Floods and Residential Mobility in France

Christine Le-Thi, Katrin Millock, Julie Sixou*

15 July, 2025

Abstract

There is mixed evidence as to whether individuals adapt to extreme climate events by moving away from vulnerable areas. Using comprehensive French administrative data at the individual level, we examine heterogeneous migration responses to flooding. We find substantial post-flood migration, with heterogeneous effects: private renters are more likely to move than homeowners or social housing tenants, and individuals in the bottom and top income quintiles are less likely to relocate than those in the middle.

At the municipality level, we find no average treatment effect on population flows, underscoring the importance of granular micro-level data. However, the proportion of homeowners is lower among population outflows from flooded municipalities. While we detect no significant effects on individual income, we observe an increase in housing transactions outside flood-prone areas, consistent with a disamenity effect as the underlying mechanism.

Keywords: Climate change, Flood, Migration, Natural Disasters, Residential location choice
JEL codes: Q54, R23

*Le-Thi: INSEE and OECD (email: Christine.LETHI@oecd.org); Millock: Paris School of Economics and CNRS (email: millock@univ-paris1.fr); Sixou: INSEE (email: julie.sixou@insee.fr). We would like to thank Thomas Bézy, Pascale Champalaune, Pauline Givord, Marine Guillerm, Hélène Ollivier, Sébastien Roux, and Lionel Wilner for their insightful comments. This paper has benefited from comments by participants at the Insee Economic Studies Department seminar, the Insee-CREST workshop, the Regulation and Environment seminar at Paris School of Economics, the Fourth International Conference on Environmental Economics at the University of Orléans, the Econometric Society Interdisciplinary Frontiers conference on Economics + Climate Science (ESIFCLIM), and the 73rd Congress of the French Economic Association. Any errors are our own.

1 Introduction

Climate change is leading to an increase in both the frequency and intensity of extreme weather events (Pörtner et al., 2022). Between 2000 and 2018, the population exposed to flooding increased (Tellman et al., 2021), and it is estimated that climate change will substantially increase the risk of displacement due to river floods by the end of the century (Kam et al., 2021). This is partly due to population growth in areas at risk of flooding.

Recent articles have documented a concentration of economic activity and population in areas in the U.S. (Indaco and Ortega, 2024) and in the global South (Kocornik-Mina et al., 2020) in high climate-risk areas with little evidence of population movement out of these areas.[1] In France, the French Ministry for the Ecological Transition estimates that 17.1 million people were exposed to river flooding in 2020, including 16.8 million in metropolitan France. Flooding is the main natural hazard in France, followed by drought.[2] According to current climate change projections, France will experience an increase in the frequency of extreme weather events, including floods (Alfieri et al., 2015; Pörtner et al., 2022). In 2021, the damage to insured property in France caused by the river flooding alone was estimated to be between 450-600 million EUR (CCR, 2022). The increased cost of extreme climate events, such as floods, has exacerbated the difficulty of insuring such risks, putting pressure on the current reinsurance scheme (Charpentier, 2008; Charpentier and Le Maux, 2014; Grislain-Letrémy and Villeneuve, 2015; Kousky et al., 2021). There is also growing evidence of disaster insurance providing perverse incentives to locate in high risk areas (Peralta and Scott, 2024). The main adaptation measures that could be taken to minimise flood damage include creating water retention areas and river dykes, flood-proofing buildings, and relocating people and assets out of flood risk areas. However, relocation of populations has been shown to be costly (Dottori et al., 2023), and it is important to determine the extent to which individuals take flood risk into account in their location decisions.

The objective of this paper is to investigate whether individuals' residential choices respond to high-frequency flood events. To do so, we use exhaus-

[1] Behrer and Bolotnyy (2023) show a similar lack of adaptive migratory responses following hurricanes in the U.S.

[2] Over the period 1982-2022, 49% of all disaster decrees were for floods, followed by 42% for droughts, and 9 % for other natural disasters. Storms are a rare event in mainland France, but a common hazard in the overseas regions.

tive data from metropolitan France combined with the history of past floods. To measure floods, we combine flood risk maps from Dottori et al. (2022) and CatNat disaster decrees. We use fiscal administrative data (Fideli-Filosofi) that track individuals from January 2017 to January 2020,[3] and census data to add controls at both the individual and municipal levels.

Our empirical strategy consists in comparing individuals living in areas a priori exposed to flood risk and where a flood decree was issued in the municipality that year (the treatment group) with individuals living in areas that are also exposed to flood risk, but where no flood decree was issued in the same year (the control group). This approach allows us to control for pre-existing sorting based on risk preferences. We also apply propensity score matching to ensure balanced treatment and control samples. We use the extended two-way fixed effects estimator proposed in Wooldridge (2023) to estimate the average treatment effect on the treated in a nonlinear model of the probability of moving, controlling for time-varying characteristics of both the individual and the municipality of residence. Our focus is mainly on inter-municipal mobility, but we also consider intra-municipal mobility.

At the individual level, our results suggest that inter-municipal mobility increases by 1 percentage point in the two years we can observe following a flood. This represents an increase of almost 30% compared to the average inter-municipal mobility rate of around 3.7% in our sample. The evidence shows substantial heterogeneous effects beyond income at the individual level. Regarding tenure status, renters in the private sector are 1.9 percentage points more likely to relocate following a flood, than at baseline, whereas homeowners are only 0.7 percentage points more likely to relocate in the year after a flood. In terms of income, individuals in the lowest income quintile are less likely to relocate following a flood than the average individual. This aligns with the theoretical prediction that individuals with the lowest income are the most likely to experience reduced mobility due to income loss following a flood. Other heterogeneous effects also support this explanation. Notably, the probability of moving is lower among the unemployed than among the employed. Compared to the average effect, the probability of relocation is also lower for individuals in the highest income quintile. This is consistent with the prediction that higher-income individuals

[3] Given the short time frame, our analysis is short term and does not allow us to assess the role of individuals' revision of their beliefs about flood risk and expected flood damages (Gallagher, 2014; Gibson and Mullins, 2020; Bakkensen and Barrage, 2021) in explaining their relocation decisions.

can better afford the necessary measures to adapt and protect themselves.

The impact of floods on residential mobility is a priori ambiguous. On the one hand, floods are likely to damage buildings and infrastructure, thereby encouraging migration out of the flooded area due to direct damage and devalued amenities. On the other hand, rebuilding lost physical capital can have positive indirect effects on local labour markets and attract new residents. Furthermore, indirect effects of productivity losses and wage reductions can spill over into non-flooded municipalities within the commuting zone. Our estimates suggest that these spillover effects are three times smaller in magnitude than the direct effects of flooding in an individual's municipality.

An analysis of aggregate population inflows and outflows at the municipal level shows that there is no average effect on population flows. However, we observe changes in the composition of population outflows at the municipal level following a flood. Notably, the proportion of homeowners in population outflows decreases.

Our article makes four contributions to the literature. First, we analyse residential mobility after floods regardless of their scale. In contrast, the rather scarce literature on mobility after floods has primarily focused on the U.S. and on extreme events on a very large scale, such as Hurricane Katrina (Deryugina et al., 2018) and Hurricane Sandy (Varela, 2022).[4] Second, unlike recent literature on mobility and climate extreme events, which has focused on county-level data (Boustan et al., 2020; Indaco and Ortega, 2024; Leduc and Wilson, 2023; Wrenn, 2024; Roth Tran and Wilson, 2025)[5] or census tract-level data (Indaco and Ortega, 2024; Ton et al., 2025), much less is known about individual responses with respect to location choice. The article most closely related to ours is Sheldon and Zhan (2022), who examine the impact of floods, coastal storms, and hurricanes on migration in the U.S, and find that households who have experienced severe disasters[6] are more likely

[4]There is a growing strand of the literature focusing on sea-level rise and the distribution of population, see Desmet et al. (2021) and Burzyński et al. (2021) for analyses at the global level. In our context, we focus on river floods.

[5]In their analysis of U.S. county-level data from 1920 to 2010, Boustan et al. (2020) find that migration responses increased with the increasing frequency of natural disasters, particularly after floods, hurricanes, and wildfires since the 1980s. Restricting the sample to disasters after 1980 revealed a 0.8 percentage point decrease in the net in-migration rate following floods. In contrast, Indaco and Ortega (2024) find no evidence of population retreat from areas exposed to a high risk of riverine flooding.

[6]In the article, the severity of a disaster is measured using the Federal Emergency Management Agency's *Individuals and Households Program* (IHP), which provides aid to

to move. In contrast to our analysis, they cannot locate households precisely and analyse mobility at the county or PUMA (Public Use Micro Data Area) level. Other related analyses include Blonz et al. (2025), who use a linear probability model to estimate the effects of flooding and wind speeds from 15 major hurricanes using a random representative sample of individuals with credit score data from the U.S. and simulated data from the First Street Foundation, and Bernard et al. (2024), who use household survey data to assess the probability of relocating within a year after self-reported housing damage from floods, cyclones, or bushfires in Australia. Apart from the different settings, our analysis differs in that we use the extended fixed effects estimator of Wooldridge (2023) to identify the impact of individual factors on mobility, based on comprehensive administrative data at the individual level.

Using administrative income declaration data allows us to track the same individuals over time and control for their characteristics.[7] This allows us to examine heterogeneous effects at the individual level and investigate who moves after a flood. A third contribution of our analysis is to add to the existing literature by examining differences in mobility based on tenure status, employment, age and type of housing. Existing evidence from the U.S. shows that more educated individuals (who are presumably wealthier) are less sensitive to flood risk (Fan and Davlasheridze, 2016), and that low-income and minority households are more likely to sort into high flood risk areas (Bakkensen and Ma, 2020). Consistent with this, Sheldon and Zhan (2022) also find that low-income households are less likely to move after a disaster.[8]

Fourth, to the best of our knowledge, this is the first analysis of individual mobility following river floods to use comprehensive data for a country in the EU.[9] We are only aware of two articles that analyse residential mobility after floods using European data, and these focus on population growth or aggregate population flows after specific extreme events (Husby et al.,

disaster victims. This is a policy instrument rather than a measure of a disaster's physical intensity.

[7]Bakkensen and Barrage (2021), in particular, document the importance of heterogeneity in subjective expectations of flood risk in their analysis of coastal flood risk in the U.S.

[8]Relatedly, following Hurricane Sandy, Varela (2022) finds that spatial polarisation is more pronounced after the event due to heterogeneous income effects in the housing market.

[9]An agent-based model by Tierolf et al. (2023) analyses the impact of sea-level rise on mobility in France.

2014; Berlemann et al., 2023). Existing analyses based on U.S. data have the specific feature that the requirements for flood insurance correlate with past flood and updated flood risk maps. These requirements could entail substantial financial costs for households, which could limit their mobility. In the French context of comprehensive disaster insurance at flat rates, we find that, in the short term, individuals adapt to flooding in their area of residence by moving out of the municipality. This indicates the potential of residential mobility as an adaptation strategy to floods, although Bakkensen and Ma (2020) find that it is a costly strategy in the U.S. context as it redistributes flood risk costs due to risk-based insurance premiums. In our analysis of the potential mechanisms behind increased mobility after a flood, we find evidence of a direct disamenity effect of flooding.

The remainder of the paper is organised as follows. We present the data in Section 2 and describe the empirical strategy in Section 3. The results are presented in Section 4. We explore and discuss potential mechanisms in Section 5. In Section 6, we conclude and discuss future research.

2 Data

2.1 Flood measure

2.1.1 Flood events : natural disaster decrees

We use information on flood events from the CatNat decrees, which are compiled in the GASPAR database. CatNat is a French public-private agency created in 1982 to address shortcomings in the insurance market by providing insurance to individuals and companies against risks that would otherwise be considered uninsurable. These risks are concentrated in a limited area and include floods, avalanches, volcanic activity and earthquakes.[10] The CatNat system records the state of natural disasters and defines the nature, duration and type of damage caused by a natural disaster that has occurred at the municipal level. The GASPAR database classifies a number of flood events;

[10]The CatNat insurance scheme, which is bundled with home insurance and has flat rates that do not vary according to risk, is based on the French constitutional principle of solidarity (paragraph 12 of the Preamble to the Constitution of October 27, 1946, which proclaims the solidarity and equality of all French citizens in the face of the burdens resulting from national disasters).

here, we focus on "floods and mudslides", the category corresponding to river floods.

The main drawback of this measure of past floods is its low resolution. Given that municipalities can be quite large,[11] not all individuals within a municipality are directly affected by the flood. To overcome this problem, we use a complementary flood hazard map, which we document in the next section. We then focus on a sample of individuals located within this floodplain at the beginning of our observation period (January 2017).

Figure 1 shows the number of floods in French municipalities in 2018 and in 2019. 96% of the flooded municipalities experienced only one flood during this period. 80% of municipalities have not experienced any flood.

2.1.2 Floodplains : River flood hazard maps for Europe and the Mediterranean basin

We locate individuals in 1-in-100 year floodplains from Dottori et al. published by the European Commission, Joint Research Centre (JRC) (2021). This is a very high-resolution flood hazard map (100 m) based on the European river network and water bodies. The map is obtained from a hydrological simulation based on the LISFLOOD model for river flows and LISFLOOD-LP for flooded areas. It is intended to reflect current flood risks: it is not based on climate change projections.

Dottori et al. (2022) carry out various validation exercises by comparing their output with official flood maps for different countries or regions (Hungary, Italy, Norway, Spain, and the UK). We also perform a similar exercise in the French case, comparing their map, limited to the French territory only, with past floods. The French Centre for Studies on Risks, the Environment, Mobility and Urban Planning (CEREMA) provides us with a detailed map for the very severe flood of the Loing River in June 2016.

The sample maps of the Loing River in Figure 2 show that the JRC flood hazard map almost perfectly overlays both the regulatory flood map defined by local authorities (PPRi)[12] and a past flood event. This gives us confidence in the plausibility of the following two assumptions. First, individuals located within the JRC flood map should be informed of their exposure to flood risk. Since 2006, it is mandatory for house sellers and landlords to inform buyers

[11] There are around 35,000 municipalities in metropolitan France. Our unit of analysis is the individual.

[12] *Plan de Prévention des Risques d'inondation* (Flood risk prevention plans)

and renters of the risks to which their property is exposed, including natural hazards.[13] Second, these individuals are also likely to have been directly affected by the flood. In the end, there are 14,213 municipalities in our sample that are included in flood prone areas for river floods with a given flood frequency of 1-in-100 years.[14]

The reason why we do not categorise individuals based on the official regulatory maps (PPRi) is that these regulatory maps are constructed locally: as such, they are highly heterogeneous across the French *départements*.[15] Moreover, not all of them are publicly available, which makes a national analysis impossible.

2.2 Residential mobility

2.2.1 Administrative data: Fideli-Filosofi

We track residential mobility using Fideli-Filosofi, a comprehensive source from the tax administration which compiles information from housing tax files as well as from several income files (FIP, POTE and PFLC). The Fideli database provides information on residential location within municipalities. Although it was originally designed as a cross-sectional database, it is now possible to build a panel thanks to a matching based on the *CSNS* identifier. Consequently, we are able to track the individuals over time, starting in 2017. These data are characterised by unprecedented spatial granularity, even though the time frame is short.

Each individual residence is declared in a household's tax files on January 1 of every year. We track the fiscal reference person of each household over time. A mover is defined as an individual who changes residence between years *t-1* and *t*. In addition, we know whether an individual moves within or outside the municipality of origin. Using the *CSNS* identifier has one limitation in our context. Children and young adults are imperfectly

[13] Mauroux (2018) shows that the introduction in July 2006 of the information act "Information des acquéreurs et locataires" affected properties on the ground floor significantly, with a reduction of 6% in the average transaction price at municipal level.

[14] Other flood hazard maps are available depending on the flood scale: they range from 1-in-10 years to 1-in-500 years. We focus here only on the medium 1-in-100 year hazard maps because we do not observe the flood damage of past events in the data on natural disaster decrees.

[15] The 96 *départements* are the second level of French sub-national administration, below the regions and above municipalities.

monitored in terms of their residential mobility.[16] As the mobility variable does not adequately cover individuals aged 0 to 25, we restrict our sample to individuals aged 26 and over, which excludes students with specific mobility patterns (Gobillon, 2001).

Mobility decisions depend on several socio-economic variables, such as income (measured here as equivalised disposable income), home ownership status and age. In order to investigate possible heterogeneous effects with respect to individual characteristics, we use additional information on household income, its source, and the age of the fiscal reference person, as provided by the Filosofi database. Table 1a shows the corresponding summary statistics for the variables used in the analysis.[17]

We use five age categories, with the reference category being individuals aged 42-52 years. We control for the tenure status of the individual, with the reference category being tenants of private landlords. Renters are more likely to move than owners because the costs of moving are usually higher for the latter. Renters only have to give one to three months' notice to their landlord, whereas selling a property can take much longer. The other categories are renters in social housing,[18] owners, and others.[19] We distinguish employment status by the main source of income. The *other* category comprises mainly maintenance payments and investment income. Equivalised disposable income is defined as disposable income divided by the number of consumption units in the household, in order to take account of differences in household size and composition.

We exclude the data for 2021, because it covers the period from January 2020 to January 2021, when individual mobility was significantly reduced due to the COVID-19 pandemic. The data for 2020 are valid as the tax declaration information relates to 1st January, before the COVID-19 pandemic in that year. Our final sample consists of 799,527 individuals (fiscal reference

[16]Some segments of the population may be prone to mismeasurement, particularly young adults moving from their parents' tax file to their own, children appearing indirectly on their parents' tax file, and people living in communities not subject to housing tax.

[17]In the U.S., flood insurance and access to credit have also been shown to affect economic outcomes after flooding (Billings et al., 2022), but we do not include such variables here since compulsory flood insurance at a flat rate and strict mortgage limits in France have prevented the kind of foreclosures that affected U.S. housing markets due to subprime loans.

[18]Social housing is difficult to obtain and is likely to reduce mobility in the French context.

[19]This category includes, for example, people living free of charge with relatives.

persons), whom we follow over three years, from January 2017 to January 2020.

2.2.2 Local amenities

We include municipality characteristics in our empirical analysis of mobility because individuals may choose their location according to their preferences for amenities, such as green space, as well as public services and transport. The amenities included in the analysis are listed in Table A.1 in Appendix, together with the source of the data. We introduce the *urban area* dummy to capture time-invariant characteristics of each municipality related to housing and labour market structure. A six-category urban-rural typology classifies municipalities according to population density and the degree of influence of the centre.

Time-varying characteristics of the municipality include the *median income in the municipality* and the *share of secondary homes*; the latter is considered a proxy for local amenities, in particular for green space. Information on secondary homes is collected from census data for the period 2017-2019,[20] thus we proxy data on secondary homes in year t with data in year $t-1$. Finally, we identify coastal municipalities by a dummy. This variable controls for both the amenity of being close to the coast (Rey-Valette et al., 2019), and for the higher risk faced by (some) inhabitants of such municipalities (the definition of disaster in the CatNat decrees we use does not include coastal flooding).[21]

3 Empirical Analysis

3.1 Identification strategy

To estimate the impact of floods on residential mobility, we compare two groups, a treatment group and a control group. We define the treatment group as individuals living in areas that are exposed to flood risk and where the municipality had a flood decree in that year. Control individuals also

[20] The latest edition goes up to 2019.

[21] We do not include disaster decrees for coastal flooding, as there are many categories of decrees for them, which could lead to more measurement error than the single category of "floods and mudslides". We demonstrate in a robustness check that our results remain unchanged when individuals in coastal municipalities are excluded.

live in areas exposed to flood risk, but where the municipality did not have a flood decree in the same year. Focusing on flood risk areas allows us to account for pre-existing residential sorting into risky and non-risky areas. Our identifying assumption relies on the fact that, conditional on living in a flood risk area, experiencing a flood is exogenous due to the random timing of floods.

Table 1a shows the summary statistics for the treatment and control groups of fiscal reference persons, presented separately. The two groups are imbalanced with respect to several socio-demographic characteristics; owners are slightly over-represented in the control group. The control group also has a higher proportion of individuals for whom pension benefits are their main source of income. The treatment group has an annual equivalised disposable income that is higher (26,000 EUR compared to 23,000 EUR).

Descriptive statistics on amenities at the municipality level are shown in Table 1b. The control and the treatment groups also differ in terms of municipality characteristics and access to various amenities. Municipalities in the treatment group have a slightly higher median income and better access to amenities such as schools, shopping facilities, health facilities and nurseries than municipalities in the control group. They are also more likely to be located on the coast. Treated municipalities are more likely to be located in dense urban centres and in the first periphery.

We provide significance tests for mean differences in characteristics between the treatment and the control groups, considering both individual-level characteristics (Table 1a) and municipality-level characteristics (Table 1b).[22] Despite considering only individuals in flood risk areas, these tests lead to the rejection of the null hypothesis of equality of means. We therefore adopt a propensity score subclassification strategy to address these imbalances and to construct comparable treatment and control groups.

We perform subclassification on the treatment propensity score. More precisely, this score represents the probability of being treated at any given time and is estimated using a logit model based on the previous covariates. All observations are then classified into six subclasses according to their probability of being treated at any given time. These subclasses are defined using propensity score quantiles. The number of treated observations in each subclass is then used to define the observation weights that will

[22] Chi-square statistics are computed for categorical variables, while F-tests are used for continuous variables.

be applied in the estimations. This enables us to adjust for differences in means between the treatment and control groups so that the distribution of their propensity score by subclass is similar. We believe that this strategy helps us to achieve a more credible control group. As expected, using the subclassification weights greatly reduces differences in means (or differences in proportions for binary variables). Figure 3 shows how these differences change when matching weights are used. For example, the difference in the proportion of individuals living in a high-density urban centre falls from 0.29 to 0.03.

An additional issue complicates the identification of a treatment effect of flood. The treatment is not absorbing, meaning that areas can be flooded repeatedly. Our definition of the treatment does not take multiple floods into account. From 2018 to 2019, only 0.8% of the municipalities in our sample experienced floods two years in a row (see Figure 1). To address the initial condition problem, we restrict our sample to individuals who have not experienced a flood in the last four years.[23] This condition ensures that we identify the treatment effects of floods that occurred during our analysis period (2017-2019), and not the long-term effects of floods that occurred before 2017.

3.2 Econometric specification of individual mobility choices

We estimate a location choice model, relying on the identifying assumption of quasi-experimental variation in the timing of floods. In the main estimations we define the dependent variable as equal to one if the individual moves outside their municipality of origin.[24]

Consider an individual i living in municipality c in year t. After a flood, her choice is to move to another municipality within metropolitan France ($M_{ict} = 1$) or not ($M_{ict} = 0$). The utility of individual i residing in municipality c is denoted by U_{ict}. We assume that it can be decomposed into a

[23]This assumption is based on previous results on the persistence of the effects of flooding, which range from four to six years for house prices (Atreya et al., 2013; Bin and Landry, 2013) and up to nine years for insurance take-up (Gallagher, 2014). In a robustness check, we shorten this window and test for static effects of flooding, where an individual in a flood risk area is treated as soon as there is a CatNat decree, regardless of previous floods in the same location.

[24]The inter-municipal mobility rate in the sample is 3.8 % in 2018, and 3.5% in 2019. The intra-municipal mobility rate in the same sample is 2.2% in 2018, and 2% in 2019 (see Table 2). In Section 4.1, we present results when intra-municipal moves are also included.

deterministic component V_{ict} and a stochastic component ϵ_{ict}. The individual chooses to leave the municipality of origin if $V_{ict1} + \epsilon_{ict1} > V_{ict0} + \epsilon_{ict0}$. Under the assumption that the idiosyncratic term ϵ_{ict} is distributed according to a type I extreme value distribution, the odds ratio of moving relative to staying in the municipality of residence is

$$\frac{Prob(M_{ict} = 1)}{Prob(M_{ict} = 0)} = e^{V_{ict1} - V_{ict0}}$$

The probability of an individual living in municipality c to move can thus be expressed as a function of the mean level of utility compared to the baseline of remaining in location c (McFadden, 1974). By normalising the utility of remaining in location c to zero, which is done without loss of generality, we obtain:

$$Prob(M_{ict} = 1) = \frac{e^{V_{ict1}}}{1 + e^{V_{ict1}}} \tag{1}$$

We specify a linear deterministic component for V_{ict1} on treatment $\mathcal{T}_{it}$:

$$V_{ict1} = X'_{it}\alpha + \beta\mathcal{T}_{it} + Z'_{ct}\gamma + \delta_i + \theta_t \tag{2}$$

where time-varying individual characteristics X_{it} include equivalised disposable income, tenure status, occupational status, and the age category of the individual; Z_{ct} includes time-varying characteristics of the municipality of origin but also the type of the municipality according to the urban-rural typology. δ_i are individual fixed effects and θ_t are year fixed effects.

Due to the incidental parameter problem, it is difficult to identify the treatment effect in a nonlinear model with individual fixed effects and a small number of time periods. We rely on the method in Wooldridge (2023) to identify the average treatment effect on the treated, τ_{rg}:

$$\tau_{rg} = \mathbb{E}[Y_r(g) - Y_r(\infty)|\mathcal{T} = 1], r = g, ...T; g = q, ...T \tag{3}$$

where g indicates the first time the cohort was subject to the treatment and t is calendar time. The case $g = \infty$ indicates the potential outcome in the never treated state. In essence, the method entails defining the treatment indicator, year dummy variables, and their interactions to obtain a time-varying treatment indicator, and to perform a pooled quasi maximum likelihood estimation. Pre-treatment covariates can be included in the estimation if they are centred around the cohort mean. Binary treatment indicators for each cohort $g \in 2018, 2019$ are defined by $\mathcal{T}_{ig}$. The year 2017 defines the first year baseline. Period s dummy variables are denoted fs_t, and the time-dependent treatment variables are defined as $W_{it} = \mathcal{T}_{iq}(fq_t + ... + fT_t) + \mathcal{T}_{iT} fT_t$.[25] The conditional mean can then be expressed as

$$\begin{aligned} E(V_{it}|\mathcal{T}_{i2018}, \mathcal{T}_{i2019}, X_i, W_i) = G[\alpha + \sum_{g=2018}^{2019} \beta_g \mathcal{T}_{ig} + X_i \kappa \\ + \sum_{g=2018}^{2019} (\mathcal{T}_{ig} X_i)\eta_g + \sum_{s=2018}^{2019} \gamma_s fs_t + \sum_{s=2018}^{2019} (fs_t X_i)\pi_s \\ + \sum_{g=2018}^{2019} \sum_{s=g}^{2019} \delta_{gs}(W_{it}\mathcal{T}_{ig} fs_t) + \sum_{g=2018}^{2019} \sum_{s=g}^{2019} (W_{it}\mathcal{T}_{ig} fs_t \dot{X}_{ig})\xi_{gs}] \end{aligned} \quad (4)$$

where G is a strictly increasing function, and $\dot{X}_{ig} = X_i - E(X_i|\mathcal{T}_{ig} = 1)$ are the cohort-specific means of the covariates.[26]

The coefficients of interest are the terms with W_{it} in the final row of Equation 4 which measure cohort-specific treatment effects. As the number of treated individuals vary by cohort, we then use the relative size of the cohorts to calculate the average treatment effect on the treated.

In addition to direct effects, floods may have indirect spillover effects on neighbouring municipalities. We test for such effects by considering events in the *aires d'attraction des villes* or AAV[27] of the individual, which may have economic spillover effects on the municipality in which the individual resides. Individuals may also be affected by flooding at their place of work, which may be in another municipality. We estimate such spillover effects by redefining the treatment variable in Equation 4 to be equal to one if there was no flood in the individual's municipality in year τ and if there was a flood in the individual's AAV, without distinguishing between the risk areas in the map

[25] For example, $W_{it} = 0$ means that if individual i is treated in cohort g, $t < g$. For never treated individuals $W_{it} = 0$, $\forall t$.

[26] For simplicity, we only show the interactions with the individual control variables here, but the estimations also include identical interaction terms with the municipality-level time-varying control variables Z_{ct}.

[27] The AAV, or functional urban area, consists of a municipality and its commuting zone.

of Dottori et al. (2022). Empirically, we find that individuals can be flooded several times based on this definition of spillover. Therefore, when estimating the effect, we restrict the sample to individuals who are not flooded and who have at least one neighbouring municipality of the same commuting zone treated during the period 2018-2019. As a result, our estimation of spillovers is based on a smaller sample of 341,875 individuals compared to the main sample of 799,527 individuals.

As discussed in the introduction, the expected signs of the indirect treatment effects through spillovers from a flooded municipality elsewhere are ambiguous. These coefficients capture indirect effects which may be either negative, due to direct damages to buildings or physical capital in the commuting zone, or positive, if the rebuilding after a flood elsewhere in the commuting zone induces positive labour market effects.

All estimations are done using quasi maximum likelihood on the pooled sample. Following Wooldridge (2023), standard errors are clustered at the individual level. We also cluster standard errors on both the individual and the municipal levels in a robustness check in Section 4.3.

3.3 Population flows at the municipality level

To complement the analysis of individual mobility choices, we also examine out-migration and in-migration at the municipal level. This allows us to examine whether there are compositional effects as in the U.S., for example in terms of income and age : people living in flood-risk areas may be poorer (Bakkensen and Ma, 2020) or older (Indaco and Ortega, 2024). To this end, we aggregate individual decisions to construct a population outflow rate at the municipality level. The variable $OUTFLOW_{ct}$ for municipality c and year t is defined as the share of $t-1$ inhabitants who left in year t:

$$OUTFLOW_{ct} = \frac{\#\text{individuals leaving municipality } c \text{ at } t}{\#\text{inhabitants of municipality } c \text{ at } t-1} \tag{5}$$

Similarly, the population inflow rate $INFLOW_{ct}$ is defined as follows:

$$INFLOW_{ct} = \frac{\#\text{individuals arriving in municipality } c \text{ at } t}{\#\text{inhabitants of municipality } c \text{ at } t-1} \tag{6}$$

For both outcomes Y_{ct} we estimate:

$$Y_{ct} = \kappa \mathcal{T}_{ct} + Z'_{ct}\mu + \zeta_c + \eta_t + \nu_{ct} \tag{7}$$

The treatment variable $\mathcal{T}_{ct}$ now equals one when there is a flood in municipality c in year t. We control for municipality (ζ_c) and year (η_t) fixed effects and include time-varying covariates Z_{ct} corresponding to municipal amenities, except for median income, which may be endogenous to floods. Indeed, floods may cause income losses by affecting productivity and labour markets. We estimate the difference-in-differences specification in Equation (7) using ordinary least squares (OLS).

If flooding makes affected municipalities less attractive, we would expect κ to be positive when measuring the effect of flooding on outflow rates and negative for inflow rates. Based on this specification, we can further investigate whether a flood has changed the composition of outgoing and incoming population flows to flooded municipalities. In this case, $Y_{c,t}$ denotes either the proportion of individuals below a given income threshold or the proportion of homeowners among these flows. Specifically, we examine whether floods increase or decrease the proportion of individuals in the bottom 25% (or 50%) of income, or the proportion of homeowners in the municipality.

4 Results

4.1 Floods significantly increase individuals' propensity to move

Our estimation results show that the probability of moving increases by 1.1 percentage points after a flood (Table 3), and that it remains at that level (1 percentage point) for the two years that we can examine.[28] Table A.2 in Appendix shows that the assumption of parallel trends holds for the year for which it can be tested. The effect corresponds to an increase of 30.1% in the year following the event compared to the average annual inter-municipal mobility rate of 3.7% in our sample. This effect appears to be driven by the 2018 cohort, a year that was marked by an exceptional number and severity of floods. Consequently, the external validity of our estimate may be limited. Notwithstanding the differences in estimation strategy and disaster type, we note that it is lower than the estimate in Bernard et al. (2024) from Australia

[28]The full estimates, which are very long given all the interaction terms, are available on request.

but higher than the estimate in Sheldon and Zhan (2022) from the U.S.[29]

The marginal effect of a flood on total residential mobility (including both intra-municipal and inter-municipal moves) is an increase of 1.2 percentage points in the two years after a flood (see Table 4). Relative to the baseline mobility rate of 5.7%, this corresponds to a 20.9% increase in the propensity to move.

A limitation of the analysis is that we lack data on adaptation measures that households could have taken at home (Osberghaus, 2017; Richert et al., 2017). If anything, this is likely to bias our estimates downwards. However, since the use of *in situ* adaptation measures likely correlate with individual preferences or characteristics, our analysis of the same individual using panel data should control for these factors.

Finally, Table A.3 shows that, after flooding, most moves (87%) out of the municipality are to areas outside the flood-risk areas as defined by the map in Dottori et al. (2022). This indicates the adaptive potential of such mobility in relation to flood risk. For intra-municipal moves, individuals are almost equally likely to end up in an area with or without flood risk.

4.1.1 Spillover effects from floods outside the municipality are an order of magnitude smaller than direct effects

We also find evidence of spillover effects from floods in the commuting zone on individuals' mobility rates in non-flooded municipalities, but these effects are much smaller in magnitude than the estimated effects of floods in the municipality of residence. Table 5 shows a small positive increase in outward mobility (0.3 percentage points) in the year following a flood, and a small negative effect (-0.4 percentage points) two years afterwards.

In Section 1, we discussed the potential indirect effects of flooding and the ambiguous nature of the expected effect. Two potential causes of these indirect effects are demand and employment effects elsewhere in the commuting zone. If these indirect effects occur through firm closures and the labour

[29] Bernard et al. (2024) estimate a 56% increase in the probability of moving in the year following (self-reported) housing damage from floods, cyclones, or bushfires in Australia. The baseline results in Sheldon and Zhan (2022) suggest a 5 to 18% increase in the likelihood of moving for households who have experienced a disaster (e.g., hurricanes, coastal storms, and floods) in their county in the past four years. Blonz et al. (2025) find a 134% increase in individual mobility following Hurricane Katrina, a 19% increase following the second-largest hurricane in their dataset, and a 5% and 4 % increase following Hurricanes Harvey and Sandy, respectively, compared to baseline mobility rates.

market, they may be delayed, which could explain why the spillover effect becomes negative two years after a flood. Overall, however, the spillover effect of floods occurring outside the municipality is more than three times smaller in magnitude than the effect of floods in the municipality of residence. One possible explanation for this is that the flood intensity is too low to affect the rest of the commuting zone.

4.1.2 Mobility effects from floods vary by tenure status, housing type, and income quintile

Evidence from the U.S. suggests heterogeneous effects of floods on individuals: in particular, low-income households are less likely to move after a disaster (Sheldon and Zhan, 2022). We extend the analysis of heterogeneous responses to floods with respect to several individual characteristics: quintiles of household equivalised disposable income, employment status, age category, tenure status, and a dummy indicating whether the dwelling is a house or a ground floor flat.

We find that the effect of a flood is weaker for the bottom 20% and the top 20% of equivalised disposable income than for individuals in the middle quintiles of equivalised disposable income (see Figure 4). An individual in the first quintile has a 0.8 percentage point higher probability of moving after a flood, compared to an increase of 1 to 1.2 percentage points in the middle quintiles.[30] This is consistent with evidence suggesting that credit constraints may limit residential mobility for low-income households (Husby et al., 2018). For the top quintile of equivalised disposable income, however, the probability of moving increases by 0.9 percentage points after a flood. This may reflect the fact that high-income households have the means to adapt and protect themselves. The results are reminiscent of those found for a hurricane strike in the U.S. (Smith et al., 2006), where middle-income households were the most likely to move out of the area after a hurricane strike, while higher income groups did not use this margin to adapt.

Figure 5 shows the estimates from the interactions with the source of income of individuals. Employed individuals display the highest marginal effect in the probability of moving after a flood, with an increase of 1.2 percentage points compared to 0.8 percentage points for an unemployed individual. This may reflect liquidity constraints for the categories unemployed, and the

[30] Marginal effects for all outcomes by individual characteristics are presented in Table A.4 in Appendix.

category *other*. Retired individuals show the smallest change in the probability of moving after a flood (an increase of 0.7 percentage points). The interactions with the age category of the individual in Figure 6 show that the post-flood mobility response reflects general mobility patterns, with a higher marginal effect on moving for individuals aged between 26 and 32 years old. The probability of moving decreases in the second year after a flood, except for the higher age groups (over 52 years old).

Figure 7 shows that tenure status is important: while the probability of moving after a flood increases by almost two percentage points (and by 1.5 percentage points at $t + 2$) for renters in the private sector, owners show an increase of 0.7 percentage points after a flood (rising to 0.9 two years later). Social housing tenants experience the smallest change in the probability of moving after a flood, with an initial increase of 0.6 percentage points, falling to 0.4 in the second year. Finally, heterogeneous effects are observed depending on whether the individual's dwelling is a house, a ground floor flat, or a flat on upper levels (see Figure 8). Individuals living on the ground floor are more likely to move after a flood (an increase of 1.9 percentage points), compared to those living on upper floors (an increase of 1.2 percentage points), and those living in houses, who experience the smallest increase (between 0.5 and 0.6 percentage points) (see Table A.4 in Appendix). The salience of flood risk when living on the ground floor could explain the difference in effect between the first two groups. Table A.5 in Appendix shows that the group living in houses are mainly owner-occupiers (82.46% of the category), who may find it difficult to sell their property after a flood. This could explain why owners of houses experience a smaller actual increase in the probability of moving after a flood. Homeowners may also be more likely to have already installed adaptation measures in their homes.[31]

4.1.3 Floods of long duration drive the effect

The main results are based on a binary treatment that does not distinguish between floods of different intensities. Although rainfall intensity before a flood is sometimes used as a measure of treatment intensity, floods are not

[31] In a survey of respondents in the French *départements* Aude and Var, Richert et al. (2017) provide evidence of heterogeneous effects in the decision to take private protective measures against flood risk. The stated responses show that planned prevention is positively correlated with threat appraisal, education, and home ownership. The responses regarding income were too few to be included in the analysis.

caused by rainfall alone, making it an imperfect proxy for the extent of damage. Instead, we measure flood intensity by its duration, as this is related to the disturbance caused. As the CatNat decrees contain information on the beginning and the end of flood events, we measure flood intensity in days. Figure 9 shows the distribution of this duration for each year. Most treated individuals are affected by events that last for one or 22 days according to the decree. This bimodal distribution suggests that our analysis population should be divided into two groups.

To test for the intensity of the event, we split the sample according to the duration of a flood. Long floods are defined as those with a duration of 22 days or more. Short floods are defined as those with a duration of 21 days (the median) or less. We then re-estimate the individual location choice model on these two sub-samples. Both sub-samples contain the same panel of never-treated individuals.

Figure 10 shows that the average marginal effect found earlier is driven by the long-duration floods. This is consistent with the fact that large-scale natural disasters cause greater damage and are more likely to affect individuals' preferences.[32] For floods lasting less than 22 days, we observe a higher immediate increase (2.2 percentage points) in the propensity to move one year after a flood, but it becomes negative (-0.8 percentage points) two years after the event. For long floods, there is an increase of 1.4 percentage points in the propensity to move one year after the flood, followed by an increase of 0.7 percentage points two years after the flood.[33]

4.2 No average effect of floods on municipality-level population flows

We next present our results from the models at the municipality level in Equation (7). The difference-in-differences estimates for aggregate flows in

[32]The marginal effects according to flood duration are presented in Table A.6 in Appendix.

[33]Table A.7 in Appendix shows estimates for the 2018 cohort only, categorised by flood duration: very short (0-5 days), medium (6-14 days), and long (15 or more days). These estimates reveal a consistent trend: an initial surge in mobility in the year after a flood, followed by a subsequent decline in the propensity to relocate two years after the event. The effect sizes for the 2018 cohort are much larger than the aggregate marginal effects, especially for floods of medium duration. For floods lasting 15 days or more, the probability of moving increases by 1.7 percentage points in the year after the flood and by 0.8 percentage points two years after the flood.

Table 6 show no effect of floods on average population outflow and inflow rates, contrary to what we find at the individual level. This is also the case when we re-estimate Equation (7) separately for the sample of floods of below-median duration (see Table A.8 in Appendix). For floods of above-average duration, we find an effect on population inflows. It indicates a decrease of 0.1 percentage points in the in-migration rate, but it is imprecisely estimated (see Table A.9 in Appendix).

The absence of an effect on the population outflows may be due to the small proportion of each municipality's population that is actually located in the floodplain, as illustrated in Figure 2. This finding is also consistent with the "micro retreat" hypothesis, according to which individuals live in a less risky area within a larger municipality at risk while enjoying its amenities (Indaco and Ortega, 2024).

Next, we examine tests of compositional changes in the population inflows and outflows (see Tables 7, 8, and 9). At this level of aggregation, we find no evidence of reduced inward or outward mobility among low-income individuals (see Tables 7 and 8). However, we do observe other compositional effects, in terms of tenure status with respect to out-migration at the municipal level. Table 9 shows a decrease of between 2.3 and 2.5 percentage points in the proportion of homeowners among those who move outside the municipality. This is consistent with tenants (particularly in the private sector) being able to move more easily. These changes may reflect negative income effects, either due to direct flood damage or to price changes in the housing market. To our knowledge, the only other analysis that controls for tenure status at an individual level (Bernard et al., 2024) finds that uninsured homeowners in Australia were the only group to experience a decrease in the probability of moving in the year following a disaster (whether that be floods, cyclones or bushfires). Our results, which are specific to the context of mandatory flat-rate disaster insurance in France, suggest that indirect economic effects through changes in house prices may hinder homeowners' ability to relocate. Recent evidence from the French housing market for the period 2019-2023 shows that past floods have significantly impacted property prices, particularly in *départements* where such events have occurred repeatedly (Ancel and Kamionka, 2024).

4.3 Robustness checks

We present a series of robustness checks in the Appendix. First, Table A.10 shows that the main results remain unchanged when the standard errors are clustered at the level of both the individual and their municipality of origin.

In the main estimation, we use the disaster decrees related to river flooding only, but control for whether the municipality has a coastline. A potential issue is that excluding coastal floods may lead to an underestimation of flood risk, thereby confounding the estimate for such individuals with the amenities associated with their coastal location. Table A.11 shows that the main estimation is robust to excluding individuals located in coastal municipalities.

We then proceed with a falsification test to validate our identification strategy. We simulate a fake treatment (a fake flood) among "never treated" individuals, while keeping the annual number of treated individuals constant. The results are shown in Table A.12. As expected, we find no effect on residential mobility on the estimated coefficients.

In another robustness check, we assume static effects (i.e., no persistence of floods) and remove the four-year filter since the last flood before our period of analysis. Table A.13 shows that the estimates without the four-year filter are not significant. This could be because some individuals have already been affected by flooding, or because the information provided by a flood event is not new in this case and people have adapted to past flooding.

Finally, we estimate the main specification on the full sample without using matching weights. As shown in Table A.14, the estimates are statistically significant, but the marginal effects are almost 50% higher. Without using the matched sample, we could mistakenly conclude that floods have a much greater effect on residential mobility.

5 Mechanisms

5.1 Potential mechanisms

We can explore the mechanisms behind our results using a simple spatial equilibrium model (Kline, 2010; Kline and Moretti, 2014). This model identifies four potential mechanisms for an increased propensity to leave the municipality of residence after a flood: direct disamenity effects from floods, productivity (wage) effects, housing cost effects, and differences in individual preferences. The model focuses on the working-age population where individuals supply one unit of labour and demand one unit of housing. An individual i living in municipality j has utility

$$w_j + A_j - r_j + \epsilon_{ij} = v_j + \epsilon_{ij} \tag{8}$$

where w_j denotes the income she receives in municipality j, A_j denotes the direct amenity of living in municipality j, and r_j is an annuitized measure of housing costs for living in municipality j.

The individual chooses to live in municipality a rather than municipality b if and only if

$$v_a - v_b > \epsilon_{ib} - \epsilon_{ia} \tag{9}$$

Assume $\frac{\epsilon_{ib}-\epsilon_{ia}}{s} \sim$ logistic (0,1) where the parameter s represents place attachment. With F being the logistic cumulative distribution function, the number of individuals who would prefer to live in municipality a rather than b can be expressed as follows:

$$L_a = F(\frac{v_a - v_b}{s}) \tag{10}$$

or

$$sF^{-1}(L_a) = w_a - w_b - (r_a - r_b) + (A_a - A_b) \tag{11}$$

Flooding can potentially impact wages, the direct amenity, and the rental cost of living in municipality j. Individual preferences for the municipality (s) also influence the propensity to move.

Equilibrium in the labour market is determined by the intersection of the labour supply and demand functions. Firms produce a homogeneous good (sold abroad) using a Cobb-Douglas production function with constant returns to scale:

$$Y_j = B_j L_j^{\alpha} K_j^{1-\alpha} \tag{12}$$

where B_j denotes local productivity, which can be affected by flooding.

The cost of capital, ρ is assumed to be determined by fully integrated international capital markets. The (inverse) labour demand can then be expressed as follows:

$$\ln w_j = C + \frac{1}{\alpha}\ln B_j - (1 - \frac{1}{\alpha})\ln \rho \tag{13}$$

with $C = \ln \alpha - (1 - \frac{1}{\alpha}) \ln (1 - \alpha)$

Variation in wages between municipalities stems only from differences in local productivity. If flooding occurs in municipality j, local productivity is likely to be negatively affected (through factory closures, or supply interruptions), which could lead to a decline in wages.

To close the model, it is necessary to define the equilibrium in the housing market. Each individual is assumed to demand one unit of housing. Housing supply is governed by the parameter k_j which determines the elasticity of the housing supply in municipality j:

$$r_j = L_j^{k_j} \tag{14}$$

A low value of k_j indicates an elastic supply, whereas in the limit, when k_j goes to infinity, the housing supply function becomes totally inelastic.

Using the example of two cities again, substituting the equilibrium wage and rental price into Equation (11) gives:

$$sF^{-1}(L_a) = \frac{e^C}{\rho^{-(1-\frac{1}{\alpha})}}(B_a^{\frac{1}{\alpha}} - B_b^{\frac{1}{\alpha}}) + (A_a - A_b) - (L_a^{k_a} - (1 - L_a)^{k_b}) \tag{15}$$

The left-hand side of Equation (15) indicates the demand for municipality a (i.e., the proportion of the total population that wishes to reside in municipality a). The right-hand side can be regarded as a supply function. A negative change in local productivity or an increase in housing costs shifts the right-hand side downwards, indicating a lower proportion of individuals locating in municipality a. We therefore test whether a fall in wages or changes in the housing costs in the flooded areas (according to our definition of the treatment) versus the less risky areas can explain the increase in out-migration after a flood. As we use individual panel data, we systematically account for individuals' idiosyncratic preferences for their municipality of residence. This is important since there is ample evidence of sorting according to flood risk (Bakkensen and Ma, 2020).

5.2 Empirical estimates of the effects of flood on individual wages and housing transactions

Table 10 shows the impact of a flood in the individual's municipality on individual income, broken down by source of revenue. If the floods had negatively affected local productivity (Leiter et al., 2009), we would expect to see a corresponding decline in wage income, as documented by Indaco et al. (2021) following Hurricane Sandy, for example. However, the results in Table 10 show no statistically significant effect on individuals' total income. Furthermore, there is no effect on the main source of income, whether from wages, pensions, unemployment benefits, or other sources.[34] Individuals may derive their income from employment outside their municipality of residence. Table 11 shows the results of testing the effect of indirect flooding, i.e., the effect of a flood elsewhere in the commuting zone on individuals' income. Also here, we find no effect on wages or other income sources.

Next, we examine the impact on housing prices (Beltràn et al., 2018). In an analysis at the aggregate level of French *départements* over the period 2019-2023, Ancel and Kamionka (2024) find negative effects of floods on housing prices, particularly in areas subject to repeated flooding. If the main effect of flooding is to decrease the equilibrium housing costs, while having no effect on local productivity and wages, we can conclude that the main driver of out-migration from a municipality affected by flood is the direct disamenity effect. We test the effect of flooding on housing prices using data from the DV3F database over the years 2017-2019.[35] This enables us to control for a wide range of housing characteristics, including the construction date and number of floors of the building, the number of annexes and cellars, the number of bedrooms and kitchens above 9 m^2, the number of garages, the number of main rooms, the number of terraces, the surface area of annexes and the parcel surface area, as well as indicators for the floor of a flat. We also control for the time-varying proxies for amenities in the municipality, such as the proportion of social housing and secondary residences. The estimating equation is as follows:

$$\log(\text{pricesqm}_{ict}) = \beta \mathcal{T}_{ct} + X'_{it}\gamma + Z'_{ct}\delta + \eta_t + \theta_c + \epsilon_{ict} \qquad (16)$$

where the dependent variable is the log of the price per square metre of transaction i in municipality c in year t. The treatment variable $\mathcal{T}_{ct}$ equals one for all years following a flood in municipality c, including the year t when the flood occurred. X_{it} is a set of variables that control for property characteristics, Z_{ct} represents the time-varying characteristics of the municipality, η_t are

[34] The data do not allow us to decompose the individual income into social transfers and wage income.

[35] The DV3F database, which contains complete property transaction data from the Directorate-General for Public Finance (Direction Générale des Finances Publiques – DGFIP), is provided by CEREMA.

year fixed effects, and θ_c are municipality fixed effects. The coefficient of interest is β, and we estimate the model separately for transactions within and outside flood risk areas. Table 12 shows that there is no change in housing prices in either the flood risk area or the area outside it within the municipality. However, a zero change in equilibrium prices could also result from a simultaneous shift in the supply curve. Therefore, we also estimate the effect of a flood on the number of housing transactions at the municipality level in both the flood risk area and the area outside it. This estimation is at the municipality and year level:

$$NTr_{ct} = \lambda \mathcal{T}_{ct} + Z'_{ct}\mu + \zeta_c + \eta_t + \nu_{ct} \tag{17}$$

where the dependent variable NTr_{ct} is either the number of transactions in the flood risk area of municipality c in year t or the number of transactions outside the flood risk area of municipality c. We include municipality (ζ_c) and year (η_t) fixed effects. On average, there are 45.2 housing transactions per municipality outside the flood risk area, compared to 13.3 housing transactions within it. Table 13 shows an average increase of 10 transactions outside a municipality's flood risk area, reflecting a shift in demand away from these areas. However, the negative effect on the number of transactions in the flood risk areas is not statistically significant. This may be because the municipalities are small, with people tending to move out of them more frequently than within them (see Table 2). Overall, we conclude that the evidence points to a direct disamenity effect of flooding operating through the housing market.

6 Conclusion

Using complete administrative data on individuals in metropolitan France over three years, we analyse the impact of floods on individuals' decisions to move. Our results show that individuals living in flood-affected areas are 30.1% more likely to move out of their home municipality in the two years following a flood. To contextualise this effect size, it is important to note that it is a short-term effect estimated over only two years, one of which was a flood-intensive year. As such, the external validity of our estimate may be limited. However, our results suggest that the mobility response is driven by floods lasting longer than the median duration. In contrast, short-duration floods induce a short-term increase in the propensity to move, which then becomes negative in the second year after the flood. We also find that floods in a municipality within an individual's commuting zone affect individuals in a non-flooded municipality. Nevertheless, this spillover effect is three times smaller than the direct effect.

For the first time, we document significant heterogeneous effects on factors other than income at an individual level. Regarding tenure status, we find that homeowners are less likely to move than renters in the private sector and in social housing. Post-flood mobility patterns reflect the general propensity to move by age group, with younger people being the most likely to move. Similarly, the propensity to move is highest among the employed compared to the unemployed and retired individuals. In terms of income, individuals in the lowest and highest income quintiles are less likely to move after a flood than those in the middle quintiles.

When analysing aggregate flows at the municipal level, we observe no average effect of flooding on residential mobility, confirming the importance of using granular individual data. Further examination of changes in population outflows and inflows reveals that the proportion of homeowners is lower among post-flood population outflows. An analysis of potential mechanisms reveals no productivity effects of flooding on individual wages or other income. Housing prices do not change in the flood risk area or in the rest of the municipality. However, the number of property transactions increases in areas outside the flood risk area of the municipality, indicating a substantial disamenity effect behind the increased propensity to move.

Our empirical analysis has two limitations. First, although we use a nonlinear model that accounts for potentially heterogeneous treatment effects over time, we are currently unable to examine the effects of multiple floods, but they concern less than 1 % of the municipalities in the sample. Second, we lack information on alternative adaptation measures that households may have adopted instead of relocating in response to the floods. Instead, we interpret the difference in estimates between the static model and the model in which we consider only the effects of a first flood after a four-year period without flooding as evidence of the effects of adaptation to previous floods.

Future research could further investigate the impact of floods on residential mobility in a number of ways. If we had a longer panel, it would be important to consider the effect of repeated treatment (de Chaisemartin and D'Haultfœuille, 2024). Additionally, the estimation of spillover effects resulting from flooding in other municipalities could be extended to encompass alternative definitions of indirect treatment. Overall, however, our analysis of highly detailed individual-level data from an entire country reveals significant mobility in response to flooding. It highlights important heterogeneity in these responses, as well as changes in population composition, both of which are crucial for understanding how people will respond to future extreme climate events.

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Figures

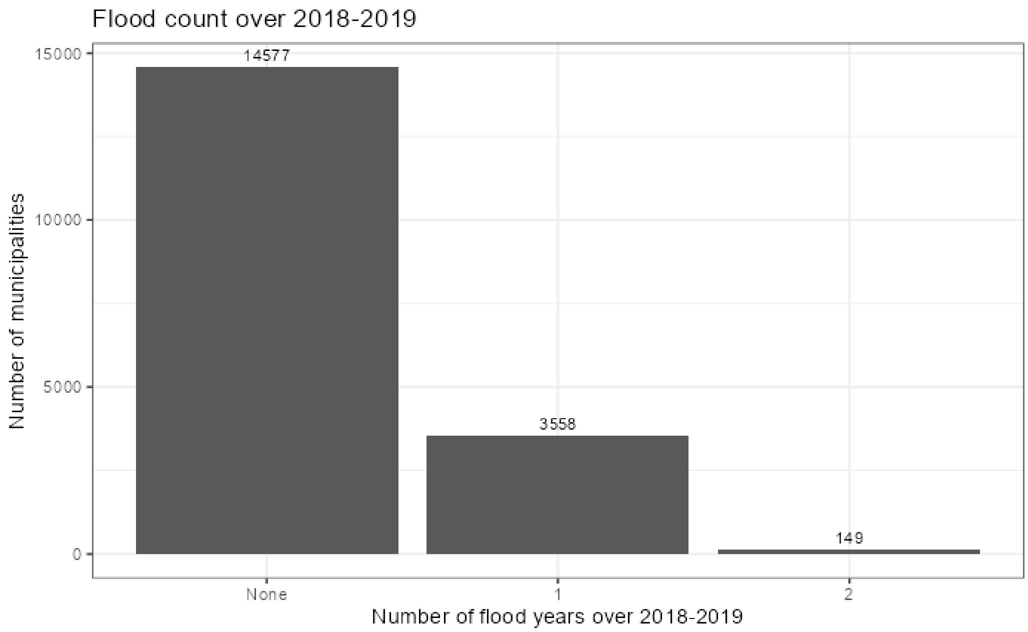

Figure 1: The distribution of floods in French municipalities during the period 2018–2019.

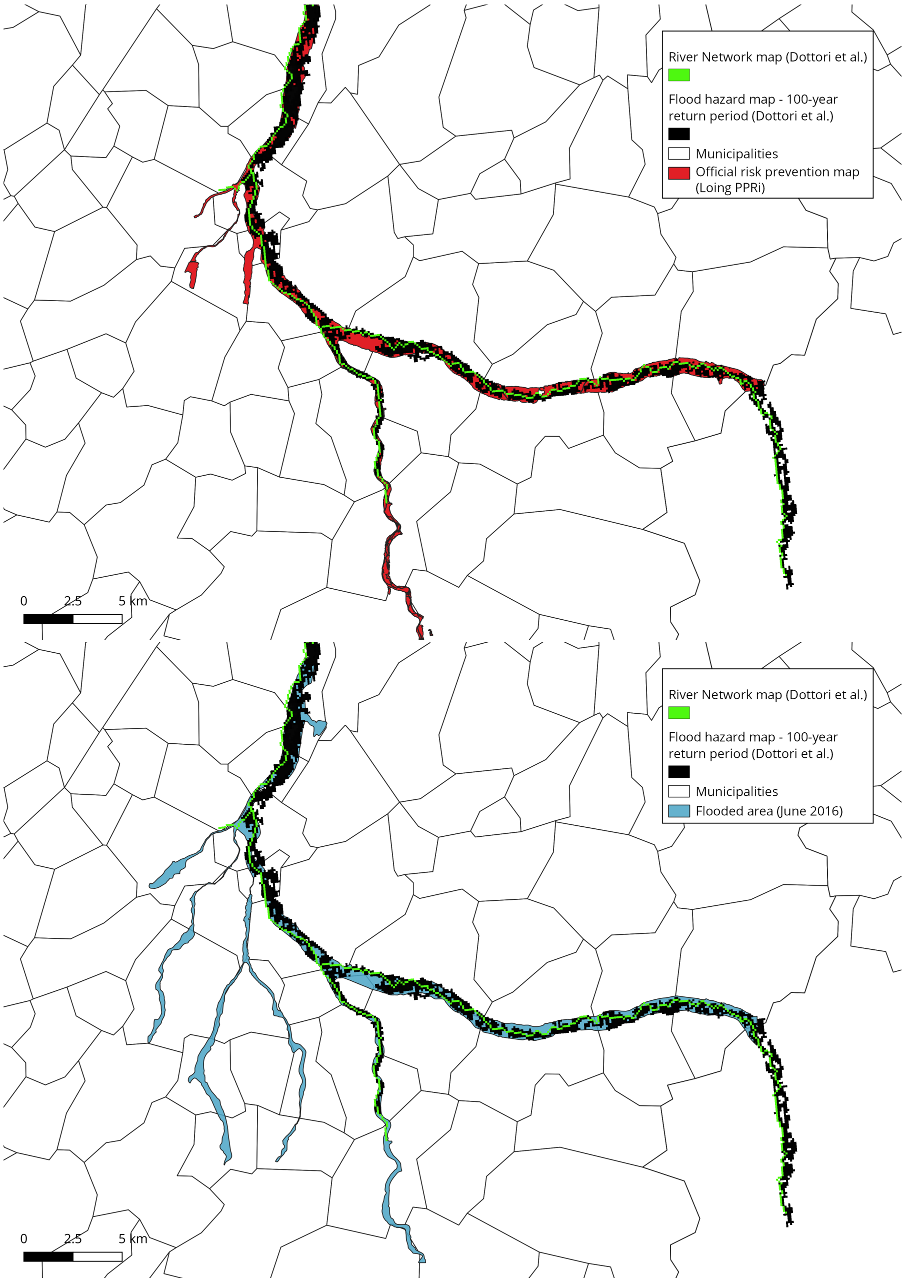

Figure 2: Comparison of different flood maps (Example of the Loing River flood). Top: official risk map (PPRi) in red and the Dottori et al. flood risk map (European Commission JRC, 2021) in black. Bottom: flooded area in past event (2016, June) in blue and the Dottori et al. flood risk map (European Commission JRC, 2021) in black.

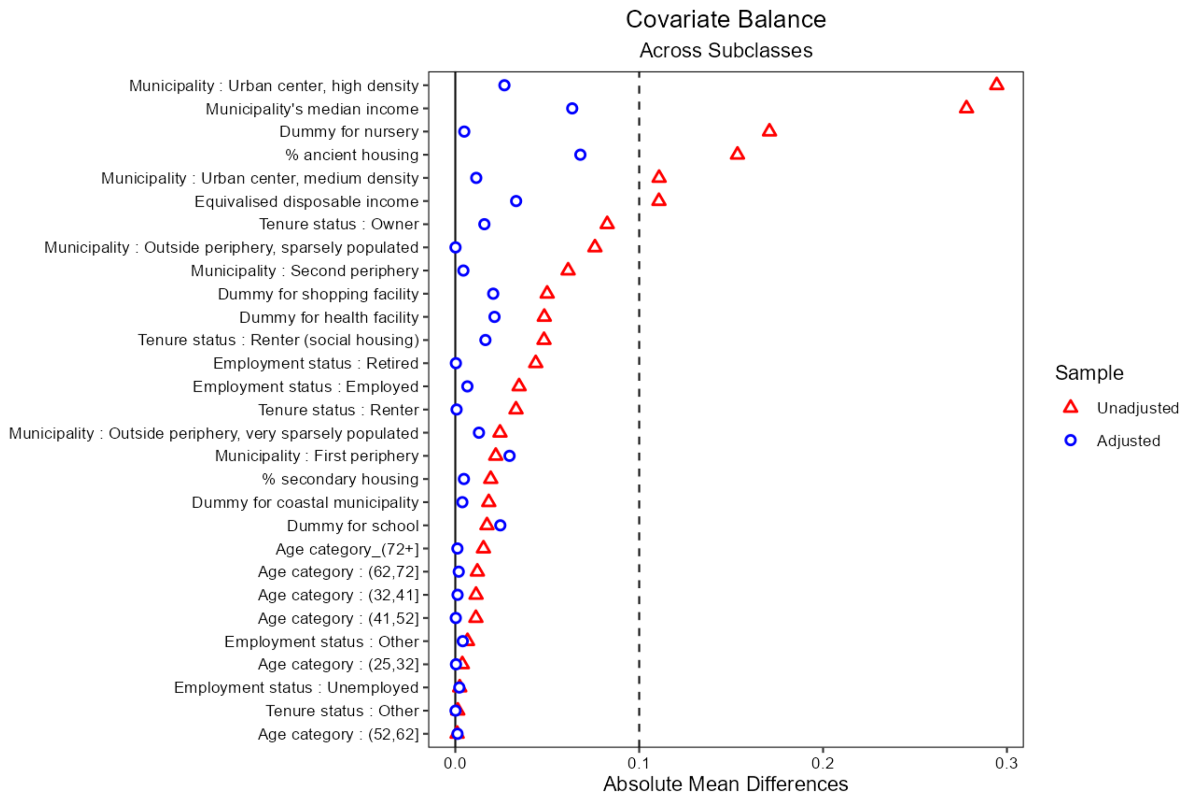

Figure 3: Covariate balance before and after matching

Note: Before propensity score matching, the absolute difference in the proportion of treated and control individuals living in an urban centre with high density was 0.29. After propensity score matching, the absolute difference falls to 0.03.

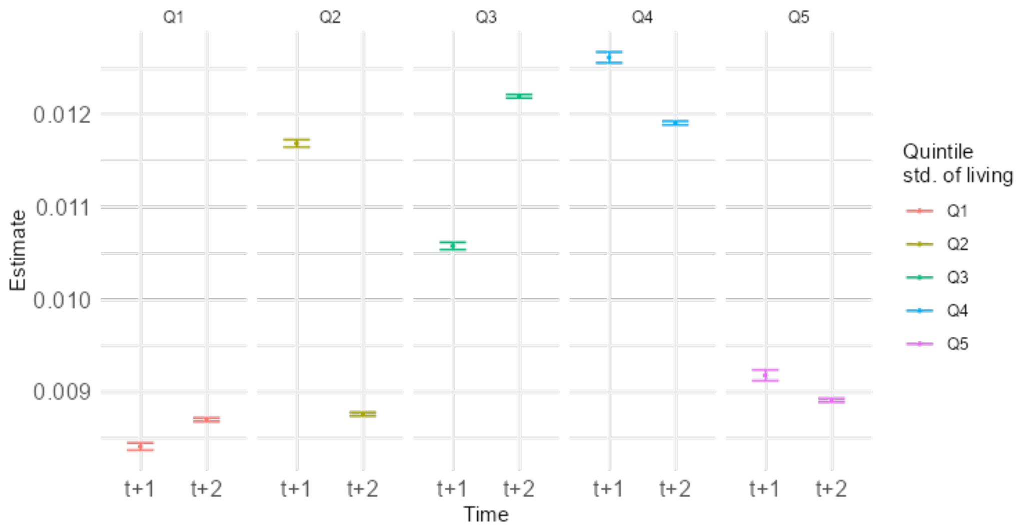

Figure 4: Income quintiles

Note: The figure plots the marginal effects by quintile of equivalised disposable income, one or two years after a flood. The dots represent the marginal effect and the whiskers denote the 95th percentile confidence interval.

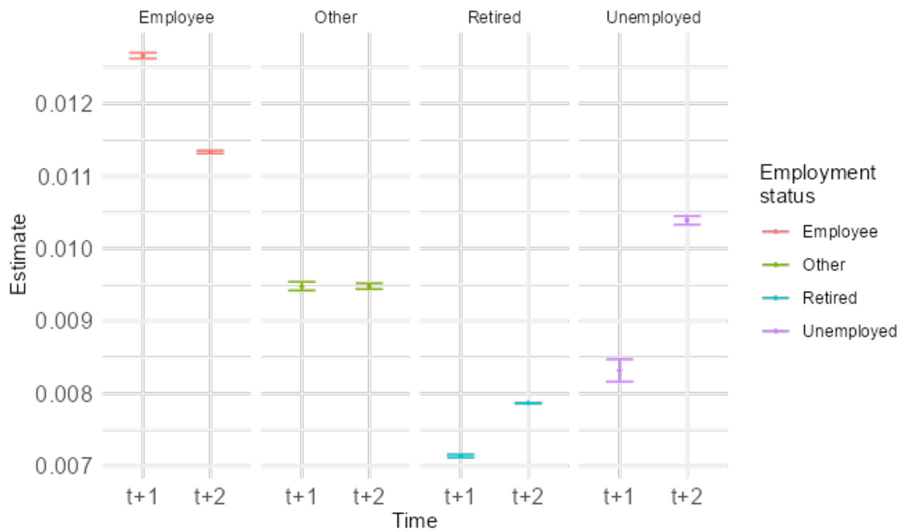

Figure 5: Employment status

Note: The figure plots the marginal effects by employment status, one or two years after a flood. The dots represent the marginal effect and the whiskers denote the 95th percentile confidence interval.

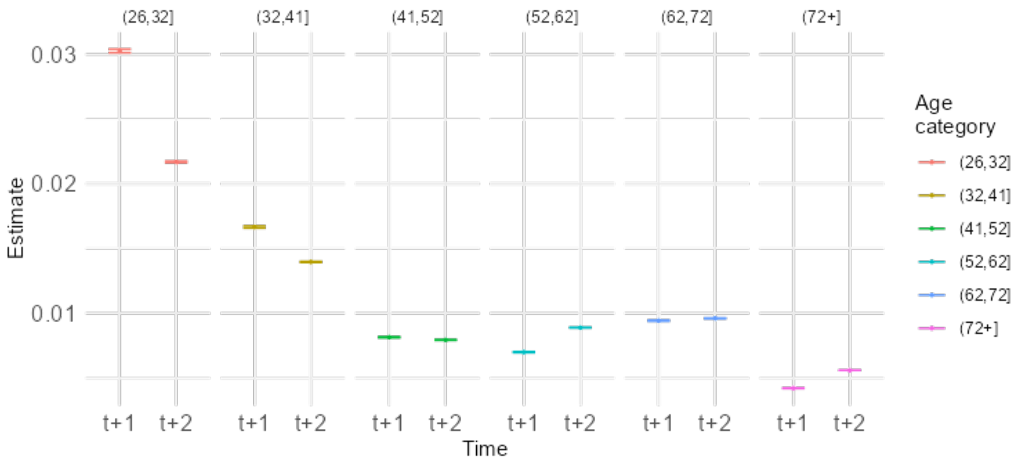

Figure 6: Age

Note: The figure plots the marginal effects by age category, one or two years after a flood. The dots represent the marginal effect and the whiskers denote the 95th percentile confidence interval.

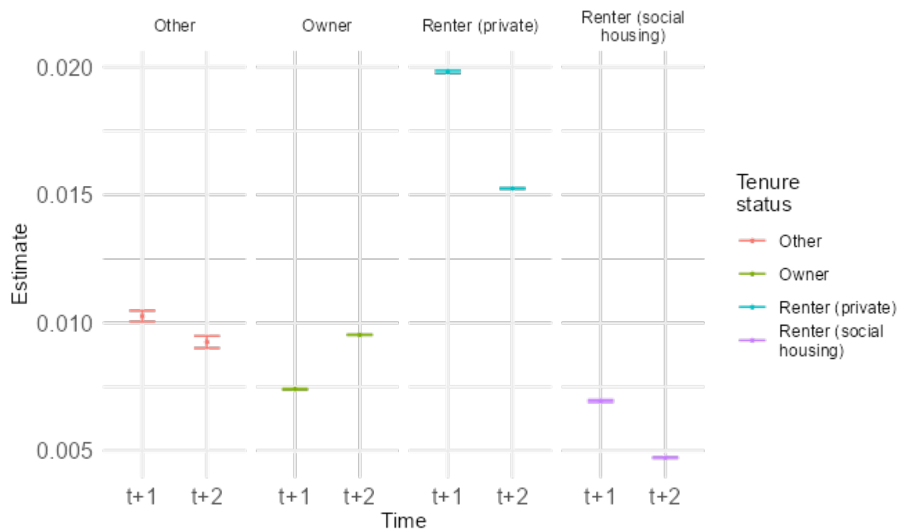

Figure 7: Tenure status

Note: The figure plots the marginal effects by tenure status, one or two years after a flood. The dots represent the marginal effect and the whiskers denote the 95th percentile confidence interval.

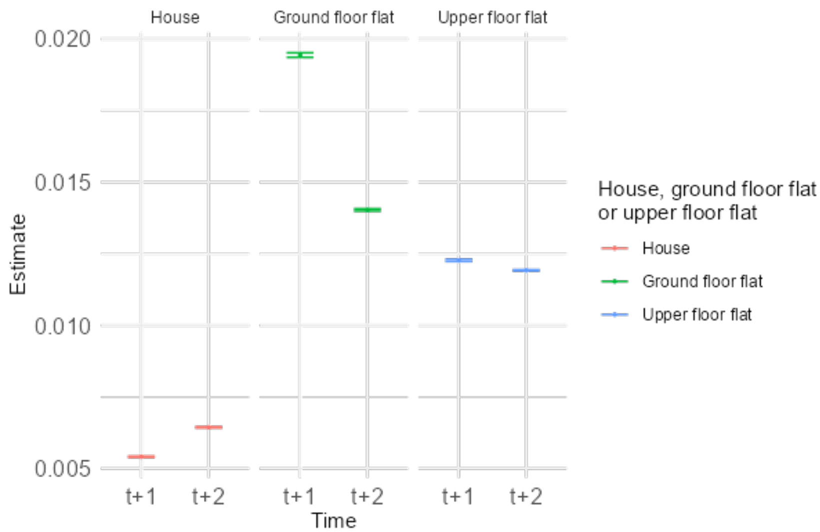

Figure 8: House or Ground floor

Note: The figure plots the marginal effects for houses, ground floor flats, and flats on upper floors, one or two years after a flood. The dots represent the marginal effect and the whiskers denote the 95th percentile confidence interval.

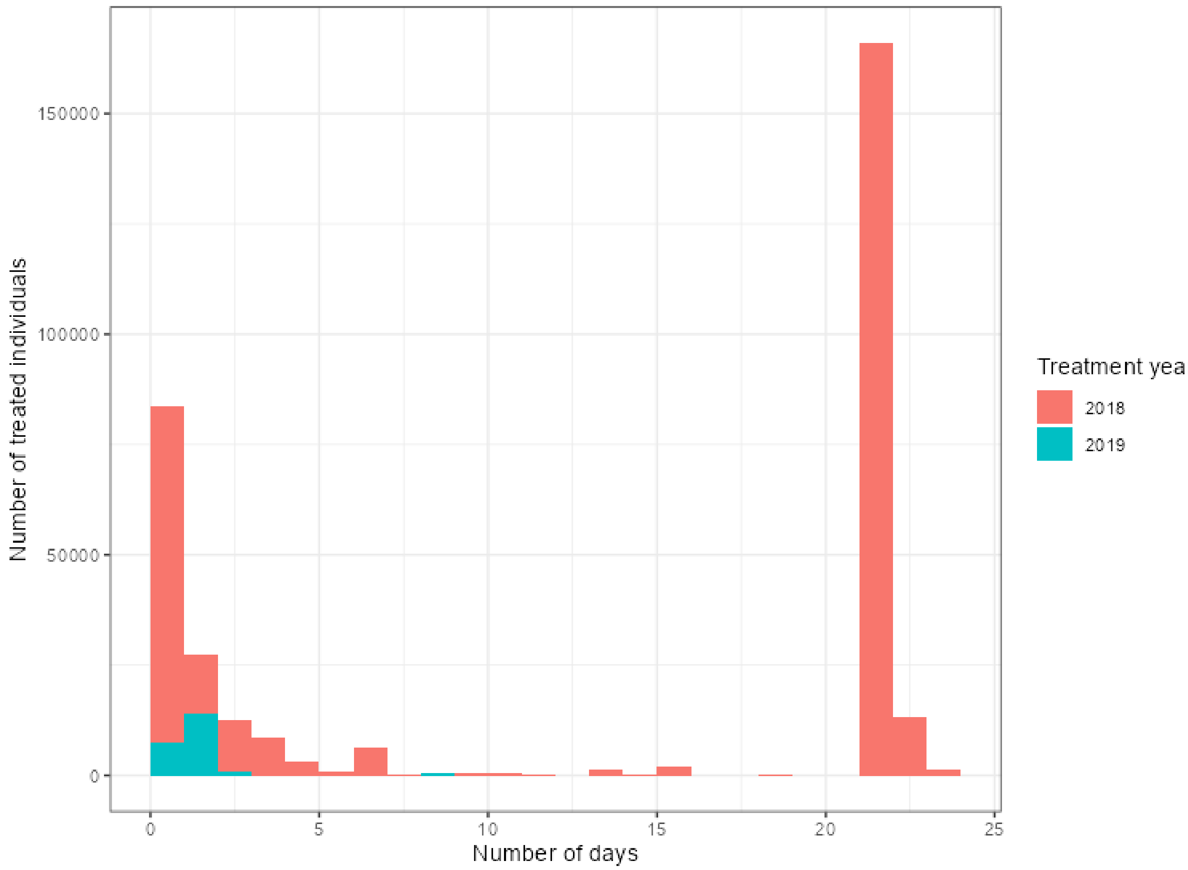

Figure 9: Histogram of treatment duration (number of days declared in natural disaster decree)

Note: Treatment duration is 1 day for 74,005 individuals, among which 67,853 are treated in 2018, and 6,152 in 2019.

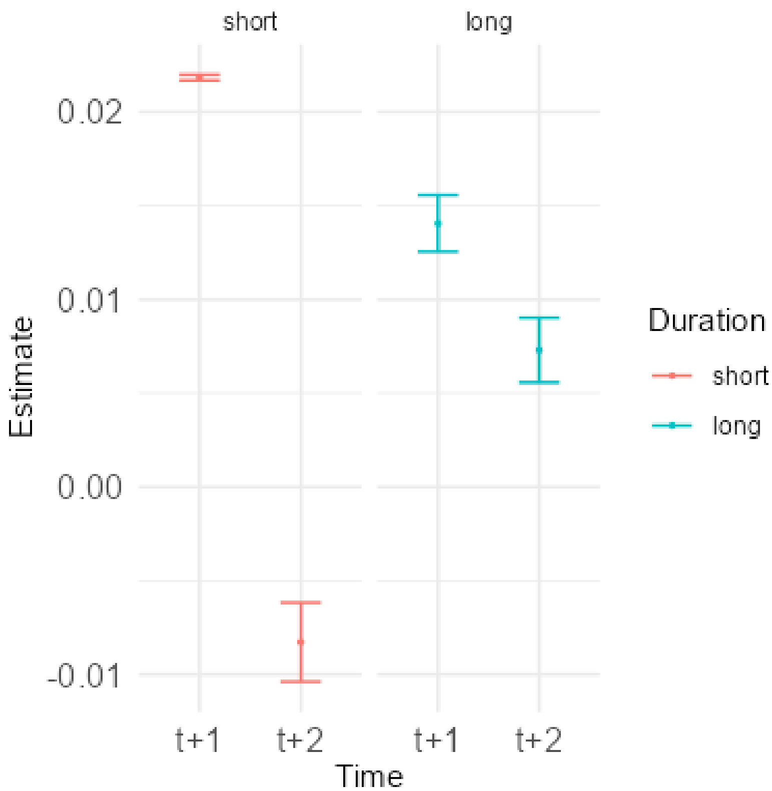

Figure 10: Flood duration

Note: The figure plots the marginal effects by flood duration in days. The dots represent the marginal effect and the whiskers denote the 95th percentile confidence interval. Short duration: 0–21 days (median duration). Long duration: 22 days or more.

Tables

Table 1: Summary statistics

(a) Characteristics of Individuals

treated	0		1		
Variable	Not Missing	Mean	Not Missing	Mean	Test
Age category	471282		328245		X2= 579.079***
... (41,52]	101266	21%	74508	23%	
... (26,32]	33850	7%	23076	7%	
... (32,41]	69268	15%	51673	16%	
... (52,62]	95145	20%	67044	20%	
... (62,72]	88570	19%	57811	18%	
... (72+]	83183	18%	54133	16%	
Tenure status	471282		328245		X2= 3617.412***
... Renter (private sector)	105376	22%	83095	25%	
... Renter (social housing)	77433	16%	65880	20%	
... Owner	283219	60%	175586	53%	
... Other	5254	1%	3684	1%	
Employment status	471282		328245		X2= 1236.376***
... Employee	243112	52%	179425	55%	
... Unemployed	17720	4%	13152	4%	
... Retired	170199	36%	106067	32%	
... Other	40251	9%	29601	9%	
Equivalised disposable income (10^4 EUR)	471282	2.3	328245	2.6	F= 4049.08***

(b) Characteristics of Municipalities

	Treated		Never Treated		
Variable	Not missing	Mean	Not missing	Mean	Test
Municipality's median income	2617	21875	11591	21561	F= 15.355***
Dummy for school	2617	0.9	11596	0.83	F= 70.425***
Dummy for shopping facility	2617	0.76	11596	0.64	F= 133.185***
Dummy for health facility	2617	0.74	11596	0.62	F= 127.252***
Dummy for nursery	2617	0.42	11596	0.25	F= 301.025***
Dummy for coastal municipality	2617	0.049	11596	0.037	F= 8.166***
Urban/Rural typology	2617		11596		X2= 107.105***
... Outside periphery, very sparsely populated	337	13%	2002	17%	
... Outside periphery, sparsely populated	598	23%	2874	25%	
... Second periphery	498	19%	2480	21%	
... First periphery	623	24%	2406	21%	
... Urban center, medium density	400	15%	1471	13%	
... Urban center, high density	161	6%	363	3%	

Statistical significance markers: * p<0.1; ** p<0.05; *** p<0.01

Note: Example of how to read the table: among the 328,245 treated individuals, 7% were aged between 26 and 32 years in 2018. The chi-square statistics are statistically significant, and we reject the hypothesis of an equal distribution between the treated and never treated groups for the age variable. Statistical significance: *: p<0.1, **: p<0.05, ***: p<0.01

Table 2: Mobility rates, inside/outside municipality of origin

Year	**Inside/outside municipality**	**Proportion**
2018	inside	2,24%
2018	outside	3,76%
2019	inside	1,96%
2019	outside	3,51%

Note: Mobility rates calculated on the estimation sample. In 2018, 2.24 % of the sample moved within their municipality of origin, while 3.76% moved outside their municipality of origin.

Table 3: The effect of a flood on the probability to move

	time	estimate	std error
1	t+1	0.011	0.0002
2	t+2	0.010	0.001

Note: The table shows the aggregate marginal effects (with standard errors) of a flood on the probability of moving out of the municipality one or two years afterwards. The aggregate marginal effect is obtained by weighting the cohort-specific effects according to the relative size of each cohort.

Table 4: The effect of a flood on intra- and extra-municipal mobility

	time	estimate	std error
1	t+1	0.012	0
2	t+2	0.012	0.001

Note: The table shows the aggregate marginal effects (with standard errors) of a flood on the probability of moving one or two years afterwards, including both moves outside and within the municipality of origin. The aggregate marginal effect is obtained by weighting the cohort-specific effects according to the relative size of each cohort.

Table 5: Spillover effects of a flood

	time	estimate	std error
1	t+1	0.003	0.00003
2	t+2	-0.004	0.001

Note: The table shows the aggregate marginal indirect effects (with standard errors) of a flood on the probability of moving out of one's municipality of origin one or two years afterwards. Indirect treatment is defined as having at least one municipality in the individual's AAV (commuting zone) treated by a flood in year t, but no flood in the individual's municipality of origin in year t. The aggregate marginal effect is obtained by weighting the cohort-specific effects according to the relative size of each cohort.

Table 6: Effect of floods on population flows at the municipality level (difference-in-differences)

Dependent Variables:	Population inflow rate		Population outflow rate	
Model:	(1)	(2)	(3)	(4)
Variables				
Treatment	-0.0002	-5.23×10^{-5}	0.0003	3.8×10^{-5}
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
% ancient housing		-0.0003***		2.86×10^{-5}
		(9.79×10^{-5})		(5.75×10^{-5})
% social housing		4.35×10^{-5}***		3.77×10^{-5}***
		(1.59×10^{-5})		(9.41×10^{-6})
% secondary housing		0.0003		-4.6×10^{-5}
		(0.0002)		(0.0002)
Fixed-effects				
municipality	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	42,565	30,215	42,639	30,224
R^2	0.63866	0.69361	0.74297	0.80789
Within R^2	7.86×10^{-6}	0.00181	2.37×10^{-5}	0.00057

Note: The table shows estimates and standard errors from OLS regressions. Treatment is defined as a flood in the municipality in year t. The population inflow rate is the number of individuals arriving in the municipality in year t divided by the number of inhabitants in the municipality in year $t-1$. The population outflow rate is the number of individuals leaving the municipality in year t divided by the number of inhabitants in the municipality in year $t-1$. Statistical significance: *: p<0.1, **: p<0.05, ***: p<0.01

Table 7: Effect of floods on population inflows below median/first quartile of equivalised disposable income (difference-in-differences)

Dependent Variables:	% below the median of eq. disposable income in the pop. inflow rate		% below national first quartile in the pop. inflow rate	
Model:	(1)	(2)	(3)	(4)
Variables				
Treatment	0.0043	0.0020	-0.0010	-0.0019
	(0.0032)	(0.0027)	(0.0026)	(0.0022)
% ancient housing		0.0002		9.05×10^{-5}
		(0.0004)		(0.0003)
% social housing		4.23×10^{-5}		0.0001^{*}
		(7.97×10^{-5})		(6.68×10^{-5})
% secondary housing		0.0001		0.0016
		(0.0015)		(0.0013)
Fixed-effects				
municipality	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	42,639	30,224	42,029	30,161
R^2	0.55132	0.64821	0.49986	0.59073
Within R^2	5.2×10^{-5}	3.58×10^{-5}	4.32×10^{-6}	0.00029

Note: The table shows estimates and standard errors from OLS regressions. Treatment is defined as a flood in the municipality in year t. The population inflow rate is the number of individuals arriving in the municipality in year t divided by the number of inhabitants in the municipality in year $t-1$. Statistical significance: *: p<0.1, **: p<0.05, ***: p<0.01

Table 8: Effect of floods on population outflows below median/first quartile of equivalised disposable income (difference-in-differences)

Dependent Variables:	% below the median of eq. disposable income in the pop. outflow rate		% below national first quartile in the pop. outflow rate	
Model:	(1)	(2)	(3)	(4)
Variables				
Treatment	0.0005	-0.0013	0.0002	0.0013
	(0.0029)	(0.0025)	(0.0023)	(0.0020)
% ancient housing		-0.0005		-0.0003
		(0.0004)		(0.0003)
% social housing		-0.0001*		-0.0001**
		(7.78×10^{-5})		(6.17×10^{-5})
% secondary housing		-0.0007		-0.0018
		(0.0018)		(0.0014)
Fixed-effects				
municipality	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	42,639	30,224	42,195	30,179
R^2	0.60386	0.69729	0.52909	0.62377
Within R^2	7.1×10^{-7}	0.00019	2.41×10^{-7}	0.00042

Note: The table shows estimates and standard errors from OLS regressions. Treatment is defined as a flood in the municipality in year t. The population outflow rate is the number of individuals leaving the municipality in year t divided by the number of inhabitants in the municipality in year $t-1$. Statistical significance: *: p<0.1, **: p<0.05, ***: p<0.01

Table 9: Effect of floods on the share of home ownership in population flows (difference-in-differences)

Dependent Variables:	% homeownership in the pop. inflow rate		% homeownership in the pop. outflow rate	
Model:	(1)	(2)	(3)	(4)
Variables				
Treatment	0.0112	0.0070	-0.0250***	-0.0227***
	(0.0091)	(0.0095)	(0.0068)	(0.0077)
% ancient housing		-0.0005		-0.0004
		(0.0016)		(0.0013)
% social housing		-0.0013***		0.0002
		(0.0003)		(0.0002)
% secondary housing		0.0036		-0.0040
		(0.0048)		(0.0039)
Fixed-effects				
municipality	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	42,639	30,224	42,639	30,224
R^2	0.37892	0.39274	0.53183	0.52516
Within R^2	4.94×10^{-5}	0.00092	0.00047	0.00052

Note: The table shows estimates and standard errors from OLS regressions. Treatment is defined as a flood in the municipality in year t. The population inflow rate is the number of individuals arriving in the municipality in year t divided by the number of inhabitants in the municipality in year $t-1$. The population outflow rate is the number of individuals leaving the municipality in year t divided by the number of inhabitants in the municipality in year $t-1$. Statistical significance: *: p<0.1, **: p<0.05, ***: p<0.01

Table 10: The effect of floods on the equivalised disposable income of individuals in flood risk areas

	Dependent variable:				
	Total (N=799,527)	Wages (N=422,537)	Pensions (N=276,266)	Unemployment (N=30,872)	Other (N=69,852)
$t+1$	-0.009 (0.008)	-0.007 (0.012)	-0.005 (0.012)	0.030 (0.019)	-0.040 (0.035)
$t+2$	0.026 (0.030)	0.058 (0.045)	0.032 (0.101)	-0.148 (0.116)	-0.050 (0.121)

Note: The table shows the aggregate marginal effects (with standard errors in parentheses) from an OLS regression of direct treatment of a flood. The dependent variable is the total income of an individual in a flood risk area (Total), whereas the following four columns only uses the total income of individuals deriving their main source of income from wage labour (Wages), the total income of individuals deriving their main source of income from pensions (Pensions), the total income of individuals deriving their main source of income from unemployment benefits (Unemployment), and the total income of individuals deriving their main source of income from other sources, i.e., maintenance payments, agricultural profits, industrial and commercial profits, non-commercial profits (Other). The aggregate marginal effect is obtained by weighting the cohort-specific effects according to the relative size of each cohort.
Statistical significance: *: p<0.1, **: p<0.05, ***: p<0.01

Table 11: The indirect effect of floods on the equivalised disposable income of individuals in flood risk areas

	Dependent variable:				
	Total (N=341,875)	Wages (N=160,719)	Pensions (N=135,864)	Unemployment (N=13,056)	Other (N=32,236)
$t+1$	-0.008 (0.010)	-0.014 (0.020)	-0.006 (0.016)	-0.023 (0.032)	-0.046 (0.060)
$t+2$	0.027 (0.034)	0.028 (0.071)	-0.112 (0.132)	-0.042 (0.107)	0.088 (0.179)

Note: The table shows the aggregate marginal effects (with standard errors in parentheses) from an OLS regression of indirect treatment of a flood. Indirect treatment is defined as having at least one municipality in the individual's AAV (commuting zone) treated by a flood in year t, but no flood in the individual's municipality of origin in year t. The dependent variable is the total income of an individual in a flood risk area (Total), whereas the following four columns only uses the total income of individuals deriving their main source of income from wage labour (Wages), the total income of individuals deriving their main source of income from pensions (Pensions), the total income of individuals deriving their main source of income from unemployment benefits (Unemployment), and the total income of individuals deriving their main source of income from other sources, i.e., maintenance payments, agricultural profits, industrial and commercial profits, non-commercial profits (Other). The aggregate marginal effect is obtained by weighting the cohort-specific effects according to the relative size of each cohort.
Statistical significance: *: $p<0.1$, **: $p<0.05$, ***: $p<0.01$

Table 12: The effect of floods on housing prices

Dependent Variable:	Price per square metre (log)			
Dummy for flood risk area	0	1	0	1
Model:	(1)	(2)	(3)	(4)
Variables				
Post-treatment	0.0025	0.0106	0.0022	0.0091
	(0.0033)	(0.0087)	(0.0033)	(0.0086)
Construction date (year)			0.0009***	0.0007***
			(5.93×10^{-5})	(8.03×10^{-5})
Number of floors (building)			-0.0330***	-0.0305***
			(0.0014)	(0.0039)
Number of annexes			-0.0090***	-0.0058***
			(0.0008)	(0.0014)
Number of cellars and other			-0.0147***	-0.0143***
			(0.0019)	(0.0042)
Number of bedrooms			-0.0360***	-0.0265***
			(0.0015)	(0.0047)
Number of kitchens above 9m²			-0.0081***	-0.0025
			(0.0012)	(0.0036)
Number of garages			0.0563***	0.0613***
			(0.0058)	(0.0145)
Number of swimming pools			0.1841***	0.1850***
			(0.0036)	(0.0103)
Number of main rooms			0.0319***	0.0316***
			(0.0017)	(0.0048)
Number of bathrooms			0.0774***	0.0604***
			(0.0021)	(0.0044)
Number of terraces			0.0535***	0.0585***
			(0.0037)	(0.0057)
Surface area of all rooms			-0.0028***	-0.0033***
			(6.63×10^{-5})	(0.0001)
Surface area of annexes			0.0040***	0.0046***
			(6.04×10^{-5})	(0.0002)
Surface area of parcel			9.09×10^{-6}*	3.42×10^{-5}***
			(5.11×10^{-6})	(4.3×10^{-6})
% social housing (municipality)			0.0002**	0.0005*
			(9.36×10^{-5})	(0.0002)
% secondary homes (municipality)			6.08×10^{-5}	0.0003
			(7.44×10^{-5})	(0.0006)
Flat on first floor			-0.0944***	-0.0928***
			(0.0043)	(0.0071)
Flat on second floor			-0.0746***	-0.0828***
			(0.0048)	(0.0075)
Flat on third floor			-0.0653***	-0.0682***
			(0.0062)	(0.0092)
Flat on fourth floor			-0.0648***	-0.0823***
			(0.0071)	(0.0097)
Flat on fifth floor			-0.0140*	-0.0264**
			(0.0081)	(0.0116)
Flat on sixth floor or above			-0.0069	-0.0316*
			(0.0086)	(0.0174)
Fit statistics				
Observations	1,773,944	114,768	1,773,944	114,768
R^2	0.57534	0.66524	0.62394	0.70275
Within R^2	1.89×10^{-6}	3.71×10^{-5}	0.11446	0.11209

Note: The table shows the estimates from OLS regressions, with the standard errors clustered at municipality level shown in parentheses. All estimations include municipality and year fixed effects. Models (1) and (3) estimate transaction prices outside of the flood risk area, while models (2) and (4) estimate transaction prices within it. Statistical significance: *: p<0.1, **: p<0.05, ***: p<0.01

Table 13: The effect of floods on the number of property transactions

Dependent Variable:	Transaction count	
Dummy for flood risk zone	0	1
Model:	(1)	(2)
Variables		
Post-treatment	10.88***	-1.009
	(2.841)	(0.7171)
% social housing	0.7255***	0.1201***
	(0.0980)	(0.0302)
% ancient housing	-0.1057***	-0.0433
	(0.0250)	(0.0314)
% secondary homes	0.3225***	0.3096***
	(0.0832)	(0.1052)
Fixed-effects		
Year	Yes	Yes
Municipality	Yes	Yes
Fit statistics		
Observations	26,189	5,766
R^2	0.99687	0.99590
Within R^2	0.02678	0.00701

Note: The table shows the estimates from OLS regressions, with the standard errors clustered at the municipality level shown in parentheses. Model (1) uses the number of transactions outside the flood risk area within a municipality as the dependent variable, while Model (2) uses the number of transactions inside the flood risk area.
Statistical significance: *: p<0.1, **: p<0.05, ***: p<0.01

Online Appendix

A. Additional Tables

Table A.1: Description of amenity variables and data sources

Amenity variable	**Data source**
Urban-rural typology 2020	Insee Classification
Equivalised disposable income (municipality)	FILOSOFI-Insee
Local shops in the municipality	Permanent Database of facilities-2023
Health facilities	Permanent Database of facilities-2023
Having a school in the municipality	Permanent Database of facilities-2023
Having a nursery	Permanent Database of facilities-2023
Coastal municipality	Loi littoral: classement des communes (Coastal law: classification of municipalities)
Share of social housing	Répertoire des logements locatifs et bailleurs sociaux-SDES (Directory of rental accommodation and social landlords-SDES)
Share of secondary/ancient housing	Census-Insee-Housing

Table A.2: Pre-trends test

	Dependent variable:
D2019:f19	0.018 (0.077)

Note: The table shows the estimated coefficient (with standard error in parentheses) of being treated in 2019 and moving in the year preceding treatment (1 January 2018 to 1 January 2019).

Table A.3: Dummy for location in a flood risk area after a residential mobility (%)

Intra/Extra-municipal	Outside flood risk area	Inside flood risk area
Intra	47	53
Extra	87	13

Note: 47% of treated individuals who move within their municipality of origin after a flood are outside a flood risk area at their new destination.

Table A.4: Marginal Effects by Heterogeneity Variable

Variable	**t+1**		**t+2**	
	Estimate	**Std. Error**	**Estimate**	**Std. Error**
Standard of living quintile				
1	0.00841	0.00002	0.0087	0.00001
2	0.01169	0.00002	0.00876	0.00001
3	0.01058	0.00002	0.0122	0.00001
4	0.01262	0.00003	0.01191	0.00001
5	0.00918	0.00003	0.00891	0.00001
Employment status				
Employee	0.01266	0.00002	0.01133	0.00001
Other	0.00948	0.00003	0.00948	0.00002
Unemployed	0.00832	0.00008	0.01039	0.00003
Retired	0.00714	0.00001	0.00787	0
Age category				
(26,32]	0.03026	0.00007	0.02169	0.00003
(32,41]	0.01667	0.00004	0.01397	0.00002
(41,52]	0.00816	0.00002	0.00795	0.00001
(52,62]	0.00701	0.00002	0.0089	0.00001
(62,72]	0.00944	0.00002	0.00962	0.00001
(72+]	0.00422	0.00001	0.0056	0
Tenure status				
Renter (private)	0.01981	0.00003	0.01525	0.00001
Other	0.01026	0.00011	0.00925	0.00012
Renter (social)	0.00695	0.00002	0.00473	0.00001
Owner	0.00741	0.00001	0.00953	0
House/ground floor				
House	0.00541	1e-05	0.00644	0.00001
Ground floor flat	0.01944	4e-05	0.01403	0.00002
Upper floor flat	0.01227	2e-05	0.01192	0.00001

Note: The table shows the aggregate marginal effects (with standard errors) of a flood on the probability of moving out of the municipality one or two years afterwards, by heterogeneity variable. The aggregate marginal effect is obtained by weighting the cohort-specific effects according to the relative size of each cohort.

Table A.5: Dummy for house or ground floor and tenure status

	Ground floor flat	House	Upper floor flat	Total
Renter (private)	40.42	11.73	33.39	23.57
Other	1.89	1.14	0.91	1.12
Renter (social housing)	24.93	4.66	31.62	17.93
Owner	32.76	82.46	34.08	57.39
Total	100.00	100.00	100.00	100.00

Note: The table shows a cross-tabulation of tenure status and the different types of housing: ground floor flats, houses, and upper floor flats. For example, 57.39% of the sample are owner-occupiers. Among individuals living in houses, 82.46% are owner-occupiers, whereas 11.73% are tenants of a private landlord.

Table A.6: Marginal effects by flood duration.

Duration	time	estimate	std error
Short	t+1	0.022	0.0001
Short	t+2	−0.008	0.001
Long	t+1	0.014	0.001
Long	t+2	0.007	0.001

Note: The table shows the marginal effects and standard errors from regressions by category of flood duration in days. Short floods are defined as those lasting up to 21 days (median duration), whereas long floods are defined as those lasting 22 days or more.

Table A.7: Marginal effects by flood duration for 2018 cohort only

time	duration	estimate	std error
t+1	Very short (0-5 days)	0.031	0.001
t+2	Very short (0-5 days)	−0.012	0.001
t+1	Medium (6-14 days)	0.153	0.006
t+2	Medium (6-14 days)	−0.120	0.005
t+1	Long (15+ days)	0.017	0.001
t+2	Long (15+ days)	0.008	0.001

Note: The table shows the marginal effects and standard errors from regressions by category of flood duration in days for the 2018 cohort only. Long floods are defined as those with a duration of 15 days or more, whereas medium duration floods are defined as those with a duration between 6 and 14 days. Very short duration floods are defined as those with a duration equal to or below 5 days.

Table A.8: Effect of floods on population flows at the municipality level (difference-in-differences) for floods of below-median duration

Dependent Variables:	Population inflow rate		Population outflow rate	
Model:	(1)	(2)	(3)	(4)
Variables				
Treatment	0.0007	0.0006	0.0003	0.0005
	(0.0006)	(0.0006)	(0.0005)	(0.0005)
% ancient housing		-0.0003***		3.42×10^{-5}
		(0.0001)		(6.19×10^{-5})
% social housing		5.06×10^{-5}***		3.83×10^{-5}***
		(1.81×10^{-5})		(1.05×10^{-5})
% secondary housing		0.0005*		7.37×10^{-5}
		(0.0003)		(0.0002)
Fixed-effects				
municipality	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	37,292	26,175	37,347	26,178
R^2	0.63425	0.68848	0.60788	0.68466
Within R^2	3.97×10^{-5}	0.00192	1.07×10^{-5}	0.00060

Note: The table shows estimates and standard errors from OLS regressions. Treatment is defined as a flood with below-median duration in the municipality in year t. The population inflow rate is the number of individuals arriving in the municipality in year t divided by the number of inhabitants in the municipality in year $t-1$. The population outflow rate is the number of individuals leaving the municipality in year t divided by the number of inhabitants in the municipality in year $t-1$.
Statistical significance: *: p<0.1, **: p<0.05, ***: p<0.01

Table A.9: Effect of floods on population flows at the municipality level (difference-in-differences) for above-median duration floods

Dependent Variables:	Population inflow rate		Population outflow rate	
Model:	(1)	(2)	(3)	(4)
Variables				
Treatment	-0.0009*	-0.0005	0.0003	-0.0003
	(0.0005)	(0.0005)	(0.0004)	(0.0004)
% ancient housing		-0.0003***		9.7×10^{-6}
		(0.0001)		(6.2×10^{-5})
% social housing		$4.66 \times 10^{-5***}$		$3.58 \times 10^{-5***}$
		(1.72×10^{-5})		(1×10^{-5})
% secondary housing		0.0004*		-0.0001
		(0.0002)		(0.0002)
Fixed-effects				
municipality	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	38,680	27,250	38,751	27,259
R^2	0.63399	0.69070	0.74754	0.81142
Within R^2	9.11×10^{-5}	0.00186	1.6×10^{-5}	0.00056

Note: The table shows estimates and standard errors from OLS regressions. Treatment is defined as a flood of above-median duration in the municipality in year t. The population inflow rate is the number of individuals arriving in the municipality in year t divided by the number of inhabitants in the municipality in year $t-1$. The population outflow rate is the number of individuals leaving the municipality in year t divided by the number of inhabitants in the municipality in year $t-1$.
Statistical significance: *: p<0.1, **: p<0.05, ***: p<0.01

Table A.10: Main model with clustering at the unit and municipality level

time	estimate	std error
t+1	0.011	0.00003
t+2	0.010	0.00002

Note: The table shows the aggregate marginal effects (with standard errors) of a flood on the probability of moving out of the municipality one or two years afterwards. The aggregate marginal effect is obtained by weighting the cohort-specific effects according to the relative size of each cohort. The standard errors are clustered at the level of the individual and the municipality of origin.

Table A.11: Main model without coastal municipalities

time	estimate	std error
t+1	0.011	0.0003
t+2	0.010	0.001

Note: The table shows the aggregate marginal effects (with standard errors) of a flood on the probability of moving out of the municipality one or two years afterwards - estimated on a sample without individuals in coastal municipalities (N=779,664 individuals). The aggregate marginal effect is obtained by weighting the cohort-specific effects according to the relative size of each cohort.

Table A.12: Falsification test

	Dependent variable:
D2018falsif:f19:Wfalsif	−0.044 (0.062)
D2018falsif:f20:Wfalsif	−0.089 (0.064)
D2019falsif:f20:Wfalsif	−0.100 (0.165)

Note: The table shows the coefficients (with standard errors in parentheses) from a falsification test in which treatment was randomised across municipalities, but the number of treated individuals stays the same.
Statistical significance: *: p<0.1, **: p<0.05, ***: p<0.01

Table A.13: Static effects of flood: main model without 4-year filter

	Dependent variable:
D2018 * f19 * W	−0.035 (0.077)
D2018 * f20 * W	−0.106 (0.080)
D2019 * f20 * W	−0.085 (0.061)

Note: The table shows the coefficients (with standard errors in parentheses) from an estimation of the main model without the four-year filter. Statistical significance: *: p<0.1, **: p<0.05, ***: p<0.01

Table A.14: Main model without matching weights

	time	estimate	std error
1	t+1	0.016	0.0002
2	t+2	0.015	0.0004

Note: The table shows the marginal effects (with standard errors) from an estimation of the main model without matching weights.