Flood and Residential Mobility in France

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Abstract

The evidence on whether people adapt to climate extreme events by moving out of vulnerable areas is currently mixed. In this article, we analyse residential mobility following floods using comprehensive French data. Our identification strategy consists in comparing individuals living in areas exposed to flood risk which were actually subject to a flood, with individuals also residing in flood risk areas but which were not subject to flood.

Our results suggest that residential mobility increases by 1 percentage point in the two years following a flood. Compared to the baseline inter-municipality mobility rate in our sample, it equates to a 30% increase in the probability of moving out of the municipality of residence following a flood. The effects are strongly heterogeneous. Mobility rates following a flood are observed to be lower for the bottom and the top quintiles of equivalised disposable income than for the middle quintiles. The effects are found to be more pronounced for private renters than for home-owners and others.

An analysis of aggregate flows at the municipality level reveals no effect of flooding on residential mobility on average, confirming the importance of using granular individual data. However, the data do suggest changes in the composition of population outflows. We observe a lower share of homeowners in the population outflows from municipalities that have flooded.

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

1 Introduction

Climate change is leading to an increase in both the frequency and intensity of weather-related extreme events (Pörtner et al., 2022). The population exposed to flooding has increased between 2000 and 2018 (Tellman et al., 2021), and climate change is estimated to 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 flood risk areas.

Recent articles have documented a concentration of economic activity and population in high climate-risk areas in the U.S. (Indaco and Ortega, 2024) and in areas of the global South (Kocornik-Mina et al., 2020), with little evidence of population movement out of these areas.[1] In France, 17.1 million people were exposed to river flooding in 2020, including 16.8 million in metropolitan France (source: the French Ministry of the Ecological Transition). According to current climate change projections, France will experience an increase in the frequency of extreme weather events, including floods (Alfieri et al., 2015). In 2021, the damage to insured property in France caused by the river floods alone was estimated to be between 450-600 million EUR (CCR, 2022). The increase in the cost of climate extreme events such as floods have exacerbated the difficulties of insuring such risks and put pressure on the current reinsurance scheme (Charpentier, 2008; Charpentier and Le Maux, 2014; Grislain-Letrémy and Villeneuve, 2015; Kousky et al., 2021). Charpentier et al. (2022) emphasized the trade-off between encouraging preventive behaviour through risk-based premiums and fairness in providing universal access to insurance. 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 damage are the creation of water retention areas, river dykes, and flood-proofing of buildings, but also the relocation of people and assets out of flood risk areas. Relocation of population has been shown to be costly, though (Dottori et al., 2023), and it is important to determine the extent to which individuals take flood risk into account in their location decisions. Migration is a well-known adaptation strategy to natural disasters (Mbaye and Zimmermann, 2016). The existing literature has mainly analysed large extreme events, which are

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

by definition quite specific, but little is known about the effects of smaller but more frequent flood events.

The impact of floods on residential mobility is 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, the rebuilding of lost physical capital may have positive indirect effects on local labour markets and attract new residents. There could also be indirect effects from productivity losses and wage reductions which could encourage out-migration from a flooded municipality. Flood damage is also likely to impoverish individuals and make relocation more difficult, especially for low-income individuals. Both direct and indirect exposure to floods may lead individuals to revise their beliefs about their estimates of flood risk and their expected flood damages (Gallagher, 2014; Gibson and Mullins, 2020; Bakkensen and Barrage, 2021), which would make them more likely to relocate if this entails an increase in expected damages, especially if individuals are risk averse.[2] It is therefore an empirical question to determine the sign of the net effect of floods on residential mobility.

The objective of this paper is to investigate whether individuals' residential choices respond to high-frequency flood events. To do so, we use exhaustive 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, and census data to add controls at both individual and municipal levels.

Our empirical strategy consists in comparing individuals living in areas a priori exposed to flood risk and where there was a flood decree in the municipality in that year (treatment group) with individuals also living in areas exposed to flood risk but where there was no flood decree in the same year (control group). This approach allows us to control for pre-existing sorting based on risk preferences. We use the extended two-way fixed effects estimator proposed in Wooldridge (2023) to estimate the average treatment effect on the treated in a non-linear model of the probability of moving, controlling for time-varying characteristics of both the individual and the municipality of residence (proxies for amenities). We focus mainly on inter-

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

municipal mobility, but also on intra-municipal mobility.

Our results at the individual level suggest that inter-municipal mobility increases by 1 percentage point in the two years we can observe following a flood. This represents a large effect relative to the average rate of inter-municipal mobility in our sample, which is approximately 3.6%. The evidence shows substantial heterogeneous effects at the individual level. The probability of relocation following a flood is observed to be lower for individuals in the lowest quintile of equivalised income. Furthermore, the probability of relocation is also lower for the upper quintile of equivalised income. The first result is consistent with the theoretical prediction that the poorest are the most likely to experience reduced mobility due to income loss following a flood. Other heterogeneous effects are in line with this explanation. Notably, the probability of moving is lower for the unemployed compared to the employed. The second result is consistent with the possibility that higher income individuals are better able to pay for the necessary measures to adapt and self-protect. Additionally, different effects are observed depending on the tenure status of the individual. In particular, the probability of relocation following a flood is 1.9 percentage points higher for renters in the private sector, but only 0.7 percentage points higher for homeowners in the year following the flood.

The analysis of aggregate population inflows and outflows at the municipal level reveals no evidence of an effect on population flows on average. However, we observe changes in the composition of population outflows at the municipal level. Following a flood, we find a decrease in the share of homeowners in the population outflow.

Our article makes three contributions to the literature. First, we analyse residential mobility after floods regardless of their scale; in contrast, the rather scarce literature on this topic has primarily focused on mobility after major extreme events (Deryugina et al., 2018; Varela, 2022; Berlemann et al., 2023). Second, unlike recent literature on mobility and climate extreme events that has focused on county-level data (Boustan et al., 2020) or census tract-level data (Indaco and Ortega, 2024; Ton et al., 2024),[3] we can follow the same individuals over time and control for their characteristics. This

[3] Sheldon and Zhan (2022) analyse the mobility decisions of households, but cannot precisely locate households and analyse mobility at the county or PUMA (Public Use Micro Data Area) level. Bernard et al. (2024) is the other exception using household survey data to assess the probability to relocate within a year after self-reported housing damage following floods, cyclones, or bushfires in Australia.

means that we can examine heterogeneous effects at the individual level and investigate the question of who moves after flood. Third, to the best of our knowledge, this is the first analysis of individual mobility after river floods using comprehensive data for a country in the EU. We complement recent work by Tierolf et al. (2023) on the impact of sea-level rise on mobility in France.

The results have important policy implications since they indicate that individuals adapt to flooding in their area of residence, in the short run, by moving out of the municipality. These results call for further investigation of the underlying mechanisms at play. Is the increase in mobility driven by direct amenity effects, or through income effects? Or does the effect pass mainly through the housing market?

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

2 Related Literature

Although a large literature has been devoted to assessing the effects of flooding on housing markets,[4] in particular in the U.S., much less is known about individual responses with respect to location choice. Previous research has focused on the U.S. case and on very large extreme events, such as Hurricane Katrina (Deryugina et al., 2018) and Hurricane Sandy (Gibson and Mullins, 2020).[5]

Previous studies have estimated significant effects of extreme flood events on residential mobility. Following Hurricane Katrina, Deryugina et al. (2018) find a large spike in mobility that declines in the years following the event. 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. For floods, they find a positive net in-migration rate in the first half of the century.

[4]See the review by Beltràn et al. (2018).

[5]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.

This paradoxical result is in line with previous work by the authors according to which flood-prone counties experienced net in-migration in the 1920s and 1930s (Boustan et al., 2012); the authors interpret this result in the light of the investment in flood protection at the time, in the form of levees and storage reservoirs. However, the frequency of disasters has increased since the 1980s, and when restricting the sample to only post-1980 disasters, Boustan et al. (2020) find a 0.8 percentage point decrease in the net in-migration rate following floods. Sheldon and Zhan (2022) directly examine the impact of flood, coastal storms, and hurricanes on migration in the U.S, and find that households who have experienced severe disasters[6] are more likely to move. These effects on migration responses following floods are not corroborated by all studies. Indaco and Ortega (2024) analyse the extent to which county-level population flows vary with natural hazard risk.[7] Their results show no evidence of population retreat from areas exposed to a high risk of riverine flood, neither at the county level nor at the more granular county tract level.

We know of only two articles that analyse residential mobility after floods using European data. Following the great flood in Saxony in 2002, Berlemann et al. (2023) find net migration into affected areas compared to the unaffected areas. The authors argue that the lack of a mandatory insurance system with risk-adjusted premiums in Germany and the substantial government disaster aid to flood victims could explain the result. Husby et al. (2014) show an immediate negative effect on population growth levels of the 1953 North Sea Flood in the Netherlands, but population growth in the following decades due to the Deltaworks flood protection programme.

An important issue is that there may be heterogeneous effects in mobility responses after floods. For example, Bakkensen and Ma (2020) show evidence of low-income and minority households sorting into high flood risk areas. Sheldon and Zhan (2022) find that low-income households are less likely to move after a disaster. Following Superstorm Sandy, Varela (2022) finds that spatial polarisation is more pronounced after the event due to heterogeneous

[6]Their measure of the severity of a disaster is based on the Federal Emergency Management Agency's *Individuals and Households Program* (IHP), the programme that provides aid to disaster victims, which is a policy instrument rather than a measure of the physical intensity of a disaster.

[7]Indaco and Ortega (2024) use a risk measure that is based only on the frequency of disasters. In contrast, the Federal Emergency Management Agency's (FEMA) National Risk Index combines the expected annual frequency of disasters with exposure, leading to a mechanical correlation between that measure and population change.

income effects in the housing market. One possible explanation for lower mobility after flooding is the presence of credit constraints (Husby et al., 2018).

Instead of relocating, individuals may also adapt *in situ* and remain in their residence provided they benefit from public flood protection. They may also take private protective measures, such as water-repellent coating of the home or water-proofing floors. Osberghaus (2017) finds that more educated household heads are more likely to resort to private protective measures. In that vein, a survey based on respondents in the French *départements* Aude and Var (Richert et al., 2017) provides evidence of heterogeneous effects in the decision to take private protective measures against flood risk.[8]

3 Data

3.1 Flood risk

3.1.1 Flood events : natural disaster decrees

We use information on flood events from the CatNat decrees, compiled in the GASPAR database. CatNat is a public-private agency created in 1982 to offset shortcomings of the insurance market by providing insurance to any individual or company against risks that are otherwise considered uninsurable, i.e., risks that are concentrated in a limited area, such as floods, avalanches, volcanic activity or earthquakes.[9] The CatNat system records the state of natural disasters and defines the nature, duration and type of damage of the natural disaster that has occurred at the municipal level. The GASPAR database classifies a number of flood events: we focus here 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, not all individuals within a mu-

[8] The stated responses show that planned prevention is positively correlated with threat appraisal, education, and home ownership. The responses on income were too few to be included in the analysis.

[9] The mutual-based CatNat insurance scheme 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 before the burdens resulting from national disasters).

nicipality 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.

3.1.2 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 (100m) 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, Norway, Spain, England and the Po river basin). 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 overlays almost perfectly both the regulatory flood map defined by local authorities (PPRi)[10] and a past flood event. This makes us confident in the plausibility of the following two assumptions. First, individuals located in the JRC flood map should be informed about their exposure to flood risk. Since 2006, it is mandatory for house sellers and landlords to inform buyers and renters of the risks to which their property is exposed, including natural hazards.[11] Second, these individuals are also likely to have been directly

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

[11] 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.

affected by the flood. In the end, our working sample is made up of the 14,087 municipalities that are included in flood prone areas for river floods with a given flood frequency of 1-in-100 years.[12]

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*. Moreover, not all of them are publicly available, which makes a national analysis impossible.

3.2 Residential mobility

3.2.1 Administrative data: Fideli-Filosofi

We track residential mobility using Fideli-Filosofi (Insee),[13] a comprehensive source from the tax administration. The Fideli database provides information on residential location within municipalities. It was originally designed as a cross-sectional database but it is now possible to build up a panel thanks to a matching based on the *CSNS* identifier. Our study pioneers the use of this statistical innovation, allowing us to follow the entire French taxpaying population over time. Our study stands out for the unprecedented granularity of the data, both in spatial and temporal terms.

Each individual residence is declared in the tax files of a household on 1st January of every year. We follow the fiscal reference person of the 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 inside or outside of the municipality of origin. It should be noted that the use of the CSNS identifier has a number of limitations. Children and young adults are imperfectly monitored in terms of their residential mobility.[14] As individuals aged 0 to 25 are poorly covered by the mobility variable, we restrict our sample to individuals aged 26 and over, which excludes students

[12] 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.

[13] Fideli-Filosofi compiles information from housing tax files as well as from several income files (FIP, POTE, PFLC and Filosofi).

[14] Some segments of the population may be prone to mismeasurement, in particular 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.

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 provided by the Filosofi database on household income, the source of this income, and the age of the fiscal reference person. Table 1a shows the corresponding summary statistics for the variables used in the analysis.

We use five age categories (the reference category being individuals aged 42-52 years old). Equivalised disposable income is defined as disposable income divided by the number of consumption units in the household to take account of differences in household size and composition. We also distinguish between owner/renter status, 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: the former only have to give one to three months' notice to their landlord, while selling a property can take much longer. Other categories are renters in social housing,[15] owners, and others.[16]

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 working sample consists of 799,539 individuals (fiscal reference persons), whom we follow over three years, from January 2017 to January 2020.

3.2.2 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, but also public services and transport. The amenities included in the analysis are listed in Table 10 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

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

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

municipalities according to population density and the degree of influence of the centre.

We include time-varying characteristics of the municipality, i.e., 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,[17] thus we proxy data on secondary homes in year t with data in year $t-1$. Finally, we identify coastal municipalities:[18] this variable controls for both the amenity of being close to the coast, 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).[19]

4 Empirical Analysis

4.1 Identification strategy

In order to estimate the impact of floods on residential mobility, we propose to compare two groups, a treatment group and a control group. Treated individuals live in areas that are a priori exposed to flood risk and where the municipality had a flood decree in that year. Control individuals also 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 along 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 separately for the treatment and control groups of fiscal reference persons. The control and the treatment groups are unbalanced with respect to several socio-demographic characteristics; owners are slightly over-represented in the control group. The control group also has a higher share of individuals receiving pension benefits as

[17]The latest edition goes up to 2019.

[18]Alternatively, a variable *distance to the coastline* could be used, as at least one case study from the South of France has shown the importance of distance to the coast in measuring the willingness to relocate (Rey-Valette et al., 2019).

[19]For now, we have not included disaster decrees for coastal floods, since there are many categories of decrees for them, and there could be more measurement error compared to the single category of "floods and mudslides".

their main source of income. Equivalised disposable income is higher in the treatment group.

Descriptive statistics on amenities at the municipality level are shown in Table 1b. The control and the treatment groups also differ in terms of the characteristics of the municipalities and access to various amenities. Municipalities in the treatment group have a slightly higher median income, and are better equipped than the control group in terms of amenities such as the presence of a school, a shopping facility, a health facility and a kindergarten. 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).[20] These tests lead to the rejection of the null hypothesis of equality of means. Due to the imbalance in these characteristics, a simple application of non-flooded individuals as controls for flooded individuals, according to our treatment definition, is considered inappropriate. We therefore adopt a propensity score subclassification strategy to address these imbalances and to construct comparable treated and control groups.

We perform subclassification on the treatment propensity score. More precisely, this score is the probability of being treated at any given time, estimated using a logit model and based on the previous covariates. All observations are classified into six sub-classes based on their probability of being treated at any given time. The sub-classes are defined using propensity score quantiles. The number of treated observations in each sub-class is then used to define the observation weights that we will use in the econometric specifications. This allows us to adjust for differences in means between the treated and control groups so that the distribution of their propensity score by sub-class is similar. We believe that this strategy helps us to achieve a more credible control group. As expected, the use of 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 proportions of individuals living in a high-density urban centre falls from 0.29 to 0.03.

Two additional issues complicate the identification of a treatment effect

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

of flood. The treatment is not absorbing and areas can be flooded repeatedly. Multiple floods are not taken into account in our definition of the treatment. 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 conditions problem, we restrict our sample to individuals who have not experienced a flood in the last four years.[21] We impose this condition to ensure 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.

4.2 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 of the municipality of origin.[22]

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 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

[21]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.

[22]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 5.1, we present results when intra-municipal moves are also included.

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_{ict} on treatment $\mathcal{T}_{it}$:

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

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 non-linear 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 (ATT):

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

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 $W_{it} = \mathcal{T}_{iq}(fq_t + ... + fT_t) + \mathcal{T}_{iT}fT_t$.[23] The conditional mean can then be expressed as

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

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

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.[24]

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 effect of treatment on the treated (ATT).

In addition to direct effects, floods may have indirect spillover effects on neighbouring municipalities. We test for such effects by considering events in the city catchment area (“aires d’attraction des villes” or “AAV”) 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 city catchment area (AAV), without distinguishing between the risk areas in the map 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 city catchment area treated during the period 2018-2019. As a result, our estimation of spillovers is based on a smaller sample of 646,984 individuals compared to the main sample of 799,535 individuals.

[24]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.

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 city catchment area, or positive, if the rebuilding after a flood elsewhere in the city catchment area 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 5.3.

4.3 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 $OUTFLOW_{c,t}$ for municipality c and year t is defined as the share of $t-1$ inhabitants who left in year t:

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

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

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

For both outcomes $Y_{c,t}$ we estimate:

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

By extension, $Y_{c,t}$ also denotes the share of individuals below a given income threshold or the share of homeowners among these flows. The treatment variable $\mathcal{T}_{c,t}$ 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 $Z_{c,t}$ 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 differences-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 structure of outgoing and incoming population flows to flooded municipalities. In particular, we examine whether floods increase or decrease the share of individuals in the bottom 25% (or 50%) of income, or the share of homeowners in the municipality.

5 Results

5.1 Individual mobility choices

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.[25] Table 13 in Appendix shows that the assumption of parallel trends holds for the year for which it can be tested. The results are robust to clustering the standard errors at the individual and municipality level, as shown in Table 18 in Appendix.

The effect corresponds to an increase of 30.1% in the year following the event compared to the average annual extra-municipal mobility rate of 3.7% in our sample. This conclusion is accompanied by a caveat. In fact, the observed 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 but higher than the estimate in Sheldon and Zhan (2022) from the U.S.[26]

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

[26]Bernard et al. (2024) estimate a 56% increase in the probability of moving in the year following (self-reported) housing damage following 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 people who have experienced a disaster (hurricanes, coastal storms, and floods) in their county in the past four years.

We also examine the effect of a flood on total residential mobility, which includes intra-municipal mobility as well as moves outside the municipality. The estimated marginal effects shown in Table 4 when including also intra-municipal mobility indicate an increase of 1.2 percentage points in the two years after a flood. Relative to the baseline mobility rate (5.7% average annual mobility rate), this increase 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.

Finally, Table 24 shows that most of the moves (87%) out of the municipality after flood are to areas outside the flood-risk areas as defined by the map of Dottori et al. (2022). This is an indication of the adaptive potential of such mobility to flood risk. For intra-municipal moves, the individual is almost equally likely to end up in an area with or without flood risk after moving.

5.1.1 Spillover effects of floods outside of the municipality

We also find evidence of spillover effects from a flood in the city catchment area on the mobility rate of individuals located in a non-flooded municipality, but these are much smaller in magnitude than the estimates of the effect of a flood 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, but a small negative effect (-0.4 percentage points) two years afterwards.

In Section 1 we discussed potential indirect effects of flood and an expected ambiguous sign of the effect. Demand effects and employment effects are two potential causes of indirect effects of flood elsewhere in the city catchment area. If indirect effects go through firm closure and the labour market, such effects may occur with a lag, which could explain why the spillover effect turns negative two years following a flood. Overall, though, the effect of spillover of floods occurring outside of the municipality is smaller in magnitude by a factor of three compared to the effect of flood in the municipality of residence. One possible explanation is that the intensity of the flood is too low to affect the rest of the city catchment area.

5.1.2 Heterogeneous effects with respect to individual characteristics

Existing evidence outside France 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 test for heterogeneous responses to floods with respect to several individual characteristics: quintiles of household equivalised disposable income, age category, employment status, 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.[27] This is consistent with the literature suggesting that budget constraints may limit residential mobility for low-income households. 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 US (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 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).

[27] Marginal effects for all outcomes by individual characteristics are presented in Table 15 in Appendix.

Figure 7 shows that tenure status matters: 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 (and by 0.9 percentage points at $t+2$) after a flood. Social housing tenants show the smallest change in the probability of moving after a flood (an increase of 0.6 percentage points in the first year, falling to 0.4 in the second year). Finally, we find heterogeneous effects depending on whether the individual's dwelling is a house, a ground floor flat, or a flat on upper levels (Figure 8). Individuals living in a ground floor flat have a higher increase in the probability of moving after a flood (1.9 percentage points), compared to individuals living in upper floor flats (1.2 percentage points), and individuals living in houses, for which the increase is the smallest (0.5 to 0.6 percentage points) (Table 15). The salience of flood risk when living on the ground floor could explain the difference in effect in between the first two groups of individuals. Table 23 shows that the group whose dwellings are a house are mainly owner-occupiers (82.46% of the category), who may find it difficult to sell their dwelling after a flood, which could explain the smaller actual increase in the probability of moving after a flood for owners of a house.

5.1.3 Heterogeneous effects with respect to the duration of a flood event

The previous results are based on a binary treatment and therefore do not allow us to distinguish floods by intensity. Rainfall intensity before a flood is sometimes used as a measure of treatment intensity, but floods are not caused by rainfall alone, so it is an imperfect proxy for the extent of damage. Instead, we measure intensity by the duration of a flood, which is related to the disturbance it causes. The CatNat decrees contain information on the beginning and the end of a flood event, so we measure flood intensity by its duration 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 re-estimate the individual location choice model on the 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 result is consistent with the fact that large-scale natural disasters cause greater damage and are more likely to affect individuals' preferences.[28] 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 a 1.4 percentage point increase in the propensity to move in the year after the flood and a 0.7 percentage point increase in the propensity to move two years after the flood.[29]

5.2 Population flows at the municipality level

We next present our results from the models at the municipality level in Equation (7). The differences-in-differences estimates for aggregate flows in 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 11 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 is is imprecisely estimated (see Table 12 in Appendix).

The absence of an effect on the population outflows may be related to the small proportion of the population of each municipality that is actually located in the floodplain, as illustrated in Figure 2. Only a small part of the municipality's area is affected by the flood risk. Such a finding is also consistent with the "micro retreat" hypothesis, according to which individuals

[28] The marginal effects for all outcomes according to flood duration are presented in Table 16 in Appendix.

[29] Table 17 in Appendix shows estimates for the 2018 cohort only and for three categories of flood duration: very short (0-5 days), medium (6-14 days), and long (15 or more days). The estimates show a similar pattern: an immediate increase in mobility in the year after a flood, followed by a decrease in the propensity to move two years after the flood. 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.

live in a less risky area within a larger municipality at risk while enjoying its amenities (Indaco and Ortega, 2024).

We turn next to tests of compositional changes in the population inflows and outflows (Tables 7, 8, and 9). At this level of aggregation, we find no evidence of reduced outward mobility for low-income individuals. We do find other compositional effects, in terms of tenure status with respect to out-migration at the municipality level. Table 9 suggests a decrease of 2.3 to 2.5 percentage points in the share of homeowners in the population outflow rates. This is consistent with tenants (at least in the private sector) moving more easily. These changes may reflect negative income effects, either through direct flood damage or through price changes in the housing market. The only other analysis to our knowledge that controls for tenure status (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 (either floods, cyclones or bushfires). Our results come from the specific setting of mandatory disaster insurance in France, and suggest that indirect economic effects through changes in house prices may reduce homeowners' ability to move. Recent evidence on the French housing market for the period 2019-2023 shows large price effects from past floods, especially in *départements* with repeated events (Ancel and Kamionka, 2024).

5.3 Robustness checks

In Table 18, we show that the main results are robust to clustering of the standard errors at both the individual and the municipality of origin level.

In the main estimation, we use the disaster decrees for river floods only, but control for whether the municipality has a coastline. One concern is that we may be underestimating flood risk when not explicitly including coastal floods and hence confounding the estimate for such individuals with the amenities associated with their coastal location. Table 21 shows that the main estimation is robust to excluding the 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 19 in Appendix. As expected, we find no effect on residential mobility on the estimated coefficients.

In another robustness check, we assume static effects (no persistence of floods) and remove the 4-year filter since the last flood before our period of analysis. Table 20 in Appendix shows that the estimates without the 4-year filter are not significant. This could be explained by the fact that some individuals have already been treated, or that the information provided by a flood event is not new in this case, and people adapt to past floods.

Finally, we estimate the main specification on the full sample without using matching weights. As shown in Table 22, the estimates are statistically significant but the marginal effects are almost 50% higher. By not using the matched sample, we could mistakenly conclude that the effect of flood on residential mobility is much higher.

6 Conclusion

We analyse the effect of floods on individual mobility decisions using complete administrative data for metropolitan France over three years. Our results indicate that individuals living in areas that experienced flooding have a 1.1 percentage point higher propensity to move out of their municipality of origin in the two years following a flood. Compared to the average mobility rate in our sample over this period, which is around 3.6%, this corresponds to a 30.6% increase in the probability of moving out of the municipality of origin. To put the estimated effect in context, 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 is limited. However, our results suggest that the mobility response is driven by floods with a duration above the median. In contrast, a flood event of short duration induces a short-term increase in the propensity to move, which then turns negative in the second year after the flood. We also find that the spillover effects of a flood in a municipality in the city catchment area affect individuals in a non-flooded municipality, but the spillover effect is smaller by an order of magnitude of three.

There are clear heterogeneous effects in the form of a lower propensity to move among those in the lowest and highest quintiles of equivalised income compared with the middle quintiles. In terms of tenure status, we find a lower propensity to move among homeowners compared to renters in the private sector and in social housing. The post-flood mobility patterns reflect the general propensity to move by age, with the younger age group having the highest likelihood of moving. Similarly, in terms of employment status, the propensity to move is the highest among the employed compared to the unemployed, and the retired.

When analysing aggregate flows at the municipal level, we observe no effect of flooding on residential mobility on average, confirming the importance of using granular individual data. Further examination of the changes in the composition of population outflows and inflows shows that the proportion of homeowners is lower in the post-flood population outflows. This may indicate that the main impact of the floods is through their effect on the housing market.

There are two limitations to our empirical analysis. First, while we use a non-linear model accounting for potentially heterogenous 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 other adaptation measures that households may have taken in response to the floods.

Future research could further investigate the impact of floods on residential mobility in a number of ways. Methodologically, one could consider nested models of the conditional choice of individuals to move to another area at risk or to move to an area at low risk, either within or outside their municipality of origin. Further investigation of this is important to assess the extent to which residential mobility could be relied upon as part of adaptation to the future increase in flood frequency and intensity predicted by the IPCC. If we had a longer panel, it would also be important to consider the effect of repeated treatment (de Chaisemartin and D'Haultfœuille, 2022).

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Figures

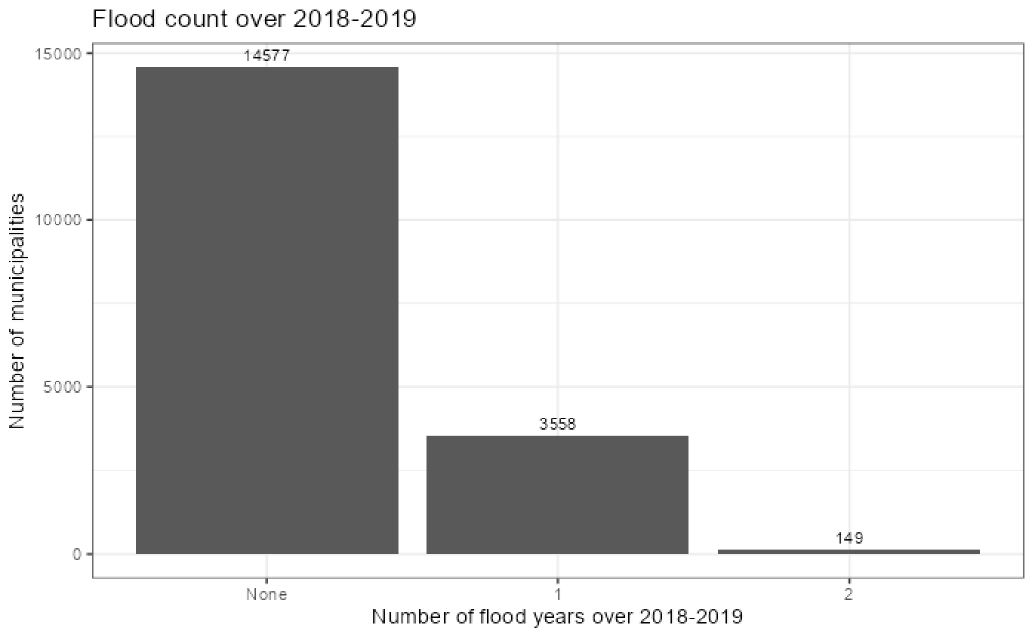

Figure 1: The distribution of floods in French municipalities during the period 2018–2019.

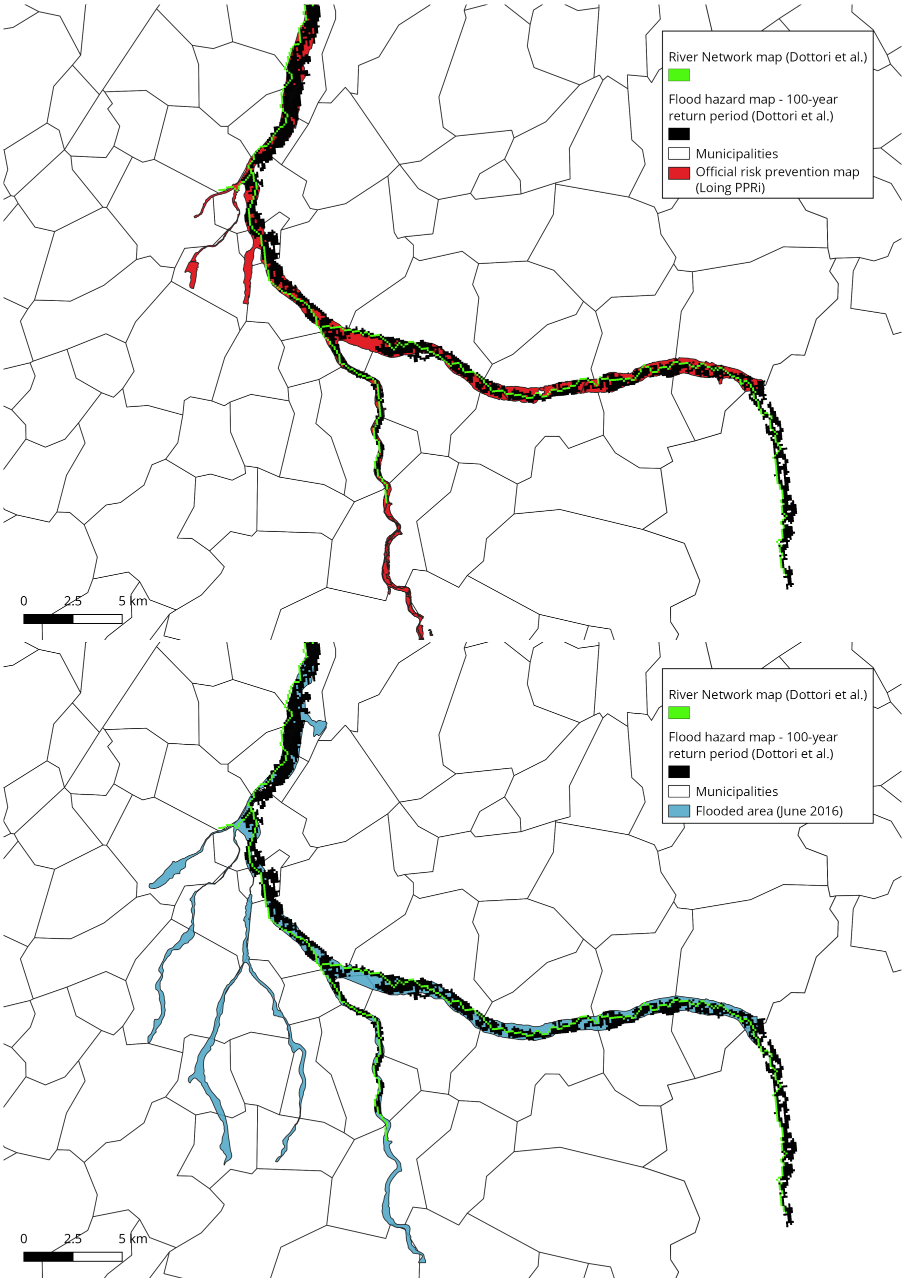

Figure 2: Comparison of different flood maps. Top: official regulation (PPRi) in red and the floodrisk map from Dottori et al. (JRC, 2021) in black. Bottom: flooded area in past event (2016, June) in blue and the floodrisk map from Dottori et al. (JRC, 2021) in black.

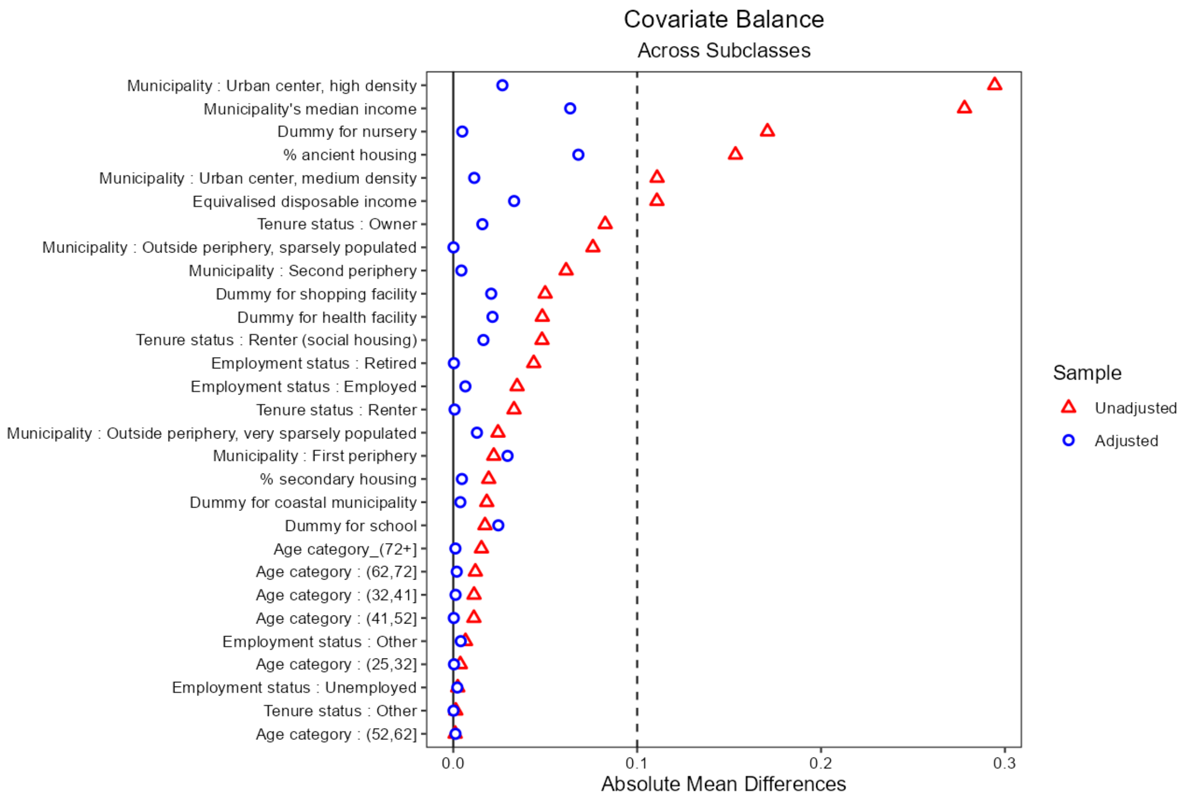

Figure 3: Covariate balance before and after matching

Note: Before propensity score matching, the absolute difference in shares of treated and controls living in an urban centre with high density is 0.29. After propensity score matching, the absolute difference is 0.03.

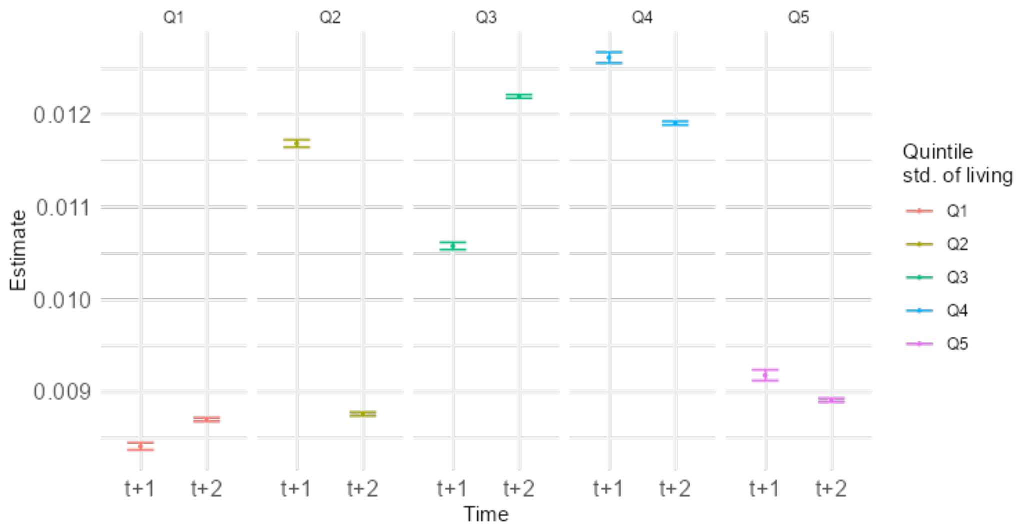

Figure 4: Quintiles

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.

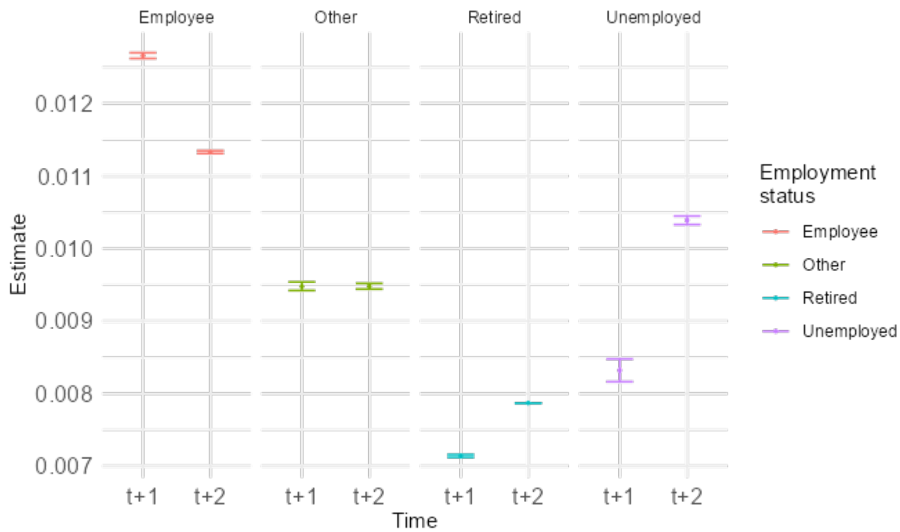

Figure 5: Employment status

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.

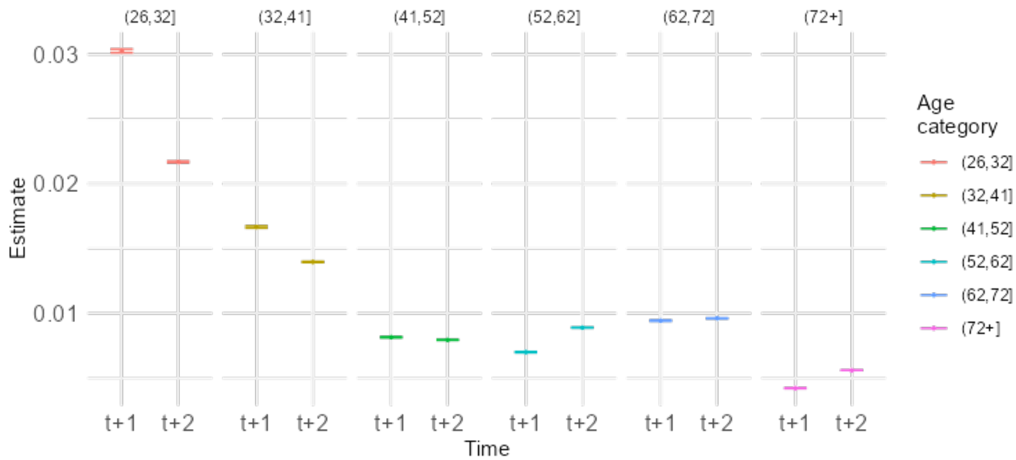

Figure 6: Age

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.

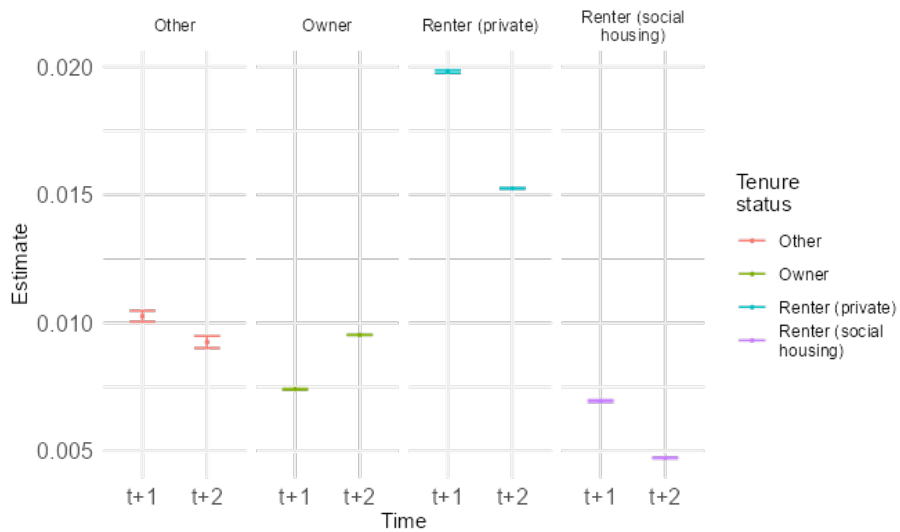

Figure 7: Tenure status

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.

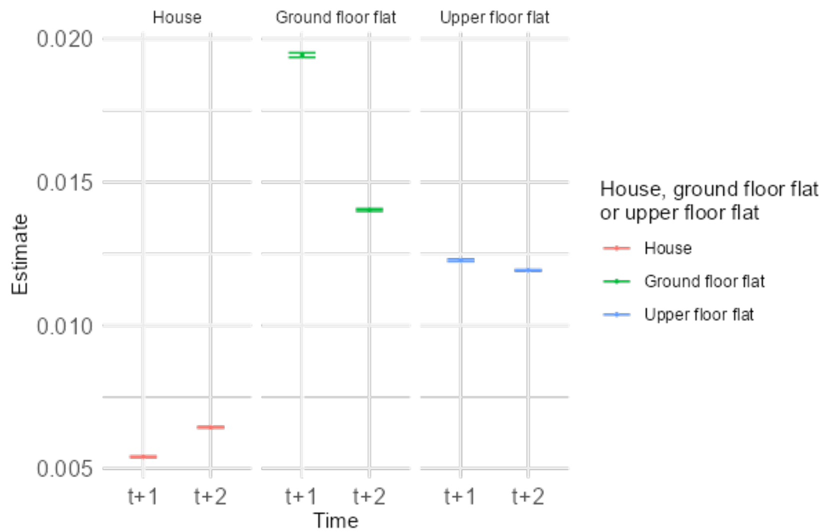

Figure 8: House or Ground floor

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.

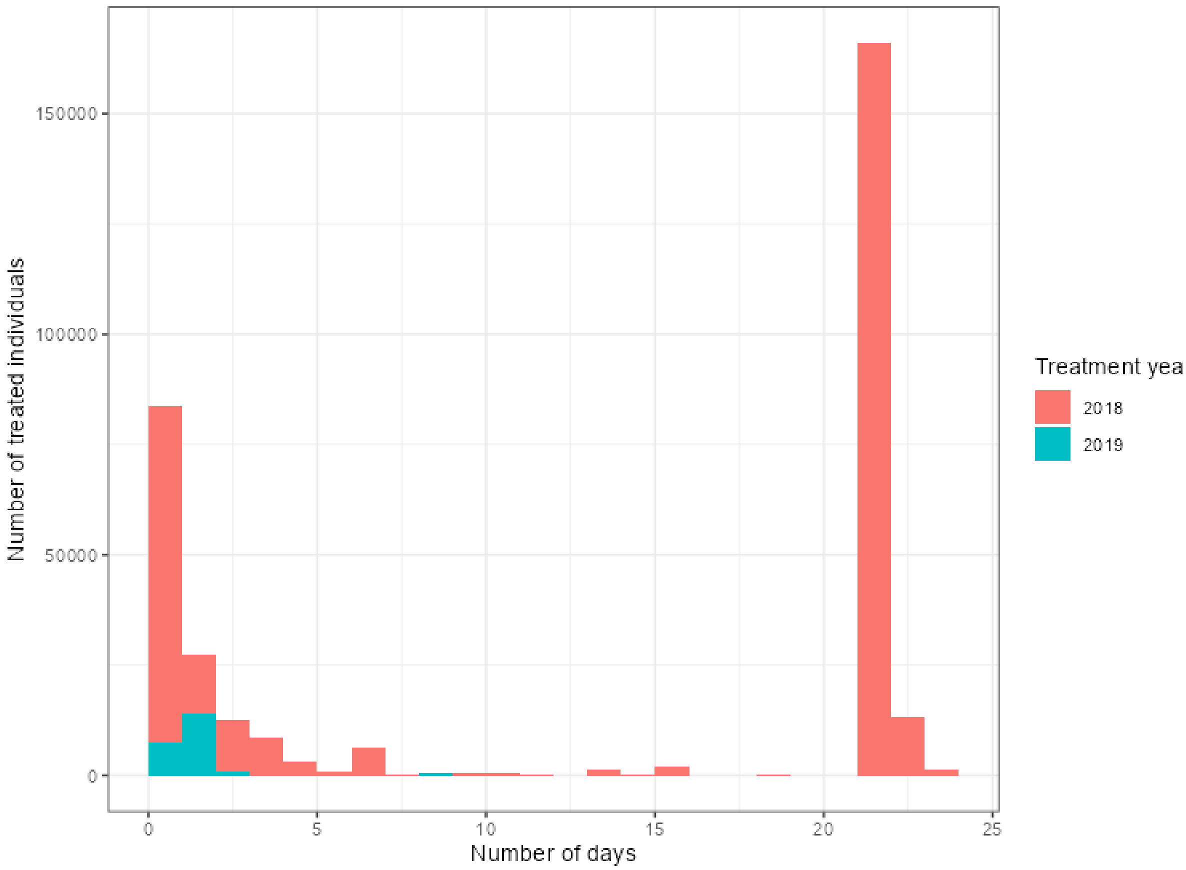

Figure 9: Histogram of treatment duration (number of days declared in natural disaster decree)

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

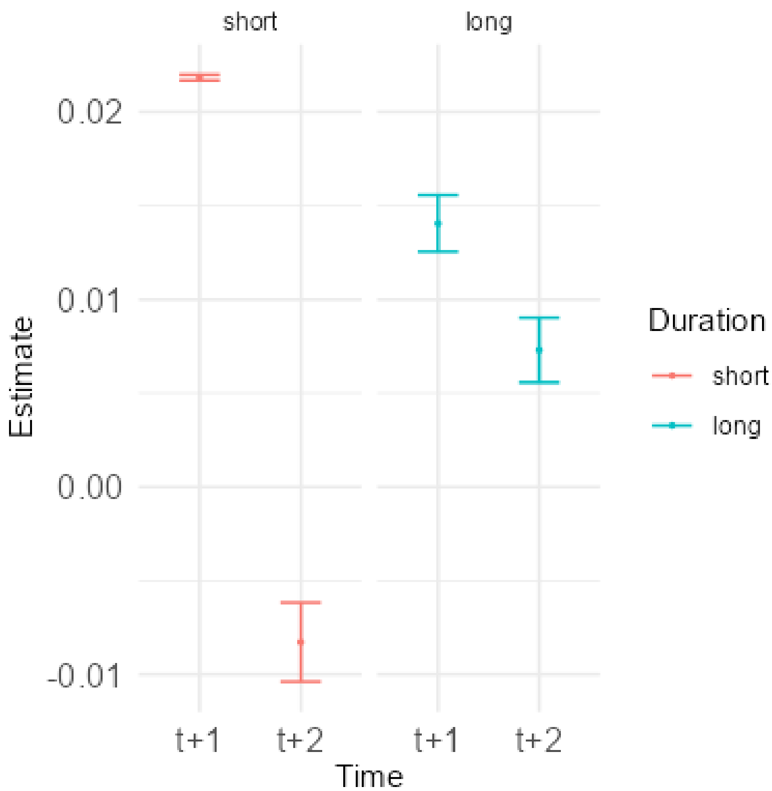

Figure 10: Flood duration

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	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	2623	22190	11701	21934	F= 9.716***
Dummy for school	2623	0.9	11710	0.83	F= 78.75***
Dummy for shopping facility	2623	0.75	11710	0.63	F= 141.51***
Dummy for health facility	2623	0.74	11710	0.62	F= 135.778***
Dummy for nursery	2623	0.42	11710	0.25	F= 308.886***
Dummy for coastal municipality	2623	0.05	11710	0.037	F= 9.136***
Urban/Rural typology	2623		11710		X2= 111.694***
... Outside periphery, very sparsely populated	338	13%	2041	17%	
... Outside periphery, sparsely populated	598	23%	2890	25%	
... Second periphery	499	19%	2507	21%	
... First periphery	625	24%	2431	21%	
... Urban center, medium density	401	15%	1477	13%	
... Urban center, high density	162	6%	364	3%	

Note: Among the 328,245 treated individuals, 7% are older than 26 years and under the age of 32 in 2018. Chi-square statistics are statistically significant and we reject the hypothesis of equal distribution between treated and never treated 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, whereas 3.76% moved outside of their municipality of origin.

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

	time	estimate	sd
1	t+1	0.011	0.0002
2	t+2	0.010	0.001

Note: Aggregate marginal effects of a flood on the probability of moving out of the municipality one or two years after a flood. The aggregate marginal effect is obtained by weighting the cohort-specific effects by the relative size of each cohort.

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

	time	estimate	sd
1	t+1	0.012	0
2	t+2	0.012	0.001

Note: Aggregate marginal effects of a flood on the probability of moving one or two years after a flood, including both moves outside and within the municipality of origin. The aggregate marginal effect is obtained by weighting the cohort-specific effects by the relative size of each cohort.

Table 5: Spillover effects of a flood

	time	estimate	sd
1	t+1	0.003	0.00003
2	t+2	-0.004	0.001

Note: Aggregate marginal indirect effects of a flood on the probability of moving out of the municipality of origin one or two years after a flood. Indirect treatment is defined as having at least one municipality in the individual's city catchment area ("AAV") 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 by the relative size of each cohort.

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

Appendix

Table 10: 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
Share of social housing	Répertoire des logements locatifs et bailleurs sociaux-SDES
Share of secondary/ancient housing	Census- Insee- Housing

Table 11: Effect of floods on population flows at the municipality level (differences-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		$5.06 \times 10^{-5***}$		$3.83 \times 10^{-5***}$
		(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 12: Effect of floods on population flows at the municipality level (differences-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		4.66×10^{-5}***		3.58×10^{-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 13: Pre-trends test (coefficient)

	Dependent variable:
D2019:f19	0.018 (0.077)
Note: Statistical sign.	*p<0.1; **p<0.05; ***p<0.01

Table 14: Clustering at the unit and municipality level (marginal effects)

	estimate	se	time
1	0.011	0.00003	t+1
2	0.010	0.00002	t+2

Table 15: 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

Table 16: Marginal effects by flood duration.

Duration	time	estimate	sd
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 estimates 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 17: 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 estimates 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 18: Clustering at the unit and municipality level (marginal effects)

	estimate	se	time
1	0.011	0.00003	t+1
2	0.010	0.00002	t+2

Table 19: Falsification test (coefficients)

	Dependent variable:
D2018falsif:f19:Wfalsif	−0.044 (0.062)
D2018falsif:f20:Wfalsif	−0.089 (0.064)
D2019falsif:f20:Wfalsif	−0.100 (0.165)
Note: Statistical sign.	*p<0.1; **p<0.05; ***p<0.01

Table 20: 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: Statistical sign.	*p<0.1; **p<0.05; ***p<0.01

Table 21: Main model without coastal municipalities (marginal effects)

temps	estimate	sd
t+1	0.011	0.0003
t+2	0.010	0.001

Table 22: Robustness test without matching weights (marginal effects)

	time	estimate	sd
1	t+1	0.016	0.0002
2	t+2	0.015	0.0004

Table 23: 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

Table 24: 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 in a flood risk area at their new destination.