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Curriculum Vitae

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Current Appointments

2020 – today	Ph.D. Candidate in Economics, BI Norwegian Business School. Thesis: *Essays in Economic Resilience: Petroleum Displacement, Climate Shocks and Insurance Markets*
2015 – today	Senior Economist, Monetary Policy Department, Norges Bank

Past Appointments

2013 – 2015	Summer Intern & Master Thesis Student, Norges Bank
2013 – 2015	Teaching Assistant, Norwegian University of Science and Technology
2013 – 2014	Volunteer in Microfinance, Alliance Microfinance AS (Guayaquil, Ecuador)
2012	Summer Intern, Norwegian Water Resources and Energy Directorate

Education

2020 – today	Ph.D. in Economics, BI Norwegian Business School
2010 – 2015	M.Sc. in Economics, Norwegian University of Science and Technology Thesis: *Monetary policy in commodity exporting countries*
2009 – 2010	Intercultural Communication, MF Norwegian School of Theology
2006 – 2009	Kristelig Gymnasium, High School (specialization in mathematics, physics, economics)

Research Interests

Applied Macroeconomics, Climate Economics, Insurance Markets, Labor Economics, Monetary Policy

Research

Working Papers

2022	"Lost in transition? Earnings losses of displaced petroleum workers" (with Jon Ellingsen), *CAMP Working Paper Series* 06/2022

Work in Progress

2025	"Weathering the Storm: The Effects of Natural Disasters on Households under Universal Insurance" (with Sigurd M. Galaasen, Emilia Garcia-Appendini and Mathis Mæhlum)
2025	"One Price Fits All? Implicit Subsidies in Uniformly Priced Natural Perils Insurance" (single-author)

Presentations

2025	NYU Stern Summer Climate Finance Conference (PhD Poster Session); CEPR Climate Change and the Environment Symposium; Bank of Canada, Bank of Italy, BI CAMP "Applied Macroeconomics in a Changing World"; NBER PhD Student Workshop and Climate Finance Conference
2024	Fagkonferansen, Norges Bank

Teaching Experience

2021–2025	Teaching Assistant, BI Norwegian Business School: GRA6631 Economic Policy; GRA6639 Business Cycles and Monetary Policy; GRA6665 Environment and Sustainable Development
2016–2018	Guest Lecturer, Norges Bank Teaching Initiative: Macroeconomics and Monetary Policy at the Norwegian University of Life Sciences, the Norwegian University of Science and Technology, and the University of Stavanger
2013–2015	Teaching Assistant, Norwegian University of Science and Technology: SØK3001 Econometrics I; SØK3003 Advanced Macroeconomic Analysis; SØK1012 Macroeconomic Analysis

Professional Activities

2025 – today	Member, Young Scholar's PhD Committee, The E-Axes Forum
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2012 – 2013	Chair, Student Organization *Econnect NTNU*

Media and Outreach

2025	"Ekstremvær kan skape den neste finanskrisen", op-ed in *Dagens Næringsliv*, July 2, 2025
2025	"Økonomene må snakke så folk forstår dem", op-ed in *Dagens Næringsliv*, Feb 16, 2025
2024	"Når ulikhet former demokratiet", op-ed in *Dagens Næringsliv*, Oct 23, 2024
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Other Information

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One Price Fits All? Implicit Subsidies in Uniformly Priced Natural Perils Insurance*

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Preliminary draft. Please do not circulate.

Abstract

This paper quantifies implicit 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 loss ratios inside and outside high-risk areas. The results show that uniform pricing leads to substantial redistribution, implicitly subsidizing high-risk properties. Focusing on flood risk, I find that the actuarially fair premium in flood zones would be 16-21 times higher than in non-flood zones. These large cross-subsidies may be an impediment to effective adaptation to climate change. 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:
Keywords: Climate Economics, Insurance Markets, Natural Disasters

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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 climate-related risks. While this system promotes collective responsibility, it also generates cross-subsidization: homeowners in high-risk areas effectively receive an implicit subsidy, whereas those in low-risk areas pay premiums that exceed their actuarially fair levels.[1] These implicit transfers may distort household 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. Moreover, as climate change increases the frequency and severity of weather-related hazards (IPCC, 2023), the magnitude of these implicit subsidies and their behavioral consequences may grow over time.

In this paper, I quantify the size of implicit subsidies by comparing the insurance premiums currently paid by households to the actuarially fair premiums that would accurately reflect location-specific natural hazard risk. The paper focuses on three central questions. First, to what extent are properties in high-risk areas subsidized, measured by the gap between actuarially fair premiums in risk and non-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, to what extent do municipalities in high-risk areas engage in preventive adaptation, and can such responses mitigate the efficiency loss from implicit subsidies?

To study implicit subsidies in the current insurance scheme, I use a dataset covering all residential properties[2] in Norway, including detailed geographic coordinates for each unit. For every property, I determine the insured value, which by industry standard corresponds to the full replacement cost. This 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) to assess, at the individual property level, whether each property

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

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

is located inside or outside a designated risk zone.

For tractability, I focus on flood risk in the current analysis. Floods are among the most costly natural hazards in Norway, accounting for about one-third of all historical insurance payouts (Table 1 in Section 3). Moreover, and crucially, they are the most systematically mappable with available hazard zone designations. By contrast, storm damage, though larger in aggregate, is likely less geographically predictable, while detailed maps for landslides and storm surges remain more limited. Flood risk is therefore a natural starting point, with the same approach extendable to other hazards in future work.

To estimate expected losses, I use municipality-level data on insurance payouts for natural hazards under household policies, covering the period from 1980 to 2024. From this dataset I extract the subset of payouts related to floods, consistent with the focus of this analysis. Because the insurance payout data is 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 loss ratios for properties inside and outside mapped flood zones, where a loss ratio is defined as expected losses relative to insured value. Because loss ratios correspond to actuarially fair premium rates, these estimates can be interpreted as implied insurance premiums by risk zone.

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. Indeed, I estimate the national loss ratio at 0.09 per mille, while the 2025 premium rate is 0.08 per mille. To assess whether properties in low-risk areas implicitly subsidize those in high-risk areas, I benchmark the estimated loss ratios across risk zones against this uniform premium. In addition, I examine the ratio of loss ratios between 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 16–21 times higher than for properties outside these zones. 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 1,250 NOK (120 USD), compared to around 150 NOK (14.4 USD) under the current uniform flood rate. This sizable gap illustrates the extent to which the current system redistributes costs, with lower-risk households contributing more than their expected share to cover flood-related losses in high-risk zones.

The next part of the analysis examines how implicit subsidies have evolved over time. I estimate loss ratios in rolling windows, to illustrate how sensitive the results can be to the timing of extreme events. Short windows are particularly volatile, as a single large flood can dominate the estimates. Yet they are also a poor proxy for expected losses, since windows dominated by either rare extremes or long periods without events do not approximate expectations. Longer windows, which better capture expected losses, reveal a persistent upward trend in loss ratios in both flood and non-flood areas. As a result, the ratio of loss ratios between the two zones has remained relatively stable. Nevertheless, the gap between flood and non-flood zones remains substantial. Across specifications with rolling windows of ten years or more, the implied premium in flood zones is on average over twenty times higher than the implied premium in non-flood zones.

Historical patterns also 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 implicit subsidies. Should damages increasingly occur outside designated flood zones, the relative disadvantage of being located within a mapped risk zone would diminish. Conversely, if losses continue to be concentrated in high-hazard zones, the degree of cross-subsidization may persist or even intensify.

Finally, the paper investigates whether municipalities in hazard-prone areas undertake more adaptation, drawing on systematic indicators from the Norwegian Climate Monitor. This dataset follows the IPCC framework for climate risk, providing information on hazard, exposure, vulnerability, and adaptation efforts for all Norwegian municipalities. This makes it possible to assess whether hazard drives protective adaptation efforts. The analysis shows 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. Broader factors such as municipality size and the resources available for planning and implementation are likely more important. Taken together, these findings suggest that while hazard-prone municipalities adapt somewhat more, the effect is limited, and implicit subsidies are unlikely to be substantially reduced through risk-driven adaptation.

Understanding and quantifying implicit subsidies in a natural perils insurance scheme with uniform pricing is important for several reasons. First, 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. Second, by masking underlying differences in risk, implicit subsidies shape housing market valuations. As long as uniform insurance coverage is guaranteed, higher prices in high-risk areas may appear justified. However, insurance against direct physical damages does not eliminate all costs of natural hazards. Disasters can also generate non-financial consequences, such as on mortality and health (Frankenberg et al., 2020), and broader indirect effects when local businesses, infrastructure, and services are disrupted (Hallegatte, 2015). Moreover, increased uncertainty about future risks can weigh on the attractiveness of affected areas. Evidence from Norway illustrates this: Kivedal (2023) document long-run negative effects of avalanches on property values, and Espegren et al. (2025) show that natural disasters have a persistent and negative effect on household housing wealth. Over time, these effects may become increasingly prevalent as climate impacts intensify. If abrupt repricing of high-risk properties occurs, this may amplify vulnerabilities in banks' mortgage portfolios and pose risks to financial stability.

This paper also relates to an ongoing policy dialogue on the design of natural perils insurance schemes under increasing climate risks. 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 sheds light on the distributional costs of uniform pricing in natural perils insurance and offers 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 implicit subsidies embedded in the current system. Section 6 analyzes how implicit 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. 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 et al., 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).

Several mechanisms explain why catastrophe insurance departs from standard insurance markets. A 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).

Unlike the classic case of adverse selection (Rothschild and Stiglitz, 1978; Akerlof, 1978), 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 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 if not evident or credible to policyholders (Mulder and Kousky, 2023).

Rising climate risk provides a real-world test of the insurability of catastrophes (Glendon et al., 2025). In several countries, insurers have raised premiums or withdrawn from high-risk areas (Kaufman et al., 2024; The Economist, 2024). Increases in premium affect household behavior, raising mortgage delinquency risks and accelerating migration away from exposed areas (Ge et al., 2025). At the same time, many households underinsure because actuarially fair premiums exceed what they can afford (Sastry et al., 2024). These findings highlight that the main challenge is not necessarily risk measurement but the affordability of coverage under increasing hazards.

Institutional arrangements for insuring natural perils vary considerably across countries. Some rely primarily on private markets (UK, Sweden, USA), while others combine private insurance with state-backed reinsurance or compensation schemes (France, Spain, Iceland, Switzerland). In a third group, government-supported schemes remain under development (Denmark, Finland, Netherlands, Taiwan). Within this landscape, Norway represents a notable case, combining mandatory private insurance with a supplementary state compensation scheme. 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, which underpins the uniform premium rate, secures universal access and administrative simplicity but weakens incentives for prevention and efficient location choices. Similar trade-offs appear in hybrid schemes in France, Spain, and Iceland, where private insurance is combined with public reinsurance.

Many empirical studies focus on risk-based insurance schemes such as in the United States, while little is known about the magnitude and consequences of implicit subsidies in solidarity-based schemes. Norway's model therefore offers a useful case to examine 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 is automatically covered for natural perils, including floods, landslides, and storms. Because mortgage lenders require homeowners to hold property insurance, which in turn includes fire coverage, virtually all residential properties are insured. Combined with the industry standard of writing policies at full replacement value, these features make coverage effectively universal.

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 between total inflows and outflows, that is, to be actuarially fair at the national level. Excess revenues accumulate as natural perils capital within each company, and this capital is used to offset future losses. 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 of roughly 350 NOK (about 33 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, many households inherit property, and local housing and labor markets restrict mobility. What appears inefficient under actuarial principles may therefore also be interpreted as 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 broader 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 analysis combines detailed microdata on residential properties with spatial risk exposure and municipal insurance payout data. The housing unit dataset is sourced from Eiendomsverdi and covers all 2.6 million private residential dwellings in Norway as of 2024, including both primary residences and secondary homes. Each unit corresponds to a separately insured dwelling, meaning that semi-detached houses and apartments are counted individually rather than as a single building. The dataset also contains information on estimated market value, size, and other key characteristics. Using data from the Norwegian Mapping Authority, each property

is assigned precise geographic coordinates, which allows for spatial analysis of exposure to natural hazards.

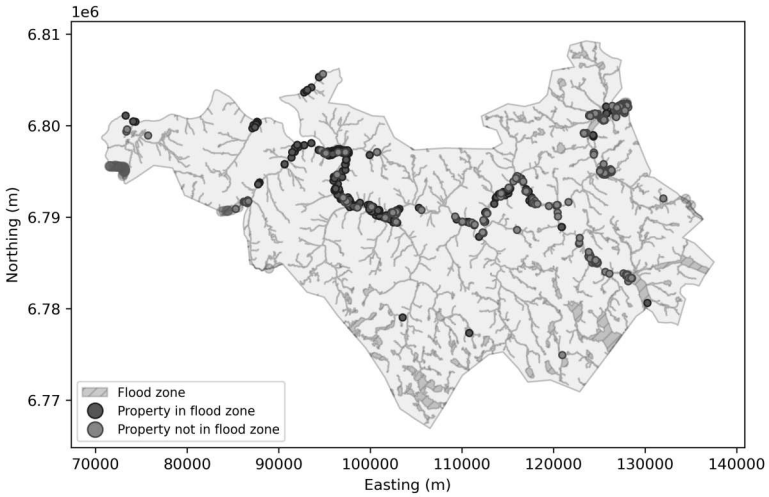
To determine whether a property is located in a high-risk zone, I combine this geospatial information with official hazard zone maps from the Norwegian Water Resources and Energy Directorate (NVE). These maps define risk zones for flooding, landslides (including quick clay areas), and storm surges. By overlaying property locations with these zones, I identify which properties are exposed to each type of 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 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, with individual properties plotted as points and colored according to whether they fall inside (red) or outside (green) a flood zone. The figures thus combine both the hazard-zone data and the property-level insurance data used in the empirical analysis.

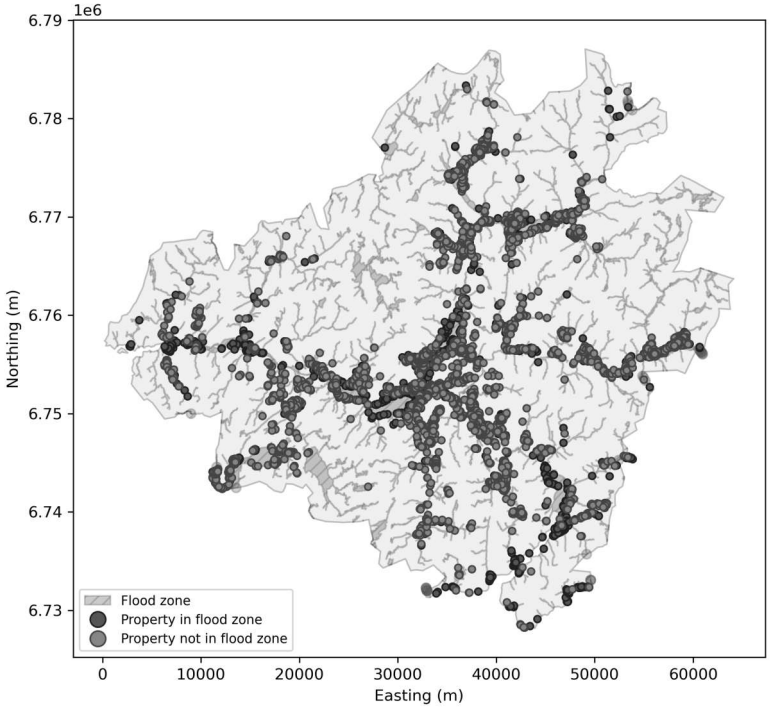
To calculate the insured value of each property, I apply standardized valuation tables provided by the Norwegian Natural Perils Pool (Norsk Naturskadepool)[3]. These tables are used by non-life insurance companies and property firms to estimate and update the replacement value of buildings, contents, 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.

The historical loss data is sourced from Finance Norway, which provides a complete record of insurance payouts for natural perils across all 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 exclusively on household policies. The ability to separate losses by hazard type is also central for this study. For the present analysis, I use the subset

[3]The standardized valuation tables can be found here.



(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 the risk zones (green color), for the municipalities of Lærdal (a) and Voss (b).

Note: All spatial coordinates refer to the EUREF89 / UTM Zone 33N coordinate reference system (EPSG:25833).

of payouts caused by flood events to calculate municipal-level loss ratios.

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.

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

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

Table 2 reports average within-municipality correlations between flood payouts and payouts from other perils. When focusing on floods, the analysis measures the implicit subsidies embedded in flood insurance. Since the insurance scheme also covers other natural hazards, an important question is how the flood results inform the magnitude of total subsidies. To evaluate this, one must consider whether flood damages covary with damages from other perils. Positive correlations would suggest that the flood-based estimates understate the extent of cross-subsidization, as high-risk municipalities are also more exposed to other hazards. Negative correlations would instead imply offsetting patterns across perils, making the overall subsidy problem smaller.

Table 2: 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

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.

The correlations are positive but modest in magnitude, and highest for storm surges. A similar pattern holds when considering the number of claims rather than total payouts. These results suggest that flood risk overlaps partly with exposure to other hazards, yet damages remain to a considerable degree peril-specific. Since the subsidy estimates are based on floods alone, the positive correlations imply that the results most likely represent a lower bound of the true extent of implicit cross-subsidization.

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. 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 losses and exposure to flood risk, calculated from property-level data as the share of insured value in mapped flood zones, allows for a detailed analysis of the link between physical hazard exposure and observed insurance payouts over time. This forms the basis for the empirical identification of loss ratios in flood-exposed versus non-exposed areas.



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

Note: Municipality boundaries are based on illustrative data from GeoNorge. Darker red shades indicate higher exposure.

4 Research Design

4.1 Definitions

In Norway, natural perils insurance is priced at a single, uniform rate. This rate is said to be actuarially fair in aggregate at the national level, meaning that national premium income should equal national expected losses. The expected loss can be written as the probability of a positive loss multiplied by the expected loss conditional on a loss occurring.

In practice, natural perils insurance is priced as a proportion of the insured value. Let ρ be the premium rate per kroner of insured value (the loss ratio), and let $\sum_i S_i$ be the total insured value across all municipalities. If X_i is the random variable representing the insurance loss in municipality i, then the national uniform premium rate ρ can be interpreted as the expected national loss ratio, i.e. the average expected claim per krone of insured value across all municipalities:

$$\rho = \frac{\mathbb{E}[\sum_i X_i]}{\sum_i S_i}$$

Using hazard maps, I identify the precise geographic location of all residential properties in Norway and determine whether each property falls within a designated risk zone. For each property, I calculate the insured value, allowing me to compute the total insured value within and outside the risk zone for each municipality. For each municipality i, I let S_i^r denote the total insured value of properties located inside the risk zone, and S_i^n the total outside the risk zone, so that the total insured value in the municipality is $S_i = S_i^r + S_i^n$. I then define the municipality-level share of exposure in risk zones as

$$f_i = \frac{S_i^r}{S_i},$$

Since both premiums and expected losses scale proportionally with insured value, f_i serves as the appropriate weight when averaging per-krone loss rates across the two zones.

At the national level, let ρ^r be the average loss ratio within the risk zones, and ρ^n the corresponding outside risk zones. Under the assumption that expected loss per krone is constant within each zone, the expected loss ratio in municipality i can be expressed as a weighted average of the nation-wide loss ratios:

$$\rho_i = f_i \, \rho^r + (1 - f_i) \, \rho^n.$$

Aggregating across all municipalities, the national loss ratio becomes:

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

The national rate is simply assumed to be 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

Let $\bar{X}_i$ denote the average insurance payout in municipality i, computed over the full sample period. Under the assumption that this sample average approximates the expected annual loss, I treat $\bar{X}_i \approx \mathbb{E}[X_i]$, where X_i is the annual loss in municipality i.

Given that the total insured value in municipality i is $S_i = S_i^r + S_i^n$, actuarial fairness implies that expected payouts equal expected premiums:

$$\bar{X}_i = \rho_i S_i$$

Dividing both sides by S_i yields an empirical estimate of the expected loss ratio:

$$l_i \equiv \frac{\bar{X}_i}{S_i} = \rho_i = f_i \, \rho^r + (1 - f_i) \, \rho^n$$

where f_i is the share of total insured value located in risk zone, as defined above. The variable l_i thus serves as an empirical proxy for the expected loss ratio in municipality i. Interpreting $\bar{X}_i$ as the expected loss and assuming that ρ^r and ρ^n are constant across municipalities, I estimate the relationship using a linear regression of l_i on the share of insured value located in the risk zone, f_i:

$$l_i = \beta_0 + \beta_1 \, f_i + \varepsilon_i, \qquad \text{where} \quad \beta_0 = \rho^n \quad \text{and} \quad \beta_1 = \rho^r - \rho^n \tag{1}$$

where ε_i captures idiosyncratic deviations. Cross-municipality variation in f_i thus identifies the differential loss rate $\rho^r - \rho^n$, which reflects the magnitude of the implicit subsidy embedded in uniform pricing.

4.3 Estimation Strategy

The baseline specification is an ordinary least squares (OLS) regression, where the dependent variable is the municipality-level loss ratio, defined as average historical payouts in municipality divided by the total insured value in municipality. The key

regressor 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, ρ^r and ρ^n, by exploiting cross-municipality variation. As expressed by equation 1, the intercept β_0 corresponds to the average loss ratio in non-flood areas ρ^n, while the slope, β_1 captures the incremental risk associated with flood zones, $\rho^r - \rho^n$. The average loss ratio in flood zones, ρ^r, is therefore obtained as the sum of β_0 and β_1.

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 account for potential spatial correlation across nearby municipalities.

A few municipalities, such as the municipality of Lærdal with largest share of insured value located in flood zone, see Figure 1, shows large influence, both in terms of leverage and Cook's distance. However, the values reflect real exposure and are not data errors. To assess robustness, I estimate alternative models that are less sensitive to outliers. Median regression is a natural benchmark, but its interpretation is less clear in this context, as most municipalities have low payouts and only some experience extremely large events. In the insurance setting, however, such extreme events are precisely the realizations we aim to capture, since they define the tail risk that drives expected losses.

As an intermediate approach, I therefore use robust linear regression (RLM) with Huber weights. This method downweights influential outliers while leaving the bulk of the data unchanged, and is implemented through iteratively reweighted least squares. The degree of downweighting depends on the tuning parameter t. Smaller values put less weight on extreme observations and move the estimates further away from OLS, while larger values make RLM estimates approach OLS. When outliers are extreme but genuine, such as natural disasters, RLM offers a compromise by reducing their influence without discarding them. In this application, RLM serves as a useful complement to OLS by showing whether results are driven by a small number of highly exposed municipalities or reflect broader patterns across the distribution. Since outliers are informative in the context of natural hazards, I retain OLS as the main specification.

Next, I assess the presence of spatial dependence. Using a queen-contiguity[4] spatial weights matrix, I compute Moran's I statistic[5] for the OLS residuals. The result indicates statistically significant positive spatial autocorrelation. That is, municipalities with high residuals tend to cluster geographically, violating the assumption of independently distributed errors. To address this, I estimate a Spatial Error Model (SEM), which accounts for spatial autocorrelation in the unobserved error component. The model is defined as

$$\mathbf{y} = \mathbf{X}\beta + \mathbf{u}, \qquad \mathbf{u} = \lambda \mathbf{W}\mathbf{u} + \varepsilon,$$

where $\mathbf{W}$ is the spatial weights matrix, λ measures the degree of spatial autocorrelation in the error term, and ε is i.i.d. noise.

The model is estimated by maximum likelihood, with standard errors obtained using HC3 corrections after transforming the regression equations. From a theoretical standpoint, the spatial error model (SEM) is well suited to this context because it allows unobserved spatially correlated factors, such as geology or infrastructure quality, to affect losses through the error term. This contrasts with the spatial autoregressive (SAR) model, which captures direct spillovers in the dependent variable. The SAR framework would be appropriate if insurance payouts relative to insured value in one municipality directly influenced the same outcome in neighboring municipalities. In the present setting, however, spatial correlation is more plausibly tied to the explanatory variable, namely the share of insured value located in flood zones.

In sum, the estimation strategy builds on OLS as the baseline, complemented by adjustments for heteroskedasticity, robustness checks for influential observations, and models that account for spatial dependence. This layered approach allows for careful assessment of the empirical relationship between mapped natural hazard exposure and observed municipal loss ratios.

[4]Queen contiguity defines polygons to be neighbors if they share either a boundary (edge) or a vertex (corner).

[5]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 high values and low values respectively, are clustered together. Negative values near -1 indicate negative spatial autocorrelation.

5 Main Results: The Size of Implicit Subsidies

To estimate the actuarially fair premium for flood risk, I compute the average national loss ratio for flood-related insurance payouts. This is obtained by dividing total historical flood payouts by total insured value across all municipalities:

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

This expression yields the national average loss per krone of insured value due to flooding, which under the assumption that historical averages approximate expected losses represents the actuarially fair premium for flood risk in a uniform pricing system. This assumption is only approximate, as losses exhibit an upward trend over time, a point I return to in Section 6. Empirically, I find that this value, ρ^r_{flood} (henceforth ρ^r), is approximately 0.03 per mille. This estimate makes intuitive sense, given that floods account for about 30 percent of all historical insurance payouts, see Table 1 in Section 3. For comparison, the estimated national premium across all natural perils is about 0.09 per mille, while the uniform rate set for 2025 is 0.08 per mille.

5.1 Primary Regression Specifications

Table 3 presents main regression results. In the baseline OLS model (1), the average loss ratio outside flood zones, ρ^n, is estimated at 0.014 per mille, while the differential effect for flood zones, $\rho^r - \rho^n$, is 0.281. This implies a loss ratio in flood zones, ρ^r, of roughly 0.295 per mille, more than 21 times higher than in non-flood zones. The estimates are statistically significant, and robust to correcting standard errors for heteroskedasticity (model 2). They are also robust to allowing for spatial correlation across municipalities (model 3) using Conley HAC standard errors with a 150 km cutoff, which allows for correlation in residuals between geographically close municipalities while assuming independence beyond that distance.

To examine sensitivity to outliers, model (4) applies robust linear regression with Huber weights. The coefficients are smaller, but the estimated flood-zone premium remains significantly higher than in non-flood areas, and results are

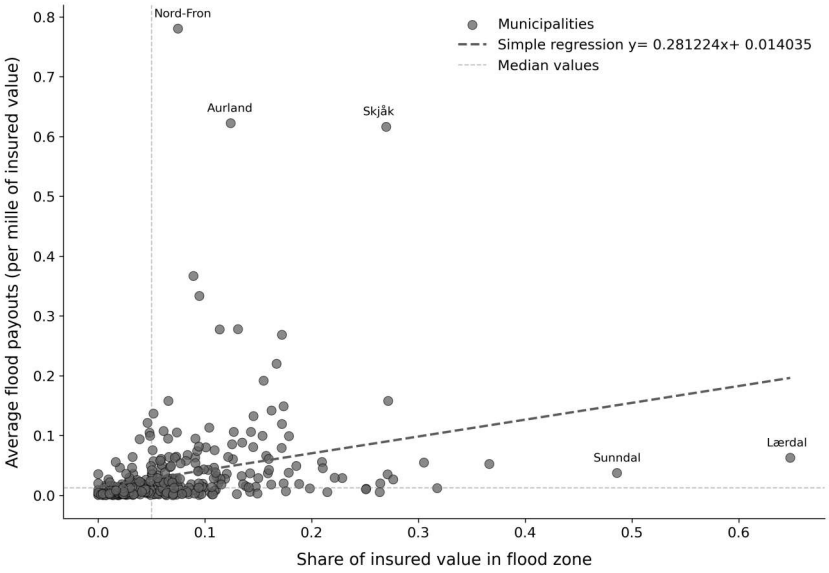
Table 3: Regression Results (All coefficients in ‰)

Model	$\beta_0 = \rho^n$	$\beta_1 = \rho^r - \rho^n$	Implied ρ^r	R^2
(1) OLS	0.0140^{**} (0.005	0.2812^{***} (0.053)	0.2952	0.072
(2) OLS (HC3)	0.0140^{**} (0.005)	0.2812^{**} (0.091)	0.2952	0.072
(3) OLS (Conley HAC, 150 km)	0.0140^{*} (0.0063)	0.2812^{***} (0.0593)	0.2952	0.072
(4) RLM Huber T (default $t = 1.345$)	0.0080^{***} (0.001)	0.1413^{***} (0.012)	0.1493	–
(5) Median regression	0.0031^{**} (0.001)	0.1695^{***} (0.011)	0.2005	0.071

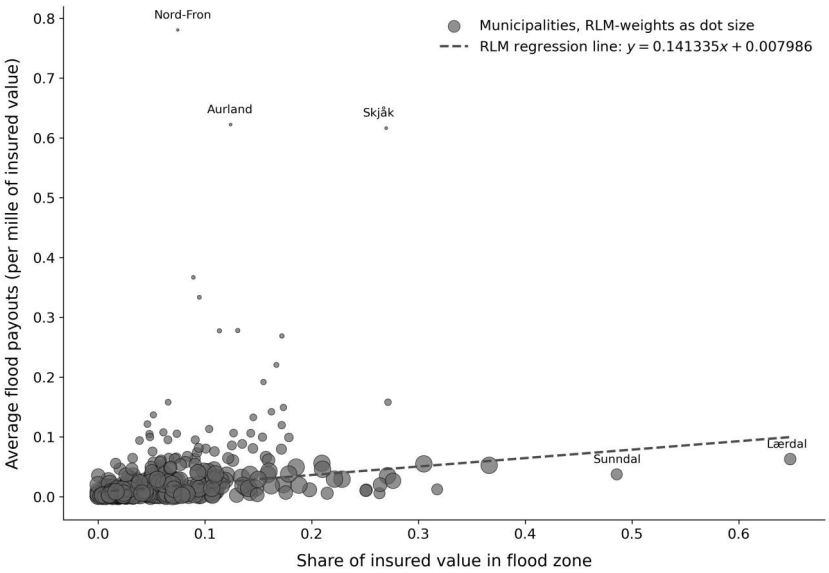
Notes: All coefficients and standard errors are reported in ‰ (per thousand NOK of insured value). Standard errors in parentheses. Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Number of observations is 357 in all regressions.

very similar across different tuning parameters, see Appendix A. The difference between OLS and robust methods is illustrated in Figure 3, which shows how downweighting extreme municipalities reduces the slope while leaving the overall positive relationship intact. Model (5), which estimates the median regression, also yields a substantial gap between zones, with an implied flood-zone premium of 0.2 per mille.

These results show that when outliers are given less weight, both the intercept and the slope decline. This occurs because municipalities with low exposure but large losses raise the estimated loss ratio outside flood zones, thereby increasing the intercept in OLS. At the same time, municipalities that combine higher exposure with severe events pull the slope upward. Downweighting such observations reduces their leverage and shifts both coefficients downward. The challenge in this setting is that these extreme realizations are an inherent part of catastrophic risk. While median regression and robust methods are informative as a sensitivity check, they may understate the economic magnitude of zone differences by downweighting precisely the events that define tail risk.



(a) Simple OLS



(b) Robust Linear Model (RLM)

Figure 3: Comparison of regression methods. Panel (a) shows a simple OLS fit between calculated loss ratios and flood zone exposure. Panel (b) presents results from a Robust Linear Model (RLM) with default Huber T weighting.

5.2 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. In particular, 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 $\lambda = 0.04$, and both coefficients remain significant: $\rho^n = 0.0163$ and $\rho^r - \rho^n = 0.2535$, see Table 4. This suggests a persistent and economically meaningful difference in loss rates between flood and non-flood zones, even 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 4: Spatial Error Model (SEM) Regression (‰ units)

	$\beta_0 = \rho^n$	$\beta_1 = \rho^r - \rho^n$	Implied ρ^r
	0.0163^{**}	0.2535^{**}	0.270
	(0.006)	(0.096)	–
Spatial parameter λ		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 as the preferred specification.

5.3 Magnitude of Implicit Subsidies

Table 5 reports the estimated ratio of average loss ratios in flood versus non-flood zones across different model specifications. Although point estimates differ, the qualitative conclusion is the same: properties in flood-exposed municipalities experience substantially higher realized loss ratios than those elsewhere, indicating a large implicit cross-subsidy under the uniform premium regime.

Table 5: Relative Loss Ratio Across Models (ρ^r/ρ^n)

Model	$\frac{\rho^r}{\rho^n}$
(1) OLS	21.1
(2) RLM Huber T (default)	18.7
(3) Median regression	62.5
(4) SEM	16.6

Notes: Table shows the implied ratio of average loss ratios in flood vs. non-flood zones, ρ^r/ρ^n, from each model specification. SEM is estimated by maximum likelihood with HC3 robust standard errors. Number of observations is 357 in all regressions.

The baseline OLS estimate implies that the average loss ratio in flood zones is about 21 times higher than in non-flood zones. Robust linear regression (RLM) produces a similar estimate of 19, while median regression yields a much larger ratio of 63. The latter reflects the fact that the median loss ratio outside flood zones is very close to zero, which inflates the relative difference. Given that outliers are substantively relevant in this setting, OLS and SEM provide the most informative benchmarks, while RLM and median regression mainly serve as robustness checks. SEM suggests a somewhat lower ratio of around 17. Despite these differences in magnitude, all models consistently show a pronounced gap between flood and non-flood areas.

The SEM estimates can be compared directly to the current national premium. The implied average loss ratio in flood zones is about 0.25 per mille, compared to

0.02 per mille in non-flood zones. For reference, the uniform national premium is set 0.08 per mille, of which roughly 0.03 is allocated to flood risk. A risk-based flood premium for a typical home insured for 5 million NOK (approx. 480,000 USD) would therefore amount to about 1,250 NOK annually (approx. 120 USD), compared to the current flood component of 150 NOK (approx. 14.4 USD). Outside mapped flood zones, the implied premium would be around 80 NOK (approx. 7.7 USD), reflecting their much lower expected loss. These comparisons underscore the magnitude of implicit cross-subsidization: households in low-risk areas effectively bear part of the cost of insuring those in high-risk zones.

6 Evolution of Implicit Subsidies Over Time

The results above document substantial implicit subsidies embedded in Norway's natural perils insurance system. A natural next question is how these subsidies evolve over time. Historical variation provides a useful perspective, as it shows how sensitive estimated loss ratios are to the timing and location of extreme events. In some decades, when large floods are absent, estimated loss ratios in flood zones may appear modest, whereas in decades with one or two severe events concentrated in specific municipalities, they increase substantially. This illustrates how short observation windows will produce volatile estimates, since a single event can dominate the results. Such windows, however, are not an informative approximation of expected losses. When using longer windows that better capture expected losses, the evidence shows a clear and persistent upward trend in estimated loss ratios, both in flood and non-flood zones, over recent decades.

Historical patterns also provide guidance for assessing future developments. Climate change is expected to increase the frequency and severity of extreme weather events. If weather patterns also become less predictable, 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 remain concentrated in high-hazard areas, subsidies could persist or expand.

Finance Norway, the provider of the municipal insurance payout data, has emphasized that natural peril payouts have increased markedly in recent years. Of the ten largest events since 1980, seven occurred after 2010 (Finance Norway,

2025). Figure 4 illustrates the rise in flood payouts, with average annual losses indeed increasing substantially in the post-2010 period.

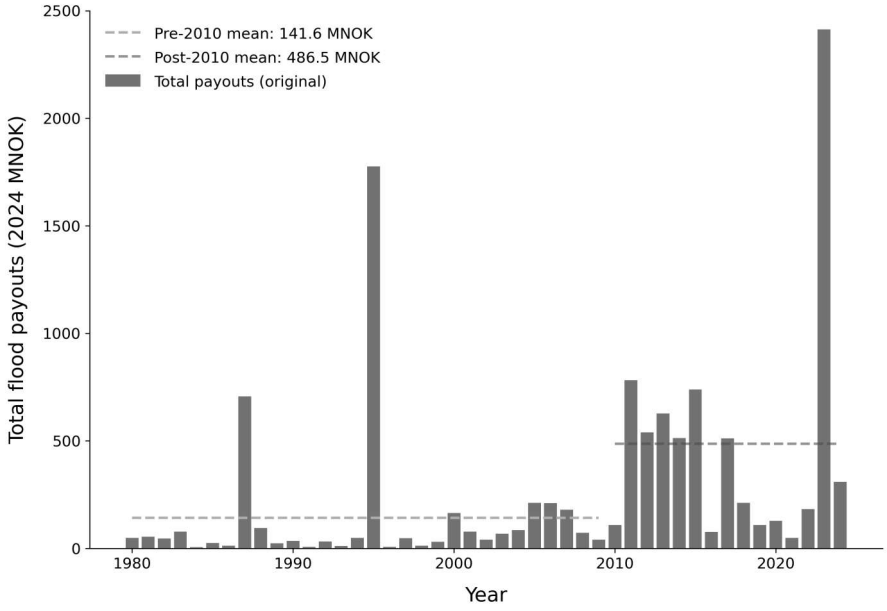
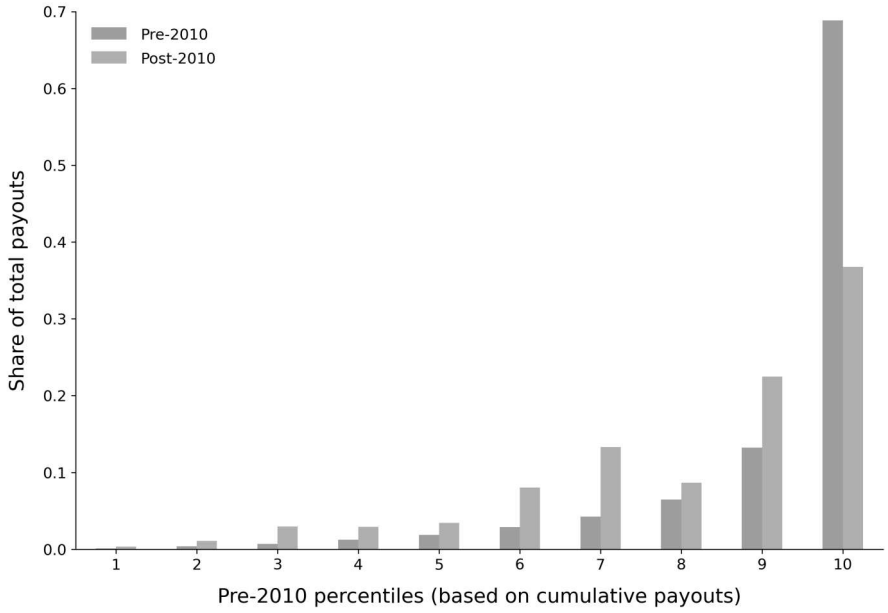


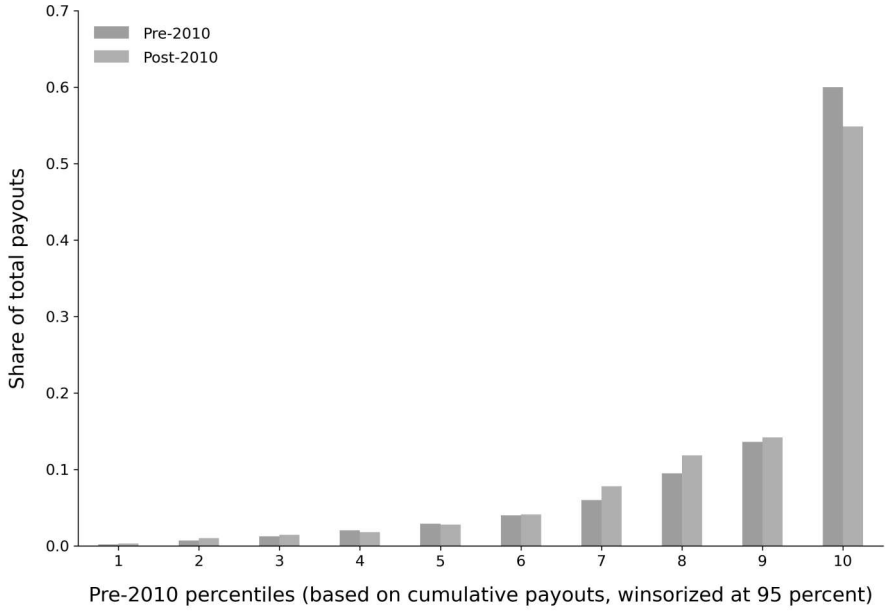
Figure 4: Total annual flood payouts (MNOK). Red dashed line shows the pre-2010 mean (up to 2009). Red solid line shows the post-2010 mean (from 2010).

A natural question, given the increase in insurance payouts over time, is whether their distribution across municipalities has changed. To examine this, I rank municipalities into percentiles based on their cumulative payouts prior to 2010 and hold these groups fixed when comparing their post-2010 shares, see Figure 5. Without winsorization (Figure 5a), the distribution appears to shift, but once extreme events are trimmed by winsorizing at the 95th percentile (Figure 5b), the pre- and post-2010 distributions look strikingly similar. This suggests that the geography of small and medium losses has remained broadly stable, while extreme event years occur more randomly. From the perspective of catastrophic risk, however, it is precisely such extreme events that matter.

To assess the evolution of implicit subsidies over time, I estimate loss ratios in rolling 20-year windows. Figure 6 reports the point estimates for risk-zone specific premiums together with their 95 percent confidence intervals. Both the estimated premium in flood zone, ρ_f, and the estimated premium in non-flood zones, ρ_n, increase over time. The rolling estimates vary across windows, and



(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 5: Distribution of payouts across municipalities by percentile groups. Panel (a) uses original payouts; panel (b) uses per-municipality winsorization at the 95th percentile.

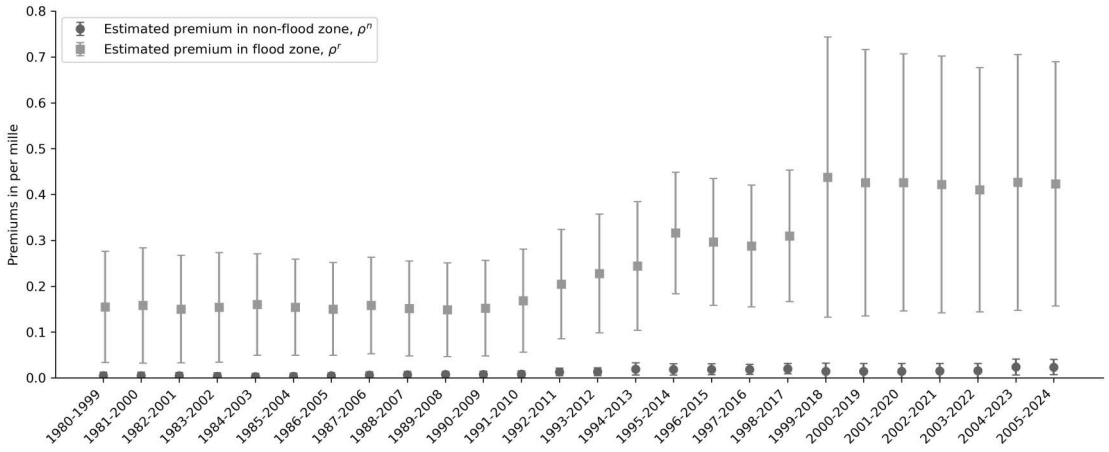


Figure 6: Rolling-window (20y) estimates of loss ratios in flood and non-flood zones, with 95 percent confidence intervals.

Note: Estimates are based on OLS regressions of municipal loss ratios on the share of insured value in flood zones, using rolling 20-year windows. Loss ratios are expressed in per mille of insured value. Confidence intervals are heteroskedasticity-robust (HC3).

the confidence intervals are wide (Appendix B), particularly when the window length is short. This is to be expected, since shorter periods place disproportionate weight on individual events, whereas the goal is to approximate expected losses, which is better reflected in longer horizons. These estimates should therefore be interpreted as indicative patterns rather than precise trends. The increase in ρ_n also explains why the relative loss ratio, ρ_f/ρ_n, does not rise in step with ρ_f, see Figure 7. Nevertheless, the implied flood-zone loss ratio remains consistently high: at its lowest, it is around 10, meaning that households in flood zones would, under actuarially fair pricing, at minimum face premiums about ten times higher than households outside flood zones.

Taken together, these exercises show that implied premiums in risk and non-risk zones are sensitive to the temporal clustering of extreme events when estimated over short periods. This volatility highlights the importance of using sufficiently long windows to approximate expected losses. When applying a 20-year window, which is reported as the main specification, the results indicate a stable and persistent increase in both flood and non-flood zone loss ratios over time.

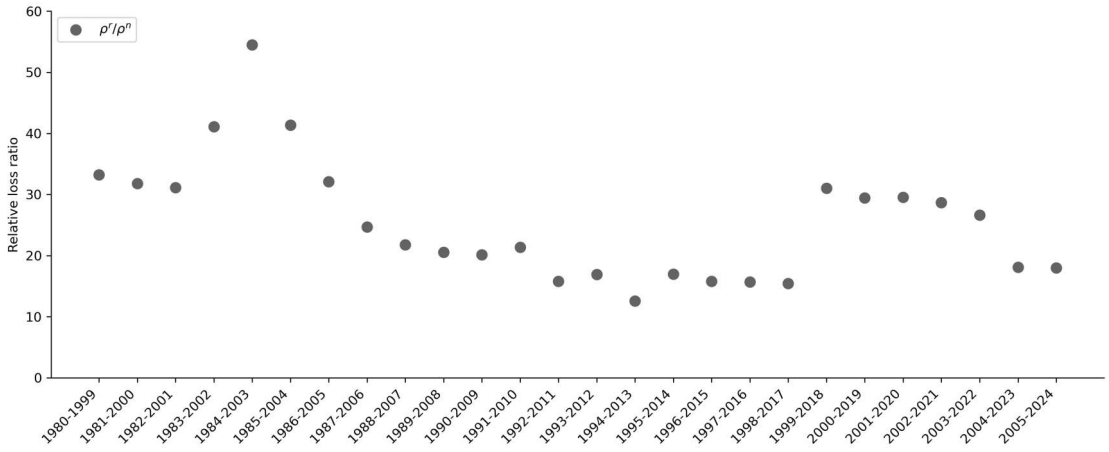


Figure 7: Ratio of loss ratios across rolling 20-year windows

Note: Each point shows the ratio of the estimated loss ratio in flood zones ρ_f to that in non-flood zones ρ_n. Based on the OLS estimates from Figure 6.

7 Risk-Driven Adaptation

Another factor influencing the scale of implicit subsidies is how local actors respond to climate risk. The large transfers documented in this paper likely weaken incentives for effective adaptation. If municipalities in high-risk areas nevertheless invest in protective measures, and these measures are effective, expected future losses may decline. This would narrow the gap between premiums in risk zones and those in non-risk zones.

To assess whether municipalities facing higher climate risk also undertake more adaptation, I draw on data from Norwegian Climate Monitor[6]. The dataset, described in detail in Rød et al. (2024), follows the Intergovernmental Panel on Climate Change (IPCC) framework 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.

[6]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).

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 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 ($f_i \equiv S_i^r/S_i$), 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 at risk. Average payouts per insured krone $\bar{Y}_i/S_i$, the outcome variable, is instead an *ex post* outcome measure. Unlike f_i, 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[7]. 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.

A natural and clean starting point for assessing risk-driven adaptation is to regress the response index (RESPONSE) on physical flood hazard (HAZARD), which is exogenous to present-day adaptation because it is based on hydrological modeling, independent of settlement patterns. A natural next step is to add

[7]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).

the share of insured value in flood zones f_i, which combines hazard maps with asset placement. By contrast, payout-based measures such as Klimamonitor's exposure measure, or the loss ratio $\bar{Y}_i/S_i$ that I use throughout the paper, are harder to interpret causally. Municipalities may adapt precisely because they have suffered high damages, while adaptation itself reduces subsequent damages. These simultaneity issues mean that coefficients on payout-based variables are difficult to interpret as evidence of risk-driven response.

Table 6 summarizes the main specifications. Across all specifications, the coefficient on the hazard measure is robustly positive and statistically significant, but the explanatory power of hazard alone is very limited ($R^2 = 0.02$). Column (1)

Table 6: Determinants of local municipality adaptation efforts.

	(1) RESPONSE	(2) RESPONSE	(3) RESPONSE	(4) RESPONSE
HAZARD ($fFlom2000$)	0.366*** (0.130)	0.389*** (0.131)	0.389*** (0.125)	0.387*** (0.123)
Insured value in flood zone ($f \equiv S^r/S$)		11.02 (12.32)		
Population density ($sBefTett2000$)			0.716*** (0.082)	0.627*** (0.109)
EXPOSURE ($eFlom2000$)				2.355 (3.759)
Observations	357	357	357	357
R^2	0.022	0.024	0.194	0.199

The dependent variable is the response index ($Respons2000$) from Klimamonitor (Rød et al., 2025). All regressions include a constant, not reported. Robust (HC3) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

shows the baseline regression of RESPONSE on HAZARD, where the coefficient is positive and significant at the 1 percent level. In column (2), I add the share of insured value in flood zones (f_i); the coefficient on f_i is small and insignificant, while the hazard effect remains essentially unchanged. Column (3) includes a control for population density, which enters strongly significant and increases the explanatory power of the regression substantially (R^2 rises to 0.19), while leaving the hazard

coefficient unchanged. Finally, column (4) adds the payout-based exposure measure from Klimamonitor. This variable is statistically insignificant, but difficult to interpret causally given simultaneity concerns. However, its inclusion does not alter the coefficients on hazard nor population density.

This analysis was motivated by the question of whether implicit subsidies in near future may be offset by local preventive action. If riskier municipalities systematically adapt more, the efficiency costs of implicit subsidies may be smaller, since part of the increased risk is offset by preventive measures. Conversely, if adaptation does not respond strongly to hazard or historical payouts, subsidies are more distortionary, as they mask risk without triggering compensating investments.

The results indicate that adaptation is positively related to modeled hazard, but the effect is modest and explains only a small share of the variation across municipalities. A 10-point increase in hazard is associated with roughly a 4-point higher response index. By contrast, population density, is strongly significant and markedly improves explanatory power, suggesting that administrative capacity and fiscal resources are more decisive for adaptation efforts than risk exposure. Taken together, these findings imply that while hazard-prone municipalities adapt somewhat more, the effect is limited relative to other determinants, and implicit subsidies are unlikely to be substantially reduced through risk-driven adaptation.

8 Conclusion

This paper sheds light on the implicit cross-subsidization embedded in Norway's natural perils insurance scheme, where a uniform premium is charged regardless of location-specific risk. Using detailed data on property-level exposure and municipal-level insurance payouts, the analysis shows that actuarially fair premiums in flood-exposed areas would be between 16-21 times higher than in non-flood zones. This implies a substantial implicit transfer from low-risk to high-risk households, and distorts pricing signals regarding climate risk.

The results also show that these imbalances have persisted and evolved over time. Loss ratios have increased in both flood and non-flood areas, which helps explain why the relative difference between zones has remained more stable even as absolute risks have risen. The scale of implicit subsidies thus reflects not only

current differences in risk but also the way damages are distributed across zones over time.

Uniform pricing also interacts with local adaptation. Municipalities in hazard-prone areas implement somewhat more preventive measures, but the effect is modest and largely explained by size and resources rather than risk exposure itself. This suggests that implicit subsidies are unlikely to diminish through risk-driven adaptation alone.

From a policy perspective, the analysis highlights trade-offs between distribution and efficiency. While uniform pricing secures broad access and equality, it may weaken incentives for mitigation and distort location choices if it masks large differences in risk. Future reforms could consider hybrid approaches that preserve solidarity while introducing partial risk-based pricing or targeted incentives for adaptation.

Finally, the findings contribute to broader debates on the design of climate risk insurance. Interest is growing in coordinated European approaches, including EU-level reinsurance. 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

A Robust Linear Regression Results for varying tuning constants t's

Table A1: RLM Huber T results for different tuning constants t

t	$\beta_0 = \rho^n$	$\beta_1 = \rho^r - \rho^n$	Implied ρ^r	Ratio ρ^r/ρ^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: Reported coefficients are in ‰ (per thousand NOK of insured value). ρ^n is the baseline loss ratio, ρ^r the implied flood-zone loss ratio.

B Rolling-Window Estimates of Loss Ratios

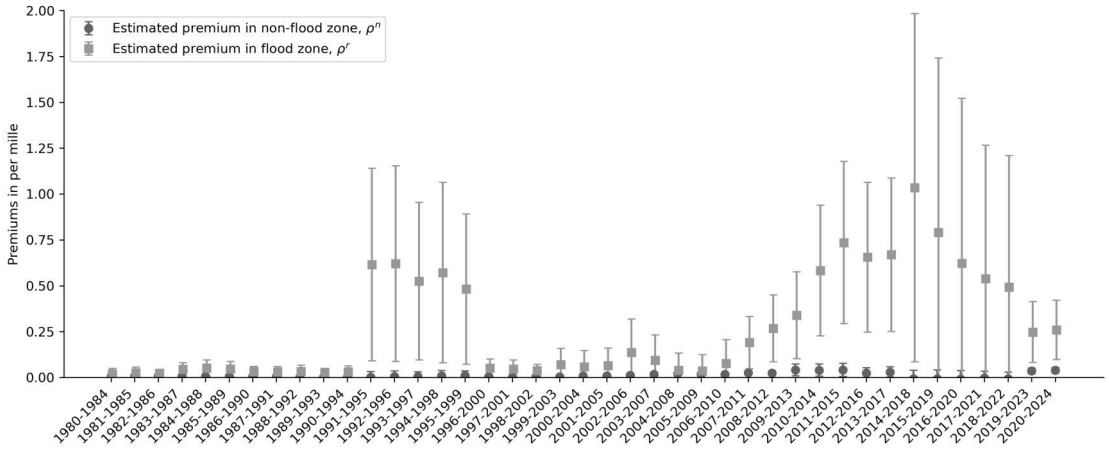


Figure A1: Rolling-window (5y) estimates of loss ratios in flood and non-flood zones, with 95 percent confidence intervals.

Note: Estimates are based on OLS regressions of municipal loss ratios on the share of insured value in flood zones, using rolling 5-year windows. Loss ratios are expressed in per mille of insured value. Confidence intervals are heteroskedasticity-robust (HC3).

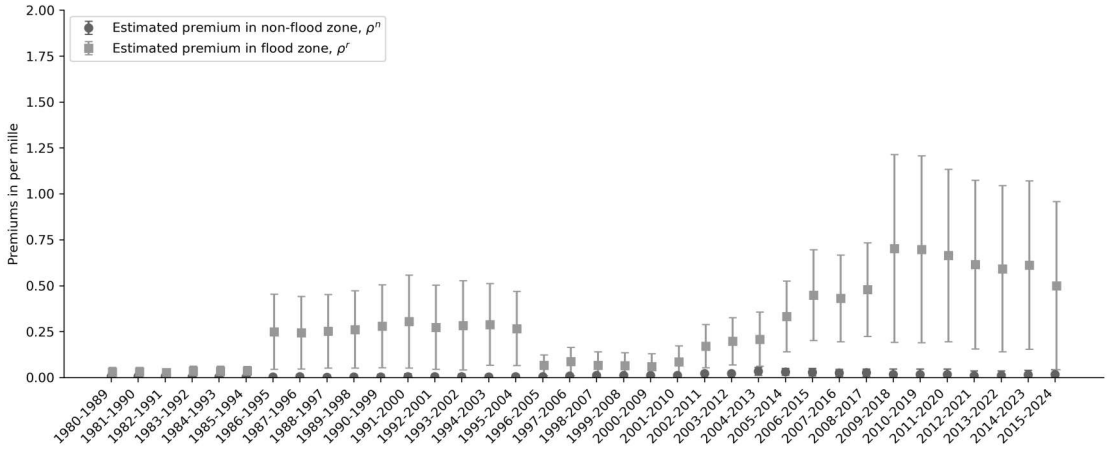


Figure A2: Rolling-window (10y) estimates of loss ratios in flood and non-flood zones, with 95 percent confidence intervals.

Note: Estimates are based on OLS regressions of municipal loss ratios on the share of insured value in flood zones, using rolling 10-year windows. Loss ratios are expressed in per mille of insured value. Confidence intervals are heteroskedasticity-robust (HC3).

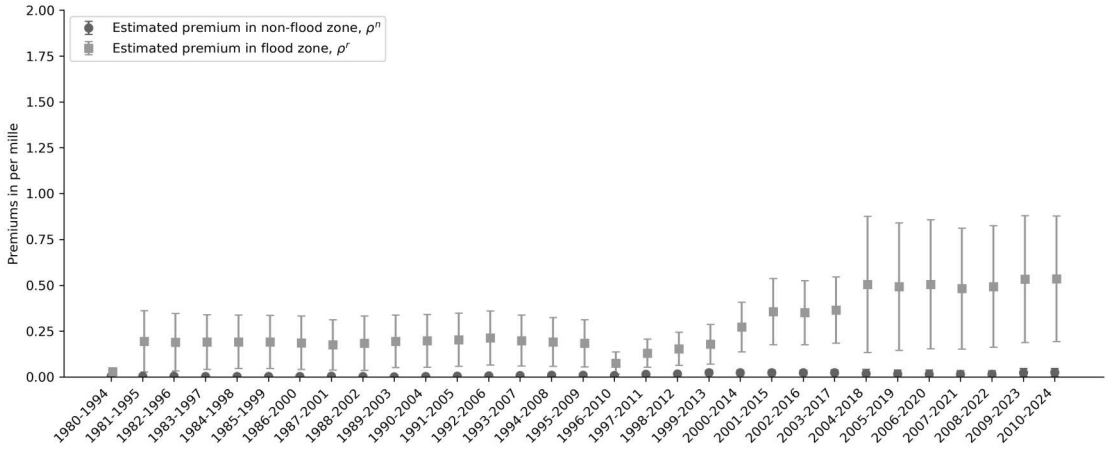


Figure A3: Rolling-window (15y) estimates of loss ratios in flood and non-flood zones, with 95 percent confidence intervals.

Note: Estimates are based on OLS regressions of municipal loss ratios on the share of insured value in flood zones, using rolling 15-year windows. Loss ratios are expressed in per mille of insured value. Confidence intervals are heteroskedasticity-robust (HC3).

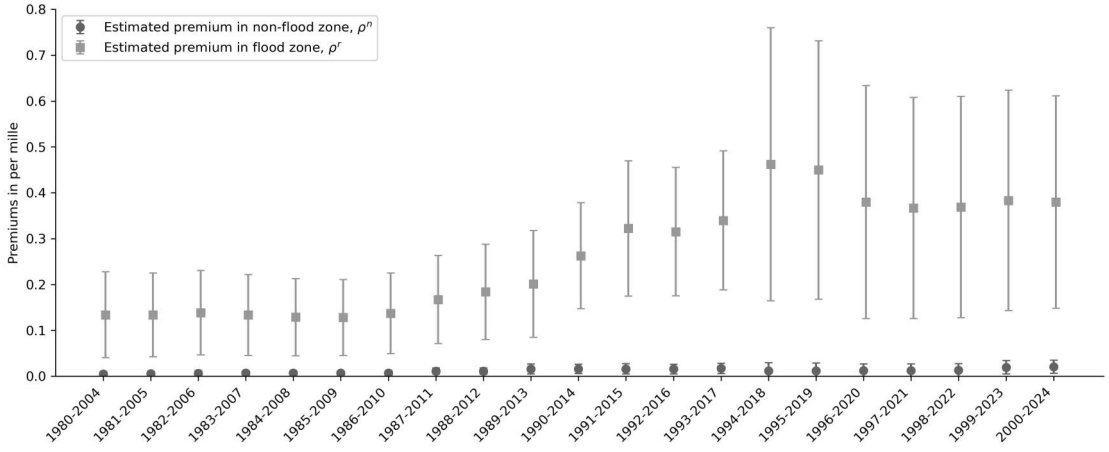


Figure A4: Rolling-window (25y) estimates of loss ratios in flood and non-flood zones, with 95 percent confidence intervals.

Note: Estimates are based on OLS regressions of municipal loss ratios on the share of insured value in flood zones, using rolling 25-year windows. Loss ratios are expressed in per mille of insured value. Confidence intervals are heteroskedasticity-robust (HC3).