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Floods do not sink prices, historical memory does: How flood risk impacts the Italian housing market[†]

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Abstract

Do home prices incorporate flood risk in the immediate aftermath of specific flood events, or is it the repeated exposure over the years that plays a more significant role? We address this question through the first systematic study of the Italian housing market, which is an ideal case study because it is highly exposed to floods, though unevenly distributed across the national territory. Using a novel dataset containing about 550,000 mortgage-financed transactions between 2016 and 2024, as well as hedonic regressions and a difference-in-difference design, we find that: (i) specific floods do not decrease home prices in areas at risk; (ii) the repeated exposure to floods in flood-prone areas leads to a price decline, up to 4% in the most frequently flooded regions; (iii) responses are heterogeneous by buyers' income and age. Young buyers (with limited exposure to prior floods) do not obtain any price reduction for settling in risky areas, while experienced buyers do. At the same time, buyers who settle in risky areas have lower incomes than buyers in safe areas in the most affected regions. Our results emphasize the importance of cultural and institutional factors in understanding how flood risk affects the housing market and socioeconomic outcomes.

1 Introduction

Research on the impact of flood risk on home prices, primarily based on U.S. data, typically finds small effects, except in the years immediately following major flood events when the price impact in affected areas is more pronounced. For example, prior to Hurricane Sandy, flood risk had little influence on home prices in New York City. However, in the years after the storm, properties in flood zones –despite being undamaged– sold for up to 8% less than properties in safer areas (Ortega and Taşpinar, 2018). Bin and Landry (2013) attribute this pattern

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to the availability heuristic (Tversky and Kahneman, 1973), suggesting that individuals must experience floods firsthand to perceive them as a significant threat and demand a price discount for homes at risk.

In this paper, we propose an alternative yet complementary hypothesis, which we term *historical memory*. We suggest that, in places with storms not as destructive as hurricanes and different housing market institutions than in the U.S., isolated flood events may be insufficient to significantly shift market beliefs and prompt the pricing of flood risk. Instead, repeated flood exposure in the same region may have a more substantial influence. If this hypothesis is true, home prices in frequently flooded areas are likely to reflect flood risk more prominently than those in rarely flooded regions, even for properties that remain undamaged. Moreover, younger buyers, having experienced fewer floods, may require a smaller discount to purchase at-risk properties compared to more experienced buyers.

We test this hypothesis through the first systematic study of the Italian housing market, which offers an ideal case study for several reasons. First, Italy faces significant flood risk, with over 10% of its population and buildings exposed to floods with a return period of less than 200 years (Trigila et al., 2021), and approximately 40 major floods recorded since 2000 (EM-DAT, 2024). Second, Italy recently experienced a major flood in the Emilia-Romagna region on May 16–17, 2023, which displaced 45,000 people and caused damages estimated at around 10 billion euros (EM-DAT, 2024). Third, flood exposure varies across regions: while flood risk affects the entire country, Northern Italy experiences more frequent events than the South. Fourth, unlike markets in the U.S. or the U.K., Italy lacks institutional requirements for flood risk disclosure during property sales and neither mandates nor promotes flood insurance. Finally, floods in Italy typically result from storms with a less catastrophic impact than the hurricanes or tropical storms common in the U.S.

Given this environmental and institutional context, we frame and test our historical memory hypothesis as follows. We argue that, without an institutional structure that encourages the sharing of information regarding flood risk, households rely on the historical memory of major floods to identify the most at-risk areas. Due to the relatively limited destructive potential of individual floods, a single event may not significantly shift market beliefs. However, repeated flood occurrences gradually reinforce risk awareness, eventually leading to its capitalization in home prices. The recent Emilia-Romagna flood provides an opportunity to test the first aspect of this hypothesis, while the variation in flood risk across Italian regions enables us to examine the second.

The main reason why there is so little research on how flood risk impacts the Italian housing market is that systematic data only started to exist in the last few years.¹ In this paper, we take advantage of a novel database that contains the near-universe of mortgages issued by Intesa Sanpaolo, the largest Italian bank. Our final dataset contains about 550,000 mortgages issued from 2016 to 2024, which is about 15% of Italian mortgage-financed transactions, and 10% of total transactions.² For each transaction, we know the sale price, the date, the income of the buyer, whether the buyer is under-36, and several physical characteristics of the transacted home, including its geographical coordinates. We use the coordinates to determine whether a home is inside a flood-prone area by performing spatial matching with risk maps provided by ISPRA, the Italian Institute for Environmental Protection and Research (Trigila et al., 2021).

¹We are only aware of one study assessing the impact of flood risk on prices (Rosato et al., 2017), using 197 data points manually collected from real estate agencies in Venice. Only recently systematic data about the housing market became available from the housing advertisement website *Immobiliare.it* (Pangallo and Loberto, 2018; Loberto et al., 2022), but concerning our research question, these data have only been used to study the impact of a sea wall in Venice (Benetton et al., 2023).

²The data are highly representative of the Italian housing market throughout the entire national territory, see Supplementary Section A.2.

Using the same approach, we also assess whether homes have been *hit* by specific flood events, such as the 2023 Emilia-Romagna flood. By “hit”, we mean that their coordinates lie within the maximal flooding area identified by the Copernicus EU program (Directorate Space, Security and Migration, European Commission Joint Research Centre , EC JRC).

First, we assess whether specific flood events lead to stronger price penalties in the affected areas. Most studies find price reductions in a 5-25% range, that only last a few years after the event, and interpret these findings as evidence for a transitory increase in attention to flood risk.³ In line with most of the literature, we follow a difference-in-difference approach that distinguishes between homes at risk and homes not at risk, as well as homes sold before or after the event. In addition to most of the literature, we further distinguish between homes that were hit by the flood and homes that were not hit but could have been, as they were in risky areas in the same municipalities as hit homes (Ortega and Taspinar, 2018). We find that the 2023 Emilia-Romagna flood (which, as discussed, has been the largest flood in Italy in the last 20 years) did not lead to any further price reduction for homes at risk that were not hit.⁴ This result, which contrasts with much of the literature, is robust across specifications, home types (e.g., focusing on ground floor apartments), and considering the second and third largest flood events in the studied period.

Second, we assess whether flood risk reduces prices, independently of specific flood events, and how this varies across regions with different levels of exposure. All else equal, economic theory predicts a price penalty for homes at risk (Bin and Landry, 2013). However, because of confounders, such as water-related amenities (Bin and Kruse, 2006; Daniel et al., 2009a), it is hard to establish causality in empirical studies,⁵ especially given that we cannot rely on repeated sales (Beltrán et al., 2019) or changes in risk maps (Hino and Burke, 2021).⁶ To address this issue, we run hedonic regressions that take into account multiple physical characteristics of transacted homes, as well as granular spatial fixed effects, down to the census tract level. We argue that these fixed effects capture enough spatial variation so that the coefficient on flood risk is likely to capture the actual penalty of being located in a flood zone. We find that homes at risk sell at approximately 1% less than homes that are not at risk. This risk penalty is not at all uniform across the Italian territory. It is only statistically significant in the most frequently flooded regions, reaching 2.5% in Liguria, 3.5% in Emilia-Romagna and 4% in Toscana.

Third, we study how these results vary across buyers with different age and income. We find that young buyers⁷ do not obtain any discount for purchasing homes at risk, while more experienced buyers obtain a discount that increases with the frequency of floods in their region. High income buyers, whether young or not, are also more likely to obtain a discount. Furthermore, in line with Zivin et al. (2023), we find that lower income buyers are more likely to purchase properties in risky areas, in part because of lower prices. As before, this effect is statistically significant only in the most frequently flooded regions.

Summing up, in the immediate aftermath of the largest Italian floods in the last 20 years, we do not observe any price reductions for homes that were in the affected municipalities even though not directly hit. At the same time, we find a small “baseline” penalty of flood risk on

³See Hallstrom and Smith (2005); Daniel et al. (2009b); Kousky (2010); Atreya et al. (2013); Bin and Landry (2013); Atreya and Ferreira (2015); Ortega and Taspinar (2018); Beltrán et al. (2019).

⁴We also find that prices of hit homes decreased by 10% in the first 9 months after the event, reversing to a 10% appreciation between 9 and 15 months after the event. Most likely, affected homes were first damaged and then renovated, resulting in a price premium after renovations ended.

⁵For instance, nice views over rivers or lakes may both increase prices and be correlated to high flood risk.

⁶In this work, we adopted the 2020 release of the ISPRA risk maps. A 2017 release is available but does not present major changes in the total risk areas with respect to the 2020 version.

⁷More specifically, under-36 buyers with an adjusted income (“ISEE”) less than 40,000€ receiving a *mutuo giovani*, namely a mortgage with favorable conditions guaranteed by the government.

prices, but this penalty increases up to four times in the most flood-prone parts of Italy. We interpret this finding as evidence for our hypothesis of “historical memory”, whereby it is not isolated floods, but the repeated exposure to floods, that drives the incorporation of flood risk in home prices. This evidence is further corroborated by our finding that only experienced buyers, who may have witnessed multiple floods in their lifetime, obtain a discount for purchasing homes at risk. Finally, our findings on the income of buyers moving to at-risk areas have welfare implications, and can be used to design effective policies.

Relation to the literature. The studies quantifying the effect of flood risk on home prices have been reviewed in Daniel et al. (2009a), Beltrán et al. (2018b) and Contat et al. (2024).

A first question is how much specific flood events heighten housing market participants’ perceptions about climate risk, leading to stronger price penalties for homes located in risk zones. Lots of studies address this question (Hallstrom and Smith, 2005; Daniel et al., 2009b; Kousky, 2010; Atreya et al., 2013; Bin and Landry, 2013; Atreya and Ferreira, 2015; Ortega and Taşpınar, 2018; Beltrán et al., 2019), generally finding a temporary increase in the price penalty that only lasts few years.⁸ For instance, Bin and Landry (2013) argue that the availability heuristic (Tversky and Kahneman, 1973) explains why individuals need to experience flood events to attach a non-negligible probability to their occurrence. They find that two hurricanes occurring in 1996 and 1999 in North Carolina, after no major hurricane since 1954, lead to price reductions of 5.7% and 8.8%, respectively. Atreya and Ferreira (2015) argue that it is important to distinguish between inundated and non-inundated homes, because price penalties may conflate the physical damage that occurred to homes and the increased attention that buyers may pay to flood risk. Ortega and Taşpınar (2018) are able to clearly distinguish between the two cases, showing that price penalties in New York homes damaged by Hurricane Sandy were up to 17-22% for several years, while penalties for homes at risk that were not damaged were around 8%. Our results also show a strong decrease in prices of affected homes, around 10% between 3 and 9 months after the Emilia-Romagna flood, but reconstruction is much faster, as prices appear to recover already after 9 months (presumably, this is linked to the difference in intensity between Hurricane Sandy and the Emilia-Romagna floods). Differently from most of the literature, however, we do not find any significant change in the price penalty for homes that were not directly hit by the flood, but still located in risky areas of affected municipalities.

The next question is how much flood risk is capitalized in home prices in “normal times”, i.e. not in the immediate aftermath of specific flood events.⁹ Almost all previous studies relied on U.S. data. Daniel et al. (2009a) review estimates that range from a -52% penalty for at-risk homes to a +58% premium (mostly due to failing to control for water-related amenities), with a mean estimate of -2.3%. Beltrán et al. (2018a) update these estimates considering more studies, and find a range between a -75.5% penalty and 61% premium, with an adjusted mean -4.6% penalty for inland flooding. More recently, in what is perhaps the most complete study on this question, Hino and Burke (2021) find smaller -2.1% and -1.4% penalties with panel data and diff-in-diff approaches, respectively. Using actuarially fair insurance costs, they argue that these discounts are much smaller than the ones that would be expected in efficient markets, ranging from -4.7% and -10.6%. Our average 1% price penalty for homes located in flood zones relates to these findings. Unsurprisingly, we find a smaller penalty compared to the U.S., as

⁸Zivin et al. (2023) are among the few that find a price premium in the years following hurricanes, suggesting that it may be due to a supply shortage due to destroyed homes.

⁹Several studies use spatial regressions to estimate these effects (Atreya et al., 2013; Bin and Landry, 2013; Zhang, 2016; Pommeranz and Steininger, 2020). Here, we do not find relevant spatial correlations after controlling for geographical units, as evidenced by Global Moran’s I tests and LISA cluster maps, so we did not follow this direction. See Supplementary Section B.2.

in Italy disclosure of flood risk is non-existent and flood insurance is in many cases not even encouraged.¹⁰

The third piece of literature that we relate to is the one looking at the socio-economic characteristics of the buyers. Although there is substantial evidence that “sophisticated” buyers, such as non-owner-occupiers (Bernstein et al., 2019), or “believers” in climate change (Baldauf et al., 2020), obtain higher discounts when purchasing at-risk properties, the evidence on the effect of age or income is more scarce. For instance, Bradt et al. (2021) find that younger and lower-income buyers are less likely to purchase flood insurance, but Fairweather et al. (2024) do not find any significant difference in terms of searching at-risk properties across income levels. We contribute to this literature by showing that, in our case, younger and lower-income buyers obtain a smaller discount than more experienced and higher-income buyers. Regarding the income of buyers who settle in at-risk areas, our main comparison is Zivin et al. (2023), who match information on buyers’ income with transactions. They show that periods in which prices increase correspond to periods in which higher-income buyers are more likely to purchase properties in affected areas. We find a similar result concerning incomes, as we find that areas at risk show slightly lower home prices, thus households with slightly lower income move there. Ellen and Meltzer (2024) also find that lower-income households moved into the areas of New York that were hit harder by Hurricane Sandy.

Roadmap. First, Section 2 describes the data from Intesa Sanpaolo, the data from ISPRA and Copernicus spatially matched to transacted homes, as well as EM-DAT dataset used to define the regional frequency of flood events. Next, Section 3 describes our econometric approach. The main results are in Section 4. Section 5 concludes.

2 Data description

2.1 Intesa Sanpaolo mortgages

Intesa Sanpaolo (ISP) is the largest banking group in Italy, financing about a quarter of all mortgages within the country.¹¹ Following a GDPR-compliant and privacy-preserving protocol, we got access to the vast majority of the mortgages that they issued from 2016 on. Our dataset contains all mortgages that are still being repaid at the time of data extraction, that is August 2024.¹² The raw dataset contains 798,237 rows. We filtered data by selecting mortgages used to finance purchases (rather than, for instance, renovations), with available coordinates and within the Italian territory, and following a few other criteria.¹³ The final dataset has 552,761 rows.

ISP provided us with two databases: **Contracts** and **Cadaster**. The first one contains information about the mortgage applicant, the type, amount and goal of the mortgage, the issuance date and the price of the associated transaction. It also contains some information on the main housing unit given as collateral. In this database, a unique entry is a mortgage contract. The **Cadaster** dataset contains information about each cadastral unit: cadastral

¹⁰It is harder to say to what extent flood risk is capitalized in home prices, because although the penalty is smaller in Italy than in the U.S., the extent of damages is also likely to be smaller, as Italian storms are less strong than hurricanes in the U.S.

¹¹<https://www.agipress.it/mutui-vassena-intesa-sanpaolo-leader-in-italia-con-il-26-del-mercato>

¹²This excludes all the mortgages that were issued but have already been fully repaid, and mortgages that were issued but have been subrogated. However, focusing on mortgages that are less than 8 years old, these cases are not very common and we estimate that even in the initial year of the sample (2016-2018) we have 80% of the mortgages that were actually issued.

¹³We also discarded the mortgages that were given to juridical persons, that are still under review, that were issued to construct housing units with the goal of reselling them, and that were acquired through an auction process.

Table 1: Summary statistics of numeric variables. p1, p25, p75 and p99 refer to the 1st, 25th, 75th and 99th percentiles.

Variable	Missing	p1	p25	Median	Mean	p75	p99
Issuance Date	0 (0%)	2016-09-21	2019-03-22	2021-04-14	2020-12-23	2022-08-04	2024-07-19
Construction Year	1192 (0.22%)	1900	1965	1974	1979	2002	2022
Surface Area (m ²)	0 (0%)	42.00	83.00	107.00	121.57	143.00	345.00
Sale Price (€)	0 (0%)	44,000	110,000	155,000	184,510	225,000	660,000
Floor (numeric)	447545 (80.97%)	0.00	0.00	1.00	1.65	2.00	8.00
Monthly Income (€)	0 (0%)	873	1,670	2,374	2,870	3,413	10,700
Latitude	0 (0%)	37.51	41.85	44.38	43.54	45.48	46.14
Longitude	0 (0%)	7.50	9.21	11.35	11.53	13.00	18.03

code (corresponding to apartment, detached house, garage, basement, etc.), size, energy class, position, floor and others. Here, a unique entry is a cadastral unit given as mortgage collateral.¹⁴

We processed and cleaned these data, to create a single database where each sample is a mortgage contract, and the linked housing unit combines the information from all cadastral units given as collateral. To do so, we summed the floor areas of the *residential* cadastral units that were given as collateral for the mortgage. This excludes, for instance, the basement or garage of a building, but it sums the floor area of, for example, two apartments that were independent cadastral units at the time of purchase but then are joined following renovation work. Another example that required data processing is the floor variable. Because some housing units are divided among multiple floors, we created a flag that takes value one if it is on multiple floors, and a numeric variable that takes the minimum floor in case of multi-floor apartments.¹⁵ More details on the data and the cleaning process are given in Supplementary Section A.1.

The ISP dataset contains the coordinates (latitude and longitude) of the housing units given as collateral for each mortgage. This information is necessary to identify the risk level of the housing units (Section 2.2), and to associate homes to specific spatial units such as municipalities, OMI microzones or census tracts.

2.1.1 Summary statistics

Table 1 shows summary statistics for numeric variables. We show the count of valid values, the count of missing values, the 1st and 25th percentiles, the median, the mean, and the 75th and 99th percentiles. On issuance date, we see that the data are evenly distributed from 2016 to 2024. Next, we see that 75% of homes were constructed after 1965, and 50% of homes have a surface area between 83 and 143 m². The median sale price is 155,000€. The vast majority of apartments are on the ground, first or second floor. The monthly income of the mortgage applicant is typically between about 1,500€ and 3,500€.

Table A1 provides summary statistics for categorical variables. The share of mortgages generally reflects city size. As expected, the most common cadastral codes correspond to residence types, which refer to the main housing units used as collateral. Among these, standard (A02) and low-cost (A03) residences account for approximately 85% of the transactions. 7% of homes for which floor information is available span multiple floors, typically the ground and first floors. Additionally, about 50% of homes have a garage, and 15% include an additional unit, such as a

¹⁴In principle, mortgage applicants could give as collateral a housing unit different from the one they are buying, and we cannot tell if this is the case from our data. However, ISP states that these cases are residual for the subset of the data that we selected. For instance, it would be standard to give a home in Italy as collateral to buy a home abroad, but we exclude these transactions from our sample.

¹⁵This is because the minimum floor is the one most at risk of flood.

basement or attic. Regarding energy efficiency, most homes fall into the lowest energy classes: G, F, and E (about 48% across these three energy classes). Finally, about one in four homes (among the ones that report this information) is equipped with air conditioning.

2.1.2 Representativity

Since this is the first time that ISP mortgage data are used for research, we need to evaluate how representative they are of the Italian housing market. We show in Supplementary Section A.2 that they are highly representative. Since ISP has branches across the entire country, the share of transactions in each province matches very well the share of transactions in administrative data (Pearson correlation: 0.94). ISP data also generally match administrative data in terms of home size, although there are relatively fewer small apartments in ISP data because buyers are less likely to apply for a mortgage in this case. In terms of prices, ISP data also match administrative data very well. For instance, when focusing only on the provincial capitals, we obtain a Pearson correlation of 0.89 between ISP and administrative data. Finally, we also show that the incomes declared by ISP mortgage applicants match those of Italian residents across provinces (Pearson correlation: 0.82), although mortgage applicants' incomes are slightly higher than the general population. In sum, our results suggest that ISP data are representative of the Italian housing market.

2.2 ISPRA risk maps

ISPRA is the Italian organization monitoring hydrological risk across Italy. Specifically, ISPRA collects and aggregates the risk estimations performed by all Italian river basin authorities, providing freely available hydrological risk maps at the national scale.¹⁶ According to these maps, 14% of Italian territory is considered at flood risk. Zooming in at the region scale (i.e., at the sub-national level), the regions showing a fraction of territory at flood risk larger than the national average are Lombardia, Veneto, Friuli-Venezia-Giulia, Emilia-Romagna, Toscana and Calabria (Trigila et al., 2021; Iadanza et al., 2021).

In this work, we used the 2020 release of the ISPRA maps, which is the most recent update, as a reference for flood risk by the Italian authorities. The most recent tools for hydrological modeling and the inclusion of areas not considered in previous releases were adopted in the 2020 release. Despite these improvements, there are still some limitations in the definition of risk areas due to the uncoordinated work of the basin authorities. The main limitation is the inconsistency between the *level* of risk. Although in principle ISPRA distinguishes between high, medium, and low risk, classified according to return time,¹⁷ this classification is inconsistent across regions.¹⁸

Therefore, we build on the ISPRA risk maps to assign a flood risk *indicator* to each home in the ISP dataset. To accomplish this task, we perform a spatial matching approach, using the coordinates of each housing unit to match it to risk zones. Throughout this work, we introduce the label “at risk” when a home is inside a risk area, without distinction across high, medium, and low levels. While we focus on being at risk, we also perform supplementary analyses on the disaggregated risk levels. From the summary statistics shown in Table A1, we note that

¹⁶<https://idrogeo.isprambiente.it/app/page/open-data>

¹⁷High-risk areas are subjected to frequent flood events, with return time (i.e., the inverse of the average frequency of occurrence) between 20 and 50 years; medium-risk areas present a return time from 100 to 200 years; low-risk locations are characterized by a return time larger than 200 years (Trigila et al., 2021)

¹⁸For example, the high-risk levels are not available for the Marche region (Trigila et al., 2021) in the 2020 release and the notable extension of the high-risk areas in Calabria was inherited from the use of a flood hazard buffer zone across the hydrographic reticulum (Trigila et al., 2021).

approximately 77% of homes are at no risk of flooding, 11% have low risk, 8% have medium risk, and 4% are at high risk (thus, 23% of homes are in a flood-risk area).

2.3 Copernicus flooded areas

The Copernicus Emergency Management Service provides geospatial information to support the management of natural disasters, like landslides, wildfires or floods (Directorate Space, Security and Migration, European Commission Joint Research Centre , EC JRC). For flooding events, this data includes detailed vector maps that outline the extent of the flooded area at different times during the emergency.

We used the Copernicus flood maps to identify homes in the ISP dataset that could have been affected by the largest flooding events in Italy of the last years, such as the Emilia-Romagna floods of May 2023. Homes were matched to the flooded areas through a spatial matching approach. A home is considered as *hit* by the flood if its geo-coordinates are located inside the maximal area affected by that flood event, regardless of the magnitude of the damages, as more detailed information is not available.¹⁹

Table A2 shows the number of hit homes for all Copernicus events that are sufficiently large to be included in EM-DAT (see Section 2.4 below). We see that the May 2023 Emilia-Romagna floods affected 1464 homes in our dataset, more than 90% of all homes affected by any other considered flood. Therefore, we use this flood as a case study, and the second and third largest floods (in Toscana and Piemonte-Liguria, respectively) as robustness tests.

2.4 Historical memory: frequency of floods across Italy

Our hypothesis is that historical memory is built through the repeated exposure to floods, not after single events. Therefore, to quantify the level of historical memory of the different Italian regions we relied on historic flood records reported in the EM-DAT (2024) database.

EM-DAT is a disaster database that contains all the floods that have occurred in Italy with at least one among: 10 fatalities; 100 affected people; a declaration of state of emergency; a call for international assistance. These objective inclusion criteria and the popularity of the database make it an ideal starting point for our analysis.

We decided to consider the simple count of flood events by region as an indicator of how frequently a region is affected by floods, disregarding their severity.²⁰ This allowed us to identify 63 event-region pairs in the 2000-2023 period²¹, Figure 1 shows them disaggregated by region.

These flood records allowed us to classify the exposure of Italian regions into 3 different levels of historical memory: Frequently flooded regions, Moderately flooded regions, and Rarely flooded regions, which correspond to the 3 terciles of the distribution shown in Figure 1. A map of the regions associated to each historical memory level can be found in Figure 4.

We also considered as a robustness two alternative measures of flood frequency: (1) we normalize the number of events on EM-DAT by region area, (2) we consider an alternative dataset that we compiled from ISPRA data. Supplementary Section B.1 provides more details.

¹⁹This spatial matching procedure relies on the exact geo-coordinates of homes. Given the sensitive nature of these data, we followed a privacy-preserving protocol that guarantees the confidentiality of ISP clients.

²⁰EM-DAT reports multiple severity measures for each event, e.g. fatalities, missing and displaced people, total damage, insured damage, etc. However, it aggregates this information by events that typically span multiple regions, making it difficult to apportion damages to each region. Moreover, for many floods some of this information is missing.

²¹EM-DAT discourages using data before 2000 because of reliability concerns.

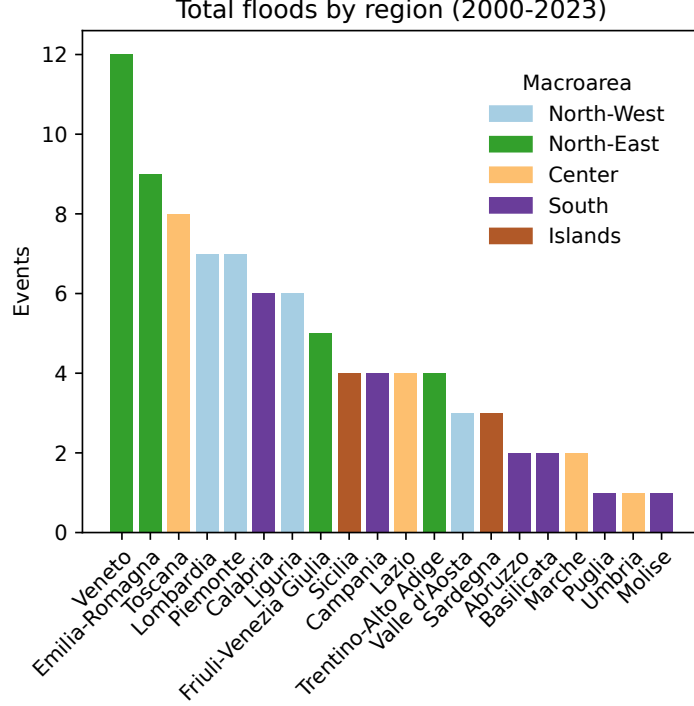


Figure 1: Flood events identified by EM-DAT, disaggregated by region, and colored by macro-area. 8/12 events in Veneto are likely to correspond to the *acqua alta* (high-tide) events that affect the city of Venice, as only Venice is mentioned by EM-DAT in these events. Without considering these events, Emilia-Romagna and Toscana are the most frequently flooded regions.

3 Econometric design

To quantify the influence of flood risk on the Italian housing market, we have addressed three separate research questions: (1) Do we observe changes in home prices after specific flood events?; (2) Does flood risk affect home prices differently in different regions?; (3) How do results change across socio-economic groups? In the following, we describe how we address all these questions by building on a baseline hedonic regression.

3.1 Baseline hedonic regression

Our baseline approach for identifying the effect of flood risk on home prices is a standard hedonic regression with granular fixed effects. Our goal is to compare the prices of very similar properties that differ only on flood risk. Denoting a transaction by (i, k, t) , where i identifies the property, k the spatial unit it belongs to, and t the time of the transaction, our baseline hedonic specification is

$$\log P_{ikt} = \alpha_k + \alpha_t + \beta R_i + \gamma' \mathbf{X}_i + \epsilon_{ikt}, \quad (1)$$

where P_{ikt} is the transaction price, α_k denotes spatial fixed effects, α_t denotes time fixed effects, R_i is a dummy variable that indicates that a home is at flood risk according to ISPRA maps, and $\mathbf{X}_i$ is a vector of property characteristics. We now discuss each of these terms one by one.

In our formulation, α_k captures all time-invariant home price differences due to being located in spatial unit k . We consider different definitions of spatial units, at different spatial aggregation levels. The widest definition of k is the municipality, with a median area of 22 km². Especially for large municipalities, it is unlikely that this fixed effect captures enough

difference in location, so we consider two further narrower definitions of α_k . These are the OMI microzone and the census tract, respectively featuring a median area of 1.5 km² and 0.03km².²² The inclusion of the α_k term completely captures the spatial correlation existing in our data, see Supplementary Section B.2. This confirms that our hedonic regression approach is adequate and spatial econometric approaches are not necessary.

Moreover, the fixed effect α_t is meant to capture price trends not linked to flood risk. To accommodate for potentially diverging trends across Italian provinces, we build fixed effects by considering the interaction of year and province indicators. We also consider monthly fixed effects to take seasonality into account.

Our specification of controls is completed with the vector $\mathbf{X}_i$ subsuming the home characteristics available in our dataset: floor, surface area, energy class, cadastral class, building year, and indicators for the presence of a garage, an annex and air conditioning.²³

As we control for most confounders relating to the temporal and spatial dimension as well as most home features, we argue that β captures the effect on home prices of being located in a flood prone area.

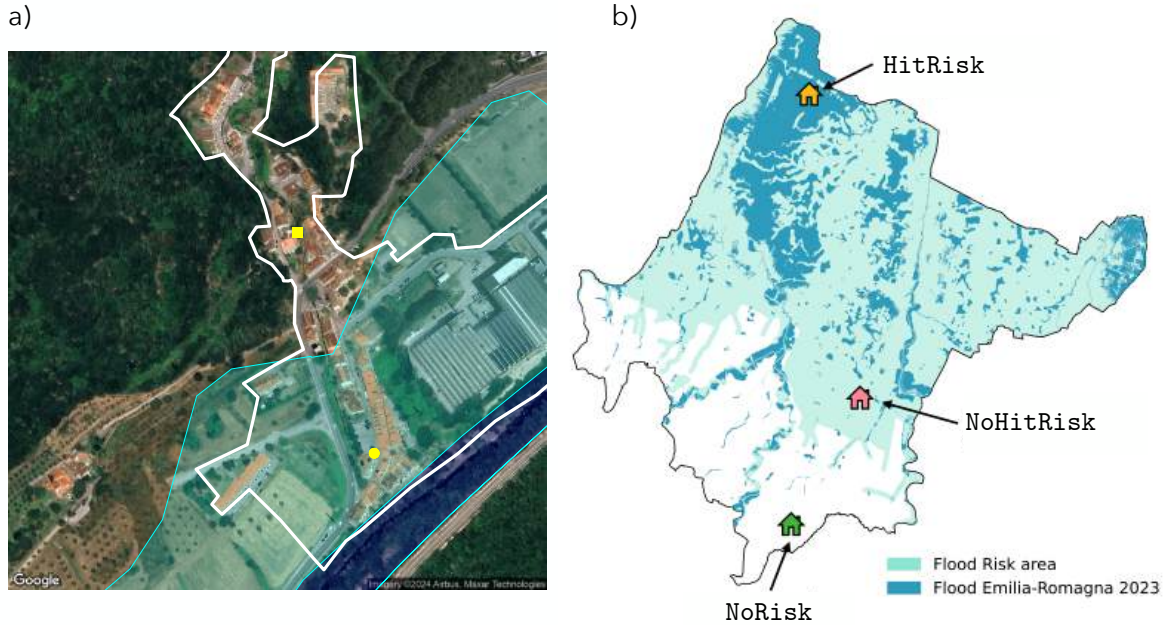


Figure 2: Graphical description of the regression framework. Panel a): An example to illustrate our identification strategy for homes at flood risk. We show two homes transacted in our dataset in yellow (after adding some noise to their positions to preserve privacy) in the village of Usella, Prato. We also show the boundaries of the census tract in white and the ISPRA risk areas in shades of blue (dark blue: high and medium risk, light blue: low risk). The home shown as a square at the top is not classified as at risk, while the other home shown as a circle is classified as at risk because it is close to the river. We argue that the residual difference in price between these two properties, after controlling for all other characteristics, is due to being located in the flood zone. Panel b): Graphical description of **HitRisk** and **NoHitRisk** homes considering the municipality of Forlì, one the cities affected by the Emilia-Romagna flood in 2023.

²²The OMI microzone is the standard spatial unit of the *Osservatorio del Mercato Immobiliare* (OMI), the housing market observatory of the Italian Tax Office. It roughly corresponds to a neighborhood, although in rural areas it may contain larger portions of territory. Instead, census tracts correspond to blocks in cities and to villages (“frazioni”) in rural areas. We use the latest available census tracts, namely from the 2011 census.

²³We build missing value dummies for most of these variables, so as to include data with missing values in the regression.

Figure 2a illustrates our identification strategy. As an example, we consider a village in the province of Prato, sided by the Bisenzio river. This river frequently floods, including most recently in November 2023, when it caused major damages to residential and industrial structures in the province of Prato (last line of Table A2, Copernicus code EMSR705). Let us suppose that the characteristics of the two homes indicated in yellow are the same. Our spatial fixed effect, which in the most fine-grained specification corresponds to the census tract whose perimeter is shown in white, only includes the village. Thus, it is likely to absorb most differences in price for homes that are at most 500 meters from each other. This way, the coefficient on R_i should only capture the exposition to flood risk.

3.2 Effect of flood events

To estimate the impact that specific flood events had on home price (research question 1) we built on Equation (1) to create a hedonic difference-in-difference specification. Following Ortega and Taşpınar (2018), we disaggregated the R_i indicator into two categories, homes in a risky area that were hit by the flood (**HitRisk**) and homes that were not hit but are located in a risk zone of an affected municipality, and so can be considered a *near-miss* (**NoHitRisk**).²⁴ This distinction is exemplified in Figure 2b.

Since we aimed at estimating the price difference for homes **HitRisk** and **NoHitRisk** sold before and after a flood event (e.g. Emilia-Romagna flood of May 2023), we incorporated a temporal component (T_i) to differentiate between homes sold before and after the flood. Thus, our diff-in-diff specification considers the following model:

$$\log P_{ikt} = \alpha_k + \alpha_t + \beta_1 \cdot \text{HitRisk}_i + \beta_2 \cdot \text{NoHitRisk}_i + \delta_1 \cdot T_i \times \text{HitRisk}_i + \delta_2 \cdot T_i \times \text{NoHitRisk}_i + \gamma' \mathbf{X}_i + \epsilon_{ikt}, \quad (2)$$

The categorical variable T reports the binned time of the transaction compared to the flood, using the period before the flood as a reference. In this specification, the coefficients that we are mostly interested in are the ones on the interaction terms, namely δ_1 and δ_2 , capturing, respectively, the additional reduction in prices for homes at risk in the flood affected area, and the additional reduction for homes not directly hit by the flood but still considered at risk. In short, δ_1 captures the direct effect due to being hit, whereas δ_2 captures the indirect effect due to the beliefs of the market.

Finally, in Equation (2) the terms β_1 and β_2 capture the baseline risk for being located in a risk area. These two coefficients should thus be similar to one another (because the distinction between homes that were hit and not hit is already considered in the interactions) and should be similar to β in Equation (1).

3.3 Spatially disaggregated impact of flood risk

Our second research question aims at exploring the influence of flood risk (R_i) on home prices across all the national territory. Our baseline equation, Equation (1), is the starting point for this analysis. However, by interacting the indicator R_i with another categorical/binary variable we can provide more insights about the heterogeneity beyond the global coefficient β .

First, we dis-aggregate the effects of buying a home at risk by frequency of past flood events, i.e., what we call historical memory. To this aim, we interact the risk indicator with a categorical indicator **HistMem** detailing the home region's historical level of exposure to floods: frequently

²⁴We experimented alternative ways to characterize near-misses, including distance thresholds, with similar results. Our preferred assumption is the municipality because it does not require specifying a hard threshold for being considered a near-miss or not.

flooded, moderately flooded or rarely flooded (see Section 2.4 for a more detailed definition). This results in the following equation

$$\log P_{ikt} = \alpha_k + \alpha_t + \rho R_i \times \text{HistMem}_i + \gamma' \mathbf{X}_i + \epsilon_{ikt}. \quad (3)$$

Next, at a more granular level, we also distinguish across specific regions, replacing the **HistMem** categorical variable by a region variable.

3.4 Disaggregation by socio-economic groups

To explore how buyers from different socio-economic groups may behave differently when buying homes at risk of flooding (research question 3), we build on the approach presented in Section 3.3 and focus on age and income as demographic variables.

We encoded the age of the buyer in the variable **Age** with two categories: **Young** and **NotYoung**. This is based on whether the mortgage was a *mutuo giovani* (Young Buyers' Mortgage) or not. Transactions financed by the *mutuo giovani* are associated with buyers under 36 with an adjusted annual income lower than 40,000€. We assumed all mortgages not labeled in the data as *mutuo giovani* to refer to **NotYoung** buyers.

For the level of income of the buyers, we divided buyers into 3 levels of income (high, medium, and low) based on the three terciles of the income distribution for each region. We define income levels by region because average income is widely different across Northern and Southern regions, and we do want this variable to capture relative income within regions.

We focus on two sub-research questions:

Question 3a: what discount do different groups of buyers obtain? By performing the triple interaction between the R_i indicator, the **HistMem** and **Age** variables, we can estimate whether young or more experienced buyers living in regions with different levels of historical flood exposure obtain different price reductions when buying homes at risk. The equation used for this analysis is the following:

$$\log P_{ikt} = \alpha_k + \alpha_t + \tau R_i \times \text{HistMem}_i \times \text{Age}_i + I + \gamma' \mathbf{X}_i + \epsilon_{ikt}. \quad (4)$$

In the above equation, the key coefficient is τ , capturing the effect of risk on home prices for each combination of age and historical flood frequency. In this regression we also included the term I to control for buyers' income, accounting for income differences between **Young** and **NotYoung** buyers (12%).

To further disaggregate this effect by the income levels of the buyer, we used the following variation of Equation (4):

$$\log P_{ikt} = \alpha_k + \alpha_t + \psi R_i \times \text{HistMem}_i \times \text{Age}_i \times \text{IncomeLevel}_i + I + \gamma' \mathbf{X}_i + \epsilon_{ikt} \quad (5)$$

where the coefficient ψ indicates the disaggregated effect of age, level of income, and historical memory, on the price of homes at risk. Thus, it makes it possible to distinguish the reduction obtained by, e.g., low-income and high-income buyers that are both young.

Question 3b: what is the income of the buyers moving to at-risk areas? Apart from the discount they obtain, low-income or high-income buyers may be over-represented in at-risk areas. To explore this, we follow Zivin et al. (2023) and estimate the following regression:

$$\log I_{ikt} = \alpha_k + \alpha_t + \beta R_i + \omega \text{Age}_i + \gamma' \mathbf{X}_i + \epsilon_{ikt}, \quad (6)$$

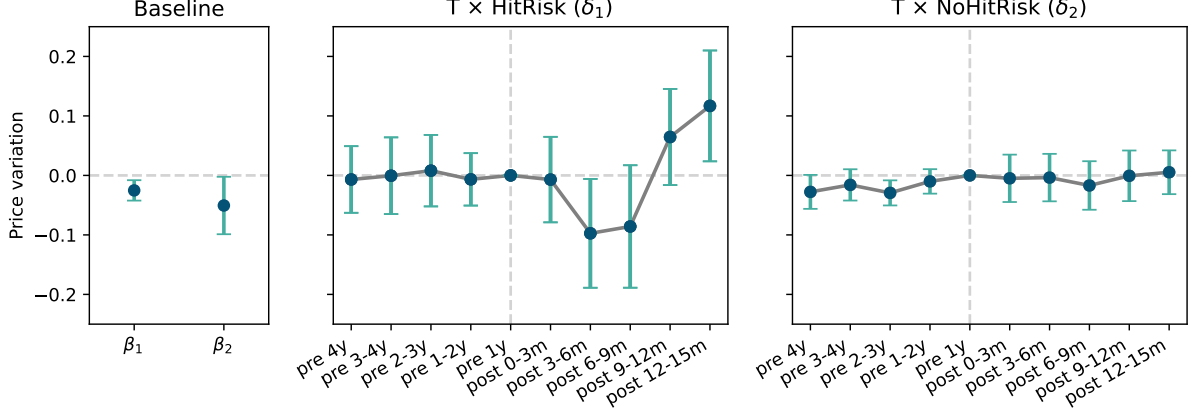


Figure 3: Time evolution of the home price variation for the 2023 Emilia-Romagna flood. Referring to Equation (2), the left panel reports the coefficients β_1 and β_2 , the central and right panels show the interaction coefficients δ_1 and δ_2 up to 15 months after the flood of Emilia-Romagna 2023. The temporal bins can be interpreted as follows. The labels *pre* and *post* identify whether a transaction has been completed before or after the considered flood event. The label *y* indicates years and the label *m* indicates months. We used the bin *pre 1y* as a reference. Each point represents the average value of the regression coefficient and the error bars indicate the 95% confidence intervals. $R^2 = 0.74$, observations = 35623.

where $\log I_{ikt}$ is the log of the household's income, Age_i is used as a dummy to control for young buyers (which have substantially lower income), and the other terms are equivalent to the ones described in Equation (1). In some specification, we also control for transaction price, in order to check if differences in income are mainly driven by cheaper homes or by alternative reasons.²⁵

4 Results

4.1 Specific floods only affect home prices in flooded areas

To assess the impact that specific floods had on home prices we first focus on the major flood that hit Italy in the last 20 years, namely the May 2023 flood in Emilia-Romagna (coded EMSN154 by Copernicus). Because this flood is very recent, we only have observations up to 15 months after the flood event. We divide the year following the event in quarters and consider the interactions of quarters with *HitRisk* and *NoHitRisk* dummies (Equation 2). For instance, the interaction between a sale in the first quarter after the event and *HitRisk* indicates the reduction in price for homes that were hit by the flood and sold within 3 months of the event.

Figure 3 shows the results. The left panel shows the baseline discount for being in a risk zone for homes that were hit (β_1) and that were not hit (β_2). These coefficients state that *HitRisk* and *NoHitRisk* homes sell –on average– around 3% less than homes in safe areas. Further details about this results will be provided in the next subsections.

Next, focusing on homes that were hit (central panel), we find no trend prior to the event, virtually no price reduction in the first 3 months after the event, and then a substantial reduction between 3 and 9 months from the event. In this period, homes sell at a further 10% less than the baseline 3% for homes at risk. However, in the last two quarters of observations, the prices actually increase compared to the baseline: homes that were hit by the flood sell at a 10% premium compared to homes that were not hit (and not in the risk zone). We interpret these results as follows. In the first three months after the event, prices did not decrease because

²⁵The price and income corrections implemented respectively in Equations (5) and (6), consider the variable with a logarithmic form.

many transactions reflect deals that were agreed upon before the flood (with possibly a pre-authorization on the mortgage amount by the bank). In the following months, the reductions in prices reflect the cost of the renovation work that falls on the buyer. Finally, 9 months after the event most renovation work has been carried out, and so the price increase reflects newly renovated homes²⁶ We think this is a reasonable timeline for renovation for the type of damage suffered by homes in this flood.

Turning to homes that were not hit, we find essentially no further reductions in prices after the event.²⁷ This is our most surprising result, in contrast with much of the prior literature. It suggests that people were already discounting being located in a flood zone (homes at risk were selling at a 3.5% discount even before the flood), and the actual event did not move their beliefs.

These results were also consistent when considering alternative parameter specifications, when analyzing only ground-floor apartments or independent houses, and when exploring other major flood events (see Supplementary Section B.1).

4.2 Homes at risk sell at lower price in frequently flooded regions (“historical memory”)

In the left panel of Figure 3, we showed that being located in an at-risk area leads to a lower home price, irrespective of the specific flood considered. To explore this question further, we estimate Equation (1) on our dataset aiming to provide a national-scale picture of flood risk across Italy.

Table 2 shows the results. We only report the effect of flood risk on price, but the other hedonic coefficients for Model 3 can be found in Table A6. In columns 1-3-5, we show the national average effect of flood risk on home prices, whereas columns 2-4-6 disaggregate this effect across frequently, moderately, and rarely flooded regions. Models 1-2 consider spatial fixed effects at the level of the municipality, while models 3-4 and 5-6 consider OMI microzone and census tract fixed effects, respectively. For each coefficient, we report the standard error and the significance level. In all cases, standard errors are clustered at the corresponding spatial level and we use the within estimator.²⁸

Considering the national effect (first row), Model 1, which assumes municipality-level fixed effects, shows a 2.9% price reduction for homes at risk, while Models 3 and 5, with OMI

²⁶We unfortunately do not have data on renovation status to test this hypothesis, but it could be tested in the future as ISP is increasingly collecting this information.

²⁷Before the event, the parallel trends assumption mostly holds except for the period between 2 and 3 years before the event, which however was the year of Covid-19, and this could bias the results. Furthermore, following Atreya et al. (2013) and Bin and Landry (2013), we also compared homes’ hedonic characteristics one year before and after the event (Table A3). We note a general agreement among the hedonic properties evaluated, especially referring to home size, location within a flood-risk area, cadastral code and the presence of garages and annexes.

²⁸We tested a few specifications for the independent variables, such as whether we should consider the logarithm of the surface area, floor number as a numeric variable or binned categories, or whether we should remove outliers. In the end, we adopted the following baseline specification: logarithmic home size (m²), binned home floor levels and removing the top and bottom 0.1% samples for all numeric variables. Supplementary Section B.2 reports the robustness analysis for alternative specifications and further tests, like the robustness analyses for the definition of the historical memory. All results shown are in line with those presented in the main text.

Table 2: Flood risk effect on home prices. For each spatial fixed effects, Models 1-3-5 report the effect of the risk on home prices estimated using Equation (1), while Models 2-4-6 dis-aggregate the effect of flood risk by the historical memory of the regions according to EM-DAT (2024), Equation (3). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Dep. var.: $\log(P)$					
Model id	1	2	3	4	5	6
Risk	-0.029*** (0.010)		-0.010*** (0.003)		-0.008** (0.003)	
Risk $\times$ Frequently flooded regions		-0.036*** (0.014)		-0.013*** (0.004)		-0.014*** (0.004)
Risk $\times$ Moderately flooded regions		-0.042*** (0.013)		-0.004 (0.006)		0.004 (0.007)
Risk $\times$ Rarely flooded regions		0.041*** (0.014)		0.003 (0.007)		0.001 (0.009)
Observations	552761		552761		552761	
R²	0.669		0.755		0.848	
Spatial fixed effects	Municipality		OMI zone		Census Tract	
Number of clusters	7203		20297		160630	
Clustered s.e.	✓		✓		✓	

microzone and census tract fixed effects, show a 1% and 0.8% depreciation, respectively.²⁹³⁰ Because results are very similar for OMI microzones and census tracts, from now on we consider OMI microzones as the baseline as they are the best trade-off between granularity and sample size.

Model 4 shows the disaggregation of flood risk effects across frequently, moderately, and rarely flooded regions. Notably, the statistically significant 1% price reduction at the national scale is mainly driven by the depreciation observed in frequently flooded regions, reaching 1.3%. The other coefficients for flood risk are not statistically significant and show an average 0.4% price reduction in moderately flooded regions and a 0.3% increment for homes at risk in rarely flooded regions. The leading role of frequently flooded regions in determining the impacts of flood risk on prices is robust considering more granular fixed effects (Model 6 of Table 2) and different data and definitions of regions' historical memory (we refer the reader to Supplementary Section B.2, Tables A7 and A8, for further details).

Further to analyzing the average effect across the entire national territory and the classifi-

²⁹It was unexpected that larger aggregation levels for spatial fixed effects would lead to stronger price reduction. In fact, we expected the opposite assuming that there are positive amenities associated with being located close to rivers (such as water views). These amenities would lead to a positive effect of flood risk on home prices (Bin and Kruse, 2006; Daniel et al., 2009a) when failed to be controlled for, such as when controlling for the municipality instead of more detailed OMI microzones or census tracts. Because we find a stronger reduction when controlling for the municipality, it is likely that in our sample there are on average no positive amenities for being located close to rivers. We think that this is reasonable given that we consider the entire national territory, including many rural areas.

³⁰As described in Section 2.2, ISPRA divides flood-prone areas into low, medium, and high risk areas, but this classification is often inconsistent across regions. Table A5 disaggregates the effect in first row of Table 2 by risk level. In all cases, being at high risk has no statistically significant effect on prices, while being at medium or low risk has a negative and statistically significant effect on prices (but whether this effect is larger in medium or low risk areas depends on the considered spatial fixed effects). We interpret these results as evidence that the risk levels are not very informative due to idiosyncratic definitions by different river basin authorities, while an indicator of risk (irrespective of the risk level) is more likely to be informative. Further details can be found in Supplementary Section B.2.

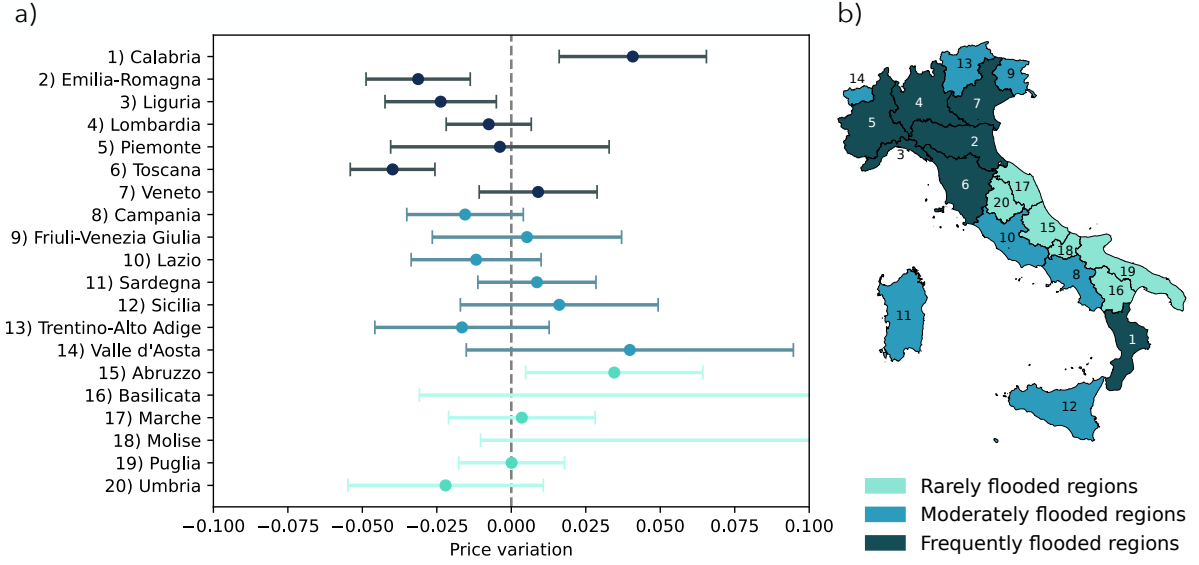


Figure 4: Effect of being at flood risk on home price, disaggregated by region. Panel a): The dots show the point estimate of the coefficients, while the error bars show 95% confidence intervals. The color code reports the region classification in frequently, moderately, and rarely flooded regions. For graphical purposes, we limited the x-axis between -0.1 and 0.1 (although not fully shown, the average price variations for Molise and Basilicata are 0.19 and 0.15, respectively). Panel b): Map of the Italian regions color-coded according to the historical memory classification. Northern regions: Piemonte, Valle d'Aosta, Liguria, Lombardia, Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia, and Emilia-Romagna. Center regions: Toscana, Umbria, Marche, Lazio, Abruzzo, and Molise. Southern and Islands regions: Campania, Puglia, Basilicata, Calabria, Sicilia, and Sardegna.

cation of historical memory, we also look at differential effects across regions. Focusing on the same specification as Model 3 of Table 2, and interacting the risk indicator with region dummies, Figure 4 shows that the effect of risk on prices varies a lot across regions. In Emilia-Romagna, Liguria, and Toscana, homes at risk sell at a substantially higher discount than the national average (3.5%, 2.5% and 4%, respectively, compared to 1%), whereas in Abruzzo and Calabria they sell at a premium (especially for Calabria, this may reflect an idiosyncratic definition of risk in ISPRA maps, see Section 2.2).³¹ In most other regions the effects are not statistically significant at the 5% level, although regions in the North and Center are more likely to show negative effects than regions in the South and Islands. Moreover, four out of seven frequently flooded regions present price reduction due to flood risk, while rarely flooded regions exhibit price increments (5/6). We do not see a clear trend in moderately flooded regions.

4.3 Differential effects across socio-economic groups

Experienced and higher-income buyers obtain stronger price reductions

The results presented in the previous sections support our hypothesis that flood-risk driven home price reductions are due to the historical memory of previous floods and not to specific events. Here, we investigate whether buyers with different socio-economic status (i.e., age and income) obtain different discounts when buying at-risk homes.

³¹Interestingly, the average flood risk coefficient for Emilia-Romagna agrees with β_1 and β_2 retrieved using the diff-in-diff set-up (Figure A4). These two coefficients do not need to correspond exactly to the coefficient on Emilia-Romagna in Figure 4 because they only refer to the affected municipalities and not to the entire region. However, their agreement enforces our results both for the hedonic-regression and diff-in-diff analyses.

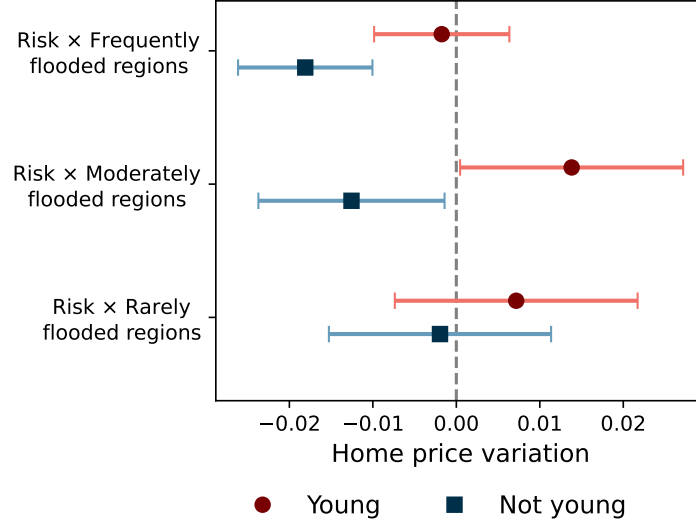


Figure 5: Flood risk effect on home prices disaggregated across historical memory regions (rows) and mortgage applicant's age, Equation (4). The age is proxied considering whether the transaction is financed by a *mutuo giovani* (red dot) or not (blue square).

We start by analyzing the differences in home prices considering buyers' age (as proxied by under-36 *mutuo giovani*, see Section 3.4). Figure 5 shows the discount obtained by **Young** and **NotYoung** buyers when purchasing homes at risk, distinguishing between rarely, moderately and frequently flooded regions. In rarely flooded regions, **Young** and **NotYoung** buyers do not get any statistically significant price change for homes in flood-prone areas. As flood frequency increases, **NotYoung** buyers exhibit higher and higher price reductions, reaching 2% in frequently flooded regions. Conversely, we do not find a clear trend for **Young** buyers: they buy homes in risky areas at a premium in moderately flooded regions but no significant effect is observed in frequently flooded regions. We interpret this result as evidence that experienced buyers (which might have witnessed several flood events in their lifetime) pay more attention to flood risk while purchasing a home.

Building on the results presented in Figure 5, we deepen our analysis by considering also the income class of the buyers, Equation (5). Figure 6 summarizes our findings. Focusing on the **Young** buyers (left panel), only high income buyers in moderately and frequently flooded regions obtain a statistically significant price reduction (around 2%) when purchasing a home in areas at risk. Instead, low- and medium-income buyers purchase homes in flood-prone areas at a premium. Instead, **NotYoung** buyers (right panel) in all income classes obtain a significant discount (around 1.5%) for at-risk homes in frequently flooded regions. This behavior holds for the moderately flooded regions when medium and high income buyers are considered. In rarely flooded regions, instead, no buyers of any age or income class exhibit significant price changes when purchasing at-risk properties. While these results could be explained by linking income to education (Bradt et al., 2021), we leave the exploration of this hypothesis to future work since it requires additional data (such as precise the education level of the buyers) that we lack.

Low-income buyers are more likely to move to at-risk areas

Having shown that buyers' income plays a key role in determining the effect of flood risk on home prices, we now want to check if households that buy homes in at-risk areas have lower or higher incomes than households purchasing homes elsewhere. Households that buy in at-risk

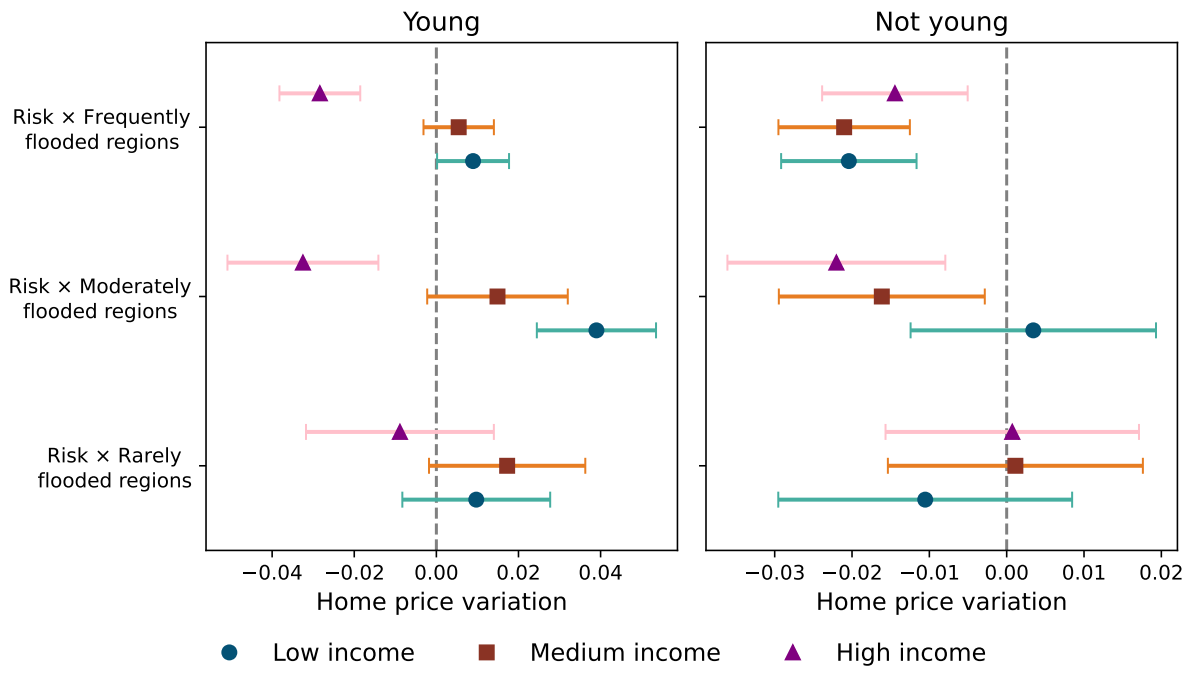


Figure 6: Flood risk effect on home prices disaggregated across flood frequency regions, mortgage applicant age, and income class of the buyer, Equation (5). The left panel shows the home price variation due to flood risk for transactions financed by the *mutuo giovani*, and disaggregated by our classification of historical memory and buyers' income class. The right panel reports the same analysis for transaction financed by a standard mortgage. The buyers' income class is estimated considering the top, middle and bottom terciles of the income distribution within the same region (see Section 3.4 for further details).

Table 3: Flood risk effect on buyers' incomes, Equation (6). Models 1-2 report the effect of the risk on buyers' income at the national scale (Model 1) and disaggregated across regions with different historical memory (Model 2). Models 3-4 show the same analyses, including the logarithm of the home sale price as an independent variable. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Dep. var.: $\log(I)$			
Model id	1	2	3	4
Price correction			✓	✓
Risk	-0.009*** (0.003)		-0.005* (0.003)	
Risk $\times$ Frequently flooded regions		-0.013*** (0.004)		-0.008** (0.003)
Risk $\times$ Moderately flooded regions		-0.004 (0.006)		-0.003 (0.006)
Risk $\times$ Rarely flooded regions		0.009 (0.008)		0.007 (0.008)
Observations	552761		552761	
R²	0.287		0.326	
Spatial fixed effects	OMI zone		OMI zone	
Number of clusters	20297		20297	
Clustered s.e.	✓		✓	

areas have a mean monthly income of 2,898€, while households that buy elsewhere have a mean monthly income of 2,953€ (1.9% larger). However, this unconditional comparison is likely to be biased if at-risk areas are concentrated in the richest parts of Italy, such as the Po Valley.

Table 3 reports the effect of flood risk on buyers' income, estimated following Equation (6). We study the risk coefficient on incomes, even including the transaction price as an independent variable. If including the price as a dependent variable makes any effect on income non-significant, it suggests that lower prices are sufficient to explain why lower-income households sort into at-risk areas. Vice versa, other factors such as lack of information on flood risk for lower-income households may be at play.

Models 1-2 do not consider the price as an independent variable. On average across the whole Italian territory (Model 1), people buying a home in a flood-risk area have an income 0.9% lower than people living in non-risk areas. Model 2 highlights that buyers' income differences are larger than the national average (and significant) for the frequently flooded regions while non-statistically significant income variation are observed in moderately and rarely flooded regions. Once the price correction is applied (Models 3-4), the Italian average risk coefficient (Model 3) increases to 0.5% and remains statistically significant at 10% level. Disaggregating the national average according to regions' historical risk classification (Model 4), we note that people buying homes in risk-prone areas are 0.8% poorer than those purchasing homes in safe zones in frequently flooded regions. This result suggests that people with lower income mostly buy homes at risk because they are cheaper, but other factors related to the flood risk contribute to explaining the income differences.

5 Conclusion

This is the first work that systematically analyzes the impact of flood risk on home prices throughout Italy. Our study reveals three key findings. First, unlike much of the existing literature, we find that even the largest recent flood in Italy—the 2023 Emilia-Romagna flood—did not lead to additional price declines for at-risk homes that were not directly hit. Second, while homes in flood-prone areas generally sell at a small discount of about 1%, this penalty is concentrated in regions with frequent flooding, where it increases up to 4%. Third, younger buyers, who have experienced fewer floods in their lifetime, do not obtain a discount when purchasing at-risk properties, whereas more experienced buyers do. Moreover, lower-income buyers are more likely to settle in flood-prone areas, particularly in the most frequently flooded regions, suggesting a socioeconomic sorting effect.

To make sense of these findings, we hypothesize that it is the repeated exposure to floods, rather than isolated events, what ultimately leads to the capitalization of flood risk in home prices. We argue that, with no institutional requirements for flood risk disclosure or insurance that encourages the sharing of information regarding flood risk, households rely on the *historical memory* of major floods to identify the most at-risk areas. This explains why price penalties emerge only in regions with frequent floods and why experienced buyers—but not younger ones—obtain price discounts for at-risk properties. Finally, we find that lower-income buyers are more likely to settle in flood-prone areas, highlighting potential socioeconomic disparities in climate risk exposure.

Thus, our paper contributes to kick off the discussion on how to enhance public awareness on home flood risk, prompting the government and private sector to design effective policies. These could include making flood risk disclosure mandatory, subsidizing flood insurance programs, and offering incentives for homeowners to invest in flood resilience measures. Future research should address how effective these policies are in making buyers consider flood risk in their purchasing decisions and mitigating the clustering of lower-income households in flood-prone areas.

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A Intesa Sanpaolo data

A.1 A more detailed description

Here we describe in more detail the variables available in each of the two ISP datasets provided.³² We first give an intuitive description of the content of the variable, then indicate its type and finally, when the variable is categorical or binary, list its main categories.

In the **Contracts** dataset the `id` variable is the unique mortgage contract code. The other relevant variables are:

- Type of mortgage applicant; categorical; with levels: single physical person, joint application by two physical persons, juridical person.
- Application status; binary; whether the mortgage has been issued, or the application is still under review.
- Application type; binary; whether the application is for a mortgage or for a loan for building a home with the goal of reselling it to final consumers.
- Auction flag; binary; whether the housing unit being given as collateral is sold as a foreclosure auction.
- Goal of the mortgage; categorical; with levels: purchase of 1st or 2nd home, subrogation of a previous mortgage from a bank outside the ISP group, renovation, etc.
- Issuance date; date.
- *Mutuo giovani*; binary, whether the mortgage has incentives for young applicants.
- Date of construction of the building; numeric (year).
- Transaction price; numeric (euros).
- Applicant income; numeric (euros). It is the income of the applicant, or the sum of the incomes of the applicants when the application is joint.
- Latitude and longitude of the main housing unit given as collateral; numeric.

In the **Cadaster** dataset the `id` variable is the unique cadastral unit. The other relevant variables are:

- Floor area; numeric (m^2)
- Cadastral category; categorical. The cadastral code is given by the Italian tax agency to measure the taxable value of housing units and distinguishes between apartment, detached housing unit, garage, basement, etc.³³
- Energy class, following the 2015 European Union Energy Performance of Buildings Directive; categorical; with levels: from A4 (the highest) to G (the lowest).

³²We only describe the variables used in this paper, however, these datasets contain several other variables such as information on the conditions of each mortgage.

³³The meaning of some of the residential cadastral units, which are the ones most relevant for our study, is the following. A01: Luxury residences; A02: Standard residences; A03: Low-cost residences; A04: Working-class residences; A05: Substandard residences; A06: Rural residences; A07: Small villas; A08: Villas; A09: Castles, artistic and historical palaces; A10: Offices or private practices; A11: Typical local residences.

- Air conditioned area: numeric (m^2).
- Floor: categorical.

We processed and cleaned these data, to create a single database where the unit is the mortgage contract and the housing unit given as collateral combines information from all linked cadastral units. In the following, we list a few steps:

1. We built a purchase flag that takes value one when the goal of the mortgage is to purchase a housing unit (as opposed to, e.g., subrogation or renovation). Then we discarded the mortgages not related to purchases.
2. We discarded the mortgages with missing coordinates, or coordinates located outside Italy, that were given to juridical persons, that are still under review and that were issued to construct housing units with the goal of reselling them.
3. We set as missing values the values of floor area and transaction price that are zero.
4. We summed the floor areas of the residential cadastral units that were given as collateral for the mortgage. This excludes, for instance, the basement or garage of a building, but it sums the floor area of, for example, two apartments that were independent cadastral units at the time of purchase but then are joined following renovation work.
5. We created a garage flag that takes value one if at least one cadastral unit given as collateral is C06, i.e. a garage or a private parking space.
6. We created an additional annex flag that takes value one if at least one cadastral unit given as collateral is C02, i.e. a basement, an attic, or similar.
7. We associated to each mortgage contract the energy class of the cadastral unit with the highest value from the **Cadaster** dataset.
8. We built an air conditioning flag that takes value one when the air-conditioned area is larger than zero.
9. We took the raw data on the floor, selected the floor of the cadastral unit with the highest value, and manually made the values of the floor consistent with one another.³⁴ Since some housing units are divided among multiple floors, we created a flag that takes the value one if it is on multiple floors, and a numeric variable for the floor that takes the value of the minimum floor in the case of multi-floor apartments.

Table A1: Summary statistics of categorical variables. We show the top-10 most frequent categories. The share across all samples is reported among brackets.

Municipality of Property	
Roma	32830 (5.94%)
Milano	24206 (4.38%)
Torino	12658 (2.29%)
Continued on next page	

³⁴For example we set “T”, “TERRA”, “Terra”, “t”, “PIANO TERRA”, “rialzato”, “RIALZATO”, “PIANO RIALZATO”, “rialzat”, “T-S1” all equal to the ground floor.

Table A1: Summary statistics of categorical variables. We show the top-10 most frequent categories. The share across all samples is reported among brackets.

Genova	9716 (1.76%)
Napoli	7222 (1.31%)
Firenze	7091 (1.28%)
Bologna	5806 (1.05%)
Bari	5663 (1.02%)
Palermo	3777 (0.68%)
Venezia	3586 (0.65%)
Missing	0 (0%)
Cadastral code	
A02: standard residences	267974 (48.48%)
A03: low-cost residences	202693 (36.67%)
A07: small villas	43614 (7.89%)
A04: working-class residences	37118 (6.71%)
A05: substandard residences	779 (0.14%)
A01: luxury residences	271 (0.05%)
A08: villas	125 (0.02%)
A10: offices or private practices	97 (0.018%)
A06: rural residences	76 (0.013%)
A11: typical local residences	12 (0.002%)
Missing	0 (0%)
Floor (categorical)	
1	28423 (5.14%)
0	24600 (4.45%)
2	18175 (3.29%)
3	10726 (1.94%)
4	6087 (1.10%)
0-1	5905 (1.07%)
5	3635 (0.66%)
6	2133 (0.39%)
0-1-2	1345 (0.24%)
Missing	447545 (80.97%)
Flag multiple floors	
No	96069 (17.38%)
Yes	9147 (1.65%)
Missing	447545 (80.97%)
Garage Flag (Indicates if the property includes a garage)	
Yes	282883 (51.18%)
No	269878 (48.82%)
Missing	0 (0%)
Additional Basement or Attic Flag (annex)	
No	473369 (85.64%)
Yes	79392 (14.36%)
Missing	0 (0%)
Energy Efficiency Class	

Continued on next page

Table A1: Summary statistics of categorical variables. We show the top-10 most frequent categories. The share across all samples is reported among brackets.

G	142384 (25.76%)
F	69803 (12.63%)
E	52573 (9.51%)
D	37175 (6.73%)
A4	21009 (3.80%)
C	19990 (3.62%)
B	17037 (3.08%)
A2	12844 (2.32%)
A1	8736 (1.58%)
Missing	162907 (29.47%)
Air Conditioning Flag (Indicates if the property has air conditioning)	
No	177367 (32.09%)
Yes	41903 (7.58%)
Missing	333491 (60.33%)
Flood risk	
No risk	425753 (77%)
Low risk	63908 (11%)
Medium risk	42994 (8%)
High risk	20106 (4%)
Missing	0 (0%)

A.2 Are the data representative of the Italian housing market?

We want to establish if the sample of mortgages issued by ISP is representative of the Italian housing market. We compare the ISP dataset to multiple public data sources at various spatial and temporal aggregation scales, focusing on the number of transactions, prices and incomes. Our main data sources for comparison are from *Osservatorio del Mercato Immobiliare* (OMI), the housing market observatory of the Italian Tax Office, and the *Ministero dell'Economia e delle Finanze* (MEF), the ministry of economics and finance. OMI provides information on the number of transactions, disaggregated by municipality and home size. OMI also provides information on prices, disaggregated by cadastral category (apartment, independent house, etc.) and OMI microzone, roughly corresponding to a neighborhood. MEF provides, by income class³⁵, number of individuals and total income, yearly at municipality level.

We first check if the number of transactions in ISP data aligns with OMI. Note that ISP data report information on the transactions connected to a mortgage, so they only represent the transactions of ISP clients who obtained a loan. By contrast, OMI data are retrieved from notary deeds and so describe the universe of transactions in Italy.³⁶ At the national scale, our data make up 10.7% of transactions across the Italian housing market; this percentage rises to 14.4% when we evaluate only the mortgage-financed transactions.³⁷

³⁵Total income is divided into eight income groups: 'less than zero euros', 'from 0 to 10,000 euros', 'from 10,000 to 15,000 euros', 'from 15,000 to 26,000 euros', 'from 26,000 to 55,000 euros', 'from 55,000 to 75,000 euros', 'from 75,000 to 120,000 euros', 'more than 120,000 euros'.

³⁶OMI provides the normalized number of transactions (NTNs), i.e., the number of transactions scaled by the fraction of the property that has been transacted at the municipality scale, also considering the home size (square meters, m²).

³⁷Between 2016 and 2022 (the last year for which we have OMI data), our dataset records 465,037 mortgages given to purchase a housing unit in Italy. In the same period, OMI declares 4,336,331 transactions, giving a

We also want to identify potential biases in the size distribution of the homes bought with an ISP mortgage with respect to the whole distribution in the Italian market. The OMI dataset reports the size of the housing units using five different size ranges: $0 < m^2 < 50$, $50 < m^2 < 85$, $85 < m^2 < 115$, $115 < m^2 < 145$ and $m^2 > 145$. To compare both datasets, we aggregate ISP data to the OMI home size ranges and introduce the variable $r(c)$ that describes the share of transactions in each home size range. Mathematically speaking, $r(c)$ is

$$r(c) = \frac{n(c)}{\sum_{c'} n(c')}, \quad (7)$$

where $n(c)$ is the number of transactions in the home size range c . Using Equation 7, we compute $r(c)$ for both ISP and OMI data.

Figure A1 shows the transaction shares grouped by provinces and home size ranges.³⁸ We observe a correlation coefficient of 0.94 (i.e., strong correlation) between the datasets. We also note that smaller housing units tend to have a larger deviation from the identity line, in the sense that ISP data seem under-represented. When looking at larger housing units, the agreement of the OMI and ISP data increases (the points align on the identity line). This is reasonable, as it is more likely to apply for a mortgage to afford large homes.

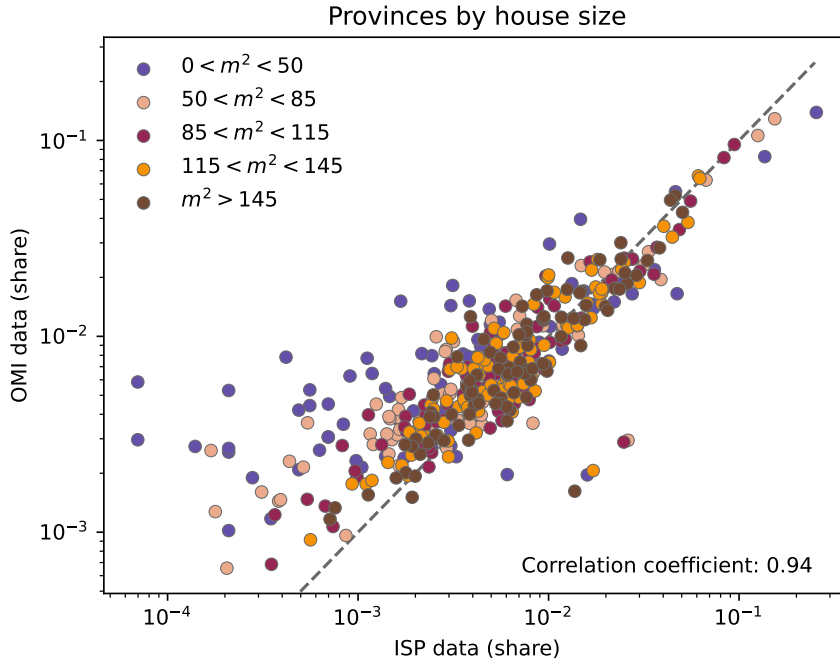


Figure A1: Comparison of transaction shares between ISP and OMI data for provinces and home size ranges. Each dot represents a province considering a specific home size range. The dashed gray line represents the identity line, where ISP and OMI datasets present equal shares. Both axes are on a logarithmic scale.

We now check if the prices computed from ISP data are similar to the prices that are given in the administrative data by OMI. For a combination of OMI microzone, maintenance status

10.7% share. The share of mortgage-financed transactions comes from the Bank of Italy survey on the housing market (<https://www.bancaditalia.it/pubblicazioni/sondaggio-abitazioni/index.html>). Taking a simple mean across all quarterly surveys between 2016 and 2023, the share of transactions financed by a mortgage is 74.5%, leading to our 14.4% estimate on the share of ISP mortgages.

³⁸We computed Equation (7) for all provinces p and size ranges c (i.e., $r(p, c) = n(p, c) / \sum_{c'} n(p, c')$) for the ISP and OMI datasets.

and cadastral category, OMI provides an estimate of the maximum and minimum price per m^2 . We consider the midpoint of this interval as the mean home price, and focus on the normal maintenance status, which makes up 88% of the data. We compute the mean price over the 2016-2023 period, for each combination of OMI microzone and cadastral category. The prices are highly correlated in the two datasets (Pearson correlation coefficient: 0.77), although the correlation is not perfect.

We are also interested in comparing prices at the municipality level. The only way to know the OMI mean price per m^2 in a municipality is to compute the weighted mean of the price per m^2 in each OMI microzone in the municipality, where weights are the fraction of transactions in the OMI microzone compared to the municipality.³⁹ To increase the sample size, we pool across cadastral categories and years.

Figure A2 shows the comparison of the municipality- and time-averaged price per m^2 in ISP and OMI data. Compared to the result at the OMI microzones level, the correlation is much higher, suggesting that ISP data aggregated at the municipality level are highly representative of the Italian housing market. In fact, this figure suggests that ISP data may also be more informative, as the case of Milano suggests. For Milano, ISP data indicate a mean price of over 3500€ per m^2 , while OMI data indicate a price of slightly more than 1500€ per m^2 . Given that Milano is one of the most expensive cities in Italy, the ISP data are likely to be more accurate.

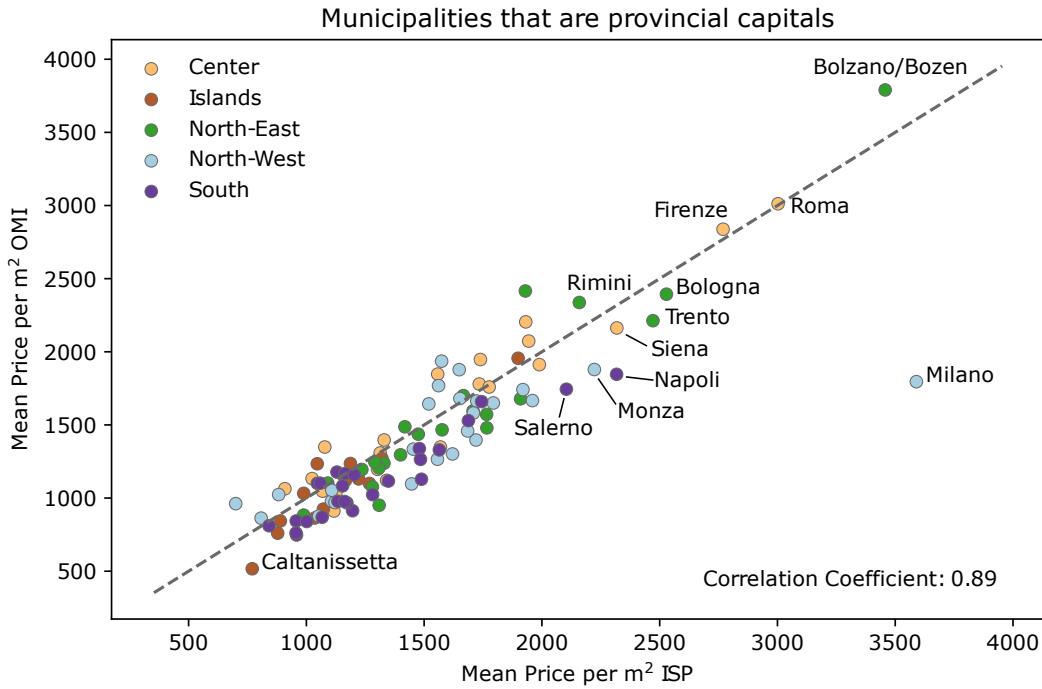


Figure A2: Comparison of prices per m^2 between ISP and OMI data. Each dot corresponds to a municipality that is a provincial capital and shows the mean price per m^2 over the 2016-2023 period. It is colored according to the macro-area of Italy the municipality belongs to. The dashed black line shows the identity line, where ISP and OMI price data are identical. We label a few municipalities and report the correlation coefficient between ISP and OMI data.

We finally check how the incomes declared by ISP mortgage applicants compare to data

³⁹Since OMI does not provide data on transactions at a level below the municipality, we use instead the fraction of housing units in each OMI microzone as a proxy. In turn, this is computed from census data by aggregating all the census tracts that correspond to any given OMI microzone.

on incomes made publicly available by MEF. We expect two substantial biases that may offset each other. On one hand, the population of ISP mortgage applicants is likely to have a higher income than the general population. On the other hand, ISP incomes are net while MEF incomes are gross.⁴⁰ Focusing on the provincial capitals, Figure A3 shows that there is a very strong correlation between ISP and MEF incomes (Pearson correlation: 0.82). Moreover, ISP incomes are slightly above MEF incomes, suggesting that the overestimation of incomes because ISP focuses on mortgage applicants rather than on the general population is slightly stronger than the underestimation of incomes due to ISP considering net rather than gross incomes.

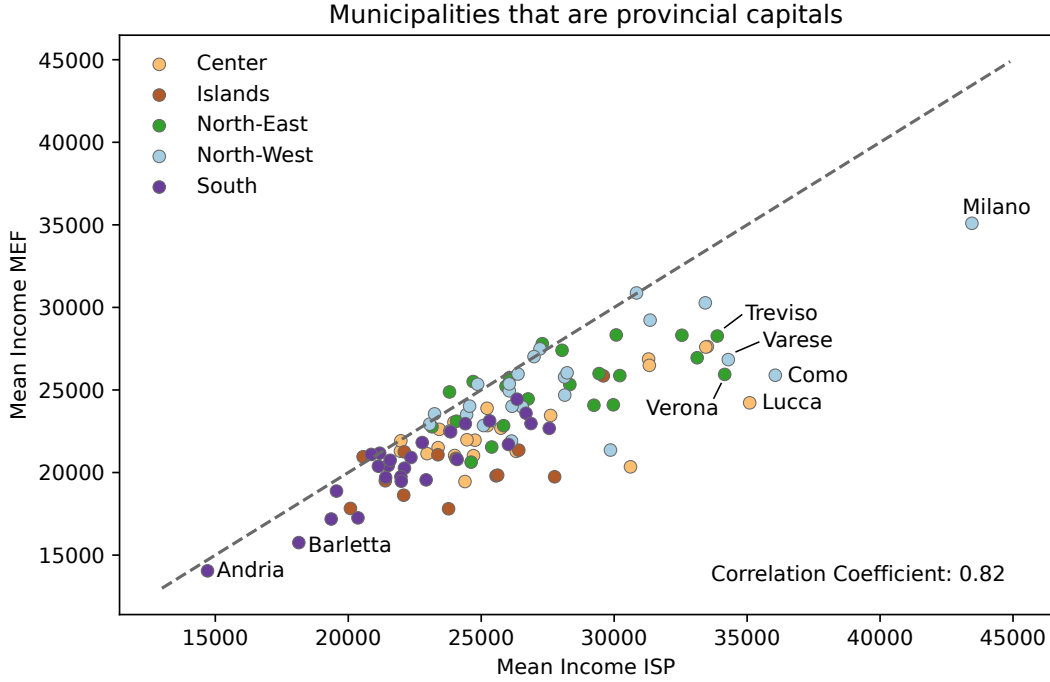


Figure A3: Comparison of incomes between ISP and MEF data. Each dot corresponds to a municipality that is a provincial capital and shows the mean income over the 2016-2021 period. It is colored according to the macro-area of Italy the municipality belongs to. The dashed black line shows the identity line, where ISP and MEF income data are identical. We label a few municipalities and report the correlation coefficient between ISP and MEF data.

B Supplementary results

B.1 Specific flood events

We evaluated the robustness of our findings on the insignificant effect of specific flood events in three ways: (i) we considered other regression specifications; (ii) we only focused on ground-floor apartments or independent houses, which are more likely to be damaged from floods than homes on upper floors; and (iii) we explore the changes in home prices after the second and third largest flood events in the studied period.

⁴⁰Moreover, MEF incomes always refer to individuals, whereas ISP incomes refer to individuals when the applicant is a single physical person and to households in case of joint applications. We address this issue by dividing applicant income by two in case of joint applications, as the vast majority of joint applications are filed by two physical persons.

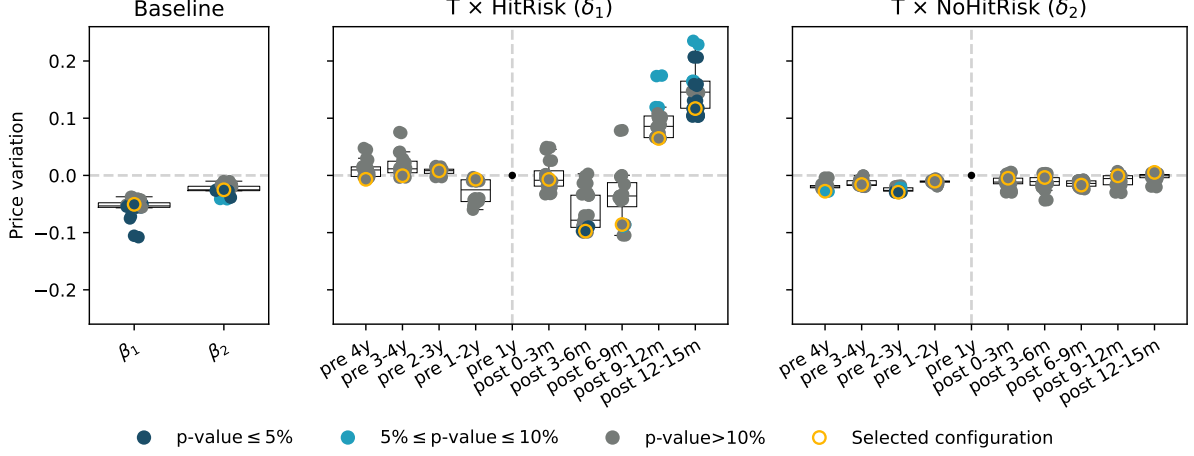


Figure A4: Home price variation across specifications using the Difference in Difference analyses (Equation 2) for the Emilia-Romagna flood. Each dot represents a parameter configuration, the color reports the statistical significance. The dots with the yellow edges identify the parameter configuration presented in the main text. R^2 [min, max] = [0.55, 0.86]; observations [min, max] = [35623, 35815].

Testing different regression specifications

We evaluate the robustness of our results by considering alternative specifications for the variables describing: home size (square meters, m^2), floor, and spatial fixed effects. Specifically, we consider three specifications for home size: the m^2 as reported in our data (indicated as linear), the logarithm of the home size (log), and ranges of home size (bins), coherently with the *Osservatorio del Mercato Immobiliare* (OMI), grouping homes by size ($m^2 < 50$, $50 < m^2 < 85$, $85 < m^2 < 115$, $115 < m^2 < 145$, and $m^2 > 145$). For the floor, our specifications include the floor as reported in the ISP data and a binned version, where all the homes with floor numbers larger or equal to 4 have been grouped. We consider also three possible spatial fixed effects in our regression, namely the census tract, the OMI microzone, and the municipality (Mun.). Moreover, we also evaluate the impact of including or removing data outliers in the regression outcomes. Specifically, when we remove the outliers from the data, we do not consider the top and bottom 0.1% of the data regarding the sale price, home size and household's income. Therefore, we investigate 36 different parameters configurations resulting from the possible specifications of home size, floor, spatial fixed effect, and outliers removal. The configuration reported in the main text considers the logarithm of home size, binned floor, fixed effects at OMI microzone, and outliers have been removed.

Figure A4 reports the robustness analysis for the 2023 Emilia-Romagna flood (Equation 2). In this case, we tested only OMI microzone and Census tract as spatial fixed effects, resulting in 24 parameter configurations.⁴¹ The results for the selected configuration agree with those for the other specifications, supporting the results reported in the main text.

Zoom in on ground-floor and independent homes

Figure A5 presents the results of estimating Equation (2) only on homes located on the ground floor or independent houses in the Emilia-Romagna region. In this case, our results lack statistical significance, probably due to the limited number of transactions for these housing units (less than a quarter of the total number of transactions in the Emilia-Romagna region). Despite this

⁴¹We omitted the municipality fixed effects because they are already considered in the definition of the “hit” municipalities and so including the fixed effects would lead to collinearity.

limit, we note that ground floor homes and independent houses in the **NoHitRisk** class and sold after the flood do not present a significant price variation, supporting our claim that individual flood events do not cause changes in the price dynamics for non-affected homes.

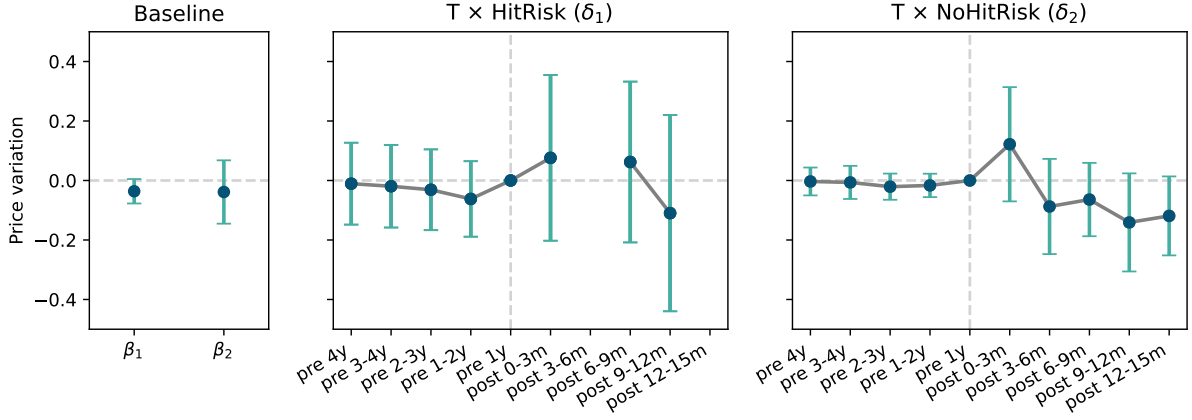


Figure A5: Time evolution of the home price variation for the 2023 Emilia-Romagna flood, considering only transactions related to ground-floor apartments or independent houses. Referring to Equation (2), the left panel reports the coefficients β_1 and β_2 , the central and right panels show the interaction coefficients δ_1 and δ_2 up to 15 months after the flood of Emilia-Romagna 2023. Each point represents the average value of the regression coefficient and the error bars indicate the 95% confidence intervals, considering the spatial fixed effect at the OMI microzone level. Number of **HitRisk** homes sold before the 2023 Emilia-Romagna flood: 451; 10 homes were sold after the event. For the **NoHitRisk** homes, 1999 homes were sold before the event and 80 after the flood (the total number of homes at ground-floor or villas in the affected municipalities is 3276). We had no data for the *post 3-6m* bin for directly hit homes. $R^2 = 0.74$, observations = 8634.

Other floods events

Aiming to extend our results on the 2023 Emilia-Romagna flood to the entire Italian housing market, we repeated the analysis considering the 2016 Piemonte-Liguria (code EMSR192) and 2023 Toscana (EMSR705) floods. As reported in Table A2, the considered events are the only two other floods –according to Copernicus– that had a substantial impact on the homes in our dataset. The Piemonte-Liguria and Toscana floods involve only few homes that were hit and sold after the events (28 and 4, respectively), suggesting that estimates would be very noisy. On top of that, we are particularly interested in the impact on homes that were not directly hit, for which we have a set of transactions comparable to the Emilia-Romagna flood (EMSN154). In fact, 3968 **NoHitRisk** homes were sold after the Piemonte-Liguria flood and 1810 from the flood in Toscana in 2023 (for the 2023 Emilia-Romagna event, EMSN154, we have 1247 transaction for the **NoHitRisk** homes).

Figure A6 shows the results for the **NoHitRisk** homes. Coherently with our baseline estimates and the 2023 Emilia-Romagna flood, there is a statistically significant “baseline” reduction in prices for homes located in risk areas, as indicated by the β_2 coefficients shown in the left panel. Regarding **NoHitRisk** homes, no further price variation is observed after the considered flood events, further supporting our argument on the need of repeated events for observing home price reductions.⁴²

⁴²Table A3 compares the statistical properties of the considered homes one year before and one year after the Piemonte-Liguria and Toscana flood events.

Table A2: Characteristics of the major flood events reported by Copernicus (2016-2023). The column “# homes aff. mun.” represents the number of homes in municipalities affected by each flood. The column “# homes at risk” counts the homes in the affected municipalities that are at flood risk according to the ISPRA maps. The column “# hit homes” indicates the number of homes within the ISP dataset located inside the maximum flooded area for each event.

Code	Location	Date	# homes in aff. mun.	# homes at risk	# hit homes
EMSR192	Piemonte & Liguria	24th Nov. 2016	25406	4077	28
EMSR260	North-West area	12th Dec. 2017	5825	4607	2
EMSR359	Emilia-Romagna	15th May 2019	5514	4185	1
EMSR483	Calabria	22nd Nov. 2020	379	94	0
EMSR486	Sardegna	28th Nov. 2020	121	8	0
EMSR487	Emilia-Romagna	6th Dec. 2020	2161	1833	4
EMSR488	Lazio	9th Dec. 2020	149	72	0
EMSR649	Sicilia	9th Feb. 2023	2534	159	1
EMSN154	Emilia-Romagna	16th May 2023	14977	10585	1464
EMSR705	Toscana	2nd Nov. 2023	21900	18964	94

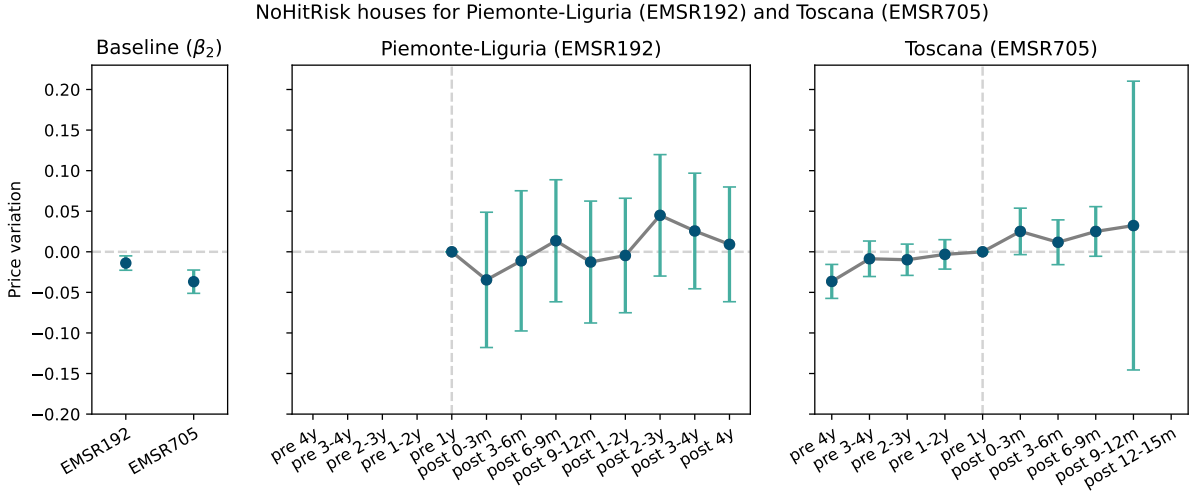


Figure A6: Time evolution of the home price variation for the 2016 Piemonte-Liguria (EMSR192) and 2023 Toscana (EMSR705) flood events. Referring to Equation (2), the left panel reports the coefficients β_2 for both events, the central and right panel show the interaction coefficients δ_2 for the Piemonte-Liguria and Toscana events, respectively. Each point represents the average value of the regression coefficient and the error-bars indicate the 95% confidence intervals, considering fixed effect at the OMI microzone. Since our dataset covers mortgage-covered transaction between 2016 and August 2024, no data points are available before one year from the Piemonte-Liguria events and after one year from the Toscana flood. For Piemonte-Liguria (EMSR192): $R^2 = 0.77$, observations = 231147. For Toscana (EMSR705): $R^2 = 0.71$, observations = 46624.

Table A3: Statistical tests comparing home characteristics one year before and after each event. For continuous variables, we applied the Mann-Whitney U-test (Mann and Whitney, 1947) and a paired t-test (Student, 1908). We also applied the later test to binary variables, together with a χ^2 test (Pearson, 1900). Categorical variables were only assessed through a χ^2 . To ensure the validity of the χ^2 test we removed categories with less than 20 samples. Cells report the p-value of the tests, while stars indicate the usual p-value ranges *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Event	Hedonic characteristics	Mann-Whitney	Paired t-test	χ^2 test
EMSN154	Logarithm of square meters	0.864	0.867	
	Cadastral code			0.745
	Construction year			0.0***
	Energy class			0.034**
	Floor			0.655
	Flag multi floor		0.0***	0.0***
	Flag garage		0.727	0.744
	Flag air conditioning		0.0***	0.0***
	Flag annex		0.11	0.114
	Flood Risk		0.883	0.902
EMSR192	Logarithm of square meters	0.076*	0.023**	
	Cadastral code			0.087*
	Construction year			0.029**
	Energy class			0.002***
	Floor			0.028**
	Flag multi floor		0.647	0.679
	Flag garage		0.013**	0.013**
	Flag air conditioning		0.074*	0.086*
	Flag annex		0.0***	0.0***
	Flood Risk		0.147	0.148
EMSR705	Logarithm of square meters	0.14	0.172	
	Cadastral code			0.008***
	Construction year			0.01***
	Energy class			0.0***
	Floor			0.163
	Flag multi floor		0.01***	0.0***
	Flag garage		0.705	0.72
	Flag air conditioning		0.0***	0.0***
	Flag annex		0.903	0.926
	Flood Risk		0.134	0.14

B.2 Hedonic regressions

We performed some complementary analyses to validate the specifications chosen for our main regressions. We present four different sets of supplementary results: (i) spatial correlation analysis to check if spatial econometric approaches are needed; (ii) robustness analysis for the risk zone definition; (iii) robustness analysis for the home characteristics included in the baseline regression, (iv) robustness of the historical memory specification of regions.

Spatial correlation validation

Samples in geo-localized datasets are likely to exhibit spatial correlation. This violates the assumption of sample independence made in linear regression models and could lead to erroneous estimates if not addressed properly (Anselin, 2013). Our hedonic regressions incorporate geographical fixed effects precisely to correct for this influence. However, we must validate whether the fixed effects are capturing completely the intrinsic spatial correlation of the data.

To do so, we applied a spatial autocorrelation test (Global Moran’s I) (Moran, 1950) on the residuals of our baseline regression (Model 3 from Table 2). If the spatial fixed-effect term (α_k) correctly captures all spatial dependence in the data, the residuals of the regression (ϵ_{ikt}) should be spatially independent. Meanwhile, if some spatial autocorrelation still remains, it indicates that the hedonic regression is misspecified and spatial approaches should be used instead.

The Moran’s I test requires inverting the spatial weights matrix (W) defining the connectivity pattern between samples. In our case, it is not computationally feasible to invert a spatial weights matrix (W) for the complete sample size of the baseline regression ($W_{homes \times homes} = 552,761 \times 552,761$). Therefore, we averaged the regression residuals of all homes in each municipality and estimated if this average indicator is spatially auto-correlated.⁴³ The connectivity pattern between municipalities was defined following a queen contiguity criteria, where two municipalities are linked together if there is any point in intersecting in their borders. The resulting binary contiguity matrix was row-normalized to generate the spatial weights matrix $W_{municipalities}$.

The resulting Global Moran’s I for our baseline regression (Table A4) is very close to 0. This indicates that the OMI microzone spatial fixed effects are correctly capturing the spatial dependence in the data and thus, our baseline regression is well specified.

We also used Local Indicators of Spatial Association maps (LISA maps) (Anselin, 1995) to visualize local spatial correlation patterns and validate that there are no specific regions where we systematically have more unreliable results. For all the regressions assessed, we did not observe a significant spatial correlation in most of the municipalities evaluated. Moreover, in the municipalities where the spatial correlation is present, it does not follow a systematic pattern that could indicate unreliable results (see Figure A7).

Validation of the flood risk definition

For the main analysis we considered an aggregated **Risk** indicator that combines the three risk levels provided by ISPRA (**High**, **Medium**, **Low** risk) into a single category. To validate this assumption we performed a robustness analysis where we use the three original categories defined by ISPRA. The equation used is the following:

$$\log P_{ikt} = \alpha_k + \alpha_t + \beta_1 \text{HighRisk}_i + \beta_2 \text{MediumRisk}_i + \beta_3 \text{LowRisk}_i + \gamma' \mathbf{X}_i + \epsilon_{ikt}, \quad (8)$$

⁴³Coarser aggregation levels like the census tract or OMI microzone still result in W matrices too large to be inverted.

Table A4: Test for spatial autocorrelation on the residuals of our baseline regression (corresponding to Equation 1). Note that we estimated the Global Moran’s I at the municipality level assuming a queen contiguity relationship between municipalities (Anselin et al., 2009). Significance levels: *** = p-value < 0.01, ** = p-value < 0.05, * = p-value < 0.1.

Regression	Global Moran’s I
Model 3 Table 2	−0.0590***

where **HighRisk**, **MediumRisk**, **LowRisk** reflect dummy variables representing whether a home is located in one of those risk levels according to the ISPRA maps. The rest of the terms are equivalent to the ones in Equation (1).

Table A5: Baseline effect of risk on prices disaggregated according to ISPRA risk levels. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Dep. var.: $\log(P)$		
Model id	1	2	3
High Risk	−0.002 (0.027)	−0.007 (0.005)	−0.001 (0.005)
Medium Risk	−0.044** (0.018)	−0.013*** (0.005)	−0.008 (0.005)
Low Risk	−0.032** (0.016)	−0.009** (0.004)	−0.012*** (0.004)
Observations	552761	552761	552761
R²	0.669	0.755	0.848
Spatial fixed effects	Municipality	OMI zone	Census Tract
Number of clusters	7203	20297	160630
Clustered s.e.	✓	✓	✓

Table A5 shows the coefficient for the risk indicators when using different types of fixed effects. With the OMI microzone fixed effects we observe that being in a **LowRisk** flood zone reduces home prices by 0.9%, while being in a **MediumRisk** and **HighRisk** area reduces prices by 1.3% and 0.7%, respectively. While it could be expected that being in medium risk zone leads to a higher discount than being in a low risk zone, it is surprising that the discount in high risk zones is the lowest, and not statistically significant. This result makes sense once we consider that only a small number of transactions occurred in high risk zones (4% of transactions across the whole dataset). In addition, the definition of high risk zone is the one that varies the most across river basin authorities (Trigila et al., 2021), suggesting that the measurement error for this variable is substantial. This is confirmed when comparing these results with the coefficient for the combined risk indicator R_i (Model 3 in Table 2). We find that being in a risky area is associated with an average price reduction of 1.0%, in between the low and medium risk estimates. This further suggests that these two categories are the most relevant ones in the whole data.

Testing different regression specifications

To ensure our regression results are robust, we also validated the impact of modifying the same regression specifications studied in the Emilia-Romagna flood (Supplementary Section B.1). This includes, the definition of the home size (logarithmic, linear, binned), home floor (binned

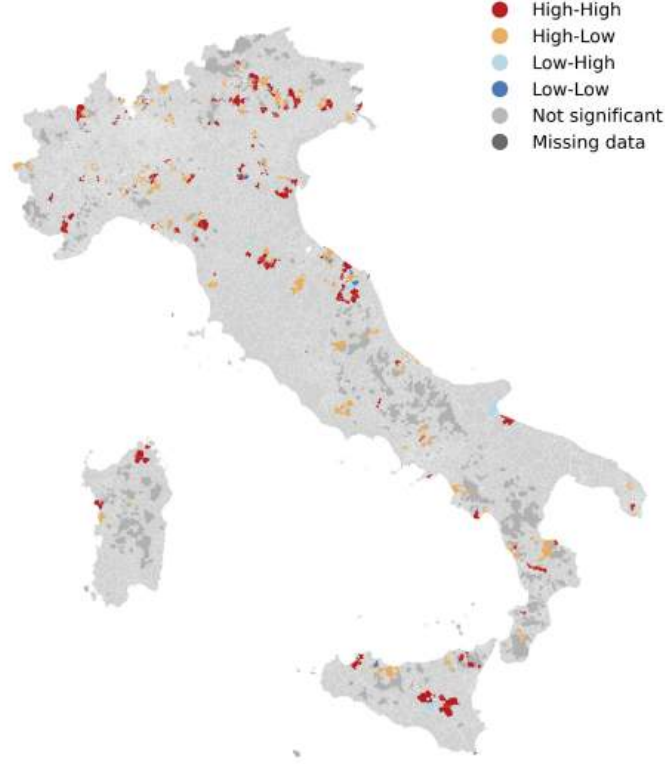


Figure A7: Local Indicators of Spatial Association maps (LISA maps) for the regression residuals for Model 3 from Table. 2. Municipalities are colored according to their type of local spatial correlation (Local Moran's I). Red (High-High): municipalities with residuals significantly larger than average, surrounded by others alike. Yellow (High-Low): municipalities with larger errors than average, surrounded by municipalities with smaller than average errors. Light blue (Low-High): municipalities with residuals significantly smaller than average, surrounded by others with larger residuals. Dark blue (Low-Low): municipalities with residuals significantly smaller than average, surrounded by others alike. Light gray (Not significant): municipalities with no spatial correlation in the residuals. Dark Gray (Missing data): municipalities without data.

or logarithmic), fixed effects (Census Tract, OMI microzone, Municipality) and removing (or not) the outliers.

Figure A8 shows the effect on the home price of being in a risk zone across Italy for all parameter configurations. Flood risk causes a statistically significant price reduction, ranging between 1% and 5%. Once we focus on frequently, moderately, and rarely flooded regions, the largest price reductions are observed for the frequently flooded regions. Instead, coefficients for the moderately and rarely flooded regions are generally smaller and less significant than those for frequently flooded regions. The yellow circle in the plot marks the specification selected for the main text, which considers: the logarithm of home size, binned floors, fixed effects at OMI microzone, and the outliers have been removed. We can observe that the results shown in the main are representative also of other parameter specifications since they are in the bulk of points. The exception is the chunk of significant negative and positive coefficients for moderately and rarely flooded regions. These coefficients are associated with the municipality fixed effects as confirmed in Figure A9, and so probably highlight other factors than flood risk.

Figure A9 details the price variation due to modifying individually each of the parameters explored. In all cases, the parameter configuration shown in the main results (highlighted in yellow) agrees with other specifications in terms of the coefficient's order of magnitude and its statistical significance. The spatial fixed effects at the municipality scale (top-right panel)

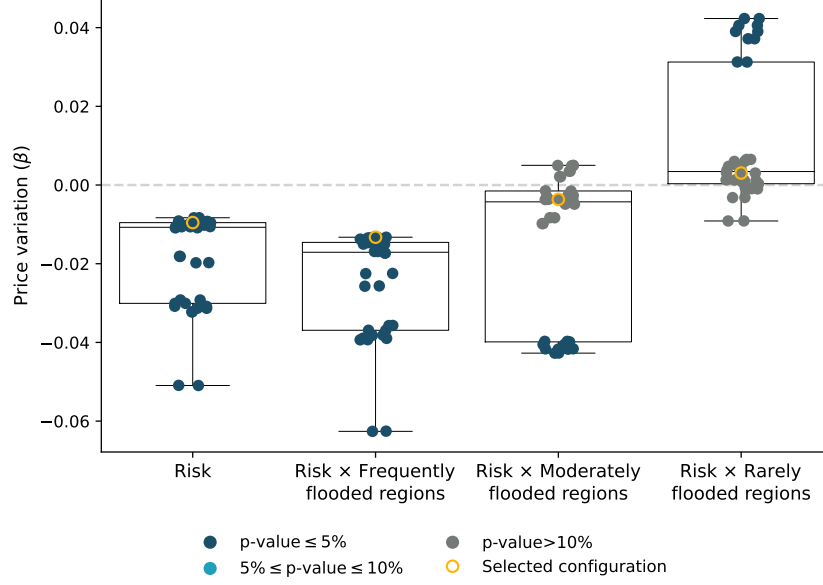


Figure A8: Effect on home prices of being in a flood-risk area (identified using ISPRA risk maps, first-left box) across Italy and according to the disaggregation in frequently, moderately, and rarely flooded regions based on the flood events recorded by EM-DAT (2024), second to fourth boxes. Each dot represents a parameter configuration, the color reports the statistical significance. The dots with the yellow edges identify the parameter configuration presented in the main text. R^2 [min, max] = [0.48, 0.85]; observations [min, max] = [552761, 555880].

present some differences. In this case, risk coefficients are lower than those associated with census track and OMI microzones. We argue that, when controlling for municipality, the effects of flood risk are mixed with those of peripheral home locations, leading to the mentioned discrepancies.

For completeness, we provide the coefficients for all the non-risk related variables (except the spatial and temporal fixed effects) of our baseline risk specification (corresponding Model 3 in Table 2). The results are shown in Table A6.

Table A6: Coefficients for all the variables in the baseline hedonic regression (first column of Table 2).

	Coefficient	Std. Error	stars
Cadastral code: A02 (ref.: A01)	-0.120	0.024	***
Cadastral code: A03 (ref.: A01)	-0.208	0.024	***
Cadastral code: A04 (ref.: A01)	-0.319	0.025	***
Cadastral code: A05 (ref.: A01)	-0.405	0.029	***
Cadastral code: A06 (ref.: A01)	-0.337	0.054	***
Cadastral code: A07 (ref.: A01)	-0.028	0.025	
Cadastral code: A08 (ref.: A01)	0.174	0.047	***
Cadastral code: A09 (ref.: A01)	-0.184	0.286	
Cadastral code: A10 (ref.: A01)	-0.239	0.054	***
Cadastral code: A11 (ref.: A01)	-0.159	0.130	
Construction year: 1955-1960 (ref.: <1955)	0.021	0.003	***
Construction year: 1960-1965 (ref.: <1955)	-0.000	0.004	
Construction year: 1965-1970 (ref.: <1955)	0.045	0.003	***
Construction year: 1970-1975 (ref.: <1955)	0.050	0.004	***
Construction year: 1975-1985 (ref.: <1955)	0.084	0.004	***

Continued on next page

Table A6: Hedonic coefficients for the first column of Table 2

	Coefficient	Std. Error	stars
Construction year: 1985-1995 (ref.: <1955)	0.175	0.004	***
Construction year: 1995-2005 (ref.: <1955)	0.270	0.004	***
Construction year: 2005-2015 (ref.: <1955)	0.343	0.004	***
Construction year: 2015-2025 (ref.: <1955)	0.404	0.006	***
Construction year: Missing (ref.: <1955)	0.046	0.013	***
Energy class: A2 (ref.: A)	0.005	0.006	
Energy class: A3 (ref.: A)	0.027	0.008	***
Energy class: A4 (ref.: A)	0.052	0.006	***
Energy class: B (ref.: A)	-0.014	0.005	**
Energy class: C (ref.: A)	-0.048	0.005	***
Energy class: D (ref.: A)	-0.062	0.005	***
Energy class: E (ref.: A)	-0.079	0.005	***
Energy class: F (ref.: A)	-0.110	0.006	***
Energy class: G (ref.: A)	-0.145	0.005	***
Energy class: Missing (ref.: A)	-0.100	0.006	***
Flag air conditioning: True (ref.: False)	0.051	0.002	***
Flag air conditioning: Missing (ref.: False)	0.009	0.002	***
Flag garage	0.107	0.002	***
Flag multi floor: True	0.015	0.004	***
Flag annex	0.018	0.002	***
Floor: 1 (ref.: 0)	-0.027	0.003	***
Floor: 2 (ref.: 0)	-0.028	0.003	***
Floor: 3 (ref.: 0)	-0.026	0.004	***
Floor: 4+ (ref.: 0)	0.008	0.005	
Floor: Missing (ref.: 0)	-0.004	0.003	
Logarithm of square meters	0.706	0.003	***

Robustness historical memory definition

To validate our definition of the historical memory of regions we repeated the hedonic regression analyses in Table 2 after considering two other measures of flood frequency: (1) an alternative dataset for historic flood events compiled from ISPRA records; (2) considering the normalization of the number of events by region area.

EM-DAT is well-known to over-represent disasters in richer areas (Felbermayr and Gröschl, 2014). Therefore, we compiled a dataset of flood events from ISPRA data and re-estimated our hedonic regressions. ISPRA collects data on flood events drawing on multiple sources, such as the Italian Civil Protection Department, ISTAT, the National Research Council, local administrations and newspapers. For each event, it reports the duration, an estimation of the damages, an estimation of the allocated aid funds, and the total number of deaths and missing or evacuated people. Although data are provided back to 1951, systematic data collection only began in 2003, so we only consider the later period for better accuracy. Data are not collected in tabular format, but we manually compiled a database reading from the yearly reports by ISPRA.⁴⁴ The ISPRA dataset contains 402 event-region pairs distributed across regions and macroareas. Since the inclusion criteria for ISPRA are less strict than EM-DAT, this results on some variations in the historical memory classifications. Even with these differences we still observe the same pattern of significance of the risk coefficients disaggregated by regions that was observed in the regression presented in the main manuscript (Table A7).

⁴⁴<https://indicatoriambientali.isprambiente.it/it/edizioni-annuario>. The latest available report is for the year 2022.

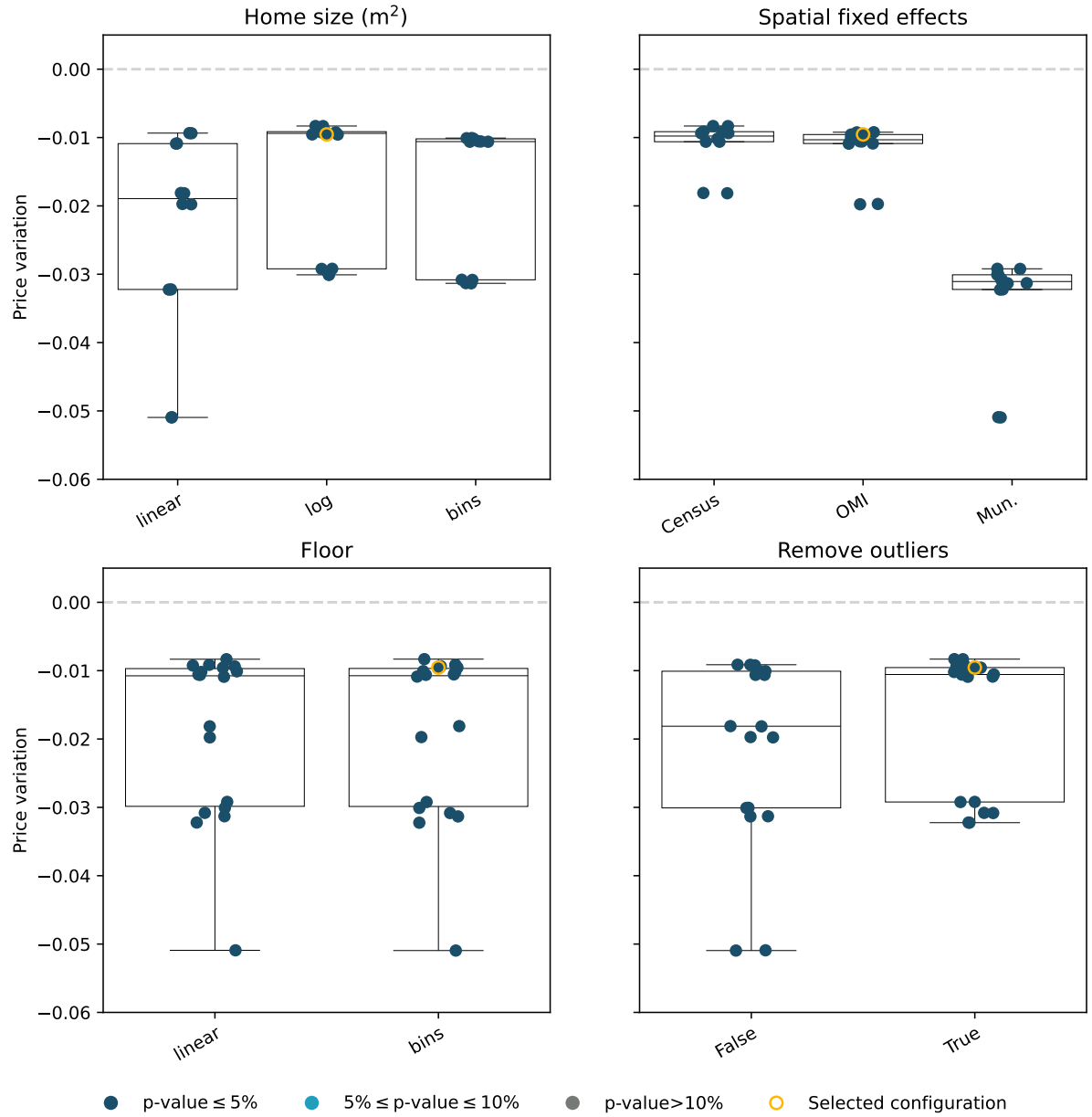


Figure A9: Changes of the home price across home size specifications –linear, logarithm (log) and bins of the square meters– for homes in flood risk areas. Each dot represents a parameter configuration, the color reports the statistical significance. The dots with the yellow edges identify the parameter configuration presented in the main text. Each panel refers to a single variable reported in the panel title, e.g., the top-left panel describes how the home size specification affects the price variations for homes in flood-risk areas. R^2 [min, max] = [0.48, 0.85]; observations [min, max] = [552761, 555880].

Table A7: Risk effect on home prices. For each spatial fixed effects, Models 1-3-5 report the effect of the risk on home prices estimated using Equation (1), while Models 2-4-6 disaggregate the effect of flood risk by the historical memory of the regions according to ISPRA. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	Dep. var.: $\log(P)$					
Model id	1	2	3	4	5	6
Risk	-0.029*** (0.010)		-0.010*** (0.003)		-0.008** (0.003)	
Risk $\times$ Frequently flooded regions		-0.032** (0.015)		-0.016*** (0.005)		-0.012*** (0.005)
Risk $\times$ Moderately flooded regions		-0.038*** (0.012)		-0.001 (0.005)		-0.003 (0.005)
Risk $\times$ Rarely flooded region		0.051** (0.021)		0.006 (0.010)		0.000 (0.013)
Observations	552761		552761		552761	
R²	0.669		0.755		0.848	
Spatial fixed effects	Municipality		OMI zone		Census Tract	
Number of clusters	7203		20297		160630	
Clustered s.e.	✓		✓		✓	

If one assumes flood risk is at least to some extent uniformly spread throughout the Italian territory, the most affected regions would tend to be the largest ones. Thus, we repeated the hedonic regression analyses in Tables 2 and A7 using the historical memory levels defined through the area normalization. As expected, significant price reductions are observed in frequently flooded regions (Table A8).

Table A8: Effect of flood risk disaggregated across historical memory regions. The table compares the results considering the historical memory classification for EM-DAT and ISPRA data. In this case, the number of flood events is normalized by the region surface area. ***: p-value<0.01, **: p-value<0.05, *: p-value<0.10.

	Dep. var.: $\log(P)$					
Model id	1	2	3	4	5	6
Dataset	EM-DAT	ISPRA	EM-DAT	ISPRA	EM-DAT	ISPRA
Normalization	✓	✓	✓	✓	✓	✓
Risk $\times$ Frequently flooded regions	-0.044** (0.021)	-0.006 (0.014)	-0.017*** (0.004)	-0.019*** (0.005)	-0.019*** (0.005)	-0.017*** (0.006)
Risk $\times$ Moderately flooded regions	-0.032*** (0.010)	-0.049*** (0.014)	-0.008 (0.006)	-0.008* (0.005)	-0.004 (0.006)	-0.008 (0.005)
Risk $\times$ Rarely flooded regions	0.022* (0.012)	0.023* (0.014)	0.005 (0.005)	0.004 (0.006)	0.006 (0.008)	0.005 (0.008)
Observations	552761		552761		552761	
R ²	0.669		0.755		0.848	
Spatial fixed effects	Municipality		OMI zone		Census Tract	
Number of clusters	7203		20297		160630	
Clustered s.e.	✓		✓		✓	