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The impact of climate change and extreme weather events on residential housing prices in Italy and Germany at the NUTS 3 level

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To Nonna Lucilla,

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The impact of climate change and extreme weather events on residential housing prices in Italy and Germany at the NUTS 3 level

Martina Perez[1]

Abstract

This thesis investigates whether residential property prices are affected by climate change and extreme weather events. The analysis is highly granular in both the spatial and time dimension, combining monthly and yearly indicators at the NUTS-3 level across 107 Italian provinces (2016–2021) and 400 German districts (2008–2021). Using panel data regression techniques, the study provides empirical evidence that climate variability and extreme events are already being capitalized into real estate prices, particularly in the housing sales market. While the rental market appears less responsive, the findings suggest that temperature anomalies, extreme precipitation, and flood risk influence residential property prices, with stronger effects observed in Italy than in Germany. These results contribute to the growing literature on the pricing of climate risk in real assets and highlight the relevance of localized climate exposure for housing markets in Europe.

Keywords: Climate change, Extreme weather events, Housing prices, NUTS 3, Italy, Germany, Climate risk, Fixed Effects Model

JEL classification: Q54, R31, R21, C33, R11

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Extended abstract

Climate change is increasingly recognized not only as an environmental challenge but also as a major socio-economic risk. Among its many implications, the impact of climate change on residential housing markets remains relatively underexplored, particularly in the European context. Housing is a key component of household wealth, a major source of public revenues through property taxation, and a critical asset class underpinning financial stability. Consequently, the effects of climate change and extreme weather events on housing values raise important questions for income and wealth distribution.

This thesis investigates whether and to what extent changes in climate conditions and the occurrence of extreme events have affected residential property markets in Italy and Germany. The focus is twofold: first, to assess the impact of climate variables and weather extremes on sale prices of residential housing; second, to explore whether similar patterns emerge in the rental market, which may reflect shorter-term perceptions of climate risk.

The study contributes to the emerging literature on climate economics and housing by providing new evidence from two major European countries, using a granular empirical approach. The analysis is conducted at the NUTS 3 level, allowing for regional heterogeneity and spatial detail. The dataset combines housing market indicators with climate data derived from the ECMWF ERA-5 dataset, which provides daily observations at high spatial resolution. Additional socio-economic controls are included to account for housing fundamentals.

The results show that climate risk is increasingly priced into housing markets, particularly in areas most exposed to extreme weather events. In Italy, variables such as temperature variability and extreme precipitation are significantly associated with lower sale prices, while exposure to flood-prone areas also plays a role. The rental market shows a similar direction of effects, though with weaker magnitude, consistent with the idea that renters face shorter time horizons and lower economic exposure to long-term climate risks.

In Germany, the results also point to negative effects, though less pronounced. Variations in average temperature and temperature variability are associated with declines in sale prices, while extreme precipitation events do not appear to have a statistically significant impact.

These findings underscore the need to increase awareness of climate risks in the real estate sector to support an orderly transition and prevent sudden market disruptions. Enhancing transparency and systematically incorporating climate risks into property valuations and financial oversight are essential. At the European level, these efforts are key also to preserve financial stability.

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1 Introduction

Climate change is one of the most debated topics of our time. Its ramifications extend far beyond the environment, affecting the economy, politics, and society. The effects of climate change, such as rising temperatures, and extreme weather events (e.g., floods, heatwaves), are putting a strain on ecosystems and communities all over the world. Climate conditions and extreme weather events have significant effects on economic activity (e.g., GDP) and asset values. Recent research estimates that the impact of extreme weather events on human activity is in the range of 19-59 trillion USD over the next 25 years, which translates into a permanent income reduction of 11-29% on average globally; these damages are already "committed" as they relate to the effects of the combination of past emissions with plausible paths of future emissions (Kotz et al., 2024).

This thesis investigates how climate change and extreme weather events affect residential housing prices in selected European countries. The policy implications of the impact of climate change and extreme events on housing are broad. First, the stake of residential housing on wealth is large, especially for people with low- to medium-income. Thus, the impact of climate conditions on residential housing values will have wealth distributional consequences. Second, municipalities and other local authorities derive a large part of their tax revenues from houses, and a decrease in the value of properties will draw down their revenues. Third, residential housing represents a significant portion of collateral held by financial intermediaries, whose value may be impacted by climate events (Alogoskoufis et al., 2021; Meucci and Rinaldi, 2022); a significant drop in the value of houses will likely entail financial stability issues (think about the 2008 Global Financial Crisis). Fourth, significant damages to real estate assets held by households and firms may force governments to restore damages with significant consequences on public finances. Fifth, an insufficient awareness of the consequences of climate change on the value of residential housing might lead to abrupt repricing of properties, exacerbating the negative effects mentioned above.

The aim of this thesis is therefore to test the hypothesis that climate change and extreme weather events are already affecting residential real estate values, prices and rents in selected European countries. To this end, separate analyses are conducted for sales and rental prices. Indeed, the two prices are expected to react differently to these events. In particular, climate risk can significantly reduce house prices, while it may have a limited impact on rental prices as long-term climate risks may not be perceived as a concern given the shorter time horizon of the perspective renter with respect to the perspective buyer and the limited economic exposure of the perspective renter with respect to the value of the property.

The following questions are addressed: have past changes in climate conditions and the occurrence of extreme events impacted residential sale prices? And how have they influenced rental prices? The goal is to interpret the findings and compare them with key insights from the previous literature that mainly refers to the effects of climate change and extreme events on US housing prices in order to detect similarities and differences with respect to the European countries.

This thesis contributes to the literature by analysing the impact of climate change and extreme weather climate events on housing prices and rents in Italy and Germany, using data at a small regional level (NUTS 3[1]). It expands on previous research by examining both sales and rental markets and comparing the results with studies conducted both in Europe and in the United States. The results provide insights for policy makers and shed light on the importance of climate risk awareness and adaptation strategies in the real estate market.

The rest of the thesis is organised as follows. Section 2 presents a review of empirical literature. Section 3 describes the data and the estimated variables. Section 4 delves into the empirical analysis. Section 5 explains the regression results. Section 6 concludes.

[1] The term NUTS 3 refers to the Eurostat classification which divides each EU country into 3 levels: NUTS 1: major socio-economic regions (i.e., macro-regions), NUTS 2: basic regions, and NUTS 3: small regions (such as provinces).

2 Literature review

2.1 The macroeconomic impact of climate change and extreme events

The economic impact of climate change and extreme weather events has been studied, particularly in terms of their consequences on productivity and growth, with mixed findings: often negative, but sometimes positive depending on context. Usman et al. (2025) show that extreme events such as heatwaves and droughts do not only reduce output in the short term, but also have persistent negative effects on the components of potential output, particularly total factor productivity. Their findings highlight that post-disaster investment in adaptation capital - such as air conditioning or insulation - tends to yield lower output gains than equivalent investment in productive capital, thereby dampening regional productivity. Brunetti et al. (2023) examine the negative impacts on GDP per capita of rising temperatures in Italy at the provincial level over the 20th century. Kotz et al. (2024) and Waidelich et al. (2024) focus their study on the impact of climate change and extreme weather events on global GDP and point out that global economic damage due to climate change cannot be assessed solely on the basis of average annual temperature. Climate variability and extreme events play a key role, especially for the most vulnerable countries. Including these factors in damage estimates improves the accuracy of economic forecasts and helps develop more effective mitigation and adaptation strategies.

While most studies focus on national-level impacts, Usman et al. (2025) highlight that natural disasters have highly localised effects, and they are difficult to detect at the national level due to their dilution when aggregated within a country. Following this approach, this thesis examines the impact of climate change and extreme weather events on housing prices in Italy and Germany at the NUTS 3 level, a granular geographic scale that allows for capturing local effects.

It is worth noting that not all the studies agree with the common view that climate change has a negative impact on the economy in all circumstances. Roth Tran and Wilson (2024) found out that in the US when natural disasters trigger government aid and/or insurance payouts, natural disasters result, both on average and in the long run, in higher personal income per capita, higher wages, and higher house prices, while employment and population remain unchanged. They suggest that part of the observed income growth after a disaster may reflect shifts in workforce composition toward higher-wage workers, as lower-wage workers are priced out of these housing markets.

2.2 The determinants of house prices

An extensive literature has analysed the main determinants of residential house prices, generally distinguishing between demand-side and supply-side factors. Demand-side determinants include household income, the real interest rate on home loans, financial wealth, demographic and labour market variables, the expected return on real estate investment. On the supply side, the determinants are generally described as an increasing function of the profitability of building activity, which is positively related to the level of house prices and negatively to real construction costs. The latter include land prices, construction wages and material costs (Égert and Mihaljek, 2007). Demand-related variables encompass regional income, unemployment rates, labour force participation (Schunre, 2005), and net migration (McQuinn, 2004).

Cunha and Lobão (2021) show that the determinants of real estate prices vary significantly depending on the geographical context. While at the EU level GDP and interest rates are key factors, at the national and regional level other elements, such as tourism and the number of building permits issued, play a determining role. These results highlight the complexity of price formation in the real estate market and suggest that there is no single model valid for all geographical contexts[2].

2.3 The effect of climate change and extreme events on housing prices

Empirical research on the impact of climate events on housing prices focuses mainly on US data. Ma and Yildirim (2023) find a negative relationship between extreme weather exposure and sale prices, while rental prices are not affected as renters are less concerned about long-term climate risks. Gourevitch et al. (2023) find that the majority of extremely overpriced real estates are located in coastal areas with no flood

[2] Using quantile regression, Zietz et al. (2007) show that variables such as floor area, lot size and number of bathrooms have a greater effect on more expensive houses than on less expensive ones. This implies that traditional methods (such as linear regressions) may overestimate the marginal value of these characteristics for low-priced homes and underestimate it for high-priced homes, highlighting the importance of analysing prices in a segmented manner.

risk disclosure regulations and low levels of climate change awareness. As a result, property prices in these areas often fail to reflect actual climate-related risks, particularly the threat of flooding. Furthermore, a large portion of overvalued properties are owned by low-income residents, who are therefore more vulnerable to home equity losses in the aftermath of flood events. Municipalities that mostly rely on property taxes for funding are also at risk, as climate-induced declines in housing values can translate into significant budgetary shortfalls. Keys and Mulder (2020) provide evidence that increasing awareness of sea level rise risk has recently led to significant shifts in housing demand in coastal Florida. While lender behaviour has remained stable, prospective buyers have become more hesitant to purchase homes in high-risk areas. Bernstein et al. (2019) find that exposure to sea-level rise is leading to significant price discounts even in the absence of an increase in short-run flooding risk. Fairweather et al. (2024) conducted a nationwide experiment to assess the impact of flood risk disclosure on the US housing market. The authors show that increased awareness of flood risk reduced the demand for houses in high-risk areas, leading to lower prices and more efficient purchase decisions. Baldauf et al. (2020) investigate the role of heterogeneity in climate change beliefs in the formation of housing prices. Specifically, they show that housing prices in the US market reflect local differences in beliefs about long-term climate risks. The authors develop a theoretical model in which individuals derive utility from living in neighbourhoods composed of agents with similar beliefs, showing that this assortment generates different price elasticities with respect to climate risks. In doing so, they find that housing located in areas with higher climate awareness ("believer neighbourhoods") sells at significantly lower prices than housing in areas where climate change is perceived to be less relevant ("denier neighbourhoods"). The results suggest that future climate risks are being capitalized into prices already, but unevenly, due to fragmented beliefs. However, the study remains agnostic as to whether it is the "sceptics" who underestimate the risk or the "believers" who overestimate it.

In Europe, Votsis and Perrels (2015) detect potential housing price differentials caused by the public release of high-resolution flood maps in Finland. The estimations identify a statistically significant price decline, suggesting that when risk information is available, the market adjusts accordingly. According to Loberto and Spuri (2023), about a quarter of Italy's real estate assets are exposed to flood risk – with a value amounting to almost EUR 1 trillion in 2020. The potential economic damage is represented by the expected annual loss, calculated by combining the probability of the event, the value of the exposed properties and their vulnerability. The latter depends on factors such as the floor level of the house and the construction materials. Estimates show that the expected annual loss could reach EUR 3 billion, even considering conservative scenarios. Moreover, the risk is very heterogeneous over the territory: areas such as Emilia-Romagna and Liguria are particularly exposed[3]. The work highlights how an accurate assessment of the effects of climate change on the real estate market requires highly granular data, as flood risk is highly localised.

Trautmann (2024) highlights that the real estate market is significantly influenced by both direct physical climate risks and indirect factors related to the green transition. Although the overall effect on prices is mostly negative, the author highlights cases of properties that may benefit indirectly, such as properties located in relatively safer areas that may experience positive spillover effects in demand. In particular, properties in cold regions may benefit directly from higher temperatures, with lower heating costs and better climatic amenities (Albouy et al., 2013; Sinha et al., 2021). Furthermore, some agricultural territories may increase their value due to the expansion of arable land due to global warming, or as a result of a general reduction in the global supply of specific crops (Ovalle-Rivera et al., 2015; Lustgarten, 2020). Finally, the transition to climate neutrality could increase the value of energy-efficient properties with sustainable climate control systems (Taruttis and Weber, 2022). Areas with an abundance of sustainable energy could attract energy-intensive industries, thus stimulating the local economy and increasing real estate demand.

The evidence for Germany and Italy also confirms that climate preferences are relevant for the housing market. Rehdanz and Maddison (2005) show, for the German case, that households are willing to pay more for houses located in area with mild and less rainy winters, while they penalise areas with excessively hot summers. Similarly, Maddison and Bigano (2003) show that in Italy households despise high summer temperatures

[3] These findings are consistent with the present analysis. As shown in Figures 13 and 14, Emilia-Romagna and Liguria emerge among the regions most affected by extreme precipitation events.

and winter precipitation, with preferences for clear skies in some areas (e.g. Milan). In both cases, therefore, the value of climatic amenities has implications for house prices.

In line with these results, Cascarano and Natoli (2023) analyse how climate variations affect search and matching processes in the Italian real estate market. Combining daily data on temperatures in several Italian cities with information from online real estate listings and physical appointments with real estate agents, the authors identify two main findings. First, extremely high temperatures significantly reduce both online and physical searches for housing, leading to an increase in average time on the market for properties and a delay in transactions. Second, these weather conditions induce a change in buyer preferences, which tend to avoid homes that are not perceived as "climate-safe," that is, not resilient to future climate risks. As a result, such homes experience persistent price reductions. So, while extreme heat discourages search, the cooler months seem to boost online search, while not generating a corresponding increase in physical search. Overall, the study highlights a key finding: climate change may act as a determinant in search mechanisms in the housing market, especially for houses less adapted to climate change.

3 Data and variables

The choice of dataset to be used to analyse the impacts of climate change and extreme weather events is a widely debated issue in the literature. With respect to extreme events, one of the most used sources for natural disasters is the Emergency Events Database (EM-DAT)[4], compiled by the Centre for Research on the Epidemiology of Disasters (CRED). Botzen et al. (2019) point out that the use of EM-DAT has several limitations: varying thresholds for inclusion of events, damage estimates based on local sources that are often inaccurate or overestimated, and a possible correlation between measures of disaster intensity and GDP per capita, as losses are higher and better documented in developed countries.

In light of these critical issues, natural disasters can be alternatively identified on the basis of high-resolution meteorological variables, together with changing climate

[4] https://www.emdat.be/.

conditions (Bilal and Kanzig, 2024; Kotz et al., 2024). Following this approach, the analysis relies on climate data from the ERA-5 dataset of the European Centre for Medium-term Weather Forecasts (ECMWF). In particular, it draws on data from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP), an initiative aimed at providing a coherent methodological framework for the assessment of climate change impacts[5]. The ISIMIP ERA-5 20CRv3[6] dataset provides daily global meteorological data on a grid with a spatial resolution of 0.5° x 0.5° in latitude and longitude, corresponding approximately to 55 km x 40 km in the Central European region. The climate data collected include: precipitation (pr), near-surface air temperature (tas), and near-surface wind speed (sfcwind). The data cover the period from 1901 to 2021. For the purposes of this thesis, the analysis is restricted to the years 1981 to 2021.

To match climate data with NUTS 3 administrative boundaries, regional maps from Eurostat were used[7]. These maps are stored in shapefile format, a widely used geospatial vector data format, commonly used in Geographic Information Systems (GIS). Within the shapefile, regions are represented as polygons, which can vary in segmentation detail[8]. Since NUTS 3 regions spanned multiple grid cells (see Appendix A.1 as an example), a weighted average of the climate data for the region was performed, with weights determined by the proportion of the area of the region lying in the 0.5° x 0.5° grids (Kotz et al., 2024; Bilal and Kanzig 2024)[9].

For Italy, the surface areas at risk of flooding in each province - expressed as a percentage of the province's total area - were obtained from the Istituto Superiore per la Protezione e la Ricerca Ambientale (ISPRA) for different flood probability scenarios[10]. These data are the result of a multi-year process that also involves the District Basin Authorities (Loberto and Spuri, 2023). The process consists of two phases: (i) identification of potentially floodable areas; (ii) attribution of a risk level to each area.

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[5] Retrieved from https://data.isimip.org/search/page/3/tree/ISIMIP3a/InputData/climate/atmosphere/20crv3-era5/.
[6] 20CRv3 stands for 20th Century Reanalysis Version 3.
[7] Retrieved from https://ec.europa.eu/eurostat/web/gisco/geodata/statistical-units/territorial-units-statistics.
[8] The 1m resolution has been used to ensure accuracy.
[9] The process involved overlaying the climate grids to the provinces, calculating the intersection areas and their coverage percentages, allowing for proper weighting of climate data.
[10] Retrieved from https://indicatoriambientali.isprambiente.it/it/pericolosita-da-alluvione/aree-pericolosita-idraulica.

In the first phase, the authorities identify potentially floodable areas on the basis of both past events and a prospective assessment that partially takes into account the effects of climate change. In the second step, three possible scenarios are assumed for the probability of flooding, expressed in expected years for an event of a given magnitude to recur (the so-called "return period"): high (return period between 20 and 50 years); medium (return period between 100 and 200 years); low (return period greater than 200 years and up to 500 years). For each of the three scenarios, the exact coordinates of the hydraulic hazard areas, the origin of the risk, and a more precise estimate of the return period are provided.

Residential property values, advertisement data on sales and rents at the NUTS 3 level administrative units ("*province*" in Italy, "*kreise*" in Germany), are available for both Italy and Germany. For Italy, monthly data were collected from Immobiliare.it for the period 2016-2021[11]. For Germany, annual data were collected from RWI - Leibniz-Institut für Wirtschaftsforschung[12], with a time coverage from 2008 to 2021. German data are hedonic prices, which means that the observed differences in prices reflect changes under comparable property characteristics. They are categorized into several segments: House Purchase, Apartment Purchase, Apartment Rental and are available both as relative prices, measuring how prices in a given district deviate from the national average prices in Germany (i.e., the ratio between regional price level and national price level), and as changes in regional price indices compared to 2008, covering the same period.

The analysis covers 107 Italian provinces and 400 German districts at NUTS 3 level. Italian provinces allow an analysis with a larger time series dimension, due to the availability of monthly data. In contrast, for German districts, the cross-sectional approach is more appropriate, as the data are available at an annual frequency and the number of German *kreise* is much higher than that of Italian provinces. To ensure comparability between Italian and German data, relative house price and rents in each

[11] Residential data were collected up to 2021 to match them with the available climate data. Retrieved from https://www.immobiliare.it/mercato-immobiliare/.

[12] RWI - Leibniz-Institut für Wirtschaftsforschung; ImmobilienScout24 (2024): Regional Real Estate Price Index for Germany - SUF, 2008-05/2024. RWI-GEO-REDX. Version: 1. RWI – Leibniz Institute for Economic Research (doi.org/10.7807/immo:redx:suf:v14). See Thiel (2024) for a description of the dataset.

province with respect to the national average were calculated for Italy based on national sale and rental data from Immobiliare.it.

For what regards the other determinants of house prices and rents, their availability at NUTS 3 level for European countries is limited, as well as their availability at the monthly frequency of Italian house prices and rents. Therefore, the analysis has to accept, in most cases, some sort of compromise. With respect to income per capita, a likely powerful explanatory variable of diversity of houses prices across different areas, Eurostat publishes nominal GDP and population at NUTS 3 level but only on a yearly frequency. Statistic on population, expressing the demographic factors behind house prices, are also available from Eurostat on an annual basis at NUTS 3 level, except for net migration and German population density that are sourced from Ardeco. With respect to financial variables, mortgage rates at a monthly basis are available from the ECB, but only at national level. Table 1 provide an overview of determinants of house prices, other than climate factors used in this study.

Table 1
Economic and demographic data

	Units	Frequency	NUTS level	Source
Nominal GDP	Millions of euros	Yearly	3	Eurostat
Population density	Inhabitants per square kilometre	Yearly	3	Ardeco/Eurostat
Net migration	Net immigrants/Total population	Yearly	3	Ardeco
Mortgage rates	Percentage	Monthly	National	ECB

Note: data on population density for Germany were retrieve directly from Ardeco. Data on population density for Italy were elaborated dividing population data from Eurostat by the province area. The different treatment of Italian data is motivated by missing data about population density in the Ardeco database for year 2021 at NUTS 3 level.

Economic and financial variables are restricted to the period covered by house price data and climate data (December 2016 - December 2021 for Italy; 2008-2021 for Germany). NUTS 3 data span for 107 Italian provinces and 400 German *kreise*, with a total of 6527 data points for Italy (monthly data; 642 data points for annual data) and 5541 data points for Germany (annual data)[13].

3.1 Descriptive analysis of price dynamics

In Italy, relative house prices and rents across 107 provinces from 2016 to 2021 exhibit significant dispersion. House prices range from approximately one-third to nearly twice the national average. In contrast, the dispersion of relative rents is notably lower than that of relative house prices. Specifically, house prices vary from around €600 to over €4,100 per square meter, while rents range from €3 to €19 per square meter (see Table 2).

In Germany, data from 400 *kreise* spanning 2008 to 2021 reveal an even greater dispersion in both relative house prices and rents compared to the Italian data. The variation is particularly pronounced for relative house prices, which show higher dispersion than relative apartment prices. It is important to note that German price and rent data are not directly comparable to the Italian figures, as they are expressed in relative terms - indexed to the 2008 price level for each respective *kreis* (see Table 4).

It should be noted that the average values of relative prices and rents differ from 1, both for Italy and for Germany. Indeed, relative data are calculated as the ratio of province data with respect to the weighted national average. Where advertisement in the largest (and most expensive) cities weights the most (Italy), the mean of relative prices and rents tends to be below one. Whereas, where the opposite occurs (Germany), the mean tends to be above one.

[13] Of the original 5.600 data points for Germany 59 were removed for missing population and/or GDP data.

Table 2

Descriptive statistics - dependent variables – Italy monthly – 2016-2021

Variable	Mean	SD	Min	Max	N
Prices	1,602	619	606	4,114	6527
Relative prices	0.82	0.32	0.32	2.15	6527
Rents	7.68	2.34	3.20	18.82	6527
Relative rents	0.76	0.23	0.29	1.80	6527

Note: prices and rents are expressed as euros per square meter. Relative prices and relative rents are computed with respect to the national average.

Table 3

Descriptive statistics – dependent variables – Italy annual – 2016-2021

Variable	Mean	SD	Min	Max	N
Prices	1,606	621	606	4,114	642
Relative prices	0.82	0.32	0.32	2.15	642
Rents	7.63	2.31	3.68	17.77	642
Relative rents	0.75	0.23	0.34	1.75	642

Note: prices and rents are expressed as euros per square meter. Relative prices and relative rents are computed with respect to the national average.

Table 4

Descriptive statistics – dependent variables – Germany annual – 2008-2021

Variable	Mean	SD	Min	Max	N
Prices -Apts	128	41	51	441	5541
Relative prices - Apts	1.03	0.43	0.17	4.12	5541
Prices - Houses	123	35	63	367	5541
Relative prices - Houses	1.25	0.58	0.33	4.69	5541
Rents - Apts	121	21	76	235	5541
Relative Rents	1.03	0.22	0.63	2.67	5541

Note: prices and rents are expressed as indices with respect to 2008 (=100). Relative prices and relative rents are computed with respect to the national average.

Figure 1 shows the distribution of the Italian sale prices at monthly and annual frequencies in terms of euros per square meter. The histograms indicate that Italian house sale prices are right-skewed. Indeed, most observations concentrated below the national average and a long right tail reflects a smaller number of high-priced houses. The distribution of absolute price data reflects both the dispersion of prices across provinces and the change of prices over the years. To isolate the cross-sectional dimension, Figure 2 represent the distribution of relative sale prices. Again, the skewness is evident at both monthly and annual frequencies. By contrast, Figures 3 and 4 show that rents exhibit a slightly more symmetric distribution, with lower overall dispersion both in absolute and in relative terms. Indeed, monthly and annual rents are more tightly clustered around the mean and median, suggesting a more balanced distribution across provinces compared to sale prices.

Figure 1
Italian sale prices – 2016-2021

(a) Monthly | (b) Annual

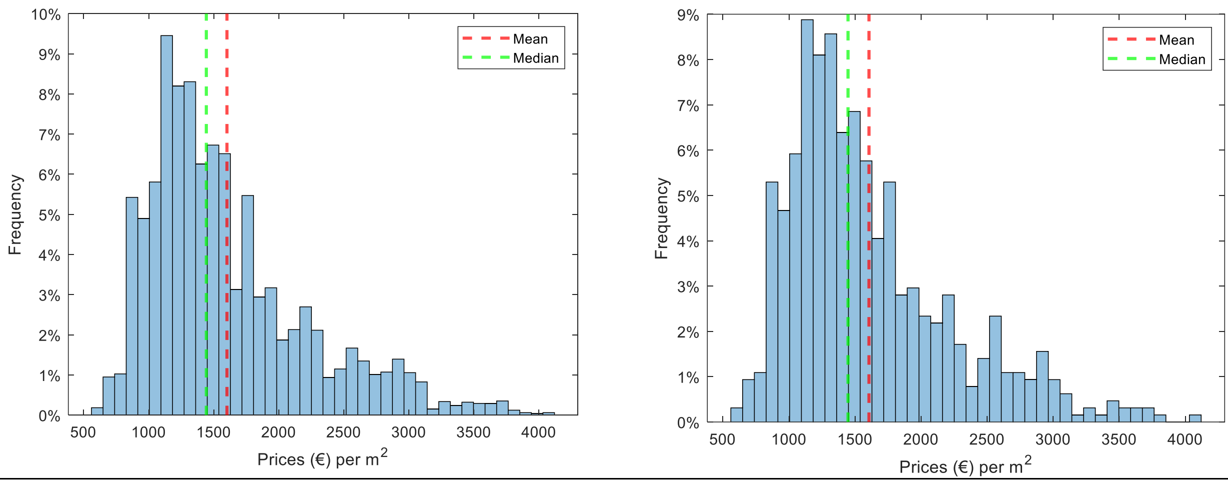


Figure 2
Italian relative sale prices – 2016-2021

(a) Monthly | (b) Annual

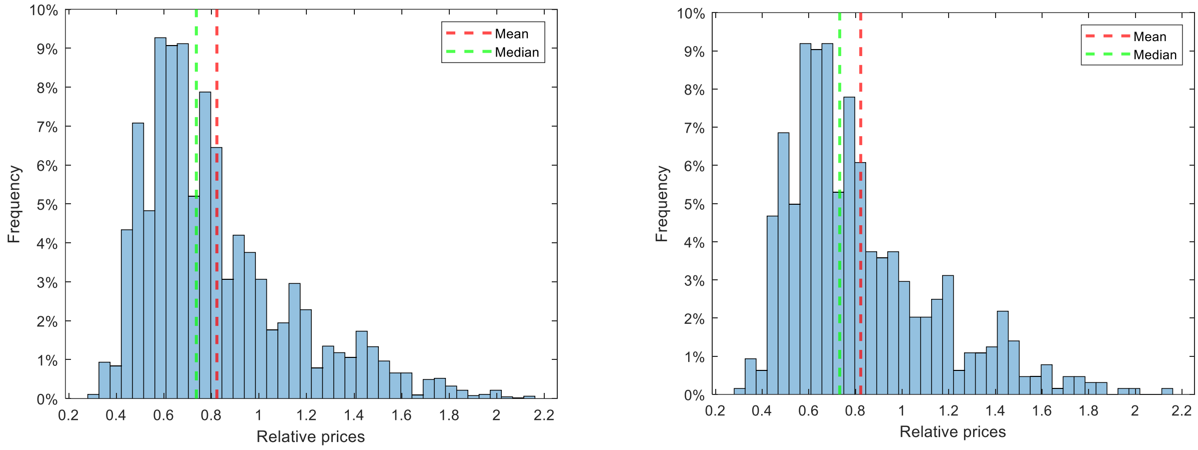


Figure 3
Italian rents – 2016-2021

(a) Monthly | (b) Annual

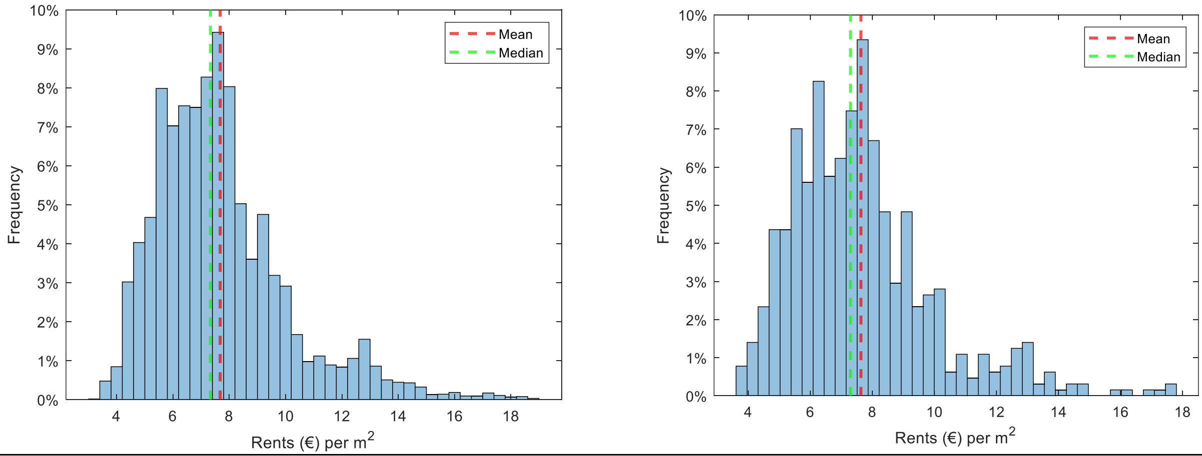
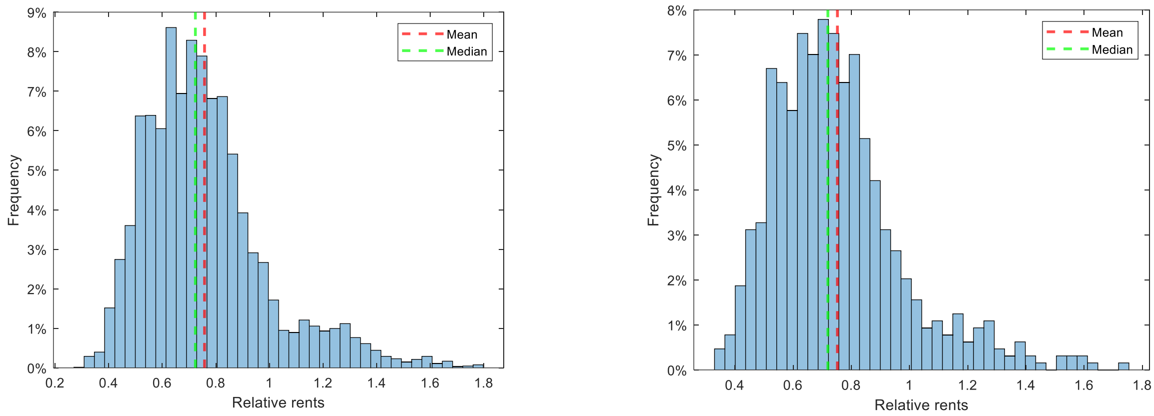


Figure 4
Italian relative rents – 2016-2021

(a) Monthly | (b) Annual



The skewness is even more pronounced in the case of absolute sale prices for both apartments and houses in Germany (Figure 5). With respect to relative sale prices, the distribution is almost symmetric in the case of apartments, whereas it tends to be right-skewed for houses (Figure 6). A right-skewed pattern emerges also for absolute (Figure 7) and relative rent prices (Figure 8). Overall, the inspection of German data suggests a greater heterogeneity in the German residential real estate market across districts with respect to Italy (see also the descriptive statistics for relative prices and rents in Table 3 and Table 4).

Figure 5
German sale prices – 2008-2021

(a) Apartments | (b) Houses

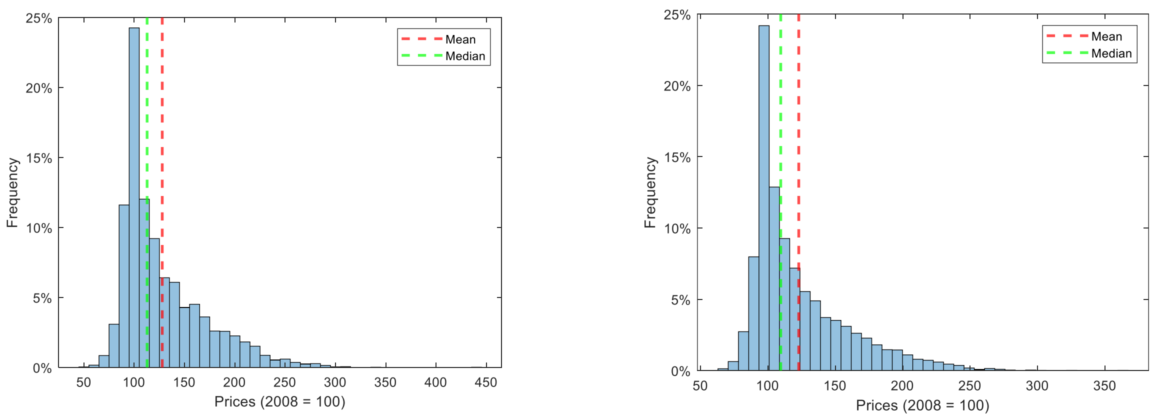


Figure 6
German relative sale prices – 2008-2021

(a) Apartments | (b) Houses

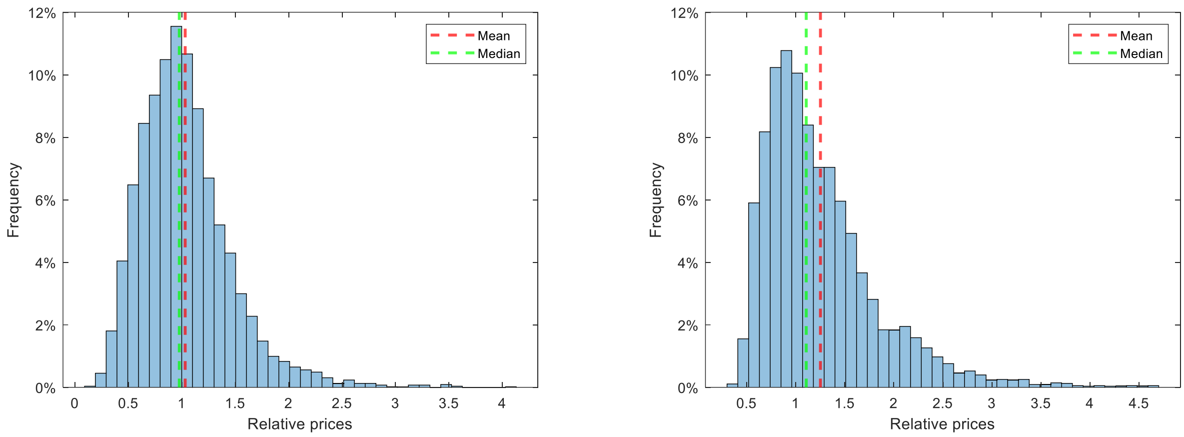


Figure 7
German rents – 2008-2021

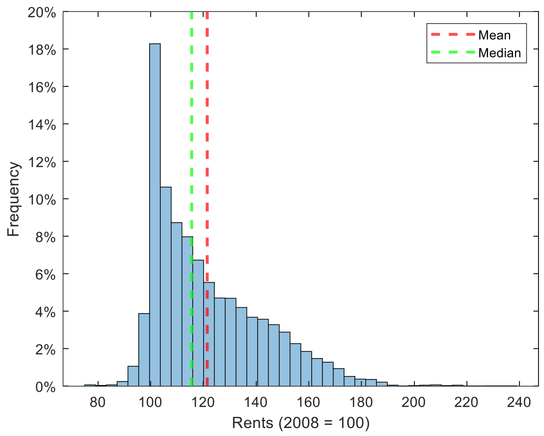
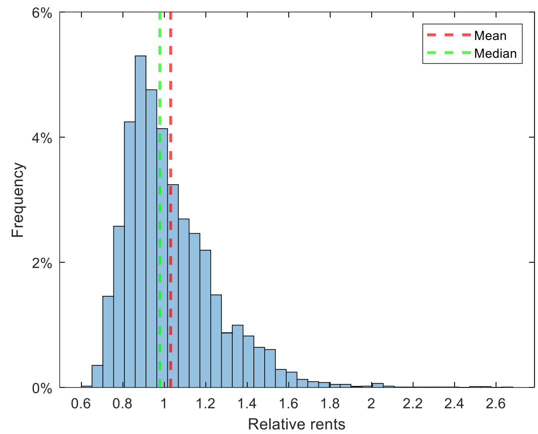


Figure 8
German relative rents – 2008-2021



Another aspect to be taken into account for the subsequent analysis is the fact that the apparent similarity between monthly and annual distribution of Italian data hides important differences in terms of the dispersion of the relevant variable within each province. Indeed, the dispersion within each province of candidate dependent variables is lower in the case of monthly observations with respect to annual observations (Figures 9 to 12). This circumstance together with the fact that some of the explanatory variables have annual frequency (and, hence, they cannot explain small monthly variations) may affect the explanatory properties of a monthly regression.

Figure 9

Italy - House prices – within province dispersion of variable – 2016-2021

(a) Monthly

(b) Annual

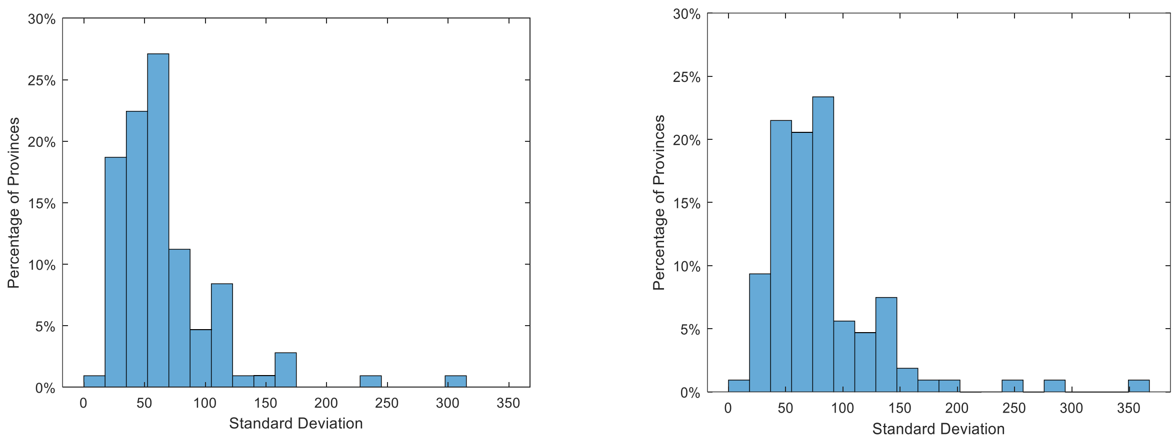


Figure 10

Italy – Rents – within province dispersion of variable – 2016-2021

(a) Monthly

(b) Annual

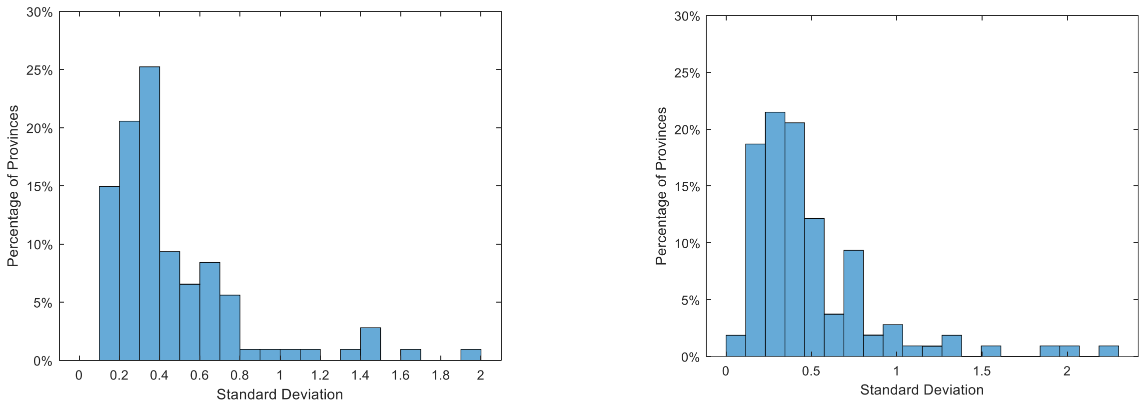


Figure 11
Italy – Relative prices – within province dispersion of variable – 2016-2021

(a) Monthly | (b) Annual

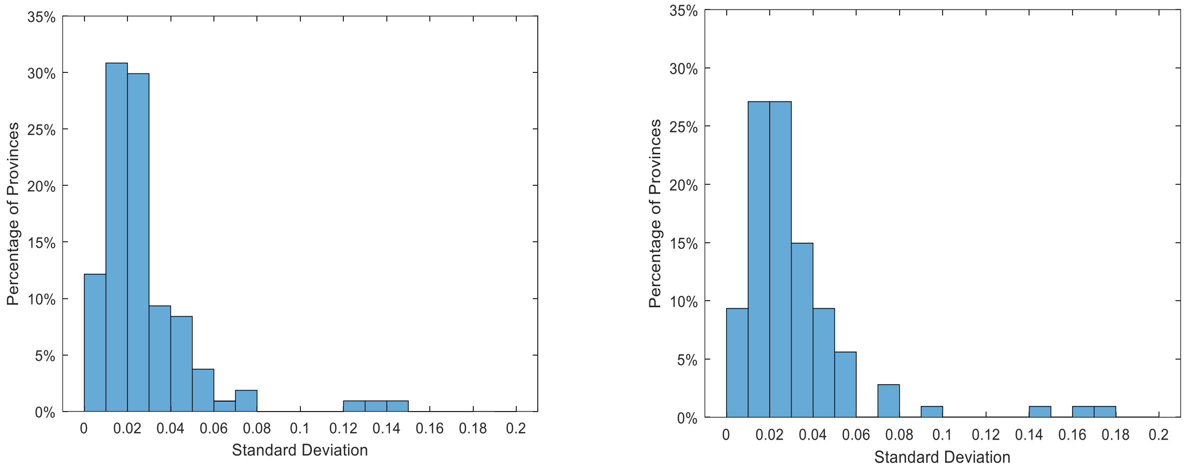
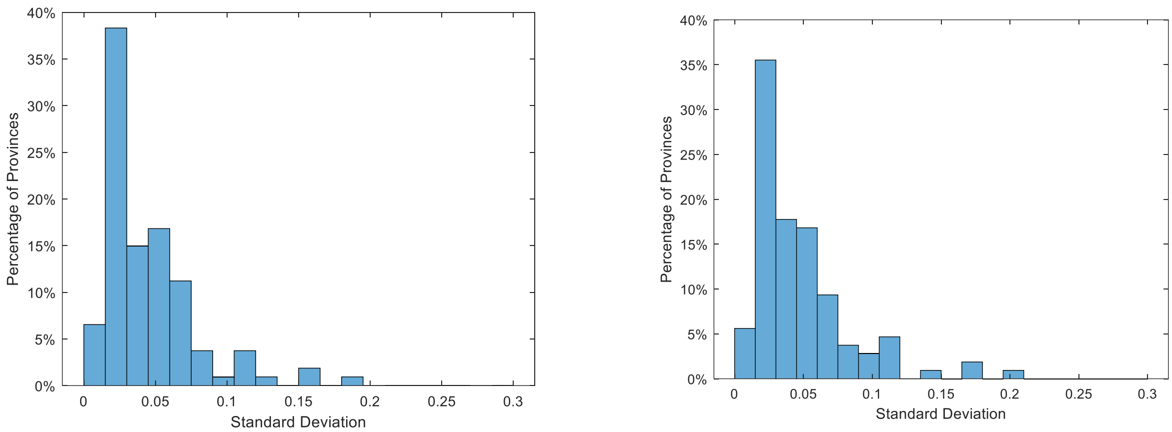


Figure 12
Italy – Relative rents – within province dispersion of variable – 2016-2021

(a) Monthly | (b) Annual



3.2 Climate variables

Following the methodology of Kotz et al. (2024), several regional climate indicators were calculated. The original methodology was modified to deal also with data at a monthly frequency (Italy). Appendix A.2 describes additional climate indicators that have been computed and then discarded, as they resulted not significant in the econometric analysis.

Annual indicators – Italy and Germany

The first set of climate variables was constructed at annual frequency and is used consistently across both Italy and Germany.

TempVar is the daily deviation from the mean temperature in each month of the year averaged across all days in the given sample (1981-2021) and then averaged over the entire year:

$$TempVar_{x,y} = \frac{1}{12}\sum_{m=1}^{m=12} \sqrt{\frac{1}{D_m}\sum_{d=1}^{D_m}\left(T_{x,d,m,y} - \bar{T}_{x,m}\right)^2} \quad (1)$$

where:

- D_m are the number of days in a given month,
- $T_{x,d,m,y}$ is the temperature in province x on day d, month m and year y,
- $\bar{T}_{x,m}$ is the mean temperature for month m in province x.

AvgTemp is the yearly mean temperature.

ExtremePrec is defined as the sum of total precipitation in a year when daily precipitation ($P_{x,d}$) exceeds the 99.9th percentile of the historical precipitation distribution (1981-2021) ($P99.9_x$):

$$ExtremePrec_{x,y} = \sum_{d=1}^{D_y} H\left(P_{x,d} - P99.9_x\right) * P_{x,d} \quad (2)$$

where:

- H represents the Heaviside step function,
- D_y are the number of days in a given year.

In the case of Italy ExtremePrec was multiplied by the percentage of high flood prone area values in each Italian province, assuming that the impact of flood will be magnified according in the area most exposed to hydrogeological risks.

Monthly indicators - Italy

For Italy, TempVar is the daily deviation from the mean temperature within each month of the year averaged across all days in the given sample (1981-2021):

$$TempVar_{x,m} = \sqrt{\frac{1}{D_m}\sum_{d=1}^{D_m}\left(T_{x,d,m,y} - \bar{T}_{x,m}\right)^2} \tag{3}$$

AvgTemp is the monthly mean temperature.
ExtremePrecHPH is defined as the sum of total precipitation in a month when daily precipitation exceeds the 99.9th percentile of the historical precipitation distribution (1981-2021) multiplied by the percentage of high flood prone area values in each Italian province:

$$ExtremePrecHPH_{x,m} = \left(\sum_{d=1}^{D_m} H\left(P_{x,d} - P99.9_x\right) * \ P_{x,d}\right) * HPH\_perc \tag{4}$$

To more accurately analyse the impact of climate variables on house prices, the variables were transformed using the 12-month difference (i.e. the simple difference from the same month of the previous year)[14]. This transformation makes it possible to capture year-to-year variations, isolating the effect of seasonal fluctuations that could influence climate variables and make it more difficult to identify long-term trends.
The correlation matrices among annual climate variables for Italy and Germany, calculated over the period available for each country, reveal rather different structures in the linear links between the indicators (Table 5 and Table 6).

Table 5
Correlation matrix between climate variables (Italy)

	AvgTemp	**TempVar**	**ExtremePrecHPH**
AvgTemp	1.000	-0.743	-0.030
TempVar	-0.743	1.000	-0.001
ExtremePrecHPH	-0.030	-0.001	1.000

[14] A prefix "Ldiff" was added to the labels to define the variables.

Table 6
Correlation matrix between climate variables (Germany)

	AvgTemp	TempVar	ExtremePrec
AvgTemp	1.000	-0.197	-0.055
TempVar	-0.197	1.000	-0.065
ExtremePrec	-0.055	-0.065	1.000

In Italy a negative correlation is observed between mean temperature and temperature variability (-0.74), indicating that in areas with increasing temperatures, the mean temperature range tends to be smaller, and vice versa. In the case of Germany, the correlation coefficients are all close to zero, with values between -0.06 and -0.20. The correlations of the extreme precipitation indicators with other climate variables are negligible for both countries.

Overall, it appears that the climate variables selected move largely independently: mean temperature, temperature variability and extreme precipitation do not overlap informatively, but tend to offer complementary perspectives (reducing the risk of multicollinearity issues). This, combined with the spatial heterogeneity (see the following maps), reinforces the methodological choice to include all three indicators simultaneously in the empirical analysis in order to more fully capture the dynamics of climate risk.

Figures 13-17 provide a visual representation of the geography of climate conditions in Italy and Germany, across three key years: 2008, 2016, and 2021[15]. The maps reveal not only differences in absolute values, but also heterogeneities in the spatial distribution and temporal evolution of climate phenomena. North-South contrasts in terms of average temperature are marked in Italy.

In Italy, the comparison between 2016 and 2021 reveals a shift in the location of extreme precipitation. While such events were already significant in Alpine and coastal regions

[15] These years were selected to represent the maximum time span available and to ensure comparability between the two countries: 2008 is the first year available for Germany, 2016 is the first observable year for Italy and also the first in common, while 2021 represents the most recent climate scenario.

in 2016, by 2021 they extended into broader areas of the South and Sicily, indicating increasing meteorological instability even in regions that had previously been less affected.

Germany, observed over a longer period, displays even more pronounced climatic changes. The evolution of extreme precipitations is again especially noteworthy: while relatively limited in 2008, they become more widespread in 2021, particularly in the western regions, where severe flood events occurred - most notably in the Rhineland - highlighting the growing exposure to hydrogeological risks.

However, in both cases, when it comes to average temperature and temperature variability, comparing just two years - at the beginning and end of the sample - do not reveal clear spatial trends, even when using a finer scale. These variables exhibit a nuanced dynamics that only become visible through a year-by-year visual analysis. To better capture this evolution, a sequence of annual heatmaps has been produced and presented in Appendix A.3, which illustrates more distinctly how local climate conditions have evolved over time.

Visual representations reinforce the notion of spatial and temporal heterogeneity in climate shocks and provide a valuable interpretative framework for understanding how such phenomena may impact local economic dynamics. They serve as an essential bridge between the observed environmental changes and the empirical analysis developed in the subsequent sections.

Figure 13
Italy - 2016

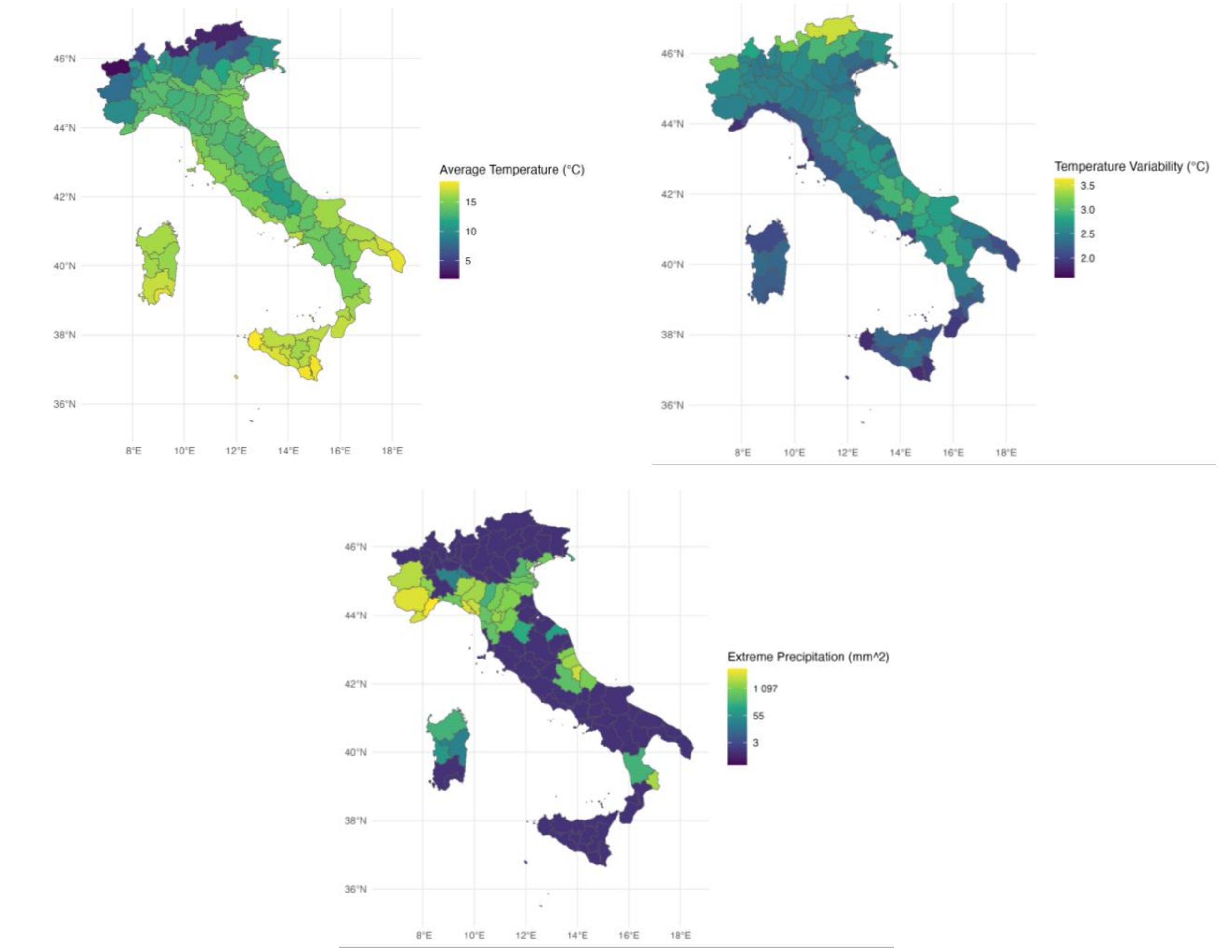


Figure 14
Italy - 2021

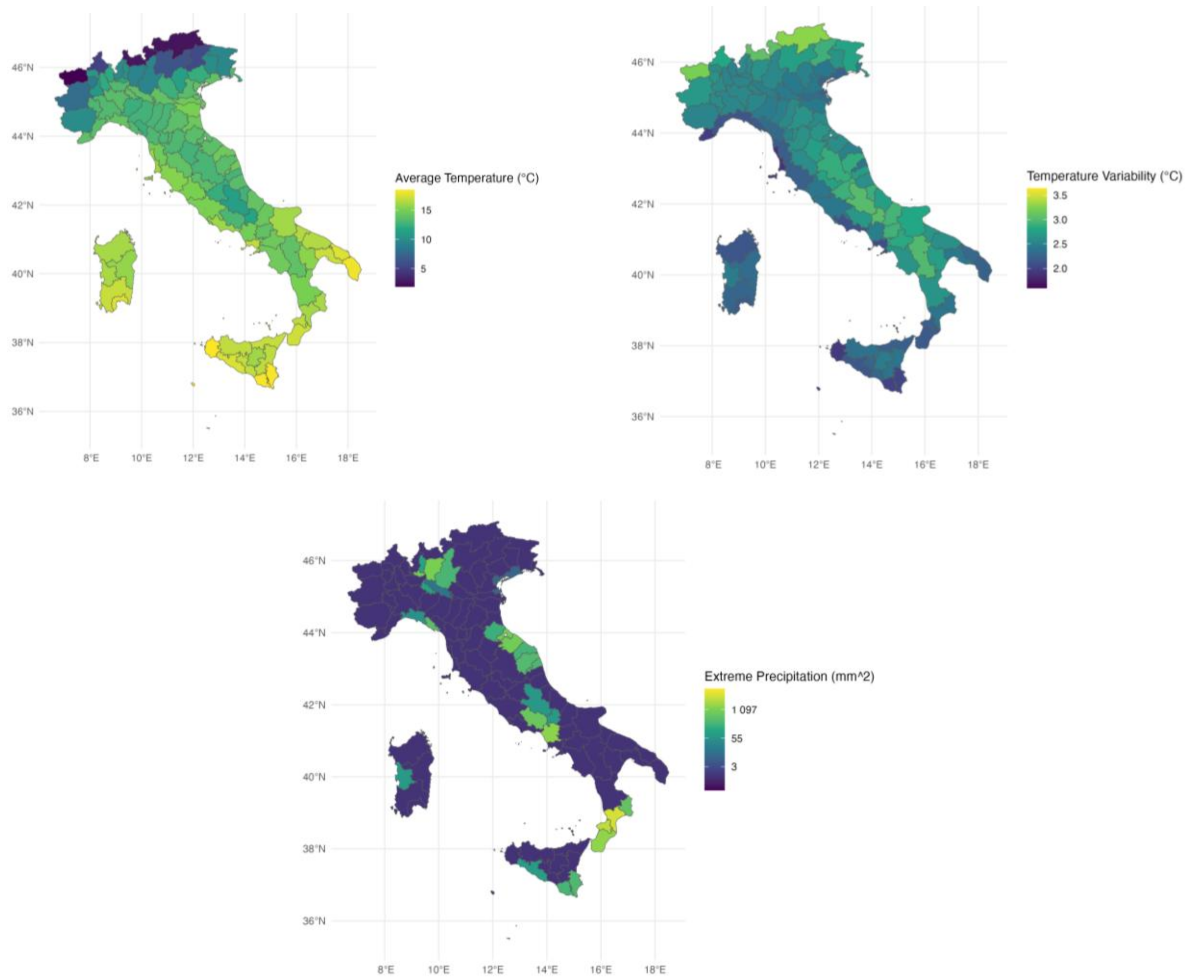


Figure 15
Germany – 2008

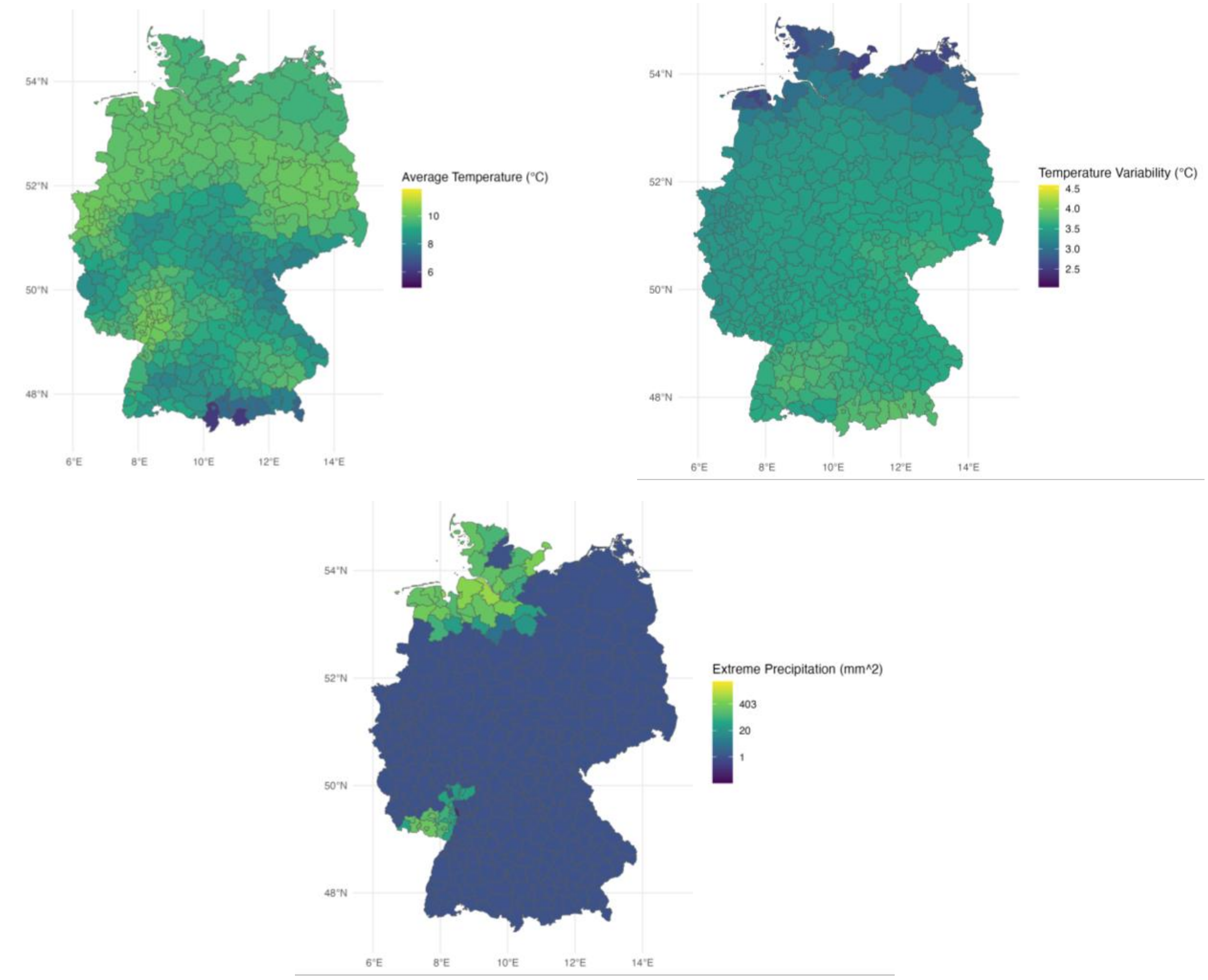


Figure 16
Germany – 2016

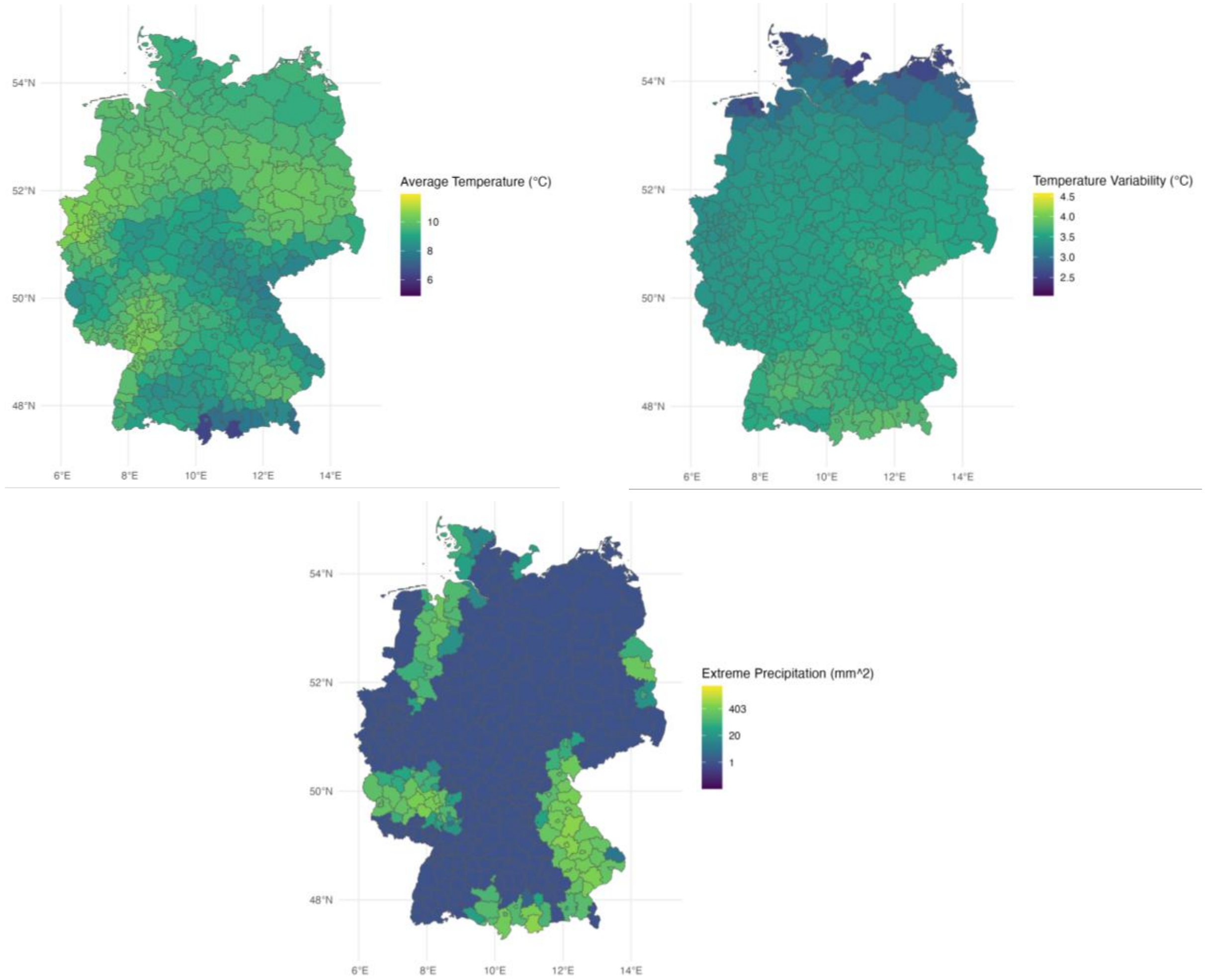
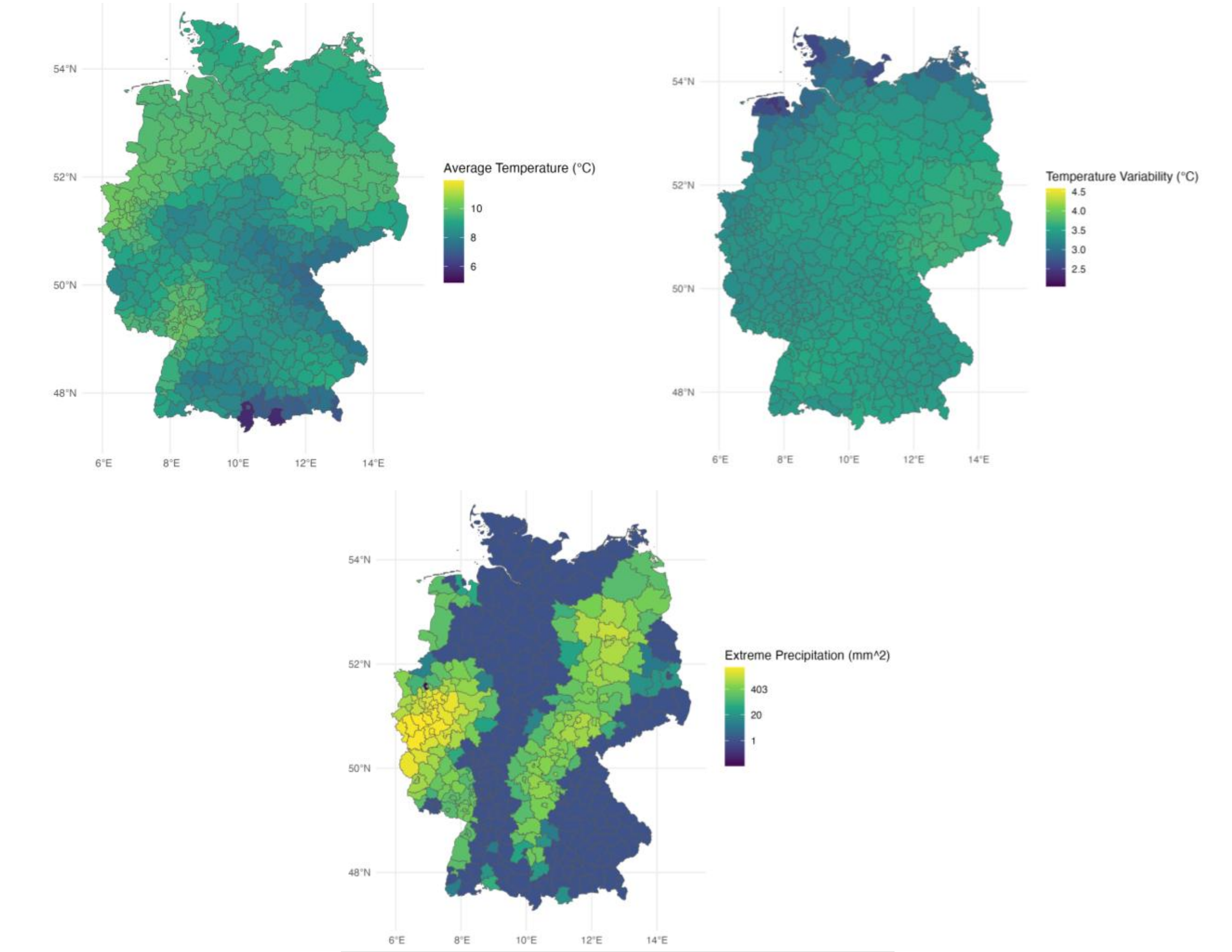


Figure 17
Germany – 2021



4 Empirical analysis

Housing demand can be expressed as a function of real price level of housing (P) and other factors shifting demand (X) (Geng, 2018). Vector X typically includes variables such as real disposable income per capita, households real net financial wealth, real interest rates, housing stock per capita, demographic demands, and institutional and structural indicators (such as tax deductions, rent regulation)[16]. Assuming that housing

[16] See for instance, Poterba (1984), Meen (2001), Aoki et al. (2002) and Özmen et al. (2019).

supply (S) is fixed at least in the short to medium term, the equilibrium real price of housing (P^*) is determined solely by demand factors.

Formally:

$$D(X, P^*) = S \tag{5}$$

P^* can then be expressed in the reduced form as a function of the variables included in vector X:

$$P^* = f(X) \tag{6}$$

Demand-side determinants include variables expressing household spending capacity (e.g., net income, wealth), user costs associated with buying and holding a house (e.g., interest rates, taxation), demographic factors influencing housing demand (e.g., population density, migration), and other factors reflecting the attractiveness and perceived value of a given location, including climate related factors.

In the present analysis, the variables included in the vector X are grouped into three components: economic variables (W), demographic variables (D), and climate-related variables (Z). W includes economic factors such as GDP per capita and mortgage rates; D captures demographic pressures on local housing markets and includes population density and net migration; Z incorporates a set of climate related indicators, such as average temperature, temperature variance, and extreme precipitation events. Moreover, as the dependent variable, house prices, is expressed in nominal terms, the same holds for the economic variables.

This leads to the following formulation:

$$p^* = f(W, D, Z) \tag{7}$$

where p^* represents nominal prices.

Based on this specification, several panel regressions were estimated with the following general structure:

$$Y_{i,t} = \alpha + \beta W_{i,t} + \gamma D_{i,t} + \delta Z_{i,t} + \varepsilon_{i,t} \tag{8}$$

where:

- $Y_{i,t}$ represents the dependent variable (logarithm of house prices and logarithm of rents);
- $W_{i,t}$ is a vector of economic variables (nominal GDP per capita and mortgage rates);
- $D_{i,t}$ is a vector of demographic variables (population density and net migration rate);
- $Z_{i,t}$ is a vector of climate variables (average temperature, temperature variance, extreme precipitation);
- $\varepsilon_{i,t}$ is the error term;
- the suffices i,t indicate location and time, respectively.

In this baseline specification, both region fixed effects and time fixed effects might be included to account for unobserved heterogeneity across space and over time. Region fixed effects control for time-invariant characteristics, while time fixed effects absorb national trends and macroeconomic shocks common to all provinces.

An alternative specification makes use of relative house prices and relative rents (i.e., percentage deviation from the national average) and economic independent variables are expressed as the ratio with respect to the national average. Mortgage rates are excluded from this specification, as they are only available at the national level and thus do not vary across regions.

$$y_{i,t} = \alpha + \beta w_{i,t} + \gamma d_{i,t} + \delta Z_{i,t} + \varepsilon_{i,t} \quad (9)$$

where:

- $y_{i,t}$ represents the dependent variable (relative house prices and relative rent prices);
- $w_{i,t}$ is a vector of economic variables (relative nominal GDP per capita and mortgage rates);
- $d_{i,t}$ is a vector of demographic variables (relative population density and relative net migration rate).

When using relative prices or relative rents as the dependent variable, time fixed effects are excluded. This is because taking the ratio with the national average effectively removes national-level trends and common macroeconomic shocks that affect all regions equally - an effect that time fixed effects would otherwise capture. In this sense, the use of relative variables serves a similar purpose to the inclusion of time fixed effects. However, region fixed effects are retained in some estimations to control for time-invariant unobserved heterogeneity across provinces.

The variables and the frequency of the data (monthly or annual) vary depending on the specific regression and the country considered (Italy or Germany). For Germany 59 observations are missing because data on population or other variables are absent for some *kreise* in some years. The panels are therefore "unbalanced".

Table 7 to Table 9 show the descriptive statistic of the explanatory variables used in the econometric analysis. In order to carry out econometric estimation using relative prices and rents as dependent variable economic and demographic variables have been also expressed in relative terms with respect to national averages.

Table 7
Italy – Descriptive statistics of independent variables – Monthly data – 2016-2021

Variable	Mean	SD	Min	Max	N
Nom GDP Per Capita	0.03	0.01	0.01	0.06	6527
Pop Density	269	378	36	2615	6527
Net Migration	0.00	0.00	-0.02	0.04	6527
Mortgage Rates	0.02	0.00	0.01	0.02	6527
Ldiff_AvgTemp	-0.03	1.90	-5.47	6.03	6527
Ldiff_TempVar	0.01	0.91	-2.56	2.65	6527
ExtremePrecHPH	14	110	0	2706	6527
Rel Nom GDP Per Capita	0.91	0.25	0.52	1.98	6527
Rel Pop Density	1.35	1.90	0.18	13.08	6527
Rel Net Migration	0.84	4.63	-30.33	20.92	6527

Note: "Rel" values refer to the ratio of the relevant NUTS 3 variable relative to the national average.

Table 8

Italy – Descriptive statistics of independent variables – Annual data – 2016-2021

Variable	Mean	SD	Min	Max	N
Nom GDP Per Capita	0.03	0.01	0.01	0.06	642
Pop Density	269	378	36	2615	642
Net Migration	0.00	0.00	-0.02	0.04	642
Mortgage Rates	0.02	0.00	0.01	0.02	642
AvgTemp	13.65	3.00	1.90	18.47	642
TempVar	2.53	0.36	1.59	3.64	642
ExtremePrecHPH	21	72	0	917	642
Rel Nom GDP Per Capita	0.91	0.25	0.52	1.98	642
Rel Pop Density	1.35	1.90	0.18	13.08	642
Rel Net Migration	0.79	4.54	-30.33	20.92	642

Note: “Rel” values refer to the ratio of the relevant NUTS 3 variable relative to the national average.

Table 9

Germany – Descriptive statistics of independent variables – Annual data – 2008-2021

Variable	Mean	SD	Min	Max	N
Nom GDP Per Capita	0.03	0.02	0.01	0.20	5541
Pop Density	534	697	36	4794	5541
Net Migration	0.00	0.01	-0.04	0.06	5541
Mortgage Rates	0.02	0.01	0.01	0.05	5541
AvgTemp	9.44	1.00	4.88	11.93	5541
TempVar	3.59	0.36	2.05	4.58	5541
ExtremePrec	108	337	0	5169	5541
Rel Nom GDP Per Capita	0.92	0.40	0.34	4.74	5541
Rel Pop Density	2.34	3.06	0.15	20.26	5541
Rel Net Migration	0.92	7.48	-59.20	89.43	5541

Note: “Rel” values refer to the ratio of the relevant NUTS 3 variable relative to the national average.

5 Regression results

This section presents the results of the empirical findings on the relationship between climate dynamics and housing market outcomes in Italy and Germany. Across all specifications, heteroskedasticity is tested and corrected using robust standard errors. In addition, the joint significance of the explanatory variables is assessed using Wald tests, the results of which confirm the consistency and robustness of the estimated models.

5.1 Main results

The first set of results reported in Table 10 refers to Italian annual data for relative housing prices and rents. The estimates are based on a pooled OLS estimation (PO), which excludes both time and regional fixed effects.

Climate variables emerge as relevant determinants of housing market outcomes. Temperature variability is negatively and significantly associated with both relative prices and rents, suggesting that households and landlords perceive climate instability as a source of risk or as a characteristic that tend to decrease the intrinsic value of residential real estates in the given area. Extreme precipitation also shows a negative and marginally significant effect in both models. Average temperature is significant only in the price equation, indicating that higher temperatures may depress housing values.

Among the control variables, GDP per capita is positively and significantly associated with both prices and rents, confirming that local income disparities drive housing market differences across provinces. Population density is positively associated with rents but not with prices, possibly reflecting the stronger demand for rental properties in more urbanized areas. Net migration does not appear to be significantly related to either outcome in this specification, which may reflect the short time frame and limited variation in migration flows across provinces.

The relative price specification allows for a direct interpretation of the estimated coefficients in terms of deviations from the national average. In the first column of Table 10, a one-unit increase in relative nominal GDP per capita is associated (i.e., an increase equal to the national GDP per capita, assuming that change in nominal GDP per capita of the given province do not affect the corresponding national average) with a 0.68-point increase in the relative housing price index. Turning to the climate variables, a 1°C increase in average temperature relative to the national average is associated with a 0.028-point decrease in relative housing prices. A 1°C increase in temperature variability leads to a more substantial reduction of 0.303 points.

Table 10
Italy – Relative house prices and rents - 2016-2021

	(1)	(2)
Dependent Variable	Relative Prices	Relative Rents
Rel Nom GDP per capita	0.680***	0.652***
	(0.000)	(0.000)
Rel Pop Density	0.015	0.013**
	(0.235)	(0.015)
Rel Net Migration	-0.001	0.001
	(0.765)	(0.628)
AvgTemp	-0.028**	0.003
	(0.028)	(0.663)
TempVar	-0.303***	-0.081**
	(0.000)	(0.044)
ExtremePrecHPH	-0.000*	-0.000*
	(0.090)	(0.051)
Method	PO	PO
N	642	642
NUTS 3 dummies	No	No
Time frequency	Yearly	Yearly
R-squared overall	0.347	0.499
R-squared within		
p-value Wald F	0.000	0.000
Std err name	Standard errors robust to heteroskedasticity adjusted for 107 clusters	Standard errors robust to heteroskedasticity adjusted for 107 clusters
Panel type	Balanced	Balanced

Note: P-values are shown in parentheses and *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 11 reports the results for log-transformed absolute housing prices and rents as the dependent variables. This model includes time fixed effects (FE) to control for national-level shocks and trends, while preserving the cross-sectional variation necessary to identify the impact of spatially heterogeneous climate exposures.

Climate variables continue to display significant and economically meaningful effects. For housing prices, average temperature, temperature variability and extreme precipitation are negatively and significantly associated with property values. While average temperature is not significant in the rent regression, both temperature variability and extreme precipitation remain negatively associated with rents, confirming that even tenants respond to climate-related variables - though less strongly than buyers (i.e. the magnitude of the coefficients is generally lower compared to the price regression). Economic and demographic fundamentals behave as expected. Nominal GDP per capita is strongly and positively associated with both prices and rents, suggesting that higher income levels contribute to increased housing demand and valuation. Similarly, population density shows a small but statistically significant positive effect in both models. Net migration is also positively and significantly correlated with housing values and rents, indicating that population inflows exert upward pressure on the housing market.

The log-linear specification allows for an economic interpretation of the results. For example, in the first column of Table 11, it emerges that an increase of €1,000 in per capita income (the coefficient is divided by 1,000 since GDP per capita is expressed in millions of euros) results in a 2.33% increase in house prices. A one-unit increase in population density (inhabitants per km^2) leads to a 0.01% increase in house prices (the full coefficient is 0.0001). An increase of net migration equal to 1% of total population of the province leads to an increase of 12% in house prices. Regarding the climate variables, a 1°C increase in average temperature leads to a 3% reduction in house prices. Additionally, a 1°C increase in temperature variability is associated with a 37.9% decrease in house prices. To assess how plausible such a sensitivity of house prices to temperature variability is, it is important to consider that the independent variable is computed using three averages: (i) daily temperature averages; (ii) monthly average of daily temperature average; (iii) average of yearly standard deviation of temperatures (calculated using (i) and (ii)). Therefore, a significant change in temperature conditions is needed to get a change of 1° C in temperature variability. For comparison, Kotz et al. (2024) obtain a contemporaneous (lag 0) coefficient of -9.3 and 49.04 considering the sum a contemporaneous and lagged (up to 10 lags) effects with respect to the annual change of temperature variability: a 1 C° increase would determine a 9.3% decrease in GDP and if repeated over 11 years a 49% decrease. With respect to rental markets the effects are much lower. A 1 C° increase in average temperature is associated with a modest 0.3% decrease in rents and an increase of 1 C° in temperature variability with a 15.4% decrease.

Table 11
Italy – House prices and rents - 2016-2021

	(1)	(2)
Dependent Variable	Log Prices	Log Rents
Nom GDP per capita	23.300***	24.744***
	(0.000)	(0.000)
Pop Density	0.000***	0.000***
	(0.001)	(0.001)
Net Migration	12.469***	11.079***
	(0.000)	(0.000)
AvgTemp	-0.032***	-0.003
	(0.000)	(0.406)
TempVar	-0.379***	-0.154***
	(0.000)	(0.000)
ExtremePrecHPH	-0.000*	-0.000**
	(0.081)	(0.028)
Method	FE	FE
N	642	642
NUTS 3 dummies	No	No
Time dummies	Yes	Yes
Time frequency	Yearly	Yearly
R-squared overall	0.384	0.543
R-squared within	0.377	0.537
p-value Wald F	0.000	0.000
Std err name	Std. Error	Std. Error
Panel type	Balanced	Balanced

Note: P-values are shown in parentheses and *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 12 presents the main results for Germany, using relative values for apartment prices, house prices, and apartment rents as the dependent variables. As for the Italian case (relative prices and rents) all models are estimated using pooled OLS without fixed effects, preserving cross-sectional variation across districts while removing national trends.

With regard to climate variables, average temperature is negatively and significantly associated with relative apartment prices, but not with house prices or rents. Temperature variability is also significant only in the apartment sales model, where it shows a negative association with prices. In contrast, extreme precipitation does not display statistically significant effects in any of the specifications. Economic and demographic fundamentals are consistently significant across all models. Relative nominal GDP per capita is strongly and positively associated with housing prices and rents in all segments of the market, while population density also shows a positive and significant relationship. Net migration, measured as the deviation from the national average, is negatively and significantly correlated with all three dependent variables. This result is somewhat counterintuitive, as pressure from new settler seems to depress real estate values.

Table 12
Germany – Relative house prices and rents – 2008-2021

	(1)	(2)	(3)
Dependent Variable	Rel Apt Prices	Rel House Prices	Rel Rents
Rel Nom GDP per capita	0.363***	0.514***	0.215***
	(0.000)	(0.000)	(0.000)
Rel Pop Density	0.024**	0.067***	0.020***
	(0.018)	(0.000)	(0.000)
Rel Net Migration	-0.006***	-0.007***	-0.003***
	(0.000)	(0.000)	(0.000)
AvgTemp	-0.048***	-0.034	-0.002
	(0.003)	(0.147)	(0.794)
TempVar	-0.122***	0.005	0.007
	(0.006)	(0.855)	(0.520)
ExtremePrec	0.000	0.000	0.000
	(0.496)	(0.276)	(0.836)
Method	PO	PO	PO
N	5541	5541	5541
NUTS 3 dummies	No	No	No
Time frequency	Yearly	Yearly	Yearly
R-squared overall	0.232	0.381	0.339
R-squared within			
p-value Wald F	0.000	0.000	0.000
Std err name	Standard errors robust to heteroskedasticity adjusted for 400 clusters	Standard errors robust to heteroskedasticity adjusted for 400 clusters	Standard errors robust to heteroskedasticity adjusted for 400 clusters
Panel type	Unbalanced	Unbalanced	Unbalanced

Note: P-values are shown in parentheses and *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 13 reports the results for Germany using log-transformed absolute housing prices and rents as the dependent variables. The models are estimated, as for the Italian case, with time fixed effects but no spatial dummies, the structure is consistent across the three housing market segments: apartment prices, house prices, and apartment rents.

Regarding climate variables, average temperature shows a significant and negative association across all models, suggesting that long-term exposure to higher temperatures is consistently associated with lower housing values, both in the ownership and rental segments. Temperature variability is also negatively associated with housing outcomes, reaching significance in the house and rent models, though not in the apartment price model. As in previous specifications, extreme precipitation does not exhibit any statistically significant effect. Economic and demographic variables are highly significant across all specifications. Nominal GDP per capita is strongly and positively associated with all housing outcomes. Population density is statistically significant only in the model for house prices while net migration specification shows a consistent and significant positive effect across all the three regressions. A possible explanation of the different sign of the net migration coefficient in Table 12 and 13 may be that in Germany new entrants tend to move into cheaper or less-demanded provinces (e.g., rural areas), so their prices rise a bit, but still stay below the national average.

With respect to Italy the sensitivity of house prices to nominal GDP change is lower: an increase of €1,000 in per capita income tends to increase residential prices and rents in a range between 0.2 and 0.3% (with respect to 2.3-2.4% for Italy).[17] The sensitivity of real estate prices to net migration approximately halve and it is about a tenth in the case of rents. A change in average temperature produces results of the same magnitude with respect to the Italian case (i.e., a 1 C° leads to a decrease in real estate prices of about 3%, with a much smaller impact for rents). Instead, temperature variability tends to produce smaller effects on real estate prices and rents than Italy.

[17] It should be noted that nominal GDP per capita in Germany is approximately 1.6 times higher than in Italy. As a result, €1,000 corresponds to 1.8% of nominal GDP per capita in Germany and 2.9% in Italy.

Table 13
Germany – House prices and rents – 2008-2021

	(1)	(2)	(3)
Dependent Variable	Log Apt Prices	Log House Prices	Log Rents
Nom GDP per capita	3.737***	2.312***	1.670***
	(0.000)	(0.000)	(0.000)
Pop Density	0.000	0.000***	0.000
	(0.115)	(0.000)	(0.638)
Net Migration	6.528***	5.426***	1.634***
	(0.000)	(0.000)	(0.003)
AvgTemp	-0.020***	-0.015***	-0.013***
	(0.000)	(0.001)	(0.000)
TempVar	-0.047	-0.068**	-0.055***
	(0.162)	(0.011)	(0.001)
ExtremePrec	0.000	0.000	0.000
	(0.763)	(0.599)	(0.176)
Method	FE	FE	FE
N	5541	5541	5541
NUTS 3 dummies	No	No	No
Time dummies	Yes	Yes	Yes
Time frequency	Yearly	Yearly	Yearly
R-squared overall	0.650	0.712	0.779
R-squared within	0.155	0.172	0.137
p-value Wald F	0.000	0.000	0.000
Std err name	Standard errors robust to heteroskedasticity adjusted for 14 clusters	Standard errors robust to heteroskedasticity adjusted for 14 clusters	Standard errors robust to heteroskedasticity adjusted for 14 clusters
Panel type	Unbalanced	Unbalanced	Unbalanced

Note: P-values are shown in parentheses and *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Overall empirical findings presented in this section provide preliminary evidence that, both in Italy and in Germany, weather variability and extreme events are already being priced in the residential real estate market, particularly in the sales market.

5.2 Robustness checks

To assess the robustness of the main findings, a set of alternative model specifications is estimated. These include regressions with additional fixed effects, different time frequency (monthly instead of yearly), and alternative variable transformations. Different model choices can affect both the significance and the magnitude of the estimated coefficients.

Starting from Italy, the focus is on comparing specifications with or without spatial and temporal fixed effects, as well as exploring monthly data.

Table 14 reports the result of a model that includes cross-sectional fixed effects to the analysis of the yearly relative housing prices and rents. The results clearly highlight a key limitation of this approach: once spatial fixed effects are included, climate coefficients become statistically insignificant in both price and rent regressions. Indeed, due to the limited within variation of the dependent variables, cross-sectional fixed effects tend to explain a large part of the variance of house prices across provinces. This finding suggests that longer time series will need to be used to properly identify the effects of climate events while controlling for other regional characteristics.

Table 14
Italy – Relative house prices and rents – 2016-2021

	(1)	(2)
Dependent Variable	Rel Prices	Rel Rents
Nom GDP per capita	0.326*	0.655***
	(0.069)	(0.000)
Pop Density	0.858***	0.013***
	(0.002)	(0.000)
Net Migration	-0.001**	0.001
	(0.014)	(0.436)
AvgTemp	0.001	0.001
	(0.887)	(0.795)
TempVar	-0.002	-0.110***
	(0.799)	(0.000)
ExtremePrecHPH	0.000	0.000
	(0.673)	(0.188)
Method	FE	FE
N	642	642
NUTS 3 dummies	Yes	No
Time frequency	Yearly	Yearly
R-squared overall	0.988	0.520
R-squared within	0.199	0.512
p-value Wald F	0.000	0.000
Std err name	Standard errors robust to heteroskedasticity adjusted for 107 clusters	Std. Error
Panel type	Balanced	Balanced

Note: P-values are shown in parentheses and *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 15 explores further robustness checks. Column (1) introduces mortgage rates as an additional control variable. However, since this variable is only available at the national level, it lacks cross-sectional variation. As expected, the coefficient is statistically insignificant and adds no explanatory power to the model. For this reason, mortgage rates are excluded from all later specifications to avoid distorting the estimation due to their aggregate nature. Column (2) and (3) implement a specification that includes both cross sectional and time fixed effects, commonly referred to as a twoway fixed effects model. Again, cross-sectional fixed effects tend to explain a large part of the relatively modest variance of house prices within provinces in the period under examination. Economic and climate variables lose statistical significance, and in some cases display counterintuitive signs (as for the coefficient on net migration that becomes significantly negative, which contradicts theoretical expectations and previous empirical findings).

Table 15
Italy – House prices and rents – 2016-2021

	(1)	(2)	(3)
Dependent Variable	Log Prices	Log Prices	Log Rents
Nom GDP per capita	9.074*	9.074*	5.298
	(0.055)	(0.054)	(0.270)
Pop Density	0.002	0.002	0.001
	(0.104)	(0.104)	(0.575)
Net Migration	-1.457**	-1.457**	0.227
	(0.036)	(0.035)	(0.720)
AvgTemp	15.240		
	(1.000)		
MortgageRates	-0.020	-0.020	-0.018
	(0.164)	(0.164)	(0.403)
TempVar	0.020*	0.020*	0.026
	(0.071)	(0.070)	(0.143)
ExtremePrecHPH	0.000	0.000	0.000
	(0.193)	(0.193)	(0.322)
Method	FE	FE	FE
N	642	642	642
NUTS 3 dummies	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
Time frequency	Yearly	Yearly	Yearly
R-squared overall	0.990	0.990	0.961
R-squared within	0.520	0.520	0.276
p-value Wald F	0.000	0.000	0.000
Std err name	Standard errors robust to heteroskedasticity adjusted for 107 clusters	Standard errors robust to heteroskedasticity adjusted for 107 clusters	Standard errors robust to heteroskedasticity adjusted for 107 clusters
Panel type	Balanced	Balanced	Balanced

Note: P-values are shown in parentheses and *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Tables 16 and 17 report the results obtained using monthly data. These specifications aim to test whether the main findings hold at higher frequency. Table 16 uses pooled OLS models with relative prices and rents as dependent variables, while Table 17 reports fixed effects models with log-transformed absolute values. However, the results from the monthly data are less consistent and generally weaker than those from annual models. The use of higher-frequency data amplifies the issue of low within-province variability in prices and rents, leading to poorer identification of the effects of climate risks. As a result, climate variables are often statistically insignificant, and in some cases display unexpected signs. In Table 16, temperature variability remains negatively and significantly associated with both relative prices and rents, and extreme precipitation shows a marginal effect in the price model. Yet, the majority of the other coefficients are not statistically significant. In Table 17, where time fixed effects are added and absolute prices are used, the climate variables lose significance almost entirely, and only extreme precipitation retains a small negative effect in both models.

Table 16
Italy – Relative house prices and rents – 2016-2021

	(1)	(2)
Dependent Variable	Rel Prices	Rel Rents
Rel Nom GDP per capita	0.638***	0.559***
	(0.000)	(0.000)
Rel Pop Density	0.017	0.019***
	(0.241)	(0.003)
Rel Net Migration	-0.002	-0.001
	(0.317)	(0.678)
Ldiff_AvgTemp	0.000	0.003***
	(0.265)	(0.000)
Ldiff_TempVar	-0.003***	-0.003***
	(0.000)	(0.001)
ExtremePrecHPH	-0.000*	0.000
	(0.073)	(0.205)
Method	PO	PO
N	6527	6527
NUTS 3 dummies	No	No
Time frequency	Monthly	Monthly
R-squared overall	0.292	0.455
R-squared within		
p-value Wald F	0.000	0.000
Std err name	Standard errors robust to heteroskedasticity adjusted for 107 clusters	Standard errors robust to heteroskedasticity adjusted for 107 clusters
Panel type	Balanced	Balanced

Note: P-values are shown in parentheses and *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 17
Italy – House prices and rents – 2016-2021

	(1)	(2)
Dependent Variable	Log Prices	Log Rents
Nom GDP per capita	21.737***	21.386***
	(0.000)	(0.000)
Pop Density	0.000***	0.000***
	(0.000)	(0.000)
Net Migration	7.486***	8.508***
	(0.000)	(0.000)
Ldiff_AvgTemp	-0.006	-0.003
	(0.251)	(0.445)
Ldiff_TempVar	-0.006	-0.003
	(0.411)	(0.607)
ExtremePrecHPH	-0.000**	-0.000*
	(0.032)	(0.099)
Method	FE	FE
N	6527	6527
NUTS 3 dummies	No	No
Time dummies	Yes	Yes
Time frequency	Monthly	Monthly
R-squared overall	0.323	0.493
R-squared within	0.318	0.487
p-value Wald F	0.000	0.000
Std err name	Std. Error	Std. Error
Panel type	Balanced	Balanced

Note: P-values are shown in parentheses and *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

For the German case, Table 18 reports the results from relative price and rent regressions that include NUTS 3 fixed effects. Economic fundamentals remain statistically significant and correctly signed across all models. However, climate variables lose significance, and their coefficients are generally close to zero. Only average temperature shows a significant and negative association with relative apartment prices, while all other climate indicators are insignificant across housing segments. These results mirror the pattern observed for Italy: when regional fixed effects are included, much of the within province variability needed to identify climate risk effects is absorbed, limiting the model's ability to detect such relationships. Notably, net migration becomes positive and significant for apartment and house prices but turns negative in the rental model. Table 19 strengthens the fixed effect structure by including both spatial and temporal dummies and using log-transformed absolute prices and rents as dependent variables. Despite the stricter control structure, climate variables regain statistical significance. Both average temperature and extreme precipitation are negative and significant across all outcomes, while temperature variability is significant only in the house price model. These findings show that when outcome variables are appropriately scaled and modelled with sufficient variation, the climate signal becomes identifiable even under restrictive specifications.

Table 18
Germany –Relative house prices and rents– 2008-2021

	(1)	(2)	(3)
Dependent Variable	Rel Apt Prices	Rel House Prices	Rel Rents
Rel Nom GDP per capita	0.115***	0.182***	0.215***
	(0.003)	(0.003)	(0.000)
Rel Pop Density	0.134***	0.161***	0.020***
	(0.000)	(0.000)	(0.000)
Rel Net Migration	0.003***	0.004***	-0.003***
	(0.000)	(0.000)	(0.000)
AvgTemp	-0.007**	0.013***	-0.002
	(0.012)	(0.001)	(0.446)
TempVar	0.003	0.004	0.007
	(0.345)	(0.263)	(0.339)
ExtremePrec	0.000	0.000	0.000
	(0.148)	(0.466)	(0.856)
Method	FE	FE	PO
N	5541	5541	5541
NUTS 3 dummies	Yes	Yes	No
Time frequency	Yearly	Yearly	Yearly
R-squared overall	0.940	0.954	0.339
R-squared within	0.069	0.083	
p-value Wald F	0.000	0.000	0.000
Std err name	Standard errors robust to heteroskedasticity adjusted for 400 clusters	Standard errors robust to heteroskedasticity adjusted for 400 clusters	Std. Error
Panel type	Unbalanced	Unbalanced	Unbalanced

Note: P-values are shown in parentheses and *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 19
Germany – House prices and rents – 2008-2021

	(1)	(2)	(3)
Dependent Variable	Log Apt Prices	Log House Prices	Log Rents
Nom GDP per capita	5.134***	4.380***	3.292***
	(0.000)	(0.000)	(0.000)
Pop Density	0.001***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)
Net Migration	-2.108***	-0.688	-0.978***
	(0.003)	(0.161)	(0.002)
AvgTemp	-0.065***	-0.037***	-0.041***
	(0.000)	(0.000)	(0.000)
TempVar	-0.022	-0.018*	-0.008
	(0.117)	(0.057)	(0.108)
ExtremePrec	0.000	-0.000***	-0.000***
	(0.113)	(0.000)	(0.000)
Method	FE	FE	FE
N	5541	5541	5541
NUTS 3 dummies	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
Time frequency	Yearly	Yearly	Yearly
R-squared overall	0.840	0.889	0.921
R-squared within	0.791	0.858	0.906
p-value Wald F	0.000	0.000	0.000
Std err name	Standard errors robust to heteroskedasticity adjusted for 400 clusters	Standard errors robust to heteroskedasticity adjusted for 400 clusters	Standard errors robust to heteroskedasticity adjusted for 400 clusters
Panel type	Unbalanced	Unbalanced	Unbalanced

Note: P-values are shown in parentheses and *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

5.3 Discussion of results

Taken together, the results point to a consistent message. While economic fundamentals are the dominant forces shaping housing prices and rents, there is evidence that climate change and extreme weather events are being priced in, especially in vulnerable areas. The distinction between sale and rental markets, as well as between absolute and relative prices, provides additional nuance and supports the initial assumption that real estate markets react differently to long-term versus short-term climate risks.

In the Italian case, the availability of monthly data offers greater temporal detail, but the observation window is much narrower (2016-2021). This reduces intra-provincial variability over time and makes it more complex to identify long-term relationships. In addition, the higher temporal frequency may introduce more noise into the data, especially for variables such as extreme weather phenomena, which often show more visible effects only over longer time horizons.

In summary, the differences in results between Italy and Germany largely reflect differences in the quality, frequency and temporal extent of the available data. Highlighting these limitations is important for a correct interpretation of the results and suggests that future research could benefit from longer and harmonised time series across European countries.

6 Conclusion

Climate change represents one of the most relevant and complex challenges of our time, with effects that extend far beyond the environmental sphere, impacting the real economy, financial stability and wealth distribution. This thesis analysed the impact of climate change and related extreme weather events on residential housing prices and rents in two major European economies - Italy and Germany - using granular data at the NUTS 3 level and differentiating between the sales and the rental markets.

Empirical results confirm the starting hypothesis: extreme weather conditions and climate variability are already reflected in real estate prices, particularly in the buying and selling segment. Analyses conducted for Italy show that variables such as temperature variability and extreme precipitation are significantly associated with lower housing prices, exposure to flooding risk seems also to play a role. The rental market, while showing a similar direction, is less sensitive, consistent with the shorter time horizon that characterizes renters' decisions and the limited economic exposure of renters with respect to the value of the property. The results for Germany confirm the presence of negative effects of climate change and extreme events, albeit smaller in magnitude than in Italy, especially with regard to average temperature and its variability. Extreme precipitations, on the other hand, do not seem to have a statistically significant impact in the German case.

When comparing with the US literature, important similarities emerge, but also some structural differences. As pointed out by Ma and Yildirim (2023), the buying and selling market in the United States also reacts significantly to climate change, while rents are less sensitive. However, US studies show greater price responsiveness especially in high-risk coastal areas, with strong effects related to subjective perceptions of climate risk and the availability of public information about risk (Gourevitch et al., 2023; Fairweather et al., 2024). In Europe, and particularly in Italy and Germany, the effects of climate variables on residential housing prices seems to be more homogeneous but less amplified, possibly due to a lower degree of disclosure about the risk associated to climate change in a particular area.

In the US, evidence shows that the homes that are most overpriced with respect to climate risk are often owned by low-income households, which are therefore exposed to high equity risks. In Europe, the literature is still limited on this front, but the results of this thesis suggest that distributional effects could become significant if climate repricing intensifies.

Overall, the analysis conducted suggests that climate change and extreme weather events are no longer prospective phenomena, but they already affect local housing markets. This has important policy implications. First, climate change and extreme weather events can amplify wealth inequalities, penalizing low-income segments of the population the most. Second, the resilience of local public finances is at risk, as a decline in property values can reduce tax revenues. Third, financial stability may be jeopardized by a widespread decline in the value of real estate, which is a major part of bank collateral. Finally, a delay in internalizing climate risks into real estate prices can lead to sudden revaluations, with systemic effects.

This analysis opens up several future research developments. A first step could be to expand the sample to other European countries, including extending the time horizon to more recent years, to capture increasingly frequent and intense climate events. In addition, it would be useful to assess the impact of other extreme phenomena, such as wildfires, droughts or sea level rise, and analyse how these interact with other economic variables, such as mortgage rates, insurance premiums, household debt or credit conditions. A further line of research could be to distinguish effects related to physical risks from those related to adaptation responses[18]. Another important direction would be to investigate spillover effects across neighbouring provinces, for instance exploring whether climate shocks in one area affect adjacent housing markets through migration flows. Moreover, given the increasing frequency of climate-related events, developing forecasting models to anticipate the future impact of extreme weather on housing prices could prove valuable for both policymakers and market participants.

More generally, awareness of climate risks in the real estate sector is crucial to ensure an orderly transition and to avoid sudden shocks. In this sense, strengthening transparency and information on climate risks and integrating them into real estate valuations and financial regulation are essential steps. At the European level, such actions are crucial not only to guide investments and protect citizens, but also to safeguard financial stability, as the real estate sector is one of the main channels of transmission of climate risks to the economic and financial system.

[18] An illustrative example is the Dutch national strategy for flood prevention and climate adaptation. See, for instance, Bloemen et al. (2019) for a detailed analysis.

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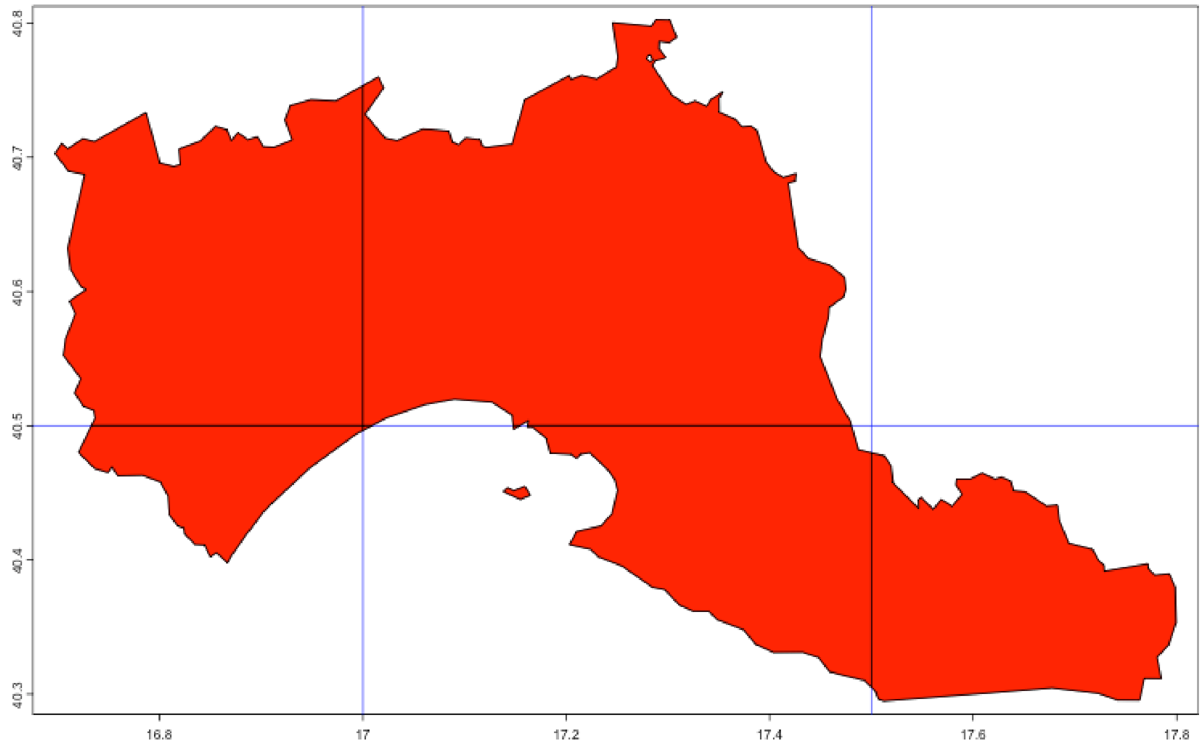
Appendix

A.1 NUTS 3 maps

Figure 1 clearly shows that, as mentioned above, NUTS 3 regions often span multiple climate grid cells.

Figure A1
Taranto, Italy – Climate data and NUTS 3 administrative boundaries



A.2 Other climate indicators

Annual indicators – Italy and Germany

AvgPr is the yearly mean precipitation. ExtremeWind[19] is defined as the sum of total wind in a year when daily near surface wind speed exceeds the 99.9th percentile of the historical precipitation distribution (1981-2021).

[19] ExtremeWind is not discussed in Kotz et al. (2024); however, it was calculated using the same methodology applied to extreme precipitation in the aforementioned paper.

Monthly indicators - Italy

AvgPr is the monthly mean precipitation. ExtremeWind is defined as the sum of total wind in a year when daily near surface wind speed exceeds the 99.9th percentile of the historical precipitation distribution (1981-2021).

The variables AvgPr and ExtremeWind were initially considered in the analysis but later excluded from the final model because the results obtained did not show statistically significant effects.

A.3 Heatmaps

Figure A2
Italy – Average Temperature Heatmap – °C

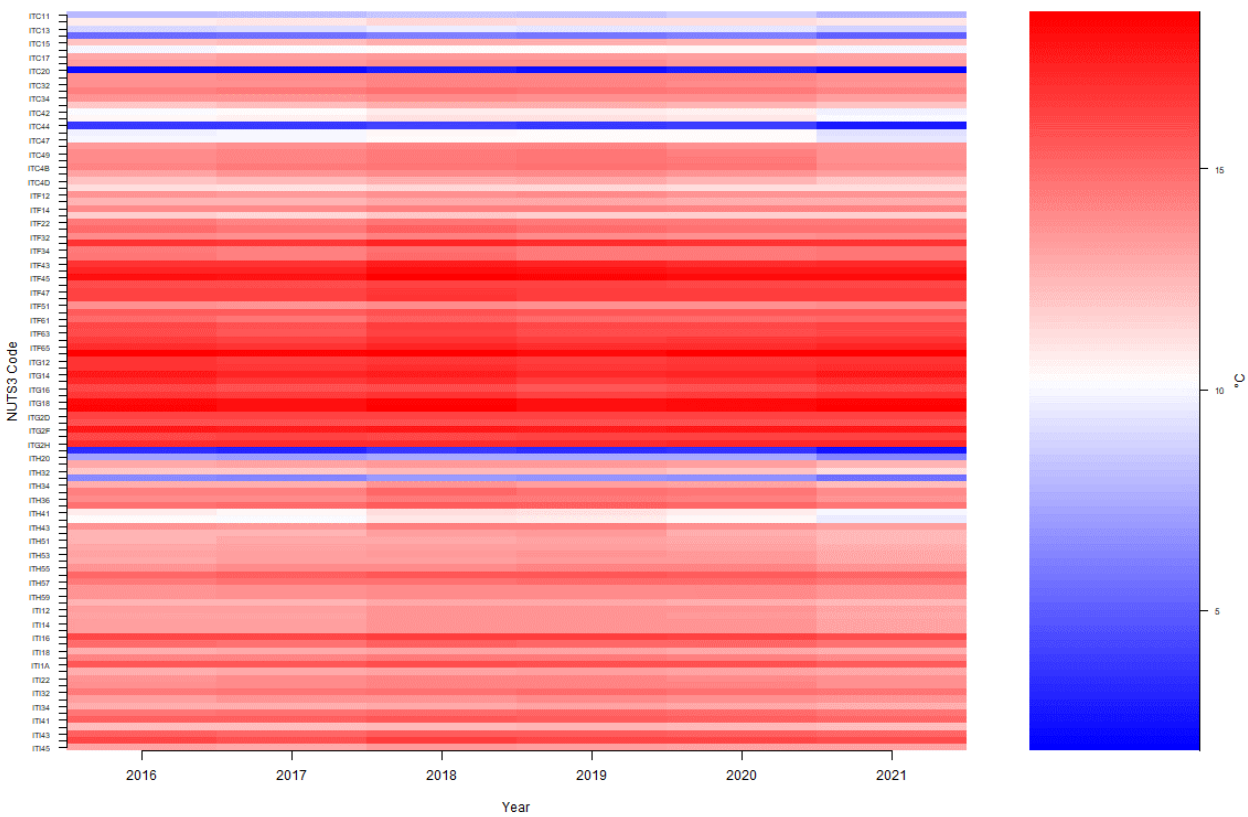


Figure A3
Italy – Temperature Variability Heatmap – °C

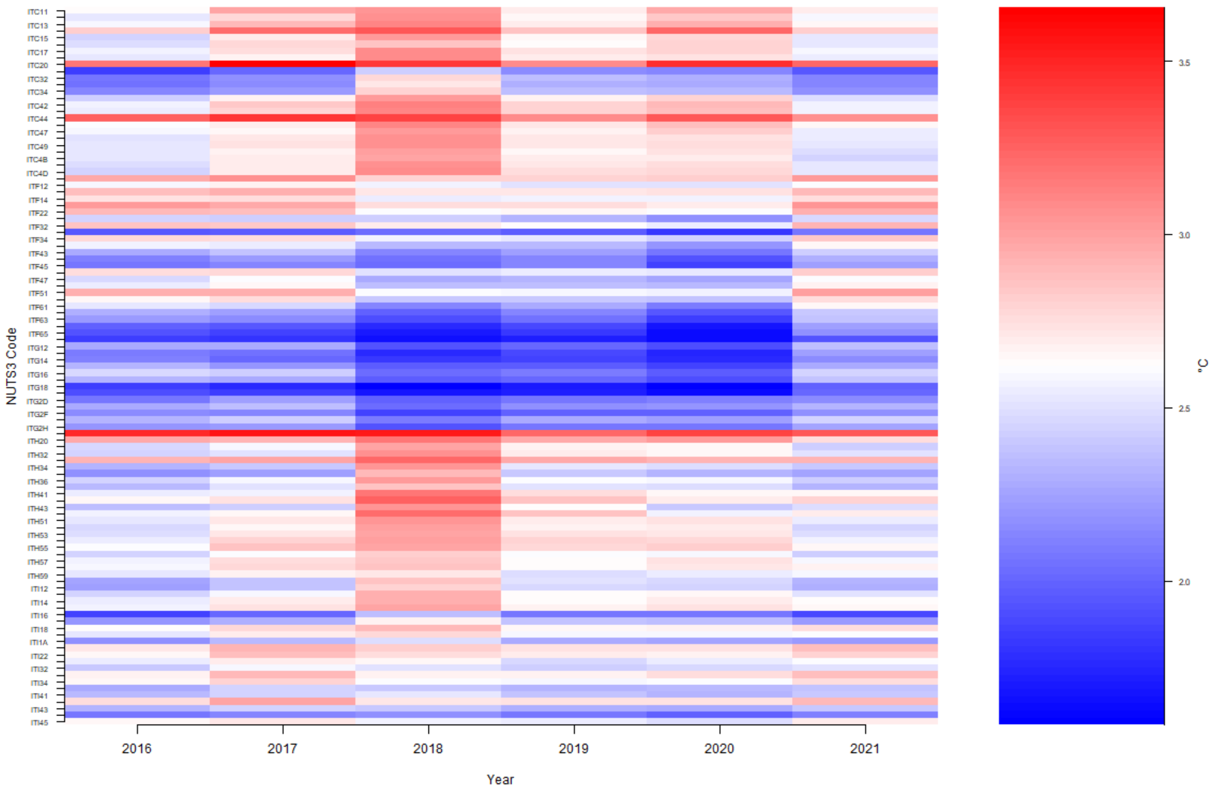


Figure A4
Germany – Average Temperature Heatmap – °C

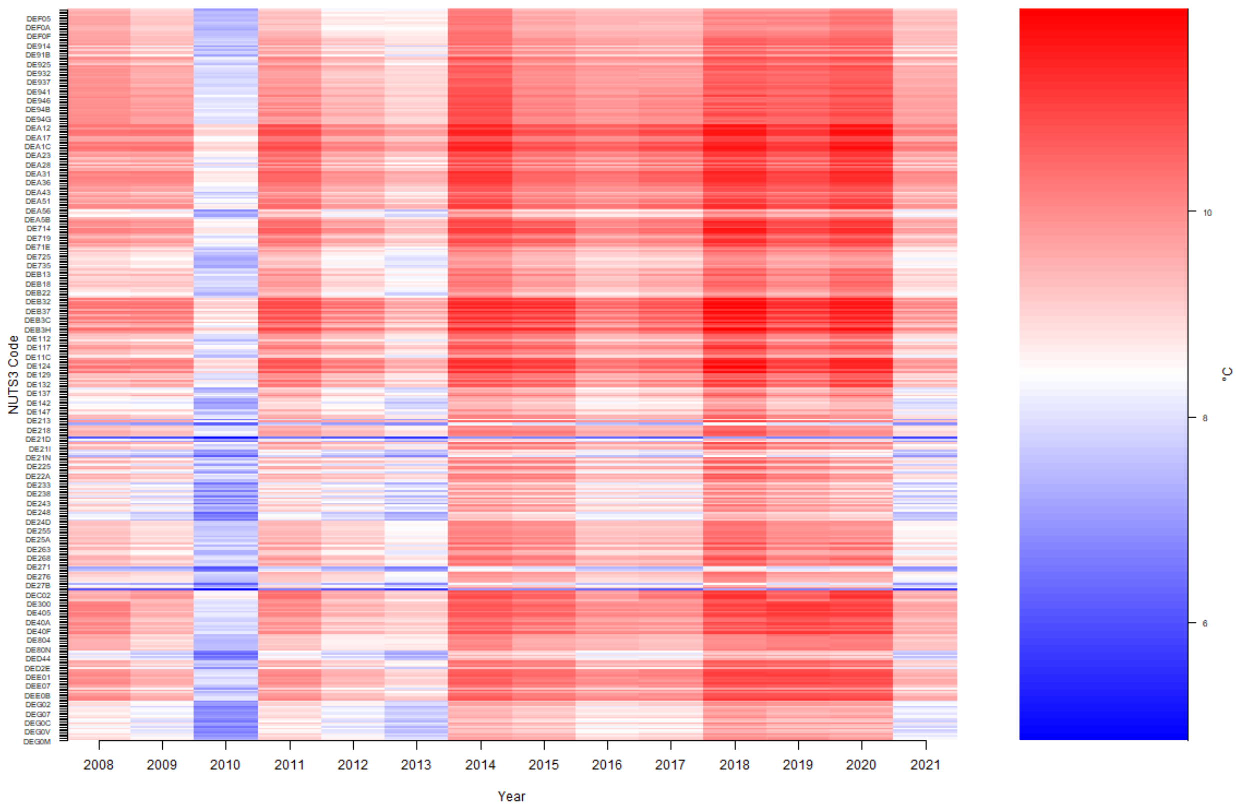


Figure A5
Germany – Temperature Variability Heatmap – °C