REAL ESTATE WEALTH INEQUALITY AND EXPOSURE TO NATURAL DISASTERS

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Real estate wealth inequality and exposure to natural disasters

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Abstract

Prior studies, relying on aggregate income data and focusing only on residents, typically find that low-income households are more exposed to flooding. However, by omitting dwellings owned by non-residents, this approach overlooks half of the housing stock exposed to flooding. Using dwelling-level data covering the entire French housing market, this paper examines how natural disaster risks are distributed across tenants, owner-occupants, and owners of rental, second, and vacant homes. The results highlight large differences with the standard approach that focuses on residents. Once properties owned by non-residents are included, flood risk appears to disproportionately affect second homes, while subsidence mainly affects owner-occupied dwellings. These patterns have important policy implications. First, untargeted flood insurance subsidies tend to benefit second-homes, whereas subsidence coverage mainly supports owner-occupied dwellings. Second, using a new approach to estimate risk discounts, this study shows that natural disaster risks are not priced into rental, second and vacant properties, driving at least 15% of the total overvaluation in flood-prone areas.

Keywords: Wealth Inequality, Insurance, Natural Disasters

JEL Codes: D31, G52, Q51, Q54

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1 Introduction

As the costs of climate change are projected to rise exponentially (Masters, 2022), it is crucial to identify which segments of the population will be most impacted by extreme weather events. This understanding is essential for designing effective adaptation policies, such as place-based interventions (e.g., managed retreat or building resilient infrastructure) and insurance subsidies, to target households at risk of suffering the greatest losses from extreme weather events (Hallegatte and Walsh, 2021; Ulibarri et al., 2022).

A new body of literature emerged in the 2000s, aiming to better understand which segments of the population are, and will be, most exposed to natural disasters (Taylor, 2000; Mohai et al., 2009; Bakkensen et al., 2024). To measure these inequalities in the housing market, this literature focused on income inequality and relied on aggregate data, finding in the large majority of cases that low-income households are more exposed to flooding (Walker et al., 2006; Masozera et al., 2007; Bakkensen and Ma, 2020; Rözer and Surminski, 2021; Wing et al., 2022; Odersky and Löffler, 2024; Wylie et al., 2025). However, this approach has three main limitations.

The first and most important limitation is that aggregate income data is based on the income of residents, which, despite covering a significant portion of the housing market, omits owners of rental, second, and vacant dwellings who do not reside in exposed areas. In the French context, I find that excluding non-residents leads to overlook more than 50% of the residential housing stock at risk of flooding.

The second limitation is that income inequalities fail to differentiate levels of exposure between renters and homeowners, with renters being considerably more vulnerable to risk due to limited wealth diversification (Fessler and Schürz, 2018). The literature is particularly scarce concerning the effect of natural disasters on the rental market (Lee and Van Zandt, 2019; Harwood, 2025). Among resident homeowners, aggregate data do not allow either for a distinction between single-property and multi-property owners, even though this is a key dimension of inequality in exposure to risk.

Finally, aggregate data may obscure important heterogeneity within municipalities. Restricting the sample to French municipalities exposed to flooding (roughly equivalent to ZIP codes in the US), I find that, on average, only 5% of the housing stock within these municipalities is subject to frequent flood risk. This underscores the importance of using disaggregated data to capture within-municipality variation that aggregate statistics may overlook.

In this paper, I address the limitations of existing data by covering the entire housing market including non-residents, and measure inequalities along a new dimension: real estate ownership. The main contribution of the paper is to show that investigating inequalities in exposure to natural disasters covering the entire housing market, including non-residents, may substantially change patterns of exposure. One might question the relevance of adopting an ownership perspective, given that the direct victims of extreme weather events are residents. I also show that these differences in exposure between ownership categories have implications for the redistributive effects of insurance subsidies and overvaluation of the housing stock in risky areas.

2 Results

To study inequalities in exposure to risks, I build a new dataset providing an exhaustive coverage of the French housing market linked with owners and renters characteristics, owners' income, owners' real estate wealth (André and Meslin, 2021), price data and insurance premiums. I recover data on insurance premium using a Machine Learning algorithm trained on survey data. I examine the distribution of the two main natural disaster risks in France: flooding and subsidence. These events represent around 90% of losses caused by events categorized as natural disasters in France. In many countries, access to ownership data remains limited. This database is one of the few gathering such exhaustive information on dwellings, renters characteristics, owners characteristics, home prices and exposure to risks. To my knowledge, it is the only one that links all these characteristics with insurance premiums.

The two main categories of natural disasters in France are flooding and subsidence. They represent respectively 52% and 32% of the 2 billion euros annual natural disaster losses between 2013 and 2022 (CCR, 2022). Subsidence refers to the process by which clay soils expand (swell) when they absorb water and shrink (retract) when they dry out. This can lead to cracks in walls, floors, and other structural elements. Figure 1 provides a visual representation of the phenomenon. With climate change, the costs of these events are rising in France but also in many other countries such as Mexico (Hackett, 2025).

I restrict exposure to flood risk to dwellings located on the first floor, as most flood-related damages occur at this level (Deniz et al., 2017; Mauroux, 2018; Dubos-Paillard et al., 2024). Similarly for subsidence, not all geographically exposed dwellings are necessarily vulnerable to subsidence, as building foundations can mitigate the risk. Mission Risques Naturels (2023) find that the presence of upper floors serves as a useful proxy for stronger foundations: for

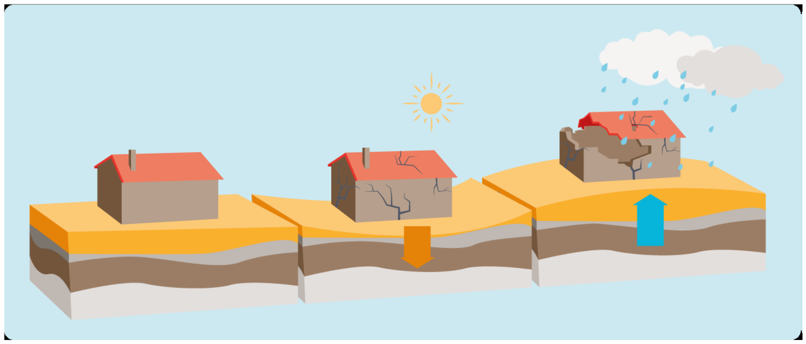


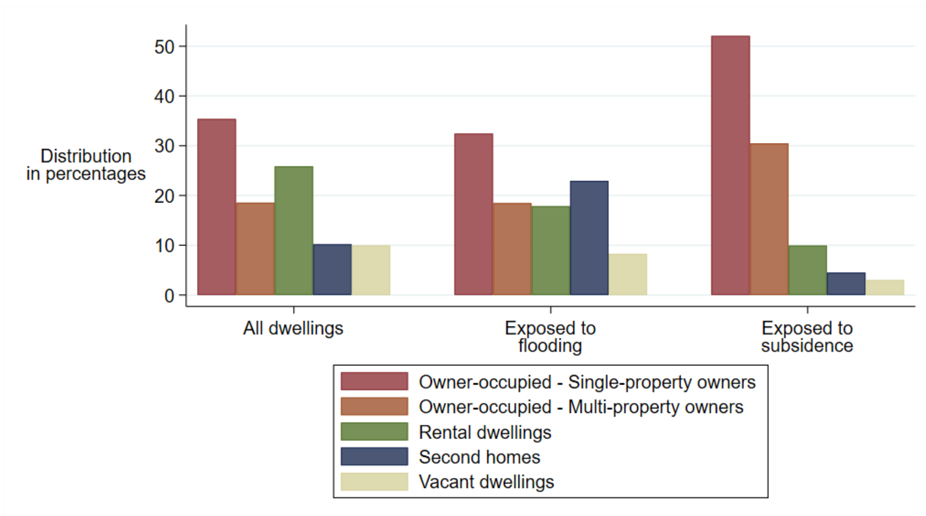
Figure 1: Subsidence phenomenon
Notes. Subsidence refers to the process by which clay soils expand (swell) when they absorb water and shrink (retract) when they dry out. This can cause foundations to settle unevenly, leading to cracks in walls, floors, and other structural elements.

instance, a seven-story building is far more likely to have deep, reinforced foundations than a single-story, detached house. Therefore, in the remainder of the analysis, I define dwellings as exposed to subsidence only if they have no upper floors. I use the term "high-risk" areas to refer to locations that are exposed to frequent flooding and/or to high level of subsidence hazard. More information on data construction is available in Section 4. More background details are available on exposure to risks, insurance, and inequalities and the housing market in France in Appendix Section A.

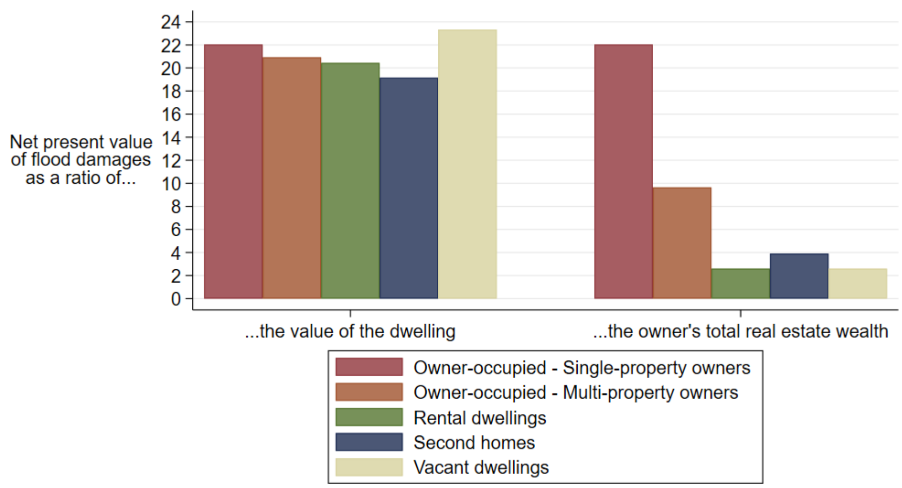
In the rest of the paper, I study inequalities on the housing market differentiating 5 exclusive categories of dwellings: owner-occupied by a single-property owner, owner-occupied by a multi-property owner, rental dwellings, second homes and vacant dwellings. They respectively represent 30%, 25%, 10%, 25% and 10% of the housing stock. I refer to rental properties, second homes, and vacant dwellings as being owned by "absentee landlords", since their owners do not reside in them year-round unlike owner-occupants or renters.

2.1 Real estate wealth inequalities

Figure 2 displays the share of dwellings by ownership category, both overall and specifically in high-risk areas. For flooding, Panel 2a shows that about 50% of exposed dwellings are owned by absentee landlords, and only 30% of exposed dwellings are occupied by single-property owners. It shows that focusing on residents would omit half of the housing stock exposed to flooding. This finding also challenges the common perception that natural disaster victims are



(a) Share of dwellings exposed to natural disasters by ownership status



(b) Net present value of flood damages as a ratio of real estate wealth

Figure 2: Real estate wealth inequalities linked to exposure to natural disasters
Notes. Panel (a) displays the share of dwellings by ownership category overall (on the left-hand side) and in high-risk areas (flooding in the middle and subsidence on the right hand side). Panel (b) shows the net present value (NPV) of flood damages as a share of real estate wealth, broken down by ownership status in areas exposed to the highest levels of risk. The left-hand panel uses the market value of the exposed dwelling as the denominator. The right-hand panel instead uses each owner's total real estate wealth as the denominator.

"left with nothing." Many at-risk homes are owned by wealthy well-diversified households who can more easily bear the costs of extreme weather events. Rental dwellings are less frequently at risk, which mitigates the exposure of renters. Interestingly, the figure reveals that second homes are disproportionately exposed to flood risk. While they make up only 10% of the housing stock nationally, they account for 20% of dwellings in flood-prone areas. Appendix Figure A.2 shows that, in coastal areas, second homes constitute 50% of flood-exposed dwellings. Tho sum-up, wealthy owners of second homes are particularly exposed to flooding, unlike renters, and owner-occupants are neither over- nor under-represented.

Panel 2b shows the net present value (NPV) of flood damages as a share of real estate wealth, broken down by ownership status, in areas exposed to the highest levels of risk. More details are available on how I derived the NPV in Section 4.4. In high-risk areas, expected discounted damages amount to approximately 20% of the dwelling's value, with little variation across ownership categories. The most important is that accounting for ownership links significantly alters the picture: single-property owners are far more vulnerable to risk than absentee landlords. For these landlords, the NPV of expected flood damages represents only about 2.5% to 4% of their total real estate wealth, making the risk appear almost negligible. In contrast, for single-property owner-occupants, damages represent a share that is five to eight times larger. This highlights substantial heterogeneity in vulnerability across ownership statuses and underscores the importance of considering this dimension when assessing the distributional impacts of natural disaster risk.

For subsidence, Panel 2a presents a different pattern, with a significant overexposure of owner-occupied homes. This is consistent with the fact that most at-risk properties are single-family homes owned by middle-income homeowners in sub-urban or rural areas. Over 75% of exposed dwellings are owner-occupied, among which two-third are owned by single-property owners. Unlike flooding, subsidence primarily affects middle-income property owners, rather than wealthy owners of second homes.

2.2 Comparison with aggregate income data

These results appear to contradict the previous literature on flood exposure, which generally finds that low-income households are more exposed to flood risk. To reconcile these findings with existing research, I replicate the analysis using municipality-level data, focusing on residents' average municipality income rather than dwelling-level ownership status for the entire housing market.[1] The results, displayed in Figure 3, align more closely with prior studies, showing that households in low-income municipalities are more exposed to flooding. For sub-

[1]Municipalities in France are on average composed of 1,000 dwellings, comparable to a census tract in the US

sidence, I find that municipalities with higher average incomes are more exposed.

However, as stressed in previous sections, this approach overlooks absentee landlords and focuses solely on residents, thus ignoring about 50% of the housing stock at risk from flooding. Once I account for the entire housing market, I observe that floods primarily affect wealthy owners of second homes, while subsidence predominantly impacts middle-income homeowners. This result underscores the importance of investigating inequalities in terms of ownership status and using fine-grained data that cover the entire housing market, rather than focusing solely on income of residents.

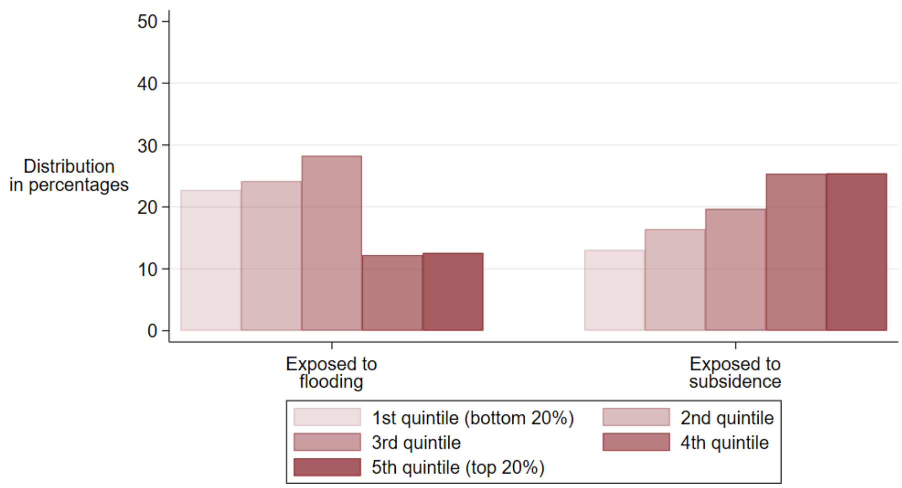


Figure 3: Share of dwellings exposed to natural disasters by average income in the municipality

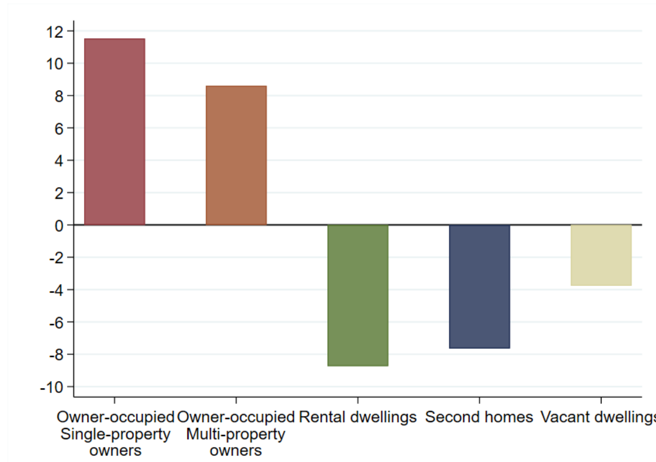
Notes. The Figure displays the share of dwellings by average municipality income in high-risk areas.

More descriptive results are available in Appendix Section B. I provide additional summary statistics on the different ownership categories (Section B.1). I plot the income distribution at the dwelling level in safe and exposed areas (Section B.2). I differentiate exposure to river versus coastal flooding (Section B.3). I study how the distribution of dwellings at risk varies by risk intensity (Section B.4). I compute the NPV of flood damages by ownership status (Section B.5). I plot insurance premiums by income decile, showing that these premiums are regressive, representing a share of income three times smaller for households in the top 10% of the income distribution compared to those in the bottom 10% (Section B.6).

2.3 Implications for the redistributive effects of subsidizing insurance

One might question the relevance of focusing on owners, given that residents are the ones directly exposed to natural disasters. In this section, I show that considering heterogeneity in ownership status is important for evaluating the redistributive impacts of subsidized insurance. When such subsidies are implemented, which is the case in several countries including the US or the UK, all owners benefit from them including non-residents.

(a) Flooding



(b) Subsidence

Figure 4: Net transfers through insurance subsidies in euros for each 100 euros transferred from safe to risky areas

Notes. The figure illustrates the extent to which each dwelling category is cross-subsidized under the CatNat system. Results are normalized to represent net transfers for each €100 transferred from low-risk to high-risk areas.

The French insurance system against natural disasters, named *CatNat*, covers around 99% of households in mainland France. In 2017, it was financed through a 12% additional premium on home insurance premiums and operates through a mechanism of cross-subsidization from dwellings in low-risk areas to those in high-risk zones. As a result, the ownership categories overrepresented in high-risk areas are those benefiting from the scheme.

To assess the extent of cross-subsidization, I conduct a back-of-the-envelope calculation, abstracting from potential behavioral responses such as relocation of the housing stock if premiums were to change, to estimate how much each category of dwelling benefits from or contributes to the scheme. Specifically, I calculate the difference between insurance premiums under the current subsidized system and those that would be paid under a counterfactual, risk-based pricing system. Further details on the methodology used to simulate these counterfactual premiums and quantify the degree of cross-subsidization are provided in Section 4.5.

Net normalized transfers are presented in Figure 4. For flooding, the results indicate that for every €100 transferred through the CatNat system, €6 benefit second homes in net terms. In the case of subsidence, €20 out of every €100 are transferred to owner-occupied dwellings, including €12 to those owned by single-property owners. In many countries where subsidence is a growing issue, there are debates around the role of the government and whether or not it should provide insurance against this risk (Sénat, 2019). In the case of CatNat, removing subsidence coverage would primarily disadvantage middle-income owner-occupants. These opposite patterns of exposure between flooding and subsidence also illustrate that climate change may have different redistributive effects depending on the type of risk to which countries are exposed.

2.4 Implications for the valuation of the exposed housing stock

If households price risks differently across ownership statuses, the patterns of exposure to risks previously documented may influence the overall valuation of the housing stock exposed to risk. I explore this question in this section and draw implications for the total overvaluation of the housing stock in risky areas.

2.4.1 Reduced-form evidence

This section examines whether flood risk is priced differently for owner-occupied homes versus those owned by absentee landlords. Considering that absentee landlords own 50% of the housing stock at risk in the case of flooding, if they fail to internalize these risks to the same extent as owner-occupants, this may have significant implications for the overall misvaluation in risky areas. Previous literature has shown that households may incorporate natural disaster risk into housing prices in heterogeneous ways (Bakkensen and Barrage, 2022; Bakkensen and Ma, 2020; Gourevitch et al., 2023). In the case of owner-occupants and absentee landlords, several mechanisms could explain such a disparity.[2] I do not empirically test these mechanisms in this

[2] In the rental market, for instance, renters may be less informed about flood risks—evidence from Bakkensen and Ma (2020) and Gourevitch et al. (2023) suggests that low-income households are less responsive to flood risk—potentially leading to rents that insufficiently reflect this risk. As a result, property values for rental dwellings may be less sensitive to flood exposure, since landlords anticipate stable rental income. For second homes or vacant properties, the personal cost of flooding (e.g., delays during reconstruction) may be lower than for primary residences, reducing the perceived disutility and thus the impact on price. Another possible explanation is that

paper. Instead, my objective is to determine whether a price discount exists between owner-occupied and non-owner-occupied properties and to quantify the size of this gap. I leave the investigation of underlying mechanisms to future research.

To assess how these different groups of owners may value risks, I develop a new identification strategy that leverages the fine-grained data available in France. I focus on owners who bought a property between 2010 and 2016. Most previous research using hedonic pricing approaches to estimate risk valuation has struggled to isolate the pure effect of risk. In particular, these studies often conflate the impact of risk with that of correlated amenities–for instance, flood-prone areas being located near the coast–or capture the influence of insurance premium adjustments in risky zones. As a result, they may fail to accurately identify the "pure" price discount associated with risk exposure (Contat et al., 2024).

The methodology I adopt relies on distinguishing vulnerable and non-vulnerable dwellings, within and outside of risky areas. For flooding, I define vulnerability based on floor level: a dwelling is considered vulnerable if it is located on the first floor. For subsidence, the key determinant of vulnerability is the strength of building foundations. Since dwellings with upper floors tend to have more robust foundations, I classify a dwelling as vulnerable to subsidence if it does not have any upper floors (Mission Risques Naturels, 2023).

To estimate the price discount associated with natural disaster risk, I employ a double-difference approach that compares vulnerable and non-vulnerable dwellings located in both safe and risky areas for each transaction i. The regression equation is written as follows:

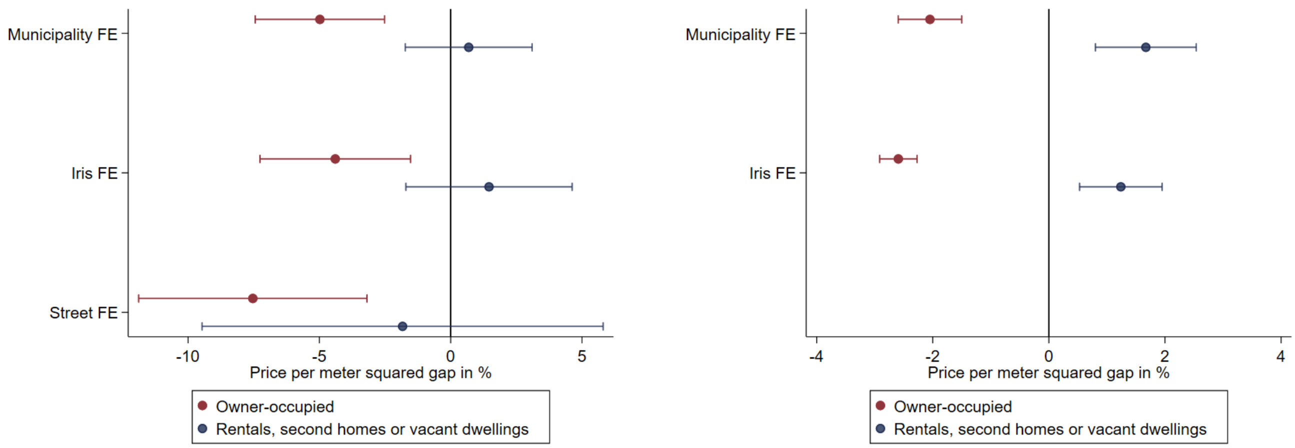
$$Price_{it} = \beta_1 Risk_i \times Vulnerable_i + \beta_2 Vulnerable_i + \beta_3 Risk_i + X_i + \gamma_t + \psi_m + \varepsilon_i \quad (1)$$

$Price_{it}$ is the price per meter squared of dwelling i acquired at time t. The coefficient of interest is β_1, which captures the interaction between vulnerability ($Vulnerable_i$) and exposure to risk ($Risk_i$). The vector X_i includes a set of controls.[3] γ_t are year of acquisition fixed effects. To account for local variation in prices due to amenities, I include several sets of geography fixed

the net present value (NPV) of damages represents only a small share of absentee landlords' overall portfolios (Figure 2b). As a result, the expected gains from acquiring information about risk may be too low to justify the cost, particularly if the potential losses they could avoid are negligible.

[3] These controls include the buyer's income, the dwelling's characteristics (e.g., surface area, type of dwelling—apartment or house—and construction date) and whether a protection plan has been put in place in the municipality at the time of the transaction. When the CatNat system was implemented in 1982, municipalities started to be covered by protection plans that restricted new construction in exposed areas. I control for the presence of a protection plan to ensure that I capture the risk valuation, and not a change in regulation in risky areas.

effects ψ_m. Specifically, I successively use fixed effects for municipalities (approximately 1,000 dwellings per unit), IRIS (approximately 750 dwellings per unit), and street (approximately 20 dwellings per unit). There is a trade-off when selecting the right set of fixed-effects: the more fine-grained it is, the lower the number of observations, but the more geographical characteristics are controlled for.



(a) Flooding

(b) Subsidence

Figure 5: Effect of natural disaster risks on prices

Notes. The figure displays the β coefficients of the regression described in Equation 1. The sets of geographic fixed effects included are indicated on the y axis. Confidence intervals are at the 95% level. Robust standard errors.

Figure 5 displays the values of the β_1 coefficient. The coefficients associated to owner-occupied homes are consistently negative and significantly different from zero at the 95% level. However, for rental properties, second homes, and vacant dwellings owned by absentee landlords, the effect is always either insignificant or positive.[4]

I provide additional analysis and robustness checks in Appendix Section C. I discuss the advantages of the approach with respect to past literature in Appendix Section C.1. I show the triple-difference regression table in Appendix Section C.2. I run the baseline regression in low-risk areas instead of high-risk in Appendix Section C.3. I divide owner-occupants and absentee landlords into more detailed categories in Appendix Section C.4. I document potential selection bias on dwellings sold in Appendix Section C.5.

[4]In the case of subsidence, I excluded street-level fixed effects because exposure is much less discontinuous in practice than for floods. Variation in risk across streets is not meaningfully distinguishable.

2.4.2 Overvaluation in risky areas

To better understand the size of the difference in risk discounts between dwelling categories, I measure how much of the total housing stock overvaluation in risky areas would decrease if those owned by absentee landlords were to price the risk the same way as owner-occupants. The overvaluation of real estate assets at risk is an important issue, as it may be the sign of a housing bubble, affecting the stability of the housing market facing increasing hazards under climate change. I focus on flood risk for this part of the analysis because the information on damage functions to measure overvaluation is not available for subsidence.

To recover the degree of overvaluation in flood-prone areas, I follow the methodology outlined in Gourevitch et al. (2023). To recover expected damages I use the damage functions of Cerema (2018) that correspond to the maps I use. Based on Figure 5, I assume that owner-occupied dwellings face a 5% price discount in high-risk areas and a 2% price discount in all flood prone-areas. There is no price discount for dwellings owned by absentee landlords in the baseline scenario. In the counterfactual scenario, they face the same price discount as owner-occupied ones. The detailed methodology is described in Section 4.6.

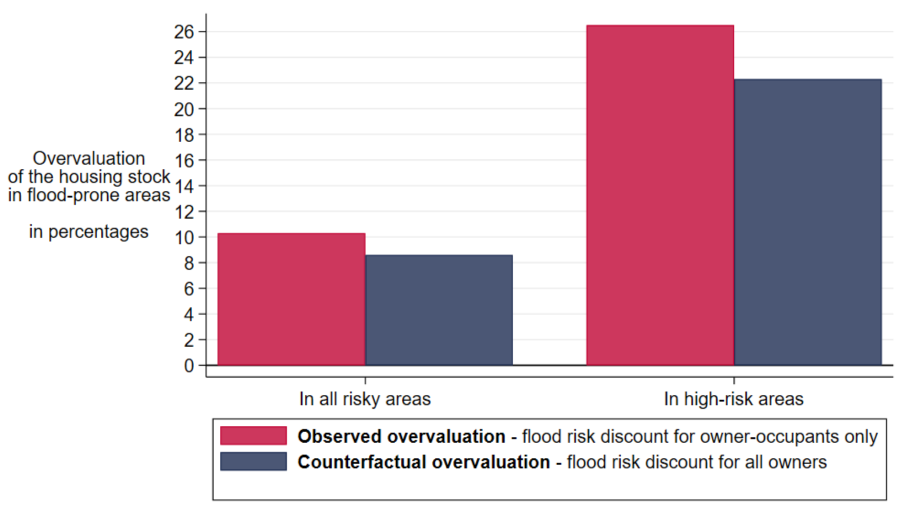


Figure 6: Housing stock overvaluation in flood-prone areas

Notes. The figure displays the degree of housing market overvaluation divided by the observed housing market valuation in flood-prone areas. The methodology is detailed in Section 4.6.

Results are displayed on Figure 6. I find that overall real estate prices would decrease by around 10.3% in flood-prone areas if all owners were to fully account for flood risk. This amount is well-aligned with previous work in the US that found overestimation reaches 8.5% (Hino and Burke, 2021) or between 6% and 13% (Bakkensen and Barrage, 2022).

The contribution here is to find is that prices would decrease by 1.7% in floodplains, and that overvaluation would go down to 8.6%, if dwellings owned by absentee landlords were to face the same price discount as owner-occupied ones. In terms of magnitude, Hino and Burke (2021) find that in the US the implementation of regulatory flood maps led to a decrease of house prices in floodplains of about 2.1%. Gourevitch et al. (2023) find similar magnitudes. As a result, the effect obtained in this paper is comparable to the effect that the introduction of regulatory flood maps had in the US.

To sum-up, I find that about 15% of the total overvaluation in flood-prone areas is driven by dwellings owned by absentee landlords. This result is explained by the fact that they represent around half of the housing stock at risk and face smaller price discounts compared to owner-occupied dwellings. It illustrates that the distribution of ownership plays a significant role in shaping the overall valuation of at-risk properties.

3 Discussion

Most of the literature studying the unequal exposure to natural disaster risks has looked at income inequality among residents and relied on aggregate data (Walker et al., 2006; Masozera et al., 2007; Bakkensen and Ma, 2020; Rözer and Surminski, 2021; Wing et al., 2022; Odersky and Löffler, 2024; Wylie et al., 2025). This approach omits a large part of owners, 50% in the case of flooding, and abstracts from an important dimension of inequality: ownership. The aim of this paper is to leverage a novel dataset that makes it possible to study exposure to natural disasters at a granular level, for the entire housing stock, precisely tracking the real estate wealth of owners. This paper shows that inequalities in exposure to natural disasters with respect to ownership status are large, and that they matter for policy design.

I find that second homes most of the time owned by wealthy and diversified households are particularly exposed to flooding, as opposed to subsidence that affects mostly owner-occupied homes owned by middle income households. These results contrast with previous literature that found that low-income households are overexposed to flooding, a result that I also find if I restrict the analysis to residents and use aggregate income data. To better capture inequalities in exposure to risks, it appears that focusing only on residents' income with aggregate data might be insufficient and lead researchers to omit a large part, if not the majority, of households exposed through the real estate assets they own.

Most importantly, these findings have implications for policy. First, I find that these patterns of exposure imply that subsidized insurance has redistributive impacts, benefiting second homes in the case of flooding and owner-occupied homes in the case of subsidence. Insurance could be designed to take into account these effects and target dwellings owned and occupied by vulnerable households. For example, one could think about differential insurance pricing for second or vacant homes. Second, it appears that natural disaster risks are not priced into housing properties owned by absentee landlords, contrary to those owned by owner-occupants. The results of this study suggest that approximately 15% of the total overvaluation in flood-prone areas is driven by dwellings owned by non-residents. From a policy perspective, this suggests that stronger measures should be directed at absentee landlords purchasing at-risk dwellings, for example by increasing property taxes on non-owner-occupied properties located in flood-prone areas. Finally, policymakers could take into account these local ownership statuses to better target place-based policies such as managed retreat or building new infrastructures.

Several limitations of this study deserve consideration. First, the geographical scope is restricted to France. Further research could expand this analysis and conduct similar work in other countries, and determine whether the exposure patterns observed in France also apply elsewhere. Second, the lack of data on insurance premiums necessitated the use of a machine-learning algorithm to estimate dwelling-level premiums. Making such insurance data more accessible would help advance research in this area. Finally, the analysis of the redistributive effects of insurance assumes no behavioral responses. In reality, households may adjust their location decisions in response to changes in insurance premiums. Additional work is needed to model location choices across different ownership statuses.

This study demonstrates that, in the absence of targeted adaptation policies, renters and single-property homeowners face the greatest vulnerability to climate change impacts, with a disproportionate share of their wealth at risk. This dynamic underscores a disconnection between those who contribute the most to emissions, often characterized by higher incomes and wealth (Chancel et al., 2022), and those who pay the cost of these emissions. Accounting for inequalities in exposure when designing insurance, regulating construction in floodplains, and building protective infrastructure can help ensure greater protection for the most vulnerable.

4 Methods

4.1 Housing data construction

To study the economic characteristics of households exposed to flood risk, I use the 2017 Demographic Database on Housing and Individuals (*FIDELI*) from *INSEE*.[5] For each owner, I observe the number of dwellings they own, which enables me to reconstruct their total real estate wealth (André and Meslin, 2021). The dataset covers the 35 million dwellings in France. The analysis presented in this paper is a cross-section of the year 2017.

For each owner and renter, the data provide detailed household characteristics, including household size, age, income, and income composition (e.g., labor income, net rental income, and other financial income). The dataset also contains information on the physical characteristics of dwellings, such as year of construction, type of dwelling (house or apartment), floor number, and ownership status (owner-occupied, rental, second home, or vacant).[6]

I also use data on housing prices at the dwelling level from the *Données des Valeurs Foncières* (DV3F), which records all housing market transactions between 2010 and 2016. I merge this dataset with *FIDELI* to obtain information on the characteristics of buyers and the ownership status of dwellings following their purchase. For both datasets, I have access to data at the dwelling level with information on the address and dwelling characteristics including surface in meter squared, category (apartment or house), number of rooms and date of acquisition.

To achieve this merge, I proceed in several steps, looping across all observations in the *DV3F* dataset. For each observation *DV3F*, I keep only observations in the *FIDELI* that are registered at the same address. I call observation A the reference observation in the *DV3F* dataset. After this:

- If no correspondence is found in the *FIDELI* dataset, I drop observation A from the merging process.

[5] *Fichiers Démographiques sur les Logements et les Individus 2017*, INSEE. The data are collected through housing and property tax records and can be accessed via the *Centre d'Accès Sécurisé aux Données* (CASD).

[6] Although the dataset includes ownership information for all dwellings in the country, I am unable to link some dwellings to detailed owner characteristics. Specifically, ownership details are missing for dwellings held by foreign or other non-resident individuals, as well as by corporate and individual owners who are not subject to personal income tax. As a result, some owner-occupied dwellings may be misclassified as being owned by single-property owners, when in fact they are held by multi-property owners who manage rental units through corporate structures. Nevertheless, due to the composition of the French rental market, the dataset still captures over 80% of all rental units nationwide. This limitation is therefore unlikely to significantly affect the results.

- If only 1 correspondence is found, I check that dwellings' characteristics in the two datasets are similar. If their surface differs by more than 5 meter squared, I drop observation A from the merging process. Otherwise, I proceed to the merge.
- If 2 correspondences or more are found, I first exclude all observations where surface differs by more than 5 meter squared as compared to observation A. After this:
  - If there is only 1 observation remaining, I proceed to the merge.
  - If 2 correspondences or more are found, I try to find the best fit to observation A. At each of the following steps, I stop when a single correspondence is found.
    1. I keep all observations with the exact same surface, same dwelling category, same number of rooms and same date of acquisition.
    2. I allow date of acquisition to differ by one year.
    3. I allow number of rooms to differ by 1.
    4. I allow number of rooms to differ by 2.
    5. I allow number of rooms to differ by 3.
    6. I allow date of acquisition to be missing.
    7. If no unique match is found, I redo the same procedure but allow surface to differ by 1 additional meter squared.

After running the algorithm, I might find 2 observations in *FIDELI* matching observation A. If that is the case, I remove observation A from the merging process.

At the end of the process I manage to merge 50% of transactions in the *DV3F* data, corresponding to 3.2 million observations. To check whether the subsample of dwellings that I managed to merge is consistent with the baseline dataset and is not subject to selection bias, I compare the average log price per meter squared by postal code in the original *DV3F* dataset and in the merged dataset. Figure A.8 shows that prices per meter squared at the postal code level are consistent across the two datasets, ensuring the quality of the merge. Unsurprisingly, merge quality is slightly lower for apartments, as it may be complicated to differentiate two apartments at the same address using dwelling characteristics.

4.2 Insurance premiums data construction

I recover the amounts spent on home insurance using the 2017 French Household Budget survey from the French National Institute of Economic Studies and Statistics.[7] The sample includes 15,000 households, which I am able to decompose by occupancy status and income deciles. In this survey, respondents were asked about how much they spent on many categories during year 2017, which enables me to recover the amounts spent on car and housing insurance. I use this information to compute CatNat contributions.

I denote the insurance premium π, which is the sum of the CatNat contribution π_c and the premium for other risks π_o. For home insurance, contributions amount to 12% of the premium for other risks π_o. It can be written as follows

$$\pi_c = r\pi_o \qquad r = 0.12 \tag{2}$$

$$\pi_c = \frac{r}{1+r}\pi \tag{3}$$

As I observe π in the French Household Budget survey, I can directly derive the share corresponding to the CatNat fee both for car and housing insurance.

To estimate the total insurance premiums paid across the 35 million dwellings in my sample, I train a machine learning model on the survey data. Using dwelling surface, number of rooms, region, dwelling type (apartment or house), resident income, and household size, I apply a lasso regression to predict premiums. The survey only provides information on premiums paid by tenants and owners of owner-occupied homes, but not for owners of rental, second, or vacant dwellings.

I train the lasso model separately for tenants and owner-occupants to estimate the premiums paid by each group. I then use the model to predict premiums in the administrative dataset. To validate the results, I split the full sample in a train set and a test set, each of them representing half of observations. Figure A.9a compares the distribution of predicted premiums against observed premiums in the test set. It appears that low premiums are slightly overestimated and high premiums are slightly underestimated. However, the correlation coefficient is 96%, highlighting the good performance of the prediction. In particular, Figure A.9b shows that when comparing observed and predicted premiums by income decile, the two end up being

[7] *Budget de Famille 2017*, INSEE. Data are confidential and must be accessed with an authorization from INSEE and through the *Centre d'Accès Sécurisé aux Données* (CASD).

very similar with a correlation coefficient of 99%.

Finally, I use the model trained on homeowners to predict premiums for second homes, rental properties, and vacant dwellings in the administrative dataset. I then adjust these predictions based on average premium differences by occupancy status, as reported by France Assureurs (2023). For instance, premiums for second homes are, on average, 20% lower than those for owner-occupied homes. Therefore, I scale all second-home premiums by 0.8. This approach assumes that the model variables (dwelling surface, number of rooms, region, resident income, and household size) are sufficient to estimate premiums in relative terms. Scaling the predictions ensures consistency with aggregate premium levels.

It is important to stress that these predicted data may be subject to two different biases. The first one is sampling bias from the survey data. This bias should be limited by the fact that these data collected by the French statistical institute are supposed to be representative of the overall population. In particular, weights are applied to correct imbalances. The second type of bias is the prediction error from the machine learning algorithm. However, given the high correlation coefficient obtained from Figure A.9, the prediction error from the machine learning algorithm should be relatively limited.

4.3 Exposure to natural disasters data construction

The maps of exposure I use for flooding are entitled *Territoires à Risque important d'Inondations* (TRI) from *Géorisques*. TRIs are the most reliable maps available for France.[8] They account for local features such as flood protections and categorize 3 types of risks: frequent (small scale but frequent events, return period of 10 to 30 years), medium (return period of 100 to 300 years) and exceptional (large scale events but extremely rare, return period of 1000 years and above). In addition, Cerema (2018) provides damage functions corresponding to these maps, enabling me to estimate expected flood damages based on their methodology. To the best of my knowledge, these are the only publicly available national-scale maps for France that allow for recovering expected damages. I mostly focus on frequent events, but also provide some robustness with other risk thresholds.

For subsidence, I rely on the exposure map produced by the *Bureau de Recherches Géologiques*

[8]The main limitation of these maps is that they do not cover the whole country: they are available only in specific areas where the risk of flooding is particularly high. However, I find that TRIs cover around 45% of dwellings in the sample, and focus on the most exposed areas, which makes these maps relatively representative of the overall flooding risk in France. I consider that the remaining 55% of dwellings are not exposed to floods.

et Minières (BRGM), which classifies areas based on soil composition into three levels of hazard intensity: high, medium, and low. This map identifies a substantial portion of the country as being at risk, with approximately 50% of dwellings located in areas classified as high or medium hazard. Among those dwellings, I consider that only buildings with no upper floors are effectively exposed to subsidence.

Figure A.10 plots the distribution of exposure to risks across the country. Table A.4 reports the share of dwellings exposed to each risk.

4.4 Computing the net present value of flood damages

The Net Present Value (NPV) of future expected damage losses for each dwelling i between 2017 and 2047 (30 years window) can be written as follows

$$\text{NPV}_i = \sum_{t=0}^{30} \text{Annual Expected Losses}_i (1 + \rho_i)^t \tag{4}$$

I consider that ρ_i is specific to each dwelling category. For non-rental dwellings, $\rho_i = 0.033$, corresponding to the average interest rate for housing investment loans over 20 years. For rental dwellings, $\rho_i = 0.035$ as there is generally a risk premium for rental investments of 0.2% on average as there is a risk of vacancies or non-payment.

To recover annual expected losses, I follow the methodology of Cerema (2018). The TRI maps give 3 return periods (frequent, medium and exceptional) and the associated flood depth. Cerema (2018) provide damage functions to convert flood depth into damages. These damage functions differentiate homes and appartments, and each category is split into damages made to buildings, contents and basements. The depth-damage functions are displayed on Table A.5.[9]

I then compute Annual Expected Damages following Cerema (2018) using weights for the different categories of scenarios:

[9]Cerema (2018) provides different damage functions depending on whether a flood lasts more or less than 48 hours. In their paper, they choose the length of the flood arbitrarily based on local knowledge of rivers. As they do not provide the classification of rivers they made, I applied a different method. Given that 42% of flood events lasted more than 48 hours between 2000 and 2020, I recover expected damages by computing the weighted average based on this historical data. E.g., for individual damages to building, damages per meter squared amount to 80 euros for events lasting less than 48 hours and 108 euros for events lasting more. In that case, the value displayed in Table A.5 is $0.58 \times 80 + 0.42 \times 108 = 91.8$.

- A 10-year frequency for frequent scenarios (weighting: 0.1)
- A 100-year frequency for medium scenarios (weighting: 0.01)
- A 1,000-year frequency for exceptional scenarios (weighting: 0.001)
- The curve is closed by assuming 1.5 times the extreme damages (a conventional assumption)

Thus, the annual expected damage for dwelling i can be calculated using the following formula:

$$\begin{aligned}\text{Annual expected losses}_i = & \frac{1}{2}(1.5 \cdot D_{\text{extr}} + D_{\text{extr}})(0.001 - 0) \\ & + \frac{1}{2}(D_{\text{extr}} + D_{\text{mid}})(0.01 - 0.001) \\ & + \frac{1}{2}(D_{\text{mid}} + D_{\text{freq}})(0.1 - 0.01) \end{aligned} \tag{5}$$

Where D_{extr}, D_{mid}, and D_{freq} represent the damages associated with exceptional, medium, and frequent scenarios, respectively.

Finally, I plug the annual expected losses in equation 4 to recover the Net Present Value of flood damages.

4.5 Computing the degree of insurance cross-subsidization across ownership statuses

To assess the degree of cross-subsidy, I perform a back-of-the-envelope calculation–I ignore potential behavioral responses like housing stock relocation if premiums were to change–to measure how much each category of dwelling is cross-subsidized by the scheme. To achieve this, I compute the difference between insurance premiums under the current subsidized system ($\pi^{subsidized}$) and those that households would pay in a counterfactual risk-based system ($\pi^{risk-based}$).

I first simulate counterfactual premiums that households would pay if a risk-based system was implemented. I recover $\pi^{risk-based}$ by multiplying observed premiums $\pi^{subsidized}$ by a risk factor, proportional to the risk to which dwelling i is exposed.

$$\pi_i^{risk-based} = \pi_i^{subsidized} \times risk\ factor_i \tag{6}$$

The risk factors I use are presented in Table A.6. For flooding, they are derived from return periods: I first compute the annual probability of flood (inverse of the return period) for each risk category $P(\text{disaster} = 1|k)$, where $k \in \{\text{low}, \text{medium}, \text{high}\}$. Given the national average annual probability of flooding $P(\text{disaster} = 1) = 0.018$ from CCR (2022), I calculate the risk factors as $P(\text{disaster} = 1|k)/P(\text{disaster} = 1)$. Finally, to estimate the multiplier for safe areas, I recover $P(disaster = 1|safe)$ by solving

$$\frac{P(disaster = 1|safe)}{P(disaster = 1)} + \sum_k \frac{P(disaster = 1|k)}{P(disaster = 1)} = 1 \tag{7}$$

and compute the corresponding ratio for safe areas.

For subsidence, since return periods are unavailable, the risk factors are selected somewhat arbitrarily, provided they satisfy the same equation 7. Alternative risk factors could be used. However, as the exposure patterns across hazard categories (high, medium, and low) are relatively similar for subsidence, it would not affect much the results (see Appendix Figure A.3).

I then measure transfers for each dwelling i

$$Transfer_i = \pi_i^{risk-based} - \pi_i^{subsidized} \tag{8}$$

$Transfer_i$ is positive if dwelling i is in a risky area and negative if it is in a safe area. I then compute $Net\ transfer_d$ for each dwelling category d, with A_d being the universe of dwellings i in category d.

$$Net\ transfer_d = \sum_{i \in A_d} Transfer_i \tag{9}$$

$Net\ transfer_d$ is positive if dwelling category d is overexposed in risky areas as compared to safe ones, negative if underexposed. I then normalize $Net\ transfer_d$ to get $Net\ transfer\ norm_d$ corresponding to transfers received by each dwelling category for each 100€ transferred from safe to risky areas.

$$Net\ transfer\ norm_d = 100 \times \frac{Net\ transfer_d}{\sum_i Transfer_i \times \mathbb{1}_{[Transfer_i > 0]}} \tag{10}$$

Figure 4 plots the net normalized transfers by ownership status.

4.6 Computing overvaluation in flood-prone areas

To recover the degree of overvaluation in flood-prone areas, I follow the methodology of Gourevitch et al. (2023). This approach is represented graphically on Figure A.11.

A dwelling's degree of overvaluation can be written

$$\text{Overvaluation}_i = \text{Fair Market Value}_i - \text{Efficient Price}_i \tag{11}$$

The fair market value is the observed price that I directly extract from the dwelling-level price data. However, I need to get an estimation of the efficient price that should be set on the market if households were to perfectly price the risk. To achieve this, I first recover the risk-free market value:

$$\text{Risk Free Market Value}_i = \text{Fair Market Price}_i / (1 + \delta_{risk,owner}) \tag{12}$$

$\delta_{risk,owner}$ is the risk discount in percentages obtained from Section 2.4.1 with risk $\in$ (flooding,subsidence) and owner $\in$ (occupants,landlords).[10] This risk discount depends on whether or not dwelling i is exposed to risk ($\delta_{risk,owner} = 0$ if dwelling i is not exposed to risk), and whether or not the owner of dwelling i discounts flood risk, assuming that homeowners have a 2% risk discount and absentee landlords do not discount flood risk.

Finally, I compute the efficient price for each dwelling i:

$$\text{Efficient Price}_i = \text{Risk Free Market Value}_i - \text{NPV}_i \tag{13}$$

The contribution here is to simulate how overvaluation would decrease if absentee landlords were to value flood risk to the same extent as owner-occupants. To get to this counterfactual, I replace $\delta_{risk,owner}$ so that $\delta_{risk,occupants} = \delta_{risk,landlords}$. Running this counterfactual yields a lower level of risk overvaluation by construction, as it makes households value flood risk to a larger extent.

[10] The approach differs from Gourevitch et al. (2023) here as they use changes in flood areas delimitation to measure δ_g and I make use of the new identification strategy described in Section 2.4.1 to measure flood risk discounts.

5 Data availability

Information on housing market characteristics comes from the *FIDELI* dataset developed by the French Institute of Statistics (INSEE) and is available through secured access: https://www.casd.eu/en/source/housing-and-individual-demographic-file/. House prices data are available upon request on the Cerema website: https://datafoncier.cerema.fr/dv3f. Survey data on insurance spending comes from the *Budget des familles* dataset, also available through secured access: https://www.casd.eu/en/source/household-budget-survey/. Maps exposure to risks are publicly available. For flooding: https://www.georisques.gouv.fr/donnees/bases-de-donnees/zonages-inondation-rapportage-2020 and for subsidence: https://www.georisques.gouv.fr/donnees/bases-de-donnees/retrait-gonflement-des-argiles-version-2026.

6 Code availability

Analyses were conducted in Stata, R, SAS and Python within QGIS. The codes used to conduct these analyses is available in the following GitHub repository: https://github.com/Thomas-Bezy/Real-estate-wealth-inequality-and-natural-disasters---replication-package.git.

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Real estate wealth inequality and exposure to natural disasters

Supplementary information

A Natural disasters and real estate wealth inequality in France

A.1 Natural disaster insurance in France

France is characterized by an insurance system against natural disasters, established in 1982 and referred to as *CatNat* (Charpentier et al., 2022). This system mandates that private insurance companies incorporate coverage for natural disasters into their standard car and property insurance policies (I focus on home insurance in this paper). While homeowners are free to decide whether to purchase home insurance, most lending institutions require such insurance to issue a mortgage. Consequently, the vast majority of homeowners opt to buy home insurance, resulting in the 99% coverage rate for flood insurance observed in mainland France (Grislain-Letrémy, 2018). In overseas departments, housing data is less reliable and coverage rate is 50%. For these reasons, I focus on mainland France in this paper.

This system is funded through an additional fee that must be included in every home insurance contract. This premium represents 12% of baseline standard insurance premium in 2017–the year analyzed in this paper–which amounts to approximately 25 euros per year per dwelling. Consequently, insurance premiums do not depend on risk. Households in safe areas, who would have paid lower premiums in a risk-based system, end up contributing more and cross-subsidize households in riskier areas. The composition of households in risky areas will therefore drive the redistributive effects of subsidizing natural disaster insurance. For example, if the housing market in risky areas is primarily composed of owners of second homes, they will be the main beneficiaries of this system.

These additional insurance premiums are then channeled to the "Caisse Centrale de Réassurance" (Central Reinsurance Fund), which acronym is CCR, a company fully owned by the French government that has a key role in the CatNat scheme. When a claim for a natural disaster is made, the private insurance company reimburses the household that filed the claim and then seeks reinsurance from the CCR.[11] The CCR commands more than 90% of the market share in the natural disaster reinsurance sector. From 1982 to 2017, the system was self-financed through CatNat premiums. However, as the costs of natural disasters have increased significantly in recent years, the CCR began to run regular deficits. This situation led the government to increase CatNat contributions from 12% to 20% in 2024.

A.2 The real estate market in France

Real estate constitutes the most important, and often the only, source of wealth for most households around the world (Chancel et al., 2022). In France, 61% of the total wealth in the country is held through real estate (Cheptitski et al., 2023), comparable to the average in the euro area. The private rental sector in France is characterized by a large share of individual "buy-to-let" investors. More than 80% of the approximately 7.5 million private rental units are owned by individual landlords residing in France, with the remainder owned by foreign owners, corporations for their employees, institutional investors, and non-profits. This structure differs from some countries where corporate landlords are more prevalent. However, "mom-and-pop" landlords play a significant role in most advanced economies, including the United States, where they operate slightly less than half of all rental units.[12]

Vacancies represent 10% of the total housing stock in the country, and this number has increased significantly in recent years (Hurard and Huault, 2024). There are three main reasons why a dwelling may be vacant: it may be listed for sale or rent on the real estate market, the owner may not have paid the estate tax that allows for occupancy, or the dwelling may be retained by the owner but remains unoccupied due to its inadequate condition.

[11] From 1982 to 2022, the CCR was responsible for 51% of the total claims. During major disasters, such as in 2017, the CCR's share of disaster-related costs increased to 70% (CCR, 2022).

[12] According to the 2021 *Rental Housing Finance Survey*, individual landlords account for 40% of units and 69% of all properties in the United States.

B Additional descriptive results

B.1 Summary statistics

Table A.1 presents the characteristics of owners and renters across the different dwelling categories.

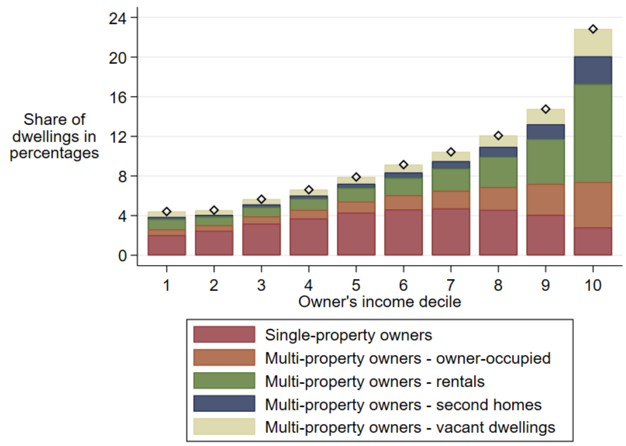
	Owner-occupied	Owner-occupied	Rentals		Second homes	Vacant dwellings
	Single-property owners	**Multi-property owners**	**Owners**	**Renters**	**Owners**	**Owners**
Share of residential housing	38%	18%	26%		8%	10%
Income by consumption unit						
25th percentile	17188	21247	22820	13376	23258	19622
50th percentile	21975	28547	32057	18123	31631	27827
75th percentile	27958	38947	46357	24040	44235	40297
Number of owned dwellings						
50th percentile	1	2	4	0	2	3
75th percentile	1	3	6	0	4	5
90th percentile	1	4	12	1	6	10
Share with financial income representing at least 5% of disp. income	6%	13%	17%	3%	16%	16%

Table A.1: Share of dwellings exposed to natural disaster risks

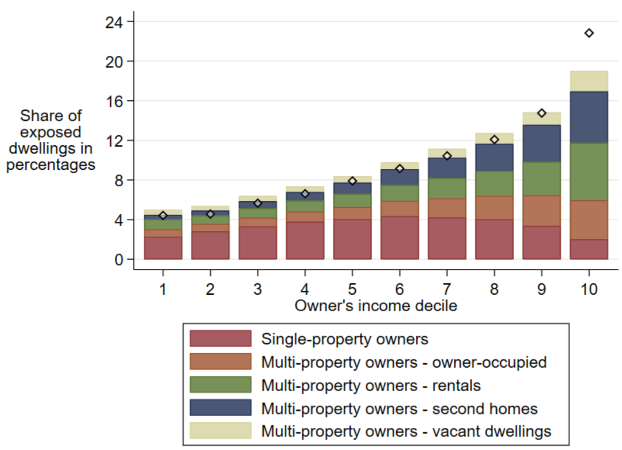
Notes. The Table presents the characteristics of owners and occupants of the residential dwellings included in this paper. Rental dwellings are represented in two columns, as they are both owned by absentee landlords and occupied by renters. Percentiles are calculated based on the number of dwellings; for example, 25% of second homes are owned by households with four or more dwellings.

The categories of dwellings most commonly occupied by the most deprived households are those owned by single-property owners and rental properties. Single-property owners are slightly wealthier than renters but, more importantly, they own at least one real estate asset, unlike the large majority of renters. Multi-property owner-occupants, in contrast, have higher incomes than single-property owners, own more real estate assets (by definition), and are better able to diversify their income, relying more heavily on financial income. Absentee landlords, owning rental properties, second homes, and vacant dwellings, are the most economically privileged group. These households are typically at the top of the income distribution, and own several properties as well as financial assets.

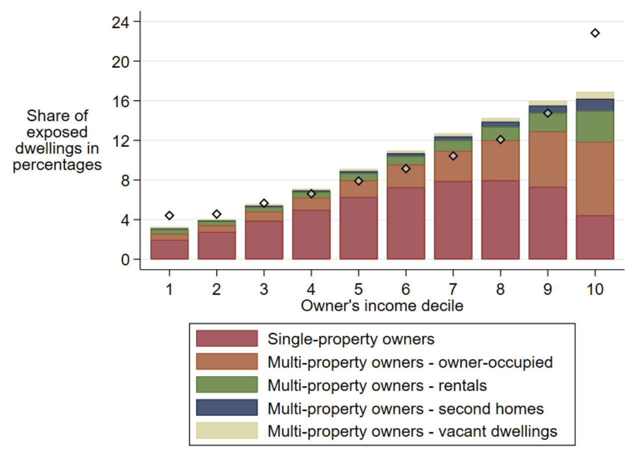
B.2 Exposure by ownership status and income at the dwelling level



(a) In France



(b) In areas exposed to flooding



(c) In areas exposed to subsidence

Figure A.1: Exposure to risks by ownership status and income

Notes. Figure A.1a displays the overall distribution of real estate wealth nationwide by owner's income decile and ownership status. Figures A.1b and A.1c present the same distribution but focus on areas exposed to flooding and subsidence. The white dots act as benchmarks for the overall distribution shown in Figure A.1a. Comparing the dots with the bars reveals the extent of overexposure and underexposure for each owner's income decile.

As I have access to disposable income at the household level, I assess how differential exposure by ownership types vary with the income distribution. Figure A.1a displays the overall distribution of real estate wealth nationwide by owner's income decile and ownership status. Figures A.1b and A.1c present the same distribution but focus on areas exposed to flooding and subsidence. The white dots act as benchmarks for the overall distribution shown in Figure A.1a. Comparing the dots with the bars reveals the extent of overexposure and underexposure for each owner's income decile.

For both flooding and subsidence, the lower end of the income distribution is primarily exposed through owner-occupied dwellings, while the upper end is mainly exposed through multi-property owners. Additionally, the data indicate that the bottom of the income distribution is overexposed to flood risk overall (Figure A.1b). This is driven by the fact that among owner-occupants, low-income households are particularly overexposed to risk. For subsidence, the middle of the income distribution emerges as the most exposed to risk (Figure

B.3 Exposure to river and coastal flooding

Figure A.2 decomposes exposure to flooding between exposure to river and coastal flooding. River flooding represents the large majority of dwellings exposed to flooding overall and 93% of flood-related losses against only 7% for coastal flooding (France Assureurs, 2021). However, coastal flooding is expected to create much more damages in the future with sea level rise.

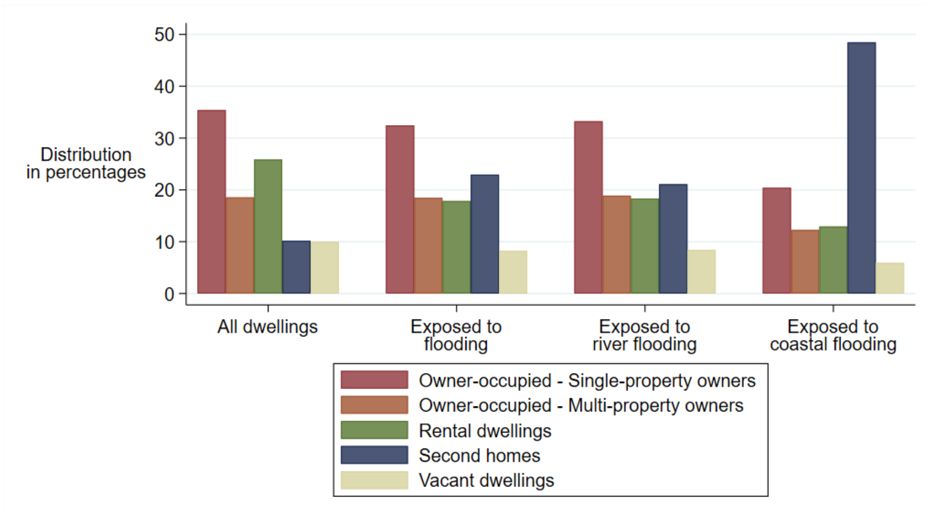
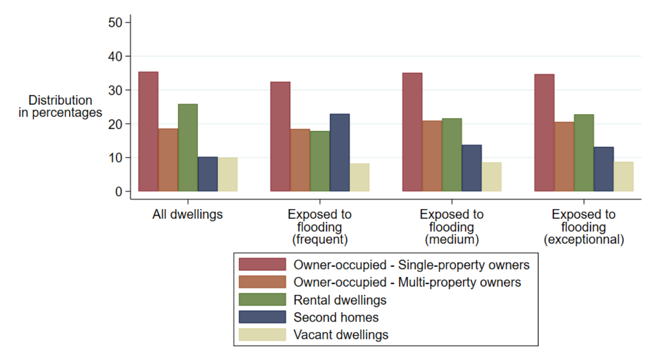


Figure A.2: Exposure to river and coastal flooding

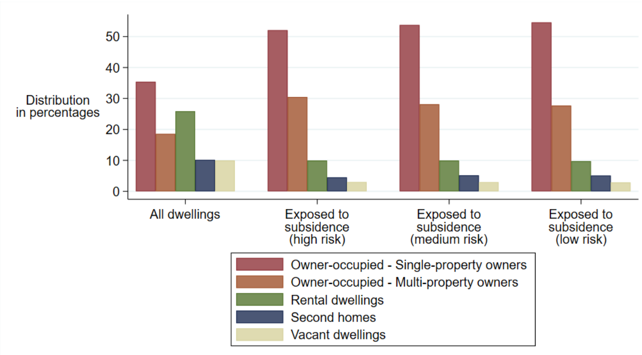
Notes. The Figure displays the share of dwellings exposed to river and coastal flooding by ownership category.

B.4 Exposure levels by risk intensity

Figure A.3 decomposes exposure by risk intensity for flooding and subsidence. For flooding, it appears that second homes are particularly over-represented in areas with a frequent risk of flooding. For subsidence however, the degree of overexposure of owner-occupied homes is not much affected by the degree of risk considered.



(a) Flooding



(b) Subsidence

Figure A.3: Effect to natural disasters by risk intensity

Notes. The Figure displays the share of dwellings exposed to flooding and subsidence by risk intensity.

B.5 NPV of flood damages by ownership status

Figure A.4 displays the distribution of the NPV of flood damages across dwelling categories. Detailed methodology on how these damages have been computed is available in Appendix Section 4. The results are similar to those of Figure 2 with second homes being over-represented in flood-prone areas. As a result, even if the over-exposure of second-homes is less clear in low-risk areas, second-homes still represent 18% of total expected flood losses while they represent only 10% of the total value of the housing stock.

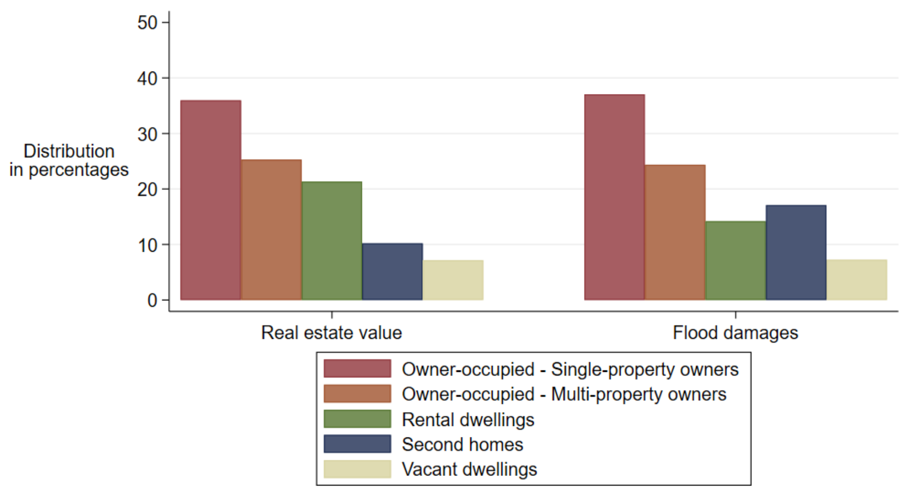


Figure A.4: NPV of flood damages accross dwelling categories

Notes. The Figure displays on the left hand side the distribution of real estate market value across dwelling categories, and on the right-hand side the distribution of the NPV of flood damages across dwelling categories.

B.6 Regressive insurance premiums

Figure A.5 illustrates that CatNat premiums are regressive, representing .25% of income for households at the bottom 10% of the income distribution and .075% for those at the top 10%.

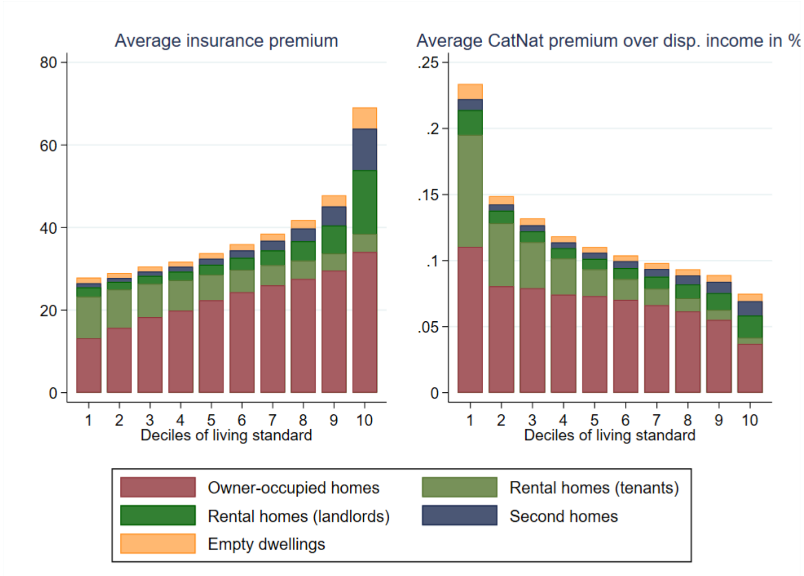


Figure A.5: CatNat premiums by income decile

Notes. The left-hand side displays the average CatNat insurance premiums by income decile in euros. The right-hand side displays the ratio of the average CatNat insurance premiums divided by income by income decile in percentages.

C Additional reduced-form analysis on heterogeneous risk valuations

C.1 Discussion on the advantages and limits of the identification strategy relative to the literature

Contat et al. (2024) provide a comprehensive literature review on the existing evidence regarding risk valuation. Most studies find that there is a price discount in flood-prone areas, but this discount is often insufficient to reach the efficient price that would fully capture the net present value of future flood events.

Three main methods have been employed to address this question. The first consists in comparing households in safe and risky areas (Zhang and Leonard, 2019; Bakkensen and Ma, 2020; Ancel and Kamionka, 2024). The main drawback of this approach is that, even after adding geographical fixed effects, part of the effect may be driven by sorting and capture the effect of amenities, such as a view of the seafront in the case of flooding. A second approach exploits changes in risk designation when mapping is updated (Hino and Burke, 2021; Gourevitch et al., 2023; Ma et al., 2024; Chen et al., 2025). The limitation here is that it is unclear whether changes in prices are driven by new information or by changes in regulation and insurance policies that increase the cost of living in risky areas, thus reducing prices in these locations. Finally, some papers use surveys to elicit willingness to pay to live in risky areas (Bakkensen and Barrage, 2022; Mulder, 2024). The main limitation of this approach, compared to a hedonic approach, is that self-revealed preferences may not reflect actual behavior.

The methodology I use in this paper is different. The fine-grained data I use enables me to differentiate between vulnerable and non-vulnerable dwellings (e.g., dwellings on the first floor versus those on upper floors in the case of flooding). By running a double-difference between vulnerable and non-vulnerable dwellings in safe and risky areas, I am able to account for most of the effect of amenities specific to risky areas.

The advantages of the approach I consider in this paper are threefold. First, it allows for a comparison of dwellings within risky areas (between vulnerable and non-vulnerable dwellings), which are theoretically exposed to similar amenities. Second, in the French context, risk is not priced into insurance premiums. As such, the coefficient reflects the "pure" risk valuation, rather than capturing an effect of changing premiums in risky areas. Finally, this is an hedonic regression, which captures actual behaviors, in contrast to surveys where it may not always be clear if answers reflect behaviors in practice.

The main limitation of this approach is that vulnerability may be correlated with certain amenities. For example, living on an upper floor may not only reduce flood risk but also provide a panoramic of the seafront, potentially confounding the results. To account for this, I provide a robustness check in Appendix Section C where I exclude dwellings that are located less than 200 meters away from coasts or rivers. Results end up being very similar.

C.2 Triple-difference specification

Table A.2 presents the triple interaction coefficients between vulnerability, exposure to risk, and absentee landlord ownership. The coefficients can be interpreted as the difference in price discounts associated to risk between dwellings owned by owner-occupants and absentee landlords. The regression suffers from limited power due to the restricted set of flood risk areas and the coarse fixed effects. Despite this limitation, all coefficients are positive and two out of five are significant at the 1% level. This suggests that there is a difference in risk valuation between owner-occupants and absentee landlords.

	Log price per meter squared		
	(1)	(2)	(3)
Flooding			
At risk*Vulnerable*Absentee landlord	0.019	0.075***	0.040
	(0.015)	(0.016)	(0.031)
Observations	677195	212558	43056
Subsidence			
At risk*Vulnerable*Absentee landlord	0.017***	0.008	
	(0.004)	(0.005)	
Observations	2371790	2140581	
Fixed effects			
Municipality	Yes		
Iris		Yes	
Street			Yes

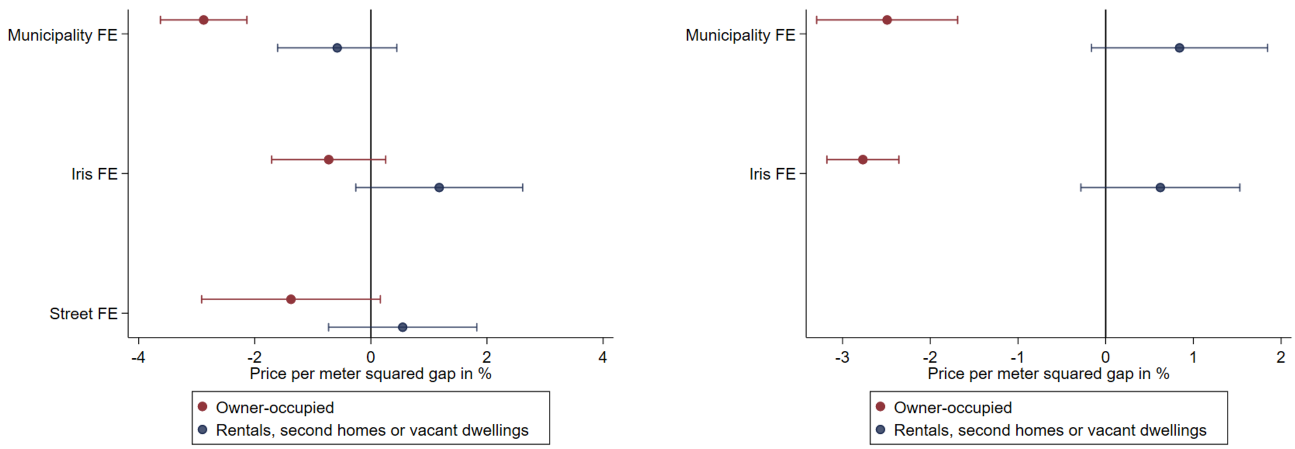
*Signif. Codes: ***: 0.01, **:0.05, *:0.1*
Standard errors clustered at the date of acquisition level

Table A.2: Effect of natural disaster risks on prices

Notes. The figure displays the interaction coefficients between being located in a risky area, being a vulnerable dwelling, and being owned by an absentee landlord. The coefficients can be interpreted as the difference in price discounts associated to risk between owner-occupants and absentee landlords. The standard controls and fixed effects used in the regression are the ones described in Section 2.4.1.

C.3 Low-risk areas

I reproduce the same regression as in Figure 5 but vary the level of risk. I now consider households exposed to exceptional events for flooding and low hazard for subsidence. Results are displayed on Figure A.6. For both categories of events, coefficients are smaller in magnitude, which is the expected result as the risk is lower in these areas. However, the patterns are very similar: coefficients are negative and often significant for owner-occupied dwellings and positive or insignificant for dwellings owned by absentee landlords.



(a) Flooding (b) Subsidence

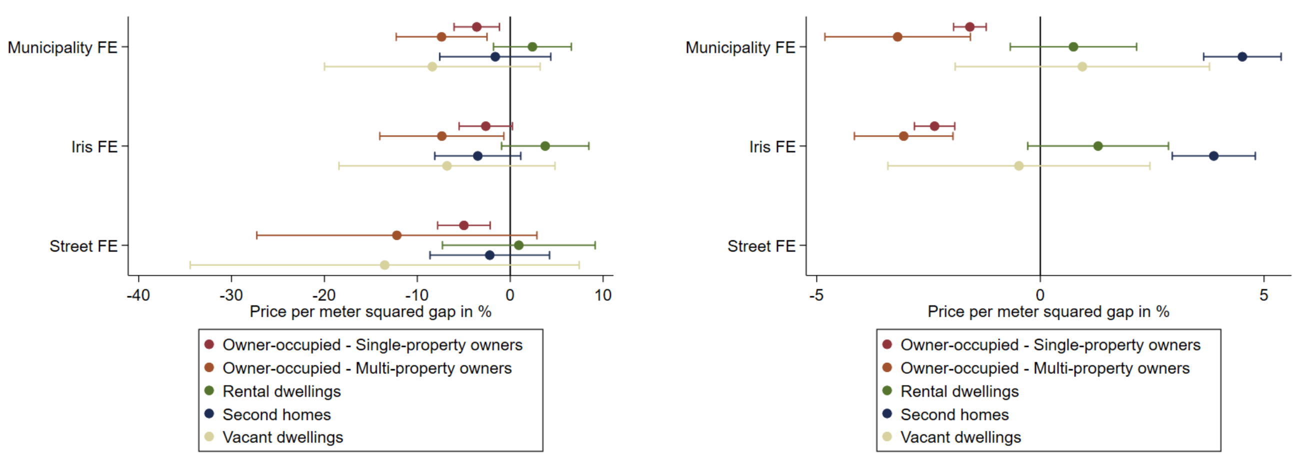
Figure A.6: Effect of natural disaster risks on prices for low-risk areas

Notes. The figure displays the β coefficients of the regression described in Section 2.4.1. The sets of geographic fixed effects included are indicated on the y axis. The areas at risk I use are the low risk areas. Confidence intervals are at the 95% level. Robust standard errors.

C.4 Detailed ownership categories

In addition, and for completeness, instead of regrouping dwellings in two categories, I consider separately dwellings owner-occupied by single-property owners, by multi-property owners, rental dwellings, second homes and vacant dwellings. Results are displayed on Figure A.7.

The coefficients for owner-occupied dwellings are consistently negative and most of the time statistically significant at the 95% level. For dwellings owned by absentee landlords, coefficients are either insignificant or positive, suggesting that misvaluation is shared across all ownership categories. The notable exception is for vacant dwellings in the case of flooding, where coefficients are sometimes negative and significant. This can be explained by the fact that the distinction between vacant and owner-occupied dwellings is not very clear. A property classified as vacant may have been the owner's primary residence at the time of sale and subsequently listed on the market, becoming vacant in the process. Alternatively, it may have been inherited from a relative who previously occupied it, and recorded as vacant before the estate tax is assessed. In both cases, the property is effectively an owner-occupied dwelling in transition. This ambiguity helps explain why vacant dwellings sometimes exhibit patterns similar to owner-occupied homes, in contrast to rental or second homes, whose usage is clearly distinct.



(a) Flooding

(b) Subsidence

Figure A.7: Effect of natural disaster risks on prices - decomposed owner categories

Notes. The figure displays the β coefficients of the regression described in Section 2.4.1. The sets of geographic fixed effects included are indicated on the y axis. Confidence intervals are at the 95% level. Robust standard errors.

C.5 Accounting for selection bias

As I only observe the price of dwellings that were sold, the price data may be subject to selection bias. To test whether selection bias might be an issue here, I check whether the probability of being sold is affected by being located in a risky area. I run the following regression, controlling for the same set of controls X_i and geographic fixed-effects ψ_m as in the main regression:

$$Sold_i = \beta Risk_i + X_i + \psi_m + \varepsilon_i \tag{14}$$

Regression coefficients β are displayed in Table A.3. On average, 10% of dwellings in the sample that were sold between 2010 and 2016. Dwellings exposed to flooding have a .6% lower probability of being sold. This lower probability seems negligible as compared to the baseline probability of being sold in the entire sample. For subsidence, there is no differential probability of being sold between risky and safe areas.

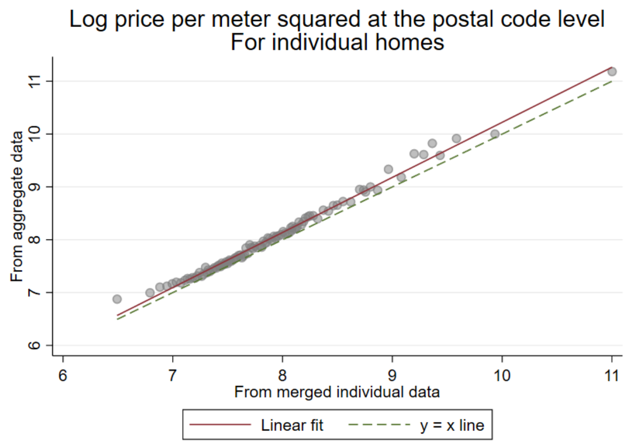
	Probability of being sold between 2010 and 2016		
	(1)	(2)	(3)
Flooding			
At risk	-0.006***	-0.003***	-0.004***
	(0.002)	(0.001)	(0.001)
Observations	7192154	2803437	609137
Subsidence			
At risk	0.000	-0.000**	
	(0.000)	(0.000)	
Observations	23521389	21601252	
Fixed effects			
Municipality	Yes		
Iris		Yes	
Street			Yes

*Signif. Codes: ***: 0.01, **:0.05, *:0.1*
Standard errors clustered at the date of acquisition level

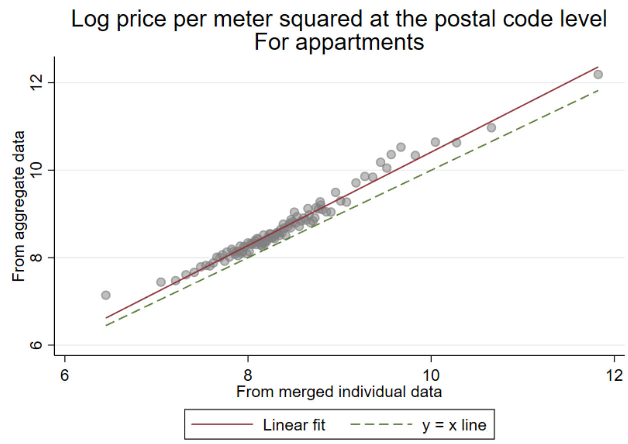
Table A.3: Effect of natural disaster risks on probability of selling

Notes. The figure displays the regression coefficients of Equation 14. The coefficients represent the difference in the probability of dwellings being sold in risky areas compared to safe areas.

D Additional Figures and Tables



(a) Individual homes

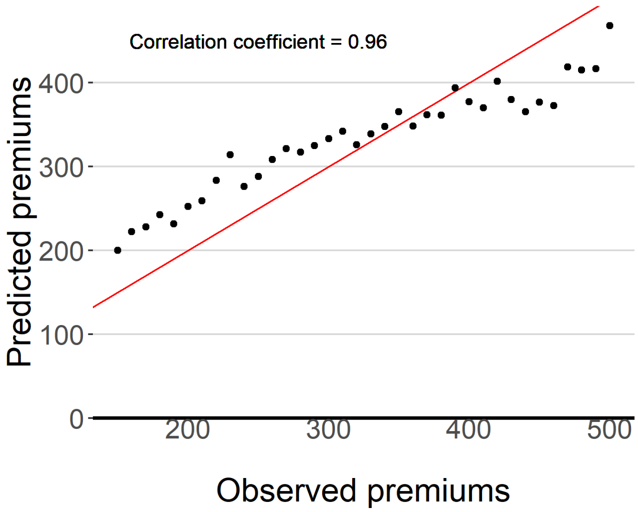


(b) Apartments

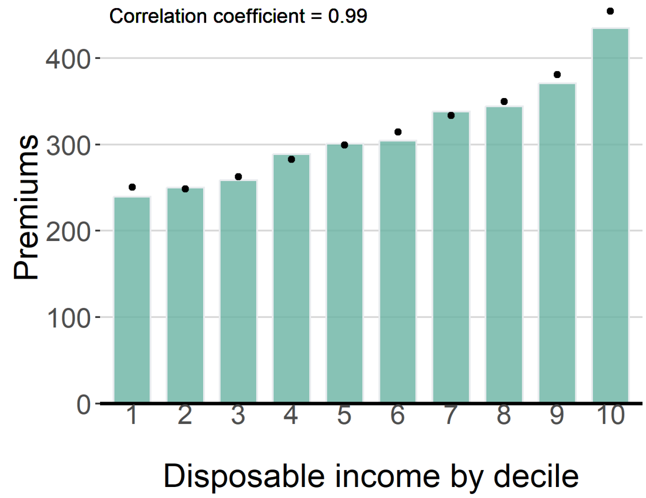
Figure A.8: Price per meter squared at the postal code level in merged vs original datasets
Notes. The Figure compares the average price per meter squared by postal code in the original *DV3F* dataset and in the merged dataset. Panel A.8a shows the results for individual homes and Panel A.8b for apartments.

Share of dwellings exposed to flooding	
Frequent (return period of 10 to 30 years)	0.5%
Medium (return period of 100 to 300 years)	2.1%
Exceptional (return period of 1000 years and above)	3.3%
Share of dwellings exposed to subsidence	
High hazard	4%
Medium hazard	13%
Low hazard	19%

Table A.4: Share of dwellings exposed to natural disaster risks
Notes. The Table displays the share of dwellings exposed to risks, considering that only dwellings on the first floor are exposed to flooding and only dwellings with no upper floors are exposed to subsidence.



(a) For homeowners



(b) For tenants

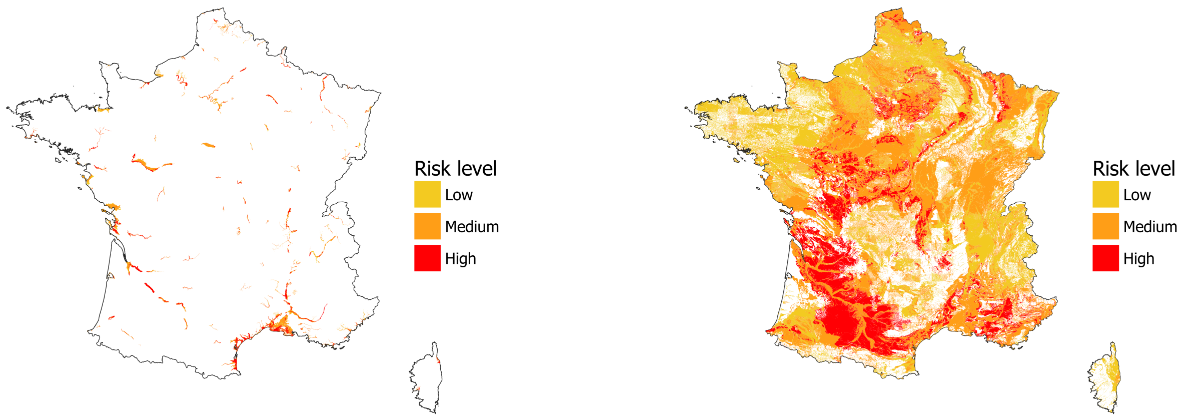
Figure A.9: Comparison between predicted home insurance premiums and survey data

Notes. The Figure . Figure A.9a plots predicted premiums against observed premiums in the test set. The red line corresponds to the function x=y. Figure A.9b compares predicted premiums (black dots) with actual survey data (green bars) by income decile. Correlation coefficients between predicted and observed premiums are displayed on top.

Minimal flood depth in meters	Homes			Appartments		
	Building	**Content**	**Basement**	**Building**	**Content**	**Basement**
0	91.8	102.2	0.9	78.9	86.1	74.3
0.5	113.8	151.6	1.2	99	129.5	82.5
1	154	190.1	1.7	135	163.2	82.5
2	237.9	194.4	8.2	175.1	166	82.5

Table A.5: Depth-damage functions per meter-squared

Notes. The Table displays the costs per meter squared associated to a given flood depth. Values are taken from Cerema (2018).



(a) Flooding (b) Subsidence

Figure A.10: Maps of exposure to risks

Notes. The left panel plots exposure to flooding according to the *Territoires à Risque important d'Inondations* (Territories at high risk of flooding), which acronym is TRI, from *Géorisques*. The right panel plots exposure to subsidence according to the *Bureau de Recherches Géologiques et Minières* (BRGM).

Disaster type	**Risk factors**
Flooding	
Frequent (return period of 10 to 30 years)	28
Medium (return period of 100 to 300 years)	11
Exceptional (return period of 1000 years and above)	3
Safe areas	0.67
Subsidence	
High hazard	12.5
Medium hazard	5
Low hazard	2
Safe areas	0.5

Table A.6: Risk factors used to simulate counterfactual insurance premiums

Notes. The table displays the risk factors used to compute counterfactual risk-based insurance premiums.

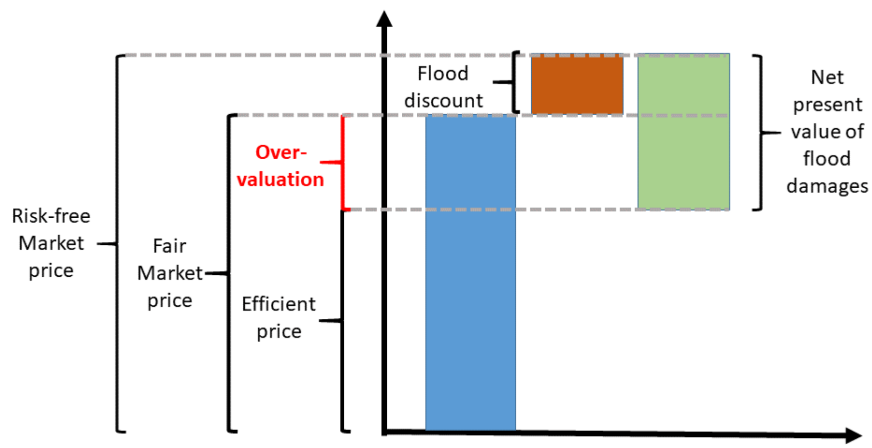


Figure A.11: Methodology to recover overvaluation