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Hot Property: A Spatial Analysis of Temperature and Housing Prices in Spain

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Abstract

This study examines the impact of extreme temperatures on housing price dynamics in Spain, considering both direct and indirect effects across geographic space. Using panel data at the provincial level and a spatial econometric model, we find that an increase in the number of days with maximum temperatures exceeding 35 °C (95ºF) over the past year is significantly associated with a decline in both sale and rental prices within the affected province. However, we also identify a positive indirect effect on housing markets in more distant provinces, particularly in the rental sector, consistent with a pattern of temperature-induced house price premium in cooler regions. A central methodological contribution of this paper is the use of spatial econometric techniques to detect and quantify these spillover effects. By explicitly modelling spatial dependence, we can disentangle local impacts from broader geographic transmission mechanisms, revealing how climate stressors reshape housing demand across regions. These findings highlight the importance of incorporating climate-related factors into real estate market analysis and the design of adaptation policies.

JEL Classification: C23, Q54, R14, R21, R31.

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1. Introduction

The economic consequences of climate change are increasingly manifesting in urban environments, with housing markets emerging as a critical frontier for understanding both direct and indirect impacts of environmental stressors. Among these, extreme heat events, particularly heatwaves, have intensified across Southern Europe, prompting growing concern over their impact on residential decision-making and property valuation. In Spain, where the frequency and severity of heatwaves have risen markedly in recent years, the interplay between climatic conditions and housing dynamics remains underexplored. This paper aims to fill this gap.

Spain provides a natural laboratory to examine how extreme temperatures impact housing values, given its pronounced exposure to heat events and its wide climatic variation within a single national regulatory framework. The country comprises large urban markets, coastal and tourism-driven housing, and vulnerable inland areas, allowing for the analysis of heterogeneous market responses to the same environmental stressor. Moreover, insights from Spain have broader implications for the Mediterranean and Southern European regions, which share similar climate trajectories and housing vulnerabilities.

Recent literature has increasingly highlighted the influence of climate-related risks on real estate markets[1]. Bernstein *et al.* (2019) show that physical exposure to sea level rise results in significant price discounts in coastal housing markets in U.S. counties, while Bui *et al.*, (2024), who integrate the hedonic property model and spatial econometric techniques into a single analytical framework to assess the economic effect of pluvial flooding in Vietnam, also find that prices for affected houses were discounted by 9% after a large flood event. Moreover, in response to the growing frequency of severe flooding and the consequent need for enhanced

[1] Contat *et al.* (2024) provide a comprehensive survey of the literature, highlighting how physical risks, such as extreme temperatures, flooding, and wildfires, as well as transition risks, including energy efficiency and decarbonisation, are progressively internalised into housing prices, loan performance, and migration patterns.

stormwater infrastructure to alleviate pressure on conventional drainage systems, Cohen *et al.* (2025) explore how Green Stormwater Infrastructure (GSI) affects house prices and how it can be financed in the city of Philadelphia.

Other authors have also studied the impact of other climate-related risks on real estate markets. In this vein, Butsic *et al*. (2011) using a hedonic model and housing data from ski resort areas in the western U.S. and Canada find that increased snowfall consistently boosts real estate values, with substantial heterogeneity in the likely impact of climate change across regions; Fang *et al*., (2024) examine the effect of the occurrence of a large-scale but distant hurricane on the local housing markets of Miami (Florida) between 2005 and 2014 and find a price penalty of 4% in hurricane striking period; and Götz *et al*. (2024), who analyse the impact of wildfires on mortgage pricing in Portugal, show that banks reacted to the wildfire disaster by charging a premium on interest margins. Similar to the pricing adjustments observed in commercial real estate following Hurricane Sandy (Addoum *et al*., 2021), our results suggest that residential housing markets in Spain are increasingly sensitive to climate-related risks. The observed spillover effects may reflect anticipatory behaviour by households and investors, reallocating demand toward less exposed regions.

The relationship between extreme temperatures and housing prices has been the subject of extensive research across various countries. Notably, several authors have centred their study in the United States (Livy, 2020; Ma and Yildrim, 2023; or Gourley, 2021). Concretely, Livy (2020) examines the impact of abnormal heating and cooling degree days[2] on housing prices in Franklin County (Ohio), revealing a stronger negative effect from cooling days, showing also that the value of temperature-related housing features shifts in response to recent climate anomalies. In the same vein, Ma and Yildrim (2023) provide evidence that high temperatures exert downward pressure on property prices through localised heat shocks. Moreover,

[2] Heating (cooling) degree days measure heating (cooling) energy demand by capturing how far, and for how long, the average daily temperature falls below (rises above) a standard base temperature, typically 18.3°C (65°F).

analysing 185,000 home sales using a fixed effects model, Gourley (2021) finds that short-term weather conditions influence housing prices, with cold winter weather linked to price increases, while summer precipitation effects vary with temperature. Finally, in the commercial real estate sector, Addoum *et al.* (2021) provide compelling evidence that Hurricane Sandy led to significant price discounts for properties exposed to climate risks in New York City, highlighting how investors rapidly internalise physical climate risks. Their findings reinforce the broader narrative that climate shocks, whether gradual or sudden, can significantly impact asset valuation across various real estate segments.

Other authors have focused their study on different countries, such as China. Kang *et al.* (2024) analyse panel data from Chinese cities (2009–2019) and find that each additional day above 35°C (95ºF) in the previous year is associated with a 0.1% drop in housing prices, stemming from reduced labour inflows, lower home-buying interest, and fewer firms entering overheated markets. More recently, using monthly city-level panel data from China (2010–2020), Chen *et al*. (2025) find that rising temperatures, particularly heat waves, significantly depress housing prices, with a 1-unit increase in standardised temperature reducing prices by approximately CNY 110/m², being the effect more pronounced in inland regions, areas experiencing fiscal stress, and those with a strong primary industry base. These findings underscore the capacity of climate stressors to be capitalised into housing values, reflecting both perceived and actual risks, underscoring the need for sustainable adaptation strategies to mitigate climate-related risks in urban housing markets. Some authors have focused their analysis on European countries. For instance, Cascarano and Natoli (2023), using data from 2 million property ads and agent appointments across Italian cities, show that extreme heat slows housing searches and delays sales. It also shifts demand away from non-climate-safe homes, lowering prices, while cold weather boosts online search activity, but not in-person visits.

Moreover, beyond its direct effects, climate change also influences residential mobility. Cattaneo and Peri (2016), using data from 115 countries between 1960 and 2000, establish a causal link between rising temperatures and migration flows, particularly in middle-income economies; whilst Docquier *et al.* (2024) highlight the role of climate expectations in shaping current migration patterns toward OECD countries. Issa *et al.* (2023) present a scoping review of the literature that explores the relationship between heat and human migration, further emphasising heterogeneity of migration responses to heat, suggesting that local context and adaptive capacity play a decisive role. Climate change also influences residential mobility and housing preferences. Schuetz (2024) shows that U.S. households adjust their housing behaviours in response to climate risks through multiple channels, including changes in location choice, investment decisions, and demand for climate-resilient housing. These behavioural shifts reflect varying levels of risk tolerance, financial capacity, and access to information. In urban settings, this dynamic has given rise to phenomena such as "climate gentrification", whereby less-exposed or cooler areas experience relative price appreciation due to climate-induced relocation (see, e.g., Keenan*, et al*., 2018 and Keenan, 2022).

In the Spanish context, environmental degradation has already demonstrated measurable effects on housing markets. The case of the Mar Menor, Europe's largest saltwater lagoon, which has been undergoing significant environmental decline in recent years due to eutrophication, illustrates how ecological decline can lead to substantial losses in property value and hinder long-term appreciation (see, e.g., Banco de España, 2021, and Lamas Rodríguez *et al.*, 2023). Similarly, Heymann (2024) outlines the multifaceted ways in which climate change is reshaping the real estate sector, encompassing insurance and financing[3], valuation, and policy. For instance, extreme temperatures heighten financial risk by damaging residential properties, increasing insurance premiums, and reducing asset values, factors that can destabilise the banking system and prompt stress testing by central banks. In response,

[3] For instance, Götz *et al.* (2024) show that wildfires in Portugal led to higher mortgage interest margins, as lenders adjusted pricing to reflect increased climate-related credit risk. Their findings underscore how physical climate shocks can be rapidly internalised by financial institutions, with implications for housing affordability and systemic stability.

central banks are integrating climate-related risks into their financial stability frameworks and developing analytical tools, such as the House Price-at-Risk (HaR) (Ganics and Rodríguez-Moreno, 2024) and Collateral-Adjusted Exposure at Risk (CEAR) (Statistics Committee Expert Group on Climate Change and Statistics and Working Group on Securities, 2024).[4]

Therefore, since the economic effects of climate change on housing markets have become a central topic in the field of spatial economics, this paper contributes to the emerging literature on this issue by examining the spatial impact of extreme heat on housing prices in Spain. In this vein, Lorenzo *et al*. (2021) show that the increasing intensity, frequency, duration, and geographic spread of heatwaves across the Iberian Peninsula have placed growing pressure on residential decision-making, reshaping both housing supply and demand.

Concretely, using monthly house sales and rental prices from Idealista.com (the largest online real estate market in Spain) and spatial econometric techniques (LeSage and Pace, 2009), we analyse how extreme heat, proxied by the number of days exceeding 35 °C over the previous year, affects both sale and rental prices across Spain's provincial capitals. Importantly, we distinguish between direct local effects and indirect spillovers to neighbouring and distant provinces, shedding light on potential climate migration patterns and the revaluation of cooler regions. By integrating spatial dynamics into the analysis, this paper offers new insights into how climate stressors are reshaping housing markets and underscores the need to incorporate environmental variables into real estate policy and planning. Therefore, the central contribution of this paper is the application of spatial econometric techniques to identify and quantify spillover effects in the relationship between extreme heat and housing prices. While previous studies have primarily focused on the local impacts of climate stressors, thereby revealing only part of the picture and overlooking broader linkages, our approach explicitly models spatial

[4] These instruments support the monitoring and projection of physical and transition risks within the financial sector, particularly in housing markets, thereby informing policy decisions and encouraging sustainable investment.

interdependencies across provinces, allowing us to capture how temperature shocks in one region influence housing market dynamics in other regions. By disentangling direct and indirect effects, we reveal a climate-induced redistribution of housing demand that extends beyond provincial boundaries. This methodological framework not only improves the accuracy of impact estimates but also provides novel insights into the spatial transmission mechanisms of climate risks in real estate markets.

Temperatures above 35°C pose serious health risks (World Health Organization, 2024; Rocklöv *et al*., 2011). Prolonged exposure impairs the body's ability to dissipate heat (Sherwood and Huber, 2010), causing cardiovascular strain, inflammation, respiratory issues, and cognitive impairments (Bouchama *et al*., 2017; Ayres *et al.,* 2009; D'Amato *et al*., 2014; Hocking *et al.,* 2001). Extreme heat also affects mood and task performance, with early-life exposure potentially causing long-term cognitive and health impacts (Noelke *et al*., 2016; Young, 2002; Isen *et al.,* 2017; Zivin *et al*., 2018). High temperatures reduce economic growth and firm performance. A 1°C rise can lower *per capita* income by 1.4 percentage points in developing countries (Dell *et al*., 2012) and slows growth in developed nations (Colacito *et al*., 2019; Jin *et al*., 2021). In the real estate market, extreme heat increases energy costs through higher air conditioning use and electricity demand (International Energy, 2023). Similarly, Sirmans *et al.* (2025) show that perceptions of climate change and disaster risk significantly influence capitalisation rates in U.S. commercial real estate, underscoring the role of investor beliefs in pricing climate-related risks.

We find that each additional day above 35 °C over the previous year is associated with a 0.08% decline in housing sales prices and a 0.15% decline in rental prices within the same province, but with increases of 0.16% and 0.30%, respectively, in neighbouring provinces. The indirect effect is stronger in more distant provinces and is associated with higher job inflows and lower housing supply in cooler provinces. These results remain robust after controlling for real estate demand and supply factors, are concentrated in hotter provinces, and persist over time as suggested by local projection analysis. These results carry important implications for multiple stakeholders. For real estate developers and investors, they highlight profitable opportunities in cooler regions, where housing demand is shifting. For urban planners and regulators, the findings suggest a likely concentration of labour demand in these areas, which could encourage investments in industrial zones and labour-intensive industries. For academics, our study contributes to the growing literature on climate change by extending knowledge of how global warming affects asset pricing in housing markets. Our findings demonstrate the value of spatial econometric modelling in uncovering how climate stressors propagate across regional housing markets. By explicitly accounting for spatial dependence, we can distinguish between the direct local effects of extreme heat and the indirect spillover effects that influence housing prices in neighbouring and distant provinces. This methodological approach uncovers a climate-induced redistribution of housing demand, offering new insights into the geographic transmission of environmental risks. The identification of these spillover effects stands as a central contribution of our study, highlighting the importance of spatial dynamics in real estate valuation and informing both academic research and regional adaptation strategies. Moreover, our findings contribute to the broader understanding of how climate risks are priced into real estate markets, as documented in Contat *et al.* (2024). The observed spillover effects suggest that housing markets are not only sensitive to local temperature shocks but also to broader spatial dynamics of climate exposure and adaptation.

The paper proceeds as follows. Section 2 outlines the spatial regression models. Section 3 presents our data. In Section 4, we report the empirical results. Section 5 provides a discussion and policy recommendations. Finally, Section 6 concludes.

2. Spatial regression models

In this section, we outline the methodology used in this paper.[5] First, it is essential to clarify the concept of spatial dependence, also known as spatial correlation. Spatial dependence occurs when the value of a variable at one location or province depends on the values observed at neighbouring locations (LaSage and Pace, 2009). This contrasts with traditional econometric approaches, such as ordinary least squares (OLS), which do not account for spatial dependence and may therefore suffer from omitted variable biases. Spatial econometric models address this issue by explicitly capturing spatial dependence through a spatial weight matrix $\boldsymbol{W}$, which represents how different locations, or provinces in our context, are connected to one another.

The spatial econometrics literature offers a variety of models to capture spatial dependence in data. In this paper, we focus on three widely used models: the spatial autoregressive model (SAR), the spatial error model (SEM), and the spatial Durbin model (SDM). All these models are estimated via maximum likelihood. See more information in the manuals of LaSage and Pace (2009) and Elhorst (2014).

The panel SAR model considers spatial correlation in the dependent variable as follows,

$$\boldsymbol{p}_t = \alpha + \rho \boldsymbol{W} \boldsymbol{p}_t + \boldsymbol{X}_t \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t \tag{1}$$

where $\boldsymbol{p}_t$ is a pooled *Nx1* vector of log house sale (or rental) prices at time *t* with *N* the total number of provinces, $\boldsymbol{W}$ is the row-stochastic nearest neighbour spatial weight *NxN* matrix, $\boldsymbol{X}_t$ is a *NxK* matrix of pooled *K* independent variables and $\boldsymbol{\varepsilon}_t$ pooled *Nx1* vector of residuals. The parameter ρ measures the degree of spatial correlation across provinces. Evidence of spatial correlation in the dependent variable requires ρ to be statistically significant, and the sign of ρ reflects the direction of the spatial correlation. The coefficients α and $\boldsymbol{\beta}$ represent the parameters to be estimated. We include province and year–month fixed effects. The province

[5] Bui *et al.* (2022) apply a similar framework to assess the impact of flood risk on housing prices, highlighting the value of spatial modelling in environmental economics.

fixed effects account for unobserved, time-invariant differences across provinces—such as geographic location (coastal *vs*. inland), economic conditions (e.g., wealthier northern regions *vs.* poorer southern Spain), or other static characteristics. The year–month fixed effects capture common temporal shocks and trends in housing prices that affect all provinces simultaneously. Spatial regression models require one observation per province and, consequently, the use of balanced panel data. In the baseline analysis, we adopt an arbitrary but conservative approach by using a row-stochastic spatial weights matrix $\boldsymbol{W}$ based on sixth-order contiguity, that is, each province is assumed to be connected to its six nearest neighbours. As a robustness check, we also consider alternative definitions of the number of nearest neighbours.

The panel SEM captures spatial dependence in the error terms, rather than in the dependent variable, and can be expressed as follows,

$$\begin{aligned} \boldsymbol{p}_t &= \alpha + \boldsymbol{X}_t\boldsymbol{\beta} + \boldsymbol{u}_t, \\ \boldsymbol{u}_t &= \lambda\boldsymbol{W}\boldsymbol{u}_t + \boldsymbol{\varepsilon}_t, \end{aligned} \tag{2}$$

where λ is the spatial error correlation parameter to be estimated. All the other variables are as explained above.

Finally, the panel SDM allows spatial dependence in both the dependent and independent variables as follows,

$$\boldsymbol{p}_t = \alpha + \rho\boldsymbol{W}\boldsymbol{p}_t + \boldsymbol{X}_t\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{X}_t\boldsymbol{\theta} + \boldsymbol{\varepsilon}_t \tag{3}$$

where $\boldsymbol{\theta}$ captures the additional spatial dependence linking the independent variables to the dependent variable.[6]

Because of the spatial correlation in the dependent variable, the interpretation of the coefficients in the SAR and SDM models is not straightforward. To illustrate, we expand the SDM in Equation (3), omitting the constant term for simplicity:

[6] The spatial Durbin error model (SDEM) accounts for spatial dependence in the dependent variable, the independent variables, and the residuals. We do not consider this model further because its results are similar to those of the spatial Durbin model (SDM), and the interpretation of the parameters is similar (see, e.g., Elhorst, 2010, and Golgher and Voss, 2016).

$$(I - \rho \boldsymbol{W})\boldsymbol{p}_t = \boldsymbol{X}_t\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{X}_t\boldsymbol{\theta} + \boldsymbol{\varepsilon}_t,$$

$$\boldsymbol{p}_t = \boldsymbol{S}(\boldsymbol{W})\boldsymbol{X}_t + (I - \rho \boldsymbol{W})^{-1}\boldsymbol{\varepsilon}_t,$$

$$\boldsymbol{S}(\boldsymbol{W}) = (I - \rho \boldsymbol{W})^{-1}(I\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{\theta}), \tag{4}$$

where I is an *NxN* identity matrix. The relationship between the independent and dependent variables is no longer represented by a single scalar coefficient for each regressor, but rather by a *NxN* matrix $\boldsymbol{S}(\boldsymbol{W})$. This implies that a change in an independent variable for one province *i* (observation) may affect the dependent variable in all other provinces, including through feedback effects from those provinces back to the original one. Each element in column *i* of matrix $\boldsymbol{S}(\boldsymbol{W})$, with *i* = 1, …, *N*, represents the spatial effect *from* province *i to* province *j*, with *j* = 1, …, *N*.

The matrix $\boldsymbol{S}(\boldsymbol{W})$ can be decomposed into direct, indirect, and total effects. The *direct* effect captures how a change in an independent variable for province *i* influences the housing price in the same province *i*. This is computed as the average of the diagonal elements of $\boldsymbol{S}(\boldsymbol{W})$, as follows:

$$Direct = \frac{tr\big(\boldsymbol{S}(\boldsymbol{W})\big)}{N}. \tag{5}$$

The *indirect* effect captures how a change in an independent variable in province *i* influences housing prices in all other provinces, excluding province *i* itself. This is calculated as the average of the off-diagonal elements of $\boldsymbol{S}(\boldsymbol{W})$, as follows:

$$Indirect = \frac{i_N{}'\boldsymbol{S}(\boldsymbol{W})i_N - tr\big(\boldsymbol{S}(\boldsymbol{W})\big)}{N}, \tag{6}$$

where i_n is a *Nx1* vector of ones. The *total* effect is calculated as the sum of the direct and indirect effects.

$$Total = Direct + Indirect. \tag{7}$$

Finally, we compute the *t*-statistics for the spatial model coefficients using a numerical approach based on the maximum likelihood estimation of the Hessian matrix (see LeSage and Pace, 2009, Chapter 3.2).[7]

3. Data

The dataset encompasses the capital cities of the forty-seven mainland provinces of Spain, with the deliberate exclusion of the three island province capitals (Las Palmas, Santa Cruz de Tenerife and Palma de Mallorca) and the two cities of Ceuta and Melilla to ensure geographical consistency.[8] Due to data availability, the temporal coverage extends from September 2009 through December 2024. This study employs monthly estimates of average housing prices, both sales and rental, expressed in euros per square meter, as provided by Idealista.com, one of Spain's most prominent and widely recognised real estate platforms.[9]

In line with the housing literature, we also incorporate province-specific control variables. Building on Campbell *et al.* (2009) and Shi (2017), we include indicators that capture demand and supply dynamics in the real estate market. Specifically, these variables encompass labour contracts, resident population, hotel-based tourist arrivals (measured by hotel overnight stays), and the number of dwellings with completion certificates and building permits. To address potential seasonality, we employ annual growth rates, which also render the series stationary.

[7] We thank Prof. J. LaSage and Prof. R.K. Page (https://www.spatial-econometrics.com/), and Prof. P. Elhost (https://spatial-panels.com/) for making the MATLAB codes freely available.

[8] The provinces included in our dataset are the following: A Coruña, Álava, Albacete, Alicante, Almería, Ávila, Asturias, Badajoz, Barcelona, Burgos, Cádiz, Cantabria, Cáceres, Castellón, Ciudad Real, Córdoba, Cuenca, Girona, Granada, Guadalajara, Guipúzcoa, Huelva, Huesca, Jaén, León, Lleida, La Rioja, Lugo, Madrid, Málaga, Murcia, Navarra, Ourense, Palencia, Pontevedra, Salamanca, Segovia, Sevilla, Soria, Tarragona, Teruel, Toledo, València, Valladolid, Vizcaya, Zamora, and Zaragoza.

[9] We draw on monthly estimates of average residential property prices sourced from the online real estate platform Idealista.com, distinguishing between sale and rental listings to capture a comprehensive view of different market segments. Due to its extensive geographic coverage, Idealista serves as a reliable and timely indicator of housing market trends across various regions of the country. These price estimates exhibit strong alignment with other official metrics, including the quarterly price per square meter for free-market housing published by the Ministry of Transport, Mobility and Urban Agenda of Spain, as well as the regional Housing Price Index and the annual Rental Housing Price Index at the municipal level, both provided by the National Institute of Statistics. Notably, Idealista's data processing methodology helps reduce distortions caused by marketing strategies or shifts in the composition of listed properties over time, such as changes in the distribution of property types. In contrast, alternative indicators lack monthly granularity, province-level detail, and the extended temporal coverage offered by the dataset used in this study.

Finally, to mitigate the influence of outliers, all these series are winsorised at the 1st and 99th percentiles.

Our main variable of interest is the number of days over the previous 365 days with temperatures exceeding 35ºC. To construct this measure, we match each province capital city to its nearest weather station based on geographic coordinates (latitude and longitude). Weather station data are obtained from AEMET, the Spanish State Meteorological Agency. For each province, we use the closest station to its capital city centre, with available records spanning November 2009 to December 2024.[10] Finally, we count the number of days per province whose maximum temperature is over 35ºC using 365-day rolling windows. Appendix A provides detailed definitions of all variables and their sources.

[Insert Table 1 and Figure 1 here]

Table 1 presents the descriptive statistics of our variables, pooling observations across all provinces. The average house sale price is €1,752.19 per square meter, while the average rental price is €7.37 per square meter. On average, cities experience 18 days per year with temperatures above 35ºC. The average province also records a similar number of labour contracts and residents, a decline in dwelling completion certificates, and an increase in hotel-based tourist activity. These averages, however, mask substantial variation across provinces. Correlation analysis reveals a negative and statistically significant association between the

[10] The provinces and their corresponding weather stations are the following: A Coruña (A Coruña Aeropuerto), Álava (Foronda–Txokiza), Albacete (Albacete Base Aérea), Alicante (Novelda), Almería (Almería Aeropuerto), Ávila (Ávila), Asturias (Mieres, Baiña), Badajoz (Badajoz Aeropuerto), Barcelona (Barcelona, Fabra), Burgos (Burgos Aeropuerto), Cádiz (Medina Sidonia), Cantabria (Santander Aeropuerto), Cáceres (Cáceres), Castellón (Castelló – Almassora), Ciudad Real (Almagro / FAMET), Córdoba (Córdoba, Embalse de Guadanuño), Cuenca (Cuenca), Girona (La Vall de Bianya), Granada (Granada Base Aérea), Guadalajara (Madrid Aeropuerto), Guipúzcoa (Donostia / San Sebastián, Igeldo), Huelva (Huelva, Ronda Este), Huesca (Valle de Hecho, Hecho), Jaén (Torres), León (León, Virgen del Camino), Lleida (Lleida), La Rioja (Logroño, Aeropuerto), Lugo (Lugo), Madrid (Madrid, Cuatro Vientos), Málaga (Málaga, Centro Meteorológico), Murcia (Murcia), Navarra (Pamplona), Ourense (Allariz), Palencia (Autilla del Pino), Pontevedra (Pontevedra), Salamanca (Salamanca), Segovia (Puerto de Navacerrada – Madrid), Sevilla (Carmona), Soria (Soria), Tarragona (Tarragona), Teruel (Teruel), Toledo (Toledo), València (València), Valladolid (Rueda), Vizcaya (Bilbao Aeropuerto), Zamora (Zamora), and Zaragoza (Zaragoza, Aeropuerto).

number of days above 35ºC and both house sale and rental prices, suggesting that provinces with more frequent extreme heat tend to have lower housing prices.

As an illustrative example, Figure 1 plots the house prices and temperatures across provinces. Panel A plots the cross-sectional average of house sale prices alongside the cross-sectional median temperature in ºC over the previous year, while Panel B does the same for rental prices. Both panels show a clear increase in sale and rental prices in the final years of the sample, accompanied by a more erratic but generally upward trend in median temperature. The remainder of the paper formally investigates this relationship.

4. Results

4.1 Moran's I test

First, we assess whether log house prices exhibit spatial dependence by applying Moran's I test. This test detects the presence of spatial correlation, which may justify the inclusion of a spatial autoregressive term in the model.[11] Moran's I takes values between -1 and 1, with negative values indicating negative spatial correlation and positive values indicating positive spatial correlation. A positive and significant Moran's I suggests spatial clustering among neighbouring observations (Ponti and Zoboli, 2024). Since we test spatial correlation across provinces, one statistic is computed for each month in the sample. Figure 2 plots the monthly Moran's I values, with shaded areas indicating periods in which the null hypothesis of no spatial dependence cannot be rejected.

[Insert Figure 2 here]

The results show that all Moran's I statistics are not only positive but also strongly significant, providing robust evidence that both housing sale prices and rental prices are subject to spatial

[11] Although Moran's I test is widely used to detect spatial autocorrelation in the residuals of OLS regression models (Clif and Ord, 1981), especially in studies of geography, regional economics, ecology and urban planning, some authors also apply this test directly to the series under study (Ou *et al.,* 2015, and Schmal *et al.,* 2017, among others). In this paper, we follow the latter approach.

dependence. This implies that price dynamics in one province are systematically related to those observed in neighbouring provinces, rather than evolving in isolation. In the next section, we proceed by estimating a set of alternative econometric specifications explained in Section 2, both with and without spatial effects, to evaluate the extent to which incorporating spatial dependence improves model performance and whether the null hypothesis of no spatial correlation can indeed be rejected.

4.2 Regression results

4.2.1 Finding the optimal model

We now estimate the alternative models outlined in Section 2. Following the specific-to-general approach proposed by Elhorst (2014), the spatial analysis begins with a non-spatial linear regression. It then sequentially tests potential extensions of the baseline specification by incorporating spatial interaction effects. This stepwise procedure ensures that the final specification adequately addresses the issues introduced by spatial dependence in the data. The set of models considered includes the OLS, SAR, SEM, and SDM. To identify the most appropriate model, we employ the likelihood ratio (LR) test, where the null hypothesis assesses whether the more general SDM can be simplified to the corresponding alternative specification without a significant loss of explanatory power. In other words, if the alternative model is statistically superior to the SDM model. The corresponding estimation results are reported in Tables 2 and 3 for log house sale prices and log rental prices, respectively.[12]

[Insert Tables 2 and 3 here]

The findings reported in Tables 2 and 3 are broadly consistent across specifications. The spatial correlation of the dependent variable, ρ, is positive and highly significant in both the SAR and SDM models, reaffirming the Moran's I results that log house prices exhibit spatial

[12] To assess the time series properties of the independent variables, we applied Augmented Dickey-Fuller (ADF) tests. The results (not shown here to save space, but available from the authors upon request) confirmed that all variables exhibit stationarity.

dependence, with magnitudes of approximately 0.08 for house sale prices and 0.10 for rental prices. Economically, this implies that a one-percentage-point increase in house sale (rental) prices in neighbouring provinces is associated with a 0.08% (0.10%) increase in local prices which represents an increase of €1.40 per square meter (€0.007 per square meter) on average,[13] providing evidence of not only statistically significant but also economically meaningful spatial spillovers across Spanish provinces.

The SEM specification also indicates significant spatial error dependence, λ, suggesting spatial correlation in the residuals. More importantly, however, the LR tests strongly favour the SDM, consistently rejecting the null hypothesis that the alternative, more restrictive models provide a better fit. Taken together, these results identify the SDM as the most appropriate specification for both house sale and rental prices, and we therefore adopt it as the preferred model in the subsequent analysis.

4.2.2 SDM direct, indirect, and total effects

The previous analyses provide strong evidence for the superiority of the SDM in capturing the dynamics of house prices across Spanish provinces. As discussed in Section 2, the coefficients estimated in the SDM, as reported in Tables 2 and 3, do not have a straightforward, one-to-one interpretation, unlike those in standard linear regression models. This is because the SDM explicitly accounts for spatial interactions of the dependent variable, meaning that changes in one province can affect both its own house prices and those of neighbouring provinces through spillover effects. To make these effects interpretable, it is necessary to decompose the estimated coefficients into direct effects, which reflect the impact of a change in a variable within the same province; indirect effects, which capture the influence on other provinces through spatial spillovers; and total effects, which combine both the direct and indirect components, as formalised in Equations (5), (6) and (7). The results of this decomposition, which provide a

[13] These values are calculated as the average house sale price, €1,752.19 times the spatial coefficient, ρ, divided by 100 in Table 2. Similar calculations are done for the house rental price.

clearer understanding of how changes propagate through the spatial network of provinces, are presented in Table 4.

[Insert Table 4 here]

Panel A presents the results for house sale prices. Focusing first on the significant direct effects, we find that an increase in the number of days with maximum temperatures above 35ºC in the previous year is associated with a decrease in house sale prices, which is significant at the 1% level. Economically, one additional day of extreme heat in the prior year corresponds to a decrease of approximately 0.08% in house sale prices, which translates to a reduction of €1.40 per square meter (and 95% confidence interval between €0.84 and €3.24 per square meter according to the house sale price percentiles in Table 1), ceteris paribus. This finding is consistent with Kang *et al.* (2024), who report that extreme heat has a negative impact on house prices in China.

Regarding demand-side variables, we do not observe any significant direct effect for job contracts. One possible explanation for this finding is that the influence of labour market conditions may be more indirect and captured through spatial spillovers or broader economic dynamics (Holly *et al*., 2020). Labour contracts shape local employment stability and income levels. However, these effects may be diluted at the individual property level, mainly when other housing market determinants (such as location, amenities, or neighbourhood characteristics) are controlled for (Osland and Thorsen, 2013). In this sense, labour contracts may contribute more to the general socio-economic environment of an area than to the pricing of a specific dwelling. An additional explanation could be the concentration of jobs in specific regions—such as coastal areas where tourism dominates or large urban centres like Madrid and Barcelona— and therefore, these effects may be captured by other variables (e.g., tourists' hotel stays) and fixed effects. However, we do find a significant positive direct effect of annual growth in the resident population: a one-percentage-point increase in the previous year's resident population is associated with an increase of 20.49% or, equivalently, €3.59 per square meter in house sale prices (calculated as 0.2049 × 0.01 × €1,752.19 per square meter). This highlights the importance of population growth as a driver of housing demand.[14]

Turning to supply-side variables, including house certifications completed and new construction, no significant direct effects are observed. This may reflect that housing supply is not keeping pace with demand[15], so increases in supply do not immediately translate into measurable effects on house prices.

Finally, we observe a negative and significant direct effect of the annual growth in the number of tourists (in hotels) on house sale prices. Specifically, a one-percentage-point increase in the number of tourists compared to the previous year is associated with a decrease of €0.28 per square meter (-0.0157 × 0.01 × €1,752.19 per square meter). This result aligns with Fernandez-Perez *et al.* (2025), who find that increases in hotel tourism reduce the probability of explosive housing price behaviour. Rising hotel stays may indicate a shift in demand away from short-term holiday rentals, especially when hotel capacity is high. This can free up more rentals for residents, easing pressure on the housing market, boosting tourism-related tax revenues, and redirecting investor interest from residential property to hotels, all of which contribute to lower house prices.

Panel A shows that the only significant indirect effect on house sale prices is the number of days with temperatures exceeding 35ºC in the previous year. A key contribution of this paper is precisely this spatially mediated effect of extreme heat on housing prices. The effect is positive and significant at the 1% level, indicating that an additional day of extreme heat in the

[14] In this regard, Cuadrado *et al.* (2024) highlight that Spain has become one of the European Union's leading immigrant-receiving countries in recent years. In absolute terms, Spain ranked fifth among destination countries with the highest number of permanent immigrants in 2023, behind the United States, the United Kingdom, Germany, and Canada (see Organisation for Economic Co-operation and Development, 2024).

[15] According to CaixaBank Research (2025), the current supply of new housing remains insufficient to meet the high demand in Spain, and this mismatch is one of the primary causes behind the rise in house prices. Moreover, the Bank of Spain has provided figures on the housing deficit for 2025, estimating a shortfall of 700,000 homes to meet current demand.

prior year is associated with an increase of approximately 0.16% in house sale prices in the neighbouring provinces, which translates to about €2.80 per square meter (and 95% confidence interval between €1.67 and €6.48 per square meter according to the house sale price percentiles in Table 1), ceteris paribus. Notably, this positive indirect effect is roughly double the magnitude of the negative direct effect of extreme heat on local house prices. This result suggests that sellers in neighbouring provinces may be incorporating and anticipating the benefits of milder temperatures into their local house prices, highlighting the role of spatial spillovers in shaping housing market outcomes under extreme climate conditions.

Extreme heat in one province can indirectly drive-up housing prices in adjacent, cooler areas through several spatial channels. From a spatial equilibrium perspective, temperature operates as a location-specific amenity, with its marginal utility varying across geographic space (Rosen, 1979; Roback, 1982). When extreme heat diminishes the perceived habitability and amenity value of a particular area, neighbouring cooler provinces become relatively more attractive to both households and firms. This shift in the perceived value of climatic amenities prompts a spatial reallocation of housing demand, leading to positive spillover effects on property values in nearby cooler zones (Albouy *et al.,* 2016).

Climate migration and relocation behaviours further reinforce these dynamics. Rising temperatures exacerbate health risks, increase energy costs, and reduce labour productivity (Deschênes and Greenstone, 2011; Graff Zivin and Neidell, 2014), thereby lowering the net utility of residing in heat-affected areas. As a result, some households and firms choose to relocate to nearby provinces with milder climates. Given the short-run inelasticity of housing supply (Glaeser and Gyourko, 2005), even modest increases in migration or second-home demand can lead to substantial price appreciation in these cooler neighbouring markets (Klaiber, 2014; Arbel *et al.,* 2019).

Expectations and perceptions of climate-related risks also shape the observed spatial patterns. Households and investors are increasingly incorporating anticipated environmental risks into current property valuations (Baldauf *et al.*, 2020). The prospect of rising cooling costs, infrastructure strain, or higher insurance premiums in heat-prone areas contributes to a relative decline in those housing values. In contrast, adjacent cooler provinces are perceived as lower-risk investments, offering potential hedges against future climate volatility. Disparities in access to insurance and credit across climatic zones may further intensify these spatial reallocations of capital (Hsiang *et al.*, 2017).

Moreover, socio-demographic sorting processes amplify these indirect effects. Higher-income and more mobile households are disproportionately likely to migrate away from heat-exposed areas toward cooler ones (Hornbeck, 2012). This movement fosters demographic upgrading, strengthens local public finances, and enhances amenities in receiving provinces, factors that further capitalise into rising property values (Coulson and Lahr, 2005).

Finally, the total effects on house sale prices, which combine the direct and indirect effects, reveal a significant overall impact of extremely high temperatures and the annual growth in the number of tourists. Both effects are statistically significant at the 5% level or better. Notably, the total effect of extreme heat is positive, driven by the strong indirect effect. By contrast, tourism growth exerts an overall negative impact, underscoring the different mechanisms through which these factors shape housing prices once spatial spillovers are considered.

Panel B of Table 4 presents the results for house rental prices. Interestingly, the significant direct effects mirror those observed for house sale prices: a negative and significant impact of the number of days with temperatures above 35ºC in the previous year and of annual growth in the number of tourists, alongside a positive and significant effect of annual growth in the resident population. Notably, the coefficient for extreme temperature is roughly twice as large as that for house sale prices, suggesting that extremely high temperatures have a stronger effect on rental prices. This may be attributed to the greater mobility of tenants compared to homeowners, enabling rental markets to respond more quickly to climate-related factors.

The analysis of the indirect effects on house rental prices reveals a richer set of significant determinants compared to house sale prices. First, consistent with the results for house sales, we find a positive and statistically strong indirect effect of the number of days with temperatures above 35ºC in the previous year. Importantly, this effect is about twice as large as that observed for house sale prices, underscoring the greater sensitivity of rental markets to climate-related factors. Specifically, an additional day of extreme heat in a given province is associated with an increase of 0.30%—equivalent to €0.0118 per square meter (and 95% confidence interval between €0.0072 and €0.0237 per square meter according to the house rental price percentiles in Table 1)—in rental prices in neighbouring provinces. This pattern suggests that landlords in provinces adjacent to extremely hot areas, but with milder temperatures, may benefit as tenants shift away from hotter locations.

We also uncover a negative and significant indirect effect of the annual growth in job contracts. A one-percentage-point increase in job contract growth in a province is associated with a decrease of approximately €0.0041 per square meter in rental prices in neighbouring provinces. This result may indicate that the flexibility of the rental market enables tenants to relocate to provinces with stronger labour markets, thereby reducing demand, and consequently rental prices, in surrounding areas. This finding is also in line with Agnew and Lyons (2018), who argue that secure employment facilitates transitions from renting to homeownership, which in turn alleviates pressure on the rental housing market and with Tsai (2021), who shows that in stable economic conditions, landlords favour long-term contracts, which limit turnover and constrain rent increases, thereby dampening rental prices.

Finally, we find a positive and significant indirect effect of resident population growth, which likely reflects the tendency of immigration to cluster in geographically proximate provinces (with a remarkable impact on the rental market) or with native flight from immigrant-receiving areas (Mussa *et al*., 2017). This finding also aligns with Dustmann *et al.* (2022), who conclude that population growth heightens housing demand, particularly in supply-constrained cities, with the effect further intensified when incoming residents are primarily renters. Taken together, these indirect effects are more influential than the corresponding direct effects, as confirmed by the total effect estimates.[16]

Table 4 reports the average indirect effects of the number of days with temperatures above 35ºC in the previous year across all Spanish provinces, while Figure 3 disaggregates these effects at the provincial level, allowing us to uncover spatial heterogeneity. To compute these effects, we consider the indirect impact from each province on all others, excluding itself, obtained as the mean of the off-diagonal column elements of matrix $\boldsymbol{S}(\boldsymbol{W})$.

Several noteworthy patterns emerge from Figure 3. First, as shown in Table 4, the impact of extreme temperatures is consistently more substantial in the rental market than in the sales market across all provinces. This difference reflects the greater flexibility and mobility of tenants compared with homeowners, making rental markets more responsive to climate-related shocks. Second, although substantial heterogeneity exists across provinces, a clear regional divide emerges: the positive indirect effect of rising temperatures is weaker in colder regions, such as northern and northwestern Spain, compared to hotter regions, such as southern and interior provinces. This indicates that the benefit of relocating from one province to a neighbouring one in response to rising extreme temperatures is smaller in colder regions than in hotter ones, a pattern that is also reflected in neighbouring house prices. Once again, the gap

[16] We also examine whether moderately high temperatures have an impact on house prices. To achieve this, we utilise the number of days with temperatures between 30°C and 35°C in the previous year and incorporate this variable into our SDM regression (Equation 3). Results reported in Appendix B indicate that these moderate temperatures have no direct effect on house prices. The indirect effect is positive and statistically significant at the 1% level in the rental market only. However, its magnitude is merely 32% (0.12% / 0.38%) of the effect observed for extreme heat, making it considerably weaker. Notably, including moderately high temperatures does not alter our main findings, which reinforce that extreme heat leads to a house price discount, whereas cooler regions experience a corresponding price premium.

is more pronounced in the rental market, where interprovincial mobility is higher and relocation costs are lower.

Overall, these results confirm our main finding: house sellers and landlords in provinces with milder climates benefit disproportionately from their proximity to hotter regions, as home buyers and tenants relocate from areas experiencing extreme heat. By contrast, in provinces with already mild temperatures, the temperature-induced price effect is much weaker.

[Insert Figure 3 here]

4.3 Temperature across varying levels of neighbour contiguity

The previous analyses reveal that the direct and indirect effects of additional days with temperatures above 35ºC in the prior year on house prices differ in sign: the direct effect is negative, while the indirect effect is positive, for both house sales and rental prices. In the baseline specification, we adopted a conservative approach by defining six nearest neighbours as those with significant spatial dependence. However, climatic similarity is likely to decrease with distance—closer provinces tend to experience more comparable weather patterns, while more distant provinces share less similar climatic conditions. To account for this, and to further test the robustness of our main hypothesis, we re-estimate the SDM using alternative neighbourhood structures, ranging from just one nearest neighbour (the closest province) up to 20 neighbours (roughly half of Spain's mainland 47 provinces), thereby allowing us to examine how the results vary with different spatial connectivity assumptions. Table 5 reports these results.

[Insert Table 5 here]

In line with our hypothesis, climate proximity exerts a significant influence on the spatial relationship between provinces, while a similar effect is observed for the direct effects. When only the closest neighbouring province is considered (Neighbours = 1), the indirect effect is either insignificant in the case of house sales or minor in magnitude for house rentals.

Consequently, the total effect of an additional day with temperatures above 35ºC in the previous year is negative and significant at the 1% level in both markets. This result confirms that geographically proximate provinces tend to share similar climatic conditions, limiting the scope for neighbouring provinces to benefit from homeowner or tenant mobility.

By contrast, although the direct effects remain essentially constant across specifications, the indirect effects become stronger as the number of neighbours increases, reflecting longer-distance spillovers. Indeed, once at least four nearest neighbours are included, the positive indirect effect dominates, driving the total effect into positive territory. At the upper bound, when 20 nearest neighbours are considered, the indirect effect of one additional extreme heat day in the previous year reaches 0.70% (or approximately €12.27 per square meter) for house sales and 0.50% (or approximately €0.0369 per square meter) for rentals. Interestingly, at this broader spatial scale, the spillover effect on the sales market exceeds that of the rental market. This pattern suggests that, while the flexibility of the rental market enhances short-distance mobility and therefore strengthens nearby spillovers, its influence diminishes across longer distances. In contrast, the sales market becomes relatively more sensitive to such extended spatial linkages. Anecdotal evidence supports this interpretation: housing markets in colder northern regions of Spain have recently experienced surging demand and rising prices, as households increasingly view these areas as attractive alternatives to hotter provinces.[17]

4.4 Local projections of impulse-response functions

Up to this point, our analysis has focused on a static perspective of spatial correlation across provinces. However, understanding how these relationships evolve over time is equally important. We examine the dynamic direct, indirect, and total effects of an additional day with temperatures above 35ºC in the previous year. To capture these dynamics, we employ local

[17] See, for instance, recent news reports in *El Mundo* ("El frío del norte calienta el mercado de la vivienda en plena subida de temperaturas," 21 January 2025), *El Confidencial* ("La España fresca y verde dispara compraventas y precios en Galicia y Asturias," 19 March 2025), and *La Razón* ("El frío del norte se calienta como alternativa a la costa ante la subida de temperaturas," 12 July 2025).

projections of impulse–response functions. This approach offers an intuitive and flexible framework by estimating separate regressions at each forecast horizon h, and has been widely adopted in recent literature (see, for example, the surveys in Jordà, 2023; Jordà and Taylor, 2025). Specifically, we adapt SDM Equation (3) by shifting the dependent variable forward by h={0, 1, 2, …, 120} months,

$$\boldsymbol{p}_{t+h} = \alpha + \rho \boldsymbol{W}\boldsymbol{p}_t + \boldsymbol{X}_t\boldsymbol{\beta} + \boldsymbol{W}\boldsymbol{X}_t\boldsymbol{\theta} + \boldsymbol{\varepsilon}_t. \tag{8}$$

Once we estimate the SDM regressions for all horizons, *h*, we plot the cumulative estimated direct, indirect, and total effects, along with their confidence bands. Figure 4 illustrates the estimated responses of log house sale prices (Panel A) and log rental prices (Panel B) to this temperature shock, together with their associated 95% confidence intervals, over the following 120 months.

[Insert Figure 4 here]

Consistent with the static effects reported in Table 4, we observe a permanent, negative, and significant direct effect of extreme heat shocks. This adverse impact stabilises after roughly 90 months in both the sales and rental markets. Turning to the indirect effects, the results point to positive spillovers in both markets, with the effect proving more persistent for rentals, in line with our earlier findings. When combining the direct and indirect components, the overall effect on house sale prices is positive and significant for up to 24 months, after which the influence of extreme heat dissipates and becomes statistically insignificant. By contrast, in the rental market, the total effect remains permanently significant, underscoring its greater flexibility and faster responsiveness to climatic shocks. Taken together, these results reinforce our central conclusion that the direct and indirect effects of extreme temperature differ in both sales and rental markets, with rentals displaying a more durable and stronger pattern.

4.5 Economic mechanisms

Our findings indicate that house sellers and landlords in provinces with milder climates benefit disproportionately from their proximity to hotter regions, as homebuyers and tenants relocate from areas experiencing extreme heat, driving up house prices. By contrast, in provinces facing extreme heat, house prices exhibit a temperature-induced discount.

The temperature-induced discount in house prices is consistent with Kang *et al*. (2024), who analyse panel data from Chinese cities between 2009 and 2019. They show that each additional day above 35 °C in the preceding year is associated with a 0.1% decline in housing prices. In addition to their results, we find evidence of temperature-induced house price increases in cooler regions. According to Kang *et al.* (2024), extreme heat weakens housing markets by reducing labour inflows, dampening home-buying interest, and discouraging firms from entering overheated areas.

To test these mechanisms, we split the panel sample into periods of high and low extreme-temperature exposure, using the full-sample median of 11 days above 35 °C in the previous year as the threshold (see Table 1). We then compare outcomes with annual growth in job contracts, residents, housing certifications, and tourists. Our estimates corroborate Kang *et al*. (2024): provinces in the bottom 50% of extreme-heat temperatures (or cooler regions) recorded an average job contract growth of 1.34% in our sample period, while those in the top 50% (or hotter regions) experienced a decline of 0.40%.

The housing supply response, however, differs. In cooler provinces (low extreme heat), housing completions and new construction contracted more sharply (on average –16.09% and –3.21%, respectively) compared with hotter provinces (–9.59% and –1.48%). Population dynamics also appear muted, with average annual growth rates of +0.15% in hotter provinces and –0.15% in cooler ones. Similarly, tourist activity showed slight divergence, with average hotel visits rising by 2.47% in high-extreme heat provinces and by 2.84% in low-extreme heat provinces.

Overall, the results suggest that the temperature-induced house price premium in cooler provinces is linked to a stronger labour market and, consequently, improved economic conditions, as well as to reduction in housing supply. This pattern aligns with evidence from commercial real estate markets, where perceived climate risks and investor sentiment have been shown to influence asset pricing (Sirmans *et al.,* 2025). Together, these mechanisms reinforce the sustained increase in house prices in cooler provinces documented in our study.

5. Discussion and policy recommendations

Since the economic effects of climate change on housing markets have become a central topic, in general, and in the field of spatial economics, in particular, this paper contributes to the emerging literature on this issue by examining the impact of extreme temperatures on housing price dynamics in Spain, considering both direct and indirect effects across geographic space.

Our findings indicate that each additional day of extreme heat in the previous year leads to a direct decrease of approximately 0.08% in house sale prices. In contrast, neighbouring provinces experience an indirect increase of around 0.16% in house sale prices. The pattern is similar for the rental market: one additional day of extreme heat corresponds to a 0.15% direct decline in rental prices, while the indirect effect in neighbouring provinces is notably stronger, with an increase of 0.30% in rental prices. Taken together, these indirect effects are more influential than the corresponding direct effects, as confirmed by the total effect estimates.

Moreover, a clear regional divide emerges: the positive indirect effect of rising temperatures on house prices is stronger (weaker) in hotter (cooler) areas, such as southern and interior (northern) provinces. This gap is particularly pronounced in the rental market, where higher interprovincial mobility and lower relocation costs amplify the effect. Finally, the temperature-induced house price premium in cooler provinces is driven by a stronger labour market and constrained housing supply.

The findings not only illuminate internal market dynamics in Spain but also offer valuable insights for other Mediterranean and Southern European regions confronting similar climate challenges.

Overall, the main contribution of this study is that it highlights the important role of spatial spillovers in shaping housing market outcomes under extreme climate conditions, particularly when examining the indirect effects of extreme hot temperatures, and in the rental market in particular. This contribution highlights that ignoring spatial dependence can lead to an incomplete understanding of climate–housing interactions. For example, the positive indirect effect is roughly twice the magnitude of the negative direct effect, suggesting that both sellers and landlords in provinces adjacent to extremely hot areas, but with milder temperatures, may benefit from this situation. Landlords, in particular, benefit more, as the higher mobility of tenants compared to homeowners enables them to relocate more quickly from overheated areas and respond more quickly to climate-related changes.

The policy implications of this study are substantial. For provinces most exposed to extreme heat, declining property values and weakening labour inflows point to the need for resilience-building measures, including subsidies for home upgrades, energy-efficient construction, cooling stations, and urban greening.[18] Conversely, cooler provinces experiencing temperature-induced inflows face rising housing demand and potential affordability challenges, which call for targeted investment in infrastructure and housing supply. Without such interventions, these regions risk heightened price pressures, displacement, and the emergence of climate-driven

[18] As Cohen *et al.* (2025) emphasise, equitable financing mechanisms for green infrastructure, such as stormwater systems, can play a crucial role in mitigating environmental risks while advancing spatial justice in urban real estate markets. Along similar lines, Han *et al.* (2024) investigate the impact of urban trees on property values and climate resilience by exploiting a tree infestation event in Toronto as a natural experiment. Their results show that each additional tree increases local housing prices by 0.45%, whereas significant canopy loss leads to a 7% decline in housing prices. While trees contribute to urban cooling and energy efficiency, their value extends beyond these ecosystem services, positioning them as a cost-effective strategy for mitigating urban heat.

gentrification. At the national level, incorporating spatially differentiated climate risks into urban planning, macroprudential regulation, and collateral valuation will be essential to maintain both housing affordability and financial stability.

For developers and investors, the findings present both risks and opportunities. Provinces experiencing extreme heat may face long-term declines in housing values, which could reduce their attractiveness as investment destinations. By contrast, provinces with milder climates are likely to become increasingly valuable, drawing in both households and capital. This reallocation highlights the importance of integrating climate considerations into investment strategies, not only to mitigate risks but also to identify growth opportunities in a rapidly evolving housing market.

In sum, this study demonstrates that climate change is no longer a distant concern for housing markets: it is already influencing household decisions, property valuations, and regional dynamics in Spain. Extreme heat is reshaping the geography of housing demand, penalising overheated areas while rewarding cooler provinces. Recognising and planning for these shifts will be vital to building a resilient, equitable, and sustainable housing sector in the face of a warming climate.

6. Conclusions

This paper examines the impact of extreme heat on Spain's housing market by combining house sales and rental prices from Idealista.com (the largest online real estate market in Spain) with spatial econometric techniques. Spain's unique blend of climatic diversity, regulatory uniformity, and heterogeneous housing markets makes it a particularly well-suited context for evaluating how extreme temperatures affect property values.

Using the number of days exceeding 35°C over the previous year as a proxy for extreme heat, we find a clear pattern: while additional hot days lead to declines in both sales and rental prices within affected provinces, neighbouring and more distant provinces with milder climates experience corresponding price increases. These spillover effects, particularly in the rental sector, indicate that temperature-induced migration is already influencing the reshaping of regional housing markets in Spain.

The evidence highlights two key mechanisms. First, provinces directly exposed to extreme heat experience relatively weaker housing demand, as potential buyers and tenants relocate to areas with milder temperatures. Second, provinces with cooler climates (especially those bordering overheated regions) benefit from these relocations through increased demand, tighter housing supply, and stronger labour inflows. The indirect effect is not only more substantial than the direct decline but also more persistent, with landlords in rental markets capturing disproportionate gains due to the higher mobility of tenants relative to homeowners. These dynamics reveal how spatial linkages can amplify and redistribute the economic consequences of climate stressors.

Our contribution lies in explicitly modelling and quantifying these spatial spillovers. Although existing literature on climate and housing has largely focused on local effects, our results show that overlooking cross-regional linkages risks underestimating the actual impact of climate stress. By integrating spatial dynamics, we demonstrate that the consequences of extreme heat are not confined to overheated provinces but reverberate through interconnected housing markets. This provides new empirical evidence for the importance of regional heterogeneity in climate risk assessments.

Further research could extend our analysis by examining heterogeneous effects across different housing types, income groups, or urban versus rural areas. Moreover, integrating other environmental stressors, such as droughts, floods, or air quality issues, would provide a more comprehensive picture of how climate change affects housing markets.

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Appendix A. Variables definition and source

This table defines the variables used in this study. The sources are included in the last column.

Variable	Description	Source
Temperature over 35ºC	Number of days with temperatures over 35ºC (95ºC) over the previous 365 days.	Spanish State Meteorological Agency (AEMET)
Job contracts	The annual growth rate in the number of new job contracts per city.	Spanish State Public Employment Service (SEPE)
Resident population*	The annual rate of growth in the resident population per city	Spanish National Statistics Institute (INE): Continuous Population Statistics
House certification (end construction)	The annual growth rate in the issuance of building completion certificates per city.	Ministry of Transport and Sustainable Mobility
House certification (new construction)	The annual growth rate in new construction supervision permits per city.	Ministry of Transport and Sustainable Mobility
Number tourists (hotels)	The annual growth rate in the number of people registered at hotel establishments per city.	Spanish National Statistics Institute (INE): Hotel occupancy survey

*Quarterly series are interpolated into monthly.

Appendix B. SDM direct, indirect and total effects for less extreme temperatures

	Panel A: House sale					
	Direct effect		Indirect effect		Total effect	
Temperature over 35ºC	-0.0007***	(-3.86)	0.0019***	(4.89)	0.0012***	(3.33)
Temperature between 30ºC and 35ºC	0.0002	(1.40)	0.0005*	(1.76)	0.0006**	(2.44)
Job contracts	-0.0129	(-1.55)	-0.0282	(-1.27)	-0.0411*	(-1.79)
Resident population	0.2017***	(3.96)	-0.0227	(-0.15)	0.1791	(1.10)
House certification (end construction)	0.0004	(0.52)	0.0010	(0.39)	0.0015	(0.52)
House certification (new construction)	-0.0018	(-1.53)	0.0010	(0.29)	-0.0008	(-0.23)
Number tourists (hotels)	-0.0162***	(-2.89)	-0.0202	(-1.30)	-0.0364**	(-2.12)

	Panel B: House rental					
	Direct effect		Indirect effect		Total effect	
Temperature over 35ºC	-0.0016**	(-11.58)	0.0038***	(13.47)	0.0022***	(8.45)
Temperature between 30ºC and 35ºC	0.0000	(-0.01)	0.0012***	(6.18)	0.0012***	(6.21)
Job contracts	-0.0083	(-1.29)	-0.0591***	(-3.63)	-0.0674***	(-3.87)
Resident population	0.2396***	(6.37)	0.7097***	(6.03)	0.9493***	(7.60)
House certification (end construction)	0.0009	(1.34)	0.0019	(0.99)	0.0028	(1.31)
House certification (new construction)	0.0005	(0.56)	0.0018	(0.72)	0.0023	(0.86)
Number tourists (hotels)	-0.0112***	(-2.81)	0.0054	(0.49)	-0.0057	(-0.47)

This table reports the estimation results for the direct, indirect, and total effects of the SDM model in Equations (5), (6) and (7), considering the six nearest neighbouring provinces. In addition to the number of days with temperatures over 35º in the previous year (Temperature over 35ºC), we also include the number of days with temperatures between 30ºC and 35ºC in the previous year (Temperature between 30ºC and 35ºC). The variables are explained in Appendix A. *t*-statistics are reported in parentheses. The sample is from September 2009 to December 2024. ***, ** and * represent significance at the 1%, 5% and 10% level, respectively.

Table 1. Descriptive statistics and correlations

Panel A: Descriptive statistics

	House sale price	House rental price	Temperature over 35ºC	Job contracts	Resident population	House certification (end construction)	House certification (new construction)	Number tourists (hotels)
Mean	1752.19	7.37	18.25	0.00	0.00	-0.13	-0.02	0.03
Median	1550.34	6.64	11.00	0.02	0.00	-0.14	-0.02	0.04
STD	716.06	2.60	18.96	0.20	0.02	1.01	0.73	0.58
Skewness	2.15	2.06	1.01	-0.72	-25.50	0.09	0.03	-0.90
Excess kurtosis	5.40	5.62	0.03	3.47	768.95	1.16	1.24	10.44
Pctl.(2.5%)	1046.46	4.49	0.00	-0.47	-0.01	-2.19	-1.54	-1.60
Pctl.(97.5%)	4018.53	14.79	62.30	0.39	0.02	1.96	1.48	1.43

Panel B: Pearson correlations

	House sale price	House rental price	Temperature over 35ºC	Job contracts	Resident population	House certification (end construction)	House certification (new construction)	Number tourists (hotels)
House rental price	0.87***	1.00						
	(0.00)							
Temperature over 35ºC	-0.21***	-0.06***	1.00					
	(0.00)	(0.00)						
Job contracts	-0.04***	-0.09***	-0.08***	1.00				
	(0.00)	(0.00)	(0.00)					
Resident population	0.12***	0.19***	0.08***	-0.11**	1.00			
	(0.00)	(0.00)	(0.00)	(0.00)				
House certification (end construction)	0.00	0.08***	0.03***	0.02	0.01	1.00		
	(0.94)	(0.00)	(0.00)	(0.15)	(0.29)			
House certification (new construction)	-0.02*	0.04***	0.02**	0.13***	-0.01	0.13***	1.00	
	(0.05)	(0.00)	(0.02)	(0.00)	(0.60)	(0.00)		
Number tourists (hotels)	0.01	0.02**	-0.02	0.67***	-0.04***	0.03**	0.08***	1.00
	(0.33)	(0.03)	(0.13)	(0.00)	(0.00)	(0.02)	(0.00)	

This table reports the descriptive statistics and the correlations of the pooled variables across all Spanish provinces. The variables are explained in Appendix A. STD represents the standard deviation. Pctl.(X) represents the distribution percentile at X%. P-values for the correlations are reported in parenthesis. The sample is from September 2009 to December 2024. ***, ** and * represent significance at the 1%, 5% and 10% level, respectively.

Table 2. Regressions for house sale prices

	OLS		SAR		SEM		SDM	
Temperature over 35ºC	-0.0005***	(-3.14)	-0.0005***	(-3.38)	-0.0005***	(-3.56)	-0.0008***	(-5.06)
Job contracts	-0.0132	(-1.58)	-0.0127	(-1.52)	-0.0122	(-1.45)	-0.0118	(-1.41)
Resident population	0.2026***	(3.92)	0.2053***	(3.98)	0.2055***	(3.94)	0.2036***	(3.96)
House certification (end construction)	0.0004	(0.44)	0.0004	(0.41)	0.0003	(0.40)	0.0004	(0.45)
House certification (new construction)	-0.0018	(-1.47)	-0.0018	(-1.49)	-0.0018	(-1.48)	-0.0018	(-1.48)
Number tourists (hotels)	-0.0153***	(-2.87)	-0.0153***	(-2.87)	-0.0150***	(-2.78)	-0.0156***	(-2.92)
W-Temperature over 35ºC							0.0015***	(4.92)
W-Job contracts							-0.0245	(-1.20)
W-Resident population							-0.0337	(-0.23)
W-House certification (end construction)							0.0006	(0.26)
W-House certification (new construction)							0.0011	(0.36)
W-Number tourists (hotels)							-0.0177	(-1.26)
Ρ			0.0860***	(4.56)			0.0780***	(4.12)
Λ					0.1608***	(8.95)		
R^2	0.0047		0.9464		0.9462		0.9466	
Num. Obs.	8648		8648		8648		8648	
Log-Likelihood	9886.79		9898.38		9898.94		9912.72	
LR-test (H0: Model j ≻ SDM) / p-value	51.86***	{0.000}	28.68***	{0.000}	27.54***	{0.000}		

This table reports the result estimations for the log house sales prices using OLS and spatial regressions (SAR, SEM and SDM) in Equations (1) to (3), considering the nearest six neighboring provinces. The variables are explained in Appendix A. *t*-statistics are reported in parenthesis. The last row reports the LR-test for the null hypothesis the model at hand is preferred to the spatial Durbin model (SDM), whose p-values are in brackets. The sample is from September 2009 to December 2024. ***, ** and * represent significance at the 1%, 5% and 10% level, respectively.

Table 3. Regressions for house rental prices

	OLS		SAR		SEM		SDM	
Temperature over 35ºC	-0.0009***	(-8.09)	-0.0010***	(-8.67)	-0.0011***	(-9.42)	-0.0016***	(-12.94)
Job contracts	-0.0114*	(-1.81)	-0.0096	(-1.52)	-0.0079	(-1.24)	-0.0069	(-1.10)
Resident population	0.2511***	(6.43)	0.2411***	(6.19)	0.2293***	(5.83)	0.2330***	(6.05)
House certification (end construction)	0.0008	(1.17)	0.0007	(1.14)	0.0007	(1.09)	0.0008	(1.16)
House certification (new construction)	0.0005	(0.53)	0.0004	(0.48)	0.0004	(0.44)	0.0004	(0.44)
Number tourists (hotels)	-0.0113***	(-2.80)	-0.0114***	(-2.85)	-0.0115***	(-2.83)	-0.0112***	(-2.82)
W-Temperature over 35ºC							0.0029***	(12.35)
W-Job contracts							-0.0506***	(-3.31)
W-Resident population							0.6222***	(5.59)
W-House certification (end construction)							0.0013	(0.74)
W-House certification (new construction)							0.0017	(0.76)
W-Number tourists (hotels)							0.0058	(0.55)
Ρ			0.1200***	(6.53)			0.0970***	(5.20)
Λ					0.2089***	(12.04)		
R^2	0.0140		0.9614		0.9611		0.9623	
Num. Obs.	8648		8648		8648		8648	
Log-Likelihood	12297.15		12318.68		12323.64		12418.39	
LR-test (H0: Model j ≻ SDM) / p-value	242.48***	{0.000}	199.42***	{0.000}	189.51***	{0.000}		

This table reports the result estimations for the log house rental prices using OLS and spatial regressions (SAR, SEM and SDM) in Equations (1) to (3), considering the nearest six neighboring provinces. The variables are explained in Appendix A. *t*-statistics are reported in parenthesis. The last row reports the LR-test for the null hypothesis the model at hand is preferred to the spatial Durbin model (SDM), whose p-values are in brackets. The sample is from September 2009 to December 2024. ***, ** and * represent significance at the 1%, 5% and 10% level, respectively.

Table 4. SDM direct, indirect and total effects

	Panel A: House sale					
	Direct effect		Indirect effect		Total effect	
Temperature over 35ºC	-0.0008***	(-4.98)	0.0016***	(4.98)	0.0008***	(2.58)
Job contracts	-0.0123	(-1.47)	-0.0280	(-1.33)	-0.0403*	(-1.81)
Resident population	0.2049***	(3.92)	-0.0159	(-0.10)	0.1890	(1.14)
House certification (end construction)	0.0004	(0.46)	0.0006	(0.24)	0.0010	(0.37)
House certification (new construction)	-0.0018	(-1.53)	0.0010	(0.31)	-0.0007	(-0.21)
Number tourists (hotels)	-0.0157***	(-2.92)	-0.0204	(-1.37)	-0.0361**	(-2.24)

	Panel B: House rental					
	Direct effect		Indirect effect		Total effect	
Temperature over 35ºC	-0.0015***	(-12.78)	0.0030***	(11.64)	0.0015***	(5.98)
Job contracts	-0.0076	(-1.24)	-0.0560***	(-3.30)	-0.0636***	(-3.54)
Resident population	0.2423***	(6.02)	0.7140***	(5.91)	0.9563***	(7.38)
House certification (end construction)	0.0008	(1.16)	0.0015	(0.78)	0.0023	(1.05)
House certification (new construction)	0.0004	(0.49)	0.0019	(0.75)	0.0023	(0.85)
Number tourists (hotels)	-0.0112***	(-2.82)	0.0051	(0.44)	-0.0061	(-0.48)

This table reports the estimation results for the direct, indirect and total effect of the SDM model in Equations (5), (6) and (7), considering the nearest six neighboring provinces. The variables are explained in Appendix A. *t*-statistics are reported in parenthesis. The sample is from September 2009 to December 2024. ***, ** and * represent significance at the 1%, 5% and 10% level, respectively.

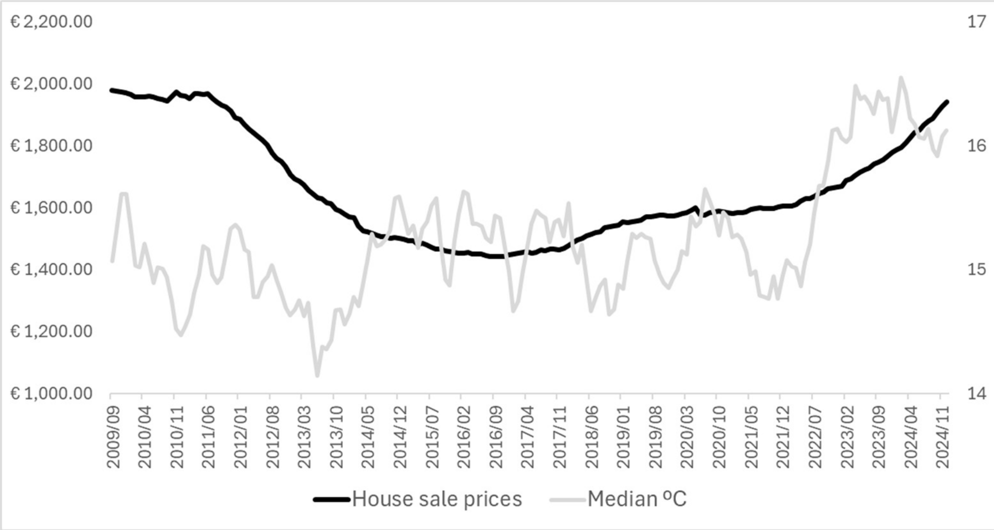
Table 5. Temperature and housing prices in more distance provinces

	Panel A: House sale					
	Direct effect		Indirect effect		Total effect	
Neighbours = 1	-0.0004***	(-2.60)	-0.0002	(-1.09)	-0.0006***	(-3.13)
Neighbours = 4	-0.0008***	(-5.12)	0.0013***	(4.57)	0.0005*	(1.67)
Neighbours = 8	-0.0007***	(-4.71)	0.0014***	(3.58)	0.0007*	(1.81)
Neighbours = 12	-0.0009***	(-6.04)	0.0032***	(7.11)	0.0023****	(5.08)
Neighbours = 16	-0.0011***	(-6.71)	0.0052***	(9.91)	0.0042***	(8.31)
Neighbours = 20	-0.0010***	(-6.70)	0.0070***	(10.76)	0.0060***	(9.55)

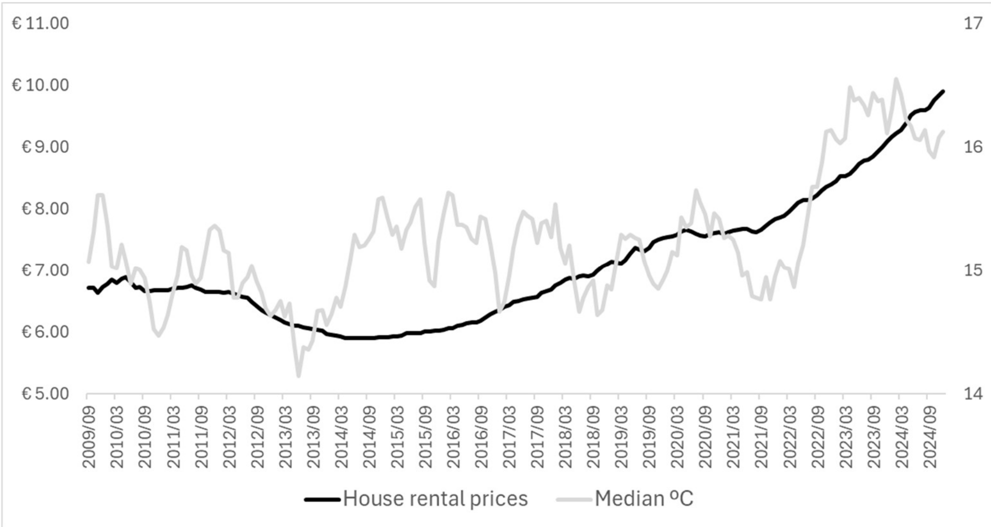
	Panel B: House rental					
	Direct effect		Indirect effect		Total effect	
Neighbours = 1	-0.0011***	(-9.21)	0.0003**	(2.08)	-0.0009***	(-6.34)
Neighbours = 4	-0.0014***	(-12.35)	0.0021***	(10.09)	0.0007***	(3.16)
Neighbours = 8	-0.0015***	(-11.53)	0.0029***	(10.41)	0.0014***	(5.44)
Neighbours = 12	-0.0014***	(-11.59)	0.0032***	(10.33)	0.0018***	(6.24)
Neighbours = 16	-0.0015***	(-12.68)	0.0046***	(13.24)	0.0031***	(9.48)
Neighbours = 20	-0.0014***	(-11.78)	0.0050***	(10.64)	0.0036***	(8.13)

This table reports the estimated direct, indirect, and total effects of the SDM model in Equations (5), (6) and (7), for the number of days with temperatures above 35ºC in the previous year, across different neighbour structures of the spatial matrix *W*. *t*-statistics are reported in parentheses. The sample spans September 2009 to December 2024. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Figure 1. House prices and temperature



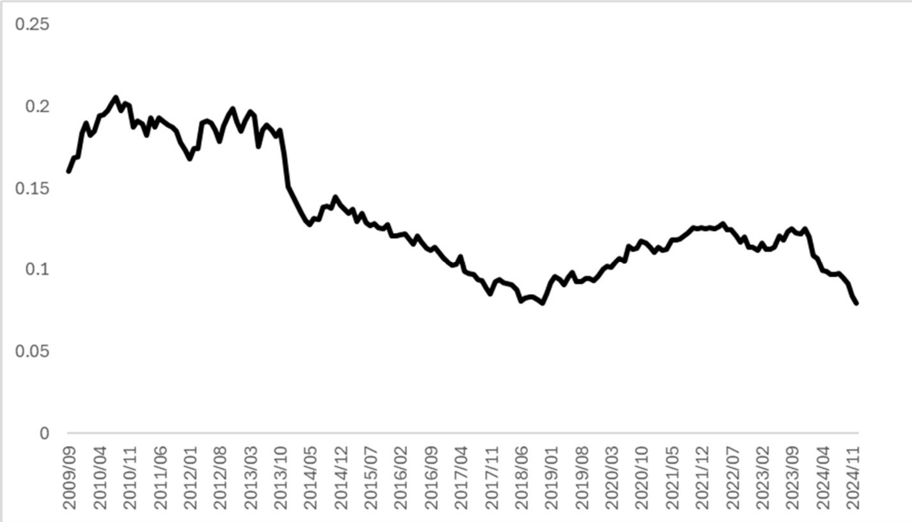
Panel A: House sale prices



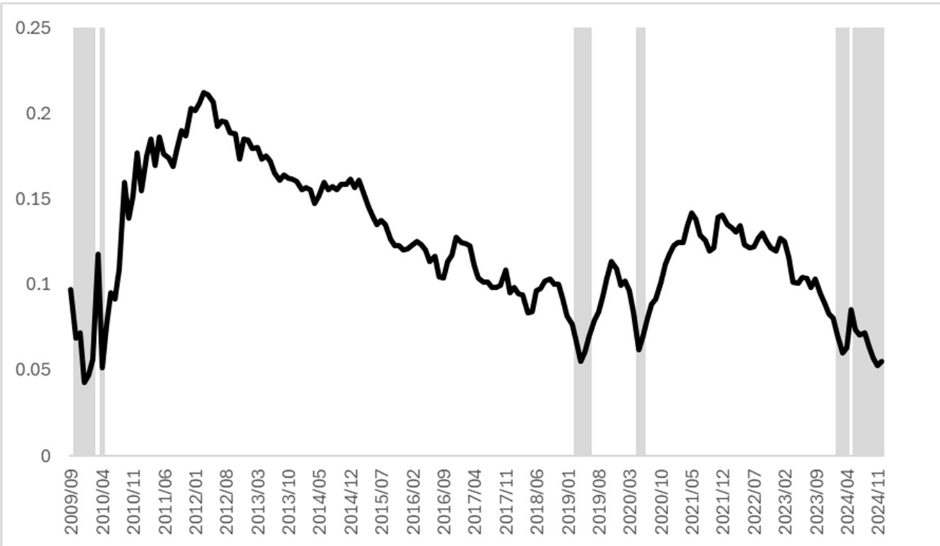
Panel B: House rental prices

This figure plots the cross-sectional average house sale and rental prices in Panels A and B, respectively across provinces. The grey line represents the cross-sectional median temperature in ºC over the previous year across provinces. The sample spans September 2009 to December 2024.

Figure 2. Moran's I test for spatial correlation



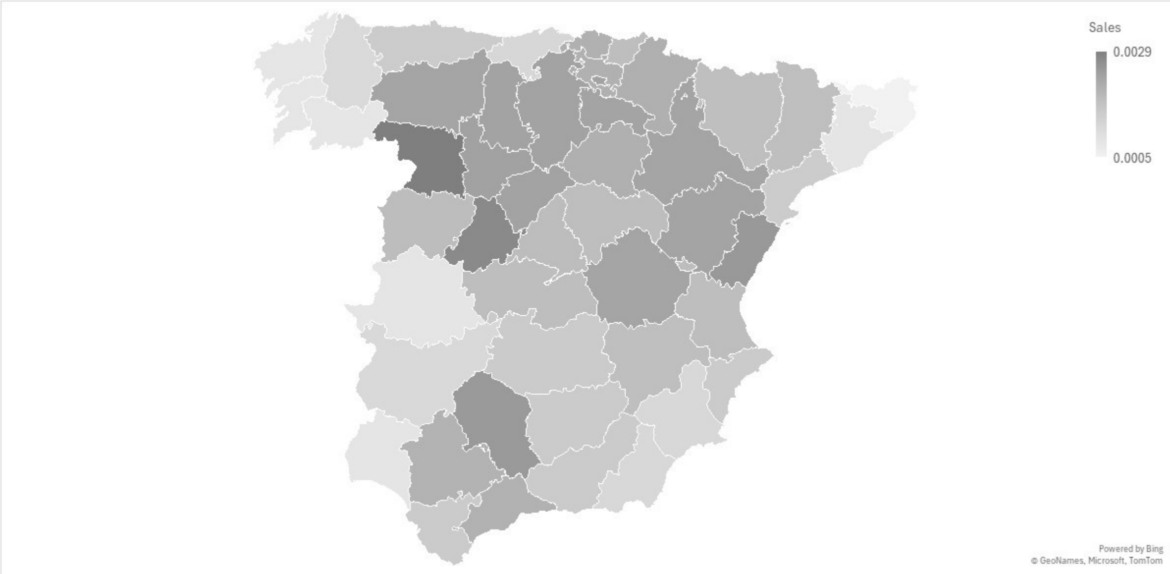
Panel A: House sale prices



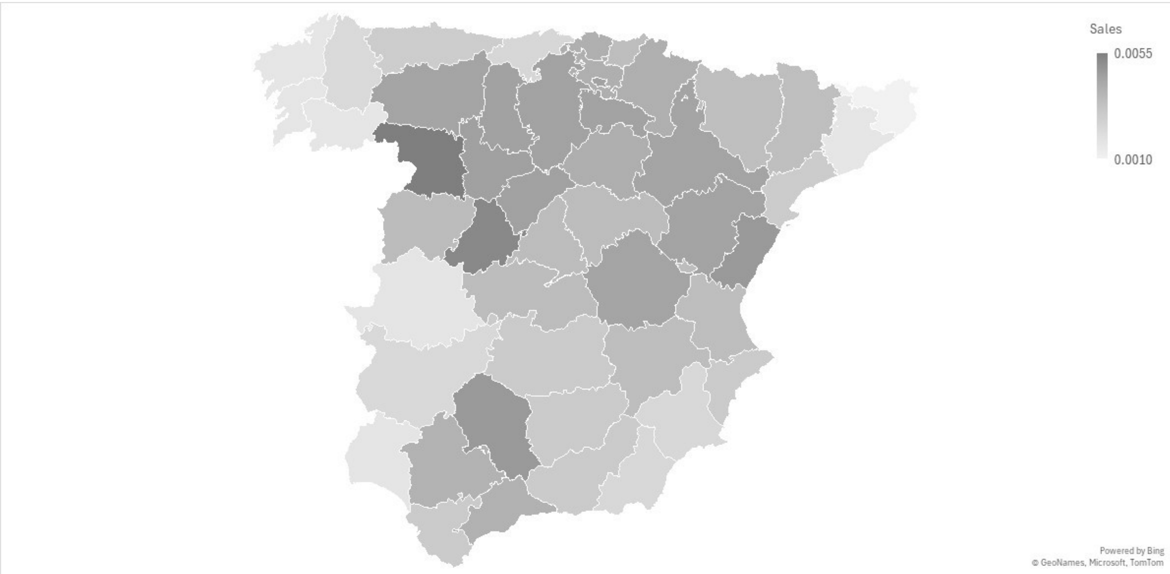
Panel B: House rental prices

This figure plots Moran's I test statistics for spatial autocorrelation (null hypothesis: no spatial autocorrelation in the cross-section), considering the nearest six neighboring provinces. Periods where the null cannot be rejected are shaded in grey. The sample spans September 2009 to December 2024.

Figure 3. Indirect effects of extreme temperatures from each province to others



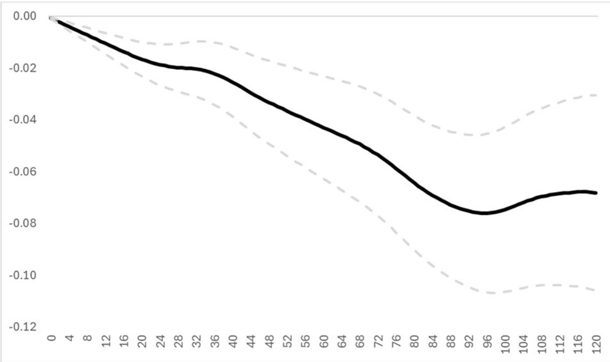
Panel A: House sale prices



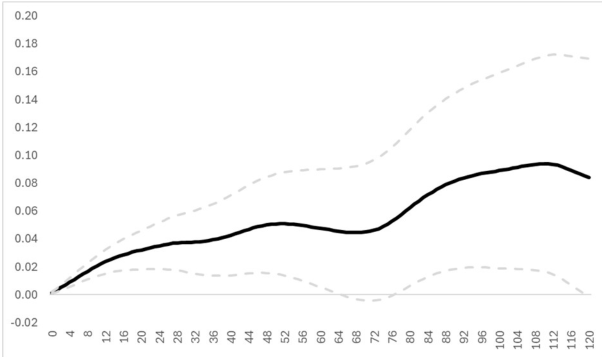
Panel B: House rental prices

This figure shows the indirect effect of the number of days with temperatures above 35ºC in the previous year from each province to the others, considering the nearest six neighboring provinces. The sample spans September 2009 to December 2024.

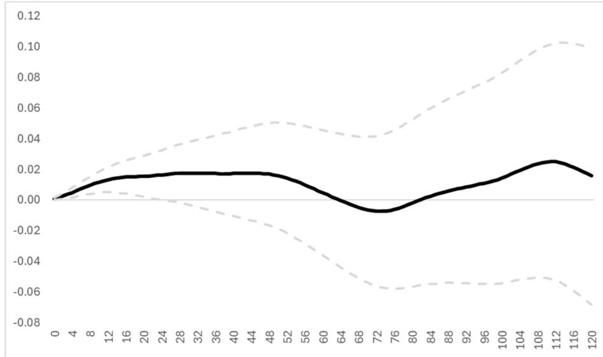
Figure 4. Local projections of cumulative impulse-response functions for SDM direct, indirect and total effects for extreme temperature shocks



Direct effect

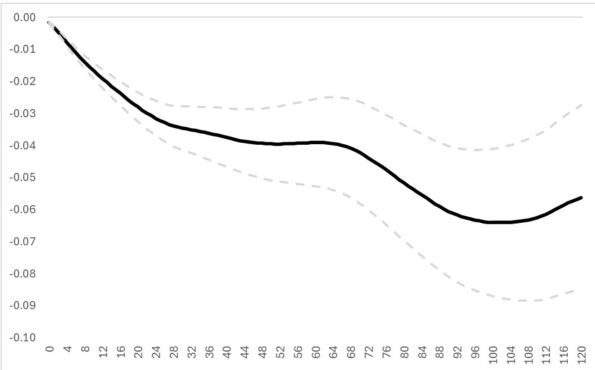


Indirect effect

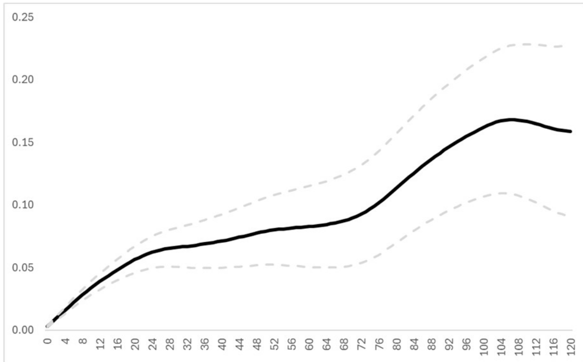


Total effect

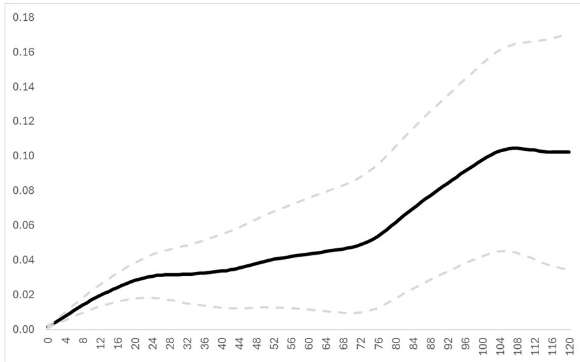
Panel A: House sale prices



Direct effect



Indirect effect



Total effect

Panel B: House rental prices

This figure plots the local projections of cumulative impulse-response graphs of Equation (8) for one additional day with temperatures over 35ºC in the previous year. The dashed grey lines represent the confidence interval at the 95%, considering the nearest six neighboring provinces. The sample spans September 2009 to December 2024.

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