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

This paper examines how natural disaster risks are distributed across tenants, owner-occupants, and owners of rental, second, and vacant homes. Prior studies, relying on aggregate income data and focusing only on residents, typically find that low-income households are more exposed to flooding. However, this approach overlooks half of the exposed housing stock–owned by non-residents. Using dwelling-level data covering the entire French housing market, I document large disparities in exposure to flooding and subsidence. 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, I show 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. Finally, place-based adaptation policies such as building resilient defenses may fail to target the most critical areas if ownership structures are ignored.

Keywords: Wealth Inequality, Insurance, Natural Disasters

JEL Codes: D31, G52, Q51, Q54

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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). Additionally, research has shown that the degree of risk valuation varies across income groups (Gourevitch et al., 2023), indicating that the total valuation of assets at risk is influenced by exposure patterns.

Inequalities in exposure to risk on the housing market are a critical concern. First, housing constitutes a large share of total wealth and at least 50% in most high-income countries (Blanchet and Martínez-Toledano, 2023). Second, there are stark disparities between renters and owners. Most renters possess only durable goods and lack other forms of wealth, making them highly vulnerable to extreme weather events, unlike owners. Finally, among owners, there is considerable heterogeneity. In France, for example, the bottom 50% of the income distribution owns 25% of real estate assets (see Appendix Figure A.4a), illustrating that this market is composed of both middle-income single-property owners and wealthy multi-property owners.

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). To measure these inequalities in the housing market, this literature focused on income inequality and relied on aggregate income data to assess the socio-economic characteristics of exposed households (Walker et al., 2006; Masozera et al., 2007; Bakkensen and Ma, 2020; Rözer and Surminski, 2021; Wing et al., 2022; Odersky and Löffler, 2024). However, this approach has three main limitations. First, 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 demonstrate that excluding them may overlook more than 50% of the residential housing stock at risk of flooding. Second, income inequalities fail to differentiate levels of exposure between renters and homeowners, with renters being considerably more vulnerable to risk due to factors inherent to their tenancy status–such as limited wealth diversification (Fessler and Schürz, 2018) and the absence of legal rights to prevent or influence rebuilding or redevelopment (McCarthy et al., 2001; Burby et al., 2003). 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 analysis to French municipalities exposed to flooding (roughly equivalent to ZIP codes in the U.S.), 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 measure environmental inequalities along a new dimension: real estate ownership. I address existing data limitations and complements past literature that has primarily focused on income inequality. One might question the relevance of adopting an ownership perspective in this context, given that the direct victims of extreme weather events are residents. First, patterns of exposure across ownership status are crucial for understanding the redistributive effects of subsidizing insurance. Implementing such subsidies, which involve taxing safe areas to finance lower premiums in risky ones, results in transfers between owners, from those in safe areas to those in risky areas. Even in the rental market, most of these transfers occur between owners: in developed countries on average, renters bear only a third of the damages (for contents), while owners bear two-thirds of the damages (for the infrastructure) (Osberghaus, 2021; Al Assi et al., 2023). Second, when examining the overvaluation of the housing stock in risky areas, the behavior and patterns of exposure of owners are ultimately what matter, as they are the ones making decisions about housing prices. Finally, when designing place-based policies, such as building a seawall, both residents and owners benefit. Owners may experience a reduction in the expected costs of future disasters affecting their dwellings and an increase in property values. Therefore, considering owners can alter the targeting of place-based policies.

I make use of novel administrative data, in France, geo-localized and merged at the dwelling level, on dwellings characteristics, owners' income, owners' real estate wealth (André and Meslin, 2021), house prices, insurance premiums and exposure to environmental risks. I examine the distribution of the two main natural disaster risks in France: flooding and subsidence. I categorize dwellings into five ownership statuses: owner-occupied by single-property owners, owner-occupied by multi-property owners, rentals, second homes, and vacant dwellings.

I find significant heterogeneity in exposure to environmental risks across ownership statuses. When examining dwellings exposed to flooding, 50% of these dwellings are owned by absentee landlords (owners of rentals, second homes, and vacant dwellings) who do not reside in risky areas. This finding challenges the common perception that natural disaster victims are "left with nothing." In reality, many at-risk homes are owned by wealthy well-diversified households who can more easily bear the costs of extreme weather events. Specifically, second homes are a major contributor to the overexposure of absentee landlords. Although they constitute less than 10% of all residential properties in France, they represent 20% of dwellings exposed to flooding. In coastal areas, this figure rises to nearly 50%. On the contrary, for subsidence, more than 75% of exposed dwellings are owner-occupied, among which two-third are occupied by single-property owners. These statistics highlight that each type of natural disaster involves substantial differences in exposure patterns and, consequently, in the redistributive effects of adaptation policies.

I demonstrate that conducting the same analysis using aggregate income data, following the standard methods used in the literature (Rözer and Surminski, 2021; Wing et al., 2022), would yield opposite results: overexposure of low-income areas in the case of flooding and overexposure of high-income areas in the case of subsidence. 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.

To illustrate the importance of considering owners rather than focusing solely on residents, I draw implications for adaptation policies that are directly linked to the patterns of exposure across ownership statuses.

First, I analyze the implications for the subsidized French insurance system against extreme weather events. This system is one of the most heavily subsidized in the world (Charpentier et al., 2022; Bézy et al., 2025), although some form of subsidization is common in many high-income countries (e.g., the US, the UK, Spain). I demonstrate that subsidizing insurance premiums has different redistributive impacts when considering ownership and occupancy statuses. For flooding, I find that for every 100€ transferred from safe to risky areas to subsidize premiums, 6€ are transferred to owners of second homes. For subsidence, the policy is largely redistributive, transferring 20€ to owner-occupants for every 100€ transferred from safe to risky areas. These results illustrate that there could be significant policy improvements by better targeting insurance subsidies, particularly for flooding.

Second, I estimate the price discount associated to risk by ownership status[1] using a novel identification strategy that leverages the fine-grained data available. With access to geolocated

[1] Natural disasters can also impact rents. Harwood (2023) study the impact of flooding on rents, but the literature remains very limited on the topic. In France, fine-grained data on rents are not available (Chapelle and Eyméoud, 2022). As a result, I provide reduced-form evidence on house prices and consider that landlords internalize the effect of natural disasters on rents.

data on dwelling characteristics, I define certain dwellings as vulnerable (being on the first floor for flooding and having weak foundations for subsidence). I then examine the double difference between vulnerable and non-vulnerable dwellings, and between those in risky and safe areas. To control for the effect of amenities, I use different sets of geographical fixed effects, up to the street-level fixed effects. Additionally, I control for a set of covariates, including the date of the transaction, owners' income, and dwelling characteristics. I find a price discount for owner-occupied dwellings exposed to risk, but no price discount for dwellings bought by absentee landlords. To illustrate the magnitude of the difference in price discounts, I measure how much of the housing market overvaluation in flood-prone areas would decrease if dwellings owned by absentee landlords were to face the same price discount as owner-occupied ones. Following the methodology from Gourevitch et al. (2023), I find that about 15% of the total overvaluation in flood-prone areas is driven by dwellings owned by absentee landlords.

Finally, to help design place-based policies targeting the most vulnerable areas, I provide a new mapping of sensitive areas based on housing market composition. Official maps released by governments, which are used to design policies, generally rely on the number of dwellings at risk in a given area to determine exposure levels.[2] I demonstrate how measuring an area's vulnerability by the number of owner-occupied dwellings at risk, instead of the total number of dwellings, changes the ranking of at-risk areas. This shift is particularly significant for flooding, where the ranking of areas changes substantially. For subsidence, since most homes exposed are owner-occupied, the maps for this risk category remain relatively similar.

Related literature. This paper contributes to the expanding field of the literature seeking to comprehend the unequal distribution of environmental risks and the underlying reasons (Chancel et al., 2023; Colmer et al., 2024). Specifically, my research extends the prior work on inequalities in exposure to natural disaster risks. A range of natural disasters have been studied in this context including wildfires (Burke et al., 2021; Wibbenmeyer and Robertson, 2022) and floods (Walker et al., 2006; Sayers et al., 2018; Bakkensen and Ma, 2020; Rözer and Surminski, 2021; Bézy et al., 2025). Wing et al. (2022) find that the costs of natural disasters disproportionately impact poorer communities in the United States. A substantial part of the literature also focused on how different categories of households are able to recover after extreme weather

[2]See for France: `https://www.donnees.statistiques.developpement-durable.gouv.fr/lesessentiels/essentiels/risques-naturels-innondation.html`

events (Deryugina et al., 2018; Howell and Elliott, 2019). Hsiao (2024) develops a location choice model to rationalize the differential exposure patterns of income groups. On the rental market, a few studies have shown that renters are considerably more vulnerable to environmental risks than owners: many characteristics of renters correlate with social vulnerability (Morrow, 1999) and renters are more constrained when managing disaster risks (McCarthy et al., 2001; Burby et al., 2003; Van Zandt and Rohe, 2011). However the literature on the effect of natural disasters on the rental market, is very scarce (Lee and Van Zandt, 2019; Harwood, 2023).

I make two main contributions to this literature. The first is data-driven: I move beyond aggregate income data to study real estate ownership inequality using dwelling-level data. Unlike most existing studies that focus on owner-occupants, I also include rental, second, and vacant homes. I find that these categories represent more than 50% of dwellings exposed to flood risk. By doing so, I am able to include a significant portion of the housing market that was omitted in previous studies, including the rental market, for which evidence is scarce. The second contribution is result-driven. I find that flooding primarily affects second homes, most of the time owned by wealthy and diversified owners, whereas the prevailing consensus in the literature is that low-income households are more exposed to flooding, a result that I find as well when using aggregate income data in France. These findings highlight the limitation of using aggregate income data to measure environmental inequalities, as it may obscure important patterns of risk exposure.

My work also builds upon prior research on the redistributive implications of insurance against natural disasters. Dinan et al. (2019) and Oh et al. (2022) study how regulating insurance leads to cross-subsidization between risky and safe areas. Holladay and Schwartz (2010) and Bin et al. (2017) assess the distributional effects of the U.S. National Flood Insurance Program (NFIP) and find that the current U.S. system is slightly regressive. In the case of France, Charpentier et al. (2022) highlight that flood risk is considerably concentrated in France, with 10% of households bearing 74% of the losses and simulate alternative insurance pricing schemes. Bézy (2024) builds a location choice model to recover the optimal level of cross-subsidy between safe and risky areas. I contribute to this literature by studying a new dimension of heterogeneity and measuring the degree of cross-subsidization across ownership statuses.

Finally, this paper contributes to the literature on risk valuation in the housing market. 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 (Hino and Burke, 2021; Bakkensen and Barrage, 2022; Gourevitch et al., 2023). Three main methods have been employed to address this question:

- 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 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.
- Exploiting changes in flood risk designation when mapping is updated (Hino and Burke, 2021; Gourevitch et al., 2023). 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.
- Using surveys to elicit willingness to pay to live in risky areas (Bakkensen and Barrage, 2022). The main limitation of this approach, compared to a hedonic approach, is that self-revealed preferences may not reflect actual behavior.

I contribute to this literature by implementing a new hedonic approach. 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 capture most of the effect of amenities specific to risky areas. Additionally, since I am in a setting where insurance premiums do not reflect risk, I can capture the "pure" risk discount instead of the effect of changes in regulation.

The remainder of the paper is structured as follows. In Section 1, I provide some context on environmental risks and structure of the real estate market in France. I describe the data in Section 2. I document exposure to risks across ownership statuses in Section 3. I derive implications for adaptation policies and valuation of the stock at risk in Section 4 and conclude in Section 5.

1 Natural disasters and real estate wealth inequality in France

1.1 Natural disaster risks and insurance

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). In this paper, I focus exclusively on the residential real estate market, which represents around 80% of total natural disaster direct damages (CCR, 2022).

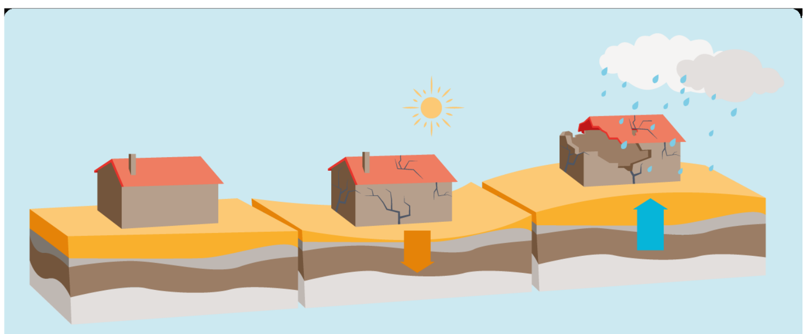


Figure 1: Subsidence phenomenon

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.

France is also characterized by a unique 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 a 99% coverage rate for flood insurance in mainland France (Grislain-Letrémy, 2018). In oversea 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" (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[3]. 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.

1.2 The real estate market in France

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.

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 (de Bondt et al., 2020). The private rental sector in France is characterized by a large

[3] 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).

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.[4]

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.

2 Data

2.1 Households and dwellings characteristics

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 possess, 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 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).

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

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

[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).

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.

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. Appendix A.1 provides further details on the merging procedure and descriptive statistics on sample representativeness. The final merged sample includes approximately 3.2 million properties that have been sold between 2010 and 2016.

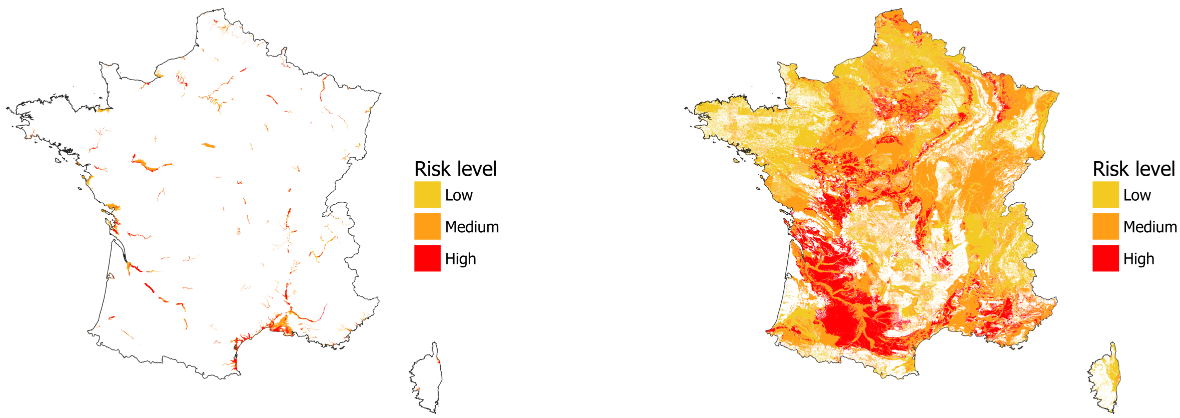
For some descriptive statistics in Appendix Section B, I additionally rely on municipality-level price data. This dataset reports the average price per square meter by municipality. In these cases, housing value is computed as the product of the dwelling's surface area and the average price per square meter in the corresponding municipality.

2.2 Exposure to natural disasters

I then collect data on exposure to the two main natural disaster risks in France: flooding and subsidence. Figure 2 presents the raw geographical distribution of exposure to these risks. Table 1 reports the share of dwellings exposed following the adjustments detailed below. Later in the paper, I use the term "high-risk" areas to refer to locations that are exposed to frequent flooding and/or to a high level of subsidence hazard.

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.[6] 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

[6] 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.



(a) Flooding

(b) Subsidence

Figure 2: Maps of exposure to risks

Notes. The left panel plots exposure to flooding according to the *Territoires à Risque important d'Inondations* (TRI) from *Géorisques*. The right panel plots exposure to subsidence according to the *Bureau de Recherches Géologiques et Minières* (BRGM).

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 1: 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.

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 describe in detail the methodology I use to recover the net present value (NPV) of flood damages in Appendix Section A.3. I mostly focus on frequent events, but also provide some robustness with other risk thresholds. Additionally, 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).

Figure 3 shows how areas classified as high flood risk by the TRIs align closely with existing flood protection infrastructure, highlighting the ability of these maps to account for local features. In the figure, each red dot represents a dwelling, while flood risk zones are shown in blue. I overlay these risk exposure maps onto the *FIDELI* administrative dataset to assign flood risk exposure at the dwelling level.

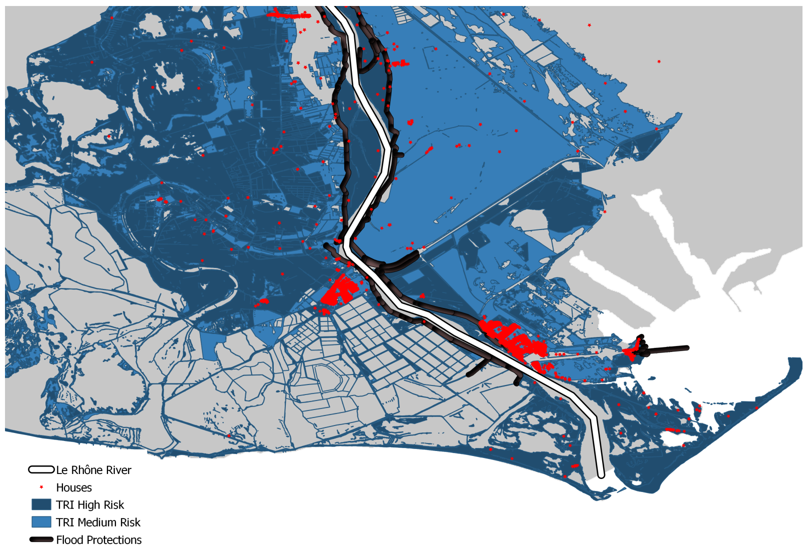


Figure 3: Coverage of TRIs in Port-Saint-Louis-du-Rhône

Notes. Each red dot represents the location of a dwelling. The grey areas correspond to regions in France that are not considered exposed to flood risk. The Rhône River is shown in white. Areas classified as high flood risk (frequent risk) according to the TRI zoning are displayed in dark blue, while areas of medium flood risk are shown in light blue. Flood protection infrastructure is represented in black.

For subsidence, I rely on the exposure map produced by the *Bureau de Recherches Géologiques 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. However, not all dwellings in these zones 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 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.

2.3 Insurance Spending

To study the redistributive effects of the CatNat scheme in Section 4.1, I use data from the 2017 French Household Budget Survey, conducted by the French National Institute of Statistics and Economic Studies (INSEE).[7] The representative survey includes approximately 15,000 households, which I am able to disaggregate by occupancy status and income decile. Respondents reported their expenditures across a wide range of categories for the year 2017, including housing insurance. I use this information to estimate household-level contributions to the CatNat scheme.

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 in 2017, contributions amounted to 12% of the premium for other risks π_o. It can be written as follows

$$\pi_c = r\pi_o \qquad r = 0.12$$

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

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.

Finally, I use the insurance payment data from the survey to estimate premiums at the individual level within the *FIDELI* dataset. To do this, I train a machine learning algorithm on the survey data, incorporating a set of demographic variables to predict insurance premiums. To validate the approach, I compare the predicted distribution of premiums by income level in the *FIDELI* dataset with the corresponding distribution in the survey data, and I obtain a correlation coefficient greater than 95%. Figure A.3 also shows that CatNat 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%. More details on this procedure can be found in Appendix Section A.2.

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

3 Results

In this section, I present new results on exposure to natural disaster risks, disaggregated by ownership status across five mutually exclusive categories of dwellings: owner-occupied by single-property owners, owner-occupied by multi-property owners, rental dwellings, second homes, and vacant dwellings. I lead the analysis at the dwelling level and not at the owner level, to avoid double counting of rental dwellings that are both occupied by a renter and owned by an absentee landlord.

3.1 Inequalities across ownership status

Table 2 presents the characteristics of owners and renters across the different dwelling categories that will be examined in the remainder of the paper. Rental dwellings are represented in two columns, as they are both owned by absentee landlords and occupied by renters.

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.

One key limitation of previous research has been the focus on owner-occupants and (less frequently) renters, thereby excluding absentee landlords from the analysis. However, as shown in Table 2, absentee landlords own a significant portion of the housing stock. Importantly, these households are generally less vulnerable to environmental risks, as they possess a well-diversified portfolio of real estate and financial assets. Therefore, environmental inequalities in housing markets cannot be solely explained by income inequalities among residents, as this would overlook a substantial source of heterogeneity in risk vulnerability driven by absentee landlords.

	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 2: 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.

3.2 Exposure to natural disaster risks by ownership status

In this section, I explore the differences in risk exposure across ownership statuses. Figure 4 displays the share of dwellings by ownership category, both overall and specifically in high-risk areas.

For flooding, the figure shows that more than 50% of exposed dwellings are owned by absentee landlords, and only 30% of exposed dwellings are occupied by single-property owners. Rental dwellings are less frequently at risk, which helps mitigate 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.7 shows that, in coastal areas, second homes constitute 50% of flood-exposed dwellings. These findings suggest that, in the case of flooding, wealthy owners of second homes are particularly exposed, unlike renters, and owner-occupants are neither over- nor under-represented.

For subsidence, the figure presents a different pattern, with a significant overexposure of

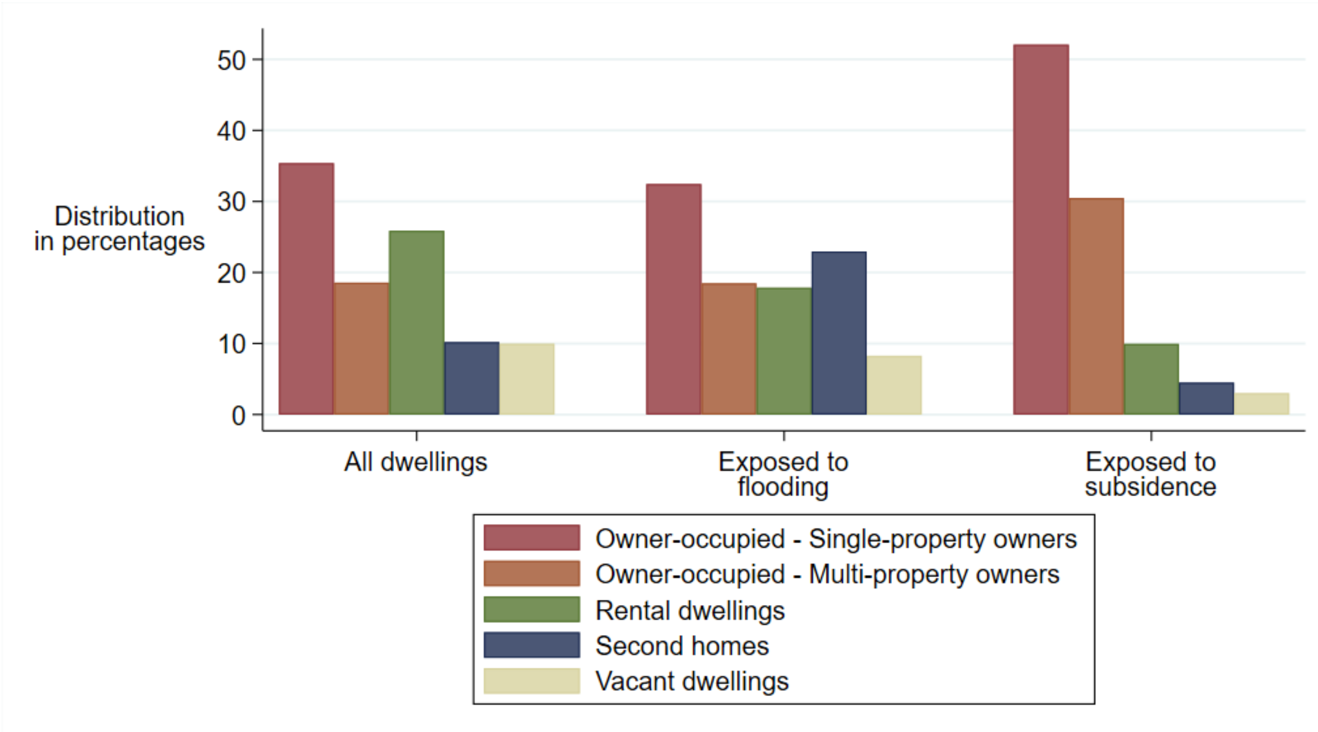


Figure 4: Share of dwellings exposed to natural disasters by ownership status
Notes. The Figure displays the share of dwellings by ownership category overall (on the left-hand side) and in high-risk areas (flooding in the middle and subsidence on the right hand side).

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.

These results appear to contradict much of the previous literature on flood exposure, which generally finds that low-income households are more exposed to flood risks. 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[8]. The results, displayed in Figure 5, align more closely with prior studies (Rözer and Surminski, 2021; Wing et al., 2022), showing that households in low-income municipalities are more exposed to flooding. For subsidence, I find that municipalities with higher

[8]Municipalities in France have an average population of 4,000 inhabitants, comparable to a census tract in the U.S.

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 full scope of the housing market, I observe that floods primarily affect wealthy owners of second homes, while subsidence predominantly impacts middle-income homeowners.

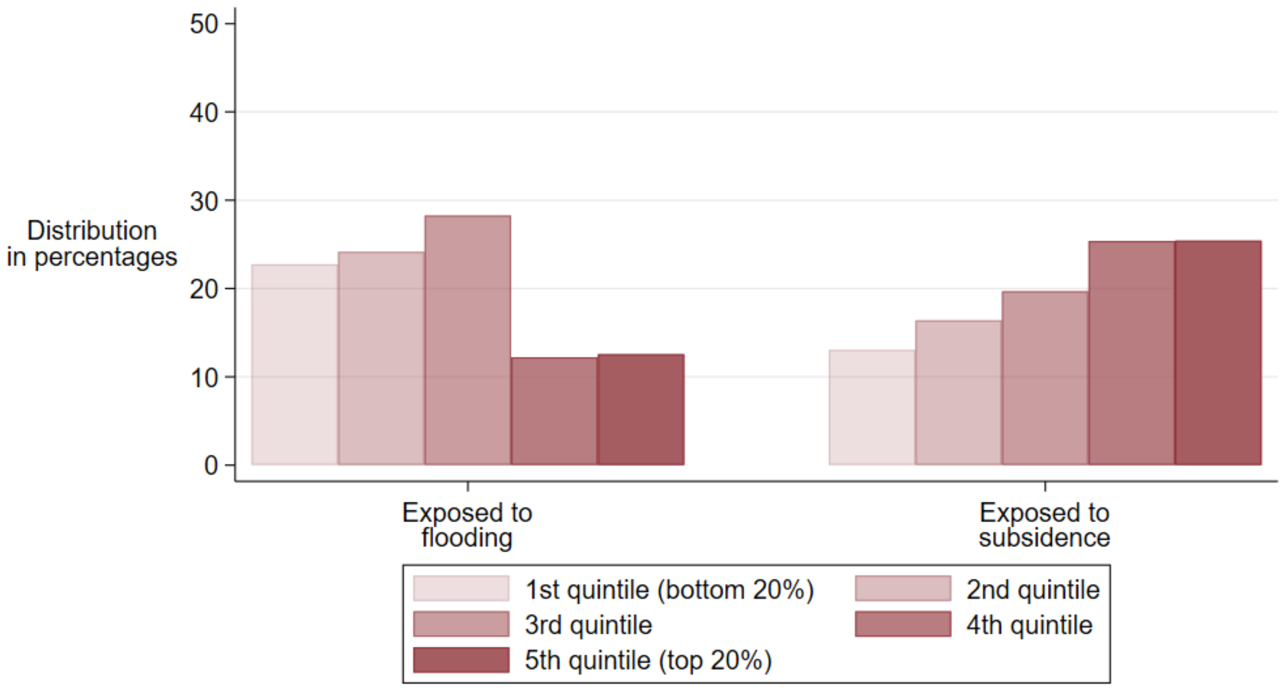


Figure 5: Share of dwellings exposed to natural disasters by average income in the municipality
Notes. The Figure displays the share of dwellings by average municipality income in high-risk areas.

Focusing on flooding, Figure 6 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. In these high-risk areas, expected discounted damages amount to approximately 20% of the dwelling's value, with little variation across ownership categories. The right-hand panel instead uses each owner's total real estate wealth as the denominator. 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, the 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 flood risk.

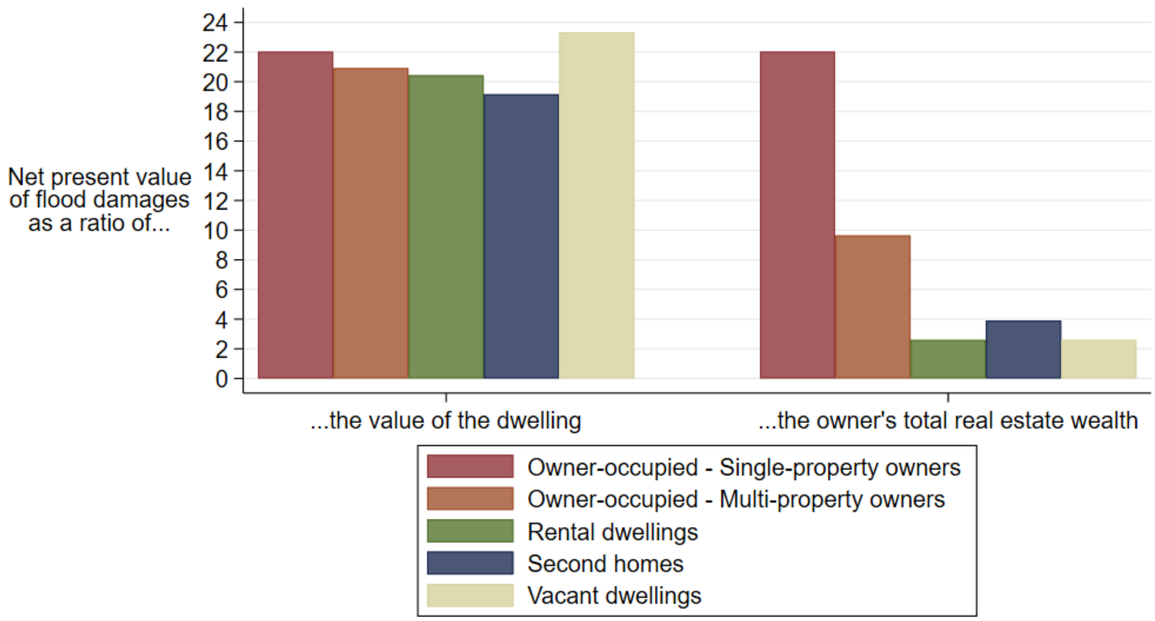


Figure 6: Net present value of flood damages as a ratio of real estate wealth
Notes. shows the net present value (NPV) of flood damages as a share of real estate wealth, broken down by ownership status in areas exposed to the highest levels of risk. The left-hand panel uses the market value of the exposed dwelling as the denominator. The right-hand panel instead uses each owner's total real estate wealth as the denominator.

More descriptive results are available in Appendix Section B. More specifically, I plot the income distribution at the dwelling level in safe and exposed areas (Section B.1), measure the distribution of the share of the housing wealth exposed to flood risk (Section B.2), recover the importance of geographical amenities in explaining the overexposure of second homes (Section B.3), show the distribution of NPV of flood damages by ownership status (Section B.4) differentiate exposure to river versus coastal flooding (Section B.5), show how the distribution of dwellings at risk varies by risk intensity (Section B.6).

4 Implications

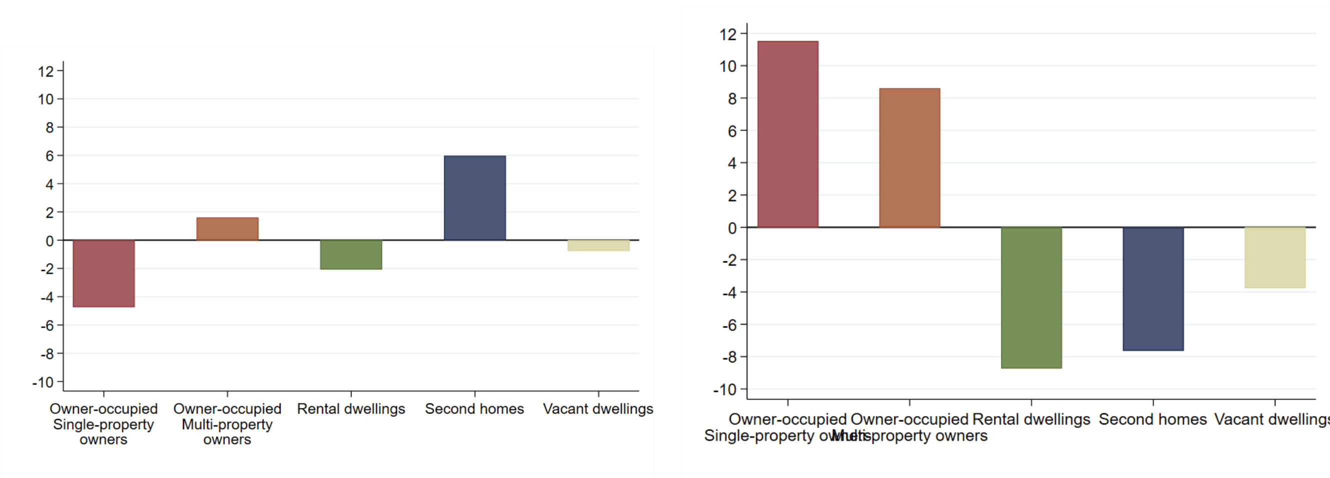
One might question the relevance of focusing on owners, given that residents are the ones directly exposed to natural disasters. In this section, I show that considering heterogeneity in ownership status is important for at least three reasons: the redistributive effects of natural disaster insurance, the valuation of the housing stock at risk, and the targeting of place-based policies.

4.1 Redistributive effects of subsidizing insurance

As outlined in Section 1, the French CatNat insurance system provides coverage against natural disasters to 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. The categories overrepresented in high-risk areas are those that disproportionately benefit from the scheme. Based on the findings from Section 3, this system appears to subsidize second homes in the case of flooding, and owner-occupied dwellings in the case of subsidence.

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 Appendix Section C.

Net normalized transfers are presented in Figure 7. 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 were 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). These findings show that, in the case of CatNat, removing subsidence coverage would primarily disadvantage middle-income owner-occupants.



(a) Flooding

(b) Subsidence

Figure 7: 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.

4.2 Valuation of the housing stock at risk

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. 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 the net present value (NPV) of damages represents only a small share of absentee landlords' overall portfolios (Figure 6). 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. However, I do not empirically test these mechanisms in this paper. Instead, my focus is on determining whether a price discount exists between owner-occupied and non-owner-occupied properties and quantifying 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 (see Section 2). 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 between 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, where most flood-related damages typically occur (Deniz et al., 2017; Mauroux, 2018; Dubos-Paillard et al., 2024). 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–an approach supported by empirical evidence (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:

$$Price_i = \alpha + \beta_1 Risk_i \times Vulnerable_i + \beta_2 Vulnerable_i + \beta_3 Risk_i + X_i + Geography_i + \varepsilon_i \qquad (2)$$

$Price_i$ is the price per meter squared of dwelling i. 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: the year of acquisition, 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[9]. To account for local variation in prices due to amenities, I include several sets of geography fixed effects. Specifically, I successively use fixed effects for commuting zones (approximately 100,000 dwellings per unit), municipalities (approximately 1,000 dwellings per unit), IRIS (approximately 750 dwellings per unit), and street (approximately 20 dwellings per unit).

The advantages of this approach 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.

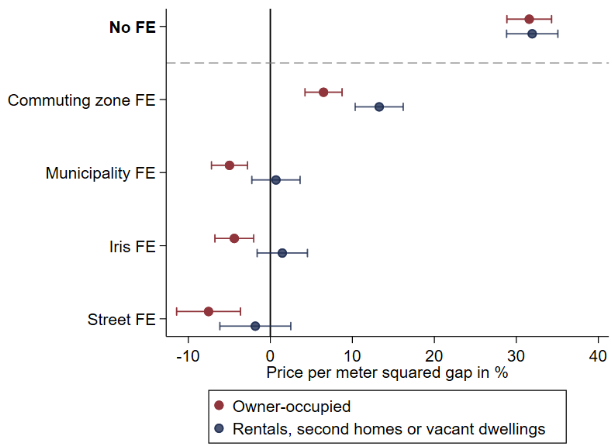
The main limitation of this approach is that vulnerability may be correlated with certain amenities. For example, living on an upper floor may not only reduce flood risk but also provide a panoramic of the seafront, potentially confounding the results. To account for this, I provide a robustness check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

Figure 8 displays the values of the β coefficient. After including at least municipality-level fixed effects, 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.[10]

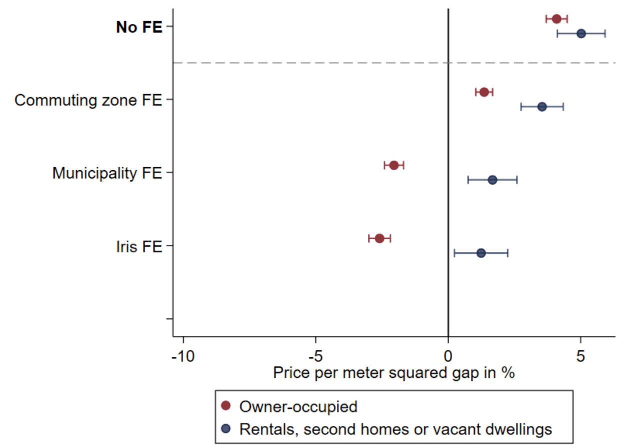
Table 3 presents the triple interaction coefficients between vulnerability, exposure to risk, and absentee landlord ownership. The coefficients can be interpreted as the difference in price discounts associated to risk between dwellings owned by owner-occupants and absentee landlords. The regression suffers from limited power due to the restricted set of flood risk areas and the coarse fixed effects, yet the coefficients are always positive once geographical fixed effects are included and, in some cases, they are significant at the 0.01 level. This suggests that there is indeed a difference in risk valuation between owner-occupants and absentee landlords.

[9] 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.

[10] 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.



(a) Flooding



(b) Subsidence

Figure 8: Effect of natural disaster risks on prices
Notes. The figure displays the β coefficients of the regression described in Section 4.2. The sets of geographic fixed effects included are indicated on the y axis. Confidence intervals are at the 95% level. Robust standard errors.

Appendix Section D provides robustness checks: decomposing the categories of dwellings by ownership status, changing the risk thresholds, excluding dwellings particularly close to coasts or rivers and changing clustering of standard errors.

To better understand the size of the difference in risk discount between dwellings 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 particularly concerning, as it may be the sign of a housing bubble, thus 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 I need 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 TRI maps I use. The detailed methodology is described in Appendix Section E. To remain conservative, based on Figures 8 and A.10, 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.

	Log price per meter squared				
	(1)	(2)	(3)	(4)	(5)
Flooding					
At risk*Vulnerable*Absentee landlord	-0.005	0.047**	0.019	0.075***	0.040
	(0.021)	(0.019)	(0.018)	(0.019)	(0.025)
Observations	2920747	2094234	677195	212558	43056
Subsidence					
At risk*Vulnerable*Absentee landlord	-0.005	0.003	0.017***	0.008	
	(0.005)	(0.004)	(0.005)	(0.005)	
Observations	2920747	2850796	2371790	2140581	
Fixed effects					
Commuting zone		Yes			
Municipality			Yes		
Iris				Yes	
Street					Yes

*Signif. Codes: ***: 0.01, **:0.05, *:0.1*
Robust standard errors

Table 3: 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 4.2.

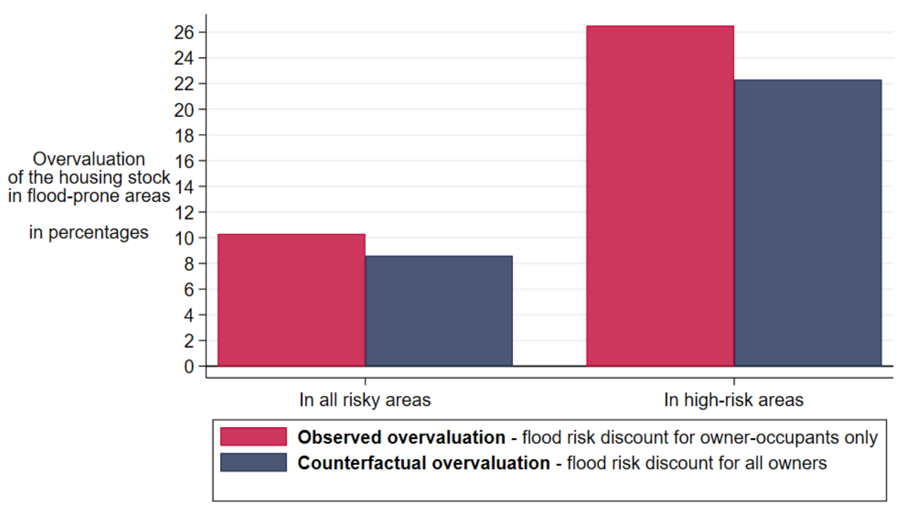


Figure 9: Housing stock overvaluation in flood-prone areas

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 Appendix Section E.

Results are displayed in Figure 9. I find that overall real estate prices would decrease by around 10.3% in flood-prone areas if they were to fully account for natural disaster risks. 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) of the current US housing market valuation in flood-prone areas. My contribution here is to find is that this overvaluation would decrease to 8.6% if dwellings owned by absentee landlords were to face the same price discount as owner-occupied ones. In high-risk areas, it appears that the real estate market is overvalued by around 26.5% and would go down to 22% if dwellings owned by absentee landlords were to face a 5% price discount.

These findings indicate that approximately 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. Moreover, since the estimates used here are intentionally conservative–assuming a 2% average discount and a 5% discount in high-risk areas–the 15% figure likely represents a lower bound.

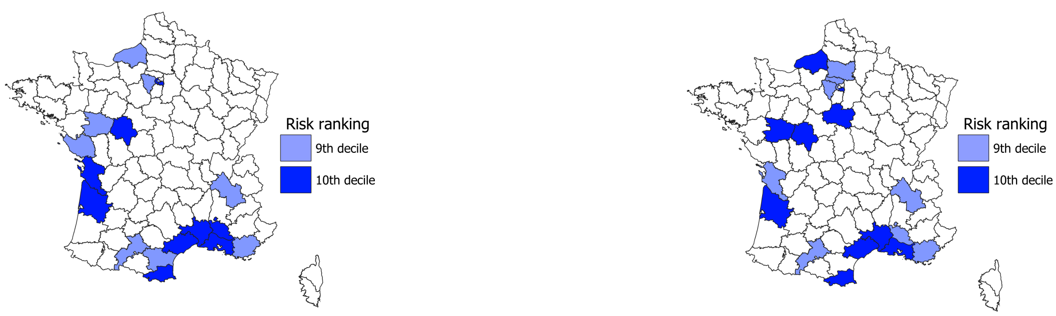
4.3 Place-based policies

In recent years, policymakers implemented more and more place-based adaptation programs such as managed retreat or building infrastructures (Hsiao, 2023; Benetton et al., 2025). As a policymaker, it is of high importance to know the areas in which it is the most efficient to allocate funding and implement these place-based policies. It might be relevant to target in priority areas with vulnerable homeowners and renters. Currently, the mapping that is used to evaluate which areas are the most exposed to risk generally displays the number of dwellings exposed to risk by *département* (equivalent to a US county)[11]. However, among these dwellings, some are second homes or vacant. In fact, owners of these dwellings would also benefit from place-based policies such as building a seawall. As a result, a mapping of critical areas that would not take into account local ownership statuses could provide an insufficient classification of areas that should be the priority target for adaptation investments.

In Figures 10 and 11, I provide a comparison of two different mappings of critical areas in

[11] https://www.donnees.statistiques.developpement-durable.gouv.fr/lesessentiels/essentiels/risques-naturels-innondation.html

France, for flooding and subsidence. The first mapping looks at the number of dwellings exposed (as in standard mapping realized by government officials), while the second counts only the number of owner-occupied dwellings exposed. For flooding, I observe that the ranking of critical areas changes, with some coastal *départements* becoming less of a priority, unlike some *départements* in Northern France, which are subject to river flooding and get a higher ranking. For subsidence, however, the maps are very similar due to the fact that most households exposed to subsidence are owner-occupants.



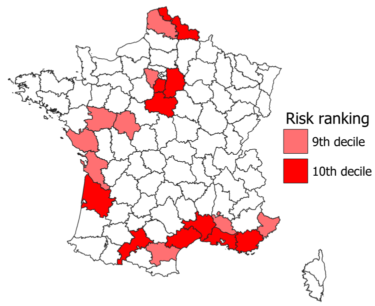
(a) Number of dwellings at risk

(b) Number of owner-occupied dwellings at risk

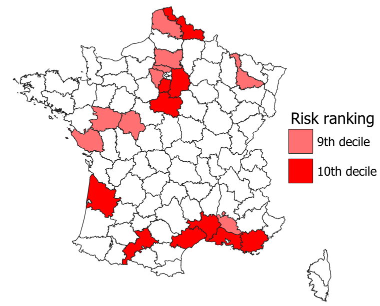
Figure 10: Mapping critical areas exposed to flooding

Notes. The figures show the ranking of *départements* in the 9th and 10th deciles in terms of the number of dwellings exposed to flooding. The left panel follows the standard methodology used by official maps and ministries, counting the number of dwellings at risk, and the right panel counts only owner-occupied dwellings.

These results illustrate that taking into account local ownership statuses might influence the allocation of funding across places that a policymaker might decide. In particular, for flooding, considering local ownership statuses might lead to putting more weight on areas exposed to river flooding in Northern France. Inequalities in ownership status are, of course, not the only dimension that should be considered when deciding where to allocate funding for adaptation. However, if a policymaker aims to take distributive considerations into account, this dimension of inequality might provide a different mapping of priority areas.



(a) Number of dwellings at risk



(b) Number of owner-occupied dwellings at risk

Figure 11: Mapping critical areas exposed to subsidence

Notes. The figures show the ranking of *départements* in the 9th and 10th deciles in terms of the number of dwellings exposed to subsidence. The left panel follows the standard methodology used by official maps and ministries, counting the number of dwellings at risk, and the right panel counts only owner-occupied dwellings.

5 Conclusion

Most of the literature studying the unequal exposure to natural disaster risks has looked at income inequality among residents and relied on aggregate data, thus omitting a large part of owners (50% in the case of flooding) and 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 environmental inequalities in exposure to natural disasters with respect to ownership status are large, and that they are highly relevant for the design of adaptation policies.

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. These findings indicate that approximately 15% of the total overvaluation in flood-prone areas is driven by dwellings owned by absentee landlords. From a policy perspective, this suggests that stronger measures should be directed at absentee landlords who purchase 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.

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A Additional information on data construction

A.1 Merging individual price data with administrative dataset

This section details how the merge between the administrative *FIDELI* dataset and prices from *DV3F* were realized. *FIDELI* is a snapshot of year 2017 and *DV3F* covers all sales from 2010 to 2016. 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.

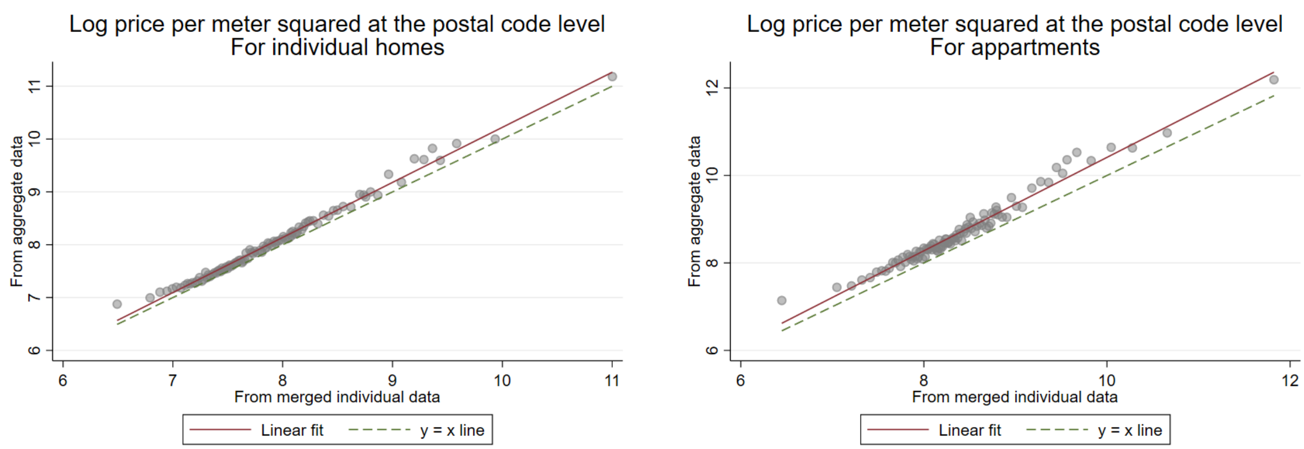
To achieve this merge, I proceed in several steps, looping across all observations in the *DV3F* dataset. For each observation *DV3F*, I keep only observations in the *FIDELI* that are registered at the same address. I call observation A the reference observation in the *DV3F* dataset. After this:

- If no correspondence is found in the *FIDELI* dataset, I drop observation A from the merging process.
- 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 a selected sample, I compare the average log price per meter squared by postal code in the original *DV3F* dataset and in the merged dataset. Figure A.1 shows that price per meter squared at the postal code level is 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.



(a) Individual homes

(b) Apartments

Figure A.1: 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.1a shows the results for individual homes and Panel A.1b for apartments.

A.2 Insurance payments

To study the redistributive effects of the CatNat scheme in Section 4.1, 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[12]. 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

$$\pi_c = r\pi_o \qquad r = 0.12 \tag{3}$$

$$\pi_c = \frac{r}{1+r}\pi \tag{4}$$

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.

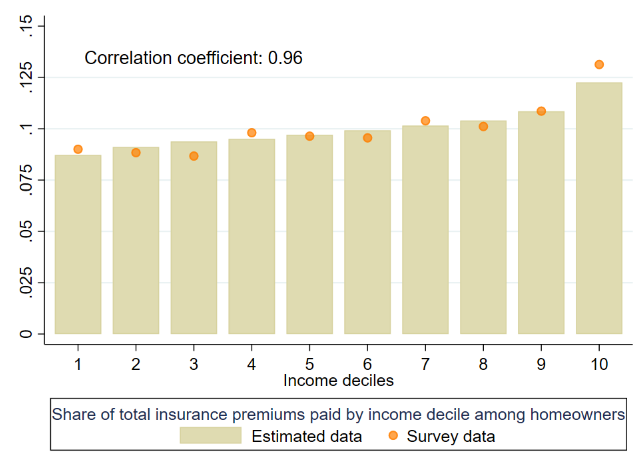
To estimate the total insurance premiums paid across the 35 million dwellings in my sample, I train a machine learning model on the survey data. Using dwelling surface, number of rooms, region, dwelling type (apartment or house), resident income, and household size, I apply a lasso regression to predict 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.

First, I train the lasso model separately for tenants and owner-occupants to estimate the premiums paid by each group. I then apply the model to predict premiums in the administrative dataset. To validate the model, Figure A.2 compares the distribution of premiums by income level for homeowners and renters. Panel A shows premiums for owner-occupied homes, while Panel B focuses on premiums for tenants. The correlation coefficients are 96% and 97%, respectively.

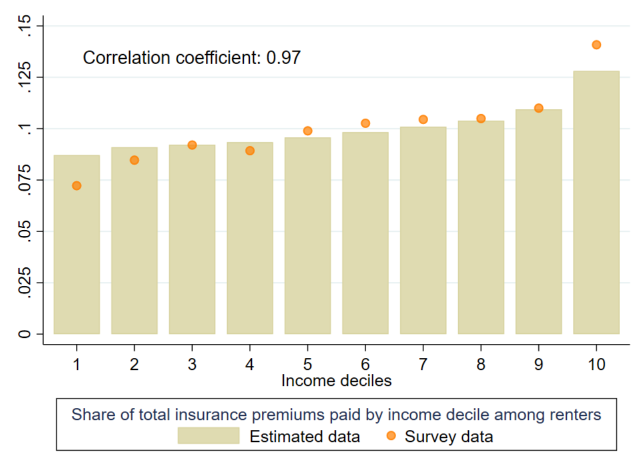
Second, I use the model trained on homeowners to predict premiums for second homes, rental properties, and vacant dwellings in the administrative dataset. I then adjust these predictions based on average premium differences by occupancy status, as reported by France Assureurs (2023). For instance, premiums 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

[12] *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).

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. For example, these variables should reliably capture the relative premium difference between a 40-square-meter dwelling and an 80-square-meter one. Scaling the predictions ensures consistency with aggregate premium levels.



(a) For homeowners



(b) For tenants

Figure A.2: Comparison between predicted home insurance premiums and survey data

Notes. The survey data gives the amount paid by homeowners and tenants in home insurance. Based on this information and a Machine Learning algorithm described in Section A.2, I derive insurance premiums at the household level for all dwellings in my sample. Figures A.2a and A.2b compare predicted with actual survey data by income decile for respectively homeowners and tenants. Interpretation: homeowners in the bottom 10% pay 8.9% of the total amount of insurance premiums in France according to survey data (orange dot), and the predicted value (yellow bar) is 8.7%.

Figure A.3 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%.

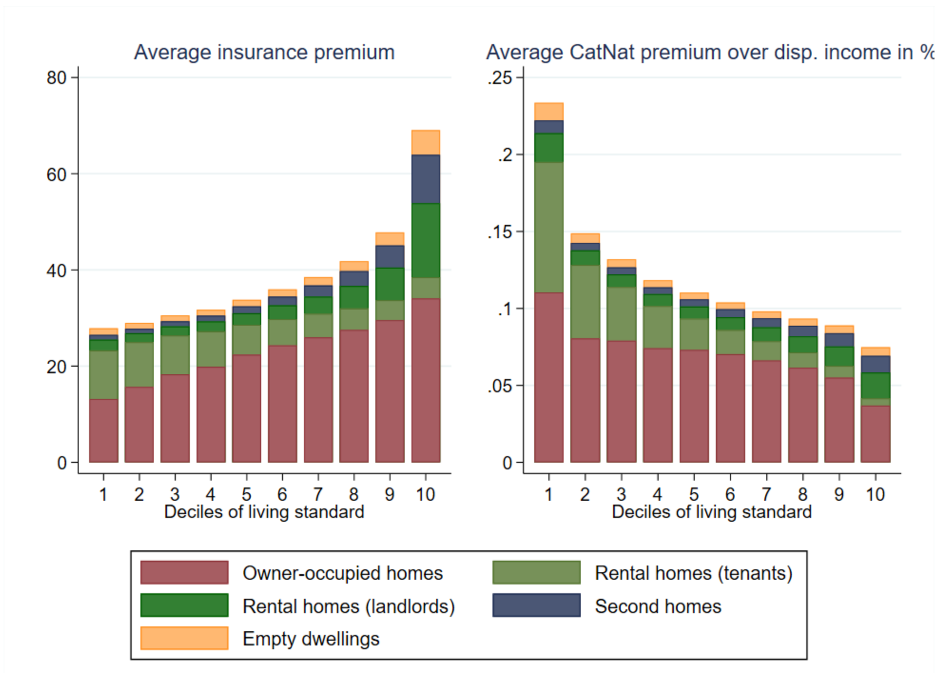


Figure A.3: CatNat premiums by income decile

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.

A.3 Recovering 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

$$\text{NPV}_i = \sum_{t=0}^{30} \text{Annual Expected Losses}_i (1+\rho_i)^t \tag{5}$$

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.1[13]

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.1: 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).

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

[13] 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.1 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:

$$\begin{aligned}\text{Annual expected losses}_i = &\frac{1}{2}(1.5 \cdot D_{\text{extr}} + D_{\text{extr}})(0.001 - 0)\\ &+ \frac{1}{2}(D_{\text{extr}} + D_{\text{mid}})(0.01 - 0.001)\\ &+ \frac{1}{2}(D_{\text{mid}} + D_{\text{freq}})(0.1 - 0.01)\end{aligned} \tag{6}$$

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 5 to recover the Net Present Value of flood damages.

B Additional descriptive results

B.1 Exposure by ownership status and income at the dwelling level

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.4a displays the overall distribution of real estate wealth nationwide by owner's income decile and ownership status. Figures A.4b and A.4c 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.4a. 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.4b). 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.2 Share of real estate wealth exposed to risk

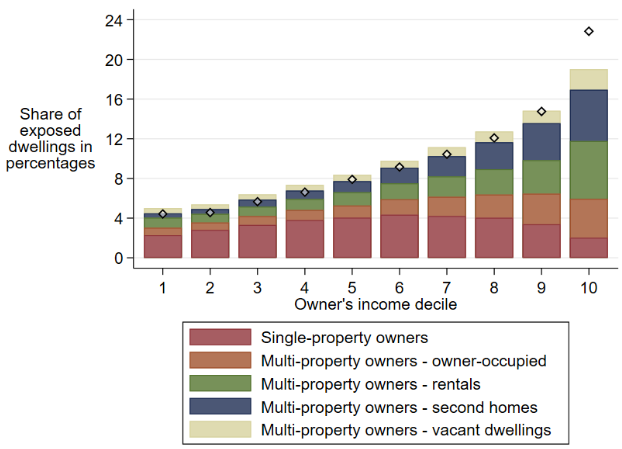
As I can observe ownership links, I can measure the share of owners' real estate wealth that is exposed to risk. I compute the share that each dwelling at risk i represents in the real estate portfolio of owner k. I denote A_k the universe of dwellings i owned by owner k. I measure the share of the real estate portfolio at risk:

$$\text{Share at risk}_i = \frac{\text{Market value}_i}{\sum_{i \in A_k} \text{Market value}_i} \tag{7}$$

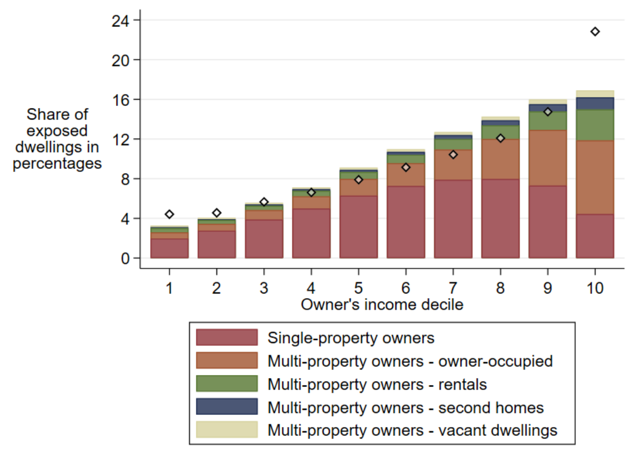
I obtain Market value$_i$ from aggregate municipality level price data, as described in Section 2. Results are displayed on Figure A.5.

It appears that, among all dwellings in flood-prone areas, only 35% represent 100% of their owners' real estate portfolio. For subsidence, more than 50% of dwellings in risky areas represent 100% of their owners' real estate portfolio. These numbers directly reflect the differential degrees of exposure of single-property owners.

(a) In France



(b) In areas exposed to flooding

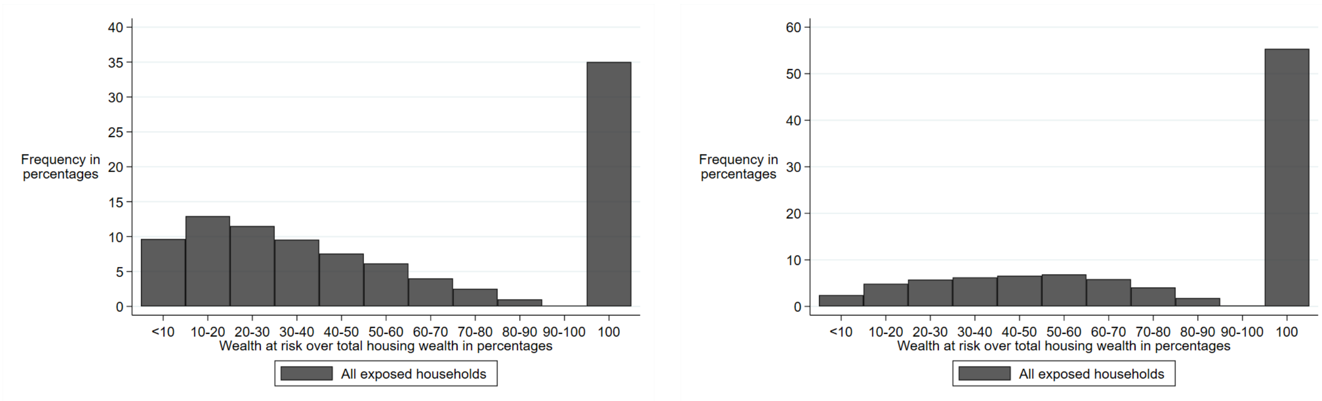


(c) In areas exposed to subsidence

Figure A.4: Exposure to risks by ownership status and income

Notes. Figure A.4a displays the overall distribution of real estate wealth nationwide by owner's income decile and ownership status. Figures A.4b and A.4c 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.4a. Comparing the dots with the bars reveals the extent of overexposure and underexposure for each owner's income decile.

The most striking result concerns multi-property owners having less than 100% of their housing wealth exposed to risk. In the case of flooding, more than 30% of exposed dwellings represent less than a quarter of their owner's housing wealth. This highlights the stark difference in vulnerability to risk between single- and multi-property owners. In the case of subsidence, however, it is only about 10% of owners that have less than a quarter of their housing



(a) Flooding

(b) Subsidence

Figure A.5: Distribution of the share of real estate portfolio exposed to risk
Notes. The Figure plots the distribution of the share of owner's real estate portfolio exposed to risk among exposed dwelling.

wealth exposed to risk.

B.3 Importance of geographical amenities to explain patterns of exposure

The objective of this section is to understand to what extent geographical amenities are driving the results obtained in Section 3.2. In particular, Figure 4 shows that second homes are over-represented in flood-prone areas, which might be due to specific amenities such as a seafront view.

To answer this question, I run the following regression for each dwelling category:

$$Risk_i = \alpha + X\beta + \varepsilon_i \tag{8}$$

$Risk_i$ is an indicator variable equal to one if dwelling i is located in a a risky area. X is a vector of controls including dwellings characteristics and including progressively geographic fixed effects. The objective is to investigate how the R^2 of this regression varies after including geographical controls for different samples of dwellings' categories. Results are displayed on Tables A.2 and A.3.

For flooding, it appears that R^2 evolve in similar fashions across dwelling categories after including geographical fixed effects, except for second homes. In that case, R^2 values are always higher than for other dwellings' categories. This result suggest that there are indeed geographical amenities substantially driving the overexposure of second homes.

In the case of subsidence, R^2 values are always higher for dwellings owned by absentee landlords than for owner-occupied ones. Given that rental properties are typically concentrated in urban areas and second homes in high-amenity areas (e.g., mountains or coastal zones), absentee landlords tend to invest less in single-family homes and rural areas where exposure to subsidence is high (Châtel et al., 2021). These high R^2 would thus suggest that geographical amenities largely account for the underexposure of absentee landlords to subsidence risk.

	Single-prop owners (1)	Multi-prop owner-occupants (2)	Multi-prop Rentals (3)	Multi-prop Second homes (4)	Multi-prop Vacant dwellings (5)
Dwellings characteristics	0	0	0	.01	0
+ Commuting zone FE	.02	.02	.02	.08	.02
+ Municipality FE	.18	.17	.13	.31	.15
+ Iris FE	.25	.23	.17	.32	.18
+ Street FE	.54	.53	.44	.57	.5

Table A.2: R^2 values when regressing exposure to flooding on geographical fixed effects

Notes. The table displays the R^2 values when regressing exposure to flooding on dwellings and geographical controls listed on the left.

	Single-prop owners (1)	Multi-prop owner-occupants (2)	Multi-prop Rentals (3)	Multi-prop Second homes (4)	Multi-prop Vacant dwellings (5)
Dwellings characteristics	0	0	.06	.05	.06
+ Commuting zone FE	.02	.02	.12	.13	.1
+ Municipality FE	.18	.17	.25	.29	.23
+ Iris FE	.25	.23	.32	.34	.3
+ Street FE	.54	.53	.70	.74	.71

Table A.3: R^2 values when regressing exposure to subsidence on geographical fixed effects

Notes. The table displays the R^2 values when regressing exposure to subsidence on dwellings and geographical controls listed on the left.

B.4 Distribution of the NPV of flood damages across dwelling categories

Figure A.6 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 B.4. The results are similar to those of Figure 4 with second homes being overrepresented in flood-prone areas.

Figure A.6: Exposure to river and coastal flooding

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.5 Exposure to river and coastal flooding

Figure A.7 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.

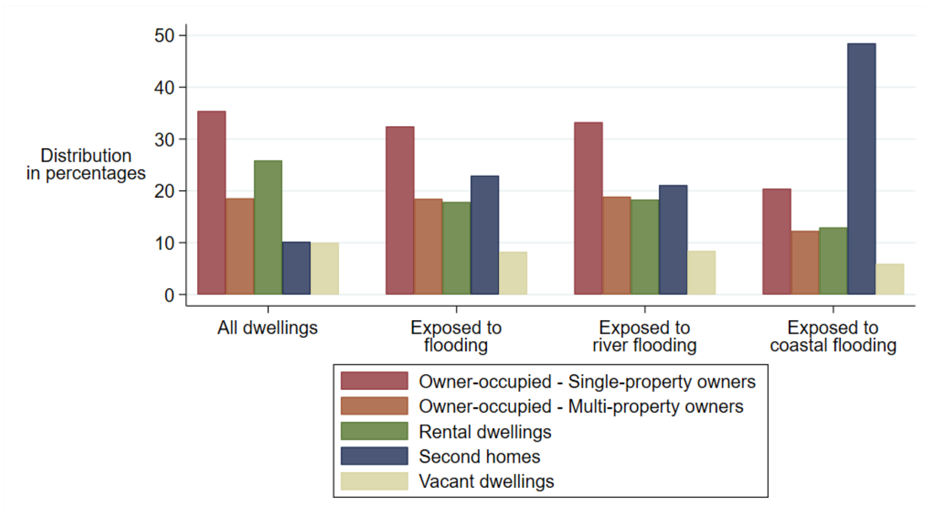
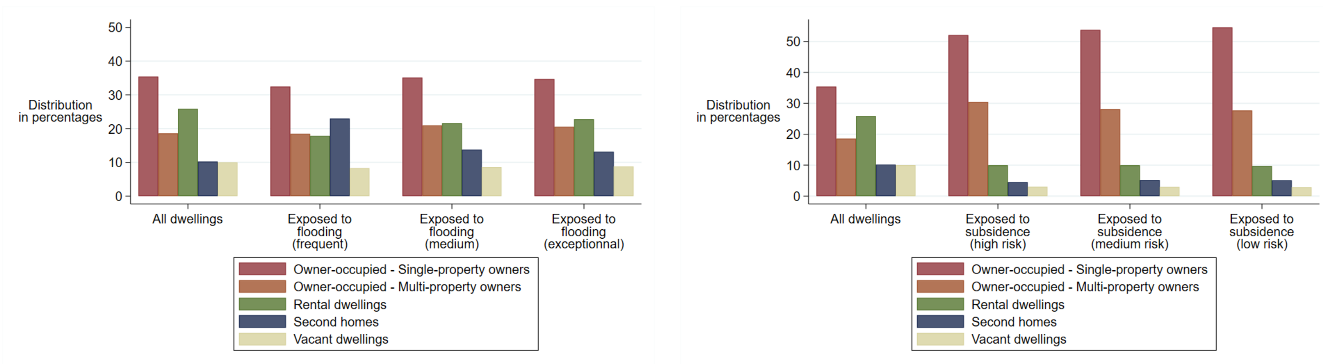


Figure A.7: Exposure to river and coastal flooding

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

B.6 Exposure levels by risk intensity

Figure A.8 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.8: Effect to natural disasters by risk intensity

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

C Recovering the degree of cross-subsidization across ownership statuses in the CatNat system

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.

$$\pi_i^{risk-based} = \pi_i^{subsidized} \times risk\ factor_i \tag{9}$$

The risk factors I use are presented in Table A.4. 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

$$\frac{P(disaster = 1|safe)}{P(disaster = 1)} + \sum_k \frac{P(disaster = 1|k)}{P(disaster = 1)} = 1 \tag{10}$$

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 10. 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.8).

I then measure transfers for each dwelling i

$$Transfer_i = \pi_i^{risk-based} - \pi_i^{subsidized} \tag{11}$$

$Transfer_i$ 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.

$$Net\ transfer_d = \sum_{i \in A_d} Transfer_i \tag{12}$$

$Net\ transfer_d$ 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.

$$Net\ transfer\ norm_d = 100 \times \frac{Net\ transfer_d}{\sum_i Transfer_i \times \mathbb{1}_{[Transfer_i > 0]}} \tag{13}$$

Figure 7 plots the net normalized transfers by ownership status.

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.4: Risk factors used to simulate counterfactual insurance premiums

Notes. The table displays the risk factors used in Section 4.1 to compute counterfactual risk-based insurance premiums.

D Robustness checks on risk valuation by ownership status

In this Section, I provide four robustness checks for the results obtained in Section 4.2 on differential degrees of risk valuation between homeowners and absentee landlords. I remove dwellings located close to coasts or rivers, I vary the risk intensity threshold, I modify the clustering of standard errors, and I decompose the two categories into the five subcategories of dwellings.

First, to account for the fact that being located on upper floors can potentially have a differential effect if a dwelling has a direct view of the coast (e.g., panoramic view that would be incorporated in house prices), I remove dwellings that are located less than 200 meters away from the border of coasts and rivers. Results are displayed on Figure A.9. as they look similar to those of Figure 8, it suggests that the direct proximity to coasts and rivers does not seem to drive my results.

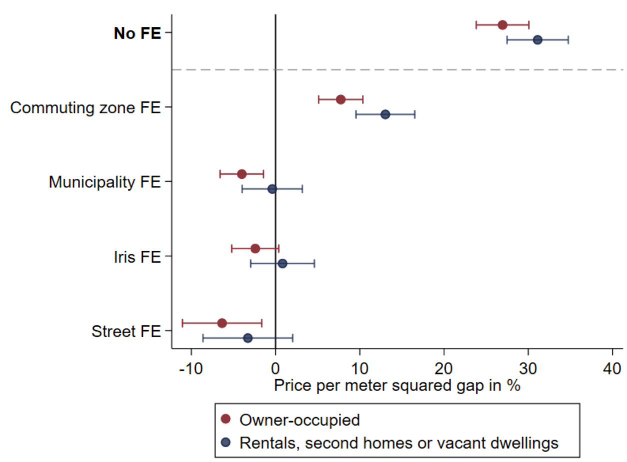
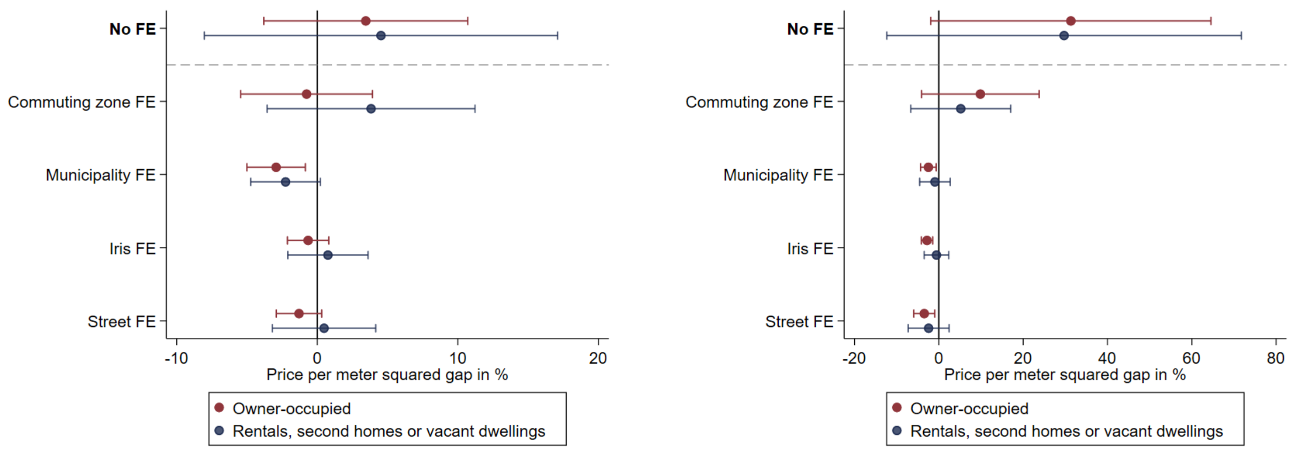


Figure A.9: Effect of natural disaster risks on prices removing dwellings close to coasts and rivers

Notes. The figure displays the β coefficients of the regression described in Section 4.2. The sets of geographic fixed effects included are indicated on the y axis. The areas at risk I use are the high-risk areas. I remove dwellings that are located less than 200 meters away from coasts and rivers. Confidence intervals are at the 95% level. Robust standard errors.

Second, I reproduce the same regression as in Figure 8 as 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.10. 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.



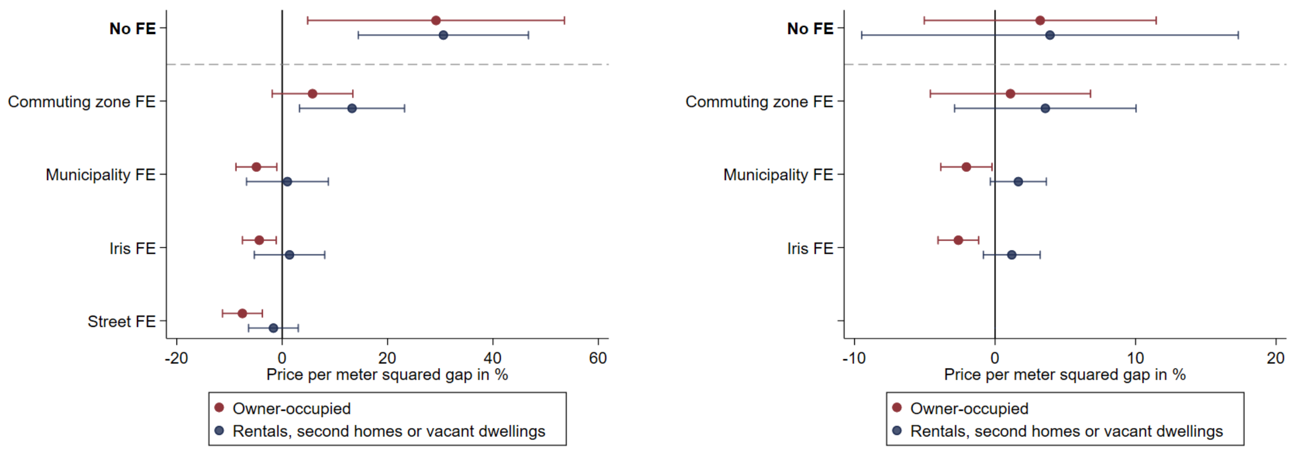
(a) Flooding

(b) Subsidence

Figure A.10: Effect of natural disaster risks on prices for low-risk areas

Notes. The figure displays the β coefficients of the regression described in Section 4.2. 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.

Third, I implement standard errors clustered at the commuting zone (*zone d'emploi*) level instead of robust standard errors. Results are displayed on Figure A.11. All negative coefficients for owner-occupied dwellings remain significant.



(a) Flooding

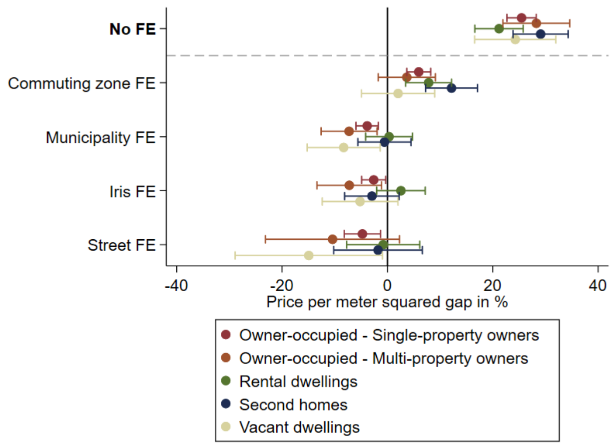
(b) Subsidence

Figure A.11: Effect of natural disaster risks on prices with clustered standard errors
Notes. The figure displays the β coefficients of the regression described in Section 4.2. The sets of geographic fixed effects included are indicated on the y axis. Confidence intervals are at the 95% level. Standard errors clustered at the commuting zone (*zone d'emploi*) level.

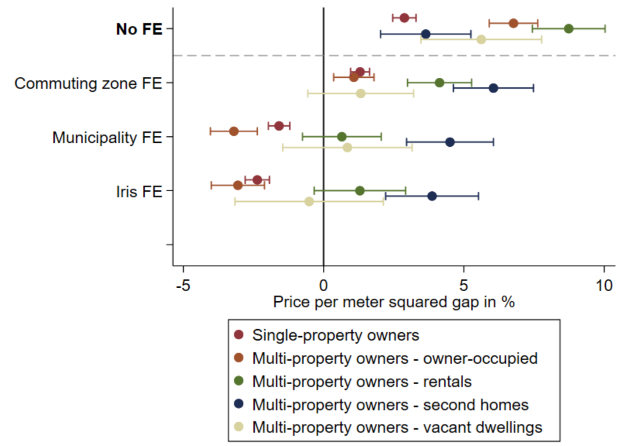
Fourth, instead of regrouping dwellings in two categories, I consider separately dwellings owner-occupied by single-property owners, by multi-property owners, rental dwellings, second homes and vacant dwellings. Results are displayed on Figure A.12.

The coefficients for owner-occupied dwellings are consistently negative and statistically significant after including municipality fixed effects. The only exception occurs in the flooding specification with street fixed effects, where coefficients lose significance—likely due to the loss of statistical power introduced by the high-dimensional fixed effects.

For dwellings owned by absentee landlords, coefficients are either insignificant or positive, suggesting that misvaluation is shared across all ownership categories. The only 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 often less clear than the distinction between owner-occupied and rental or second homes. 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.12: Effect of natural disaster risks on prices - decomposed owner categories

Notes. The figure displays the β coefficients of the regression described in Section 4.2. The sets of geographic fixed effects included are indicated on the y axis. Confidence intervals are at the 95% level. Robust standard errors.

E Methodology to recover 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.13.

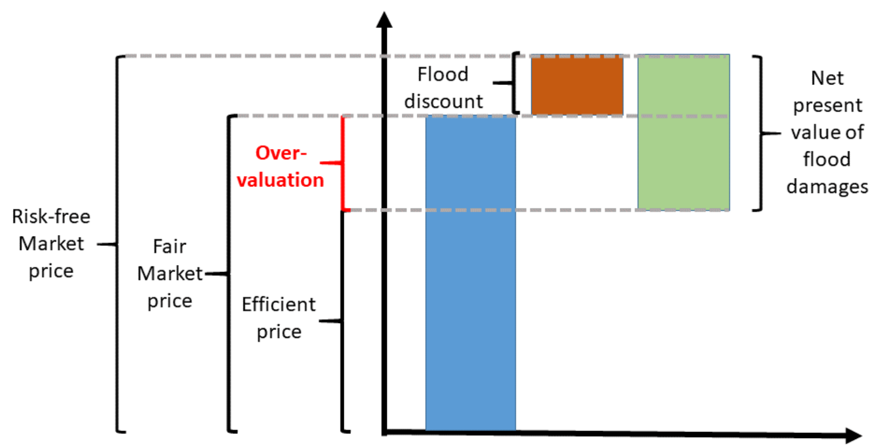


Figure A.13: Methodology to recover overvaluation

A dwelling's degree of overvaluation can be written

$$\text{Overvaluation}_i = \text{Fair Market Value}_i - \text{Efficient Price}_i \tag{14}$$

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:

$$\text{Risk Free Market Value}_i = \text{Fair Market Price}_i / (1 + \delta_{risk,owner}) \tag{15}$$

$\delta_{risk,owner}$ is the risk discount in percentages obtained from Section 4.2 with risk $\in$ (flooding,subsidence) and owner $\in$ (occupants,landlords).[14] 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%-4% risk discount and absentee landlords do not discount flood risk.

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

$$\text{Efficient Price}_i = \text{Risk Free Market Value}_i - \text{NPV}_i \tag{16}$$

The detailed methodology to recover the NPV of flood damages is described in Section B.4. I consider homeowners have a flood risk discount of 2% on average in all risky areas. Following this approach, I obtain a degree of total housing market overvaluation in flood-prone areas of 10.3%. While contextual differences exist, this result is broadly consistent with previous studies conducted in the U.S. (Bakkensen and Barrage, 2022; Hino and Burke, 2021).

Finally, 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.

[14] 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 4.2 to measure flood risk discounts.