

Climate Hazards Meet Overpriced Cities: Linking Environmental Risks to Real Estate Markets Across the Globe

Working paper

October 2025

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Abstract

We examine how climate hazards influence housing affordability, measured by the price-to-income ratio (PTI), across a global cross-section of cities. While previous research links PTI mainly to credit conditions and bubble dynamics, the role of climate hazards remains largely unexplored. Using hierarchical cluster analysis to group climate indicators and quantile regressions to capture effects across the distribution of PTI, we find that climate factors matter little at the median and lower end of the PTI distribution, but strongly influence the most overpriced markets. Higher cooling degree day, reflecting prolonged warming, raise PTI ratios by enhancing the amenity value of milder winters, whereas extreme hot days above 35 °C lower PTI, are associated to a reduced demand under acute heat stress, and therefore to lower PTIs. Our results which highlight both the risks of raising temperatures and the amenity value of warmer winters imply that temperate cities should prepare for intensified affordability pressures as warming winters drive further overpricing, while tropical cities may experience easing PTI but face severe health and infrastructure risks. Policies must integrate housing, finance, and climate adaptation to address these divergent challenges.

Keywords: Climate change, price-to-income, temperature raising, amenity, quantile regressions.

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1. Introduction

The determinants of the price-to-income (PTI) ratio in urban real estate markets have been extensively examined in the literature (e.g., Himmelberg et al., 2005; Duprey & Klaus, 2022; Kuebler & Rugh, 2013; André et al., 2014; Pavlidis et al., 2016; Wu et al., 2012). Most studies focus on issues related to credit conditions and systemic risk, treating the PTI ratio primarily as a measure of housing affordability. The underlying premise is that housing prices cannot diverge indefinitely from the income levels of potential buyers. If prices consistently outpace income growth, households will eventually be unable to purchase homes, reducing demand and exerting downward pressure on prices (André et al., 2014).

Households generally choose between owning and renting, and this decision depends on the relative levels of house prices and rents. When prices rise faster than rents, renting becomes more attractive, easing pressure on housing prices while putting upward pressure on rents and, vice versa. Persistent deviations from these dynamics, such as those documented by André et al. (2014), raise concerns about social inequality, as vulnerable populations—including minorities and other underprivileged groups—are disproportionately affected by the reduced affordability that accompanies rising housing prices (e.g., Kuebler & Rugh, 2013; Zhang et al., 2016; Ben-Shahar et al., 2019; Hamstead, 2024).

In contrast, the relationship between PTI ratios and climate risks remains far less understood. While a considerable body of research has examined how environmental amenities and climate-related hazards influence housing prices, the direct link to PTI has received only limited attention. Emerging evidence shows that climate risk and expectations of future hazards can depress property values in vulnerable areas by prompting sales at a discount (e.g., Beltrán et al., 2018; Beck and Lin, 2020; Addoum et al., 2024; Skouralis et al., 2024; Schuetz, 2024; Blok and Fuerst, 2025; Agarwal et al., 2025). At the same time, local amenities—such as favorable weather—are powerful drivers of housing demand and prices. Some studies even find that moderate temperature increases can raise property values in certain regions (e.g., Maddison, 2003; Meier & Rehdanz, 2017; Sinha et al., 2021), potentially pushing prices away from local income fundamentals and thereby elevating PTI ratios.

This study bridges these two strands of the literature by examining, for the first time, the determinants of PTI ratios in relation to climate risks. While earlier works identify channels linking climate factors to housing outcomes, they largely focus on single countries, metropolitan areas, or narrowly defined hazards, leaving an incomplete understanding of how affordability ratios vary across a broad cross-section of cities worldwide. Moreover, most prior research centers on housing prices rather than the PTI ratio itself, and none of these studies consider how the effects of climate hazards may be concentrated at the extremes of the affordability distribution—where traditional mean-based regressions are ill-suited for empirical analysis.

Indeed, the evidence to date is dominated by average-effect estimates (e.g., Maddison, 2003; Rehdanz and Maddison, 2008; Meier and Rehdanz, 2017; Schuetz, 2024; Menéndez et al., 2024), limiting the ability to generalize findings and to explain the behavior of overheated markets with high PTI ratios relative to more typical markets. Our contribution is twofold. First, we assemble a large cross-section of major global cities, enabling a more comprehensive evaluation of PTI ratios and their relationship to climate hazards. Second, we pay particular attention to the right tail of the PTI distribution—capturing the most overpriced markets—and explicitly link these extreme affordability outcomes to climate risks, by the means of quantile regression analysis, a connection that remains absent in the existing literature.

Our results show that the dynamics of the most overpriced housing markets worldwide differ markedly from those of more typical markets. In cities at the right tail of the PTI distribution, both climate risks and climate-related weather amenities are capitalized into housing prices. Specifically, higher values of cooling degree days are associated with increases in PTI ratios at the upper quantiles, whereas extreme temperatures are linked to reductions in PTI. Taken together, these findings reveal new social gaps to be expected from climate change. They suggest that overpricing is likely to intensify in regions where moderate temperature increases enhance the amenity value of climate change—provided these cities are not highly exposed to other climate hazards. By contrast, tropical cities, where temperatures already approach physiological and comfort limits and where climate risks are more acute, may experience declining PTI ratios as extreme heat reduces housing demand, thereby easing affordability pressures.

The rest of this document is organized as follows. In section two we provide a brief literature review especially linking housing prices to climate factors. In section three we present our methodology which consists of cluster analysis and quantile regressions. In section four we can find our main results and robustness checks, while section five contains our main conclusions.

2. Related literature

There is growing evidence that climate risk is an increasingly relevant factor priced by real estate markets. Research stress out that physical risks related to climate change, including vulnerability to wildfires, flooding, and sea level rise (SLR), are becoming more and more priced into property and rental markets in a variety of countries and cities. For instance, inland floodplain properties trade at a discount (Beltrán et al., 2018), in the same vein that homes exposed to flood threats do (Skouralis et al., 2024; Beck & Lin, 2020). In this context, it has been demonstrated that city-level adaptation announcements are essential to reducing price declines

in SLR-exposed locations (Agarwal et al., 2025), and that moderate flood hazards reduce rents as well (Blok & Fuerst, 2025).

Other climate hazards are associated to similar patterns: wildfires in California caused a 13% surge in nearby housing prices due to post-disaster migration (Hennighausen and James, 2024), and there is evidence that reductions in air pollution under the U.S. Clean Air Act were strongly capitalized into property prices (Sager & Singer, 2025). At the same time, risk capitalization is not universal. Murfin and Spiegel (2020) find no significant sensitivity of U.S. coastal home prices to projected SLR, and Menéndez et al. (2024) report limited evidence of flood risk discounts in Spain. This evidence highlights those institutional and behavioral factors, including political orientation (Bernstein et al., 2022) and climate beliefs (Baldauf et al., 2020), which may act as mediators between climate risk and real estate prices.

Among the many signs of climate risk, increases in temperature have received particular attention. Here, findings are notably mixed, reflecting the interaction of two countervailing mechanisms. On the one hand, a climate-amenity effect implies that moderate warming can raise property values in cold regions by improving comfort and reducing heating needs. Meier and Rehdanz (2017) provide evidence that an inverted U-shaped relationship between housing prices and cooling degree days (CDD) in the United Kingdom, while Sinha et al. (2021) show that U.S. households exhibit a positive willingness to pay for warmer winters. On the other hand, a climate-risk effect captures the negative economic impacts of excessive heat. Chen et al. (2025) find that a one-unit temperature increase negatively impact housing prices, with stronger effects in inland and fiscally weaker regions. Welfare losses from high-heat exposure have also been quantified by Kuruc et al. (2025), who estimate a \$1.53 per-hour utility loss during extreme heat at the U.S. All in all, we have that temperature may impact differs real estate prices across climate zones, levels of development, and income groups.

Despite extensive evidence at the city or national level, cross-sectional city-level analyses remain scarce. Notable exceptions include Maddison (2003), who used cross-country data to show that a 2.5 °C temperature rise yields welfare gains for high-latitude countries but losses for low-latitude ones, and Tuholske et al. (2021), who employed fine-resolution climate and population information to document a marked increase in urban heat exposure between 1983 and 2016. On their side, McKinnon et al. (2024) analyze global observations and climate model projections to show that hottest days are warming at rates comparable to mean temperatures, with implications for variability and extremes.

Our research also relates to a vibrant urban studies literature examining how climate risk interacts with the built environment. Zhao et al. (2014) and Zhang et al. (2023) show that urban heat island (UHI) and urban dry island effects shape local temperature and wet-bulb stress across North America and globally, while Jung

(2024) links UHI patterns in Singapore to mid-century planning decisions. Perera et al. (2023) study how urban densification compounds energy demand and reduces renewable power reliability in cities, while Hamstead (2024) highlights how housing and energy inequalities mediate heat and cold insecurities.

Finally, a key motivation of our study is exploring the non-linear relationship between real estate prices and climate risk. Several prior works point to such non-linearities. Meier and Rehdanz (2017) explicitly identify an inverted U-shaped temperature–price relationship, while Chen et al. (2025) reveal heterogeneity across fiscal capacity and geography that implies threshold effects. Liao et al. (2025) use nonlinear lag structures to show sharply increasing hospitalizations under extreme heat in China, illustrating that damages may accelerate once critical temperature levels are crossed. These insights suggest that climate risk may influence real estate markets in ways that cannot be captured by simple linear models.

3. Methodology

3.1. Cluster Analysis

To detect groups of related climate hazard indicators and mitigate multicollinearity in the quantile regression models, we first conducted a *hierarchical cluster analysis*. This method is based on the correlation matrix of the climate-risks indicators at the city level. This procedure helped inform our choice of explanatory variables by identifying sets of indicators with similar patterns from which we could select only one representative indicator. Cluster analysis is an *unsupervised* machine learning method that groups variables into sets, or clusters, such that members of the same cluster are more similar to one another than to members of other clusters. This approach particularly helps to detect redundancy and reveal underlying structures in the dataset.

Hierarchical clustering starts by treating each variable as its own cluster and then iteratively merges the two most similar clusters until all variables are grouped into a single hierarchy. The similarity (or dissimilarity) measure is derived from the correlation matrix converted to a distance given by $d_{ij} = 1 - |r_{ij}|$, where r_{ij} is the correlation between indicators i and j . The rationale for using hierarchical clustering in this context is twofold: first, it reduces dimensionality by identifying clusters of indicators that are strongly correlated, which helps to minimize multicollinearity in our quantile regression, as we do not have a large number of observations; and second, it improves interpretability by reorganizing the correlation heatmap (see Figure 1) so that coherent groups of highly correlated indicators are positioned together.

3.2. Quantile Regression

In traditional linear regression, the model is expressed as $y_i = \beta x_i + e_i$, with $E y_i = E \beta x_i = \hat{y}$, where $\hat{y}$ is the conditional mean of y_i given x_i . In contrast, quantile regression (Koenker and Bassett, 1978) assumes the τ^{th} quantile of y_i conditional on x_i is equal to:

$$Q_{y_i|x_i}(\tau) = x_i' \beta(\tau), \quad (1)$$

where $Q_{y_i|x_i}(\tau)$ represents the τ^{th} quantile of the price to income ratio, denoted as y_i ; x_i is the climate hazard indicators included in the model after cluster analysis, and $\beta(\tau)$ is the coefficient measuring the association between the climate hazards and the τ^{th} quantile of the price to income ratio.

Note that we do not include other socio-economic determinants in our set of covariates, since our focus is on estimating the total effect of climate hazards at the city level and housing overvaluation. In the cross-section of cities, climate variables are exogenous to socio-economic determinants; thus, if the latter affect the outcomes of interest, they would operate as mediators (or collider factors). In either case, their inclusion would bias the estimated effect. By contrast, climate risk factors would likely act as omitted confounders if excluded from the model, as they clearly interact with one another without a well-defined causal ladder (see Cinelli et al., 2024, for an introduction to the distinction between “good” and “bad” controls).

4. Data

We employ fourteen climate hazard indicators sourced from the World Resources Institute (<https://www.wri.org/>) that were selected to be directly relevant for city-level climate risk and consequently with the potential of affecting real estate prices. They are defined as follows:

Table 1. Climate Hazard Indicators at the City Level

Variable Name	Description
Tmax_highest:	The highest daily maximum temperature recorded in a given year, representing the most extreme heat event.
Tmax95pctl_days:	The annual number of days when the daily maximum temperature is at or above the local 95th percentile, reflecting the frequency of unusually hot days relative to climatological norms.

Variable Name	Description
Tmax40_days:	The annual number of days when daily maximum temperature reaches or exceeds 40 °C, indicating the occurrence of extreme heat events.
Tmax35_days:	The annual number of days when daily maximum temperature reaches or exceeds 35 °C, representing the frequency of very hot days relevant to health and infrastructure impacts.
CDD21:	Cooling degree-days with a reference temperature of 21 °C, calculated as the sum of degrees by which daily average temperatures exceed 21 °C across the year; this indicator represents potential demand for cooling energy.
Twb31_days:	The annual number of days when the maximum daily wet-bulb temperature equals or exceeds 31 °C, a threshold associated with severe risks to human health due to combined heat and humidity stress.
heatwave_duration:	The length (in days) of the longest consecutive run of at least three days with daily maximum temperature at or above the local 90th percentile, characterizing the duration of extreme heat events.
heatwave_count:	The number of distinct events per year in which at least three consecutive days experience daily maximum temperatures at or above the local 90th percentile, representing the annual frequency of heatwaves.
malaria_days:	The annual number of days when average daily temperature falls within the optimal range for the activity and survival of adult malaria-transmitting mosquitoes (<i>Anopheles</i> spp.), indicating climatic suitability for transmission.
arbovirus_days:	The annual number of days when average daily temperature is within the optimal range for the activity of arbovirus-carrying mosquitoes (e.g., <i>Aedes aegypti</i>), associated with risks of dengue, chikungunya, and Zika transmission.
pr_highest:	The total millimeters of precipitation recorded on the wettest day of the year, representing the most extreme daily rainfall event.
pr90pctl_days:	The annual number of days with daily precipitation at or above the local 90th percentile, indicating the frequency of heavy rainfall events.
drought_days:	The annual number of days when the Standardized Precipitation Index (SPI) is at or below -1, representing meteorological drought conditions.
landsliderisk_days:	The annual number of days when a city with high landslide susceptibility also records high values of the Antecedent Rainfall Index, reflecting heavy or prolonged rainfall that may trigger slope failures.

Note: Authors' elaboration using categories in the World Resources Institute

We complement the information on climate hazards for cities with information for the price to income ratio in these same cities, sourced from www.numbeo.com. Numbeo is the world's largest crowdsourced database on cost of living and quality of life. It offers data and insights on expenses, housing prices, crime perceptions, healthcare standards, transportation quality, and many other real estate indicators.

Our final dataset consists of 15 variables capturing climatic, health, and price to income indicators across 195 cities. The dataset spans all inhabited continents, representing a wide range of climatic and economic.

Cities such as Jakarta, Mumbai, Dhaka, Lagos, and Karachi experience tropical or subtropical climates with high temperatures and humidity, while cities like Helsinki, Stockholm, Edmonton, and Moscow are located in temperate or cold climates with pronounced seasonal variation. Many cities, including London, New York, Tokyo, Paris, and Singapore, are highly developed with advanced infrastructure, high income levels, and well-established urban services, whereas others, such as Addis Ababa, Karachi, and Guayaquil, face emerging economy conditions with more limited resources and infrastructure. The dataset also captures intermediate cases, including rapidly developing metropolises like Beijing, Shanghai, Istanbul, and Dubai, which combine substantial economic growth with diverse climate exposures. This diversity ensures the dataset encompasses a broad spectrum of urban experiences, from tropical megacities and temperate European capitals to arid Middle Eastern centers and high-altitude South American cities, providing a rich context for analyzing climatic and socio-economic risks and their impacts on real estate markets.

In Table 2 we present the summary statistics for our 15 variables. Cooling Degree Days (CDD21) have a mean of 205 and a median of 108, ranging from near zero to 759, reflecting substantial variation in heat exposure over the cities in our sample. The number of days exceeding 35°C and 40°C averages 5.95 and 1.58, respectively, with medians much lower than the means, indicating skewed distributions due to occasional extreme heat events. Days above the 95th percentile of maximum temperature average 15.4, while the highest maximum temperature averages 9.09. Wet-bulb temperature days above 31°C have a mean of 26.5 showing that extreme humidity-heat conditions are rare in most cities in our sample but extreme in some of them. Drought days average 22, and heatwaves occur on average 2.19 times per year, lasting 5.74 days, indicating moderate but occasionally prolonged extreme conditions. We removed negative values for drought days from the dataset to estimate summary statistics in Table 1, as these likely represent errors or missing data coded as negative numbers. Because of this correction, we excluded drought days from our main analysis to ensure consistency and avoid biasing the results.

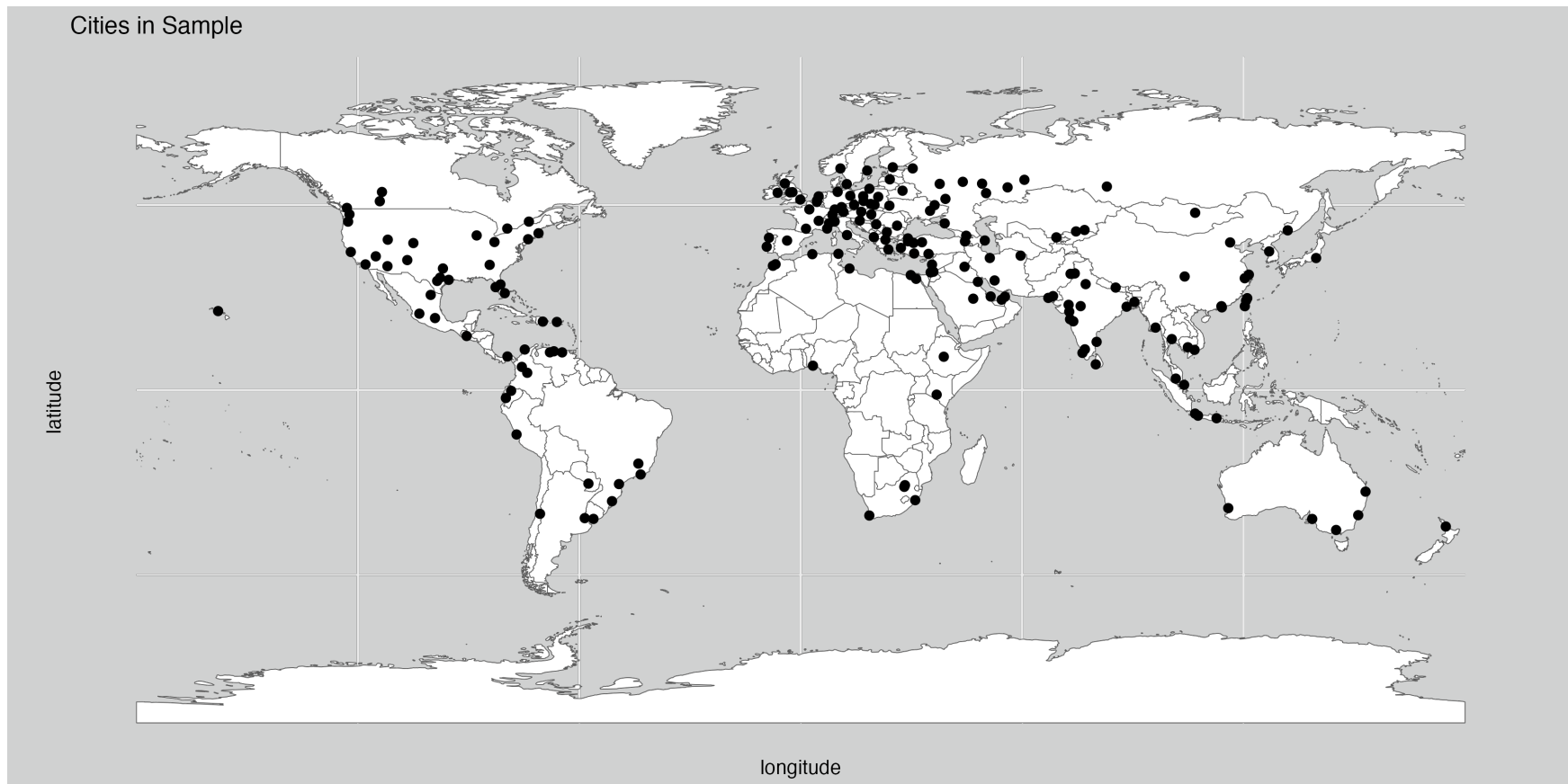
Landslide risk days average 3.73, generally low but reaching up to 34.7 in some areas. Extreme precipitation, measured by pr90pctl_days and pr_highest, has means of 10.9 days and 9.45 mm, reflecting spatial variability in heavy rainfall. Vector-borne disease risk varies widely, with arbovirus and malaria days averaging 12.8 and 19.5, and ranges exceeding 88 and 90 days in some cities. Finally, the price-to-income ratio averages 14, with a wide range up to 46.6, highlighting substantial differences in cost of living relative to income. Overall, the data show considerable heterogeneity across variables, with many distributions skewed due to extreme events or outliers.

Table 2. Summary Statistics

variable	mean	median	min	max	sd
CDD21	205	108	0.0341	759	223
Tmax35_days	5.95	1.06	0.0341	49.9	10.8
Tmax40_days	1.58	0.0341	0.0341	35.9	5.46
Tmax95pctl_days	15.4	14.3	0.0341	48.2	5.07
Tmax_highest	9.09	9.03	6.1	13.4	1.3
Twb31_days	26.5	0.0341	0.0341	92	34.2
drought_days	22	19.9	0	54.7	14.6
heatwave_count	2.19	2.18	0.0375	3.89	0.48
heatwave_duration	5.74	4.52	0.0375	38.9	4.65
landsliderisk_days	3.73	4.9	0	34.7	3.98
pr90pctl_days	10.9	10.2	5.62	35.8	3.19
pr_highest	9.45	8.34	0.532	29.4	4.6
arbovirus_days	12.8	6.27	0.0341	88.7	18.4
malaria_days	19.5	14.8	0.0341	90.3	19.4
price_income	14	12.4	1.9	46.6	8.78

Note: Summary statistics for 15 climatic risk variables and the price to income ratio across 195 cities. Values reported include the mean, median, minimum, maximum, and standard deviation. Extreme or missing values were addressed where necessary, including the removal of negative values for drought days. The table highlights the variability and distribution of key indicators across diverse climatic zones and levels of urban development.

Figure 1. Cities in the Study Sample



Note: Our sample consists of 195 cities with information on climate hazards and price to income ratios for 2023.

5. Results

In the first part of our results, we present the outcomes of the clustering analysis, followed by the quantile regression, which constitutes our main set of findings.

5.1. Cluster Analysis:

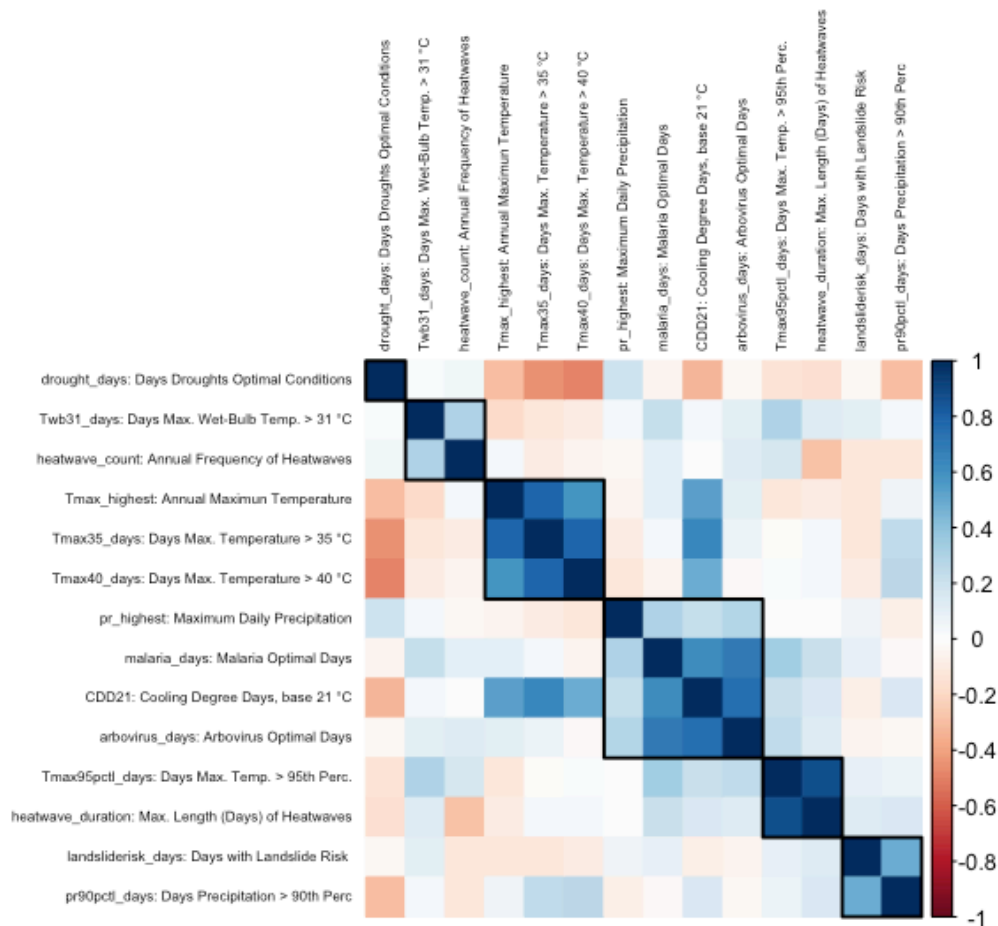
To identify patterns of similarity and to address potential multicollinearity in the quantile regression models, we applied a hierarchical cluster analysis of the correlation matrix. This approach provided guidance for the selection of explanatory variables by grouping indicators with similar correlation profiles. The correlation structure and resulting clusters are visualized in Figure 2. Correlation strength is represented by color, ranging from dark blue (strong positive correlation, close to 1) to dark red (strong negative correlation, close to -1), with white representing weak or no correlation. Rectangles highlight six clusters identified through hierarchical clustering. We could summarize the six groups in the following lines:

Heat stress: consists of Twb31_days (days with wet-bulb temperature $>31^{\circ}\text{C}$) and heatwave_count (annual frequency of heatwaves). These two indicators are strongly positively correlated, reflecting that high wet-bulb temperatures occur predominantly during frequent heatwaves. **Heat extremes:** consists of Tmax_highest (annual maximum temperature), Tmax35_days (days $>35^{\circ}\text{C}$), and Tmax40_days (days $>40^{\circ}\text{C}$). Strong positive correlations exist among these variables, indicating that cities with more extreme temperatures also experience a higher number of hot days, capturing the intensity and frequency of extreme heat events. **Vector-borne disease suitability:** Here we find pr_highest (maximum daily precipitation) malaria_days, CDD21 (cooling degree days), and arbovirus_days. Within this cluster, positive correlations suggest that climatic conditions favoring malaria and arbovirus transmission also coincide with higher cumulative heat load (CDD21), and high precipitation, linking thermal suitability with potential disease risk. **Persistence of heat stress:** Houses Tmax95pctl_days (days exceeding local 95th percentile) and heatwave_duration (length of longest heatwave). Moderate positive correlations indicate that long-duration heatwaves tend to coincide with more days exceeding extreme local temperatures. **Precipitation extremes:** consists of landslides_risk_days and pr90pctl_days (days with precipitation above the 90th percentile). These two variables are positively correlated, highlighting that cities with very heavy single-day rainfall also tend to experience more frequent conditions for landslides. **Droughts.** Consists only of the indicator drought_days. This indicator presents abnormal negative values which places it in its own clusters, making it unfit to be included in the main quantile regression specifications.

Overall, the clustering analysis reveals that the fourteen climate indicators naturally group into coherent categories representing heat extremes, heat stress, precipitation extremes, vector-borne disease suitability, pro-

longed heatwaves, and drought risk. This grouping informs variable selection for subsequent modeling by highlighting which indicators are strongly interrelated and may capture overlapping aspects of climate hazards.

Figure 2. Cluster Analysis of Climatic Risk Factors



Note: The figure presents six clusters derived from hierarchical clustering of climatic risk indicators across 198 cities. Correlation strength is indicated by color, ranging from dark blue (strong positive correlation, near 1) to dark red (strong negative correlation, near -1), with white representing weak or no correlation. Rectangles outline the six clusters identified.

5.2. Impact of climate risk factors on the PTI ratio

In what follows, we present our results on the effects of five climate hazards on cities. These results cover five of the six clusters previously described, with the sole exception of the first cluster in Figure 2, which consists of only drought days and was excluded due to the anomaly patterns in that series explained earlier. This new set of results differentiates across levels of the PTI by applying quantile regressions. In other words, we estimate the impact of each climate risk factor on the price-to-income ratio at different quantiles of its distribution across cities. Figure 3 reports the coefficients of the quantile regression model for quantiles ranging from 0.2 to 0.8. The shaded areas represent 95% bootstrapped confidence intervals.

The intercept is relatively stable across quantiles, though with some widening confidence intervals toward the tails. Among the climate hazard indicators, several distinct patterns emerge. Heatwave Count shows a positive association with the PTI ratio that strengthens monotonically toward higher quantiles, suggesting that more frequent heatwaves are disproportionately associated with higher PTI values in cities at the upper end of the distribution. Albeit the effect is only significant at the very high end of the distribution, corresponding to quantiles close to the 80th percentile.

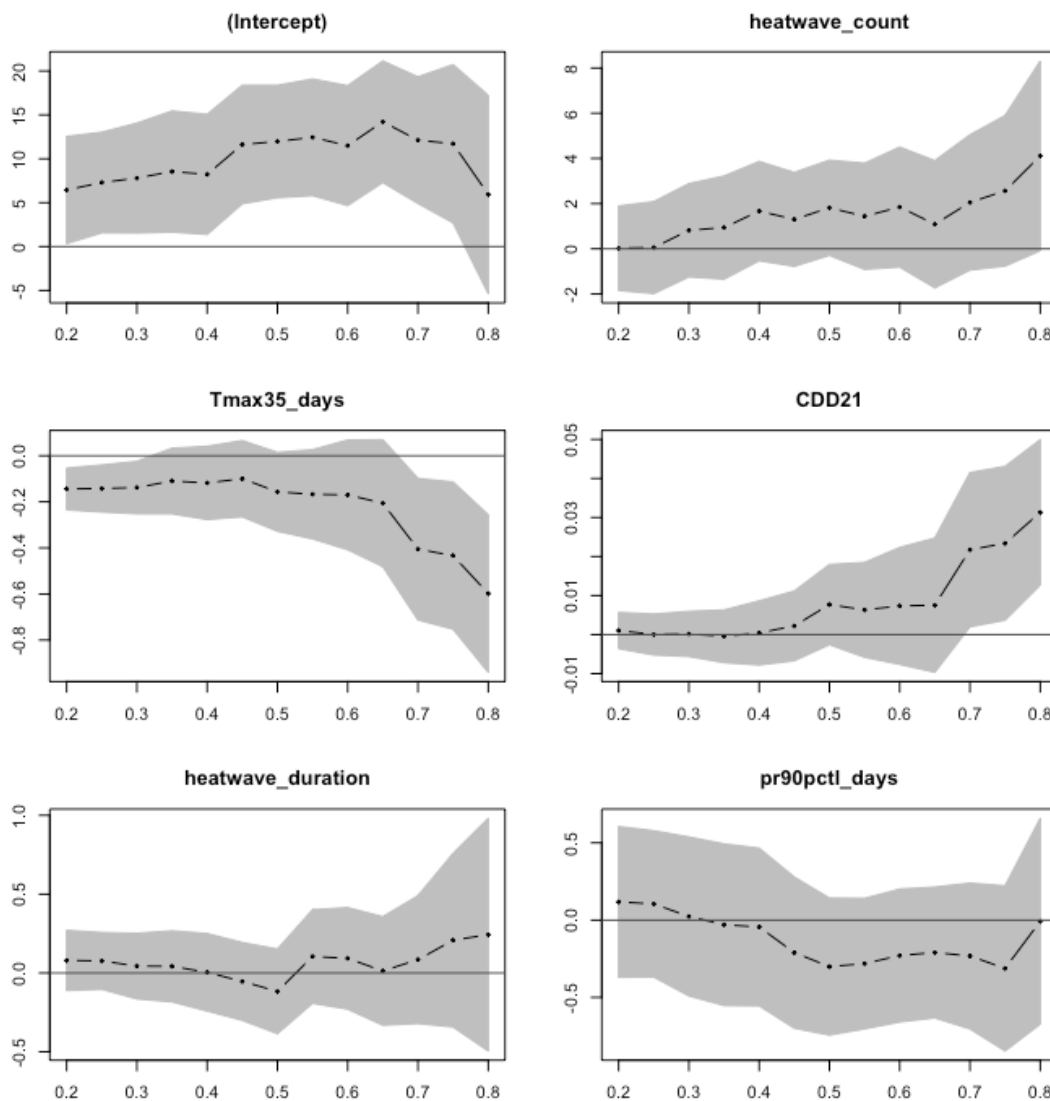
On its side, Tmax35 (number of days above 35°C) exhibits a negative and increasingly pronounced effect in higher quantiles, indicating that extreme temperature days are linked to relatively lower PTI ratios in more overvalued markets. This is an interesting result as it means climate change, associated with more frequent peaks in daily temperature, may partially counterbalance over-valuation at traditionally less affordable cities around the world.

Nonetheless, CDD21 (cooling degree days above 21 °C) exerts a consistently positive influence on the price-to-income ratio, with the effect strengthening and reaching statistical significance at the upper quantiles. This pattern indicates that greater cooling needs are associated with higher housing prices relative to income, and the impact is most pronounced in already less affordable markets. Beyond reflecting a potential climate premium, where rising temperatures raise the value of homes with superior cooling capacity or other heat-resilient amenities, this relationship may also arise because income growth tends to lag in hotter environments owing to productivity losses, higher living costs, or sectoral disruptions, further amplifying the ratio.

Heatwave Duration appears relatively flat across the middle quantiles, but rises steeply in the upper part of the distribution, but these effects are never significant due to the large confidence intervals associated to them. Finally, precipitation days above the 90th percentile show a generally negative effect that becomes more pronounced in higher quantiles, again non-statistically-significant over the distribution of PTI.

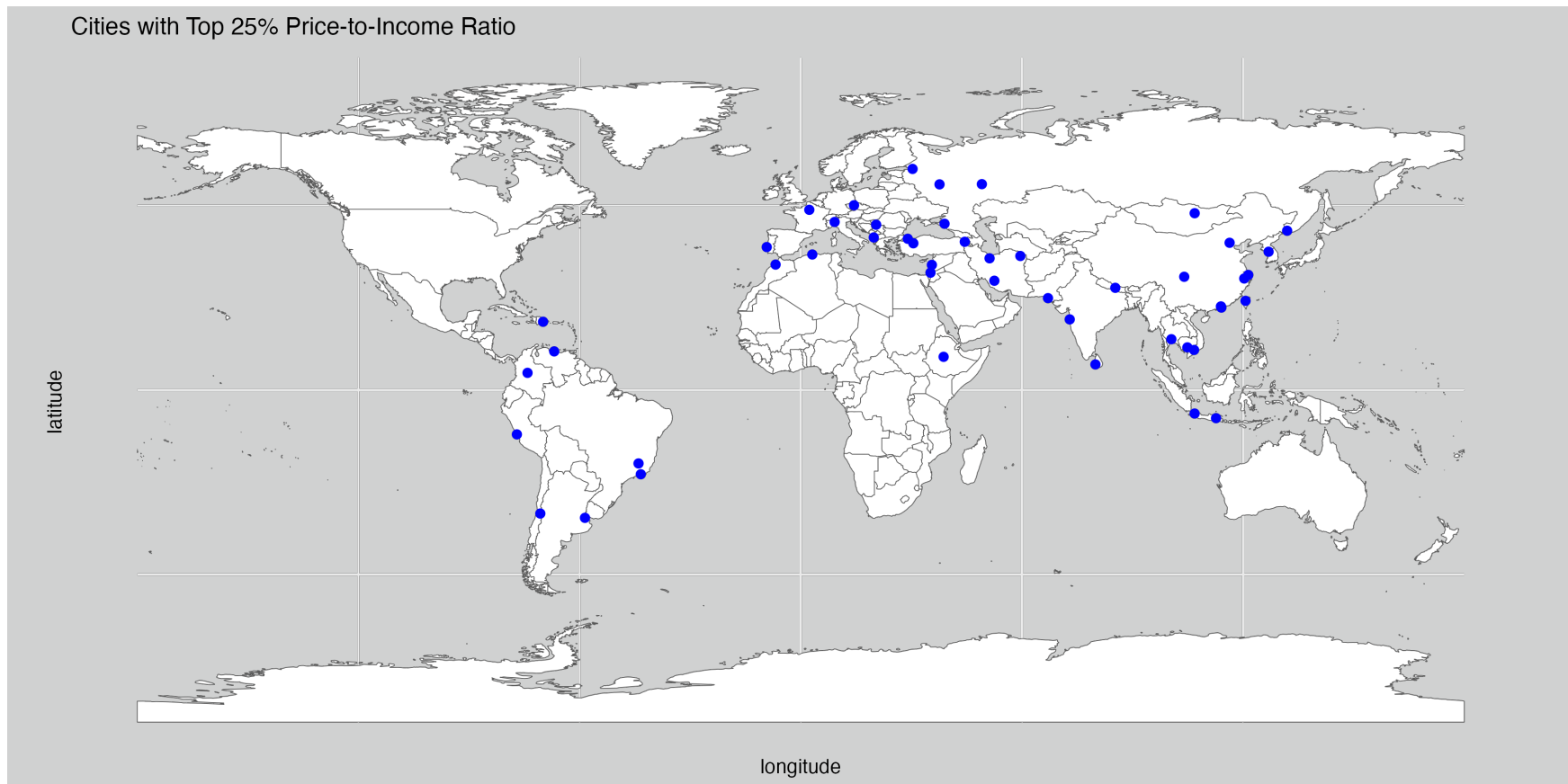
All in all, the documented effects are particularly relevant for markets at the upper end of the PTI distribution. In Figure 4, we identify the cities that are especially sensitive to climate factors. As shown, this subsample—defined as the top 25% of the PTI distribution—includes a wide variety of cities.

Figure 3. Quantile Regression on Price-to-Income Ratios



Note: Quantile regression results explaining the Price-to-Income ratio using five variables from the original 14 climate hazard indicators: CDD21, Tmax35, Heatwave Count, Heatwave Duration, and Precipitation above the 90th percentile of the local distribution. The vertical axis shows the estimated effect on the Price-to-Income ratio, while the horizontal axis represents quantiles from $\tau = 0.2$ to $\tau = 0.8$. Extreme quantiles are excluded to reduce imprecision in tail estimates. Shadowed areas correspond to bootstrapped confidence intervals at 95%.

Figure 4. Highest 25% of Cities According to the Price to Income Ratio in Our Study Sample



Note: The figure highlights the top 25% of cities in terms of Price-to-Income ratios, based on Numbeo data for 2023.

The group of cities in Figure 4, which belong to the top 25% of the global price-to-income distribution is remarkably diverse, spanning both emerging and advanced economies. Many belong to low-income or middle-income countries with predominantly tropical geographies and relatively low salaries, such as Jakarta, Bogotá, Rio de Janeiro, Mumbai, Bangkok, and Addis Ababa. At the same time, the list also includes cities in high-income countries with more temperate climates, such as Paris, Lisbon, Prague, Milan, and Seoul. This combination highlights that two forces are simultaneously at play: on the one hand, the amenity value that makes certain locations attractive despite affordability pressures, and on the other hand, the heightened exposure to climate risks. Our quantile regression results suggest that these two effects are not only present but also interact, shaping the dynamics of housing affordability in the world's most overpriced markets.

Table 3 presents the quantile regression estimates for the PTI ratio at the median ($\tau = 0.5$) and at the upper tail of the distribution ($\tau = 0.8$). The models are estimated with standardized variables (zero mean, unit variance), which allows for comparison of effect magnitudes across predictors in the style of standardized beta-coefficients models in statistics.

At the median ($\tau = 0.5$), none of the climate hazard variables show statistically significant effects, although the coefficients for CDD21 and Tmax35_days are already of opposite sign. This pattern becomes more pronounced and statistically significant at the higher quantile ($\tau = 0.8$), which corresponds to cities with elevated Price-to-Income ratios.

At $\tau = 0.8$, both CDD21 and Tmax35_days exert significant effects of similar magnitude but opposite direction: higher values of CDD21 are associated with substantially higher PTI, while higher values of Tmax35_days are associated with lower ratios. The similarity in standardized effect sizes highlights that these two variables, though measured in different units (days vs. temperatures), counterbalance each other in shaping affordability outcomes in high-ratio cities. This suggests that the housing market response to climate stress is heterogeneous, depending on whether risk is captured through longer periods of elevated cooling needs (CDD21) or through extreme hot days (Tmax35).

Other variables—such as heatwave count, heatwave duration, and extreme precipitation (above the 90th percentile)—do not show robust or consistent effects across quantiles. Heatwave count and duration are positively signed at higher quantiles, but their confidence intervals are wide and include zero, pointing to weaker associations.

Overall, the results emphasize that the drivers of real estate overvaluation differ across the distribution of PTI: climate factors do not significantly affect median affordability levels but become highly relevant in the upper

tail, where affordability constraints are most acute. The contrasting effects of CDD21 and Tmax35_days in particular underscore the importance of distinguishing between prolonged climatic stress and short-term extreme events when assessing housing market vulnerabilities.

Table 3. Regression Results for Higher Quantiles of the Price to Income Ratio

variable	Effects	Lower CI	Upper CI	P-Value
tau=0.5				
(Intercept)	-0.14731	-0.27946	-0.05695	0.06280
Heatwave Count	0.09926	-0.00302	0.17889	0.15900
Temp. Max (35 D)	-0.19346	-0.31471	0.0111	0.13800
CDD21	0.19539	-0.09025	0.28897	0.21200
Heatwave Duration	-0.06156	-0.0856	0.19982	0.49700
Precip. 90th Percent.	-0.10911	-0.22671	0.05463	0.26600
tau=0.8				
(Intercept)	0.59026	0.45228	0.79551	0.00003
Heatwave Count	0.22488	-0.05741	0.37969	0.09400
Temp. Max (35 D)	-0.73854	-0.96342	-0.29834	0.00491
CDD21	0.79558	0.24161	1.0516	0.00444
Heatwave Duration	0.12869	-0.19296	0.58105	0.56600
Precip. 90th Percent.	-0.00271	-0.2227	0.12476	0.98500

Note: Table 3 reports standardized quantile regression coefficients (with 95% bootstrapped confidence intervals and associated p-values) estimating the effects of climate hazard indicators on the price-to-income (PTI) ratio at the median ($\tau = 0.5$) and upper tail ($\tau = 0.8$) of the distribution across cities. Positive coefficients indicate that higher values of the climate variable are associated with higher PTI ratios. Statistically significant effects are observed only at $\tau = 0.8$, where prolonged warming (CDD21) raises PTI and extreme heat (days >35 °C) lowers PTI, highlighting that climate impacts emerge primarily in the most overpriced markets.

6. Conclusions

This study provides fresh evidence on the role of climate risks in shaping housing affordability across a large global sample of cities. Using hierarchical clustering and quantile regression analysis, we show that climate hazards have negligible effects on PTI ratios in typical housing markets but become highly significant in the most overpriced ones. Prolonged warming, captured by cooling degree days, is associated with higher PTI ra-

tios at the upper end of the distribution, reflecting the amenity value of milder winters and warmer conditions. In contrast, extreme heat events, as measured by the number of days exceeding 35 °C, are linked to lower PTI ratios in high-PTI markets, suggesting that acute heat stress can dampen demand and partially counteract housing overvaluation.

These findings highlight the dual nature of climate change as both an amenity and a risk. Cities experiencing moderate warming that enhances comfort, particularly during winter, may see housing markets become even less affordable as climate change progresses. Conversely, cities already exposed to high baseline temperatures and frequent extreme heat events are likely to face downward pressure on PTI ratios as housing demand weakens, potentially improving affordability but at the cost of higher social, demographic, and health risks. The contrasting effects of prolonged warming and extreme heat underscore the importance of distinguishing between gradual climatic trends and short-term extreme events when assessing housing market vulnerabilities.

Policy implications to be extracted from our results are various. In high-income or temperate cities where warmer winters may further inflate PTI ratios—such as Paris, Lisbon, or Seoul—policymakers should prepare for worsening affordability pressures by expanding the supply of affordable housing, revising zoning to allow higher-density development, and considering climate-sensitive property taxation to curb speculative demand. Financial regulators and lenders should incorporate differentiated climate signals into property valuation and mortgage underwriting to avoid fueling bubbles in markets where warming-related amenities drive overpricing. Infrastructure planning in these markets should also anticipate higher energy demand and cooling needs to prevent future supply bottlenecks.

In contrast, tropical and already hot cities such as Jakarta, Bangkok, or Addis Ababa are more likely to experience reduced overpricing but face serious societal challenges from extreme heat, including rising mortality, deteriorating public health, and climate-induced migration. For these cities, policy priorities should focus less on affordability – related to climate change – and more on adaptive strategies, such as investing in green infrastructure, cooling centers, and heat-resilient urban planning to maintain livability. At the national and regional level, governments should develop early-warning systems to monitor PTI dynamics, prepare for possible migration flows from heat-stressed areas, and coordinate housing and infrastructure investments accordingly. By revealing that climate change can simultaneously worsen affordability in some markets while easing it in others, our results call for policies that integrate housing economics and climate adaptation, tailored to the distinct climatic and market conditions of each city.

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