# One Price Fits All? Cross-Subsidies in Uniformly Priced Natural Perils Insurance*

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**Abstract**

This paper quantifies cross-subsidies in Norway's natural perils insurance scheme, where a uniform premium is charged regardless of location-specific natural hazard risk. Using individual property data, hazard zone maps, and municipal insurance payouts, I estimate the actuarially fair premiums inside and outside high-risk areas that would apply under a two-tier risk-based scheme. The results show that uniform pricing leads to substantial redistribution, implicitly subsidizing high-risk properties. Focusing on households and flood risk, I find that the actuarially fair premium in flood zones would be about 13 times higher than the uniform premium charged today, and approximately 65 times higher than in non-flood zones. These cross-subsidies imply extensive sharing of the risks and losses related to natural disasters, but likely reduce incentives and impede effective adaptation. The findings shed light on the trade-offs between efficiency and distribution in natural perils insurance, and inform broader discussions on scheme design.

**JEL classification**: G22, Q54, Q58, G21
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# 1 Introduction

Norway's natural perils insurance scheme is universal by regulatory mandate, with uniform pricing applied regardless of a property's exposure to natural-peril risk. While this system promotes collective responsibility and maintains affordable coverage, it also generates cross-subsidization: homeowners in high-risk areas effectively receive a subsidy, whereas those in low-risk areas pay premiums that exceed their actuarially fair levels.[1] These implicit transfers provide a high degree of risk-sharing at the potential cost of distorting behavior. When insurance prices do not reflect actual risk, they create a form of moral hazard because households face weaker incentives to adapt, invest in mitigation, and avoid building in hazard-prone areas. As climate change increases the frequency and severity of weather-related hazards (IPCC, 2023), the magnitude of these cross-subsidies and their behavioral consequences may grow over time, although greater unpredictability of weather events could pull in the opposite direction.

As a first step toward understanding how uniform pricing may affect household behavior, it is essential to quantify the size of the cross-subsidies generated by the scheme. In this paper, I do so by comparing the uniform premium currently paid by households with the two actuarially fair premiums that would apply under a two-tier risk-based scheme that differentiates between properties inside and outside mapped hazard zones. Three central questions guide the analysis. First, to what extent are properties in high-risk areas subsidized, measured both by the gap between the actuarially fair premium in high-risk zones and the current uniform premium, and by the gap between actuarially fair premiums in high- and low-risk zones? Second, how have these risk zone-adjusted premiums evolved over time, and how might projected increases in extreme weather events further alter their scale? Third, given that municipalities in Norway are on the front line of climate adaptation (Norwegian Environment Agency, 2025), to what extent do municipalities in high-risk areas engage in adaptation efforts, and can such responses mitigate the efficiency loss from cross-subsidies?

Uniform or near-uniform pricing remains a common feature of many national catastrophe insurance schemes. According to OECD (2021), several programs apply flat premiums based only on the insured value, without adjusting for geographic location or building characteristics. Examples include the national coinsurance and reinsurance pools in France and Spain, the earthquake coverage in New Zealand, and solidarity-based systems in Iceland and parts of Switzerland. Despite their

[1] Actuarially fair pricing refers to premiums set strictly according to expected losses, reflecting the true underlying risk of the property without cross-subsidization.

prevalence, empirical evidence on how such solidarity-based systems function remains limited. Most of the fast-growing literature on household insurance and climate risk focuses on risk-based schemes (e.g., Oh, Sen, and Tenekedjieva (2021); Sastry, Sen, and Tenekedjieva (2023); Keys and Mulder (2024); Boomhower, Fowlie, Gellman, and Plantinga (2024)), leaving open the question of how uniform pricing affects the distribution of insurance costs and the incentives for climate adaptation. Norway's system is distinctive in applying a single, mandatory premium rate nationwide across all natural perils and property types. Moreover, coverage is effectively universal with very high take-up rates, and comprehensive because policies are written at full replacement value. Section 2.1 describes these institutional features in further detail. This design therefore provides a particularly clean empirical setting to quantify cross-subsidies in a fully solidarity-based system and to discuss their broader efficiency and distributional implications.

Quantifying cross-subsidies requires information on insured values, hazard exposure and expected losses. The analysis begins by drawing on a dataset covering all 2.6 million residential properties[2] in Norway, including detailed geographic coordinates for each unit. For every property, I determine the insured value, which corresponds to the full replacement cost according to industry standards. This value is calculated using standardized cost tables applied by insurance companies that specify typical reconstruction costs per square meter by building type and region. I then combine this data with hazard zone maps from the Norwegian Water Resources and Energy Directorate (NVE)[3] to assess, at the individual property level, whether each property is located inside or outside a designated risk zone.

For tractability, I focus on flood risk in this analysis. The natural perils insurance scheme covers damages from floods, storms, storm surges, and landslides.[4] However, systematic hazard mapping is not available for all perils. NVE provides detailed maps for floods, landslides, and storm surges, but not for storm hazards. Among the mapped perils, approximately 7.5 percent of residential properties are located within designated flood zones, compared to less than 1 percent in each of the landslide and storm surge zones. Floods are also among the most costly natural hazards in Norway, accounting for about one-third of all historical insurance payouts (Table 1 in Section 3). Therefore, because flood risk is both economically significant and spatially well defined, and has been a focus of recent studies on insurance and climate

[2]In this context, residential properties refer to dwellings insured under household policies, excluding commercial and municipal buildings.

[3]These maps are designed to inform local land-use planning, civil protection, and emergency preparedness, and are therefore well suited for analyzing physical exposure to natural hazards.

[4]Tsunamis, meteorite impacts, earthquakes, and volcanic eruptions are also covered, but these events are extremely rare in Norway.

risk (e.g., Sastry (2022); Mulder and Kousky (2023)), it provides a natural starting point for the analysis. The same approach can be extended to other hazards in future work.

To inform expected losses, I use municipality-level data on insurance payouts for natural peril losses under household policies, which are not subject to selection bias because coverage is virtually universal. The data cover the period from 1980, when the scheme started, to 2024 and are deflated to 2024 NOK. From this dataset, I extract the subset of payouts related to floods, consistent with the focus of this analysis. Because the insurance payout data are only available at the municipal level, I aggregate the property-level dataset accordingly. For each municipality, I compute the share of total insured value located within a mapped flood zone. I then relate this measure to the historical average loss per unit of insured value at the municipal level, which I use as an approximation of expected losses. These averages are computed over the entire sample period (Section 6 explores the consequences of relaxing this assumption). By exploiting variation across municipalities in both exposure and realized historical losses, I estimate the conditional expectations of losses per unit of insured value for properties inside and outside mapped flood zones. I refer to these conditional expectations as loss ratios. Because loss ratios correspond to actuarially fair premiums, they form the basis for the zone-specific premiums used in the analysis.

Given that the natural perils insurance scheme in Norway is designed to be actuarially fair at the national level, the uniform national premium should reflect the national average loss ratio. Using data on household insurance policies and residential properties only, I estimate a national average loss ratio of 0.05 per mille across all covered perils, of which roughly 0.02 per mille reflects flood risk, see Section 5.1. For comparison, the uniform premium rate covering all property types was 0.07 per mille in 2024 and increased to 0.08 per mille in 2025. To assess whether properties in low-risk areas implicitly subsidize those in high-risk areas, I compare the estimated actuarially fair premiums across risk zones with the uniform flood premium. I also examine the ratio between actuarially fair premiums in flood and non-flood zones, which provides a direct measure of the imbalance embedded in the uniform pricing scheme.

The results show that under actuarially fair pricing, the average premium for properties in designated flood zones would be 13.2 times higher than the uniform premium in place today. The difference between the actuarially fair premiums in flood and non-flood zones is substantial. The estimated premium in flood zones is 0.2278 per mille, whereas the corresponding premium outside flood zones is 0.0035

per mille, roughly two orders of magnitude lower. This translates into an implied ratio of about 65 between premiums in flood and non-flood zones.[5] For a typical home in a flood risk area insured for 5 million NOK (approx. 480,000 USD), this implies an annual flood premium of nearly 1,140 NOK (109 USD), compared to around 85 NOK (8.2 USD) under the current uniform flood premium.[6] This sizable gap illustrates the extent to which the current system redistributes costs, with lower-risk households contributing more than their actuarially fair share to cover flood-related losses in high-risk zones.

The next part of the analysis examines how estimated premiums in flood and non-flood zones, and the associated cross-subsidies, change when relaxing the assumption that expected losses can be represented by their long-run historical average. Because losses have increased markedly since 2010 (see Figure 4), the relevant time horizon for approximating expected losses is uncertain. To explore this, I estimate actuarially fair premiums using expanding windows that gradually extend the sample backward in time. This approach reveals how estimated premiums evolve as additional historical data are incorporated. Shorter windows, dominated by recent costly flood events, yield higher but also more uncertain estimates of the premium in flood zones. As earlier years are added, recent extremes carry less weight, resulting in lower and more precisely estimated premiums. Notably, premiums outside mapped flood risk areas also rise in the most recent windows, suggesting that flood-related losses have become less tied to officially mapped flood zones and increasingly occur outside them. Consequently, the ratio between the premium in flood and non-flood zones is lower when estimated over short horizons and higher when longer periods are used. In the shortest window, the premium in flood zones remains roughly twenty times higher than the premium in non-flood zones. This pattern may indicate that increasingly unpredictable weather in recent years has reduced, but not eliminated, the degree of cross-subsidization, even as aggregate risk has continued to rise.

Historical patterns provide guidance for thinking about the future. If climate change affects the predictability of weather patterns and extreme events, the distribution of losses across zones may shift, altering the scale of cross-subsidies. Should damages increasingly occur outside designated flood zones, the relative disadvantage

[5]This estimate is subject to considerable uncertainty, since the denominator is close to zero. The associated standard errors are therefore substantial.

[6]Comparable actuarial benchmarks are scarce, but Canada provides a useful point of reference, as its flood insurance is risk-based. A government report finds that flood insurance in high-risk areas can be cost-prohibitive, and that risk-based insurance premiums in some areas could reach $10,000–15,000 or more for flood endorsements alone (Canada's Task Force on Flood Insurance and Relocation, 2022). For comparison, most Canadian homeowners can obtain overland flood coverage for about $100–300 per year, according to industry sources citing the Insurance Bureau of Canada (Insurance Business, 2021).

of being located within a mapped risk zone would diminish. Conversely, if losses become increasingly concentrated in high-risk zones, the degree of cross-subsidization may persist or even intensify.

Finally, I investigate whether municipalities in hazard-prone areas undertake more adaptation. The uniform premium mutes price signals about underlying risk not only for households but also for municipalities, whose buildings are insured under the same scheme. Because local authorities bear primary responsibility for land-use policy, infrastructure, and climate adaptation, it is relevant to ask whether municipalities in more exposed areas compensate for the missing price signal through stronger adaptation efforts. If they do, targeted prevention measures could make flood zones less risky to live in and thereby reduce the cross-subsidies embedded in the system over time. To examine this, I use indicators from the Norwegian Climate Monitor, which follows the IPCC framework for climate risk, and reports hazard, exposure, vulnerability, and adaptation measures for all municipalities in Norway. This makes it possible to assess whether flood hazard is associated with adaptation efforts at the municipality level. The results show a positive and statistically significant association that is robust across specifications, but the magnitude is modest and accounts for only a limited share of the cross-sectional variation. Factors related to population density – captured as part of the vulnerability indicator – appear more important for explaining differences in adaptation levels. Densely populated municipalities are considered more vulnerable because extreme events can affect a larger number of people and assets. Taken together, these results suggest that adaptation is positively associated with hazard exposure, although its overall extent remains limited.

Understanding and quantifying cross-subsidies in a natural perils insurance scheme with uniform pricing is important for several reasons. If households in vulnerable regions do not receive accurate financial signals of their underlying risk, they may underinvest in mitigation measures and make location choices that increase their long-term exposure to natural hazards. Over time, these effects may become increasingly prevalent as climate impacts intensify.

Cross-subsidies also influence how properties in exposed areas are valued by masking underlying differences in risk. At face value, higher prices in high-risk areas may appear justified, as long as uniform insurance coverage remains in place. However, even comprehensive insurance against direct physical damages does not eliminate all the broader costs of natural disasters. Disasters generate wider consequences, such as on mortality and health (Frankenberg, Sumantri, and Thomas, 2020), and indirect effects when local businesses, infrastructure, and services are

disrupted (Hallegatte, 2015). They also shape household beliefs and behavior in financial markets: Gallagher (2014) shows that flood insurance take-up in the United States rises sharply after a disaster but gradually declines, consistent with households updating their beliefs about flood risk based on recent events rather than on systematic information about underlying risk. Evidence from Norway further illustrates that such broader effects weigh on the attractiveness of affected areas: Kivedal (2023) document long-run negative effects of avalanches on property values, and Espegren, Galaasen, Garcia-Appendini, and Mæhlum (2025) show that natural disasters have a persistent and negative effect on household housing wealth.

Abrupt repricing of high-risk properties can occur even without policy reform, for example if risk perceptions shift, hazard information changes, or reinsurance costs increase. Such declines may strain household finances, reduce collateral values, and increase vulnerabilities in banks' mortgage portfolios, posing broader risks to financial stability. If a transition from a uniform to a risk-based regime is considered, careful design is essential. Gradual adjustments, temporary caps, and appropriate reinsurance can smooth the transition while preserving the long-run price signal.

This paper also relates to the broader discussion of bundling versus unbundling of natural peril risks. The Norwegian scheme applies a single premium rate across all hazards, effectively bundling heterogeneous risks into one pooled price. An important question in the design of catastrophe insurance schemes is whether to differentiate across perils. For hazards that are highly unpredictable and geographically widespread, risk-based pricing would yield little variation across locations, implying that a bundled premium may remain appropriate. For perils like floods, where risks are spatially concentrated and more predictable, unbundling would allow premiums to better reflect underlying exposure differences.

The relevance of these questions extends well beyond Norway. As highlighted earlier, many countries rely on catastrophe insurance schemes with uniform or near-uniform premiums. At the same time, a growing policy dialogue has emerged on how to design such systems under increasing climate risks and how to close the insurance protection gap. In Europe, and particularly within the EU, there is growing interest in exploring more coordinated approaches across national schemes, including proposals for an EU-level public-private reinsurance mechanism to improve coverage and risk pooling (EIOPA and ECB, 2024). While institutional contexts vary, insights from the Norwegian case shed light on the distributional costs of uniform pricing in natural perils insurance and offer useful perspective on the trade-offs between efficiency and broad insurance coverage.

The remainder of the paper is structured as follows. Section 2 reviews related

literature and discusses the insurance of catastrophic risk more generally, with a particular focus on the Norwegian scheme. Section 3 presents the data and descriptive statistics. Section 4 outlines the research design and estimation strategy. Section 5 reports the main results on the size of cross-subsidies embedded in the current system. Section 6 analyzes how cross-subsidies have evolved over time and discusses how increases in extreme weather events may alter their scale. Section 7 explores the extent of risk-driven adaptation efforts by local authorities. Section 8 concludes.

# 2 Insuring Catastrophic Risk

Insurance markets rest on the principle of pooling risks across many individuals. When premiums equal expected losses, risk-averse households are willing to pay for certainty to avoid uncertain, potentially ruinous losses (Friedman and Savage, 1948). Standard insurance theory defines conditions for insurability, such as independence of risks and affordable premiums (Rejda, McNamara, and Rabel, 2022). Catastrophic risks challenge these assumptions because losses are spatially correlated, making diversification difficult. Some authors therefore describe catastrophe risk as uninsurable in private markets, while others argue that such risks are insurable in principle but institutionally demanding (Jaffee and Russell, 1997). The Norwegian natural perils insurance scheme illustrates one way in which catastrophe risk can be made insurable in practice, combining virtually universal[7] participation with a uniform national premium rate.

Another central concern is the intertemporal mismatch between steady premium inflows and rare but massive outflows, which requires reinsurance and other global risk-sharing mechanisms (Jaffee and Russell, 1997). Recent evidence suggests that global diversification is under strain as climate change increases the likelihood of simultaneous large-scale losses, driving up reinsurance prices (Keys and Mulder, 2024; Swiss Re Institute, 2025). These developments may also affect Norway's uniform premium, as the scheme relies on international reinsurance markets for losses above a defined threshold.

Unlike the classic case of adverse selection (Rothschild and Stiglitz, 1978; Akerlof, 1978), catastrophe insurers often hold more granular information than households, creating asymmetries that motivate risk-based pricing. Recent work shows that these asymmetries also arise between insurers: firms with detailed risk models can distinguish high- and low-risk properties more accurately, while those relying on

[7]The institutional features are further described in Section 2.1.

coarser measures tend to attract disproportionately risky policyholders and therefore either charge higher premiums in exposed areas or withdraw from those markets (Boomhower et al., 2024). Evidence from the U.S. further indicates that premiums have become increasingly sensitive to local hazard exposure (Keys and Mulder, 2024). While such pricing better reflects underlying risk, it may come at the cost of perceived transparency if the rationale for increasing premiums is not evident or credible to policyholders (Mulder and Kousky, 2023). The Norwegian scheme provides the mirror image of these risk-based systems: information about hazard risk exists but is not priced. Moreover, with virtually universal participation, there is no selection in coverage.

Rising climate risk provides a real-world test of the insurability of catastrophes (Glendon, Kousky, and Schauble, 2025). In several countries, insurers have raised premiums or withdrawn from high-risk areas (Kaufman, Kishan, and Lopez, 2024; The Economist, 2024). Increases in premiums affect household behavior, raising mortgage delinquency risks and accelerating migration away from exposed areas (Ge, Johnson, and Tzur-Ilan, 2025). At the same time, many households underinsure because actuarially fair premiums exceed what they can afford (Sastry, Sen, Tenekedjieva, and Scharlemann, 2024). These findings highlight that the main challenge is not necessarily risk measurement but the affordability of coverage under increasing hazards. In contrast, premiums have remained relatively stable in Norway and underinsurance is precluded, as industry standards require that all property insurance policies are written at full replacement value.

According to OECD (2021), national catastrophe insurance programmes differ mainly in how premiums are structured and in the degree of public involvement. Several systems – such as those in France, Spain, Iceland, New Zealand, Switzerland, and Norway – apply flat or near-flat premiums based solely on the insured value, without adjusting for location or construction characteristics. Others, such as in Japan, Turkey, and the United States, use simplified or partially risk-based models, while only a few, including Germany and some US submarkets, apply fully risk-based pricing. The extent of government participation also varies: some programmes operate as public insurers with explicit state guarantees (France, Spain, New Zealand), whereas Norway's natural perils scheme operates through a private co-insurance pool with no explicit state guarantee.

Within this landscape, Norway represents a notable case. It combines mandatory natural perils insurance through fire insurance for physical assets, administered by private insurers and pooled across companies through the Norwegian Natural Perils Pool, with a separate public compensation scheme that covers losses to

assets not eligible for ordinary insurance, such as public infrastructure and land damage. Together, these mechanisms provide one of the most comprehensive systems of coverage for natural perils (The Norwegian Ministry of Agriculture and Food, 2014). The solidarity principle that underpins the uniform national premium ensures universal access and administrative simplicity but weakens incentives for prevention and efficient location choices. Similar trade-offs are observed in hybrid systems in France, Spain, and Iceland, which combine private insurance with public reinsurance while maintaining largely uniform premiums.

Cross-subsidization has been studied in a wide range of sectors, including utilities, health insurance, transport, and financial markets. Hurst, Keys, Seru, and Vavra (2016) show that government-sponsored enterprises in the U.S. mortgage market apply uniform rates across regions, creating implicit transfers between borrowers facing different default risks. Their findings illustrate that such redistribution can arise in financial markets whenever risk-based pricing is constrained. In natural perils insurance, however, the growing empirical literature has focused mainly on risk-based schemes, particularly in the United States. Much less is known about the magnitude and implications of cross-subsidies in solidarity-based systems. Norway's model therefore provides a useful case to analyze how uniform pricing redistributes costs and shapes incentives for climate adaptation.

## 2.1 The Norwegian Natural Perils Insurance Scheme

In Norway, the natural perils insurance scheme is structured such that any property insured against fire damage is automatically covered for natural perils, including floods, landslides, and storms. Because holding property insurance, which includes fire coverage and thus natural perils insurance, is both a legal requirement for mortgage holders and common more broadly, virtually all residential properties are insured.[8] Combined with the industry standard of writing policies at full replacement value, these features make coverage effectively universal and comprehensive.

The scheme is coordinated through the Norwegian Natural Perils Pool, a mandatory arrangement among private insurers. Each company settles claims with its own policyholders, after which the pool redistributes losses across members according to market share. The uniform premium is set annually to ensure long-term balance

[8]Data from Finance Norway show that in 2025, insurers reported 1,744,450 policies for residential real estate objects (houses and cabins). Eiendomsverdi AS recorded 1,749,352 properties of the same types. This corresponds to a take-up rate of about 99.7 percent. These figures exclude housing cooperatives and jointly owned buildings, although it is highly unlikely that such dwellings would be uninsured in the Norwegian context, as these are typically covered through collective building insurance.

between total inflows and outflows, that is, to be actuarially fair at the national level. Since 2012, the rate has ranged between 0.065 and 0.08 per mille of insured fire value (The Norwegian Ministry of Justice and Public Security, 2019), implying an annual premium covering all perils of roughly 400 NOK (about 38 USD) for a typical dwelling insured for 5 million NOK (around 480,000 USD).

Several arguments have historically been advanced in favor of maintaining a uniform rate (The Norwegian Ministry of Justice and Public Security, 2024). At the time of the system's design, administrative simplicity and limited availability of localized risk data were central considerations. Even today, risk projections remain uncertain, particularly due to climate change. This complicates actuarially precise differentiation. The experience from the United States illustrates these challenges. The federally managed National Flood Insurance Program (NFIP) has sought to introduce more risk-based pricing, yet reliance on outdated flood maps in regulation and information provision, and political pressure leading to legislated caps on annual premium increases, have constrained reform efforts (Mulder and Kousky, 2023).

A further rationale for a uniform rate is affordability: actuarially fair premiums in high-risk areas could be unaffordably high, potentially excluding households and undermining broad insurance coverage. Another argument emphasizes that natural hazards are partly stochastic and widespread, supporting cost-sharing across policyholders. From a Rawlsian perspective, the uncertainty of future climate risks may itself justify solidarity-based arrangements, if households cannot know in advance whether their property will be exposed. Moreover, location choices are not fully voluntary. Housing is a long-term and illiquid investment, households may inherit property, and local housing and labor markets restrict mobility. What appears inefficient under actuarial principles may therefore also be interpreted as a recognition that residential location is shaped not only by individual preferences but also by structural conditions such as intergenerational ties, regional disparities, and policy choices related to land use, historical settlement patterns, tax incentives, and regulatory frameworks. In this sense, cross-subsidization functions as a form of insurance against being on the wrong side of an unpredictable risk distribution.

Finally, the scheme is designed to complement, rather than replace, public responsibility for long-term risk mitigation. Land-use regulation and infrastructure investment remain the primary instruments in this regard.

Despite its strengths in maintaining universal coverage, the system has faced criticism. The solidarity principle reduces incentives for households to invest in risk-reducing measures, and may encourage inefficient location choices. These concerns are likely to intensify as climate risks increase. Nevertheless, these critiques have

not prompted reform of the uniform pricing model, whose core principles have so far remained outside the scope of policy reviews.

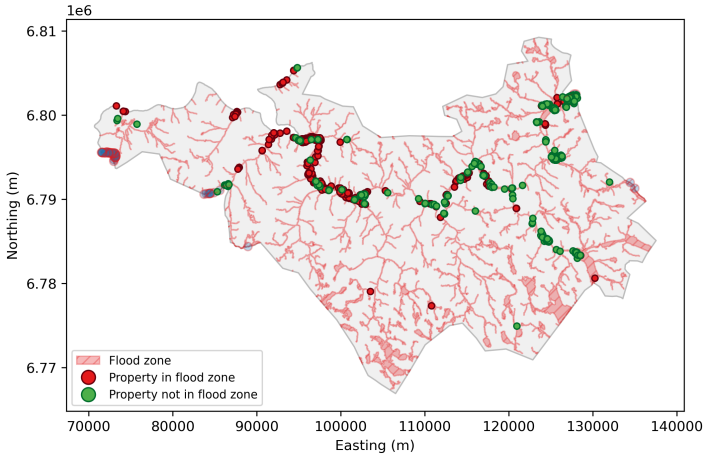
# 3 Data and Descriptive Statistics

This paper combines detailed microdata on residential properties with spatial risk exposure and municipal insurance payout data. The housing unit data is sourced from **Eiendomsverdi AS**, a Norwegian provider of automated valuation models and databases for the national residential real estate market. Its name, which translates literally to *property value*, reflects its core activity of estimating the market value of individual dwellings using transaction data and property characteristics. Eiendomsverdi is widely used by Norwegian banks and other financial institutions. Each observation corresponds to a distinct dwelling that would constitute a separate property in the housing market, meaning that semi-detached houses and apartments are counted individually rather than as a single building. The dataset includes information on estimated market value, dwelling size, and other structural attributes, but does not contain any personal information about ownership or current occupancy.

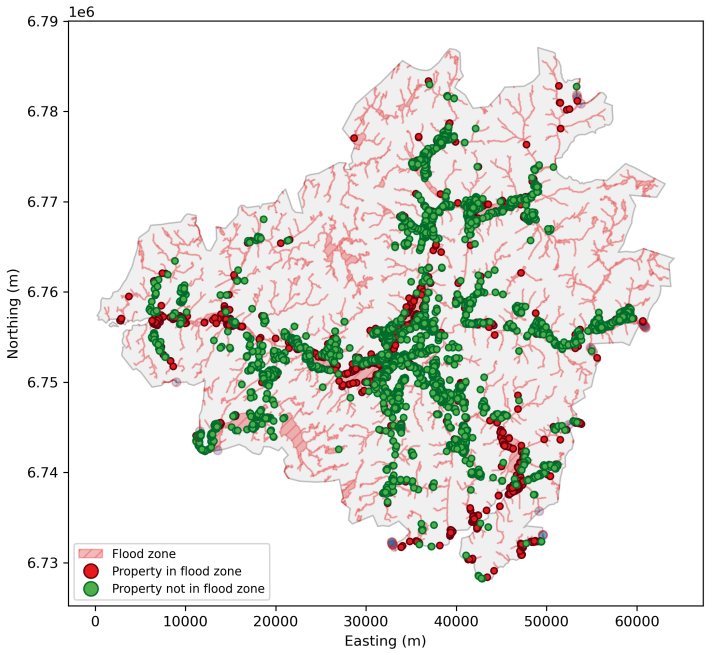
To determine the exact location of each property, I use data from the **Norwegian Mapping Authority**, which provides precise geographic coordinates and enables spatial analysis of exposure to natural hazards. To calculate the insured value of each property, I apply standardized valuation tables provided by the **Norwegian Natural Perils Pool**, which are publicly available online.[9] These tables are used by non-life insurance companies and property firms to estimate and update the replacement value of buildings, contents, and equipment in line with cost developments. The tables specify both the building-type-specific square meter costs and location factors that capture regional variation in construction costs. To calculate the insured value, I multiply the size of the property by the relevant square meter cost and apply the corresponding location factor.

To determine whether a property is located in a flood zone, I combine the geospatial information with official hazard zone maps from the **Norwegian Water Resources and Energy Directorate** (NVE). NVE is the government agency responsible for mapping and updating flood and other natural hazard zones in Norway. The maps are publicly available[10] and are based on hydrological and topographical modeling of current risk under observed climatic conditions. Specifically, I use NVE's flood awareness maps from 2024, which identify areas with potential flood risk. These

[9]The standardized valuation tables can be found here.
[10]These maps are available through Geonorge.




**(a)** The Municipality of Lærdal (approx. 1200 insurance units)




**(b)** The municipality of Voss (approx. 9900 insurance units)

**Figure 1:** Hazard maps with overlaid property locations, distinguishing between properties inside (red color) and outside flood zones (green color), for the municipalities of Lærdal (a) and Voss (b).

*Note:* Each dot represents an individual insured property. Property coordinates are obtained from the Norwegian Mapping Authority (Kartverket) and used to determine whether each property is located inside or outside the official flood zones delineated by the Norwegian Water Resources and Energy Directorate (NVE). Red dots indicate properties within a flood zone, while green dots indicate properties outside. Because many properties overlap, individual dots may not all be visible at this scale. The number of insurance units (distinct dwellings) is therefore indicated in the subcaptions to give an impression of the municipality size. The two municipalities, Lærdal and Voss, are shown to illustrate variation in exposure: approximately 65% of the total insured value in Lærdal lies within a flood zone, compared to about 9% in Voss. All spatial coordinates refer to the EUREF89 / UTM Zone 33N coordinate reference system (EPSG:25833).

maps have a level of spatial detail suited for municipal land-use planning and are intended for use in environmental impact assessments, risk and vulnerability analyses, and the designation of flood hazard zones in municipal plans. They are gradually updated as new data and modeling improvements become available. By overlaying property locations with these zones, I identify which properties are exposed to flood hazard. Of the approximately 2.6 million homes in Norway, about 193,500 (roughly 7.4 percent) fall within a designated flood risk area.

Figure 1 illustrates this procedure for two municipalities: Lærdal, where 65 percent of the total insured property value in the municipality is located inside a flood zone, and Voss, where the share is only 9 percent. The maps display the official flood zones in the background (shaded areas), with individual properties plotted as points and colored according to whether they fall inside (red) or outside (green) a flood zone. The figures combine the property-level data with hazard-zone maps.

The historical loss data is sourced from **Finance Norway**, which provides a complete record of insurance payouts for natural perils across all 357 Norwegian municipalities from 1980 to 2024. The dataset includes the number of claims, the type of affected property, the total compensation amount (including both paid and reserved payouts), and the specific cause of damage, such as storm, flood, or landslide. A key feature is that it distinguishes between household and firm policies, and in this analysis I focus on household policies, since these correspond to private residential properties. The ability to separate losses by hazard type is also central for this study. For the present analysis, I use the subset of payouts caused by flood events to calculate municipal-level loss ratios. All payout amounts are deflated to 2024 values using the consumer price index.

Table 1 summarizes the total number of claims and payout volumes for each hazard type over the full period 1980–2024. Storms are the most frequent and costly events, followed by floods and landslides. In total, flood-related damages account for about one-third of all payouts. Storm surges occur more often than landslides but have generated smaller monetary losses. Other hazards, such as earthquakes, tsunamis, and meteorite impacts, are extremely rare and contribute only a negligible share of total payouts.

Since the payout data is only available at the municipality level, I aggregate the property-level dataset accordingly. For each municipality, I calculate the share of total insured residential value located within designated flood zones. Figure 2 provides a national overview, mapping this share across all municipalities in Norway. The values range from 0 percent to 65 percent, meaning that in the most exposed municipality, Lærdal, which is also shown in Figure 1a, 65 percent of insured

**Table 1:** Insurance Payouts by Natural Hazard Type, 1980–2024

| Hazard Type | Number of Claims | Payouts (2024 MNOK) | Share (%) |
|---|---|---|---|
| Storm | 308,601 | 19,088.3 | 47.9 |
| Flood | 65,786 | 11,553.6 | 32.3 |
| Landslide | 16,035 | 4,920.3 | 15.3 |
| Storm surge | 19,299 | 1,871.1 | 4.5 |
| Other | 1,256 | 22.1 | 0.0 |

*Note:* The figures are based on insurance payouts from natural damages covered under the Norwegian Natural Perils Insurance Scheme, with data obtained from Finance Norway. The numbers are aggregated over the full sample period (1980–2024) and report the total number of claims, total payouts in 2024 million NOK (MNOK), and each hazard type's share of the total. The table reports payouts for all policies covered by the scheme, including household, commercial, agricultural, and municipal properties. The table is sorted by total payout value. In addition to the perils explicitly listed (storm, flood, landslide, and storm surge), the scheme also covers tsunamis, meteorite impacts, earthquakes, and volcanic eruptions. These are included in the residual "Other" category, which accounts for a negligible share of total losses.

residential property value is located within designated flood zones. Visual inspection suggests some degree of positive spatial correlation, which motivates a more formal exploration of spatial dependence later in the analysis.

The combination of municipality-level insurance payouts and flood exposure – calculated from property-level data as the share of insured value located within mapped flood zones in a municipality – enables a detailed analysis of the relationship between hazard exposure and observed payouts over time. This forms the basis for estimating actuarially fair premiums in flood and non-flood zones. The research design for this estimation is described in Section 4.

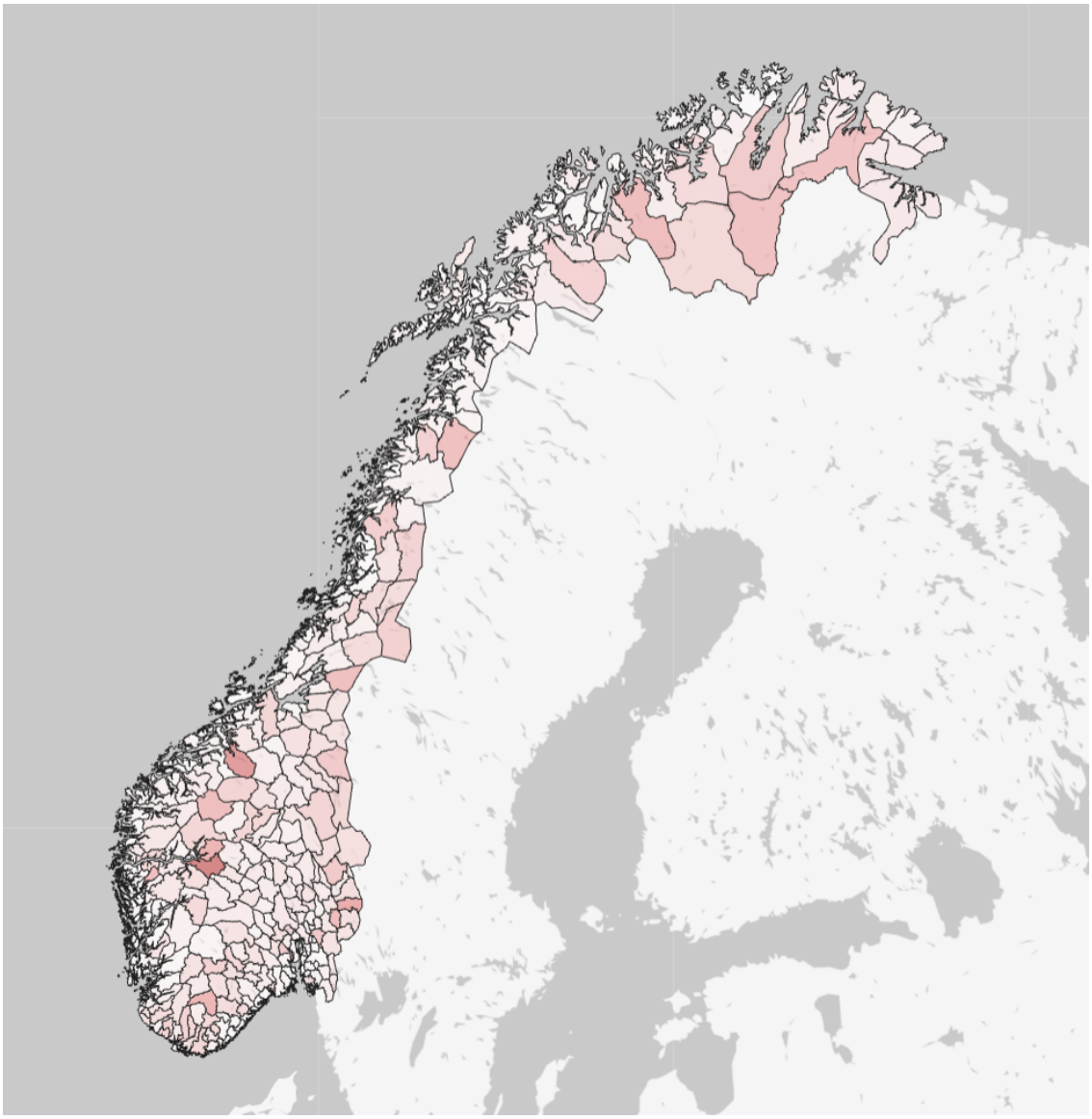


**Figure 2:** Municipal exposure to flood zones: Share of insured residential property value located in mapped flood zones, by municipality.

*Note:* The map shows the share of insured residential property value located within mapped flood zones for each municipality in Norway. Each property is georeferenced using coordinates from the Norwegian Mapping Authority (Kartverket) to determine whether it lies inside or outside the official flood zones provided by the Norwegian Water Resources and Energy Directorate (NVE), as illustrated in Figure 1. These property-level classifications are then aggregated to the municipality level to calculate the share of insured value located within flood zones. The municipal boundaries are based on map data from GeoNorge. Darker red shades indicate a higher share of insured value located in flood zones. The municipality with the highest exposure is Lærdal, where approximately 65% of the total insured residential value lies within a mapped flood zone; this municipality is shown in more detail in Figure 1a.

# 4 Research Design

## 4.1 Definitions

In Norway, natural perils insurance is priced at a single, uniform rate. The premium rate is set to cover expected national losses, which implies that it is actuarially fair in aggregate at the national level.

In practice, the insurance is priced as a proportion of the insured value. Let $\rho$ be the national uniform premium rate per unit of insured value, and let $S_i$ denote the total insured value in municipality $i$. If $X_i$ is the random variable representing the annual loss from natural perils in municipality $i$, the uniform premium $\rho$ can be interpreted as the expected national loss ratio, i.e., the expected loss per unit of insured value across all municipalities:

$$\rho = \frac{\mathbb{E}\big[\sum_i X_i\big]}{\sum_i S_i}. \tag{1}$$

Now assume that, instead of a single uniform premium, the system applies two premiums that reflect hazard risk. At the national level, let $\rho^r$ denote the actuarially fair premium rate for properties in high-risk zones, and $\rho^n$ the corresponding rate in low-risk zones. These can be written as

$$\rho^r = \frac{\mathbb{E}\big[\sum_i X_i^r\big]}{\sum_i S_i^r}, \qquad \rho^n = \frac{\mathbb{E}\big[\sum_i X_i^n\big]}{\sum_i S_i^n}, \tag{2}$$

where $X_i^r$ and $X_i^n$ denote the annual losses in municipality $i$ inside and outside mapped risk zones, and $S_i^r$ and $S_i^n$ denote the corresponding insured values. Total losses and insured values satisfy $X_i = X_i^r + X_i^n$ and $S_i = S_i^r + S_i^n$, and expected losses decompose as:

$$\mathbb{E}[X_i] = \mathbb{E}[X_i^r] + \mathbb{E}[X_i^n] \quad \text{for each municipality } i. \tag{3}$$

Furthermore, assume that expected loss per unit of insured value is constant within each zone across municipalities, so that

$$\mathbb{E}[X_i^r] = \rho^r S_i^r \quad \text{and} \quad \mathbb{E}[X_i^n] = \rho^n S_i^n \quad \text{for all } i. \tag{4}$$

Define the actuarially fair municipal premium rate as

$$\rho_i = \frac{\mathbb{E}[X_i]}{S_i}. \tag{5}$$

Combining these expressions and using $S_i = S_i^r + S_i^n$ yields

$$\rho_i = \frac{S_i^r}{S_i}\rho^r + \frac{S_i^n}{S_i}\rho^n = f_i\,\rho^r + (1 - f_i)\,\rho^n, \tag{6}$$

where $f_i$ is the share of insured value located in high-risk zones, $S_i^r/S_i$. Equation 6 shows that, under the assumption that $\rho^r$ and $\rho^n$ are national premiums and constant within each risk zone, the actuarially fair premium in municipality $i$ can be expressed as a weighted average of the two risk zone–specific premiums.

Aggregating across all municipalities recovers the national premium rate in equation (1), which can equivalently be expressed as a weighted average of the within–zone loss ratios:

$$\rho = \frac{\sum_i S_i^r}{\sum_i S_i}\,\rho^r + \frac{\sum_i S_i^n}{\sum_i S_i}\,\rho^n. \tag{7}$$

The national rate is thus a weighted average of the within–zone loss ratios, where the weights correspond to each zone's share of total insured value.

## 4.2 From Definitions to Estimation

Now, let $\bar{X}_i$ denote the average historical insurance payout in municipality $i$ over the full sample period, 1980–2024. I use this sample mean as an estimator of the expected loss, such that $\bar{X}_i \approx \mathbb{E}[X_i]$, where $X_i$ denotes the annual loss in municipality $i$. Approximating the expectation with a finite-sample mean implies a discrepancy between $\bar{X}_i$ and $\mathbb{E}[X_i]$. I define this approximation error in loss-ratio form as

$$u_i \equiv \frac{\bar{X}_i - \mathbb{E}[X_i]}{S_i},$$

which allows the empirical loss ratio to be written as

$$\frac{\bar{X}_i}{S_i} = \frac{\mathbb{E}[X_i]}{S_i} + u_i = \rho_i + u_i \tag{8}$$

where $\rho_i = \mathbb{E}[X_i]/S_i$ from Equation 5 denotes the unobserved expected loss ratio in municipality $i$. Now, combining this with Equation 6 yields

$$\frac{\bar{X}_i}{S_i} = f_i\,\rho^r + (1 - f_i)\,\rho^n + u_i \tag{9}$$

which can be estimated using a linear regression of the municipal loss ratio, $\frac{\bar{X}_i}{S_i}$, on the share of insured value located in the risk zone, $f_i$:

$$\frac{\bar{X}_i}{S_i} = \beta_0 + \beta_1 f_i + u_i, \qquad \text{where} \quad \beta_0 = \rho^n \quad \text{and} \quad \beta_1 = \rho^r - \rho^n \tag{10}$$

Here, $u_i$ captures idiosyncratic deviations arising from finite-sample variation in historical losses around their expected values. Cross-municipality variation in $f_i$ thus identifies the differential loss rate $\rho^r - \rho^n$. Together with the intercept estimate for $\rho^n$, this provides estimates of both the loss ratio inside flood zones ($\rho^r$) and outside flood zones ($\rho^n$). Since loss ratios correspond to actuarially fair premium rates, these estimates can be interpreted directly as the premiums that would apply in flood and non-flood areas under a two-tier risk-based scheme. The gap between these zone-specific premiums and the uniform national rate forms the basis for quantifying cross-subsidies in the paper.

When using $S_i$ to represent the total insured value in municipality $i$, I implicitly assume that the spatial distribution of properties and insured values has remained constant over time. Using the 2024 housing stock aligns with the use of 2024 hazard maps, and utilizing the most recent set of hazard maps avoids conflating changes in risk with changes in the predictive accuracy or coverage of earlier maps. Historical maps would reflect evolving data quality and modeling approaches in addition to genuine shifts in underlying hazard probabilities.

Consistency of the estimated loss ratios $\hat{\rho}^r$ and $\hat{\rho}^n$ requires that the approximation error in using historical average losses $\bar{X}_i$ to proxy expected losses $\mathbb{E}[X_i]$ does not systematically vary with municipalities' exposure to mapped flood zones. Formally,

$$\mathbb{E}\big[(\bar{X}_i - \mathbb{E}[X_i])/S_i \,\big|\, f_i\big] = 0. \tag{11}$$

Intuitively, how well $\bar{X}_i$ approximates $\mathbb{E}(X_i)$ – that is, the approximation error itself – cannot on average be larger or smaller in municipalities with a high share of insured value in flood zones than in those with a low share.

In the Norwegian setting, this assumption is supported by the construction of the official flood maps, which delineate areas that may be exposed to flooding based on hydrological and topographical information, at a level of detail tailored to municipal planning, and are not defined from insurance payout data. Conditional on this exposure measure, it is natural to treat sampling error in municipal loss ratios as idiosyncratic.

The main challenge to this assumption going forward is climate change. If climate change raises expected flood losses proportionally across municipalities,

historical averages will misstate current expectations in a broadly similar way. If, however, expected losses increase more in already flood-prone areas (high $f_i$), then long-run averages may understate current risk more in these municipalities, inducing approximation errors that are correlated with $f_i$. I therefore interpret $\hat{\rho}^r$ and $\hat{\rho}^n$ as empirically grounded, historically based average loss ratios inside and outside mapped flood zones, and complement the baseline estimates with expanding-window exercises that give more weight to recent high-loss years to assess the robustness of the estimated premiums.

**Multiple perils and disentangling peril-specific premiums**

In principle, the uniform national premium rate $\rho$ reflects the aggregate contribution from several natural perils, such that

$$\rho = \sum_{k \in \mathcal{K}} \rho^{(k)} = \rho^{(\text{flood})} + \rho^{(\text{storm})} + \rho^{(\text{storm surge})} + \rho^{(\text{landslide})} + \dots, \tag{12}$$

where each component $\rho^{(k)}$ represents the national average loss ratio attributable to peril $k$. Because the total premium is an additive combination of multiple hazards, one could in principle estimate a single model including all exposure shares $f_{i,k}$ simultaneously:

$$\rho_i = \sum_k \left[ f_{i,k}\, \rho_k^r + (1 - f_{i,k})\, \rho_k^n \right], \tag{13}$$

where $\rho_i$ denotes the overall municipal loss ratio. However, the challenge is not primarily multicollinearity across the exposure shares $f_{i,k}$, but rather that the dependent variable $\rho_i$ aggregates expected losses from all perils. The availability of disaggregated payout data by peril makes it possible to estimate each $\rho_i^{(k)}$ separately, using peril-specific losses as the dependent variable. This approach exploits more granular information on the underlying loss process and allows each regression to recover the actuarially fair premium for that particular peril.

For a given municipality $i$, the peril-specific actuarially fair premium can then be expressed as

$$\rho_i^{(k)} = f_{i,k}\, \rho_k^r + (1 - f_{i,k})\, \rho_k^n, \tag{14}$$

where $f_{i,k} = S_i^{r,k}/S_i$ denotes the share of insured value located in the mapped risk zone for peril $k$, and $\rho_k^r$ and $\rho_k^n$ denote the loss ratios inside and outside these zones, respectively.

Accordingly, I estimate each peril separately. For example, the flood-specific

premium is estimated as

$$\rho_i^{(\text{flood})} = \frac{\bar{X}_{i,\text{flood}}}{S_i} = f_{i,\text{flood}}\,\rho^r_{\text{flood}} + (1 - f_{i,\text{flood}})\,\rho^n_{\text{flood}} + u_{i,\text{flood}} \tag{15}$$

Since $\rho_i^{(\text{flood})}$ is defined only from flood-related payouts, other hazards such as storm surges or landslides are not determinants of this variable. Even if the share of properties in flood zones is correlated with the share in other hazard zones, this does not affect the interpretation of the regression, because the dependent variable is peril-specific and unrelated to losses from the omitted hazards. Identification instead relies on the assumption that the approximation error arising from using historical average losses does not systematically vary with municipalities' exposure $f_i$. Under this assumption, the regression recovers the conditional expectations of losses per unit of insured value inside and outside mapped flood zones.

## 4.3 Estimation Strategy

In the estimating regression, the dependent variable is the municipality-level loss ratio, defined as average historical payouts in the municipality divided by the total insured value in municipality. The key explanatory variable is the share of insured value located in mapped flood zones within each municipality. Under the assumptions outlined above, this specification identifies the average loss ratio inside and outside flood zones, $\rho^r_{flood}$ and $\rho^n_{flood}$, by exploiting cross-municipality variation. As expressed by equation 10, the intercept $\beta_0$ identifies the average loss ratio outside flood zones $\rho^n_{flood}$, while the slope, $\beta_1$, captures the additional risk inside flood zones, $\rho^r_{flood} - \rho^n_{flood}$. The implied loss ratio in flood zones is thus $\rho^r_{flood} = \beta_0 + \beta_1$.

Because municipalities differ greatly in size and total insured value, I estimate both unweighted and weighted versions of equation 10. An unweighted OLS regression gives each municipality equal weight and will represent the average relationship across municipalities. In contrast, a weighted least squares (WLS) regression with weights proportional to each municipality's total insured value gives greater influence to municipalities with larger insurance portfolios. Conceptually, this distinction reflects two different ways of averaging losses. OLS measures the average loss ratio across municipalities, corresponding to the expected loss in a representative municipality. WLS, by contrast, measures the average loss ratio across insured exposure, corresponding to the expected loss per insured value. This latter aggregation aligns with the actuarial definition of a fair premium and is therefore the most relevant measure of cross-subsidization under a uniform national rate. WLS thus serves as

the main specification in the analysis.

Tests such as Breusch–Pagan indicate heteroskedasticity in the residuals, which is expected given the large variation in exposure across municipalities. I therefore report HC3 heteroskedasticity-robust standard errors. In addition, I compute Conley HAC standard errors to allow for correlation across geographically close municipalities, for example due to common exposure to regional weather events or other spatially correlated shocks.

A few municipalities, such as the municipality of Lærdal, which has the largest share of insured value located in flood zones (see Figure 1), show substantial influence in terms of both leverage and Cook's distance. These observations reflect genuine exposure rather than data errors, but they raise the question of robustness. To address this, I estimate alternative models that reduce sensitivity to extreme observations. Median regression usually provides a useful robustness check, though its interpretation is less straightforward when most municipalities experience few losses and only some face very large events. For natural perils insurance, these extreme outcomes are not statistical noise but the defining tail realizations that drive expected losses and hence actuarially fair premiums. Median regression may in that sense understate the economic significance of catastrophic events, but it is a useful complementary specification.

Robust linear regression (RLM) with Huber weights offers an intermediate approach by downweighting but not discarding influential observations. This method reduces the leverage of highly exposed municipalities while keeping the bulk of the data unchanged. The degree of downweighting depends on the tuning parameter $t$: smaller values place less weight on extreme observations and shift the estimates further away from OLS, while larger values make RLM converge toward OLS. Appendix A2 reports results for alternative values of $t$, which demonstrate that the main conclusions are robust to different weighting schemes. In practice, RLM serves as a complement to OLS. Since rare but severe events are inherent to catastrophe risk, I treat RLM as a robustness exercise.

Finally, I consider spatial dependence beyond the correlation structure already captured by spatially robust (Conley HAC) standard errors. Neighboring municipalities may share unobserved characteristics such as hydrology, topography, infrastructure, or planning practices, which can induce spatial correlation in loss ratios. To test this, I compute Moran's $I$[11] statistic using a queen-contiguity spatial

[11] Moran's I is a measure of spatial autocorrelation that ranges between -1 and 1, with 0 suggesting a random distribution. Positive values near 1 indicate positive spatial autocorrelation, meaning that similar high or low values are clustered together. Negative values near -1 indicate negative spatial autocorrelation.

weights matrix. In this matrix, two municipalities are defined as neighbors if they share a boundary or a corner. Each municipality's residual is compared to the average of its neighbors. Moran's $I$ is positive when municipality residuals are geographically clustered, and close to zero when residuals are randomly distributed. In my case, the statistic indicates significant positive spatial autocorrelation. This suggests that similar residuals tend to cluster geographically, violating the assumption of independently distributed errors. To address this, I estimate a spatial error model (SEM), which explicitly allows the regression error in one municipality to depend on a weighted average of the errors in neighboring municipalities. This specification captures spatially correlated unobservables without assuming that payouts in one municipality directly spill over into those of its neighbors.[12]

In sum, the estimation strategy builds on weighted least squares (WLS) as the main specification, complemented by unweighted OLS for comparison, robust estimators that reduce the influence of extreme observations, and models that allow for spatial dependence. This layered approach provides a transparent and careful assessment of the empirical relationship between hazard exposure and observed municipal loss ratios.

## 4.4 Empirical Design Considerations

The empirical design is deliberately cross-sectional. By exploiting variation across municipalities in both exposure and realized historical losses, I recover the conditional expectations of losses per unit of insured value inside and outside mapped flood zones. These conditional expectations are referred to throughout the paper as loss ratios and correspond to actuarially fair insurance premiums. Accordingly, the estimates do not have a causal interpretation. Consistency requires that the approximation error from using historical average losses does not vary systematically with municipalities' exposure.

Aggregation to the municipal level inevitably obscures heterogeneity within municipalities. With property-level loss data, the expected loss ratio could be estimated directly rather than inferred from an econometric model at the municipal level. However, historical loss data are currently available only at this level. The municipal scale is therefore both empirically and conceptually appropriate in this context, as municipalities are the relevant units shaping local exposure, infrastructure, and land-use policy.

[12] A spatial autoregressive (SAR) model would instead be appropriate if outcomes in one municipality directly influenced those in neighboring municipalities, which is less plausible in this setting.

# 5 Main Results: The Size of Cross-Subsidies

## 5.1 National Benchmark for Flood Risk

To obtain a benchmark for comparison, I estimate the uniform flood premium using the empirical national loss ratio, defined as average historical insurance payouts for flood damage divided by total insured value across all municipalities:

$$\rho^{(\text{flood})} = \frac{\sum_i \bar{X}_{i,\text{flood}}}{\sum_i S_i}$$

This expression yields the national average loss ratio attributable to flood risk, see Equation 12. As the focus of this paper is on household flood risk, the estimate is based on insurance payouts on household policies and the insured values of private dwellings. Empirically, I find that this value, $\rho^{(\text{flood})}$, is 0.0173 per mille. The sample average is used as an estimator of expected losses, which is appropriate if the process is stationary and losses fluctuate around a stable mean. In practice, however, losses exhibit an upward trend over time, which may cause the sample mean to differ from the long-run expectation. I address this issue in Section 6 by re-estimating loss ratios in expanding windows.

## 5.2 Estimating Zone-Specific Premiums

I now present the results from estimating zone-specific premiums using the regression specification in equation 10, which in the case of flood risk corresponds to equation 15. For simplicity, I omit the subscript "flood" in what follows and refer to the estimated premiums as $\hat{\rho}^r$ for the flood premium and $\hat{\rho}^n$ for the non-flood premium.

Table 2 presents the main regression results. The preferred specification is weighted least squares (WLS), with weights proportional to each municipality's total insured value. This captures the average loss ratio per unit of insured value, the actuarially relevant measure of expected losses. Unweighted ordinary least squares (OLS) is reported for comparison, and represents the average relationship across municipalities. I also report robustness checks including RLM and median regression that reduce the influence of extreme observations, OLS with spatial HAC standard errors to allow for correlation that decays with distance, and SEM that captures spatially correlated unobservables across neighboring municipalities.

In the WLS model, model 1 in Table 2, the estimated actuarially fair premium in non-flood zones is 0.0035 per mille, while the corresponding premium in flood zones is 0.2278 per mille, a difference of two orders of magnitude. In the unweighted OLS

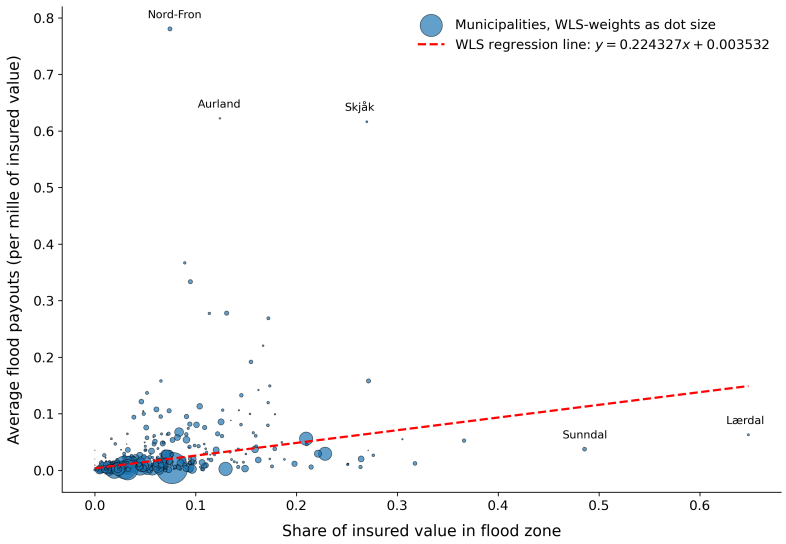
**Table 2:** Regression Results (All coefficients in ‰)

| Model | $\hat{\beta}_0 = \hat{\rho}^n$ | $\hat{\beta}_1 = \hat{\rho}^r - \hat{\rho}^n$ | Implied $\hat{\rho}^r$ | $R^2$ |
|---|---|---|---|---|
| (1) WLS (HC3) | 0.0035<br>(0.0025) | 0.2243***<br>(0.0443) | 0.2278***<br>(0.0429) | 0.075 |
| (2) OLS | 0.0140**<br>(0.0054) | 0.2812***<br>(0.0534) | 0.2952***<br>(0.0497) | 0.072 |
| (3) OLS (HC3) | 0.0140***<br>(0.0053) | 0.2812***<br>(0.0906) | 0.2952***<br>(0.0864) | 0.072 |
| (4) OLS (Conley HAC, 150 km) | 0.0140**<br>(0.0063) | 0.2812***<br>(0.0593) | 0.2952***<br>(0.0564) | 0.072 |
| (5) Spatial Error Model (SEM) | 0.0163***<br>(0.0060) | 0.2530***<br>(0.0963) | 0.2694***<br>(0.0922) | 0.164 |
| (6) RLM Huber T (default $t = 1.345$) | 0.0079***<br>(0.0012) | 0.1413***<br>(0.0118) | 0.1493***<br>(0.0110) | – |
| (7) Median regression | 0.0031***<br>(0.0011) | 0.1695***<br>(0.0110) | 0.1726***<br>(0.0102) | 0.071 |

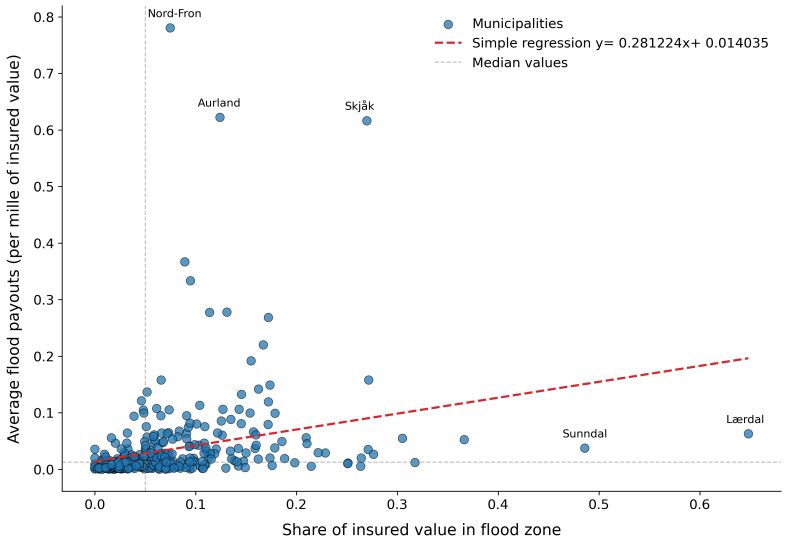
*Notes:* All coefficients and standard errors are reported in ‰. Standard errors in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Number of observations is 357 in all regressions. The dependent variable is the municipality-level loss ratio, defined as average historical payouts over the total sample period divided by total insured value. The explanatory variable is the share of insured value located within mapped flood zones in each municipality. $\hat{\beta}_0$ represents the estimated average loss ratio outside flood zones ($\hat{\rho}^n$), while $\hat{\beta}_1$ captures the additional loss ratio inside flood zones ($\hat{\rho}^r - \hat{\rho}^n$). The implied loss ratio within flood zones is $\hat{\rho}^r = \hat{\beta}_0 + \hat{\beta}_1$. Model (1) reports results from a weighted least squares regression (weights by insured value) with HC3 heteroskedasticity-robust standard errors. Models (2)–(4) report unweighted OLS estimates with standard, HC3, and Conley (HAC, 150 km cutoff) standard errors, respectively. Model (5) reports a spatial error model (SEM) allowing for spatially correlated residuals. Models (6) and (7) provide robustness checks using robust linear (Huber T) and median (quantile) regression estimators.

model, model 2, both the non-flood premium and the flood premium are higher, at 0.0140 and 0.2952 per mille, respectively. These differences reflect that municipalities with large insurance portfolios tend to have lower realized flood losses, both inside and outside mapped flood zones. Assigning greater weight to these municipalities in WLS therefore reduces the estimated premiums in both zones. Figure 3 visualizes the difference in weighting between OLS and WLS. Panel (a) shows the WLS fit with weights proportional to each municipality's total insured value. Panel (b) shows the unweighted OLS fit with equal weights across municipalities. The bubble size reflects the observation weight, and the dashed lines are the fitted regressions with HC3 robust standard errors.

The estimated premium in non-flood zones is statistically insignificant only in the WLS model, indicating that once municipalities are weighted by insured value, expected flood-related losses in low-risk areas are minimal. From an economic




**(a)** Weighted Least Squares (WLS)




**(b)** Unweighted OLS

**Figure 3:** Comparison of regression methods. Panel (a) shows a weighted least squares (WLS) fit between municipal loss ratios and flood-zone exposure, where each observation is weighted by total insured value. Panel (b) shows the corresponding unweighted ordinary least squares (OLS) fit.

*Note:* Each dot represents one municipality. The vertical axis shows the loss ratio per municipality, defined as average historical insurance payouts due to floods over the full sample period divided by total insured value. The horizontal axis shows the share of insured value located within mapped flood zones. Bubble size reflects the relative weight assigned to each municipality—proportional to total insured value in panel (a) and equal in panel (b). The dashed lines indicate the estimated regression fits, based on weighted least squares (WLS) in (a) and unweighted OLS in (b), both estimated with HC3 heteroskedasticity-robust standard errors. The comparison illustrates how weighting by insured value places greater influence on larger municipalities.

perspective, however, the true premium should be strictly positive, since flood damage can occur outside mapped flood zones. Moreover, the weighting scheme in WLS reduces the estimated premium in non-flood zones more than it reduces the estimated premium in flood zones, which explains why the relative difference between flood and non-flood zones, $\hat{\rho}^r/\hat{\rho}^n$, rises under WLS from about 21 in OLS to about 65 (see Table 3). Because WLS emphasizes where most capital is at risk, it provides the most policy-relevant measure of expected losses and serves as the main reference for interpreting cross-subsidies in Section 5.3.

Robustness checks support the main results in Table 2. The OLS estimates are robust to heteroskedasticity (model 3) and to spatial correlation across municipalities (model 4). Model 4 uses Conley HAC standard errors with a 150 km cutoff, which allow for correlation in residuals between geographically close municipalities while assuming independence beyond that distance. A more structural approach uses a spatial error model (SEM, model 5). Moran's $I$ for the OLS residuals indicates modest positive spatial autocorrelation. SEM absorbs unobserved spatially correlated factors through the error term, removes the residual correlation and yields coefficients that are similar to OLS. A more detailed description is provided in Appendix A1.

To assess sensitivity to outliers, model 6 applies robust linear regression (RLM) with Huber weights. The estimated non-flood premium lies between the OLS and WLS values, while the estimated flood premium is lower than in both OLS and WLS. However, the estimated flood premium remains well above the non-flood premium, and the results are stable across tuning parameters, as shown in Appendix A2 Table A2.1. Appendix A2 Figure A2.1 plots the RLM regression line with bubble sizes proportional to the RLM weights and shows that downweighting extreme municipalities reduces the slope but preserves the overall positive relationship.

Model 7 estimates the median regression, which provides a complementary perspective. Because the distribution of flood exposure is highly skewed, the median municipality has little property located in flood zones and experiences low average losses. The median regression thus captures the central tendency among low-risk municipalities rather than the tail realizations that drive aggregate losses. Interestingly, the estimated non-flood premium is similar under WLS and median regression. This similarity arises because both estimators assign less weight to small municipalities with large losses. WLS does so through insured-value weights, while the median estimator does so through robustness to outliers.

Overall, the results show that regardless of specification, the estimated flood premium is substantially higher than the estimated non-flood premium. The differences between estimators primarily reflect how each method treats small municipalities or

outliers rather than fundamental differences in the underlying pattern of risk.

## 5.3 Relative Magnitudes and Economic Interpretation

Table 3 reports two sets of ratios. The first column shows the ratio of the estimated actuarially fair flood premium to the national uniform flood rate, $\hat{\rho}^r/\rho^{(\text{flood})}$. The second column reports the ratio between the estimated actuarially fair flood and non-flood premiums, $\hat{\rho}^r/\hat{\rho}^n$. Although point estimates differ across specifications, the qualitative conclusions are aligned. The estimated actuarially fair premium in flood zones is roughly an order of magnitude larger than the current uniform flood premium, and many times larger than the actuarially fair premium in non-flood zones. This points to substantial implicit cross-subsidies under the uniform pricing regime.

The preferred WLS model implies that the estimated actuarially fair flood premium is about 13 times higher than the uniform rate. OLS and SEM yield

**Table 3:** Comparison of the estimated actuarially fair flood premium to the uniform and the estimated actuarially fair non-flood premium

| Model | $\hat{\rho}^r/\hat{\rho}^{(\text{flood})}$ | $\hat{\rho}^r/\hat{\rho}^n$ |
|---|---|---|
| WLS (HC3) | 13.17*** | 64.51 |
| | (2.48) | (54.41) |
| OLS (HC3) | 17.06*** | 21.03 |
| | (4.99) | (13.33) |
| Spatial Error Model | 15.57*** | 16.52 |
| | (5.32) | (10.74) |
| RLM Huber T | 8.63*** | 18.69*** |
| | (0.63) | (3.85) |
| Median Regression | 9.98*** | 54.94** |
| | (0.59) | (21.79) |

*Notes:* Each cell reports the estimated ratio, with standard errors shown in parentheses below. Significance levels: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Column (1) gives the ratio of the actuarially fair flood premium to the flood component of the national uniform rate ($\hat{\rho}^r/\rho^{(\text{flood})}$). The uniform flood-rate component is 0.0173 ‰, see Section 5.1. Column (2) shows the ratio between the estimated actuarially fair flood and non-flood premiums. ($\hat{\rho}^r/\hat{\rho}^n$). Standard errors in column (1) are computed as $\text{SE}(\hat{\rho}^r)/0.0173$, while those in column (2) are obtained via the delta method using the estimated variance–covariance matrix of $(\hat{\beta}_0, \hat{\beta}_1)$. All values are in ‰. Regressions are based on all 357 municipalities.

somewhat higher ratios of about 17 and 15.5, respectively, while the robust RLM and the median regression imply more moderate ratios in the range 8.6–10. All estimates in the first column are statistically significant. These results indicate that, regardless of estimation method, actuarially fair pricing would require a premium in flood zones that is substantially larger than the current uniform rate.

Turning to the gap between the premium in flood and non-flood zones, the WLS model implies that the estimated premium in flood zones is about 65 times higher than the corresponding premium in non-flood zones. This ratio is estimated with considerable uncertainty, since the denominator ($\hat{\rho}^n$) is close to zero and the associated standard error is large. The OLS, RLM, and SEM specifications produce lower and more tightly estimated ratios in the 16–21 range, reflecting their different weighting schemes compared with WLS. Because large municipalities with high insured values tend to have relatively low average flood losses in this sample, this weighting reduces the premium in non-flood zones more than the premium in flood zones, and therefore widens the ratio, $\hat{\rho}^r/\hat{\rho}^n$. The median regression yields a ratio close to WLS at about 55, since the median municipality has little flood exposure and low losses, so that both WLS and the median estimator place limited weight on smaller municipalities with extreme losses. Across all specifications, the implied gap between flood and non-flood areas remains large.

To illustrate the magnitudes implied by the WLS estimates, the estimated premium in high-risk flood zones is about 0.2278 per mille, compared with 0.0035 per mille in non-flood zones. For reference, the uniform national premium is 0.08 per mille, of which approximately 0.0173 per mille is allocated to household flood risk. For a typical home insured for 5 million NOK (around 480,000 USD), a risk-based flood premium would amount to about 1,140 NOK per year (about 109 USD), compared with the current uniform flood component of roughly 85 NOK (about 8.2 USD). Outside mapped flood zones, the implied actuarially fair premium would be around 17.5 NOK (about 1.68 USD), reflecting much lower expected losses. These comparisons underscore the magnitude of cross-subsidization: households in low-risk areas effectively bear part of the cost of insuring those in high-risk zones.

The analysis measures the cross-subsidies arising from flood risk in the insurance scheme. Since the scheme also covers other natural perils, it is useful to consider how the flood-based estimates relate to the magnitude of total subsidies. This depends on whether flood damages covary with damages from other perils. Positive correlations would indicate that high flood risk tends to coincide with high risk from other hazards, so that the flood-based estimates understate the extent of cross-subsidization. Negative correlations would instead suggest offsetting patterns

across perils, reducing the overall subsidy problem.

Table 4 reports average within-municipality correlations between insurance payouts due to flood damage and payouts due to other perils. The correlations are positive but modest in magnitude and highest for storm surges. A similar pattern appears when using the number of claims rather than total payouts. These results suggest that flood risk overlaps partly with exposure to other hazards, while losses remain to a considerable degree peril-specific. The positive correlations imply that the flood-based results likely represent a lower bound on the true extent of cross-subsidization in the system.

**Table 4:** Within-municipality correlations of flood payouts with other perils

**(a)** Payouts in 2024 MNOK

| | Flood |
|---|---|
| Storm | 0.088 |
| Storm surges | 0.229 |
| Landslides | 0.138 |

**(b)** Number of payouts

| | Flood |
|---|---|
| Storm | 0.119 |
| Storm surges | 0.259 |
| Landslides | 0.228 |

*Note:* The figures are based on insurance payouts from natural damages covered under the Norwegian Natural Perils Insurance Scheme, with data obtained from Finance Norway. The full sample period (1980-2024) is used. Entries are averages of within-municipality correlations. For each peril pair, only municipalities with sufficient variation and at least two paired observations are included. Results give equal weight to each municipality.

# 6 Expanding-Window Estimates of Premiums

The results above document large cross-subsidies embedded in Norway's natural perils insurance system. An important next step is to examine how these estimates change when relaxing the assumption that expected losses can be represented by the long-run historical average. Finance Norway, the provider of the municipal insurance payout data, reports that insurance payouts due to natural damages in general, and flood damages as well, have increased markedly in recent years. Figure 4 illustrates this pattern, showing that average annual flood payouts have risen in the post-2010 period, increasing from a pre-2010 mean of about 142 MNOK (in 2024 values) to a post-2010 mean of 487 MNOK. A few individual years stand out in particular. The 1995 flood caused extensive damages across large parts of Eastern Norway. More recently, the extreme weather event Hans in 2023 generated record-high insurance payouts, partly because it affected regions that are not typically exposed to such extreme precipitation. Because losses in general have trended upward, it is not clear which time horizon provides the most informative approximation of expected losses.

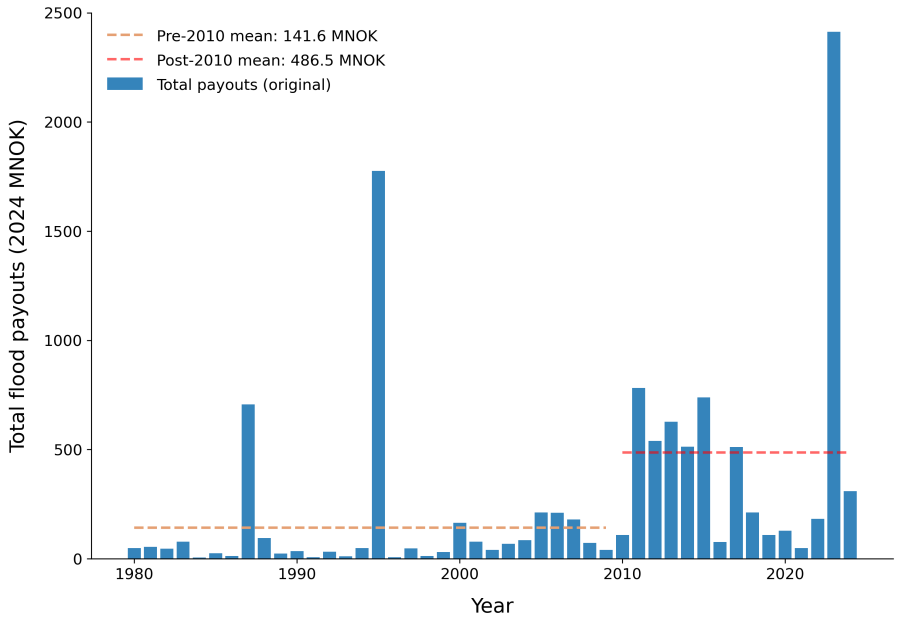



**Figure 4:** Total annual flood payouts (MNOK). Orange dashed line shows the pre-2010 mean (up to 2009), while the red dashed line shows the post-2010 mean (from 2010 and onward).

*Note:* The figure shows total annual insurance payouts for flood-related damages in Norway, measured in 2024 million NOK (MNOK). Data are obtained from Finance Norway and cover all flood events insured under the Norwegian Natural Perils Insurance Scheme. The vertical bars represent yearly totals, while the dashed lines mark the average annual payout before and after 2010, respectively, highlighting the increase in flood-related losses in the later period.

To explore this, I estimate actuarially fair premiums in flood and non-flood zones using expanding windows that gradually extend the sample backward in time. Figure 5 shows these estimates with 95 percent confidence intervals. The rightmost estimate is based on the last decade, 2015–2024. Each subsequent point adds ten earlier years until reaching the full sample 1980–2024, which corresponds to the main specification reported earlier in the paper. Estimates based on recent years are higher and less precise, reflecting the impact of several costly flood events over the last two decades. As earlier years are added, recent extremes carry less weight, resulting in lower and more precisely estimated premiums.

An interesting pattern is that the estimated premium outside flood zones also rises in the most recent windows. This may suggest that weather-related damages have become more unpredictable in recent years, affecting both flood and non-flood areas. Importantly, this pattern should not reflect outdated risk information, since the analysis uses the most recent hazard maps from 2024. Instead, it points to an

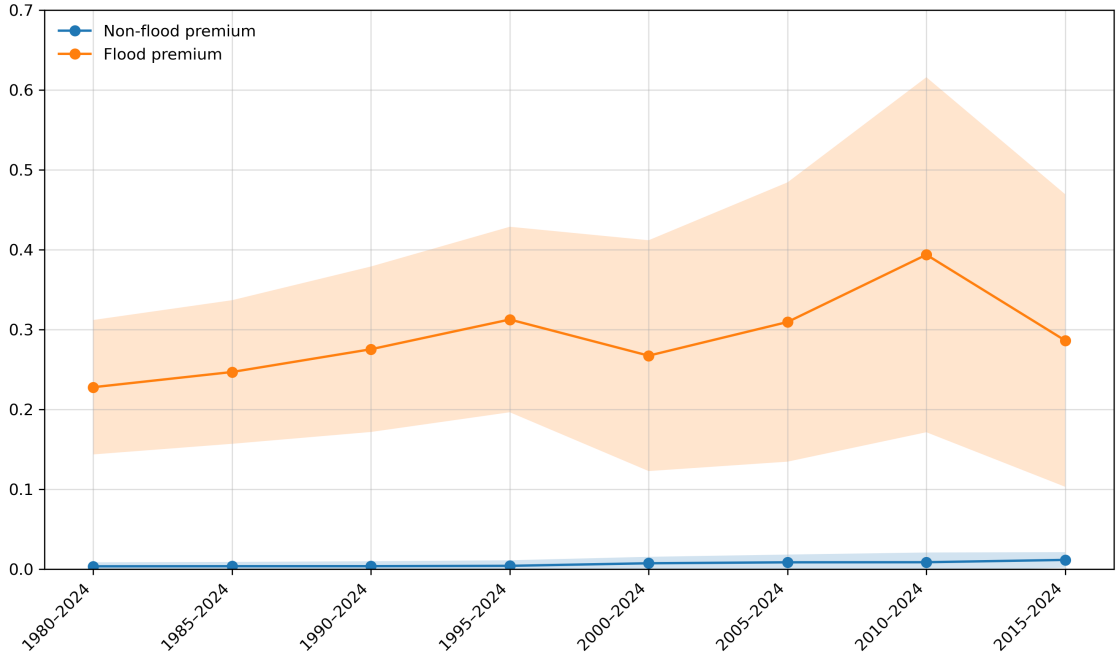



**Figure 5:** Expanding-window estimates of actuarially fair premiums in flood and non-flood zones based on WLS regressions, with 95 percent confidence intervals.

*Note:* Estimates are based on weighted least squares (WLS) regressions of municipal loss ratios on the share of insured value located in flood zones, using expanding windows that successively extend the sample backward in time. The estimate based on the full sample period corresponds to the main results reported earlier in the paper, while shorter windows rely on more recent observations. The estimate for 2015–2024 reflects the most recent decade of losses. This approach is motivated by the upward trend in insurance payouts over time, which makes it non-trivial to determine which time period best approximates expected losses. Premiums are expressed in per mille of insured value, and confidence intervals are heteroskedasticity-robust (HC3).

increasing mismatch between observed damages and mapped flood risk. As a result, the ratio between flood and non-flood premiums is lower when estimated over short horizons and higher when longer historical periods are used.

Figure 6 compares the estimated flood-zone premium to the national uniform flood premium, where the latter reflects a weighted average of flood and non-flood premiums. The figure shows that this ratio declines when the estimation window is restricted to recent years. This pattern is consistent with the expanding-window results in Figure 5, which indicate that both the flood and non-flood premiums increase in short windows, but the increase is larger outside the mapped flood zones. As a result, the national benchmark premium rises more quickly than the flood-zone premium, leading to a lower ratio in the most recent windows.

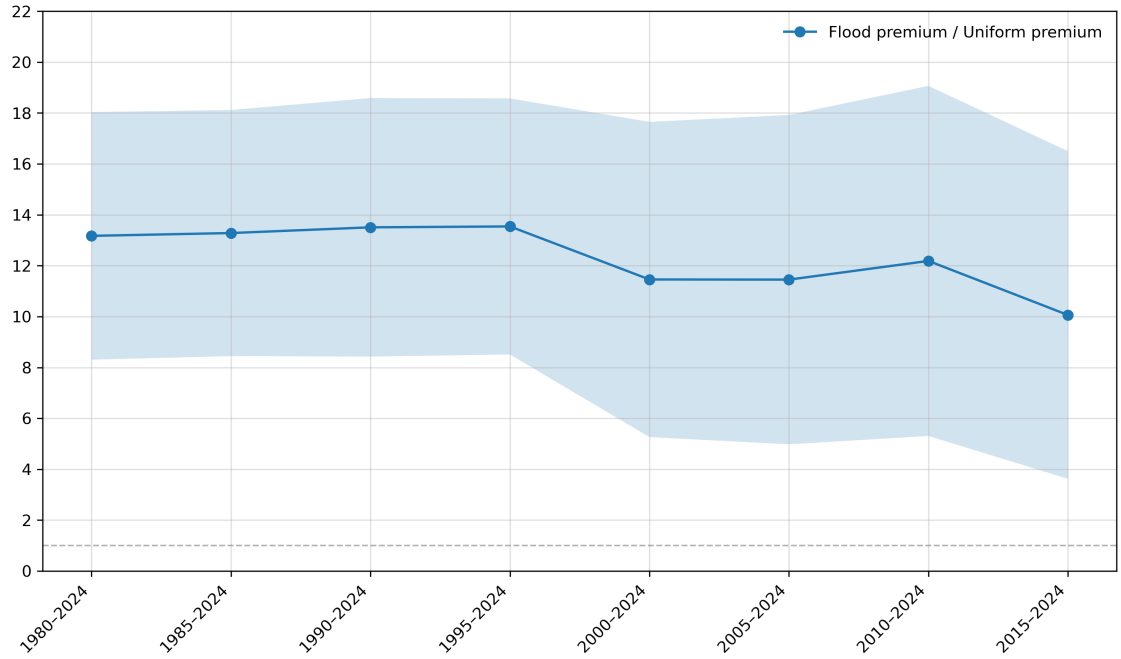



**Figure 6:** Flood vs national flood premium ratio ($\hat{\rho}^r / \hat{\rho}^{(flood)}$)

*Note:* Ratios are obtained from expanding-window WLS regressions. The y-axis shows how many times higher the estimated flood premium is relative to the national household flood premium computed within each estimation window. The x-axis lists the window endpoints, where the rightmost point corresponds to 2015–2024 and each preceding point adds ten earlier years until reaching the full sample 1980–2024 used in the main analysis. Premiums are expressed in per mille of insured value.

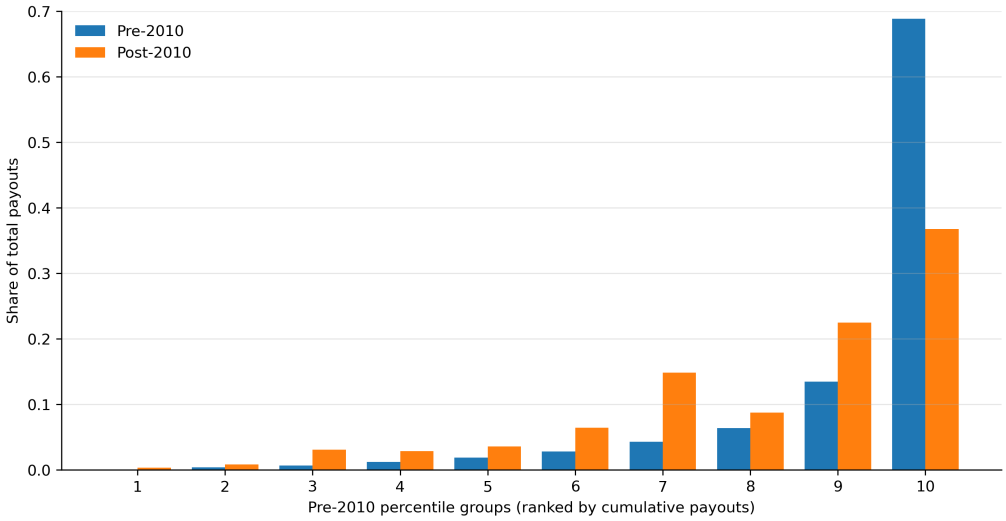
Taken together, this exercise shows that the estimated premiums in risk and non-risk zones are sensitive to the period used to approximate expected losses. This sensitivity provides useful insight into how climate-related risks and cross-subsidies may evolve going forward. Climate change is expected to increase the frequency and severity of extreme weather events. If weather patterns also become more

unpredictable, damages may increasingly occur outside designated flood zones. In that case, the relative disadvantage of being located inside a risk zone would diminish, implying smaller subsidies. Conversely, if losses become increasingly concentrated in high-hazard areas, subsidies could persist or even expand.

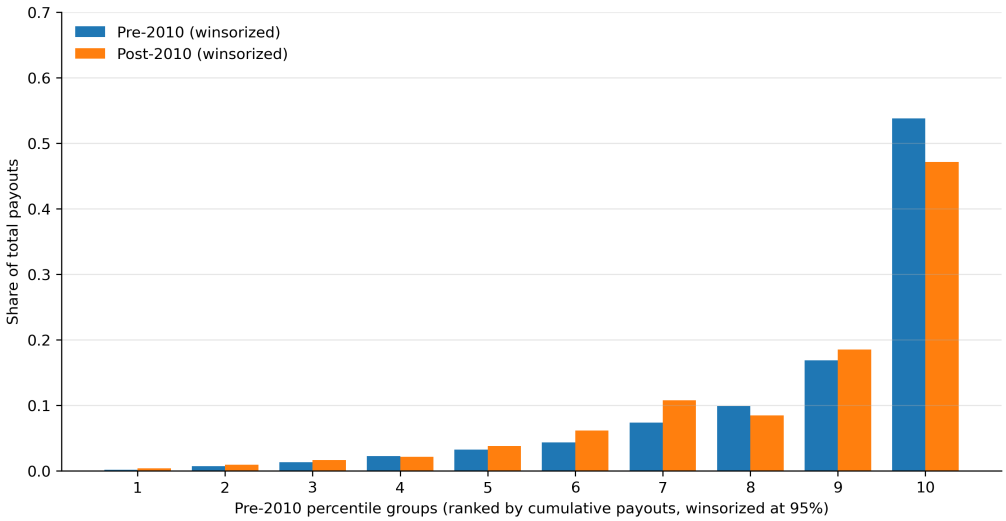
The analyses above focus on how estimated premiums and the degree of cross-subsidization vary depending on the time period used to approximate expected losses. A complementary question is whether the spatial distribution of losses across municipalities has changed as aggregate losses have increased. To examine this, I rank municipalities by the total value of their flood insurance payouts before 2010 and divide them into ten percentile groups based on this ranking. These groups (deciles 1–10) are then held fixed when comparing each group's share of total payouts before and after 2010, as shown in Figure 7. This approach captures whether the spatial concentration of losses has changed over time. The year 2010 serves as a natural break, as average annual payouts have been markedly higher in the post-2010 period (see Figure 4), and Finance Norway has highlighted this year as the onset of a period with substantially higher natural peril losses.

I also apply winsorization at the 95th percentile within each municipality to reduce the influence of extreme years in individual municipalities. This adjustment removes municipality-specific outliers without imposing a uniform national cutoff and thus provides a way to assess whether observed spatial patterns are driven by the large events.

Without winsorization (Figure 7a), the distribution shifts somewhat. Once extreme values are winsorized at the 95th percentile (Figure 7b), however, the pre- and post-2010 distributions become more similar. These patterns may indicate that the recent increase in payouts is largely driven by extreme events occurring in new locations, rather than by a systematic shift in where smaller and more frequent losses occur. This could indicate that while ordinary flood damages remain geographically stable, large disasters are more irregular in their spatial occurrence and strike somewhat more randomly. A deeper examination of the drivers behind these extreme events, and their spatial patterns, lies beyond the scope of this paper but represents an important topic for future research.




**(a)** Pre vs. post 2010 shares by pre-2010 percentiles (original).




**(b)** Pre vs. post 2010 shares by pre-2010 percentiles (winsorized at 95%).

**Figure 7:** Municipal distribution of flood insurance payouts before and after 2010. Panel (a) uses original payouts data; panel (b) uses per-municipality winsorization at the 95th percentile.

*Note:* The figure shows the distribution of flood insurance payouts across municipalities by percentile groups, based on data for the period 1980–2024. The x-axis displays pre-2010 percentile groups (1–10) ranked by cumulative payouts, i.e., the total amount each municipality received before 2010. The y-axis shows each group's share of total payouts. Blue bars represent the pre-2010 period and orange bars the post-2010 period. Panel (a) compares pre- and post-2010 shares using original data, while panel (b) presents the same comparison after winsorizing payouts at the 95th percentile within each municipality.

# 7 Risk-Driven Adaptation

Another factor influencing the scale of cross-subsidies is how local authorities respond to climate risk. Uniform pricing distorts price signals about underlying risk, and this also applies to municipalities, whose buildings and other physical assets are insured under the same scheme. However, local governments carry a particular responsibility for land use policy and climate adaptation, and municipalities in high-risk areas may therefore still invest in protective measures. If these measures are effective, expected future losses may decline, potentially lowering the actuarially fair premium in risk zones and narrowing the gap between the estimated actuarially fair premiums in risk and non-risk areas.

### Data and Variable Description

To assess whether municipalities facing higher flood hazard also undertake more adaptation, I draw on data from Norwegian Climate Monitor[13]. The dataset, described in detail in Rød et al. (2024), follows the Intergovernmental Panel on Climate Change (IPCC) framework for assessing climate risk, and provides harmonized indicators of *hazard* (geographic exposure to natural perils), *exposure* (the concentration of assets in risk-prone areas), *vulnerability* (socioeconomic susceptibility to damage), and *response* (local adaptation efforts) for all Norwegian municipalities. All indicators are scaled 0–100 to facilitate comparability.

A key feature of this framework is the explicit separation between hazard and exposure. Hazard is defined as the underlying physical risk, such as the modeled probability and intensity of floods. This is therefore a purely geographic measure, independent of whether people or assets are present. Exposure, by contrast, reflects the extent to which values and populations are located in areas subject to these hazards. In this dataset, exposure is measured through historical insurance payouts in NOK, which implies that the indicator is not adjusted for municipality size, such that larger municipalities will, to some extent, mechanically appear more exposed.

The analysis in previous sections differs in that it relies on two alternative measures that essentially combine these two dimensions. The share of insured value inside flood zones, $f_i$, which is the regressor in the above analysis, utilizes both information on hazard maps and property locations. It is best interpreted as an *ex ante* measure of risk, indicating how much of the built environment is potentially

[13]Norwegian Climate Monitor is a coordinated data collection effort across sectors of society, designed to provide a systematic overview of both climate adaptation measures and attitudes toward adaptation. It is organized by The Norwegian Research Centre on Sustainable Climate Change Adaptation (Noradapt).

at risk. Average payouts per unit of insured value $\bar{X}_i/S_i$, the outcome variable, is instead an *ex post* outcome measure. Unlike the regressor, it reflects not only hazard and exposure but also vulnerability and adaptation, since it measures the intensity of damages that have actually materialized.

The response indicators of local adaptation efforts are constructed from surveys and administrative records[14]. These capture the extent to which municipalities integrate climate risk into planning, mobilize resources, implement organizational and physical measures, and coordinate adaptation across sectors. The index is not scaled for municipal capacity, which means that larger municipalities tend to score higher than smaller ones, most likely because of larger budgets and greater administrative capacity.

I also supplement the Climate Monitor indicators with municipal financial and demographic data from Statistics Norway. Municipal net operating margin as a percent of gross operating revenues and free revenues per capita, defined as the sum of local tax revenues and block grants, are included as control variables to capture fiscal capacity and budgetary space for adaptation. In addition, I use population size and population per $km^2$ to account for differences in scale and population density, which may affect both vulnerability and the incentives and capacity to undertake adaptation efforts.

### Empirical Approach and Results

A natural and transparent starting point for assessing risk-driven adaptation is to estimate a simple OLS model relating municipal adaptation efforts, as measured by the response index described above, to physical flood hazard, as measured by the hazard index. Flood hazard is determined by natural and hydrological conditions and can therefore be viewed as predetermined with respect to present-day adaptation efforts. By contrast, payout-based measures such as the exposure index are more likely to suffer from simultaneity: municipalities may adapt precisely because they have experienced high damages, while effective adaptation in turn reduces subsequent losses. These simultaneity issues imply that coefficients on payout-based variables are difficult to interpret.

Table 5 summarizes the main specifications. Across all specifications, the coeffi-

[14]Response indicators measure local adaptation efforts across four domains:
(i) integration of climate risk into planning (The Norwegian Directorate for Civil Protection surveys 2018–2023), (ii) mobilization of resources through grant applications and awards (Norwegian Environment Agency 2015–2023), (iii) implementation of organizational and physical measures (Norwegian Climate Monitor surveys 2021 and 2024), and (iv) cross-sector integration and long-term orientation (Norwegian Climate Monitor surveys 2021 and 2024).

**Table 5:** Determinants of municipal adaptation efforts.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Flood hazard | 0.339** | 0.364** | 0.319*** | 0.316*** | 0.281** |
| *index* | (0.132) | (0.127) | (0.120) | (0.118) | (0.112) |
| Population density | | 0.714*** | 0.609*** | 0.509*** | |
| *index* | | (0.082) | (0.101) | (0.130) | |
| Population | | | | | 0.117 |
| *in 1,000s* | | | | | (0.092) |
| Flood exposure | | | | 2.540 | |
| *index* | | | | (2.688) | |
| Net operating margin | | | 0.230 | 0.225 | 0.206 |
| *in percent* | | | (0.172) | (0.172) | (0.170) |
| Free revenues | | | −1.782* | −1.832* | −2.642** |
| *in 10,000s* | | | (0.987) | (1.030) | (1.133) |
| Constant | 23.07*** | 10.44 | 29.29** | 30.75** | 46.27*** |
| | (7.81) | (7.72) | (12.95) | (13.43) | (13.18) |
| Observations | 356 | 356 | 356 | 356 | 356 |
| $R^2$ | 0.019 | 0.191 | 0.214 | 0.220 | 0.199 |

*Notes:* The dependent variable is the municipal response index from Norwegian Climate Monitor Rød et al. (2025), which measures the extent of adaptation efforts undertaken by municipalities. Flood hazard (*fFlom2000_0_100*), population density (*sBefTett2000_0_100*), and flood exposure (*eFlom2000_0_100*) are from the same source, and provide standardized municipal indices of flood hazard, exposure, and adaptation efforts. Municipal data on net operating margin as percent of gross operating revenues and free revenues per capita (Table 12134), together with population size (Table 11342), are obtained from Statistics Norway. All specifications are estimated using ordinary least squares (OLS) with heteroskedasticity-robust (HC3) standard errors reported in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

cient on the hazard index is robustly positive and statistically significant, but the explanatory power of hazard alone is very limited ($R^2 = 0.02$). This is shown in Column (1), which reports the baseline regression of municipal adaptation efforts on modeled flood hazard. The estimated coefficient is positive and significant at the 1 percent level, indicating that municipalities exposed to higher flood hazard tend to report more extensive adaptation efforts, but that hazard alone accounts for only a small share of the variation across municipalities.

Column (2) adds a control for population density, which enters strongly positive and highly significant. The inclusion of this variable increases the explanatory power substantially ($R^2$ rises from 0.02 to 0.19) while leaving the hazard coefficient largely unchanged, suggesting that both factors capture important dimensions of adaptation activity. Population density is part of Climate Monitor's vulnerability index, reflecting the idea that densely populated municipalities are more vulnerable because extreme events can affect a larger number of people and assets. As a robustness check, I replace the population density index with Statistics Norway's

official measure of population per km$^2$. The results are similar: the coefficient remains positive and strongly significant.

Column (3) further adds controls for the municipality's net operating margin and free revenues per capita. The coefficient on free revenues is negative and statistically significant, indicating that municipalities with higher per capita revenues tend to report fewer adaptation efforts. This pattern may reflect that municipalities with higher free revenues per capita have less need to rely on external funding schemes covered by the Climate Monitor's adaptation measure. Conversely, municipalities facing tighter budget constraints may be more active in applying for state or regional support, which in turn increases the likelihood that such efforts are recorded as formal adaptation initiatives.

Column (4) adds the payout-based exposure index. This variable is statistically insignificant but difficult to interpret due to simultaneity issues. However, its inclusion does not meaningfully affect the coefficients on hazard or population density.

Finally, Column (5) replaces the population density measure with the population size. The estimated coefficient remains positive but is no longer statistically significant. Population density – rather than population size per se – is conceptually closer to the vulnerability dimension in the IPCC framework and emphasized as an important determinant of climate risk (Rød et al., 2025).

In essence, this analysis was motivated by the question of whether cross-subsidies in the near future may be offset by preventive action undertaken at the municipal level. If riskier municipalities systematically adapt more, the efficiency costs of cross-subsidies may be smaller, as part of the increased risk is offset by preventive measures. Conversely, if adaptation does not respond strongly to hazard exposure, cross-subsidies become more distortionary, as they mask underlying risk without inducing compensating investments.

The results indicate that adaptation is positively associated with modeled hazard, but the effect is modest and accounts for only a small share of the variation across municipalities. A one-point increase in the hazard index is associated with roughly a 0.4-point higher score on the response index capturing adaptation efforts. This effect is statistically robust, yet the low overall $R^2$ suggests that much of the variation in adaptation is driven by other factors. For instance, population density is strongly significant and markedly improves explanatory power, suggesting that such underlying vulnerability may be more decisive for adaptation efforts than risk exposure itself. Free revenues, in turn, are negatively associated with adaptation, possibly reflecting that municipalities with greater fiscal autonomy have less need

to rely on external funding schemes captured by the Climate Monitor's adaptation measure. If so, this pattern also highlights the difficulty of accurately measuring adaptation efforts: the response index may not perfectly reflect the full scope of local preventive actions, particularly those financed from municipalities' own budgets.

# 8 Conclusion

This paper quantifies the cross-subsidies arising from flood risk in Norway's natural perils insurance scheme, which applies a uniform premium irrespective of location-specific risk. Using detailed data on property-level exposure combined with municipal insurance payouts, I estimate actuarially fair premiums under a two-tier risk-based scheme. The results imply that the fair premium in flood-exposed areas would be about 13 times higher than the current uniform premium and roughly 65 times higher than in non-flood zones, although the latter ratio is subject to substantial uncertainty. These cross-subsidies generate sizeable implicit transfers from low-risk to high-risk households and weaken price signals related to climate risk.

The estimated premiums and thus the magnitude of cross-subsidies depend on the time horizon used to approximate expected losses. In the expanding-window analysis, shorter windows dominated by recent costly events yield higher premiums in both flood and non-flood zones, consistent with the marked rise in insurance payouts over the 1980–2024 period. This pattern points to greater uncertainty about where flood damages occur. If weather becomes increasingly unpredictable, this strengthens the case for solidarity-based pricing, which, in a Rawlsian perspective, can be interpreted as insurance against exposure to unpredictable hazards. However, if losses become increasingly concentrated in high-risk zones, the degree of cross-subsidization may persist or even intensify.

In Norway, municipalities have primary responsibility for land-use planning and climate adaptation. I find that municipalities facing greater hazard exposure undertake somewhat more adaptation efforts, but the association is modest. Differences in adaptation are more strongly related to population density, and thus to the number of people and assets at risk, than to physical hazard exposure alone.

From a policy perspective, the analysis highlights a trade-off between distribution and efficiency. Uniform pricing promotes broad access and equality but can weaken incentives for mitigation and distort location choices if it masks large differences in risk. As climate impacts intensify, these distortions may become more pronounced. Future reforms could introduce targeted incentives for adaptation or hybrid schemes that preserve solidarity while moving partially toward risk-based pricing.

The findings also contribute to broader debates on the design of climate risk insurance. Interest is growing in coordinated EU approaches. While institutional contexts vary, the Norwegian case illustrates both the distributional costs of uniform pricing and the broader challenge of balancing efficiency, resilience, and solidarity in natural perils insurance.

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# Appendix

## A1 Spatial Dependence

To test for spatial autocorrelation in the regression residuals, I compute Moran's I using a queen-contiguity spatial weights matrix. I find modest, but positive and significant spatial dependence: the Moran's I statistic for the OLS residuals is 0.0924 (p-value = 0.016), suggesting that model errors are spatially clustered: municipalities with higher-than-predicted payouts tend to be located near other municipalities with similar patterns.

To account for spatial dependence in the regression residuals, I estimate a spatial error model (SEM), which captures unobserved spatially correlated factors through the error term. In this specification, the spatial autocorrelation parameter is estimated at 0.04, and both coefficients remain significant: $\hat{\rho}^n = 0.0163$ and $\hat{\rho}^r = 0.2694$, see Table A1.1. This suggests a persistent and economically meaningful difference in premiums between flood and non-flood zones, also after accounting for spatial structure. Moreoever, the SEM specification effectively removes spatial autocorrelation in the residuals: Moran's I drops from 0.0924 in the OLS model to 0.0006 with a p-value of 0.35, indicating that the spatial error correction captures the omitted spatial structure.

**Table A1.1:** Spatial Error Model (SEM) Regression (‰ units)

| | $\beta_0 = \rho^n$ | $\beta_1 = \rho^r - \rho^n$ | Implied $\rho^r$ |
|---|---|---|---|
| | $0.0163^{***}$ | $0.2535^{***}$ | $0.2694^{***}$ |
| | (0.0060) | (0.0963) | (0.0922) |
| Spatial parameter $\lambda$ | | 0.041 | |
| Moran's $I$ (residuals) | | 0.0006 | |
| Obs | | 357 | |
| Pseudo $R^2$ | | 0.164 | |

*Notes:* All coefficients and standard errors are reported in ‰ (per thousand NOK of insured value). Heteroskedasticity-robust standard errors in parentheses. Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Moran's $I$ computed on spatially filtered residuals.

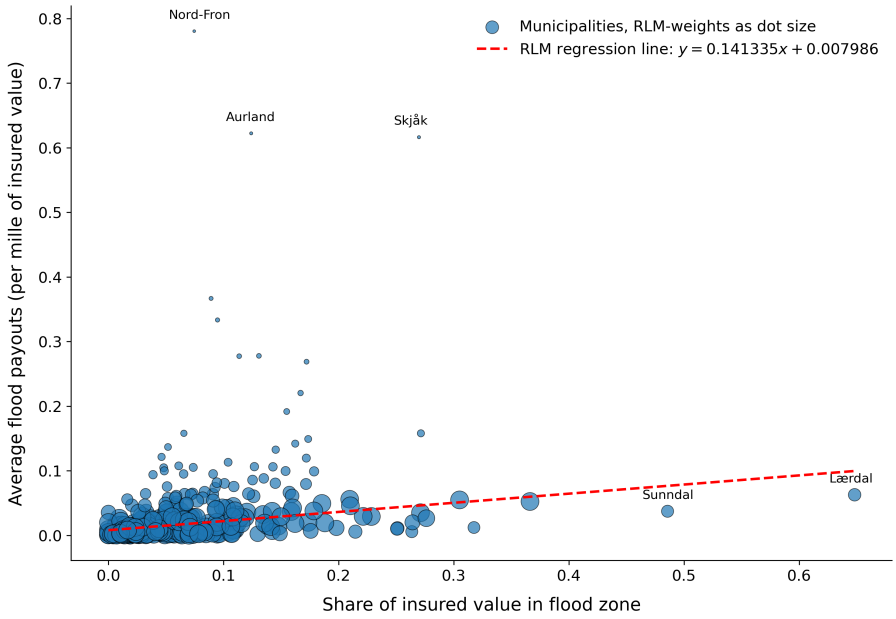
For robustness, I also estimate a spatial autoregressive model (SAR), which allows for direct spillovers across neighboring municipalities. While the coefficients are similar, the SAR model is less theoretically appropriate in this context, as there is little reason to expect that insurance payouts in one municipality in themselves would causally affect those in adjacent areas. For this reason, I focus on the SEM.

# A2 Robust Linear Regression Results

**Table A2.1:** RLM Huber T results for different tuning constants $t$

| $t$ | $\hat{\beta}_0 = \hat{\rho}^n$ | $\hat{\beta}_1 = \hat{\rho}^r - \hat{\rho}^n$ | Implied $\hat{\rho}^r$ | Ratio $\hat{\rho}^r/\hat{\rho}^n$ |
|---|---|---|---|---|
| 0.8 | 0.006 | 0.144 | 0.150 | 24.7 |
| 1.0 | 0.007 | 0.142 | 0.149 | 22.0 |
| 1.2 | 0.007 | 0.141 | 0.149 | 20.1 |
| 1.345 | 0.008 | 0.141 | 0.149 | 18.7 |
| 1.5 | 0.009 | 0.141 | 0.150 | 17.3 |
| 2.0 | 0.011 | 0.146 | 0.156 | 14.8 |
| 2.5 | 0.012 | 0.154 | 0.166 | 14.0 |
| Mean | 0.008 | 0.144 | 0.153 | 18.8 |
| Median | 0.008 | 0.142 | 0.150 | 18.7 |

*Notes:* Estimates are obtained from robust linear models with Huber's T loss function for different values of the tuning constant $t$. Reported coefficients are in ‰. $\rho^n$ corresponds to the actuarially fair premium in non-flood zones, while $\beta_1 = \rho^r - \rho^n$ measures the additional loss ratio for properties in flood zones. The implied actuarially fair premium in flood zones is given by $\rho^r = \rho^n + (\rho^r - \rho^n)$, and the last column reports the ratio of the implied flood-zone premium to the non-flood premium, $\rho^r/\rho^n$.




Robust Linear Model (RLM)

**Figure A2.1:** Robust Linear Model (RLM) with default Huber T weighting (t=1.345).

*Note:* Each dot represents one municipality. The vertical axis shows the loss ratio per municipality, defined as average historical insurance payouts due to floods over the full sample period divided by total insured value. The horizontal axis shows the share of insured value located within mapped flood zones. Bubble size reflects the relative weight assigned to each municipality. The dashed line indicate the estimated regression fit.