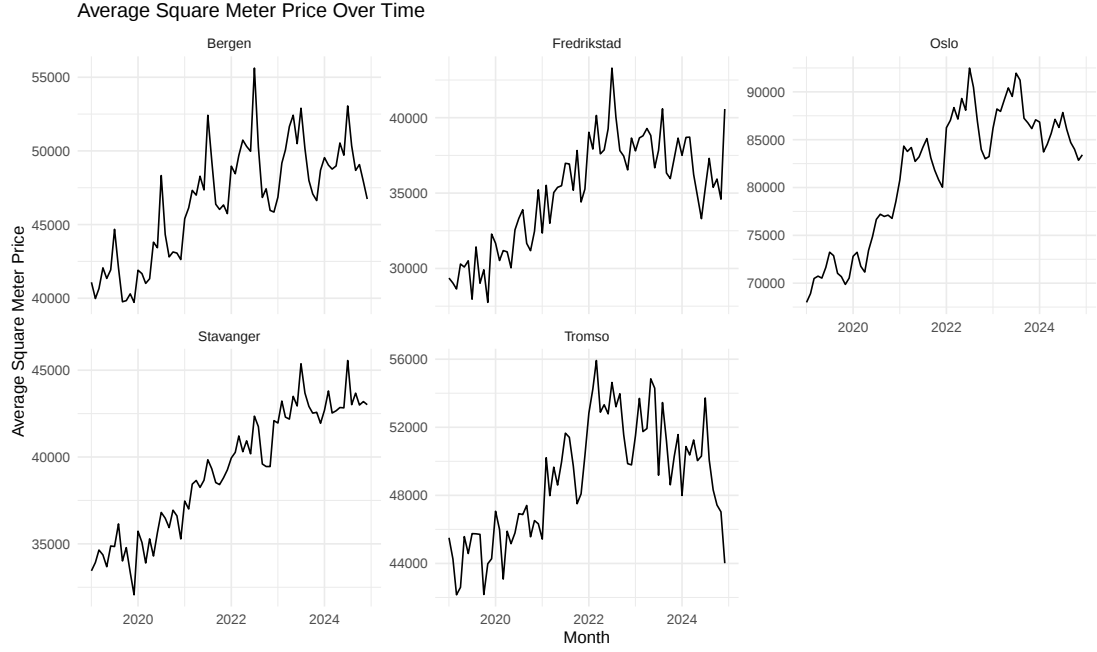


Figure 1: Monthly average square meter price, by city

From Figure 2, we see that the risk distribution among properties is very different for the three indices. While the pluvial flood risk is centered around 0.5 and approximates a normal distribution, the joint risk measure and the avalanche risk is more skewed to the right indicating that most homes has a low risk. The latter also has an accumulation of properties with a risk equal to the highest value one. We also see that the joint risk measure may reflect a combination of the pluvial flood and the avalanche risk indices, since the joint measure both shows skewness to the right and a local maximum around 0.5. Hence, while the joint measure indicates any sort of risk for a weather related disaster, this is further decomposed in the risk measures for pluvial floods and avalanches, even though different methods are used to construct these risks.

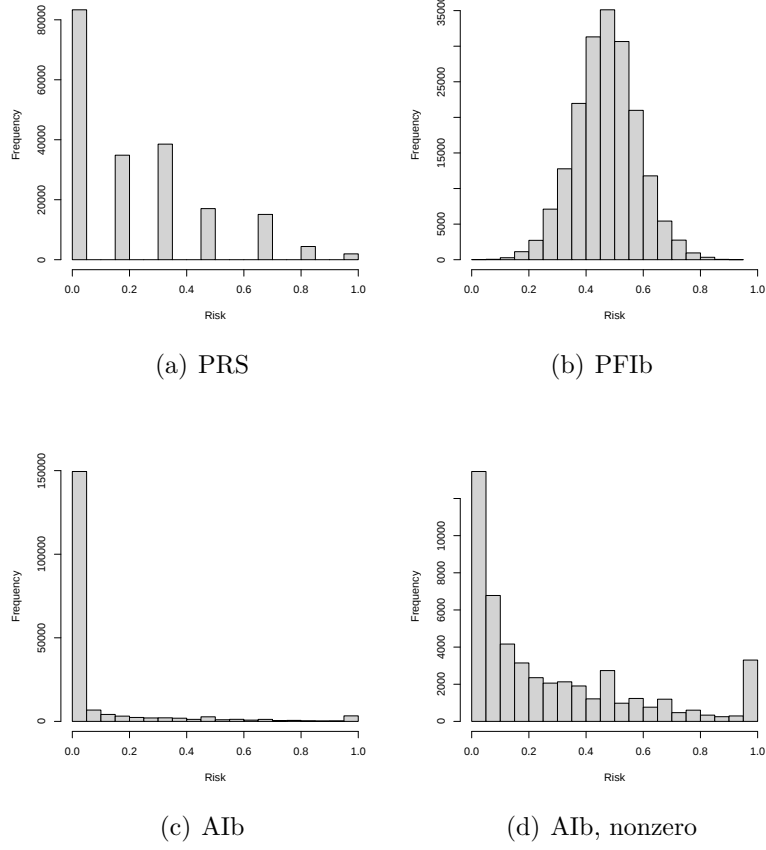


Figure 2: Histograms showing the distribution of risk among the properties sold in the data set for the different risk measures.

There are also large differences between cities for the risk indices, as seen in Tables 1, 2 and 3. PRS is higher in Bergen and Tromsø on average, while it is lowest in Oslo. The pluvial flood index is highest in Tromsø, and the avalanche index is highest on average in Bergen. Hence, PRS seems to be impacted mostly by pluvial floods in Tromsø and avalanches in Bergen. The pluvial flood index is quite similar on average for all cities except Tromsø, varying between 0.461 and 0.489, but the standard deviation is somewhat higher in Fredrikstad and Stavanger. For the avalanche index, there is larger variation between the cities. Stavanger, Fredrikstad,

Oslo and Tromsø have quite low average indices, while Bergen is significantly higher. The standard deviation is also much higher in Bergen, suggesting that some buildings in the data set has a very large index in Bergen. This is also supported by the median value in Bergen being quite low, even if it is higher than the other cities.

Table 1: Summary Statistics of PRS for Different Regions

Region	Min	1st Qu.	Median	Mean	3rd Qu.	Max	s.d.
Overall	0.0000	0.0000	0.1667	0.2195	0.3333	1.0000	0.246
Oslo	0.0000	0.0000	0.1667	0.1949	0.3333	1.0000	0.234
Stavanger	0.0000	0.0000	0.1667	0.2288	0.3333	1.0000	0.255
Fredrikstad	0.0000	0.0000	0.1667	0.2029	0.3333	1.0000	0.250
Bergen	0.0000	0.0000	0.3333	0.2778	0.3333	1.0000	0.257
Tromsø	0.0000	0.0000	0.3333	0.2846	0.5000	1.0000	0.268

Table 2: Summary Statistics of PF1b for Different Regions

Region	Min	1st Qu.	Median	Mean	3rd Qu.	Max	s.d.
Overall	0.000	0.401	0.472	0.474	0.545	0.940	0.110
Oslo	0.000	0.404	0.470	0.469	0.537	0.900	0.100
Stavanger	0.060	0.410	0.490	0.486	0.570	0.940	0.124
Fredrikstad	0.030	0.400	0.490	0.489	0.580	0.880	0.129
Bergen	0.000	0.3900	0.4600	0.4611	0.5300	0.9100	0.118
Tromsø	0.100	0.4800	0.5533	0.5541	0.6400	0.9200	0.119

Table 3: Summary Statistics of AIb for Different Regions

Region	Min	1st Qu.	Median	Mean	3rd Qu.	Max	s.d.
Overall	0.000	0.000	0.000	0.073	0.004	1.000	0.195
Oslo	0.000	0.000	0.000	0.048	0.000	1.000	0.158
Stavanger	0.000	0.000	0.000	0.026	0.000	1.000	0.129
Fredrikstad	0.000	0.000	0.000	0.03835	0.000	1.000	0.139
Bergen	0.000	0.000	0.0320	0.1871	0.300	1.000	0.278
Tromsø	0.000	0.000	0.000	0.0559	0.000	1.0000	0.174

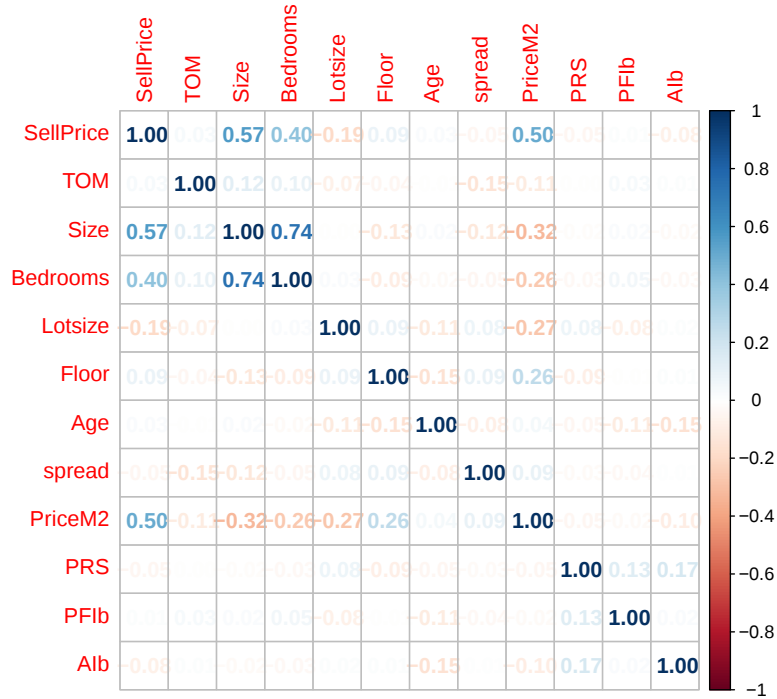


Figure 3: Correlation between variables

We have several variables on house characteristics for each transaction in our dataset. Some of these may be more related to the sell price of the home than others, and we start investigating this by looking at correlations between variables. As shown in Figure 3, the variables most highly correlated with the sell price is the size of the dwelling, the number of bedrooms, and the square meter price (the latter being generated from the price and the size). There is also some correlation between the sell price and floor and age. However, there are no signs of a strong (linear) relationship between the sell price and any of the risk indices. PRS, PFib and Aib have a correlation with the sell price of -0.05, -0.01 and -0.05, respectively. There is also some correlation between PRS and PFib and between PRS and Aib, in line with PFib and Aib measuring part of what is included in PRS. However, there are some signs of a negative relationship between sell price and the pluvial flood risk index

and the avalanche risk index, with correlations of -0.12 and -0.18, respectively. This may suggest that newer buildings to a larger extent is build in areas where there is a higher risk for pluvial floods and avalanches, or that risk reducing measures has been taken for newer buildings. Even though there are only some weak patterns in the correlations, there may still be nonlinear or partial relationships between variables which we can analyze further.

We focus on events caused by water damages and avalanches, since we have the most detailed data on this in our data set. Using data from Finance Norway, which includes insurance claims related to these types of damages, we are able to assess points in time when there were large events that may have impacted the households' subjective risk perception.

In Figure 4, time series plots for insurance claims related to avalanches and water damages (external factors causing water damages not including fluvial floods, mainly pluvial floods) are shown. We see that certain months have a large number of insurance claims. These are mainly related to large weather-related events causing damages to many homes. For avalanches, we have two spikes: December 2020 with nearly 2 000 claims and August 2023 with close to 1 000 claims. There was a massive landslide in Gjerdrum municipality on the morning of December 30 2020, causing massive damages and 10 fatalities. The spike in August 2023 is most likely related to the extreme weather "Hans" affecting a large amount of the country (and other neighboring countries) with large amounts of rainfall in areas where this normally not has been common. There were a lot of claims related to pluvial floods in August 2023, as seen in Figure 4, where there were around 7 500 insurance claims, in addition to the claims related to avalanches. For pluvial floods there is also a spike in September 2019, caused by extreme rainfall especially affecting Fredrikstad. The spike in January 2024 for water damages is mainly related to extremely low temperatures causing frost damages in homes. Even if this is external factors causing water damages, it is not related to pluvial floods and as such we will not investigate this further.

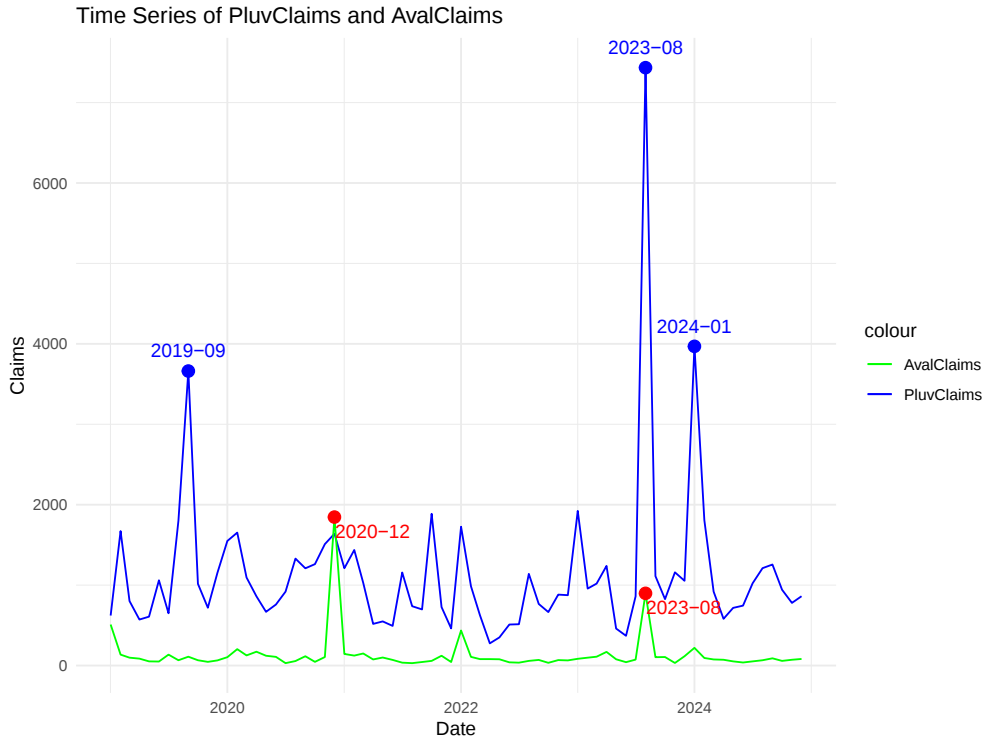


Figure 4: Insurance Claims

Public awareness is supported by data from Google Trends, shown in Figure 5. The figure shows search activity for terms related to natural disasters and extreme weather across the country; “extreme weather”, “quick clay” and “water damage”. As seen in the figure, there is a lot of search activity around the times of certain events related to extreme weather as mentioned above. Additionally, these spikes are quite sharp, indicating that the common interest for these issues is not very persistent after an event, suggesting myopic behavior. Search for water damages is a bit more stable over the different months over time, but with spikes related to some of the relevant events.

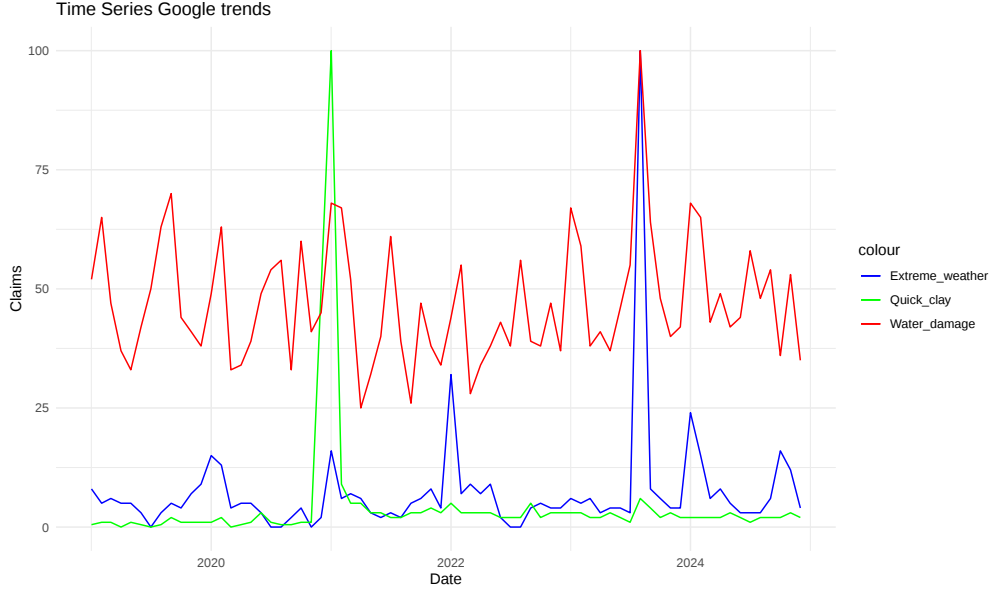


Figure 5: Google Trends data

5 Results

Baseline hedonic estimates quantify price capitalization of each risk index on the full sample, with economic magnitudes discussed alongside statistical precision. Heterogeneity is examined across cities and construction vintages to reveal how topography, hazard mix, and building era mediate effects. Event-study and differences-in-differences analyses around extreme-weather episodes test dynamics and validate identification, and robustness checks compare model-based versus building-level indices under alternative controls and fixed-effect structures.

5.1 Hedonic model

In this section, we will estimate hedonic models to evaluate the effect of the different risk scores and indices on sell prices as outlined in section 3.1. In the following outputs, PRS denotes the physical risk score, $PFIb$ the pluvial flood index for buildings,

and *Alb* the avalanche indication for buildings. *lSellPrice* is the log of the sell price, *lArea* the log of the area, *Bedrooms* the number of bedrooms, and *lAge* the log of the age of the dwelling. Time FE implies time fixed effect at a monthly level by adding month number dummies, Building type FE implies controlling for the type of dwelling using dummy variables, City FE implies controlling for city fixed effects by adding dummy variables for the cities, and Grunnkrets FE implies adding dummy variables for each of the 1440 smaller areas in the data set. The constant term is omitted from the output but included in the regression. We also include a dummy variable for whether an apartment is above the ground floor when estimating the effect of the pluvial flood index. This can control for a potential lower risk for pluvial flood damage when not at the ground level, and may also be relevant for assessing the sell price in itself in the hedonic model due to consumer preferences.

We have carried out a stepwise regression for a hedonic model for all of the three indices, starting with only the index (PRS, PFIB or Alb) and then adding various dwelling specific characteristics and fixed effects to control for these. The final model includes the index, as well as area of the dwelling, number of bedrooms, age of the dwelling. It also controls for type of dwelling, time (month) fixed effects, and grunnkrets (small region) fixed effects. The stepwise regressions for the three indices are shown in Appendix A, and the final models are shown in Table 4.

As shown in Table 4 and in Appendix A, all of the indices has a significant negative effect on the price when controlling for dwelling specific characteristics and including different fixed effects. Furthermore, the effect of the area, number of bedrooms and the age has a very similar effect in all models. Since all indices are scaled to be between 0 and 1, we can interpret the estimated coefficients for the risk index as the percentage decrease in the house price if the index increases from 0 to 1. For example, for the physical risk damage, if the risk goes from 0 (no risk at all) to 1 (very high risk for at least one disaster), the price is expected to decrease by 3.1%. Subsequently, an increase in the risk from 0.4 to 0.7 (an increase of 0.3) would yield an expected price decrease of around 1%. The estimated effect is highest for the pluvial flood index at -0.056, and lowest for the avalanche indicator at -0.014. However, these indices are not directly comparable as their distributions differ substantially.

Table 4: Regression results. All three indices

	<i>Dependent variable:</i>		
	lSellPrice		
	(1)	(2)	(3)
PRS	-0.031*** (0.002)		
PFIb		-0.056*** (0.004)	
AIb			-0.014*** (0.002)
lSize	0.628*** (0.002)	0.621*** (0.002)	0.621*** (0.002)
Bedrooms	0.037*** (0.001)	0.037*** (0.001)	0.037*** (0.001)
lAge	-0.090*** (0.001)	-0.090*** (0.001)	-0.090*** (0.001)
UpperFloors		0.041*** (0.001)	
Building type FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
City FE	No	No	No
Grunnkrets FE	Yes	Yes	Yes
Observations	185,875	176,588	176,588
R ²	0.893	0.895	0.894
Adjusted R ²	0.892	0.894	0.894
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01			

For the different cities, we see from Table 5 that the physical risk score has a negative significant effect on the sell price in Oslo, Fredrikstad, Bergen, and Tromsø, while the effect is positive and significant in Stavanger. The magnitude of the negative effect is quite similar around -0.03, while the positive effect in Stavanger is 0.018. The positive effect from the physical risk score on prices in Stavanger may be related

to some particularly high priced areas due to e.g. popularity that also have a large risk for some type of damages.

The pluvial flood index has a negative significant effect on prices in all cities except Tromsø, where it is insignificant, as shown in Table 6. The effect is highest in Fredrikstad and Stavanger at -0.078 and -0.072, while it is lower in Oslo (-0.052) and Bergen (-0.044).

When estimating the effect of the avalanche indicator, we see in Table 7 that this is only found to be significant for Bergen and Tromsø, showing a negative effect of -0.020 and -0.042, respectively. The risk for avalanches are most prone in these two cities, as shown by the larger indicator numbers in these two cities summarized in Table 3.

Table 5: Regression results. Physical risk score, for each city.

	<i>Dependent variable:</i>				
	Oslo	Fredrikstad	lSellPrice Stavanger	Bergen	Tromso
PRS	-0.028*** (0.002)	-0.032*** (0.010)	0.018*** (0.006)	-0.037*** (0.004)	-0.034*** (0.007)
lSize	0.665*** (0.002)	0.466*** (0.008)	0.580*** (0.005)	0.597*** (0.004)	0.503*** (0.006)
Bedrooms	0.040*** (0.001)	0.050*** (0.003)	0.033*** (0.002)	0.027*** (0.001)	0.048*** (0.002)
lAge	-0.054*** (0.001)	-0.149*** (0.003)	-0.144*** (0.002)	-0.128*** (0.001)	-0.118*** (0.002)
Building type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Grunnkrets FE	Yes	Yes	Yes	Yes	Yes
Observations	112,995	8,044	17,247	38,118	9,471
R ²	0.912	0.765	0.847	0.842	0.869
Adjusted R ²	0.911	0.757	0.844	0.840	0.866

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 6: Regression results. Pluvial flood index, for each city.

	<i>Dependent variable:</i>				
	Oslo	Fredrikstad	ISellPrice Stavanger	Bergen	Tromso
PFIb	−0.053*** (0.005)	−0.078*** (0.020)	−0.073*** (0.012)	−0.050*** (0.008)	−0.002 (0.014)
lSize	0.664*** (0.002)	0.462*** (0.008)	0.552*** (0.005)	0.573*** (0.004)	0.504*** (0.007)
Bedrooms	0.039*** (0.001)	0.050*** (0.003)	0.037*** (0.002)	0.029*** (0.001)	0.044*** (0.002)
lAge	−0.056*** (0.001)	−0.150*** (0.003)	−0.144*** (0.002)	−0.127*** (0.001)	−0.115*** (0.003)
UpperFloors	0.041*** (0.001)	0.038*** (0.007)	0.039*** (0.004)	0.044*** (0.002)	0.038*** (0.004)
Building type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Grunnkrets FE	Yes	Yes	Yes	Yes	Yes
Observations	105,524	7,556	15,872	34,568	8,228
R ²	0.914	0.764	0.853	0.846	0.871
Adjusted R ²	0.913	0.756	0.851	0.844	0.868

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 7: Regression results. Avalanche indicator, for each city.

	<i>Dependent variable:</i>				
	Oslo	Fredrikstad	ISellPrice Stavanger	Bergen	Tromso
AIb	−0.003 (0.003)	−0.026 (0.016)	0.007 (0.012)	−0.020*** (0.003)	−0.042*** (0.010)
lSize	0.663*** (0.002)	0.459*** (0.008)	0.555*** (0.005)	0.579*** (0.004)	0.497*** (0.006)
Bedrooms	0.040*** (0.001)	0.051*** (0.003)	0.036*** (0.002)	0.029*** (0.001)	0.046*** (0.002)
lAge	−0.056*** (0.001)	−0.151*** (0.003)	−0.145*** (0.002)	−0.129*** (0.001)	−0.117*** (0.002)
Building type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Grunnkrets FE	Yes	Yes	Yes	Yes	Yes
Observations	108,494	7,856	15,986	35,530	8,722
R ²	0.912	0.766	0.853	0.845	0.871
Adjusted R ²	0.911	0.758	0.850	0.843	0.867

Note:

*p<0.1; **p<0.05; ***p<0.01

When separating on the year the building was built, we see that there is some variation in how climate risk is relevant for the price. As shown for PRS in Table 8, the risk is insignificant at the 5% level for buildings built between 1990 and 1999, while the effect is highest for buildings from the eighties and for buildings from the sixties or older. Buildings from 2000 also have a smaller effect on price from PRS than buildings from the eighties and older.

For pluvial floods, shown in Table 9, the main difference is between buildings built before and after 1990, where prices for those built after 1990 are less impacted by the pluvial flood index. The same pattern can be seen for the avalanche indicator in Table 10, which is only significant for buildings built in 1969 or older.

Table 8: Regression results. Physical risk score, for different year the building was built.

	<i>Dependent variable:</i>				
	-1969	1970-1979	lSellPrice 1980-1989	1990-1999	2000-
PRS	-0.031*** (0.002)	-0.025*** (0.005)	-0.037*** (0.006)	-0.014* (0.008)	-0.016*** (0.003)
lSize	0.609*** (0.002)	0.440*** (0.005)	0.575*** (0.006)	0.670*** (0.008)	0.764*** (0.003)
Bedrooms	0.038*** (0.001)	0.039*** (0.002)	0.040*** (0.002)	0.034*** (0.003)	0.031*** (0.001)
lAge	0.055*** (0.003)	-0.154*** (0.031)	-0.097*** (0.026)	-0.219*** (0.023)	-0.090*** (0.001)
Building type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Grunnkrets FE	Yes	Yes	Yes	Yes	Yes
Observations	94,611	20,935	16,661	8,756	44,912
R ²	0.896	0.921	0.924	0.924	0.923
Adjusted R ²	0.895	0.918	0.920	0.917	0.921

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 9: Regression results. Pluvial flood index, for different year the building was built.

	<i>Dependent variable:</i>				
	-1969	1970-1979	lSellPrice 1980-1989	1990-1999	2000-
PFIb	−0.058*** (0.006)	−0.065*** (0.012)	−0.059*** (0.013)	−0.046*** (0.017)	−0.048*** (0.008)
lSize	0.604*** (0.002)	0.444*** (0.005)	0.582*** (0.006)	0.654*** (0.008)	0.749*** (0.003)
Bedrooms	0.038*** (0.001)	0.038*** (0.002)	0.037*** (0.002)	0.034*** (0.003)	0.032*** (0.001)
lAge	0.064*** (0.003)	−0.176*** (0.032)	−0.085*** (0.026)	−0.224*** (0.024)	−0.096*** (0.002)
UpperFloors	0.044*** (0.001)	0.014*** (0.003)	0.028*** (0.003)	0.027*** (0.004)	0.066*** (0.002)
Building type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Grunnkrets FE	Yes	Yes	Yes	Yes	Yes
Observations	88,092	19,888	15,550	8,177	40,041
R ²	0.898	0.921	0.925	0.927	0.929
Adjusted R ²	0.896	0.918	0.920	0.920	0.927
<i>Note:</i>			*p<0.1; **p<0.05; ***p<0.01		

Table 10: Regression results. Avalanche indicator, for different year the building was built.

	<i>Dependent variable:</i>				
	-1969	1970-1979	lSellPrice 1980-1989	1990-1999	2000-
AIb	−0.024*** (0.004)	−0.015* (0.008)	−0.009 (0.008)	0.004 (0.010)	−0.006* (0.003)
lSize	0.606*** (0.002)	0.440*** (0.005)	0.577*** (0.006)	0.657*** (0.008)	0.752*** (0.003)
Bedrooms	0.037*** (0.001)	0.039*** (0.002)	0.040*** (0.002)	0.035*** (0.003)	0.033*** (0.001)
lAge	0.057*** (0.003)	−0.182*** (0.031)	−0.091*** (0.026)	−0.214*** (0.024)	−0.097*** (0.002)
Building type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Grunnkrets FE	Yes	Yes	Yes	Yes	Yes
Observations	90,885	20,647	16,264	8,250	40,542
R ²	0.896	0.921	0.924	0.926	0.926
Adjusted R ²	0.895	0.918	0.920	0.919	0.924

Note:

*p<0.1; **p<0.05; ***p<0.01

5.2 Event studies

As illustrated in Figure 4, there has been certain major events that may have impacted public awareness and thus the subjective risk for pluvial floods and avalanches both in the short and long run. We will investigate the effect of the extreme rainfall in Fredrikstad in September 2019, the landslide in Gjerdrum in December 2020 and the extreme weather event “Hans” in August 2023 as three major events that may have impacted the risk assessment both locally and nationally.

5.2.1 September 2019

Since the extreme rainfall was related to pluvial floods, we investigate the effect on house prices of this event related to pluvial floods both in Fredrikstad and the other cities. As shown by the results in Table 11, there does not seem to be a price effect from risk assessment due to the extreme event. However, when controlling for the potential interaction effect for different horizons, we observe that the coefficient on the risk component varies. This may suggest that there is some dynamic effects on how risk is perceived after an event, or some potential seasonal effects in risk assessment.

Table 11: Regression results. Pluvial flood index, Fredrikstad.

	<i>Dependent variable:</i>				
	lSellPrice				
	(1)	(2)	(3)	(4)	(5)
PFIb	−0.067 (0.050)	−0.076*** (0.020)	−0.075*** (0.020)	−0.088*** (0.021)	−0.058* (0.033)
Sept2019R	−0.013 (0.052)				
Sept2019_3MR		−0.037 (0.078)			
Sept2019_36MR			−0.095 (0.095)		
Sept2019_612MR				0.102* (0.056)	
Sept2019_12MR					−0.028 (0.036)
lSize	0.462*** (0.008)	0.462*** (0.008)	0.462*** (0.008)	0.462*** (0.008)	0.462*** (0.008)
Bedrooms	0.050*** (0.003)	0.050*** (0.003)	0.050*** (0.003)	0.050*** (0.003)	0.050*** (0.003)
lAge	−0.150*** (0.003)	−0.150*** (0.003)	−0.150*** (0.003)	−0.150*** (0.003)	−0.150*** (0.003)
UpperFloors	0.038*** (0.007)	0.038*** (0.007)	0.038*** (0.007)	0.038*** (0.007)	0.038*** (0.007)
Building type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Grunnkrets FE	Yes	Yes	Yes	Yes	Yes
Observations	7,556	7,556	7,556	7,556	7,556
R ²	0.764	0.764	0.764	0.764	0.764
Adjusted R ²	0.756	0.756	0.756	0.756	0.756

Note:

*p<0.1; **p<0.05; ***p<0.01

5.2.2 December 2020

The landslide in Gjerdrum in December 2020 may have had impacts on risk assessment across the country as it became an event of national interest due to the fatal outcomes. Since we do not have data on Gjerdrum municipality in this data set, we investigate the effect on the Gjerdrum landslide on all of the cities in our data set simultaneously. In Table 12, we see that the negative effect of the risk for avalanches increases after the Gjerdrum event. The effect is largest in the three first months after the event, and also one year after the event. This may indicate both myopic behavior, and also some seasonality in how risk is perceived. We also see in Figure 5 that there is a small increase in search activity for quick clay about one year after the landslide in Gjerdrum. The public awareness of that it had been one year since the incident, through e.g. media attention, may have been a catalyst for the increased awareness of avalanche risks in this period.

Table 12: Regression results. Landslide December 2020

	<i>Dependent variable:</i>				
	lSellPrice				
	(1)	(2)	(3)	(4)	(5)
Alb	−0.006* (0.003)	−0.015*** (0.002)	−0.016*** (0.002)	−0.016*** (0.002)	−0.011*** (0.003)
Dec2020R	−0.015*** (0.004)				
Dec2020_3MR		−0.020** (0.009)			
Dec2020_36MR			0.004 (0.008)		
Dec2020_612MR				−0.003 (0.007)	
Dec2020_12MR					−0.010*** (0.004)
lSize	0.621*** (0.002)	0.621*** (0.002)	0.621*** (0.002)	0.621*** (0.002)	0.621*** (0.002)
Bedrooms	0.037*** (0.001)	0.037*** (0.001)	0.037*** (0.001)	0.037*** (0.001)	0.037*** (0.001)
lAge	−0.089*** (0.001)	−0.089*** (0.001)	−0.089*** (0.001)	−0.089*** (0.001)	−0.089*** (0.001)
UpperFloors	0.041*** (0.001)	0.041*** (0.001)	0.041*** (0.001)	0.041*** (0.001)	0.041*** (0.001)
Building type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Grunnkrets FE	Yes	Yes	Yes	Yes	Yes
Observations	171,748	171,748	171,748	171,748	171,748
R ²	0.895	0.895	0.895	0.895	0.895
Adjusted R ²	0.894	0.894	0.894	0.894	0.894

Note:

*p<0.1; **p<0.05; ***p<0.01

5.2.3 August 2023

In August 2023, the extreme weather “Hans” caused damages both due to pluvial floods, fluvial floods, avalanches, and other types of damages, and it impacted several parts of the country. Hence, we investigate the effect of this event related to all of our three risk indices and across the country.

As seen in Tables 13, 14 and 15, the effect of risk on house prices changes in certain time intervals. For PRS, shown in Table 13, the interaction term for model (1) is positive, indicating that the negative effect of risk is smaller after August 2023. We also have a positive effect from the interaction term in model (5), being quite similar in absolute value as the effect of the risk term, indicating that the physical risk score is insignificant one year after Hans.

For the pluvial flood index, shown in Table 14, we also see significant effects for the interaction terms in (1) and (5). However, these are negative, indicating that the risk for pluvial floods has a larger negative effect on prices one year after Hans.

The avalanche index, shown in Table 15 only has a significant interaction effect in (2). This is the interaction term for three months after the event, indicating that myopic behavior related to risk assessment for avalanches after Hans since the joint effect from avalanche risk on house prices is more than twice as large the three months after Hans. This is in line with what we saw after the landslide at Gjerdrum for the avalanche risk index.

This shows that there may be some differences in how risk is perceived dynamically. The risk for pluvial floods seems to be affected by the season of the house sale, while the risk for avalanches increases shortly after an event.

Table 13: Regression results. Hans August 2023, PRS

	<i>Dependent variable:</i>				
	lSellPrice				
	(1)	(2)	(3)	(4)	(5)
PRS	−0.022*** (0.002)	−0.019*** (0.002)	−0.019*** (0.002)	−0.020*** (0.002)	−0.021*** (0.002)
Aug2023R	0.010*** (0.003)				
Aug2023_3MR		0.003 (0.007)			
Aug2023_36MR			−0.007 (0.008)		
Aug2023_612MR				0.006 (0.005)	
Aug2023_12MR					0.023*** (0.006)
lSize	0.627*** (0.002)	0.627*** (0.002)	0.627*** (0.002)	0.627*** (0.002)	0.627*** (0.002)
Bedrooms	0.037*** (0.001)	0.037*** (0.001)	0.037*** (0.001)	0.037*** (0.001)	0.037*** (0.001)
lAge	−0.089*** (0.001)	−0.089*** (0.001)	−0.089*** (0.001)	−0.089*** (0.001)	−0.089*** (0.001)
UpperFloors	0.040*** (0.001)	0.040*** (0.001)	0.040*** (0.001)	0.040*** (0.001)	0.040*** (0.001)
Building type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Grunnkrets FE	Yes	Yes	Yes	Yes	Yes
Observations	180,865	180,865	180,865	180,865	180,865
R ²	0.894	0.894	0.894	0.894	0.894
Adjusted R ²	0.893	0.893	0.893	0.893	0.893

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 14: Regression results. Hans August 2023, PFIb.

	<i>Dependent variable:</i>				
	lSellPrice				
	(1)	(2)	(3)	(4)	(5)
PFIb	−0.052*** (0.004)	−0.056*** (0.004)	−0.056*** (0.004)	−0.055*** (0.004)	−0.054*** (0.004)
Aug2023Rp	−0.018** (0.007)				
Aug2023_3MRp		−0.008 (0.010)			
Aug2023_36MRp			0.010 (0.011)		
Aug2023_612MRp				−0.011 (0.008)	
Aug2023_12MRp					−0.023** (0.010)
lSize	0.621*** (0.002)	0.621*** (0.002)	0.621*** (0.002)	0.621*** (0.002)	0.621*** (0.002)
Bedrooms	0.037*** (0.001)	0.037*** (0.001)	0.037*** (0.001)	0.037*** (0.001)	0.037*** (0.001)
lAge	−0.089*** (0.001)	−0.089*** (0.001)	−0.089*** (0.001)	−0.089*** (0.001)	−0.089*** (0.001)
UpperFloors	0.041*** (0.001)	0.041*** (0.001)	0.041*** (0.001)	0.041*** (0.001)	0.041*** (0.001)
Building type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Grunnkrets FE	Yes	Yes	Yes	Yes	Yes
Observations	171,748	171,748	171,748	171,748	171,748
R ²	0.895	0.895	0.895	0.895	0.895
Adjusted R ²	0.895	0.895	0.895	0.895	0.895

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 15: Regression results. Hans August 2023, AIb.

	<i>Dependent variable:</i>				
	lSellPrice				
	(1)	(2)	(3)	(4)	(5)
AIb	−0.016*** (0.003)	−0.015*** (0.002)	−0.016*** (0.002)	−0.016*** (0.002)	−0.016*** (0.002)
Aug2023Ra	−0.0001 (0.004)				
Aug2023_3MRa		−0.022** (0.008)			
Aug2023_36MRa			0.002 (0.011)		
Aug2023_612MRa				0.005 (0.006)	
Aug2023_12MRa					0.008 (0.007)
lSize	0.621*** (0.002)	0.621*** (0.002)	0.621*** (0.002)	0.621*** (0.002)	0.621*** (0.002)
Bedrooms	0.037*** (0.001)	0.037*** (0.001)	0.037*** (0.001)	0.037*** (0.001)	0.037*** (0.001)
lAge	−0.089*** (0.001)	−0.089*** (0.001)	−0.089*** (0.001)	−0.089*** (0.001)	−0.089*** (0.001)
UpperFloors	0.041*** (0.001)	0.041*** (0.001)	0.041*** (0.001)	0.041*** (0.001)	0.041*** (0.001)
Building type FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Grunnkrets FE	Yes	Yes	Yes	Yes	Yes
Observations	171,748	171,748	171,748	171,748	171,748
R ²	0.895	0.895	0.895	0.895	0.895
Adjusted R ²	0.894	0.894	0.894	0.894	0.894

Note:

*p<0.1; **p<0.05; ***p<0.01

6 Discussion

One of the most striking findings of our analysis is the statistically significant negative effect of climate risk on housing prices in the Norwegian market across most cities and model specifications. Norway does not have a legally mandated disclosure requirement for natural hazard risk in property listings, thus making it less obvious that buyers in general should be aware of this and react to it in the housing market. One might, therefore, have expected a limited effect of risk on house prices, as not all buyers possess the same information. Only buyers that have actively searched for information about risk for disasters will possess this information. Our results, however, indicate that risk is still relevant for the price of a home. A possible explanation is that information on flood and landslide risk is publicly available through mapping services from entities like the Norwegian Water Resources and Energy Directorate (NVE), and that a growing share of homebuyers actively seek out and utilize such information. This underpins the robustness of our findings and points to a tangible market effect of climate risk, even in the absence of formal information requirements.

Our study finds that climate-related natural hazards exert a statistically significant negative impact on house prices in Norwegian cities. All three risk indicators; PRS (3,1 %), PFIB (5,6 %), and AIB (1,4 %), are negatively associated with property values, even when controlling for structural attributes and locational fixed effects. This suggests that buyers and market actors factor climate risk into pricing. Hence, there is a degree of market efficiency wherein buyers incorporate information on risk for weather-related damages into their asset valuation, which underlines the economic salience of hazard exposure.

However, other factors may also be important for taking risk into account. The observed price discounts may not fully account for all potential direct and indirect costs, particularly if homebuyers exhibit cognitive biases or operate with incomplete information. Related literature suggests that capitalization effects are significantly stronger in markets with mandatory risk disclosure policies (Hennighausen and Suter, 2020; Eren et al., 2022), which is not mandatory in Norway.

These results are not in line with standard economic theory, but they represent

information for financial regulators. Climate risk is considered a material threat to financial stability, see e.g. Nieto (2019), yet studies have often lacked granular, market-based data on how this risk translates into tangible asset values (Aurouet et al., 2023).

One of the most important transmission channels of physical risk to the banking sector is through the housing market, which serves as the primary collateral for bank lending in Norway. A decline in house prices due to climate risk directly affects the Loss Given Default (LGD) on mortgages, increasing potential losses for lenders. This study gives an empirical estimate of the physical risk premium in the housing market, offering a quantitative input that can be used by financial institutions to refine their internal credit risk models, as encouraged by regulators, and by supervisory authorities to conduct more accurate climate stress tests of the banking system.

The results demonstrate that the type of climate risk priced into the housing market varies significantly by city, a finding directly attributable to local topography and geography. The price discount associated with Alb is statistically significant only in Bergen (-2.0%) and Tromsø (-4.2%), cities associated with steep mountainous terrain immediately surrounding urban settlements. Conversely, the price impact of PFIB is most pronounced in the relatively flatter, low-lying cities of Fredrikstad (-7.8%) and Stavanger (-7.2%), which are situated on major river estuaries or coastal plains where surface water accumulation is a more dominant threat. These variations underscore the importance of local context in climate risk valuation, indicating that the market is not pricing an abstract, uniform concept of “climate risk” but is instead responding rationally to the specific, dominant, and observable local hazards.

The event study analysis indicates that the price impact of climate risk is not static but dynamic, shifting in response to salient natural disasters. Most notably, the negative effect of the Alb intensified significantly nationwide in the three months immediately following the highly publicized Gjerdrum quick clay landslide of December 2020 (additional price discount of 2.0% for properties with higher avalanche risk during this period, on top of the baseline effect).

This dynamic response can be explained through the lens of behavioral economics, specifically the “availability heuristic”, a cognitive bias where individuals overweight

the probability of events that are recent, vivid, and easily recalled from memory (Brown et al., 2018). The Gjerdrum landslide, with its extensive and dramatic media coverage and tragic loss of life, dramatically increased the salience of landslide risk in the public consciousness, as evidenced by spikes in related online search activity (Le, 2024; Hennighausen and Suter, 2020). This heightened, albeit temporary, risk perception translated into a greater willingness-to-pay to avoid such risks, thereby increasing the price discount in the housing market where this risk is larger.

The results also suggest a degree of myopic behavior, as the intensified effect diminishes in the 3-to-12-month period post-event before re-emerging significantly one year later. This pattern of dissipation is a common finding in studies of post-disaster housing markets, as the memory of the event fades from public attention. The re-emergence of the effect after one year could be linked to seasonal reminders, such as the anniversary of the event or the onset of winter conditions associated with higher landslide and avalanche frequency, which may re-trigger the availability heuristic. This finding implies that household risk perception is not solely based on objective, long-term probabilities, but is heavily influenced by the flow of recent, emotionally charged information (Kousky et al., 2020).

A major contribution of this study is the comparative evaluation of risk measures with different levels of spatial and methodological detail. The PRS measure, derived from zonal overlays, exhibits less robust price associations than building-level indices based on machine learning and high-resolution terrain data, even though it is at the apartment level. This may suggest that buyers and market actors respond more strongly to localized risk attributes, also when these are not explicitly disclosed in public registries. This underscores the value of using data-centric, high-resolution risk assessment methodologies, a transition advocated for in the wider climate risk literature.

A perhaps counterintuitive finding of this study is that older buildings appear to be associated with lower capitalized climate risk when looking at correlations (see Figure 3). However, the negative price effects of both PFIb and Alb were stronger for buildings constructed before 1970 (see Tables 9 and 10), while the effects were weaker or insignificant for more modern constructions. This runs contrary to the common

expectation that newer buildings, constructed under more modern and ostensibly stricter regulations, should be safer.

Table 8 implies that risk exposure measured by PRS is not strongly penalized for older homes, possibly because they tend to be in safer areas. The price effects from flood risk are larger for older homes when risk exists, even though older homes on average has lower risk. Table 10 indicates that avalanche risk is historically concentrated in older urban zones. Current developments may also lead to these areas being more prone to avalanches. This may be a result of structures in highly exposed zones being destroyed or removed over time, leaving only those located in relatively safe areas. Recent decades have also seen urbanization through housing development in previously undeveloped, and often hazard-prone, locations, since low-risk land becomes scarce. Older urban cores may also benefit from established natural drainage infrastructure, whereas newer suburban developments may have less robust systems.

This interplay complicates assumptions underlying current building regulations and suggests that hazard-aware land-use planning may be more critical than incremental improvements in building codes. It also raises equity considerations since homeowners of newer dwellings may bear disproportionate climate risk relative to those in older neighborhoods. It may also indicate that buyers are more concerned about risk if they are buying an older home than a newer home.

A potential extension of our analysis would be to investigate whether the effect of climate risk varies across different price segments of the housing market. It is conceivable that buyers of more expensive properties have different preferences for, or awareness of, risk compared to buyers in lower price segments and vice versa. Such an analysis is challenging, partly because both the price and the price per square meter varies systematically between apartments and single-family homes, as well as between areas. However, our current model controls for such price effects to a considerable degree through the inclusion of fixed effects for basic statistical units (*grunnkretser*), which captures local price levels and neighborhood characteristics that are stable over time. Nevertheless, we acknowledge that a segmented analysis could provide further insight, and this remains an interesting avenue for future research.

This study, while comprehensive, is subject to several limitations that open avenues for future inquiry. First, our analysis is confined to two specific hazards: pluvial floods and avalanches, in addition to the index incorporating all types of damages. A more complete picture would require isolating other significant hazards such as coastal storm surges, and quick clay slides. Second, the potential for omitted variable bias remains an inherent challenge in all hedonic models since other factors may also be important and also related to risk indices. Third, our risk indices are based on historical data; they do not explicitly incorporate forward-looking climate change projections, which forecast an intensification of precipitation and other risk factors. Finally, our dataset is restricted to including only sold used homes from the period of the sample. This may introduce some selection bias. Building on these findings and shortcomings, we should focus on expanding this analysis for future research.

7 Conclusion

Our study reveals an interaction between climate-related natural hazards and house prices in Norwegian cities, demonstrating the influence different risk indicators measuring different types of damages on property values. These findings confirm that buyers and market actors actively integrate climate risk into their valuation processes, reflecting a level of market efficiency. However, the observed price discounts from risk might not encapsulate all possible costs associated with such risks, especially considering incomplete information processing by homebuyers.

Variations across cities highlight the importance of regional aspects in shaping climate risk assessment, with specific hazards being more or less relevant in different urban environments. Moreover, our analysis shows that these impacts are dynamic, often influenced by recent and salient natural disasters. This points to behavioral economic principles such as myopia and amnesia.

Interestingly, our data suggests that older buildings exhibit lower capitalized climate risk compared to newer constructions, complicating common assumptions about building safety standards. This could point to a broader pattern of urban expansion into more hazard-prone areas, raising important questions about land-use

planning and equitable risk distribution among homeowners, or different behavior among buyers of old vs new buildings.

Overall, this study illuminates the implications of climate risks on property valuations, offering valuable empirical estimates to refine credit risk models and enhance climate stress testing within the banking sector. As awareness and salience of such risks grow, and perhaps also the risk itself grows for many buildings due to more extreme weather, stakeholders should continue to integrate these considerations to promote financial stability, and to support sustainable urban development.

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A Hedonic regressions

Table 16: Regression results. Physical risk score

	<i>Dependent variable:</i>				
	lSellPrice				
	(1)	(2)	(3)	(4)	(5)
PRS	−0.111*** (0.004)	−0.102*** (0.003)	−0.100*** (0.003)	0.026*** (0.002)	−0.031*** (0.002)
lArea		0.571*** (0.003)	0.554*** (0.003)	0.602*** (0.002)	0.628*** (0.002)
Bedrooms		0.048*** (0.001)	0.054*** (0.001)	0.034*** (0.001)	0.037*** (0.001)
lAge		−0.022*** (0.001)	−0.017*** (0.001)	−0.053*** (0.001)	−0.090*** (0.001)
Building type FE	No	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	Yes	Yes
City FE	No	No	No	Yes	No
Grunnkrets FE	No	No	No	No	Yes
Observations	195,101	185,875	185,875	185,875	185,875
R ²	0.004	0.347	0.379	0.685	0.893
Adjusted R ²	0.004	0.347	0.379	0.685	0.892

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 17: Regression results. Pluvial flood index.

	<i>Dependent variable:</i>				
	lSellPrice				
	(1)	(2)	(3)	(4)	(5)
PFIb	−0.112*** (0.010)	−0.133*** (0.008)	−0.131*** (0.008)	0.026*** (0.006)	−0.056*** (0.004)
lSize		0.575*** (0.004)	0.557*** (0.004)	0.602*** (0.003)	0.621*** (0.002)
Bedrooms		0.047*** (0.001)	0.052*** (0.001)	0.032*** (0.001)	0.037*** (0.001)
lAge		−0.021*** (0.001)	−0.018*** (0.001)	−0.048*** (0.001)	−0.089*** (0.001)
UpperFloors		0.124*** (0.002)	0.124*** (0.002)	0.059*** (0.002)	0.041*** (0.001)
Building type FE	No	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	Yes	Yes
City FE	No	No	No	Yes	No
Grunnkrets FE	No	No	No	No	Yes
Observations	185,308	171,748	171,748	171,748	171,748
R ²	0.001	0.352	0.383	0.686	0.895
Adjusted R ²	0.001	0.352	0.383	0.686	0.895

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 18: Regression results. Avalanche indicator.

	<i>Dependent variable:</i>				
	lSellPrice				
	(1)	(2)	(3)	(4)	(5)
Alb	−0.173*** (0.005)	−0.234*** (0.005)	−0.234*** (0.004)	−0.032*** (0.003)	−0.014*** (0.002)
lArea		0.572*** (0.004)	0.554*** (0.003)	0.598*** (0.002)	0.621*** (0.002)
Bedrooms		0.048*** (0.001)	0.053*** (0.001)	0.034*** (0.001)	0.037*** (0.001)
lAge		−0.028*** (0.001)	−0.024*** (0.001)	−0.050*** (0.001)	−0.090*** (0.001)
Building type FE	No	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	Yes	Yes
City FE	No	No	No	Yes	No
Grunnkrets FE	No	No	No	No	Yes
Observations	185,308	176,588	176,588	176,588	176,588
R ²	0.005	0.350	0.381	0.684	0.894
Adjusted R ²	0.005	0.350	0.381	0.684	0.894

Note: *p<0.1; **p<0.05; ***p<0.01

Acknowledgements:

Housing Lab is partly funded by the Norwegian Ministry of Finance and the Norwegian Ministry of Modernisation and Municipalities. Housing Lab also receives financial support from OBOS, Krogsveen, Sparebank1-Gruppen, and Pareto Bank. We are grateful for the financial support. All views expressed in our papers are the sole responsibility of Housing Lab, and do not necessarily represent the views of our sponsors.

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ISSN: 2703-786X (Online)

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