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KEYWORDS

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JEL CODE

C22, C33, Q54, R31

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Italy's unique geographical context exacerbates these risks, with roughly a quarter of the country's housing stock located in flood-prone areas. This study investigates how floods impact house prices across different Italian municipalities, focusing on property types, conservation status, and municipal characteristics.
Using a staggered two-way fixed effects difference-in-differences (TWFE DiD) model, we examine the impact of floods specifically on municipalities that are not metropolitan centers or provincial/regional capitals. Our findings indicate a persistent negative effect on housing values in affected areas, with maximum sale prices per square meter declining by 1.6% to 3.2%.
Notably, properties in semi-central zones experience sharper declines, particularly among affordable housing units. These insights are essential for policymakers and stakeholders in light of the increasing frequency and intensity of extreme weather events related to climate change.

Extreme climate events and household wealth

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Abstract

Italian households' wealth is significantly influenced by real estate holdings, with a high home-ownership rate of 75.2% making the housing market a crucial component of household wealth. However, this wealth is increasingly vulnerable to extreme weather events, particularly floods and landslides, which threaten property values. Italy's unique geographical context exacerbates these risks, with roughly a quarter of the country's housing stock located in flood-prone areas. This study investigates how floods impact house prices across different Italian municipalities, focusing on property types, conservation status, and municipal characteristics. Using a staggered two-way fixed effects difference-in-differences (TWFE DiD) model, we examine the impact of floods specifically on municipalities that are not metropolitan centers or provincial/regional capitals. Our findings indicate a persistent negative effect on housing values in affected areas, with maximum sale prices per square meter declining by 1.6% to 3.2%. Notably, properties in semi-central zones experience sharper declines, particularly among affordable housing units. These insights are essential for policymakers and stakeholders in light of the increasing frequency and intensity of extreme weather events related to climate change.

Keywords: Floods; House Prices; Italy; Staggered DiD
JEL Codes: C22; C33; Q54; R31

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1 Introduction

The wealth of Italian households is deeply tied to real estate, with housing representing their primary form of asset ownership. According to the Italian National Statistical Institute (ISTAT, 2019), residential assets were valued at €5,294 billion in 2017 — an amount 4.6 times larger than household disposable income and more than three times Italy's GDP (Cannari et al., 2016; Caprara et al., 2018; De Bonis et al., 2020). In 2023, 75.2% of people in Italy lived in owner-occupied dwellings, a figure which exceeds the EU average by about six percentage points (Eurostat, 2024).[1] This strong concentration of wealth in real estate makes property values crucial to household financial security.

Yet Italian household wealth is highly exposed to climate hazards, particularly floods and landslides. One in four Italian homes is located in a flood-risk zone (Trigila et al., 2021), and annual flood-related losses alone are estimated at up to 0.15% of GDP (Loberto and Spuri, 2023). Climate change amplifies this vulnerability: extreme precipitation events are becoming more frequent and intense across all of Europe (IPCC, 2023). While it is hard to claim that climate change is directly causing every individual disaster, it definitely impacts on the upward trend in both intensity and frequency of climate events. Globally, climate-induced damage to residential properties is projected to reach $25 trillion (The Economist, 2024), hence the urgency for strategic adaptation. A growing strand of literature investigates the possible effects on society and the economy of assets negatively exposed to climate hazards. Floods attract particular attention in the literature because of their capacity to significantly disrupt housing markets. Empirical studies show that major flood events can cause significant short-term declines in property prices, even if values tend to recover over time (Atreya and Ferreira, 2015; Beltrán et al., 2019).

Given Italy's high exposure to flood hazards, the growing intensity of extreme weather events, and the heavy concentration of national household wealth in real estate, understanding how floods affect property values is crucial for policymakers, researchers, and stakeholders alike. The urgency of this issue was made clear by the devastating floods in Emilia-Romagna in Spring 2023, which caused certified damages of €8.5 billion.[2]

This paper investigates the impact of floods on residential house prices in Italy. We estimate how flood events influence property values and examine whether these effects differ across municipalities, neighborhoods, dwelling types, and conservation status. Building upon the work of Athey and Imbens (2022) on research design under random assignment of adoption dates, we employ a staggered two-way fixed effects difference-in-differences analysis. We rely on municipality-level data on floods that hit Italian municipalities in the period between 2018-2020 [3], as well as semester data of average maximum and minimum sale price in €/m^2[4].

The remainder of this paper is organized as follows. Section 2 reviews the literature on the effects of climate events on the real estate market. In Section 3, we present the data and methods employed. In Section 4, we report the empirical findings of estimated models. Finally, Section 5 concludes by drawing some policy implications.

2 Literature Review

In recent years, climate disasters have become more frequent and destructive—a pattern closely linked to the acceleration of climate change. As these events intensify, a growing strand of literature focuses on the increasing economic losses due to physical climate risks. While climate shocks have immediate environmental and infrastructural effects, their consequences have the long term capacity of disrupting and reshaping local economies, social dynamics, and financial markets. In what follows, we review empirical evidence on how climate-induced events affect economic activity, with a specific focus on

[1] It is worth noting that this ownership rate varies across demographics, with higher rates observed among couples and in smaller communities compared to urban centers.

[2] In light of the increasing frequency and severity of extreme weather events, the 2024 Budget Law requires all companies operating in Italy to obtain insurance coverage against natural disasters such as floods and landslides by December 31, 2024.

[3] Source: Italian Institute for Environmental Protection and Research (*Istituto Superiore per la Protezione e la Ricerca Ambientale* - ISPRA).

[4] Real Estate Market Observatory (*Osservatorio del Mercato Immobiliare* - OMI) of the Italian Revenue Agency (*Agenzia delle Entrate*)

real estate markets. We focus on housing, as an ideal object of study: it is the most widespread asset class globally and, particularly in Italy, highly vulnerable to climate-related hazards (The Economist, 2024). Also, the literature on climate-related risks is crucial to enhance risk disclosure and support informed policy decisions—from climate adaptation and mitigation strategies to financial regulation.[5]

Physical climate hazards can be broadly categorized into chronic and acute risks (Campiglio et al., 2023): chronic hazards (e.g., temperature rise, sea-level rise) and acute hazards (e.g., hurricanes, floods, droughts). While the former unfold gradually over time and are directly attributable to climate change, the latter occur suddenly and their frequency and severity increases with climate change (IPCC, 2023).

A first branch of the literature studies how gradual climate shifts—such as extreme temperatures or sea-level rise—affect property values.[6] Using US county-level data, Ma and Yildirim (2023) show that exposure to extreme heat increases awareness of climate risks and depresses house prices, especially in communities concerned about sea-level rise. For Italy, Cascarano and Natoli (2023) combine meteorological data with multiple housing-market datasets and find that higher temperatures reduce housing demand, leading sellers to lower prices—particularly for less heat-resilient properties (e.g., those lacking energy-efficient features or outdoor shading).

Sea-level rise generates similar market reactions: exposed properties in the U.S. sell at a discount of roughly 7% (Bernstein et al., 2019), and discounts are larger in areas where residents are more concerned about global warming (Baldauf et al., 2020). Yet not all studies find price effects—households may underestimate or discount future risks when flood inundation periods are short (Murfin and Spiegel, 2020).

A second research strand investigates how sudden disasters—such as hurricanes and floods—affect house prices. A recurrent finding is that perception drives valuation. Prior to major events, flood-zone houses often show no risk premium; only after a damaging event do significant price differentials emerge (Bin and Landry, 2013). After Hurricane Sandy, properties unexpectedly hit by flooding in New York City experienced temporary price drops of around 6–7% (Cohen et al., 2021). Other studies show heterogeneous effects depending on property type and market structure: hurricanes in Jamaica reduce apartment prices and new mortgage values (but not the value of residential houses), while extreme rainfall depress the value of new mortgages. (Spencer, 2023).

Floods generally trigger temporary price discounts that are highly variable and gradually fade, with no long-term effects on estates located in a flood zone (Lamond et al., 2010). In the UK, inundated properties initially lose up to 25% of their value, recovering over four to five years (Beltrán et al., 2019). Direct exposure to climate disaster also trigger differential responses: in the US Atreya and Ferreira (2015) find that properties directly affected by flooding experience significantly greater price discounts compared to those in floodplains but not inundated. In the UK, Belanger and Bourdeau-Brien (2018) find that flood risk reduces property values, with the effect being particularly significant for waterfront properties. The reaction of financial institutions can amplify vulnerabilities: lenders often fail to adjust mortgage valuations after floods, implicitly transferring risk to buyers and public insurance schemes (Garbarino and Guin, 2021).

Despite Italy's high exposure to flood hazards and the centrality of real estate to household wealth, no empirical study has yet quantified how actual flood events affect housing sale prices. Existing research for Italy focuses on expected losses, e.g. the work of Loberto and Spuri (2023) estimating around €3 billion of expected annual losses due to €1 trillion of housing value being located in flood-risk areas[7], rather than on realized market reactions. With roughly one in four homes located in flood-prone areas and home-ownership representing a primary vehicle of wealth accumulation, estimating post-event price effects is crucial for households, policymakers, and financial institutions. Our study fills this gap by providing, for the first time, empirical evidence on how flood events affect housing transaction prices in the Italian real estate market.

[5] Risk disclosure is increasingly viewed as a prerequisite for a smooth transition toward sustainable development, as emphasized by the Network for Greening the Financial System (NGFS, 2019).

[6] Parallel research examines effects on economic activity (e.g., Colacito et al., 2019; Acevedo et al., 2020; Brunetti et al., 2023), financial markets (stocks and bonds) (e.g., Anttila-Hughes, 2016; Balvers et al., 2017; Bansal et al., 2019; Griffin et al., 2019; Choi et al., 2020; Faccini et al., 2023), bonds (e.g., Painter, 2020; Schulten et al., 2021; Goldsmith-Pinkham et al., 2023), and banking activity (e.g., Klomp, 2014; Noth and Schüwer, 2023). For an overview, see Campiglio et al. (2023).

[7] See also Faiella (2013), who estimate expected annual losses of €1.6 billion when landslide risks are included.

3 Data and Methods

3.1 Data

We use flood data retrieved from ISPRA environmental yearbook for the years 2018, 2019, and 2020 to estimate the effect of floods on house prices in Italy. The dataset includes provinces and regions hit by each single event, death toll and estimated damage. We use the description reported in 'main effects on the ground' (*principali effetti al suolo*) and extract the municipalities mentioned in the text.[8]

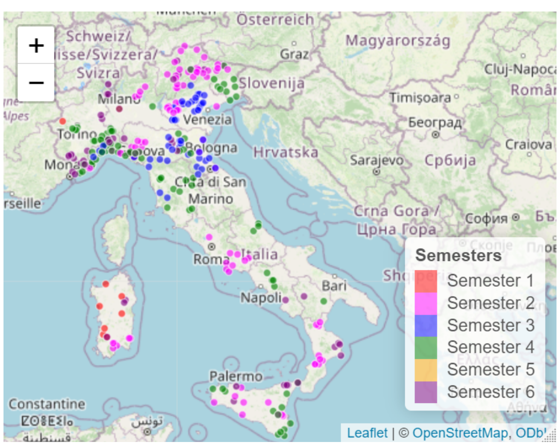
As can be seen in Table (1) and Figures (1) and (2), the events are not uniformly distributed in time and space. In particular, the Italian regions with the highest number of municipalities flooded between 2018 and 2020 are Veneto, Emilia-Romagna, Liguria, Piemonte and Sicilia, whereas Puglia, Marche, Molise, Umbria and Valle D'Aosta had no flood events registered in the same period (see Table 1). Moreover, the events are concentrated in the second semester which corresponds to the rainfall season in Italy, i.e., autumn and the beginning of winter (see Figures 1 and 2).

Table 1: Number of Floods by Region and Year (2018-2020)

Region	Number of Floods	Number of Floods (2018)	Number of Floods (2019)	Number of Floods (2020)
Veneto	46	19	25	2
Emilia-Romagna	37	9	24	4
Liguria	35	5	25	5
Piemonte	30	1	19	10
Sicilia	27	9	13	5
Trentino-Alto Adige	22	17	1	4
Toscana	20	2	18	0
Sardegna	16	13	0	3
Friuli-Venezia Giulia	15	5	10	0
Calabria	13	9	0	4
Lombardia	12	4	1	7
Lazio	8	8	0	0
Campania	5	0	4	1
Abruzzo	3	0	3	0
Basilicata	2	0	1	1
Apulia, Marche, Molise, Umbria, Valle D'Aosta	0	0	0	0
Total	291	101	144	46

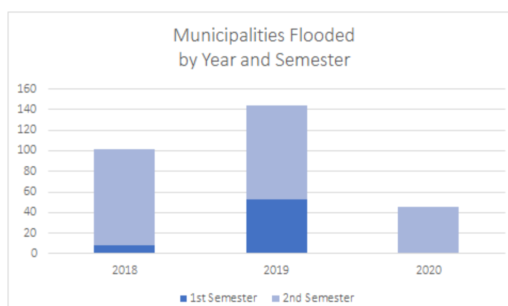
Source: ISPRA data, Authors' elaboration

Figure 1: Municipalities Flooded by Semester (2018-2020)



Source: ISPRA data, Authors' elaboration

Figure 2: Number of Municipalities Flooded by Semester and Year (2018-2020)

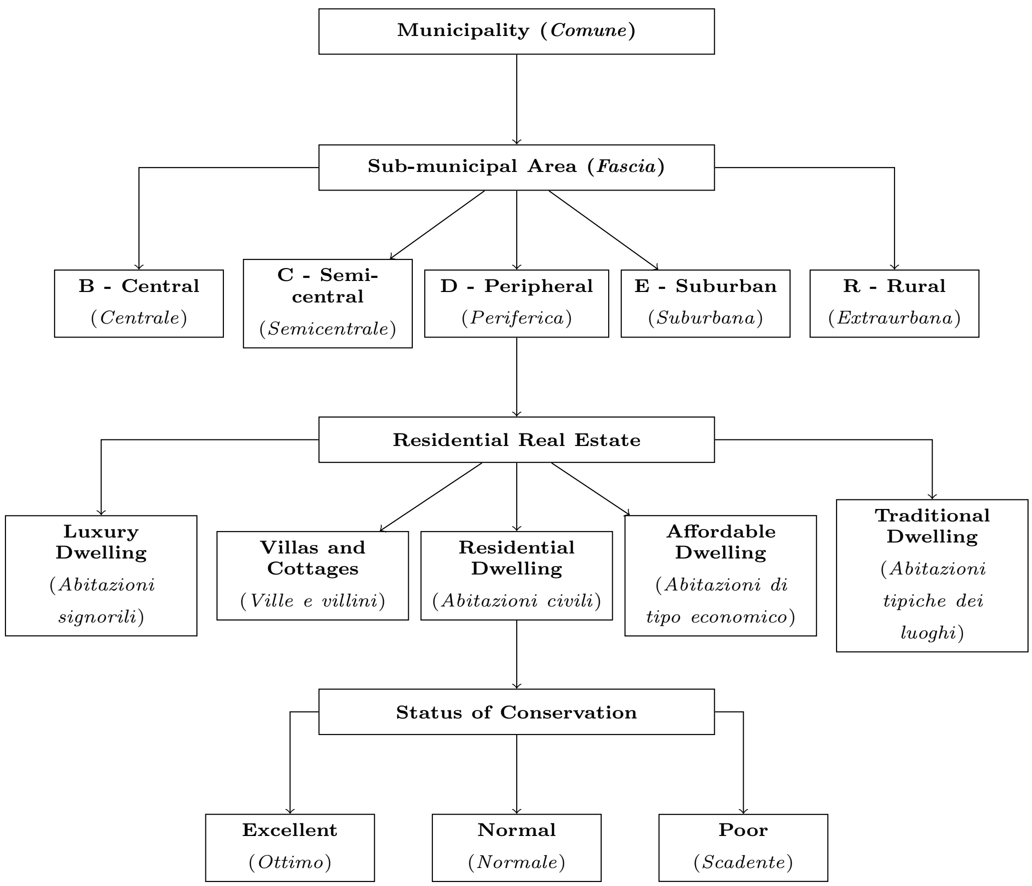


Source: ISPRA Data, Authors' elaboration

[8]In doing so, we are able to assess which municipality was hit by an specific flood event. However, it is important to note that our data does not encompass additional details such as estimated damage, the extent of flooding within each municipality, or the financial assistance received from governmental sources post-event. These details are aggregated at the basin level and cannot be disaggregated to the municipality level for our analysis.

Concerning data on house prices we rely on the dataset retrieved from the Real Estate Market Observatory (Osservatorio del Mercato Immobiliare - OMI) of the Italian Revenue Agency (Agenzia delle Entrate). This data is released every semester and contains information on maximum and minimum sale market values and rent prices in €/m^2. As illustrated in Figure (3) below, the OMI dataset has information on the territorial sub-municipal areas (*fascia*) within each municipality, type of dwelling, as well as status of conservation. Each sub-area is an aggregation of contiguous, homogeneous areas and represents a geographical territory within the municipality. The municipal territory is divided into the following zones: Central, Semi-central, Peripheral, Suburban, and Rural(Agenzia delle Entrate, 2018).[9]

Figure 3: OMI Dataset's Structure



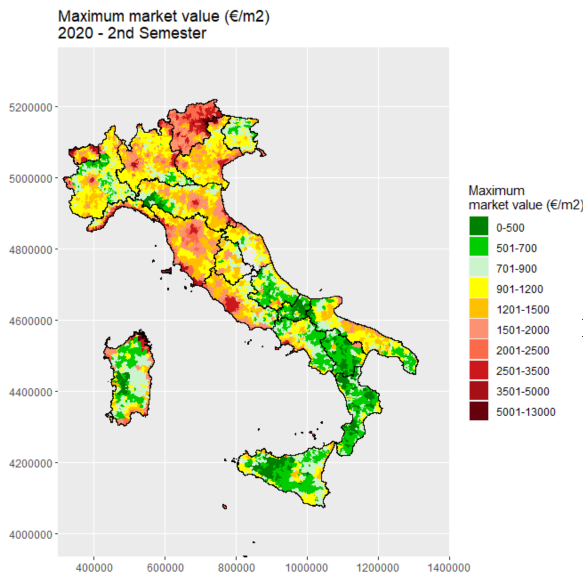
Source: Authors' elaboration

Figures (4 and 5) show the distribution of mean maximum sale price in €/m^2 (our outcome variable) in Italian municipalities in the second semester of 2020 and the change in the mean maximum market values in % between 2018 and 2020, respectively. As illustrated in Figure (4), the highest housing market values are concentrated in the northern regions, particularly across Trentino-Alto Adige, in Lazio, and in Toscana, with notably high values in urban and economically vibrant areas such as Milan, Rome, Bologna and in expensive touristic areas like Venice, Valle d'Aosta, Dolomites, North-east Sardegna. In contrast, southern regions and islands exhibit significantly lower values. Figure (5)

[9]It is worth noting that the dataset also contains information at the so-called OMI Zone level, where each Zone is a portion of the territorial area representing a homogeneous segment of the local real estate market, i.e. it exhibits substantial uniformity in valuation due to consistent economic and socio-environmental conditions. This uniformity translates into homogeneity in the market values of real estate units, typically falling within a range where the difference between the minimum and maximum value does not exceed 50% (Agenzia delle Entrate, 2018). Since we are interested in exploiting the variability of house prices, the prices we consider, within each municipality, are those aggregated at the territorial sub-municipal areas level (*fascia*).

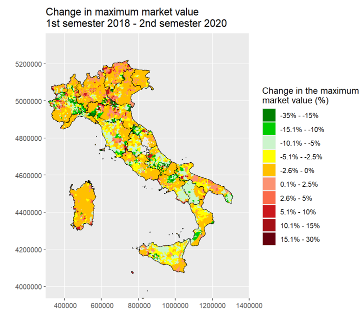
illustrates the changes in housing prices between 2018 and 2020, showing modest variations overall, with notable increases in maximum sale prices concentrated in Trentino-Alto Adige, along the Po Valley, in Milan, and some scattered coastal areas. Figure (6) illustrates the change in maximum sale prices per square meter in Imola, highlighting the areas most affected by the 2019 flood. The green zones indicate a decline in market value following the extreme weather event. This suggests a possible relationship between flood occurrences and housing market dynamics, which is further investigated in the next section.

Figure 4: Mean Maximum market value of Dwellings by Municipality (€/m^2)



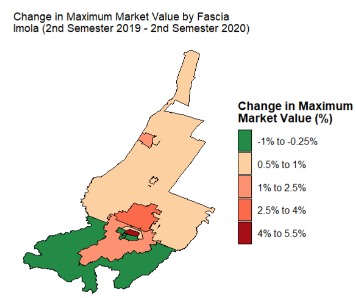
Source: OMI data, Authors' elaboration

Figure 5: Change in the mean maximum market value of Dwellings by municipality (in %) 2018-2020



Source: OMI data, Authors' elaboration

Figure 6: Change in the mean maximum market value of Dwellings by Zone in Imola (in %) 2019-2020



Source: OMI data, Authors' elaboration

3.2 Methodology

To assess the impact of flooding on property values, we employ a panel data regression model represented in Equation (1).

$$\text{lnCompr\_max}_{m,f,d,j,t} = \alpha + \beta_1 \text{PostTreatment}_{m,t} + \gamma_m + \eta_y + \lambda_f + \delta_d + \phi_j + \epsilon_m \tag{1}$$

where our outcome variable is the natural logarithm $\text{lnCompr\_max}_{m,f,d,j,t}$ of maximum sale price[10] in municipality m, sub-municipal area or *fascia* f, type of dwelling d, status of conservation j, and time t, at half-yearly frequency. $\text{PostTreatment}_{m,t}$ is a dummy variable that is equal to one in the period and municipality in which the flood occurred and thereafter. γ_m, η_y, λ_f, δ_d, and ϕ_j represent fixed effects for municipality, year, sub-municipal area, type of dwelling, and status of conservation. ϵ_m is the error term clustered by municipality. The coefficient of interest β_1 estimates the average proportional change in the maximum property values in post-flooding periods compared to pre-flooding periods.

[10] Measured in €/m^2

In an additional specification, we explore the temporal dynamics of the flood using the time to treatment ($\text{Time\_to\_treat}_{m,t}$) dummies, which allow us to capture how the impact of flooding varies over time for treated municipalities. By including these terms from five semesters prior to five semesters post-flooding, we capture the log-term effect of flooding (see Equation 2). Although our setting does not involve multiple cohorts with staggered adoption, we draw on insights from Athey and Imbens (2022) regarding best practices in research design for causal inference. Specifically, we assess the validity of the parallel trends assumption using an event study approach and estimate treatment effects dynamically over time. Additionally, we cluster standard errors at the municipality level to mitigate potential serial correlation biases following the recommendations of Bertrand et al. (2004).

$$\begin{aligned} \text{lnCompr\_max}_{m,f,d,j,t} = \alpha + \beta_{-5}\text{Time\_to\_treat}_{m,t} + \beta_{-4}\text{Time\_to\_treat}_{m,t} \\ + \ldots + \beta_{5}\text{Time\_to\_treat}_{m,t} + \gamma_m + \eta_y + \epsilon_m \end{aligned} \tag{2}$$

where β_{-5} through β_5 are the coefficients related to the $\text{Time\_to\_treat}_{m,t}$ dummy and capture the effect of flooding over time.[11]

4 Empirical results

In this section, we present the main outcomes of the regression models exploring the effects before and after the flood event, followed by the results exploring the staggered treatment.

In the initial pre-post exercise we estimate the effect of flood on maximum sale prices considering four different subsamples: i. the complete sample including both treated and non-treated municipalities; ii. a sample containing only those regions in which at least one municipality is treated; iii. a sample with treated municipalities only; iv. a sample only with treated municipalities excluding metropolitan cities and region or province capitals.[12]

As can be seen in Table (2), the coefficient of interest on the post-treatment dummy is negative and statistically significant at the 5% level when using sub-sample iv that includes only treated municipalities that are neither metropolitan cities nor region or province capitals (columns 4 to 4c). The magnitude of the coefficient is very small but the results are robust to the inclusion of municipality, year, sub-municipal area, type of dwelling, as well as status of conservation fixed effects.

Table 2: Maximum Sale Price and Flood Event

	(1) Complete Sample	**(2) Treated Regions**	**(3) Treated Municipalities**	**(4) Treated Municipalities (No Capital)**	**(4a) Treated Municipalities (No Capital)**	**(4b) Treated Municipalities (No Capital)**	**(4c) Treated Municipalities (No Capital)**
PostTreatment	0.003	0.003	-0.001	**-0.003***	**-0.003***	**-0.003***	**-0.003***
	(0.008)	(0.008)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)
PostTreatmentxOther	-0.001	-0.001	-0.001				
	(0.008)	(0.008)	(0.008)				
Num.Obs.	373068	347413	26954	16368	16368	16368	16368
R2	0.8	0.809	0.735	0.814	0.837	0.896	0.914
FE							
Municipality	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓
Fascia					✓	✓	✓
Type of Dwelling						✓	✓
Status of Conservation							✓

$*p < 0.01$, $**p < 0.05$, $***p < 0.001$
Robust standard errors clustered at municipality level.
Sample specifications include: complete sample; only treated regions; only treated municipalities; only treated municipalities expect capitals (region or province) and metropolitan cities.

[11] Robustness tests are provided in Appendix B. These include the estimation of the staggered model incorporating fixed effects for sub-municipal area, type of dwelling, and status of conservation. Additionally, a Propensity Score Matching (PSM) analysis is conducted, followed by a TWFE regression on the matched sample to ensure the robustness and consistency of the results across different analytical specifications and controls.

[12] The inclusion of four subsamples ensures robust estimates by addressing spatial heterogeneity via comparable regional controls in (ii), by isolating direct flood effects in (iii), and by excluding outliers with distinct market dynamics in (iv). This approach mitigates biases from non-comparable controls and clarifies whether effects generalize across metropolitan and non-metropolitan contexts.

Subsequently, we estimate the staggered treatment effect, as specified in equation (2), to allow for potential time differences in the effects of the flood event (the treatment) on house prices. Notice that by estimating the staggered treatment effects, we can better understand how outcomes evolve while testing for parallel trends to ensure that any observed difference in post-treatment outcomes (0-5 semesters after the flood) is indeed due to the event and not to pre-existing trends.

In the staggered treatment estimations, we consider only treated municipalities which correspond to sub-sample iii. We further disaggregate the sample of treated cities to look at the heterogeneous effect of flooding on different types of municipality, different sub-municipal areas, different types of dwelling, and status of conservation.

The analysis of different types of municipalities allows us to explore potential heterogeneity in the treatment effects. Results are illustrated in Table (3) and indicate that for the sub-sample comprising only treated municipalities excluding those that are region or province capitals (column (4) in Table 3), the flood event has a negative and statistically significant effect on house prices and the magnitude (in absolute value) increases in time from -0.3% in the semester of the occurrence of the event to -0.24% in the fifth semester after the flood. A similar, though weaker effect, is also clear when using the overall sample (column (5) in Table 3). In this case the coefficients are statistically significant from the second semester after the flood until five semesters after.Figure (7) offers a graphical representation of coefficients for the sub-samples of all treated municipalities and treated municipalities excluding region and province capitals: it can be seen that for this second group the effect is notably more pronounced.

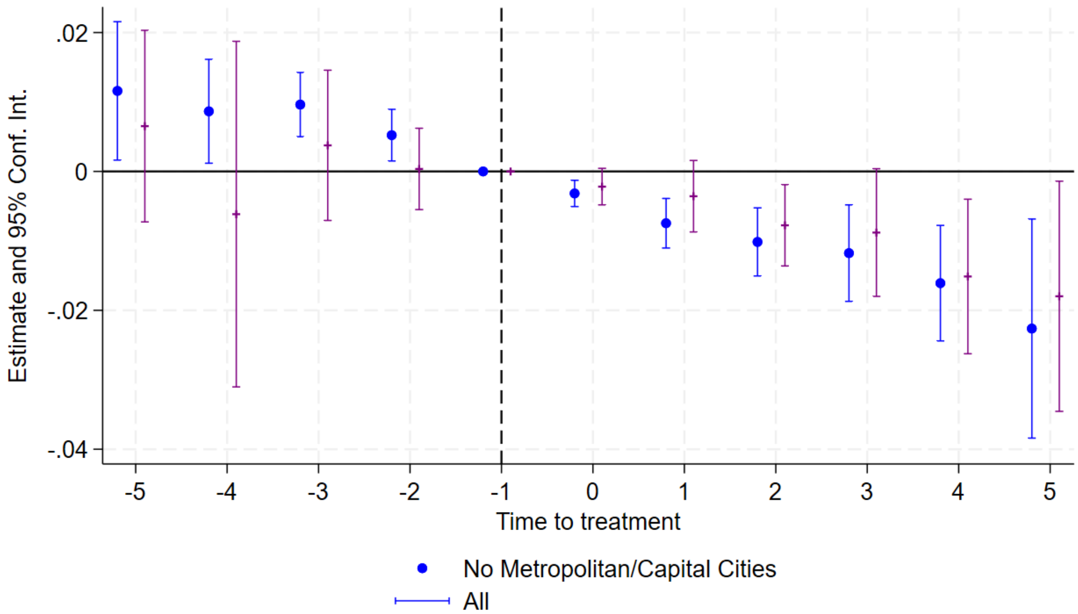
Table 3: **Maximum Sale Price and Flood Event.** Staggered Treatment by Type of Municipalities

	(1) Treated Metropolitan Cities	**(2) Treated Region Capitals**	**(3) Treated Province Capitals**	**(4) Treated Municipalities (No capitals or metropolitan cities)**	**(5) Treated Municipalities (All)**
-5	0.002	0	0.001	0.014*	0.007
	(0.009)	(0.01)	(0.011)	(0.006)	(0.007)
-4	-0.030	-0.032	-0.019	0.009*	-0.006
	(0.024)	(0.026)	(0.02)	(0.004)	(0.013)
-3	-0.016	-0.022	-0.003	0.009***	0.004
	(0.022)	(0.027)	(0.013)	(0.003)	(0.005)
-2	-0.015	-0.018+	-0.004	0.005*	0
	(0.008)	(0.008)	(0.005)	(0.002)	(0.003)
0	0.002	0	-0.001	-0.003**	-0.002
	(0.007)	(0.007)	(0.003)	(0.001)	(0.001)
1	0.003	0.004	-0.001	-0.007***	-0.004
	(0.012)	(0.01)	(0.005)	(0.002)	(0.003)
2	-0.010	-0.009	-0.007	-0.010***	-0.008**
	(0.017)	(0.014)	(0.006)	(0.003)	(0.003)
3	-0.008	-0.013	-0.008	-0.012**	-0.009+
	(0.025)	(0.023)	(0.011)	(0.004)	(0.005)
4	-0.030	-0.029	-0.015	-0.018***	-0.015**
	(0.02)	(0.021)	(0.012)	(0.005)	(0.006)
5				-0.024**	-0.018*
				(0.008)	(0.008)
Num.Obs.	4099	4285	10586	16368	26954
R2	0.443	0.5	0.55	0.814	0.735
FE: Municipality	✓	✓	✓	✓	✓
FE: Year	✓	✓	✓	✓	✓

$+p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$
Robust standard errors clustered at municipality level.

at

Figure 7: **Maximum Sale Price and Flood Event.** Staggered Treatment by Type of Municipalities



Estimate and 95% c.i. in y-axis, time to treatment in the x-axis. Robust standard errors clustered at municipality level. Municipality and Year FEs. Sample: Only treated municipalities.

So far we have controlled for sub-areas within municipalities by including the corresponding fixed effects (see Appendix B) and considering different types of municipality. However, sub-municipal areas represent spatially different zones, which are also typically characterized by different socio-economic features (e.g. affluent people are expected to live in central zones rather than in periphery ones). It is therefore interesting to consider the impact of flood events separately by sub-municipal areas, as it may provide some initial indication on whether the costs of these extreme events are evenly distributed across zones. The staggered treatment estimation is then replicated by sub-areas (B - Central, C- Semi-central, D - Peripheral, E - Suburban, and R - Rural) controlling for municipality and year fixed effects.

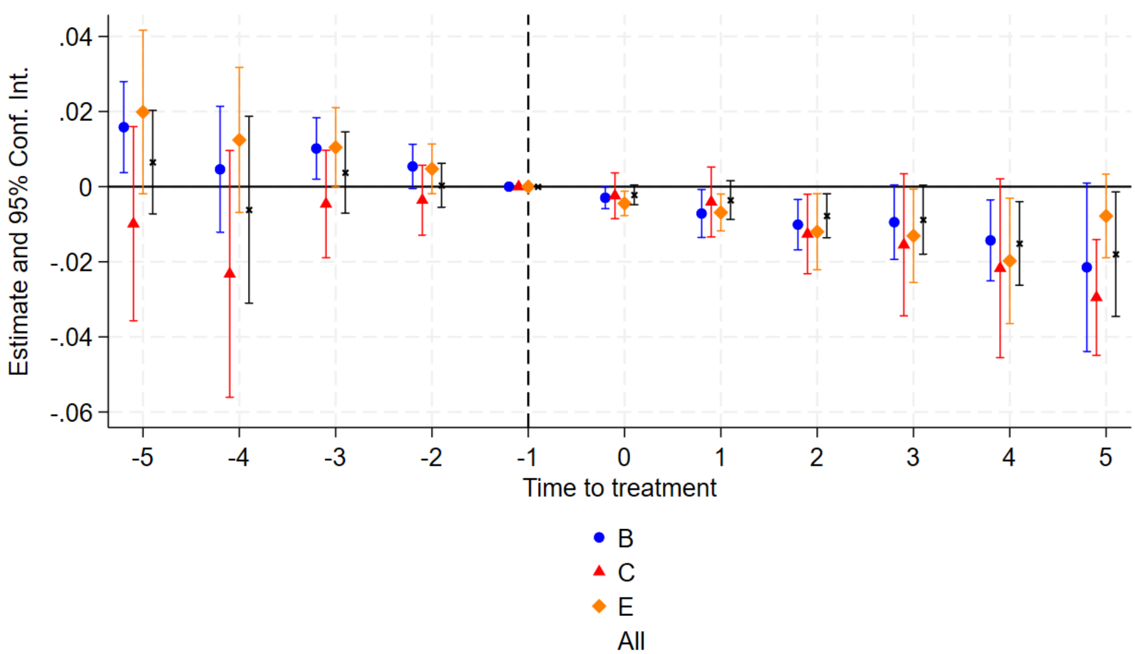
Table 4 shows significant effects in all sub-areas except peripheral and rural. The effect is particularly clear for central areas, lasting up until five semesters after the occurrence of the flood. We also find negative and statistically significant results in some semesters for areas C (semi-central) and E (suburban). Figure 8 plots coefficients and confidence intervals of the event study including only the areas with the most significant results, i.e., Central, Semi-Central and Suburban.

Table 4: **Maximum Sale Price and Flood Event.** Staggered Treatment by Fascia

	(1) B Central	(2) C Semi-central	(3) D Peripheral	(4) E Suburban	(5) R Rural	(6) All (Only Other)
-5	0.016*	-0.010	0.002	0.0020+	0.011*	0.007
	(0.006)	(0.013)	(0.009)	(0.011)	(0.005)	(0.007)
-4	0.005	-0.023	-0.025	0.012	0.012**	-0.006
	(0.009)	(0.016)	(0.021)	(0.010)	(0.004)	(0.013)
-3	0.010*	-0.005	-0.006	0.010+	0.011***	0.004
	(0.004)	(0.007)	(0.011)	(0.005)	(0.003)	(0.005)
-2	0.005+	-0.004	-0.006	0.005	0.007**	0
	(0.003)	(0.005)	(0.006)	(0.003)	(0.002)	(0.003)
0	-0.003*	-0.002	-0.001	-0.004**	-0.001	-0.002
	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
1	-0.007*	-0.004	0	-0.007**	-0.002	-0.004
	(0.003)	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)
2	-0.010**	-0.013*	-0.005	-0.012*	-0.003	-0.008**
	(0.003)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)
3	-0.009+	-0.015	-0.008	-0.013*	0.002	-0.009+
	(0.005)	(0.009)	(0.009)	(0.006)	(0.005)	(0.005)
4	-0.014**	-0.022+	-0.016	-0.020*	-0.004	-0.015**
	(0.005)	(0.012)	(0.011)	(0.008)	(0.004)	(0.006)
5	-0.021+	-0.030***	-0.024+	-0.008	-0.001	-0.018*
	(0.011)	(0.008)	(0.014)	(0.006)	(0.004)	(0.008)
Num.Obs.	6967	3523	7192	5509	3763	26954
R2	0.891	0.748	0.738	0.745	0.891	0.732
FE: Municipality	✓	✓	✓	✓	✓	✓
FE: Year	✓	✓	✓	✓	✓	✓

$+p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$
Robust standard errors clustered at municipality level. Sample: All treated municipalities.

Figure 8: **Maximum Sale Price and Flood Event.**Staggered Treatment by Fascia



Estimate and 95% c.i. in y-axis, time to treatment in the x-axis. Robust standard errors clustered at municipality level. Municipality and Year FEs. Sample: All treated municipalities.

Subsequently, we estimate the staggered treatment effect dividing our samples by types of dwelling (luxury dwelling, villas and cottages[13]; residential dwelling; affordable dwelling) within each municipality.

[13] We grouped together these two categories as we do not have enough observations for luxury dwellings.

As can be seen in Table (6) and Figure (9), we find that the largest effects are concentrated among affordable dwellings during the first four semesters following the event. After the fifth semester, the negative impact of the flood on sale prices becomes statistically insignificant, suggesting that the effect gradually fades over time. Flooding also affects the maximum sale prices of both residential and luxury properties, although the timing and magnitude differ across segments. For luxury dwellings—such as villas and cottages—the impact is immediate and negative, with effects significant at the 5% level in the short run but becoming statistically insignificant by the fifth semester. In contrast, for residential properties, the initial decline is more moderate but persists for a longer period, as it still significant at the 5% level five semesters after the occurrence of the flood, and its magnitude increases over time.

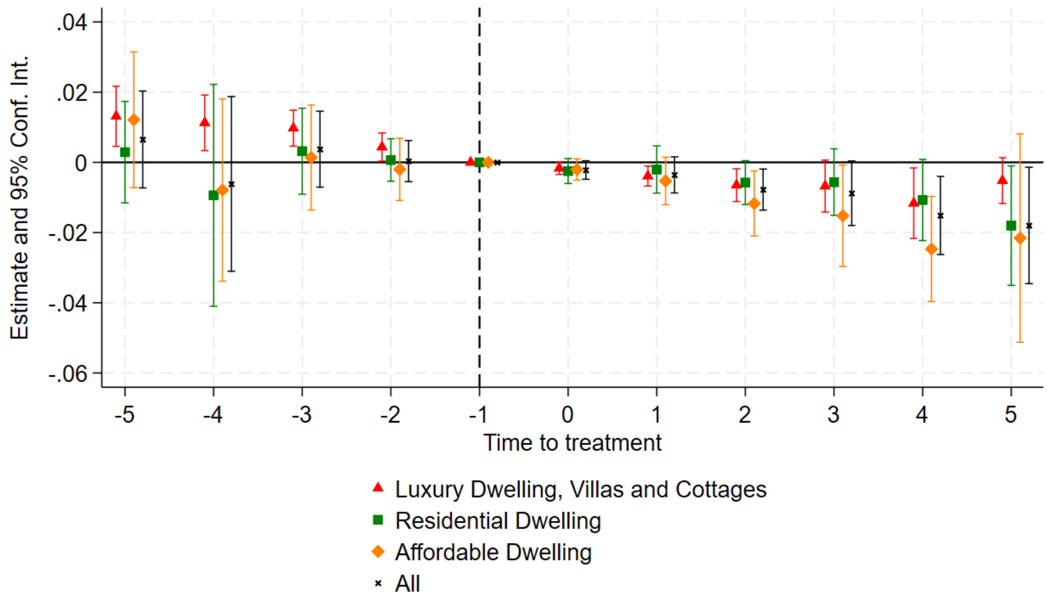
Table 5: **Maximum Sale Price and Flood Event.** Staggered Treatment by Type of Dwelling

	(1) Luxury Dwelling, Villas and Cottages	**(3) Residential Dwelling**	**(4) Affordable Dwelling**	**(5) All**	
-5	0.013**	0.003	0.012	0.007	
	(0.004)	(0.007)	(0.010)	(0.007)	
-4	0.011**	-0.009	-0.008	-0.006	
	(0.004)	(0.016)	(0.013)	(0.013)	
-3	0.010***	0.003	0.001	-0.006	
	(0.003)	(0.006)	(0.008)	(0.005)	
-2	0.004*	0.001	-0.002	0	
	(0.002)	(0.003)	(0.004)	(0.003)	
0	-0.002+	-0.002	-0.002	-0.002	
	(0.001)	(0.002)	(0.002)	(0.001)	
1	-0.004**	-0.002	-0.005	-0.004	
	(0.001)	(0.003)	(0.003)	(0.003)	
2	-0.007**	-0.006+	-0.012*	-0.008**	
	(0.002)	(0.003)	(0.005)	(0.003)	
3	-0.007+	-0.006	-0.015*	-0.009+	
	(0.004)	(0.005)	(0.007)	(0.005)	
4	-0.012*	-0.011+	-0.025**	-0.015**	
	(0.005)	(0.006)	(0.008)	(0.006)	
5	-0.005	-0.018*	-0.022	-0.018*	
	(0.003)	(0.009)	(0.015)	(0.008)	
Num.Obs.	7806	11731	7375	26954	
R2	0.848	0.817	0.811	0.735	
FE: Municipality	✓	✓	✓	✓	
FE: Year	✓	✓	✓	✓	✓

$+p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Robust standard errors clustered at municipality level. Municipality and Year FEs. Sample: All treated municipalities.

Figure 9: **Maximum Sale Price and Flood Event.** Staggered Treatment by Type of Dwelling



Estimate and 95% c.i. in y-axis, time to treatment in the x-axis. Robust standard errors clustered at municipality level. Municipality and Year FEs. Sample: All treated municipalities.

Finally, we estimate the staggered treatment effect by dividing our samples by status of conservation (excellent; normal; poor). We notice negative and statistically significant results at the 5% level for dwellings with a normal status of conservation from the semester in which the flood occurs until five semesters after (see column two of Table 6 and blue line in Figure 10). Price of properties in excellent status of conservation do not seem to be particularly affected and the same can be inferred for for poorly conserved dwellings[14]

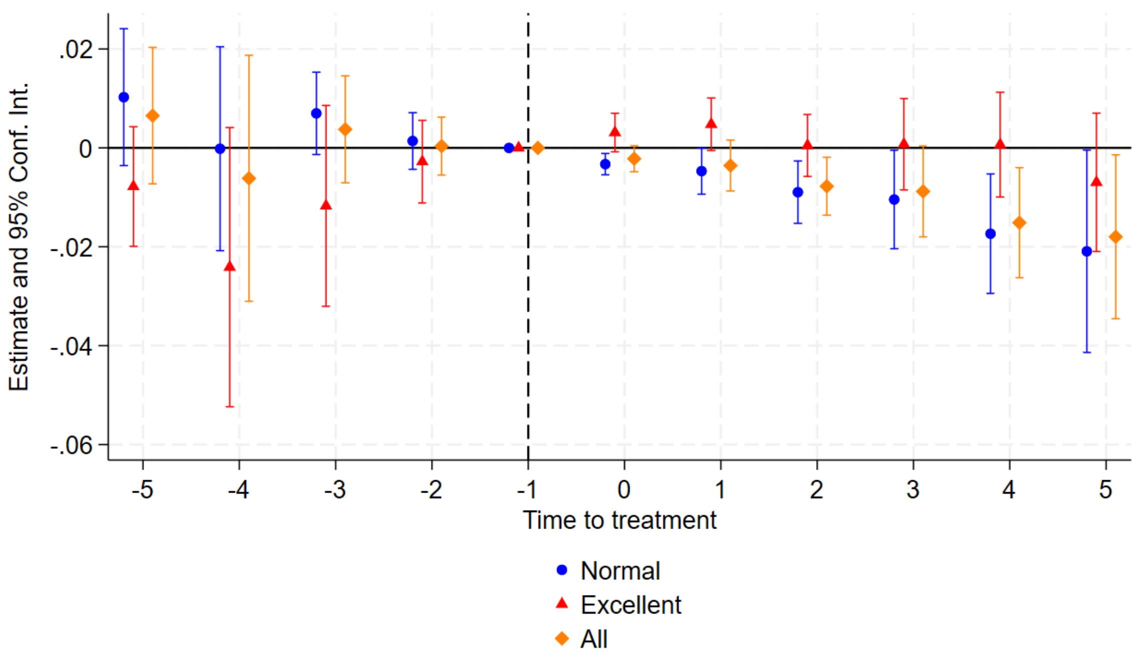
[14]It should be noted that these results should be interpreted carefully given the limited number of observations for poor conservation status.

Table 6: **Maximum Sale Price and Flood Event.** Staggered Treatment by Status of Conservation

	(1) Excellent	(2) Normal	(3) Poor	(4) All (Only Other)
-5	-0.008	0.010	0.040	0.007
	(0.006)	(0.007)	(0.028)	(0.007)
-4	-0.024+	0	0.040	-0.006
	(0.014)	(0.010)	(0.028)	(0.013)
-3	-0.012	0.007+	0.039*	0.004
	(0.010)	(0.004)	(0.017)	(0.005)
-2	-0.003	0.001	0.025	0
	(0.004)	(0.003)	(0.015)	(0.003)
0	0.003	-0.003**	0.007	-0.002
	(0.002)	(0.001)	(0.014)	(0.001)
1	0.005+	-0.005*	-0.011	-0.004
	(0.003)	(0.002)	(0.031)	(0.003)
2	0	-0.009**	-0.012	-0.008**
	(0.003)	(0.003)	(0.031)	(0.003)
3	0.001	-0.010*	-0.009	-0.009+
	(0.005)	(0.005)	(0.035)	(0.005)
4	0.001	-0.017**	0.002	-0.015**
	(0.005)	(0.006)	(0.031)	(0.006)
5	-0.007	-0.021*	0.005	-0.018*
	(0.007)	(0.010)	(0.037)	(0.008)
Num.Obs.	4979	21809	166	26954
R2	0.799	0.737	0.964	0.735
FE: Municipality	✓	✓	✓	✓
FE: Year	✓	✓	✓	✓

$+p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$
Robust standard errors clustered at municipality level. Municipality and Year FEs. Sample: All treated municipalities.

Figure 10: **Maximum Sale Price and Flood Event.** Staggered Treatment by Status of Conservation



Estimate and 95% c.i. in y-axis, time to treatment in the x-axis. Robust standard errors clustered at municipality level. Municipality and Year FEs. Sample: All treated municipalities.

5 Conclusion

In this paper, we investigate the impact of floods on housing prices in Italian municipalities. Using a staggered TWFE DiD model, we find that floods lead to a reduction in maximum sale prices per square meter by 1.6% to 3.2%, with the effect lasting up to five semesters post-event in municipalities that are neither metropolitan cities nor capital of region/province. Considering the sample of all treated municipalities, the result is slightly smaller (yielding a reduction between 1-2.6% in maximum sale price. The impact is more pronounced in semi-central zones, where prices decline by 3% to 4%, and among affordable housing units, which see reductions between 1.8% and 4.8%. Properties in normal conservation status are similarly affected, experiencing a price decline of 1.8% to 3.8%. By contrast, dwellings in excellent conservation status remain unaffected, suggesting that property conservation status may provide some resilience against extreme weather-events.

Our findings carry critical implications for policymakers and stakeholders in the context of escalating climate risks. The disproportionate impact of floods on affordable housing and semi-central areas suggests that climate-induced events may exacerbate existing housing inequalities, putting economically vulnerable households at greater risk. As Italy ranks among Europe's most vulnerable countries to natural disasters, addressing these disparities is vital for safeguarding household wealth and ensuring housing market stability.

References

Acevedo, S., Mrkaic, M., Novta, N., Pugacheva, E., and Topalova, P. (2020). The effects of weather shocks on economic activity: what are the channels of impact? *Journal of Macroeconomics*, 65:103207.

Agenzia delle Entrate (2018). Manuale della Banca Dati Quotazioni dell'Osservatorio del Mercato Immobiliare.

Anttila-Hughes, J. (2016). Financial market response to extreme events indicating climatic change. *The European Physical Journal Special Topics*, 225:527–538.

Athey, S. and Imbens, G. W. (2022). Design-based analysis in difference-in-differences settings with staggered adoption. *Journal of Econometrics*, 226(1):62–79.

Atreya, A. and Ferreira, S. (2015). Seeing is believing? evidence from property prices in inundated areas. *Risk Analysis*, 35(5):828–848.

Baldauf, M., Garlappi, L., and Yannelis, C. (2020). Does climate change affect real estate prices? only if you believe in it. *The Review of Financial Studies*, 33(3):1256–1295.

Balvers, R., Du, D., and Zhao, X. (2017). Temperature shocks and the cost of equity capital: Implications for climate change perceptions. *Journal of Banking & Finance*, 77:18–34.

Bansal, R., Kiku, D., and Ochoa, M. (2019). Climate change risk. *Federal Reserve Bank of San Francisco Working Paper.*

Belanger, P. and Bourdeau-Brien, M. (2018). The impact of flood risk on the price of residential properties: the case of england. *Housing Studies*, 33(6):876–901.

Beltrán, A., Maddison, D., and Elliott, R. (2019). The impact of flooding on property prices: A repeat-sales approach. *Journal of Environmental Economics and Management*, 95:62–86.

Bernstein, A., Gustafson, M. T., and Lewis, R. (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of financial economics*, 134(2):253–272.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly journal of economics*, 119(1):249–275.

Bin, O. and Landry, C. E. (2013). Changes in implicit flood risk premiums: Empirical evidence from the housing market. *Journal of Environmental Economics and management*, 65(3):361–376.

Brunetti, M., Croce, P., Gomellini, M., and Piselli, P. (2023). Dinamica delle temperature e attività economica in Italia: un'analisi di lungo periodo. Technical Report Numero 787 – Luglio 2023, Questioni di Economia e Finanza (Occasional Papers).

Campiglio, E., Daumas, L., Monnin, P., and von Jagow, A. (2023). Climate-related risks in financial assets. *Journal of Economic Surveys*, 37(3):950–992.

Cannari, L., D'Alessio, G., and Vecchi, G. (2016). I prezzi delle abitazioni in italia, 1927-2012 (house prices in italy, 1927-2012). *Bank of Italy Occasional Paper*, (333).

Caprara, D., De Bonis, R., and Infante, L. (2018). La ricchezza delle famiglie in sintesi: l'italia e il confronto internazionale (household wealth in italy and in advanced countries). *Bank of Italy Occasional Paper*, (470).

Cascarano, M. and Natoli, F. (2023). Temperatures and search: evidence from the housing market. *Available at SSRN 4362881.*

Choi, D., Gao, Z., and Jiang, W. (2020). Attention to global warming. *The Review of Financial Studies*, 33(3):1112–1145.

Cohen, J. P., Barr, J., and Kim, E. (2021). Storm surges, informational shocks, and the price of urban real estate: An application to the case of hurricane sandy. *Regional Science and Urban Economics*, 90:103694.

Colacito, R., Hoffmann, B., and Phan, T. (2019). Temperature and growth: A panel analysis of the united states. *Journal of Money, Credit and Banking*, 51(2-3):313–368.

De Bonis, R., Liberati, D., Muellbauer, J., and Rondinelli, C. (2020). Consumption and wealth: new evidence from italy. *Bank of Italy Temi di Discussione (Working Paper) No*, 1304.

Eurostat (2024). Housing cost burden rate by tenure status - EU-SILC survey. Accessed: 2024-11-06.

Faccini, R., Matin, R., and Skiadopoulos, G. (2023). Dissecting climate risks: Are they reflected in stock prices? *Journal of Banking & Finance*, 155:106948.

Faiella, I. (2013). Uso sostenibile del suolo in italia: analisi e proposte. In *conference paper, Calamità idrogeologiche: aspetti economici-Accademia dei Lincei, Rome*, volume 8, pages 20–50.

Garbarino, N. and Guin, B. (2021). High water, no marks? biased lending after extreme weather. *Journal of Financial Stability*, 54:100874.

Goldsmith-Pinkham, P., Gustafson, M. T., Lewis, R. C., and Schwert, M. (2023). Sea-level rise exposure and municipal bond yields. *The Review of Financial Studies*, 36(11):4588–4635.

Griffin, P., Lont, D., and Lubberink, M. (2019). Extreme high surface temperature events and equity-related physical climate risk. *Weather and Climate Extremes*, 26:100220.

IPCC (2023). Ipcc, 2023: Climate change 2023: Synthesis report, summary for policymakers. contribution of working groups i, ii and iii to the sixth assessment report of the intergovernmental panel on climate change [core writing team, h. lee and j. romero (eds.)]. ipcc, geneva, switzerland.

ISTAT (2019). The wealth of italian households and non-financial corporations. Technical report, ISTAT.

Klomp, J. (2014). Financial fragility and natural disasters: An empirical analysis. *Journal of Financial stability*, 13:180–192.

Lamond, J., Proverbs, D., and Hammond, F. (2010). The impact of flooding on the price of residential property: A transactional analysis of the uk market. *Housing Studies*, 25(3):335–356.

Loberto, M. and Spuri, M. (2023). L'impatto del rischio di alluvione sulla ricchezza immobiliare in italia (the impact of flood risk on real estate wealth in italy). *Bank of Italy Occasional Paper*, (768).

Ma, L. and Yildirim, Y. (2023). High temperature, climate change and real estate prices.

Murfin, J. and Spiegel, M. (2020). Is the risk of sea level rise capitalized in residential real estate? *The Review of Financial Studies*, 33(3):1217–1255.

NGFS, A. (2019). A call for action: Climate change as a source of financial risk. *Network for Greening the Financial System: London, UK.*

Noth, F. and Schüwer, U. (2023). Natural disasters and bank stability: Evidence from the us financial system. *Journal of Environmental Economics and Management*, 119:102792.

Painter, M. (2020). An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics*, 135(2):468–482.

Schulten, A., Bertolotti, A., Hayes, P., and Madaan, A. (2021). Getting physical: Scenario analysis for assessing climate-related risks. In *World Scientific Encyclopedia of Climate Change: Case Studies of Climate Risk, Action, and Opportunity Volume 3*, pages 211–217. World Scientific.

Spencer, N. (2023). Extreme weather and real estate: A case study of the jamaican housing market. Technical report, Inter-American Development Bank. Accessed: 2025-01-31.

The Economist (2024). Homeowners face a $25trn bill from climate change. *The Economist*.

Trigila, A., Iadanza, C., Lastoria, B., Bussettini, M., and Barbano, A. (2021). Dissesto idrogeologico in italia: pericolosità e indicatori di rischio—edizione 2021. *Ispra, Rapporti*, pages 356–2021.

Appendix A Data Sources

Table 7: Data and sources – Extreme Events

Period	Description	Source
2018	Floods	ISPRA Environmental Data Yearbook Available at: https://annuario.isprambiente.it/sys_ind/79
2019	Floods	ISPRA Environmental Data Yearbook Available at: https://annuario.isprambiente.it/sys_ind/404
2020	Floods	ISPRA Environmental Data Yearbook Available at: https://annuario.isprambiente.it/sys_ind/734

$+p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Appendix B Robustness

Figure 11: **Staggered Treatment by FEs** (1. Municipality; 2. Municipality and Year; 3. Municipality, Year, and Fascia; 4. Municipality, Year, Fascia, and Type of Dwelling; 5. Municipality, Year, Fascia, Type of Dwelling, and Status of Conservation). Estimate and 95% c.i. in y-axis, time to treatment in the x-axis. Robust standard errors clustered at municipality level. **Sample:** only treated municipalities.

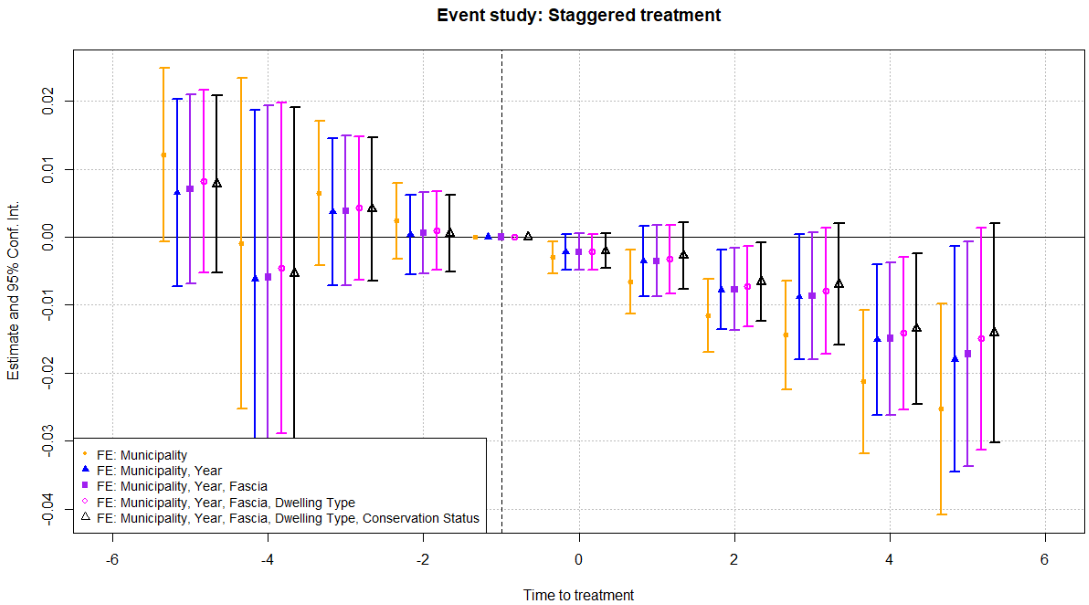


Table 8: **Staggered Treatment by FEs** (1. Municipality; 2. Municipality and Year; 3. Municipality, Year, and Fascia; 4. Municipality, Year, Fascia, and Type of Dwelling; 5. Municipality, Year, Fascia, Type of Dwelling, and Status of Conservation). Estimate and 95% c.i. in y-axis, time to treatment in the x-axis. Robust standard errors clustered at municipality level. **Sample:** Only Treated Municipalities.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
-5	0.012+	0.007	0.007	0.008	0.008
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
-4	-0.001	-0.006	-0.006	-0.005	-0.005
	(0.012)	(0.013)	(0.013)	(0.012)	(0.012)
-3	0.006	0.004	0.004	0.004	0.004
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
-2	0.002	0	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
0	-0.003*	-0.002	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
1	-0.007**	-0.004	-0.004	-0.003	-0.003
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
2	-0.012***	-0.008**	-0.008*	-0.007*	-0.007*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
3	-0.014***	-0.009+	-0.009+	-0.008+	-0.007
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
4	-0.021***	-0.015**	-0.015**	-0.014*	-0.013*
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
5	-0.025**	-0.018*	-0.017*	-0.015+	-0.014+
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Num.Obs.	26954	26954	26954	26954	26954
Mean	1905.98	1905.98	1905.98	1905.98	1905.98
R2	0.735	0.735	0.765	0.848	0.868
FE: Municipality	✓	✓	✓	✓	✓
FE: Year		✓	✓	✓	✓
FE: Fascia			✓	✓	✓
FE: Type of Dwelling				✓	✓
FE: Status of Conservation					✓

$+p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Figure 12: **Staggered Treatment by FEs** (1. Municipality; 2. Municipality and Year; 3. Municipality, Year, and Fascia; 4. Municipality, Year, Fascia, and Type of Dwelling; 5. Municipality, Year, Fascia, Type of Dwelling, and Status of Conservation). Estimate and 95% c.i. in y-axis, time to treatment in the x-axis. Robust standard errors clustered at municipality level. **Sample:** Only Treated Municipalities (Other).

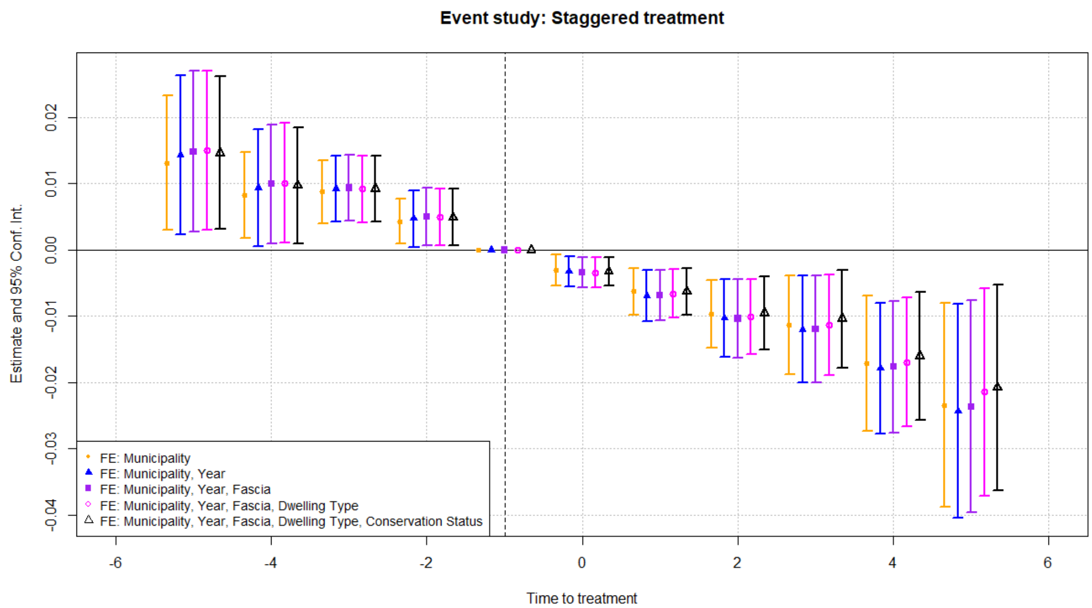


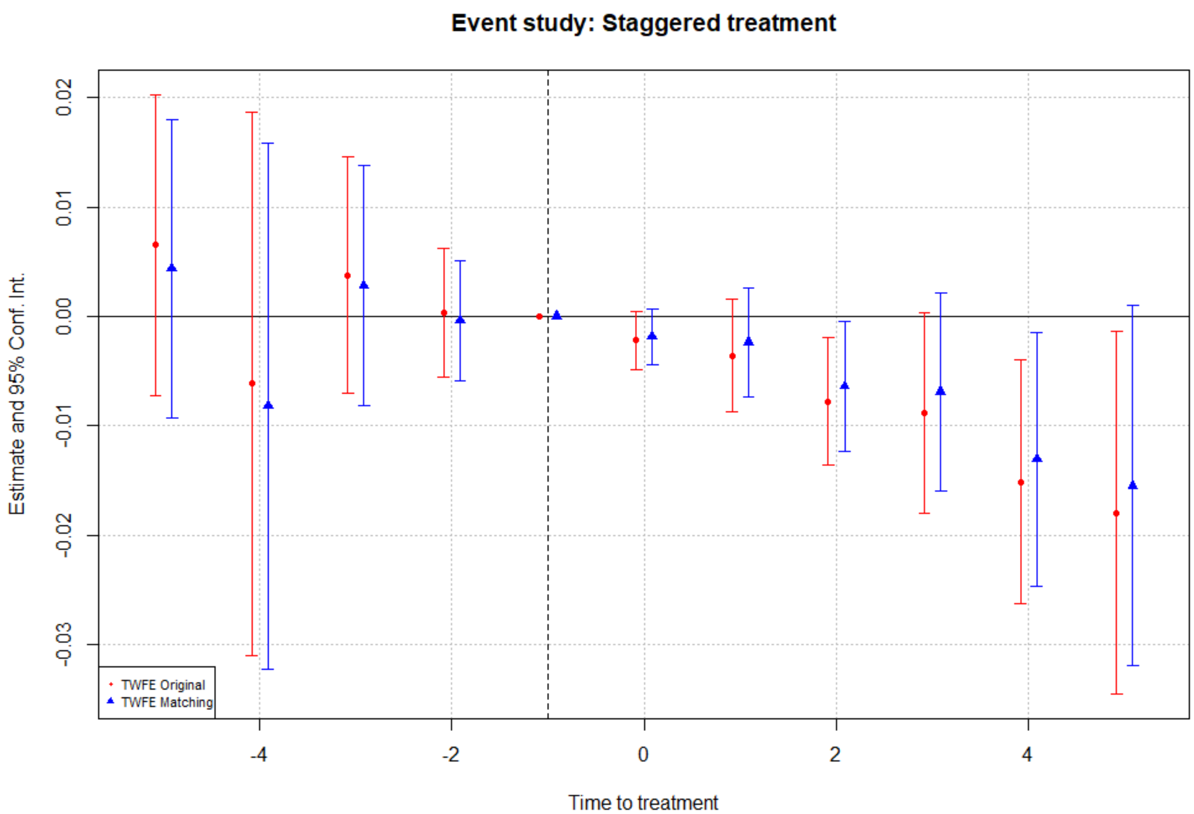
Table 9: **Staggered Treatment by FEs** (1. Municipality; 2. Municipality and Year; 3. Municipality, Year, and Fascia; 4. Municipality, Year, Fascia, and Type of Dwelling; 5. Municipality, Year, Fascia, Type of Dwelling, and Status of Conservation). Estimate and 95% c.i. in y-axis, time to treatment in the x-axis. Robust standard errors clustered at municipality level. **Sample:** Only Treated Municipalities (Other).

	(1)	(2)	(3)	(4)	(5)
-5	0.013*	0.014*	0.015*	0.015*	0.015*
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
-4	0.008*	0.009*	0.010*	0.010*	0.010*
	(0.003)	(0.004)	(0.005)	(0.005)	(0.004)
-3	0.009***	0.009***	0.009***	0.009***	0.009***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
-2	0.004*	0.005*	0.005*	0.005*	0.005*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
0	-0.003**	-0.003**	-0.003**	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
1	-0.006***	-0.007***	-0.007***	-0.007***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
2	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
3	-0.011**	-0.012**	-0.012**	-0.011**	-0.010**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
4	-0.017**	-0.018***	-0.018***	-0.017***	-0.016**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
5	-0.023**	-0.024**	-0.024**	-0.021**	-0.021**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Num.Obs.	16368	16368	16368	16368	16368
Mean	1711.83	1711.83	1711.83	1711.83	1711.83
R2	0.735	0.814	0.837	0.896	0.914
FE: Municipality	✓	✓	✓	✓	✓
FE: Year		✓	✓	✓	✓
FE: Fascia			✓	✓	✓
FE: Type of Dwelling				✓	✓
FE: Status of Conservation					✓

$+p < 0.1$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

To ensure the robustness of our findings, we conducted a Propensity Score Matching (PSM) analysis followed by TWFE regression on the matched sample. First, we estimated propensity scores using a logistic regression model, where the likelihood of being flooded was regressed on key pre-treatment covariates, including the percentage of floodable municipal area under medium flood hazard scenario, percentage of soil consumption, province and being or not the capital city of the province. The predicted probabilities from this model were then used to perform nearest-neighbor matching, matching each treated unit with a control unit that had a similar propensity score. This approach helps mitigate selection bias by creating a balanced sample where treated and control units are comparable. Subsequently, we employed a TWFE model on the matched data, regressing the outcome variable on the interaction of time-to-treat including municipality and year fixed effects and clustering standard errors at the municipality level (see figure 13).

Figure 13: **Staggered Treatment All Municipalities (Original Model vs. Matching Control)** (1. All treated municipalities (red); 2. Treated municipalities and matching control group (blue). Estimate and 95% c.i. in y-axis, time to treatment in the x-axis. Robust standard errors clustered at municipality level. Municipality and Year FEs.



We repeat the same robustness test excluding from our sample all municipalities that are the capital of the province they belong to (see figure 14).

Figure 14: **Staggered Treatment Municipalities that are not a capital (Original Model vs. Matching Control)** (1. All treated municipalities that are not the capital of the province (magenta); 2. Treated municipalities that are not the capital of the province and matching control groups that are not the capital of the province (yellow). Estimate and 95% c.i. in y-axis, time to treatment in the x-axis. Robust standard errors clustered at municipality level. Municipality and Year FEs.