The Incidence of Flood Risk

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Abstract

This paper documents the vulnerability and exposure to flood risk with fine-grain data in France for the universe of owner-occupied, rented, second, and vacant dwellings, linking these properties to the disposable income and housing wealth of their owners and tenants. Vulnerability to floods exhibits large heterogeneity. Tenants and homeowners owning only their primary residence are highly vulnerable due to limited housing wealth, whereas most landlords diversify their assets, exposing only a fraction of their housing wealth to flood risks. In addition, I find that high-income owners and tenants are underrepresented in flood-prone areas. As a result, the income of owners is 5.5% lower in risky areas, and the income of tenants is 8% lower. These patterns of residential distribution appear to be driven by amenities to a large extent, but also by high-income owners and tenants actively avoiding flood risks. This results in a two-dimensional inequality: low-income households are both more vulnerable and more often exposed to flood risk. I show that these findings matter for adaptation policies: (1) The cost of buying-back homes at risk could be divided by five if it focused on low-income homeowners. (2) A subsidized insurance policy such as the current French CatNat system redistributes 3% of total annual losses caused by floods from the bottom 60% to the top 40% through regressive premiums, because of poor targeting toward the most vulnerable households.

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In 2021, the economic cost of natural disasters reached 343 billion dollars worldwide, and two developed countries, Germany and Belgium, set all-time records for their most costly weather-related disasters (Masters, 2022). In both Europe and France, flooding is the costliest type of event (European Commission, 2022). The economic burden of floods is anticipated to surge (Hallegatte et al., 2013; Smith and Katz, 2013) for two main reasons. First, the frequency and severity of floods are expected to rise due to climate change, especially along the coasts. Second, urban expansion leads to a substantial increase in both the number of households exposed to risk and the overall value at risk (Rentschler et al., 2023). These phenomena raise a critical question: who bears the financial burden of flooding?

In the first instance, the burden of flooding falls upon the victims. Their residences suffer damage, necessitating reliance on government assistance, insurance coverage, and the completion of reconstruction before they can resume normal life. In some cases, where there is neither insurance coverage nor government support available, victims may never receive compensation for their losses.

However, in the majority of developed countries, the responsibility for rebuilding destroyed homes lies indirectly with the government and, consequently, the taxpayers who fund it. In France, the insurance system receives government subsidies, resulting in all households paying an additional 12% fee on their home insurance contracts to aid the victims of natural disasters. Consequently, the burden extends to households residing in safe areas as well. Given the persistent economic growth of urban centers (Balboni, 2019; Kocornik-Mina et al., 2020; Lin et al., 2021) and the continual expansion of seaside resorts (Châtel et al., 2021; Smith, 2021), it appears probable that a considerable portion of exposed households belongs to the high-income bracket, often with exposure through second homes or rental dwellings. This implies that the burden of flood risk may be shifted onto lower-income households, who end up funding the reconstruction of dwellings owned by the wealthier ones. The aim of this paper is to answer this question, by quantifying the exposure to flood risk by income group.

Previous evaluations of natural disaster impact across income groups used aggregate income data, considering the income of residents (Walker et al., 2006; Sayers et al., 2018; Bakkensen and Ma, 2020; Rözer and Surminski, 2021; Wing et al., 2022). However, this approach presents two significant limitations. First, it conflates the exposure of homeowners and tenants, who may exhibit distinct vulnerability levels and sorting patterns. Second, from the results of this paper, it appears that 50% of dwellings in exposed areas are owned by households residing outside these vulnerable locations. Consequently, assessing owners' exposure cannot rely on local aggregate income and wealth data.

In this paper, I make use of novel administrative data (André and Meslin, 2021) that provide the exact location of every dwelling in France and link them with information on the income and wealth of owners and tenants. This unique dataset covers all types of dwellings, including owner-occupied, rental, second, and empty homes. The last two categories are often overlooked in the literature, and rental homes are generally not matched to their owners. I overlap these data with exposure maps. I then compute the number of dwellings at risk and their value, categorized by owners' income and wealth levels. This approach enables me to measure how owners diversify their real estate wealth when facing the threat of being flooded and to evaluate sorting patterns over flood risk. Finally, I derive implications of these findings on the incidence of two adaptation policies: home buyouts and government-subsidized insurance against extreme weather events. This study provides the first analysis exposure to floods by income and wealth, differentiating owners and tenants at the most granular level possible.

I focus on expected exposure derived from exposure maps rather than past damages for two main reasons. The first reason is that expected risks appear to be more relevant for policy design, as exposure maps serve as the best available predictor of future exposure. Past damages resulting from natural disasters can be influenced by rare, unpredictable, and large-scale events, such as the Alex storm in the *Vallée de la Roya* in France in 2020. Therefore, considering past event damages to assess exposure would overweight to these large-scale events, which are unlikely to be representative of future disaster damages. The second reason is that exposure maps are finer-grained than aggregate insurance data, allowing me to capture variations at the dwelling level.

First, on the owners' side, I find that floods have large heterogeneous impacts due to significant differences in asset diversification across wealth and income distributions. For each owner, I compute the share of housing value exposed to flood risk. My findings indicate that the widely held belief that natural disaster victims are "left with nothing" is not true for all households. For 40% of exposed owners, a highly violent flood would indeed result in a complete loss of their housing wealth. In the large majority of cases, these households are homeowners owning only their place of residence and no other housing wealth. However, for the majority of owners, a similar event would only lead to the partial destruction of their housing wealth, with less than half of it being at risk in 40% of cases. These findings underscore the importance of distinguishing between the types of dwellings affected: the impact of having an owner-occupied home flooded differs significantly from having a rented, second, or empty home underwater.

Finally, tenants remain the most vulnerable households as most of them only own their furniture which are very much exposed to flooding. Only 15% of them own housing wealth and 28% earn financial income, highlighting an extremely low degree of diversification.

Second, second homes owned by middle- to high-income households, which constitute less than 10% of all residential properties in France, represent 20% of the dwellings at risk. In coastal areas, they represent almost 50% of dwellings exposed. However, when controlling for municipality fixed-effects, distance to the coast, and dwelling characteristics, the degree of overexposure diminishes by a factor of 5. These results suggest that amenities along the coasts and rivers are the primary factors driving the overexposure of second homes, rather than owners actively considering flood risk.

Third, across all types of dwellings, high-income owners and tenants sort consistently less over flood risk areas than their low-income counterparts. Controlling for municipality fixed effects, distance to the coast, and dwelling characteristics does not completely close this income gap, suggesting that flood risk may indeed influence the investment decisions of high-income owners compared to low-income ones. However, I find no evidence that in risky areas, high-income homeowners more frequently avoid living on the ground floor, which is more exposed to flooding, compared to low-income ones.

Fourth, while the overexposure of second homes contributes to increasing the exposure of high-income households, this effect is less pronounced than the overexposure of low-income ones through other types of dwellings. This results in an average income of owners and tenants being respectively 5.5% and 8% lower in exposed areas compared to safe ones. This suggests the presence of a two-dimensional inequality: low-income households have a lower capacity to diversify their assets in the face of flooding risks, and are also more frequently exposed than their high-income counterparts.

Fifth, I draw implications from these findings for two adaptation policies. The first policy relates to home buyouts, in which the government acquires flooded properties for demolition. Typically, these initiatives are event-driven and do not specifically target income groups based on their vulnerability to flood impacts. I simulate an ambitious policy that involves repurchasing all at-risk homes. My analysis reveals that if such an initiative were to prioritize homeowners in the bottom 50% of the income distribution, it could potentially reduce buyout costs by five, highlighting substantial cost-saving opportunities when governments take economic vulnerabilities into account while designing buyout programs.

Finally, I analyze the implications for the subsidized French insurance against extreme weather events. This type of insurance scheme is gaining in popularity in recent years, in response to the significant undercoverage observed in certain countries such as the U.S. (Wagner, 2022). In France, this insurance system is funded through a mandatory, uniform rate additional premium[1] imposed on all households across the country to provide coverage for natural disaster victims. First, I demonstrate that the fee structure exhibits regressive characteristics. Second, perhaps surprisingly in the light of the previous results on the overexposure of low-income households, I find that the system transfers money from low-income households to high-income ones. This result is explained by the fact that contributions are indexed on insurance premiums, which makes high-income households contribute less as a share of their housing wealth. Consequently, simulations show that this insurance system is expected to shift 3% of annual natural disaster losses from the bottom 60% to the top 40% each year through regressive premiums. I propose potential strategies to enhance the financing of such insurance schemes, which could be valuable for policymakers willing to implement similar systems in other countries.

Related literature. My work intersects with several existing bodies of literature. Firstly, it aligns with the expanding field of environmental justice (Taylor, 2000; Mohai et al., 2009; Banzhaf et al., 2019), which seeks to comprehend the unequal distribution of environmental risks and the underlying reasons. Specifically, my research extends the prior work on sorting patterns over flood risk. In the U.K., using aggregate income data, studies by Walker et al. (2006), Sayers et al. (2018), and Rözer and Surminski (2021) have observed that low-income households tend to be more frequently located in flood-prone areas. Similar results were found for Germany by Osberghaus (2021) using survey data. Furthermore, there is a burgeoning literature on this topic in the United States. Wing et al. (2022) found that the costs of natural disasters disproportionately impact poorer communities, which also tend to have a higher proportion of White residents. Bakkensen and Ma (2020) discovered that low-income and Hispanic households tend to cluster in high-risk areas. Both studies used aggregate census data to assess exposure by income group. However, Sastry (2022), using transaction-level data, found evidence of credit-rationing in flood-prone areas, discouraging credit-constrained borrowers from residing along the coast and resulting in higher exposure for high-income property owners. Consequently, the majority of the literature, which relies on aggregate income data, suggests greater exposure for low-income households. In contrast, Sastry (2022), focusing on homeown-

[1] This additional premium represents 12% of housing insurance contracts and 6% of car insurance contracts.

ers and utilizing transaction-level data in the specific context of Florida, identified evidence of sorting behavior over flood risk among high-income households. My contribution to this literature is data-driven and distinctive in two key ways: it distinguishes between the exposure of property owners and tenants, a differentiation not feasible with aggregate income data, and it differentiates by type of dwelling, encompassing owner-occupied, rental, second, and empty homes. The latter two categories are often overlooked in most of the papers cited above, despite representing 30% of the dwellings at risk in my analysis and implying markedly distinct vulnerability levels.

My work also builds upon prior research concerning wealth inequality dynamics within the housing market. In France, the wealth held by the bottom 50% of the population accounts for only 5% of the total national wealth (Chancel et al., 2022) and is mainly composed of real estate assets (Fagereng et al., 2020; Bach et al., 2020). For low-income homeowners who lack any other form of wealth aside from their primary residence, diversifying their assets is often exceedingly challenging and, in most cases, unfeasible. This lack of diversification among those at the lower end of the wealth spectrum exposes small homeowners to a heightened level of risk from large-scale climate-related events. My contribution to this body of literature is empirical, involving the measurement of the varying degrees of wealth vulnerability to floods across the spectrum of property owners.

This paper is closely connected to the literature on insurance against extreme weather events. One prominent thread in this literature centers on insurance affordability and its associated advantages. Studies such as Kousky and Kunreuther (2014), Grislain-Letrémy (2018), and Hudson (2018) have examined this issue within the contexts of the U.S., French overseas departments, and Europe, respectively. My work directly contributes to this literature, particularly in the case of the French CatNat system, which was initially designed to make insurance more affordable. Nevertheless, I argue that affordability alone may not end up being sufficient for an insurance system to be equitable, drawing attention to the example of the CatNat fee, which results in insurance premiums lower than those in other countries but exhibits regressive characteristics.

Finally, another significant segment of the literature examines the redistributive implications of insurance against natural disasters. Studies like 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. Additionally, Ben-Shahar and Logue (2016) and Dinan et al. (2019) observe that the NFIP transfers income from a multitude of inland areas to a minority of coastal ones. More closely aligned with my research context, Charpentier et al. (2022) highlight that flood risk is considerably concentrated in France, with 10% of households bearing 74% of the losses. They also underscore the high exposure to extreme weather events in affluent areas, implying that the French insurance system may primarily benefit wealthier households. My contribution to this literature involves the empirical measurement, leveraging unique fine-grained data, of how each category of property owners actually benefits from a government-subsidized insurance system such as CatNat.

The remainder of the paper is structured as follows. In Section 1, I provide some context on flood risk in France and how it is covered by insurance. I describe the data in Section 2. I provide descriptive results on the heterogeneity in vulnerability to floods in Section 3. In section 4, I study the patterns of sorting over flood risk and section 5 investigates potential mechanisms. Finally, in section 6, I draw conclusions for the incidence of adaptation policies and conclude in Section 7.

1 Flood Risk in France

Between 1980 and 2022, floods accounted for nearly 43% of climate-related economic damages in Europe, amounting to 280 billion euros over the period and establishing themselves as the most financially burdensome type of event on the continent (European Commission, 2022). In France, according to the 2021 report from the French insurance association (France Assureurs, 2021b), floods were also responsible for the highest amount of damages, with an annual average of 1 billion euros from 1989 to 2020. Projections indicate that losses are anticipated to increase by 87% over the 2020-2050 period, reaching approximately 1.8 billion euros annually. Of this increase, 65% can be attributed to a higher number and value of properties at risk, while climate change factors would account for only 26% of the rise. This underscores the importance of gaining a better understanding of how individuals make location decisions in relation to flood risk to mitigate the impacts of climate change. It's noteworthy that a majority of the losses, specifically 68% of total losses, are concentrated in residential dwellings, in contrast to commercial buildings which account for the remaining 32% of total losses (CCR, 2022). For the remainder of this study, our focus will be exclusively on residential real estate.

On average, among all insured dwellings, approximately 0.5% to 1% are victims of flooding each year (France Assureurs, 2021b). The average cost of a residential dwelling insurance policy stands at 10,000 euros, exclusive of the deductible[2]. In Germany, the average building flood insurance claim is twice as high as the average content-related claim (Osberghaus, 2021). Unfortunately this specific figure is not available for France. Applying these proportions to France means the average building insurance claim (benefiting the owner) would be 6,667 euros, equivalent to around 5% of the value of dwellings situated in municipalities exposed to floods between 2017 and 2019. On the other hand, the average content-related claim (benefiting the tenant, if any) would be 3,333 euros.

France is also characterized by a unique insurance system against natural disasters, established in 1982 and referred to as *CatNat* [3]. This system mandates that private insurance companies incorporate coverage for natural disasters into their standard automotive and property insurance policies. The funding mechanism involves a mandatory additional fee, constituting 6% of the initial premium for car insurance and 12% for housing insurance. Of the contributions collected, 88% is channeled to the "Caisse Centrale de Réassurance" (CCR), a reinsurance company wholly owned by the French government, with the remaining 12% directed to the "Fonds de Prévention des Risques Naturels Majeurs," also known as the "Fonds Barnier." This fund is specifically allocated for the acquisition of properties situated in high-risk areas.

When a disaster occurs, the municipality is required to submit a CatNat form for review. This evaluation is conducted by a committee, which includes representatives from the CCR, as well as members from the Ministries of the Economy and the Environment. If the application is not rejected, the municipality receives the CatNat designation, and insurance companies then provide compensation to the victims of the disaster. Ultimately, the CCR acts as a reinsurer for these insurance companies, covering the costs they have incurred[4].

This arrangement ensures that French households can access insurance at an affordable price, resulting in a 98% uptake of housing insurance throughout the country. Insurance companies are also largely aligned with the CatNat system, with the CCR commanding more than 90% of the market share in the natural disaster reinsurance sector (CCR, 2022). Without such a

[2]The deductible is determined by law. If a municipality experiences its first flood, the deductible is 380 euros. Subsequently, for municipalities that undergo multiple flood events without implementing a risk protection plan (PPR) aimed at documenting the location of risks and urban development, the deductible increases. Specifically, after the third event without a PPR, it doubles, after the fourth it triples, after the fifth it quadruples, reaching 1520 euros. For more details, refer to the *Mission risques naturels* website. Among the 34,965 municipalities in France in 2021, 505 had their deductibles doubled, 127 had them tripled, and 22 had them quadrupled (France Assureurs, 2021b).

[3]See McAneney et al. (2016) for a review of alternative government-sponsored insurance systems

[4]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 the disaster-related costs increased to 70% (CCR, 2022).

program, the insurability of extreme weather events would be severely compromised due to the exorbitant cost and the spatial correlation of such events, rendering diversification considerably more complex for private insurance companies (Jaffee and Russell, 1997). Furthermore, since insurance companies bear only a small portion of the overall cost, they tend not to significantly adjust premiums based on the risk of exposure (Sansévérino-Godfrin, 1996; Grislain-Letrémy and Peinturier, 2010; Grislain-Letrémy, 2018).

Apart from the exceptional case in 1999, France has not required government intervention for rebuilding dwellings after extreme weather events since the inception of the CatNat system in 1982. However, the substantial escalation in the cost of natural disasters in recent years has resulted in a significant reduction in the CCR's reserves, with a decrease of 50% from 2015 to 2021 (Cour des comptes, 2022). This situation raises important questions regarding the long-term sustainability of the CatNat system. Consequently, there is a growing support for raising contributions on housing insurance from the existing 12% to 19% (CCR, 2023). We will discuss the incidence of such a reform in Section 6.

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 from INSEE[5]. I am able to recover the characteristics of both owners and tenants based on the merging realized by André and Meslin (2021). For owners, I observe the characteristics of mom and pop owners and as well as those who hold real estate through property management companies. However, characteristics of owners are not available when real estate is owned by LLCs or institutional investors. Households' characteristics correspond to household size, age, income and structure of income (labour income, net rental income, other financial income, pensions). Throughout the rest of the paper, I consistently refer to income, or equivalently living standard, as the *disposable income per consumption unit*, following the methodology of INSEE (2023)[6]. The analysis presented in this paper is a

[5] *Fichiers Démographiques sur les Logements et les Individus 2017*, INSEE. Data are collected through housing and property taxes and are confidential. They must be accessed with an authorization from INSEE and through the *Centre d'Accès Sécurisé aux Données* (CASD).

[6] The value of a consumption unit is defined as 1 for the first member of a household, 0.5 for every additional member in the household and 0.3 for children below 14 years old.

cross-section, but I also have access to repeated cross-section from 2016 to 2022.

This dataset also provides information on the characteristics of buildings, including construction date, dwelling type (whether it is a house or an apartment), floor number, and the type of occupancy (owner-occupied, rental, second home, or empty dwelling). The distinction between owner-occupied and second homes is the requirement that a household must spend a minimum of six months per year in an owner-occupied dwelling, whereas second homes are typically used for shorter duration. Second homes are documented in this administrative database, as they can have implications for varying tax schemes, particularly regarding housing taxes in select municipalities. Lastly, there could be three main reasons explaining why a dwelling can be empty: it may be listed for sale or rent on the real estate market, the owner may have yet to pay the estate tax that allows for occupancy, or it may be retained by the owner but remains unoccupied due to its inadequate condition.

In the remaining of the paper, we will refer to three categories of households exposed to floods:

- Exposed homeowners: households having their main place of living at risk.
- Exposed landlords: households owning dwellings at risk in which they do not reside.
- Exposed tenants: households occupying a dwelling rented from a landlord. Tenants can also own a second home or another type of dwelling, but they do not own their place of living.

After excluding non-resident owners, social housing and other private investors not covered in the dataset such as LLCs, I am left with 26.5 million dwellings out of the 35.7 million dwellings in France in 2017. The dataset thus covers around 75% of the total housing market in France.

Previous studies that relied on aggregate income data encountered limitations as they couldn't distinguish between property owners and tenants; these data sources used aggregate income of residing households but lacked the granularity required to make this distinction. This dataset provides an exceptional opportunity to scrutinize flood exposure at an exceedingly granular level – that is, at the level of individual dwellings. In addition, it encompasses all categories of dwellings, including second homes and empty properties, which have, in many instances, been neglected within the existing literature, despite constituting a substantial 30% of dwellings in flood-prone regions. Although these dwellings often remain vacant, there is a tangible cost associated with their reconstruction when they are impacted by floods. This is particularly relevant in the context of the French government-guaranteed insurance. In such scenarios, the financial burden of repairing these structures is collectively borne by households across the entire country, underscoring the critical need to gain a deeper understanding of the extent to which these dwellings are exposed to risks and the associated patterns of sorting.

Finally, I gather data on house prices at the municipality level from *Données des Valeurs Foncières*. This dataset gives the average annual number of sales and price per meter squared by municipality. Housing value is defined in this paper as the product of the surface of the dwelling and the price per meter squared at the municipality level.

2.2 Exposure to Floods

I study two types of flooding events: river and coastal flooding. Over the 2020-2050 period, they are expected to account respectively for 93% and 7% of total damages caused by floods (France Assureurs, 2021b). The maps of exposure I use are the Flooding Risks Areas (FRAs)[7]. FRAs are the most reliable maps available for France. They account for local particularities 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). We will mostly focus on frequent events as they represent the largest share of total losses[8]. FRAs are also available for overseas departments. However, they do not cover the whole country and are available only in specific areas where the risk of flooding is particularly high. After overlaping the maps with the geolocation of dwellings in France, I find that FRA maps cover around 45% of dwellings in France in most exposed areas, which still make these maps accurate and representative of the overall flooding risk in France. I consider that the remaining 55% of dwellings are not exposed to floods. Additionally, I consider that only dwellings located on the ground floor are exposed to flood risk. One can see the area covered by FRAs for river flooding in Figure 2a and for coastal flooding in Figure 2b.

I also exploit the Approximate Envelopes of Potential Flooding maps (AEPF)[9]. These maps

[7] *Territoires à Risque important d'Inondations* (TRI) from *Géorisques*.

[8] This information comes from discussions with insurers and *Mission Risques Naturels*. No official number is available in France.

[9] *Enveloppe Approchée des Inondations Potentielles* (EAIP) from the French Ministry of the Environment. AEPF maps are the official maps used on the *French government's website*. The shapefiles used in this paper are not

have the advantage of covering the whole Metropolitan France. However, they do not cover overseas departments and do not take into account local flood protections. They use a "maximalist" approach, which means that they cover areas that would be affected if a very extreme scenario was to happen (superior to a 1000 years return period). Also, they do not include any measure of risk intensity. I use these maps to check for the robustness of the results obtained with FRAs. Results are very robust, but not displayed in this version of the paper. They are available upon request.

In Figure 1, one can observe the difference between the two types of maps. It appears that AEPF maps correspond to exposure to large-scale events, whereas FRAs measure exposure to more frequent and small scale events. Most important, one can notice how FRA High Risk zoning follows flood protection lines, in particular on the upper part of the figure. This illustrates how flood protections are taken into account when modelling FRAs. We can also observe that FRA Middle Risk zoning do not follow flood protection lines anymore, which makes sense as floods have a higher probability of going beyond protections during larger-scale events.

2.3 Insurance Spending

To study the redistributive effects of the CatNat scheme in Section 6, I recover the amounts spent on car and housing insurance by income group using the 2017 French Household Budget survey from the French National Institute of Economic Studies and Statistics[10]. The sample includes 15,000 households, which I decompose in 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 housing (or car) insurance, contributions amount to 12% (or 6%) of the premium for other risks π_o. It can be written as follows

$$\pi_c = r\pi_o \qquad r = \{0.06, 0.12\}$$

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

publicly available and were requested to the Ministry of the Environment.

[10] *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).

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.

In the survey, I only observe the premiums paid by tenants and by owners of owner-occupied homes, but I do not know the amounts paid by owners of rental, second and empty dwellings. To derive how much households pay for these types of dwellings, I run a machine learning algorithm trained on the survey data, to attribute to each observation in my sample of 26.5 million dwellings the estimated premium paid by owners and (if applicable) tenants. Using dwelling's surface, number of rooms, region, type of dwelling (apartment or house), resident's income and household size, I estimate the premium paid by each household using a lasso model. Based on France Assureurs (2023), I then re-scale these amounts for premiums paid by owners of second, rental and empty homes. For example, I know that premiums for second homes are on average 20% lower than premiums for owner-occupied homes. I thus re-scale all premiums for second homes accordingly.

The first underlying assumption of this approach is that the variables included in the model (dwelling's surface, number of rooms, region, resident's income and household size) are sufficient to get a reliable estimation. I argue that, at the aggregate level, most of the variation in insurance premiums should indeed be explained by these variables. To support this idea, Figure 8 compares the distribution of housing insurance premiums by income decile in the survey data and the estimated premiums on the dataset covering all dwellings in France. Panel A takes into account only premiums paid by residents of owner-occupied homes and Panel B those paid by tenants of rental homes. The correlation coefficients are respectively 96% and 97%. The second assumption is that across each category of dwelling (owner-occupied, rental, second and empty homes), households' criteria to decide how much to pay in insurance premium are similar. It comes from the fact that I use premiums paid only by owners of owner-occupied dwellings and tenants to estimate the premiums paid by owners of rental, second and empty homes. As I re-scale these amounts to match France Assureurs (2023), I only need the variation *across income groups* to be similar, not the absolute values.

3 Heterogeneous vulnerabilities

In this section, I measure vulnerability to flood risk by calculating the share of housing wealth that is exposed to flooding. I use this ratio as a metric for quantifying exposure to floods in relation to total housing wealth. Other forms of financial assets are not included here, since direct observations of these assets are not available in my data. My exposure index thus represents an *upper bound* estimate of the proportion of total wealth that is exposed to flooding. As I have around 1% of dwellings in my sample exposed to floods, for the large majority of households the ratio of exposed housing wealth over total housing wealth is equal to zero. In the remainder of this section, I focus on households renting or owning at least one dwelling at risk.

The level of vulnerability among tenants is particularly high. Most of them only own furniture of their rented accommodations. My sample data reveals that less than 15% of exposed tenants possess residential properties and only 28% exhibit positive financial incomes. These findings underscore that, for the majority of tenants residing in flood-prone regions, their entire wealth is highly vulnerable to the impact of flooding.

Figure 3a displays the distribution of the ratio of housing wealth at risk over total housing wealth for the four different types of dwellings[11]. I find a substantial degree of exposure among homeowners, where 100% of their housing wealth is at risk in 75% of cases. For the remaining 25% of at-risk homeowners, some may own a second property or engage in rental activities. These findings underscore that the majority of homeowners at risk do not significantly diversify their real estate assets when it comes to mitigating flood-related risks. In addition, 55% of exposed homeowners report positive financial incomes.

The situation differs significantly for exposed landlords. Figure 3a illustrates that they have 100% of their housing wealth at risk in only in 5% of cases. For half of exposed landlords, the proportion of their total housing wealth at risk is below 30%. Furthermore, 74% of these households report positive financial income. These findings imply that landlords exhibit a more robust risk diversification strategy: a smaller portion of their real estate assets is exposed to flood risk, and they invest more in other financial instruments.

Figure 3b illustrates that, in total, approximately 40% of exposed homeowners have their entire housing wealth exposed. This finding challenges the common perception that flood victims inevitably "lose everything." While this circumstance does apply to 40% of households, a substantial portion of exposed households shows a greater capacity for diversification in the context of flood risk.

[11] As I use average house prices at the municipality level to measure the housing wealth at risk, one may argue that these prices are endogeneous and that the housing market already priced flood risk. Dubos-Paillard et al. (2023) find that the price discount of flood risk should be of 3% to 7% in France. I replicated Figure 3, but increasing the value at risk by 7% to measure an upper bound of the value at risk before the market priced flood risk. Results are very similar. Figures are available upon request.

Finally, I regress the ratio of wealth exposed over total housing wealth against income and housing wealth levels among owners with at-risk properties. The results are presented in Figure 4. It becomes apparent that individuals with the lowest housing wealth are the most adversely affected by floods. I observe the same pattern with respect to income.

These findings underscore the substantial heterogeneity in vulnerability regarding flood risk. Approximately 40% of owners exposed to flooding have less than 50% of their total housing wealth at risk, and often possess additional financial wealth. These landlords tend to be wealthier and have higher incomes compared to the broader population. Conversely, 40% of owners have their entire housing wealth exposed and display minimal diversification concerning flood risk. Furthermore, tenants, who typically own only their furnishings and lack other forms of wealth, face significant losses in the event of flooding. These observed patterns highlight the substantial variability in vulnerability, emphasizing the importance of distinguishing between these three categories of households.

4 Sorting over Flood Risk

In this section, I analyze the patterns of sorting over flood risk. I provide descriptive evidence on exposure by type of dwelling and income levels and then investigate the underlying mechanisms.

Figure 5 shows the share of dwellings exposed to floods by type. Owner-occupied homes constitute 55% of all dwellings in France, but they make up 50% of the dwellings in flood-exposed regions. Conversely, second homes, which account for less than 10% of all dwellings in France, are overrepresented, being twice as prevalent in flood-exposed areas. In the case of coastal flooding, second homes represent almost 50% of the exposed dwellings. Rental and vacant dwellings, are slightly underrespresented in flood-exposed areas. These observations show that in areas prone to flooding, the share of second homes increases substantially and substitutes for the three other types of dwellings.

As I also have access to the income of owners and tenants, I examine how the likelihood of residing in flood-exposed areas differs with respect to income across the different categories of dwellings. I run the following regression

$$Risk_i = \alpha + \sum_{k=2}^{100} \beta^k Percentile_i^k + \varepsilon_i$$

I define $Risk_i$ as an indicator variable for whether dwelling i is located in an exposed area. $Percentile_i^k$ is an indicator variable, taking a value of one if the household residing in or owning dwelling i falls within the k*th* income percentile (calculated as income divided by household size). Consequently, the parameter β^k captures the variation in the probability of being located in an exposed area for households within the k*th* percentile, relative to those in the first percentile. I run this regression for three types of dwellings: owner-occupied, second homes, and rental properties. In the case of rental properties, two separate regressions are run, one where $Percentile_i^k$ represents the income of the landlord, and the other where it corresponds the income of the tenant. Percentile thresholds are those of the aggregate income distribution in the country.

Results are displayed on Figure 6. Both for homeowners, landlords and tenants, low-income households exhibit a higher probability of residing in flood-exposed areas when compared to their high-income counterparts. These results imply that, in the context of selecting the location for their residence, high-income households are underrepresented in flood-prone areas as compared to their low-income counterparts.

Among second homes, we observe a U-curve with respect to income. This pattern suggests that as income increases, households display a preference for locating their second homes along coastal regions, which happen to be flood-prone areas. However, once income surpasses a certain threshold, around the 80th percentile in my context, households appear to shift their preference, choosing to own second homes in alternative locations. In France, high-income households frequently opt for second homes in mountainous regions or in the Paris area (Châtel et al., 2021). As most owners of second homes are middle- to high-income households, the bulk of observations are concentrated above the 50*th* percentile, resulting in a lower exposure to flood risk of high-income households on average.

To get more sense about the size of these effects, I compute the income gap between exposed and non-exposed areas. I run the following regression:

$$Log(Income_i) = \alpha + \beta Risk_i + \varepsilon_i$$

Table 1 displays the β coefficients.

Looking at Panel A and focusing exclusively on homeowners (column 1), rental (column 3) and empty dwellings (column 4), it appears that owners situated in flood-exposed areas exhibit, on average, a lower income of respectively 6%, 14% and 7% when compared to the rest of the population. When examining Figure 5, it seems that the proportions of these properties are similar between flood-exposed and non-exposed areas. This implies that within each category of dwelling, high-income owners tend to exhibit a propensity to steer clear of flood-prone regions, unlike low- and middle-income ones, and these two effects seem to balance each other out.

For second homes (column 2), we observe an income gap of 7.4% that may be due to the preference for other amenities than the coast for high-income owners of second homes, as discussed earlier.

I find that low-income tenants (column 5) exhibit a pronounced inclination to settle in flood-risk areas. This sorting behavior leads to a substantial income gap of 8% between flood-exposed and safe areas. Low-income tenants are typically representative of households with limited financial resources. These findings underscore the fact that, in addition to their high vulnerability to floods due to low diversification, low-income tenants also confront an elevated level of exposure to these risks.

In Panel B, I add successively the different types of dwellings to see how they contribute to the total income gap between exposed and non-exposed areas. In column 1, we note the previously identified income gap of 6% for homeowners. When second homes are introduced (column 2), this gap decreases but remains negative. It illustrates that the overexposure of second homes increases the exposure of high-income households, but does not counterbalance the overexposure of low-income homeowners. Adding successively rental and vacant dwellings (columns 3 and 4) increases even more the income gap between exposed and safe areas.

The overall picture that emerges suggests that high-income households sort less over flood risk than low-income ones. In addition, as these households are more often exposed through their second home, they are also less vulnerable to flooding, whereas the exposure of low-income households tends to occur through their primary place of residence. This distinction highlights two dimensions of inequality: low-income households are both more *exposed* and more *vulnerable* to flood risk.

5 Mechanisms

In this section, I investigate the mechanisms that can explain the overexposure of both second homes and low-income owners and tenants.

5.1 Amenities and dwellings characteristics

I investigate how amenities along coasts and rivers, as well as dwelling characteristics, may explain the sorting patterns observed in Section 4. Figure 7 shows the distribution of each type of dwelling as distance to the coast increases. We observe that when distance to the coast is very small, there is a significant increase in the share of second homes, representing up to 50% of dwellings with a direct view of the coast. This pattern illustrates that certain coastal amenities may play a crucial role in explaining the overexposure of second homes. To a lesser extent, we observe a similar pattern for riverine amenities.

To quantify the impact of these amenities, I run the following regression

$$Dwelling\_type_i^l = \alpha + \beta Risk_i + X_i + \varepsilon_i$$

$Dwelling\_type_i^l$ is an indicator variable equal to 1 if dwelling i is of type $l \in$[Owner-occupied; Second homes; Rental dwelling; Vacant dwelling]. $Risk_i$ is an indicator variable equal to 1 if dwelling i is at risk. β thus captures the degree of overexposure ($\beta > 0$) or underexposure ($\beta < 0$) in percentage points. X_i is a set of fixed effects for municipality, distance to the nearest coast, the nearest river[12], dwelling's surface, construction date and street fixed effects.

The coefficients β are presented in Table 2. In column 1 is displayed the raw degree of overexposure by type of dwelling, as depicted in Figure 5. Moving to column 2, the sample is narrowed down to municipalities that have at least one dwelling located in a risky area. Notably, the housing market composition changes in these municipalities, particularly for owner-occupied and rental dwellings. In column 3, I introduce municipality fixed effects to control for variations in amenities between municipalities. On average, in municipalities with at least one dwelling at risk, there are 4,500 dwellings, indicating that these municipalities are relatively small areas. Moving on to column 4, I incorporate controls for the distance to the nearest coast and river. The coefficients in column 4 thus compare dwellings within the same pool of around 4,500 dwellings, with comparable distances to the coast and river. This approach aims to capture a significant portion of the effect of amenities. In column 5, fixed effects for the surface and date of construction of each dwelling are added to the model. In column 6, I add street fixed effects.

One can observe that the overexposure of second homes decreases by a factor of five between

[12] There are 100 fixed effects for distance to coast and river, corresponding to distance percentiles.

columns 2 and 3 when controlling for municipality fixed effects. When comparing dwellings in the same street (column 6), the coefficient for second homes is almost zero. This finding illustrates how the overexposure of second homes is likely driven more by differences in amenities across municipalities than by flood risk avoidance strategies. Now, comparing columns 1 and 6, we notice that the coefficients are considerably smaller in absolute value in column 6. This suggests that amenities appear to explain a substantial portion of the degree of overexposure and underexposure by type of dwelling.

I then use the same approach to see how amenities and dwellings characteristics may explain the income gaps within each type of dwelling. Similarly to Table 1, I run the following regression and add vectors of fixed effects X_i, the same as in Table 2.

$$Log(Income_i) = \alpha + \beta Risk_i + X_i + \varepsilon_i$$

The results are presented in Table 3. When comparing columns 1 and 2, we observe that the income gap between exposed and safe areas persists when considering only municipalities exposed to flood risk and is generally even larger. After controlling for the set of fixed effects, the income gap decreases significantly, especially for second homes where the income gap is insignificant in most specifications. However, across all other types of dwellings, a consistent result emerges: average income remains lower in exposed areas. Even when controlling for the full set of fixed effects in column 6, income is still 4% lower among owners and 2% lower among tenants. While there might be some remaining amenity effects, it is also plausible that high-income households react differently to flood risk than low-income ones.

5.2 Location on the ground floor

To study whether the income gaps we measured on Table 3 are due to strategic avoidance of flood risk by high-income households, I study the choice to locate on the ground floor. Being located on the ground floor substantially increases the probability of being exposed to flooding. Except from very rare cases, upper floors are not directly affected by floods.

As I have access to the floor number at which every household resides, I investigate whether high-income households could avoid flood risk by locating on upper floors in flood risk areas. I run the following regression.

$$Ground\_floor_i = \alpha + \beta_1 Risk_i + \beta_2 Log(Income_i) + \beta_3 Risk_i * Log(Income_i) + X_i + \varepsilon_i$$

Where $Ground\_floor_i$ is an indicator variable equal to 1 if household i is located on the ground floor. The coefficient β_3 captures the additional probability of being located on the ground floor in percentage points when income increases by 1%, comparing safe and risky areas. I then add fixed effects, represented here by the vector X_i.

The results are presented in Table 4. None of the coefficients are significant. It suggests that preference for the ground floor is not able to explain the income gaps that were observed in Table 3. High-income households thus do not sort more over ground floors than low-income ones. However, they could still intentionally avoid being exposed to flooding along other dimensions. For example, after a flood event that would update their perception of the risk, they could be more able to move away from risky areas.

5.3 Heterogeneous updating processes - work in progress

I plan to use delineation maps of past flood events to see whether income groups update differently to floods. The objective will be to see whether after a flood event, high-income households leave flooded areas and prefer to have establish their second home there. This could explain the patterns we observed earlier on.

6 Implications for policy

In this section, I discuss the consequences of these findings on two adaptation policies: home buyout and subsidized flood insurance.

6.1 Home buyout programs

Home buyout programs involve governments purchasing at-risk properties, often at a negotiated price, for demolition. In France, the *Fonds Barnier* manages such initiatives, especially after major floods. In the United States, the Federal Emergency Management Agency oversees a buyout program for addressing similar risks, focusing on purchasing and removing vulnerable properties.

Home buyout programs offer a "fair" solution to assist victims of natural disasters. These programs enable affected individuals to sell their properties at a fair price, facilitating a move from high-risk areas to safer locations. Moreover, it can be economically beneficial, especially when a dwelling is subjected to recurrent flooding, as purchasing and demolishing such properties often becomes a cost-effective choice.

Home buyout programs, while effective, face significant challenges due to their high costs and logistical complexities. Many households in flood-prone areas are willing to sell their properties at market prices to entities like the *Fonds Barnier* and relocate. However, limited resources often prevent these programs from meeting the full extent of the demand they receive.

Typically, home buyout policies are implemented after specific events, and they often lack a targeted approach that considers households' vulnerabilities. In the subsequent section, I conduct a simulation of a policy that involves purchasing all at-risk homes in France. While this scenario is very unlikely to happen, it serves as a useful exercise in comprehending how improved targeting in home buyout policies can significantly reduce their overall costs.

The results, as displayed in Table 5, are presented as the share of the total buyout cost for the proposed policy. For instance, if the government opts to purchase all at-risk owner-occupied homes belonging to the bottom 50%, the cost would only amount to 18% of the total buyout expense. These findings underscore the potential for significantly reducing the cost of buyout policies through more precise targeting strategies.

6.2 Subsidized weather insurance

As discussed in Section 1, the French CatNat insurance system against natural disasters provides coverage to 98% of households in the country. The financing of this system relies on an additional premium of 12% for housing insurance contracts and 6% for automotive insurance contracts. The key advantage of this system lies in its ability to offer extensive coverage at an affordable cost to nearly all households in France, a goal that many other countries such as the United States often fail to achieve (Wagner, 2022). However, this system operates through cross-subsidies from safe to exposed areas, giving rise to distributive implications. In this section, we delve into these distributive considerations.

Using data from the French Household Budget survey presented in Section 2.3, I assess the weight of CatNat premiums on households' budget. Panel A of Figure 9 displays the total amount paid in CatNat additional premium across income deciles, following the methodology described in Section 2.3. Panel B shows the ratio of these additional premiums over disposable income. We see that while higher income households contribute more to the system in total, CatNat contributions impose a significantly heavier burden on households at the bottom

10%, four times higher than for those at the top 10%. CatNat premiums as a share of income are higher for all income deciles in comparison to the top 10%. These findings illustrate the regressive nature of these additional premiums.

Furthermore, considering the findings from Section 3, it appears that the CatNat system lacks efficient targeting of households with the greatest needs. Low-income homeowners experience heightened vulnerability through their primary residences, while high-income individuals are more exposed through their second homes. In this context, the CatNat system extends its benefits uniformly to all income groups, regardless of the substantial disparities in vulnerability.

To gain a deeper understanding of how the CatNat system redistributes money across income groups, I calculate the distribution of *CatNat premiums* and compare it to the distribution of *expected damages*. CatNat premiums represent the premiums displayed in Figure 9. Expected damages are the anticipated compensation that a household would receive if their at-risk dwelling were to be flooded. I estimate these damages based on the dwelling's value[13]. For each decile d I measure

$$Catnat\_Premiums_d = \frac{\sum_{i \in I_d} CatNat\_premium_i}{\sum_i CatNat\_premium_i}$$

with $CatNat\_premium_i$ being the CatNat premium paid by household i and I_d being households in decile d.

$$Expected\_Damages_d = \frac{\sum_{i \in I_d} \sum_{j \in J_i} Risk_j * Ground\_floor_j * Value_j}{\sum_i \sum_{j \in J_i} Risk_j * Ground\_floor_j * Value_j}$$

with $Risk_j$ being an indicator variable for whether dwelling j is located in a risky area, $Ground\_floor_j$ an indicator variable for whether dwelling j is is on the ground floor and $Value_j$ being dwelling j's value based on its surface and the average price per meter squared in the municipality[14]. J_i is the universe of dwellings owned by household i.

Panel A of Figure 10 illustrates the distribution of *CatNat premiums* and *expected damages*

[13]Since the value of a dwelling can capture characteristics beyond the core value of the building, I conducted a parallel analysis using the surface of dwellings and obtained very similar results. Detailed results are available upon request.

[14]I differentiate the value at risk for owners and tenants: according to Osberghaus (2021), the average claim for tenants is twice lower than the average claim for landlords. I thus consider that $Value_j$ depends on whether household j rents or own the house. More precisely, when the dwelling is a rental dwelling: $Value_j = 1_{[j=tenant]} 1/3 * Total\_value_j + 1_{[j=landlord]} 2/3 * Total\_value_j$. If the dwelling is not rented, I apply the standard formula.

across income deciles. It appears that the first decile pays 7.5% of the total CatNat premiums and bears 6% of the total expected damages. Consequently, assuming that total premiums equal total damages, the first decile incurs a net loss from the system, given that the expected damages are lower than the premiums they pay. In contrast, the top decile receives more compensation from CatNat than what they pay in premiums.

Drawing from the estimates in Panel A, Panel B of Figure 10 shows the average net gains or losses for each income decile for a total amount of damages of 1 billion euros, which approximately corresponds to the average annual flood-related losses in France (France Assureurs, 2021a). When summing the net losses of the bottom 60% (or equivalently the gains of the top 40%), we observe a net transfer of approximately 30 million euros, which represents about 3% of total annual losses. This amount is redistributed from the bottom 60% to the top 40%.

As I have found that low-income households were more exposed to flood risk than high-income ones in Section 4, this result may appear surprising: low-income households should benefit more from the system than high-income ones as they are also more exposed. However, what matters here is the ratio of expected damages over premiums paid. We know from France Assureurs (2023) that premiums paid for rental homes are lower than those paid for primary homes. Figure 11 illustrates that premiums paid for rental and empty dwellings as a share of housing value are lower than for other types of dwellings. As income increases, the share of rental homes increases as well, resulting in a lower ratio of premiums over housing value. As a result, (1) high-income households are indeed less exposed but also (2) pay less in CatNat premiums as a share of what they own than low-income households. The second effect being stronger than the first, it results in high-income households benefiting more from CatNat than low-income ones.

It's important to acknowledge that this simulation is a simplified version of the CatNat system. First, the system covers not only flood-related risks but also those related to subsidence caused by droughts, storms, and hurricanes. However, in this representation, we simplify the CatNat system as if it exclusively covered floods. Second, approximately 20% of the expected damages are directed toward companies on average. For the purposes of this analysis, we focus solely on residential dwellings and abstract from these commercial claims. Third, in practice, all at-risk buildings are not flooded simultaneously. What we are measuring here are the "expected" damages, which represent a theoretical estimate of average damages over time. Lastly, we simplify the scenario by excluding the possibility of the CatNat system operating at a deficit. In the real world, the system might face situations where the amount of money collected through premiums does not precisely match what is required to compensate households affected by floods.

The simplifications made in this analysis imply that the results should not be regarded as a comprehensive assessment of the CatNat system. Instead, they provide an estimate of the magnitude of redistribution in favor of flood-prone areas because of a public system like CatNat.

Despite enabling all households to be covered at an affordable price, the CatNat system is thus financed through regressive premiums that participate to subsidize the second-homes at risk of high-income landlords.

7 Conclusion

Most of the literature studying the incidence of flooding have primarily relied on aggregate data. This paper leverages a novel dataset that enables to study flood exposure at the most granular level possible. Data cover 75% of dwellings in France, furnishing comprehensive information regarding the income and housing wealth characteristics of both property owners and tenants. This framework allows me to discover new evidence on vulnerability and exposure to flood risk, and derive policy implications for adaptation.

First, low-income tenants and homeowners often have their entire wealth, up to 100%, exposed to flooding. In contrast, a large proportion of high-income individuals and landlords have only a minority of their total wealth exposed to flood risk. This finding underscores the substantial heterogeneity in vulnerability across different income and wealth categories.

Second, middle- to high-income households prefer to locate their second homes in high-risk areas. Consequently, there is a considerable over-representation of second homes in these risk-prone regions, amounting to a factor of two. Most of this overexposure seems to be explained by amenities along the coasts and rivers.

Third, low-income homeowners and tenants tend to more frequently choose to reside in high-risk areas compared to their high-income counterparts.

Fourth, the pronounced over-exposure of high-income households in risky areas through their second homes does not compensate the overexposure of low-income households. Consequently, in the aggregate, income is lower by around 6% for owners and 8% for tenants in exposed areas. Low-income households thus face a double inequality: they are both more vulnerable and more exposed to flood risk.

These findings carry significant implications for adaptation policies. By targeting beneficiaries more effectively, the cost of buyback policies can be substantially reduced. Furthermore, subsidized insurance schemes like the French CatNat system could be enhanced by setting premiums that do not burden low-income households and by taking into account heterogeneous vulnerabilities to flood risk. Given the growing popularity of such insurance schemes, especially in the United States where the issue of under-coverage against natural disaster risks is pressing (Wagner, 2022), these findings offer valuable insights for policymakers seeking to design similar systems. Potential strategies include indexing premiums to the price per square meter or implementing an additional fee for second homes, both of which can make the system more progressive and prioritize those in need of coverage.

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8 Figures and Tables

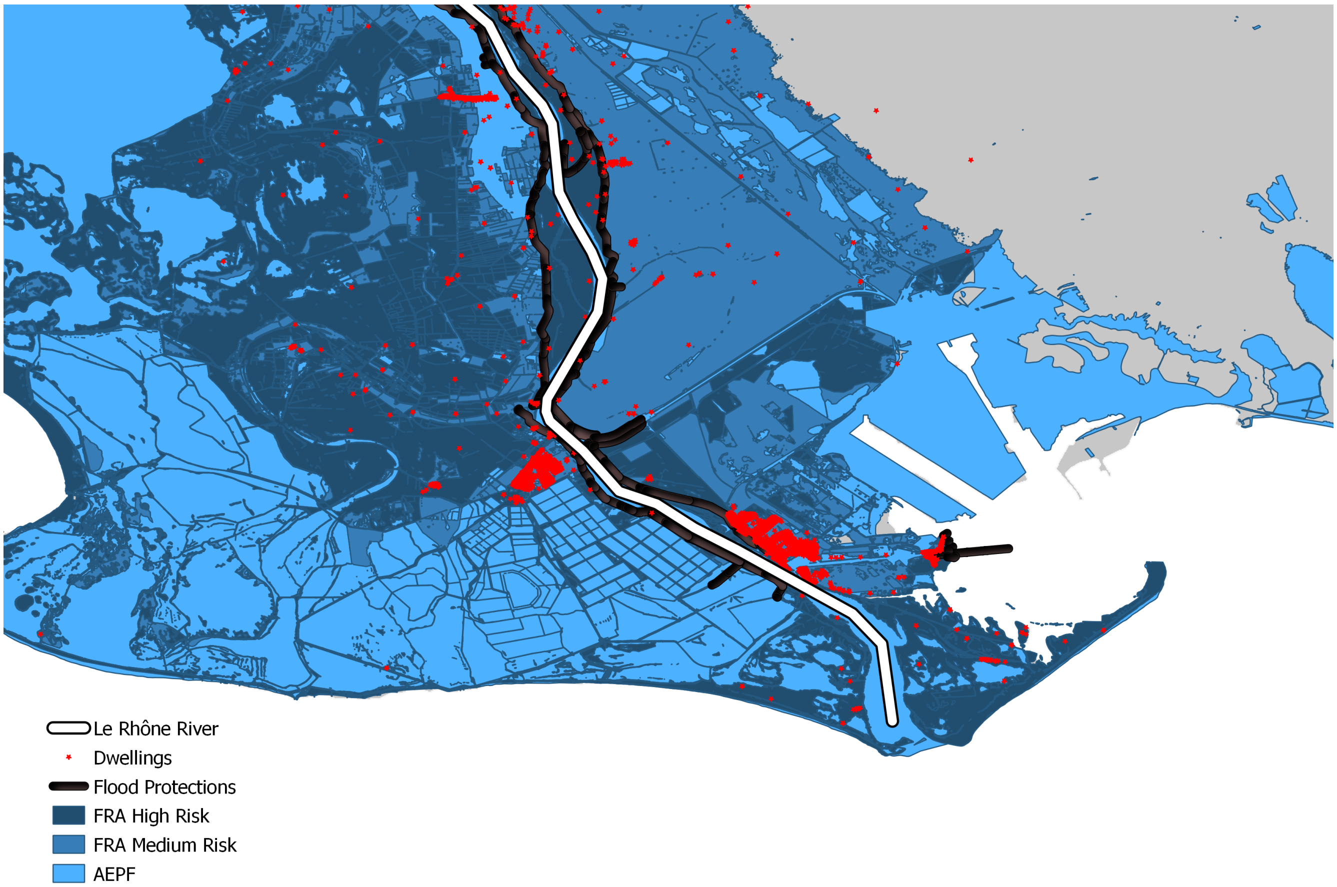
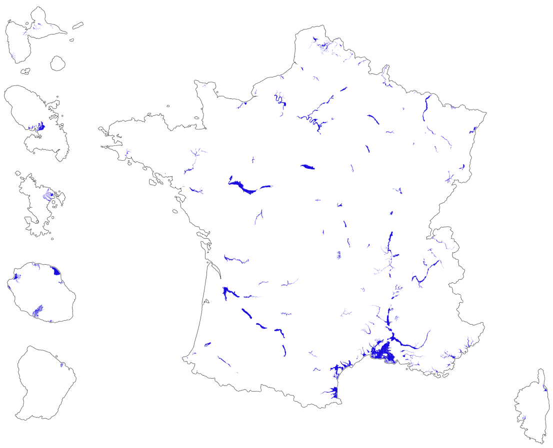
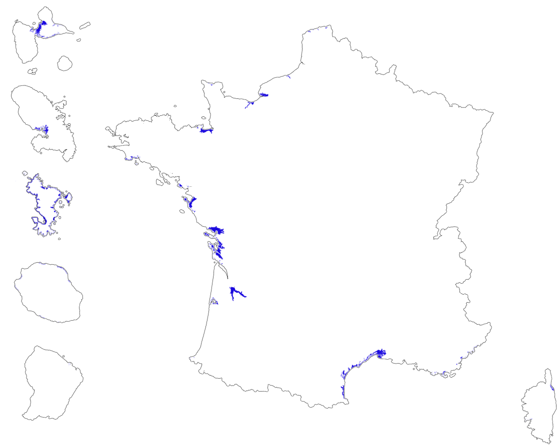


Figure 1: Coverage of FRAs and AEPF in Port-Saint-Louis-du-Rhône

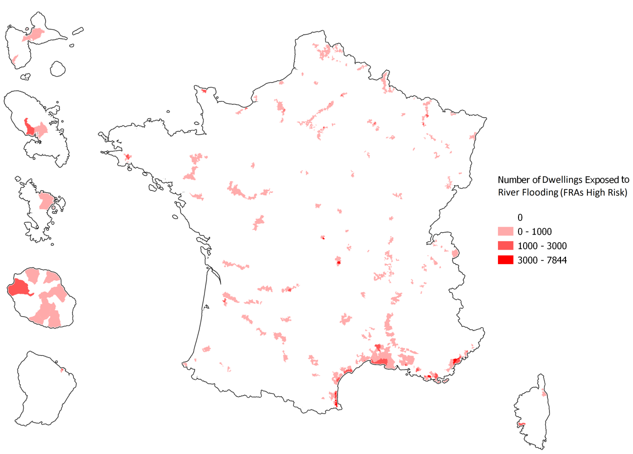
Notes. Every red dot corresponds to the location of a dwelling. The grey area is the part of France that is not affected neither according to FRAs nor by AEPF maps. The river Le Rhône is represented in white. In dark blue is the FRAs frequent risk zoning. In mid-blue the FRAs Medium Risk zoning. The AEPF map is represented in light blue. Flood protections are displayed in black.



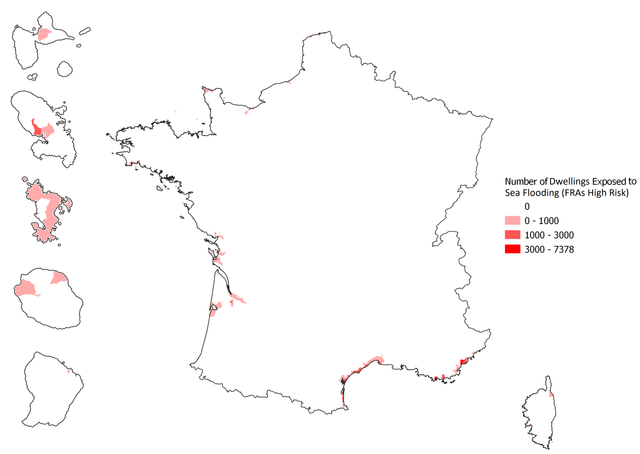
(a) Coverage of FRAs river flooding



(b) Coverage of FRAs coastal flooding



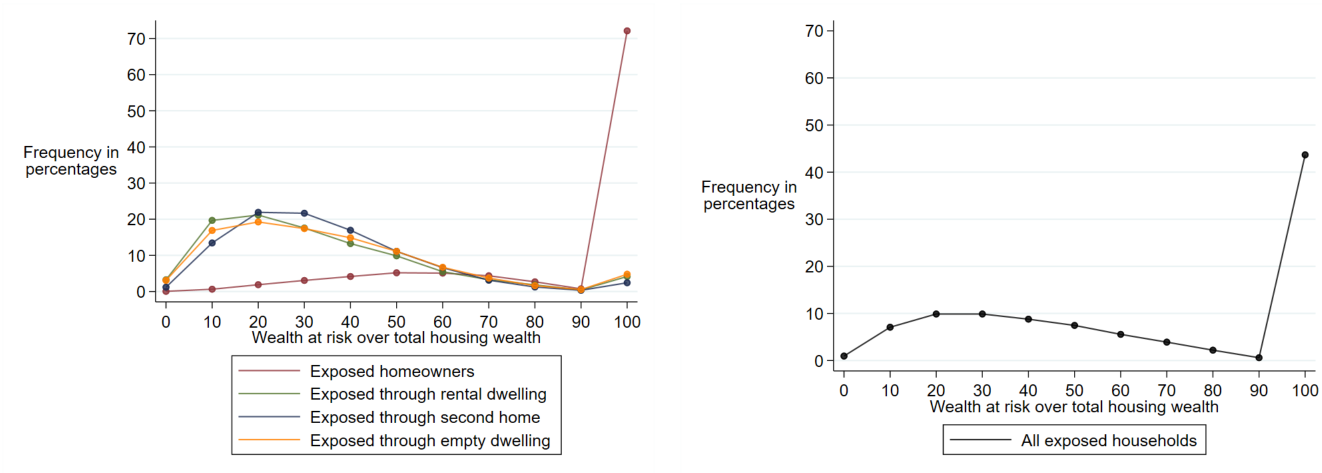
(c) Exposure to FRAs river flooding



(d) Exposure to FRAs coastal flooding

Figure 2: FRA Maps of Exposure

Notes. On the center of each figure is Metropolitan France and on the left hand side are the five overseas departments. From the top to the bottom: La Guadeloupe, La Martinique, Mayotte, La Réunion and La Guyane. In Figures 2a and 2b, the blue zones are areas exposed to flooding according to FRAs. Figures 2c and 2d display the number of dwellings exposed to frequent flooding risk by municipality.

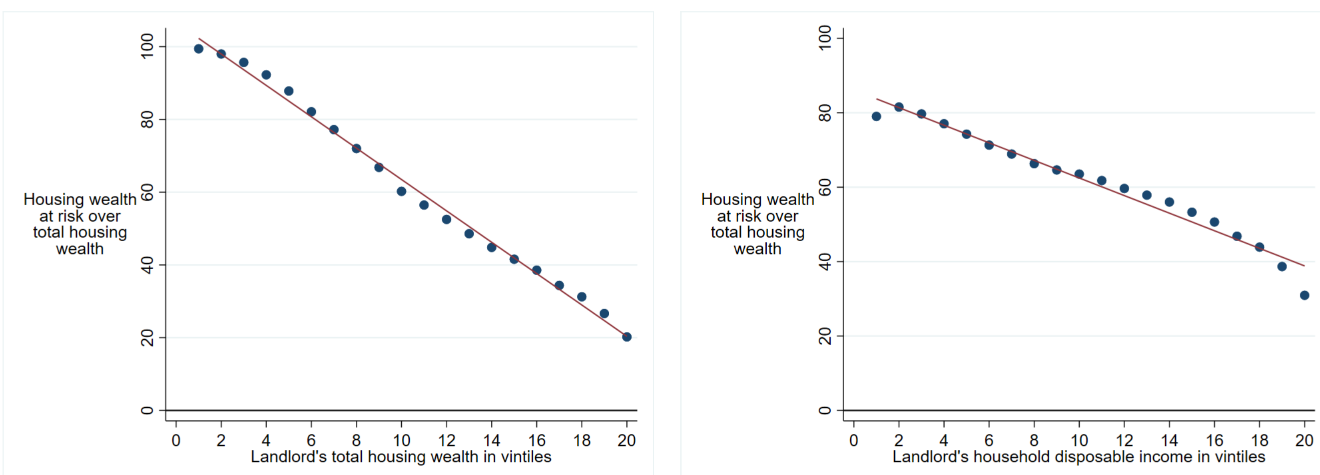


(a) By type of dwelling

(b) Aggregate distribution

Figure 3: Distribution of the ratio of housing wealth at risk over total housing wealth

Notes. The Figure displays the distribution of the ratio of housing wealth at risk over total housing wealth for all exposed owners. Panel A differentiates by type of dwelling and Panel B groups all owners together.



(a) By housing wealth vintiles

(b) By income vintiles

Figure 4: Housing wealth at risk over total housing wealth by wealth and income levels

Notes. Panel A shows the distribution of the ratio of housing wealth at risk over total housing wealth by vintiles of housing wealth and Panel B by income vintiles. Only exposed owners are included in the sample. The red line corresponds to the linear fit.

Figure 5: Exposure to flood risk by type of dwelling

Notes. The Figure displays the share of each dwelling category successively (1) at the national scale, (2) in flood exposed areas, (3) in areas exposed to river flooding and (4) in areas exposed to coastal flooding.

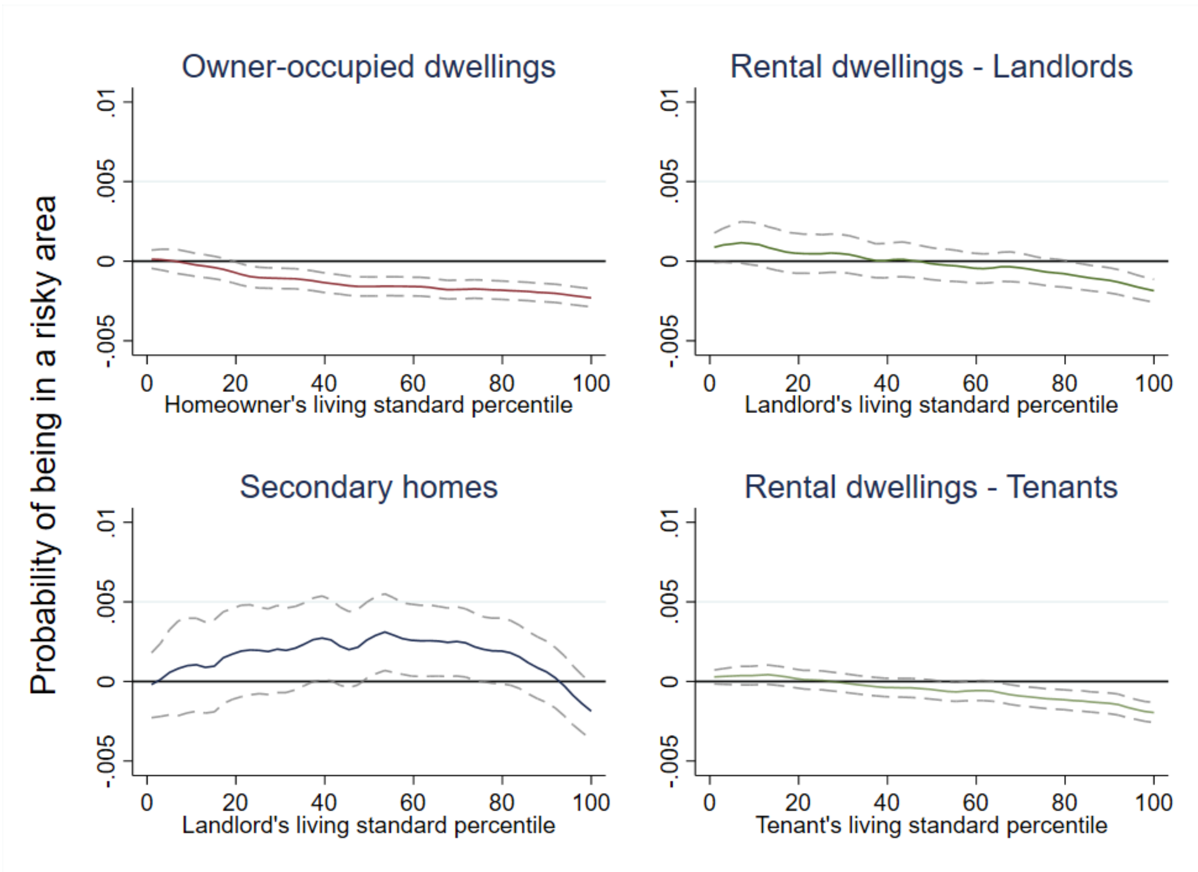
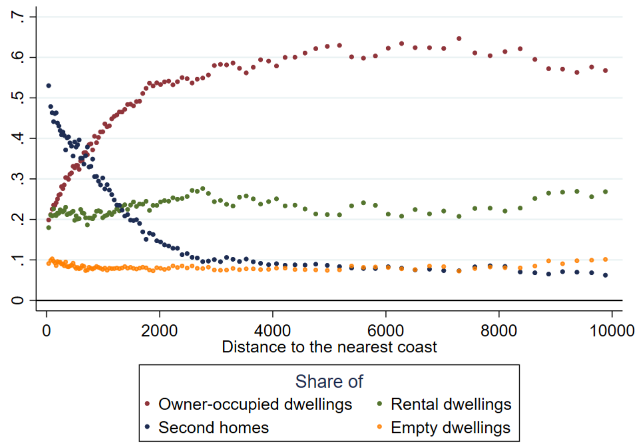
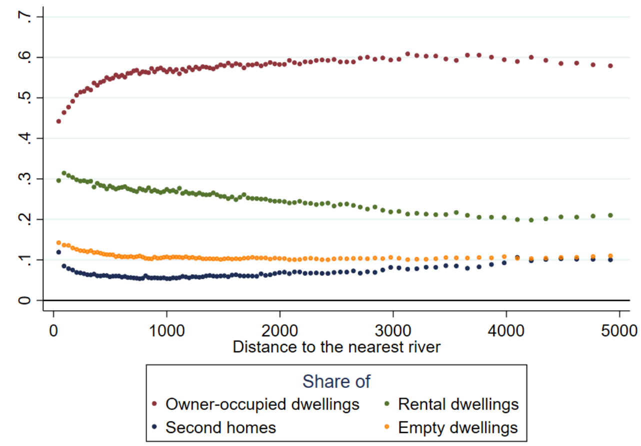


Figure 6: Probability of being exposed relative to the first income percentile by dwelling type

Notes. The Figure plots the beta coefficient of the regression $Risk_i = \alpha + \sum_{k=2}^{100} \beta^k Percentile_i^k + \varepsilon_i$ detailed in Section 4 for owner-occupied, rental and second homes. The regression line are smoothed using kernel-weighted local polynomial smoothing. Percentile 1 is omitted on the graph and is the reference value.



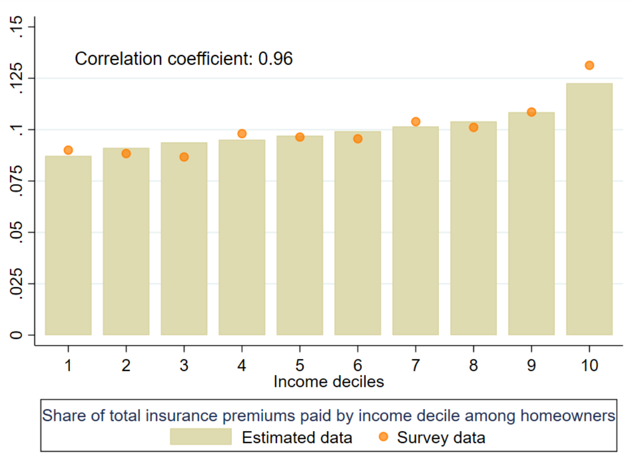
(a) Along coasts



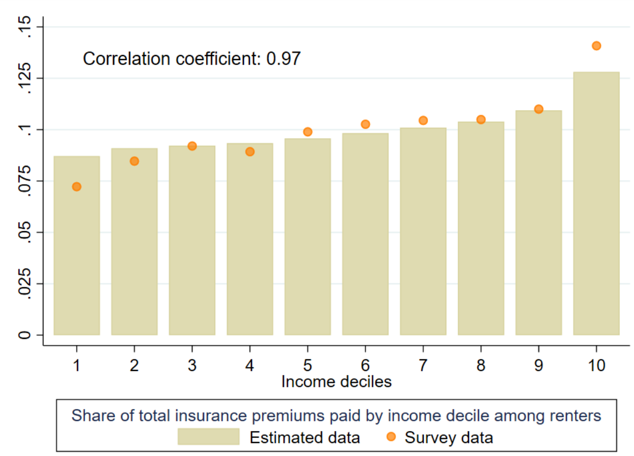
(b) Along rivers

Figure 7: Housing market composition along coasts and rivers

Notes. The Figure plots the share of owner-occupied, rental, second and empty dwellings by bins of distance to the closest coast (Panel A) and to the closest river (Panel B). Bins are constructed as percentiles of distance to the coast.



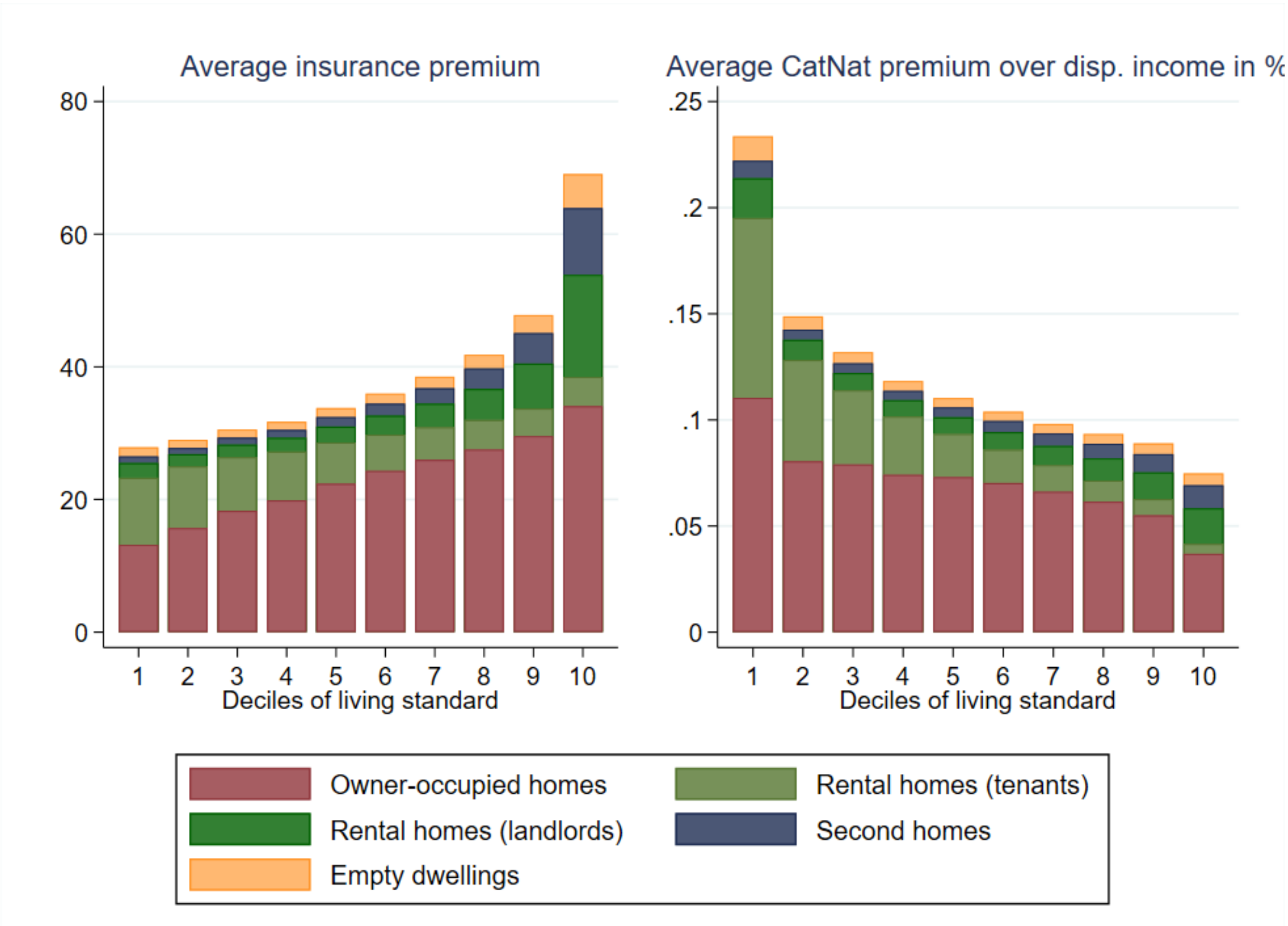
(a) For homeowners



(b) For tenants

Figure 8: 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 2.3, I derive insurance premiums at the household level for all dwellings in France. Figures 8a and 8b 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%.

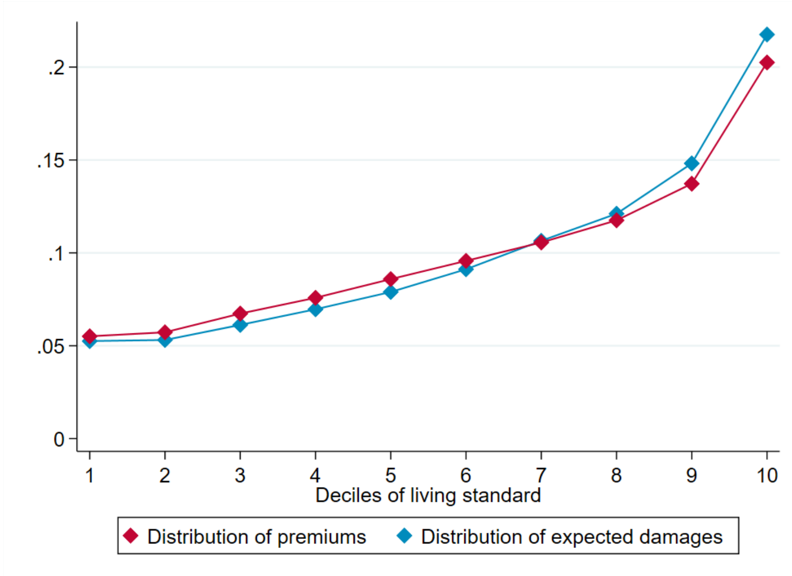


(a) Average CatNat premium

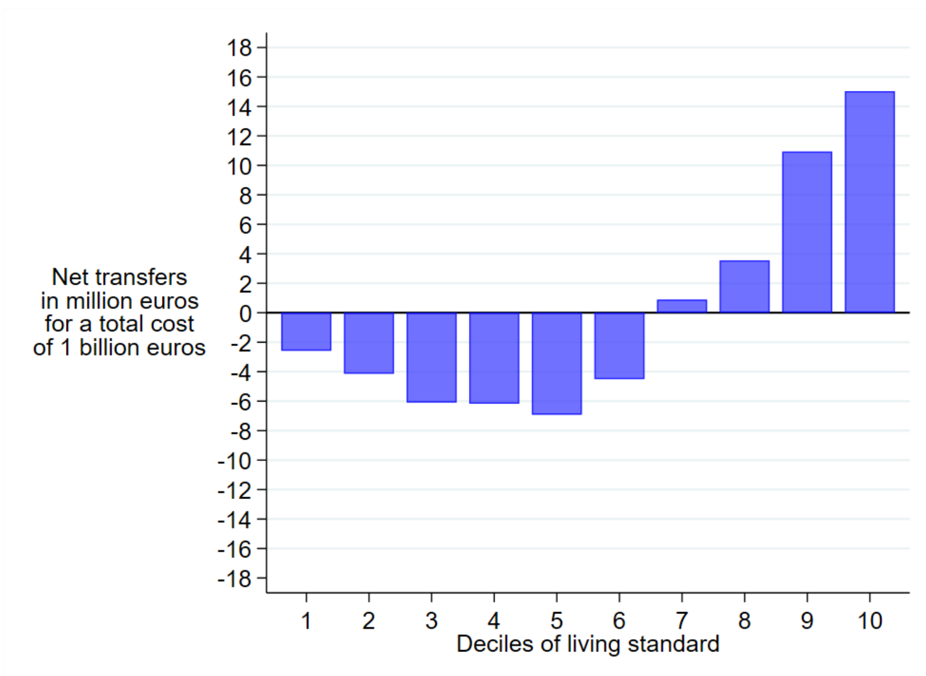
(b) As a share of disposable income

Figure 9: Distribution of CatNat premiums by income decile

Notes. CatNat insurance premiums are obtained following the Machine Learning prediction and the formula described in Section 2.3. There are five categories of households paying home insurance CatNat premiums: homeowners, tenants, owners of rental homes, owners of second homes and owners of empty dwellings. In Panel A, I sum the total amount of premiums by category and divide these amounts by the number of households in each decile to get the average premium by income decile. In Panel B, I divide these amounts by average disposable income.



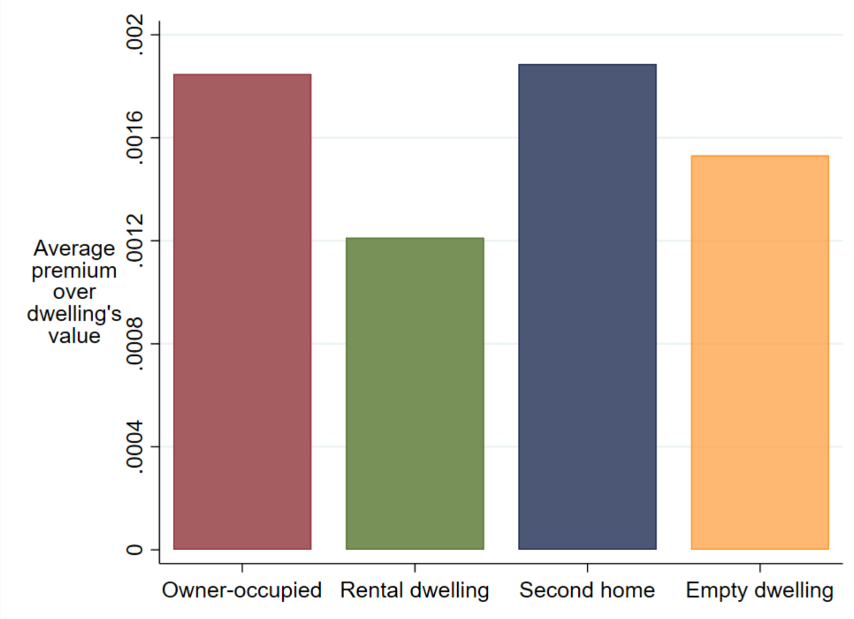
(a) CatNat premiums and expected damages distributions



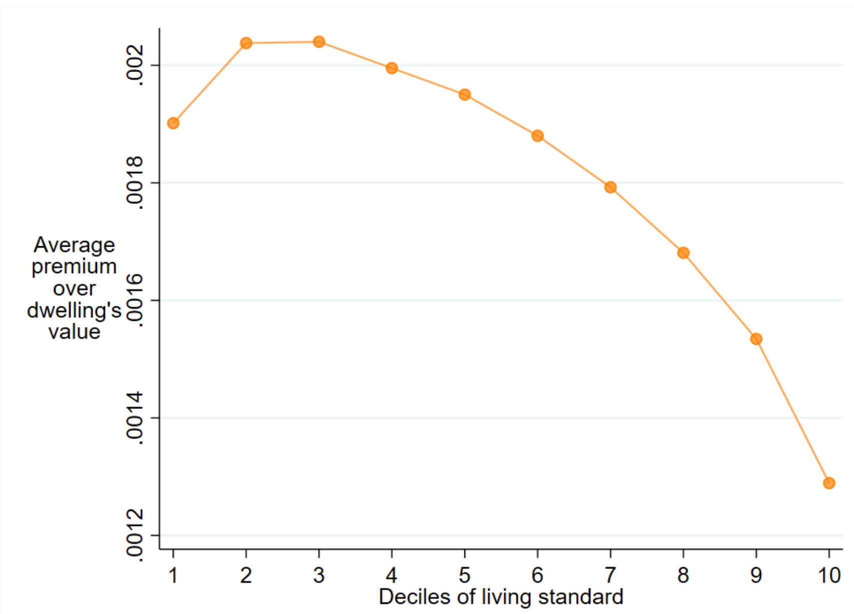
(b) Net expected transfers for a total loss of 1 billion euros

Figure 10: Net expected transfers induced by the CatNat system

Notes. Panel A plots the distribution of CatNat premiums and expected damages by income decile. E.g., the bottom 10% pays around 7.5% of CatNat premiums and bears 6% of expected damages. Panel B is obtained by computing the gap between the two distributions of Panel A and multiplying it by 1 billion. It displays the net losses or gains by income decile.



(a) By type of dwelling



(b) By deciles of living standard

Figure 11: Average premium over dwelling's value

Notes. Panel A plots the average premium over dwelling's value by type of dwelling. Panel B plots the same ratio by deciles of living standard. Insurance premiums are obtained through the Machine Learning algorithm described in Section 2 and re-scaled according to France Assureurs (2023).

Panel A: Income gap by type of dwelling

	Owner's log living standard				Tenant's log living standard
	(1)	(2)	(3)	(4)	(5)
Dwelling located in a risky area	-0.059***	-0.074***	-0.136***	-0.073***	-0.079***
	(0.002)	(0.003)	(0.004)	(0.007)	(0.004)
Owner-occupied dwellings	Yes	No	No	No	No
Second homes	No	Yes	No	No	No
Rental dwellings	No	No	Yes	No	Yes
Empty dwellings	No	No	No	Yes	No
Observations	16309325	2942577	7100906	3047349	7195108

*Signif. Codes: ***: 0.001, **:0.01, *:0.05*
Robust standard errors in parentheses

Panel B: Aggregate income gap

	Log living standard			
	(1)	(2)	(3)	(4)
Dwelling located in a risky area	-0.059***	-0.019***	-0.052***	-0.055***
	(0.002)	(0.002)	(0.002)	(0.002)
Owner-occupied dwellings	Yes	Yes	Yes	Yes
Second homes	No	Yes	Yes	Yes
Rental dwellings	No	No	Yes	Yes
Empty dwellings	No	No	No	Yes
Observations	16309325	19251902	26352808	29400157

*Signif. Codes: ***: 0.001, **:0.01, *:0.05*
Robust standard errors in parentheses

Table 1: Income gap between exposed and non-exposed areas

Notes. The table displays the beta coefficients of the regression $Log(Income_i) = \alpha + \beta Risk_i + \varepsilon_i$ detailed in Section 4. Panel A shows the results for five different regressions corresponding to each type of dwelling. For rental dwellings, I measure the income gap both for landlords and tenants. Panel B displays the income gap for owners adding successively the different types of dwellings.

	Dwelling located in a risky area					
	(1)	(2)	(3)	(4)	(5)	(6)
Owners of owner-occupied homes	-0.063***	-0.008***	0.031**	0.062***	0.029***	0.043***
	(0.001)	(0.001)	(0.010)	(0.008)	(0.005)	(0.002)
Owners of second homes	0.126***	0.148***	0.031**	0.016*	0.020**	0.006***
	(0.001)	(0.001)	(0.010)	(0.008)	(0.007)	(0.002)
Owners of rental dwellings	-0.048***	-0.113***	-0.053***	-0.063***	-0.039***	-0.041***
	(0.001)	(0.001)	(0.005)	(0.005)	(0.006)	(0.002)
Owners of empty dwellings	-0.016***	-0.027***	-0.009***	-0.015***	-0.010***	-0.008***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)
Only exposed municipalities	No	Yes	Yes	Yes	Yes	Yes
Municipality FE	No	No	Yes	Yes	Yes	Yes
Distance to the coast FE	No	No	No	Yes	Yes	Yes
Distance to the river FE	No	No	No	Yes	Yes	Yes
Suface FE	No	No	No	No	Yes	Yes
Construction date FE	No	No	No	No	Yes	Yes
Street FE	No	No	No	No	No	Yes
Observations	29748793	7439378	7439378	7439378	7274968	593113

*Signif. Codes: ***: 0.001, **:0.01, *:0.05*
Standard errors in parentheses

Table 2: Housing market composition with fixed effects

Notes. The table displays the beta coefficients of the regression $Dwelling\_type_i^l = \alpha + \beta Risk_i + X_i + \varepsilon_i$ detailed in Section 5. Coefficients in column 1 correspond to the difference in the share of each dwelling category in percentage points between safe and exposed areas. Column 2 includes only municipalities with at least one dwelling at risk. I add successively fixed effects for municipality (column 3), distance to the nearest coast and river in percentiles (column 4), surface and date of construction of the dwelling (column 5), street level (column 6). In column 1, standard errors are robust. They are clustered at the municipality level in columns 2 to 5 and at the street level in column 6.

	Income gap between safe and exposed areas					
	(1)	(2)	(3)	(4)	(5)	(6)
All owners	-0.055***	-0.122***	-0.053***	-0.066***	-0.058***	-0.040***
	(0.002)	(0.002)	(0.008)	(0.008)	(0.008)	(0.003)
Observations	29400157	7343810	7343809	7343809	7181893	583824
Owners of owner-occupied homes	-0.059***	-0.106***	-0.040***	-0.042***	-0.045***	-0.019***
	(0.002)	(0.002)	(0.008)	(0.008)	(0.007)	(0.003)
Observations	16309325	3646843	3646843	3646843	3578379	261601
Owners of second homes	-0.074***	-0.118***	-0.015	-0.012	-0.021**	-0.013
	(0.003)	(0.003)	(0.012)	(0.011)	(0.008)	(0.008)
Observations	2942577	600382	600378	600378	582907	84629
Owners of rental dwellings	-0.136***	-0.183***	-0.084***	-0.089***	-0.079***	-0.044***
	(0.004)	(0.004)	(0.011)	(0.011)	(0.010)	(0.007)
Observations	7100906	2277668	2277667	2277667	2221992	168881
Owners of empty dwellings	-0.073***	-0.162***	-0.064***	-0.072***	-0.066***	-0.045***
	(0.007)	(0.007)	(0.014)	(0.014)	(0.012)	(0.012)
Observations	3047349	818917	818915	818915	798610	62690
Renters	-0.079***	-0.059***	-0.026*	-0.023	-0.030**	-0.018**
	(0.004)	(0.004)	(0.012)	(0.012)	(0.010)	(0.007)
Observations	7195108	2308101	2308101	2308101	2251750	171313
Only exposed municipalities	No	Yes	Yes	Yes	Yes	Yes
Municipality FE	No	No	Yes	Yes	Yes	Yes
Distance to the coast FE	No	No	No	Yes	Yes	Yes
Distance to the river FE	No	No	No	Yes	Yes	Yes
Suface FE	No	No	No	No	Yes	Yes
Construction date FE	No	No	No	No	Yes	Yes
Street FE	No	No	No	No	No	Yes

*Signif. Codes: ***: 0.001, **:0.01, *:0.05*
Standard errors in parentheses

Table 3: Income gap between exposed and non-exposed areas with fixed effects

Notes. The table displays the beta coefficients of the regression $Log(Income_i) = \alpha + \beta Risk_i + X_i + \varepsilon_i$ detailed in Section 5. Coefficients in column 1 correspond to the income gap in percentages between safe and exposed areas within each dwelling and household categories. Column 2 includes only municipalities with at least one dwelling at risk. I add successively fixed effects for municipality (column 3), distance to the nearest coast and river (column 4), surface and date of construction of the dwelling (column 5), street level (column 6). In column 1, standard errors are robust. They are clustered at the municipality level in columns 2 to 5 and at the street level in column 6.

	Dwelling located on the ground floor			
	(1)	(2)	(3)	(4)
Being in a risky area x log income of				
Owners of owner-occupied homes	-0.014	-0.011	-0.004	0.002
	(0.008)	(0.008)	(0.006)	(0.003)
Observations	3658039	3658039	3589241	255827
Owners of second homes	-0.003	0.004	0.009	0.000
	(0.011)	(0.010)	(0.008)	(0.008)
Observations	600852	600852	583372	70779
Owners of rental dwellings	-0.010	-0.010	-0.006	-0.003
	(0.006)	(0.006)	(0.006)	(0.005)
Observations	2281267	2281267	2225424	165288
Owners of empty dwellings	0.001	0.001	-0.001	-0.006
	(0.007)	(0.007)	(0.007)	(0.008)
Observations	820141	820141	799788	61754
Renters	-0.001	-0.000	0.005	0.006
	(0.006)	(0.006)	(0.006)	(0.004)
Observations	2311749	2311749	2255228	167709
Only exposed municipalities	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Distance to the coast FE	No	Yes	Yes	Yes
Distance to the river FE	No	Yes	Yes	Yes
Suface FE	No	No	Yes	Yes
Construction date FE	No	No	Yes	Yes
Street FE	No	No	No	Yes

*Signif. Codes: ***: 0.001, **:0.01, *:0.05*
Standard errors in parentheses

Table 4: Effect of income on being located on the ground floor

Notes. The table displays the β_3 coefficients of the regression $Ground\_floor_i = \alpha + \beta_1 Risk_i + \beta_2 Log(Income_i) + \beta_3 Risk_i * Log(Income_i) + X_i + \varepsilon_i$ detailed in Section 5. The table includes only municipalities with at least one dwelling at risk. I add successively fixed effects for municipality (column 1), distance to the nearest coast and river (column 2), surface and date of construction of the dwelling (column 3), street fixed effects (column 4). Standard errors are clustered at the municipality level from column 1 to 3 and at the street level in column 4.

Income Percentiles	Owner-occupied dwellings	Rented Homes	Secondary Homes	Empty Dwellings	**Total**
Bottom 50%	18%	5%	3%	2%	28%
Middle 40%	26%	9%	8%	4%	47%
Top 10%	9%	8%	6%	2%	25%
Total	53%	22%	17%	8%	**100%**

Table 5: Cost of the buyout policy by income and wealth groups

Notes. The percentages in the table correspond to the cost of buying back all exposed dwellings in a given category as a share of the cost of buying back all exposed dwellings. E.g., if the government opts to purchase all at-risk owner-occupied homes belonging to the bottom 50%, the cost would only amount to 18% of the total buyout expense.