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TEMPERATURES AND SEARCH: EVIDENCE FROM THE HOUSING MARKET

by Michele Cascarano* and Filippo Natoli**

Abstract

Climate and weather variations affect search and matching processes. We provide evidence for the housing market by combining daily temperatures in Italian cities with online search for 2 million ads and in-person appointments with real estate agents. Two results stand out. First, extremely hot temperatures reduce search, both online and physical, increasing time to sale and delaying housing transactions. Second, they induce a preference shift away from properties that are not climate-safe, leading to persistently lower prices. Extreme temperature effects are asymmetric as colder months induce an increase in online (but not physical) search.

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Contents

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1 Introduction[1]

Individual search processes, such as job or housing search, are continuously shaped by aggregate shocks, which concur to determine the dynamics of quantity and price over time. For example, aggregate shocks to labor productivity have been documented to determine cyclical fluctuations in unemployment (Mortensen and Pissarides, 1994), while city-level shocks can generate booms and busts in local house prices (Piazzesi and Schneider, 2016, Head et al., 2014, among others). One exogenous driver that is receiving attention due to ongoing climate change, yet almost disregarded in the search literature, is weather. Temperature, whose volatility is on the rise across the globe, can affect search in various ways. For example, as extreme heat and cold are known to be unpleasant and unhealthy (Graff Zivin and Neidell, 2014; Barreca et al., 2016), temperature fluctuations might increase search costs for those activities that require spending time outdoors. Moreover, pronounced swings might induce changes in beliefs about future climate-related risks (Busse et al., 2015, Choi et al., 2020, Hong et al., 2020), potentially affecting job or housing preferences.

We take up this issue by empirically investigating the effects of extreme temperatures on housing search in Italy. For this purpose, we construct a unique data set for Italy, covering both online and in-person housing search in the major Italian cities. Using data on property listings, we track online clicks and contact requests at monthly frequency for about 2 million advertisements of homes for sale between 2016 and 2019 and, for the first time, we also track scheduled in-person appointments of buyers and sellers with real estate agents. In our baseline analysis, we employ daily temperature data at municipality level to explore the effects of very hot temperatures on online and physical search in each city, focusing on the immediate impact as well as on the dynamic implications using panel local projections.

We find that an increase in the number of days with average temperatures above 25°C within a month reduces housing search, both online and physical. The number of clicks on online ads and the number of contact requests received by sellers fall across the board,

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together with a decrease in both buyer-agent and seller-agent appointments. This broad-based slowdown in housing search translates into a significant increase in the time to sale of housing units already in the market. The effects on search also have repercussions on home sales and prices. We find that a decrease in demand is coupled with a reduction in the number of housing transactions, and with a decrease in the asking prices posted on housing ads.

Interestingly, though demand recovers after the temperature shock, the reduction in prices looks permanent. We explain this evidence by documenting a shift in housing preferences induced by hot temperature episodes. We exploit the rich variety of houses for sale available in the data set and find heterogeneous effects of temperature across housing types: the slowdown in demand mainly characterizes those properties that are not perceived as structurally *climate-safe*, such as those featuring low energy classes (entailing higher future energy expenditures) and no outdoor living spaces (providing relief from the heat). Such evidence aligns well with a "wake-up call" effect of high temperatures, for usually inattentive agents, on the future economic risks of climate change. In our settings, it translates into significant downward price pressure only for non-climate-safe apartments. This effect does not seem to be driven by heterogeneity in housing demand, as the same heterogeneity also shows up *within* the pool of houses with similar prices per square meter in each city, suggesting that the preference shift is broad-based across different housing clientele. To investigate whether the two potential effects of temperature – the direct impact and the wake-up call – might be thought of as distinct transmission channels, we repeat our analysis on the advertisements of homes for *rent*, as shorter-term renting decisions should be less affected by longer-run risk considerations. Results show that while an increase in the number of very hot days per month also reduces clicks and contact requests in the rental market, they do not induce a significant reduction in rent rates in the medium run. This confirms, on one side, the existence of a direct, physical effect on search that is broad-based in the housing market; on the other side, it adds evidence on the wake-up call channel that, being switched off in the rental market, leads to less downward pressures of temperatures on rent rates than on sale prices.

Additional findings, obtained by exploiting the full distribution of observed daily temperatures in each month and city, also document the influence of either mild or extremely cold weather on the housing market and validate the main empirical specification. Two results stand out: first, temperature effects are highly non-linear, with the occurrence of mild temperatures not generating any significant boost or damage to housing search, in line with other results found in the literature (Barreca et al., 2016; Schlenker and Roberts, 2009, among others). Second, extremely cold temperatures generate asymmetric effects on search: while physical search slows down as it does when temperatures are too high – showing a U-shaped temperature-search relationship – online search *increases* in cold months. This result, maybe due to the lower availability of outside options for leisure (or greater mobility constraints) in very cold rather than very hot periods, reveals that complementarity/substitutability in search instruments can be significantly weather-dependent.

This paper contributes to the literature in three ways. First, by leveraging on a granular dataset of the Italian housing market, it sheds light on the potential of extreme temperatures to affect search activities. In this perspective, it directly speaks to the literature analyzing the role of search frictions in housing markets (see Piazzesi and Schneider, 2016 and Han and Strange, 2015, among others), highlighting both a direct effect of high temperatures and a climate-related preference shift. The latter effect, which builds on previous results on the psychological effects of temperatures (see Busse et al., 2015 and DellaVigna, 2009 for a review), shows how the wake-up call on future climate risks induced by the occurrence of very hot temperatures can also impact search processes, providing evidence for a key market such as housing. Through these channels, local weather variations have macroeconomic implications as they are able to generate aggregate, persistent effects on house prices.

Second, it uncovers a new direct way for climate change to affect house prices, feeding the ongoing debate in the climate finance literature (see Giglio et al., 2021a for a review). In that strand, the papers have focused on the pricing of the long-run sea-level-rise risk in coastal areas while there is no evidence, as far as we know, of a high-frequency, climate-related *driver* of house prices. While temperatures do not necessarily damage the properties' structures, they have the potential to influence housing search everywhere. Related to that, we also complement previous theoretical evidence on infra-annual patterns in the housing markets by Ngai and Tenreyro (2014), which rests on deterministic differences across seasons and abstracts from any climate-related implication.

Last, this paper indicates a potential link between weather variations and household wealth, highlighting a previously disregarded transmission channel of climate change on the economy. From this perspective, our results suggest that the impact of extreme temperatures extend well beyond the known labor supply effects – on hours worked and labor productivity (Somanathan et al., 2021, among others); moreover, it describes a new adaptation measure (or hedging strategy) put in place by households, i.e. that of buying climate-safe dwellings.

Related literature This paper speaks to different streams of economic literature. First, by providing evidence of a new factor shaping search activities, it links to the papers that investigate the drivers of aggregate fluctuations in the labor or housing markets (Mortensen and Pissarides, 1994 and Piazzesi and Schneider, 2016, among others). Regarding the latter, it connects to the literature on demand-side effects on housing search (Pissarides, 2000; Piazzesi and Schneider, 2009; Diaz and Jerez, 2013, among others; see Han and Strange, 2015 for a review of the literature). From a theoretical point of view, it relates to the stream of quantitative models that analyzes phases of buoyant vs. depressed housing markets, usually named "hot" and "cold" markets (for example, Wheaton, 1990 and Krainer, 2001). In this perspective, our findings on the decline in housing search due to an increased incidence of hot temperatures might speak both to Novy-Marx (2009), who relates time to sale to variations in market tightness (the buyer-to-seller ratio), and to Ngai and Tenreyro (2014), who argue that thick markets (i.e., with a large number of both buyers and sellers) lead to more housing transactions due to a higher probability of high-quality matches. By uncovering search effects of temperatures over time and across housing types, we inform two strands of the housing literature. On one hand, our findings on the evolving impact of temperatures on online and in-person appointments, with lagged implications on transactions and prices, speak to the stream related to the role of search in house price dynamics (Head et al., 2014; Burnside et al., 2016; Guren, 2018, among others). On the other hand, the heterogeneous effects based on housing resilience to climate change contribute to the literature analyzing housing search activity in cross-section (Goodman and Thibodeau, 1998; Islam and Asami, 2009; Genesove and Han, 2012; Piazzesi et al., 2020). With respect to both, we unveil a previously disregarded driver of search heterogeneity, which is directly related to climate change.

Second, this paper informs the literature on climate economics and climate finance. In recent years, the analysis of the economic effects of climate change has gained traction (Dell et al., 2012; Burke et al., 2015; Acevedo et al., 2020; Natoli, 2023; see Dell et al., 2014 for a review). In particular, the literature has found that the impacts in advanced economies go well beyond agriculture, including housing (Colacito et al., 2019). However, it is not clear whether house prices incorporate the risks related to climate change or respond to the occurrence of climate-related natural events. On this topic, results are still mixed. Giglio et al. (2021b) estimate the rate of return of a real estate investment, showing how this incorporates the long-term risks of climate change. On the risk of sea level rise, some papers argue that the risk exposure of houses located in coastal areas can be reflected in their price depending on the concentration of buyers sensitive to climate change (Bernstein et al., 2019; Baldauf et al., 2020; Keys and Mulder, 2020); on the contrary, others find that the same risk is not priced in risky dwellings (Murfin and Spiegel, 2020). On shorter-run risks, Hino and Burke (2021) find that information available in publicly available flood risk maps is not reflected in property values. Regarding the impact of temperatures on house prices, the literature, pioneered by Roback (1982), has mostly focused on the relationship between the presence of climate amenities and urban growth (Blomquist et al., 1988; Kahn, 2009; Bunten and Kahn, 2014; Albouy et al., 2016; Galinato and Tantihkarnchana, 2018), disregarding the analysis of the direct impacts on housing markets.[2]

Third, as we explore a new direct effect of temperature, we also speak to the literature that analyzes the economic implications of human heat stress. For example, hot temperatures are found to reduce total hours worked in climate-exposed industries (Graff Zivin and Neidell, 2014) together with a fall in labor productivity and an increase in absenteeism (Somanathan et al., 2021), as well as a decrease in the time allocated to outdoor leisure in hot days. Moreover, we suggest the presence of indirect effects of global warming, spurring adaptation of the housing market to increasingly frequent hot temperatures. The idea that episodes of extreme temperatures can influence housing demand through increased attention to the future

[2]Two recent exceptions are Semenenko and Yoo (2019) who find, in a multi-country setting, that volatility in temperatures has negative effects on house price returns, and Gourley (2021), who highlights that the interaction between temperatures and precipitations in different seasons can shape the curb appeal of a house.

repercussions of climate change (wake-up call) is analogous to what is documented by Choi et al. (2020), who show that hot temperature episodes lead investors to become aware of the risks associated with the green transition and consequently reduce their portfolio exposure to carbon-intensive securities. As such, our result on the price of climate-safe houses can be interpreted through the lens of behavioral models (see DellaVigna, 2009 for a review), which have documented departures from rationality in the form of present bias (Laibson, 1997), projection bias (Loewenstein et al., 2003) or salience (Bordalo et al., 2013). In this context, Busse et al. (2015) explore the psychological effects of daily temperatures on the sale of different types of cars. We contribute by showing how multiple dimensions of a search process can be impacted by temperatures differently, and how behavioral effects – leading to price revisions – seem here to be especially triggered by hot temperatures, valued by buyers as an indicator of looming climate change risks.

In addition, we contribute to the literature by showing additional evidence of non-linear effects of temperatures on market interactions, in line with what has been previously found for agriculture (Schlenker and Roberts, 2009) and human mortality (Barreca et al., 2016), among others. We highlight this non-linearity particularly looking at physical housing search, complementing previous findings on the connection of seasonal temperature variations and house prices (Ngai and Tenreyro, 2014).

2 Temperatures and housing search

Housing search involves buyers, sellers, and real estate agents. All of them are exposed to outdoor temperatures multiple times during the search and matching process. Buyers, as is customary in Italy, explore their favorite neighborhoods to browse housing ads posted at agencies' office windows or in front of buildings; then, they make repeated visits to the houses for sale they are interested in. Agents spend most of their time outdoors, either meeting buyers and sellers for house visits or exploring neighborhoods themselves to get new sales mandates. Both sellers and buyers physically go to the agent's office at least once to give him/her the sale mandate (the former) or to make a bid (the latter), and then to the notary's office to finalize the transaction. For these reasons, housing search can be considered costly in terms of temperature exposure especially in larger cities where distances are greater and traffic is heavier. Imagine a housing search on very hot days. Three temperature-related effects might be at work. Heat-related illnesses (in extreme cases, heat strokes) can impede buyers from visiting houses, or agents from receiving new mandates. Moreover, as hot temperatures are known to reduce individual productivity also in leisure time (Starr-McCluer, 2000, Graff Zivin and Neidell, 2014) buyers may be less productive in identifying dwellings they like. Both effects may slow down search and decision processes, reducing the number of bids in the short run. Finally, high temperatures may also cause cognitive biases. For example, the perception of waiting time worsens in hot days (Baker and Cameron, 1996) and social interactions with strangers is perceived as more unpleasant (Griffit and Veitch, 1971). In our context, hot temperatures might simply discourage search and create bad sensations: by shaping time consumption preferences away from housing search, it can reduce appointments and bids.

Along these channels, hot temperatures might affect housing search in the short run. In addition, temperatures might also have *dynamic* effects by affecting household beliefs over time. In the case of the housing market, temperatures can shape preferences toward houses that are perceived as more resilient to future hot weather. This can have repercussions on current and future housing demand and, through this channel, on aggregate price dynamics.

As extreme temperatures affect both demand and supply in the housing market, their implications might link to different theoretical frameworks related to housing search. On one side, from the perspective of a typical search model based on random matching, temperatures impeding search on the buyer's side may reduce market tightness (i.e. the number of buyers relative to sellers in the market), increasing time to sale per announcement and reducing total transactions.[3] On the other side, as suggested by a different strand of the literature, good matches between buyers and sellers – and potentially higher sale prices – are more likely when markets are thick, with houses for sale being widely available: in this perspective, very high temperatures can slow down the build-up of the housing for-sale inventory.

In what follows, we will make an empirical analysis to describe the implications of tem-

[3]The pass-through on prices might then occur as a quantity effect (fewer buyers entail fewer bids, so lower average bid prices), as a valuation effect (lower bid prices), or a combination of the two.

peratures during the whole search process. To keep track of fluctuations over time in search at the advertisement level, we use data on online searches. To focus on the effects on physical search only, we instead rely on in-person appointments between buyers and sellers with real estate agents.

3 Data

For our empirical analysis, we combine weather data with multiple data sources on the Italian real estate market. We present them in the next sections and report descriptive statistics.

3.1 Weather data

We employ the MARS Meteorological Database, developed by the Joint Research Centre of the European Commission (AGRI4CAST project), which contains meteorological observations from weather stations interpolated on a regular 25x25 km grid, on a daily basis from 1979 to 2019, for the EU and neighbouring countries. We consider data on daily temperatures (in degrees Celsius), averaged over 24 hours, and on daily precipitations in millimeters obtained by cumulating precipitations observed within 24 hours. For both variables, we interpolate gridded data on a 5x5 km sub-grid to get finer detail, and then average them at the municipality level for all Italian province capital cities. As our ads and appointment samples span from 2016 to 2019, we retain daily observations of city-level temperatures and precipitations for that period.

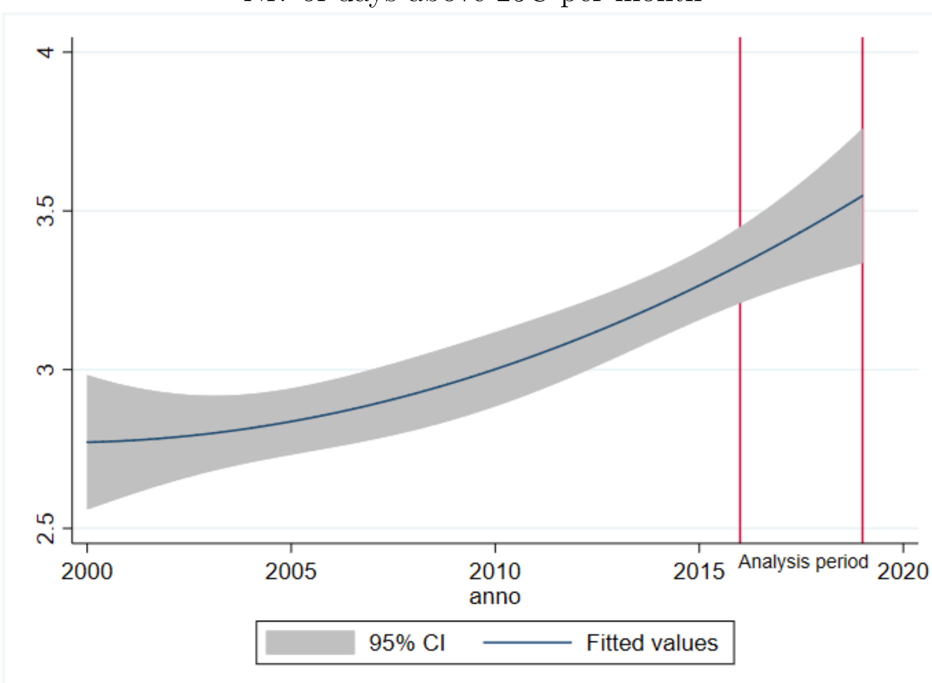
In line with the literature, we adopt as a preferred measure of the incidence of extreme temperatures the number of days within a period with mean temperature above 25°C.[4] Above this value, individual productivity has been found to drop at increasing rates (Fisk et al., 2006; Tanabe et al., 2013; Somanathan et al., 2021). As housing search unfolds during the warmest hours of the day – in which the temperature is much higher than the daily average – this threshold looks sufficiently high to capture negative temperature effects due to heat stress.

[4]This approach is standard in the literature, with slight variations. Some papers rely on the same measure, but use a 30° C temperature threshold (e.g., Addoum et al., 2020); others compute it over maximum instead of average temperatures (Bauer et al., 2019; Pankratz and Schiller, 2021; Cascarano et al., 2022). As average and maximum temperatures are clearly correlated, using one or the other cannot alter results dramatically.

We compute this measure at a monthly frequency and use that as the main regressor in most of the empirical analyses. Finally, we also build another measure of temperature exposure by constructing bins of days with average temperatures between consecutive thresholds that span the entire temperature distribution following Schlenker and Roberts (2009), Barreca et al., 2016 and Addoum et al. (2021); we employ this measure in a series of robustness exercises. Figure 1 displays the evolution of our preferred measure of extreme temperatures, computed over the last 20 years and averaged across all Italian province capitals. In line with the secular global rise in temperatures, the number of hot days in Italy has also trended upwards, reaching 3.5 days within the average month (12% of time) - obviously, during summer months, this number is even four times larger. Importantly, it has continued to increase in the period under investigation (2016-2019), confirming the link between climate change and temperature effects even in this short sample period.

Figure 1: Temperature dynamics

Nr. of days above 25C per month



Notes: The blue line represents the estimated quadratic annual trend of the average number of days over 25C degrees per month; the light blue area depicts the 95 percent confidence bands.

In addition to temperature and precipitation data, we also include data on other extreme climate-related weather events taken from the European Severe Weather Database (ESWD).

This source contains information on localized disruptive events that can be grouped into the following categories: strong winds, snow, hail, avalanches, lightning, and precipitation. Excluding the latter to avoid duplications, we consider extreme events within cities as a control variable in our estimates.

3.2 Immobiliare.it

To inspect the effects of hot temperatures on the real estate market, we make use of three data sources encompassing information on online search, physical search and realized housing transactions. For the former, we rely on Immobiliare.it, the major online portal for real estate listings in Italy. Once a week, Immobiliare.it makes a snapshot of all advertisements that are online at that moment.[5] For each ad, the snapshot offers a complete set of housing information including the date of the snapshot; the geographic coordinates of the dwelling; a large number of characteristics of the property, of the building in which it is located, the ad publisher and the contract type; and the asking price. Importantly, it reports two statistics on the interest shown for each ad: the number of clicks received and the number of contact requests to the ad publisher made through the portal. Table A.1 summarizes all the information contained in each snapshot, available at weekly frequency from January 2016 onward.[6] At the time of this writing, snapshots are regularly provided to the Bank of Italy in real-time. For a detailed description of the Immobiliare.it database, see Loberto et al. (2018). As far as we know, such a rich data source has rarely been used to date for economic research. Two exceptions are Guglielminetti et al. (2021) and Benetton et al. (2022), which explore the effects of the pandemic on housing search (the former) and of the installation of a climate adaptation device on house prices (the latter).

From weekly snapshots, we construct a panel dataset of all the listings published between January 2016 to December 2019 for residential properties for sale at the city level.[7] The

[5]Immobiliare.it sells cloud space to subscribers (mostly real estate agencies, but also private citizens) to store housing ads in the database. Subscribers can then choose, based on their subscription, which of them go online and modify their choice at any time without approval.

[6]Some of the reported variables in the table are not reported in the snapshot but are constructed by Bank of Italy's staff making semantic analysis on the textual description of the ads.

[7]We stop our sample in end-2019 to avoid including the pandemic period, in which lockdowns and containment measures made physical housing search impossible in different periods and geographic areas.

dataset encompasses advertisement-level data for 108 provincial capital cities, which include all the major cities in the country.[8] Each advertisement appears in the dataset from the date in which it was posted to the date in which it was removed (i.e., the first time the ad stops being online).[9] We retain advertisements of residential units only, as non-residential property implies different search procedures. For the main analysis, we focus on houses for sale, which represent the main body of the Immobiliare.it advertisement dataset. In the last part of the paper, in which we discuss possible adaptation mechanisms, we also consider dwellings for rent in order to assess the possibly differentiated effects of temperature on search behavior. Excluding rents, our sample of homes for sale consists of over 2 million ads for residential houses for sale

Our main variables of interest are, for each ad: the number of clicks, which counts how many times website users visited the ad's web page during the week (*clicks*); the number of contacts made by potential buyers to the ad publisher through an online form available on the ad's web page (*contacts*); the asking price per square meter, calculated as the dwelling's posted price divided by its floor area. As pointed out in Pangallo and Loberto (2018) and Loberto et al. (2018), *clicks* and *contacts* can be regarded as good proxies of housing demand, as *clicks* is a predictor of ad's time on market and of downward revisions of the asking price. However, the aforementioned authors proxy demand in a different way: while *clicks* may be regarded as a barometer of ads' attractiveness, *contacts* identify a more concrete interest in the house and, usually, the willingness to request an in-person appointment to visit the house – accepting to be exposed to possibly unpleasant temperatures. While online housing search can be carried out in cool places, thus avoiding temperature exposure, it can nonetheless respond to unfavorable temperatures if the latter is able to shape search desires more broadly. Regarding asking prices, they can inform on possible supply reactions, when temperatures are too high, via valuation effects: as they represent an upper bound for realized prices in the Italian housing market, a negative variation in the posted price for a single ad would entail,

[8]Even if there are currently 107 institutional provinces in Italy, the Barletta-Andria-Trani province in Apulia has multiple capitals (Barletta, Andria, and Trani). As all of them count more than 50,000 inhabitants we consider all the three capitals in our dataset. At the same time we drop from our sample the city of Carbonia (city capital of South Sardinia) for the under-representativeness of this municipality in our sample (we observe less than 20 ads in each month)

[9]In a few cases, removal date has been imputed to those ads that receive no clicks for an entire week, as publishers have the possibility to hide online ads making them not visible.

on average and ceteris paribus, a lower selling price.

For ease of computation, as well as to align the frequency with the other data source used in this analysis, we aggregate weekly data to the monthly frequency, obtaining a total of more than 10 million home-for-sale ads-month observations.

3.3 Tecnocasa

Along with online search data, we use data on physical housing search. In particular, we rely on data on real estate agents' appointments, uniquely provided for this project by Tecnocasa Group. Tecnocasa is the largest real estate agent in Italy, comprising almost 2,500 local sales offices and 11,000 agents across the whole country. For our purpose, they collected data on all appointments taken by potential buyers and sellers with agents working in all of Tecnocasa's local sales offices and provided us with a count for each city at the monthly level. Appointments with real estate agents can be taken from both buyers and sellers at many stages of their search processes, but they always imply commuting to the agent's or housing location – which requires spending time outdoors. The dataset spans the period between January 2016 and December 2019, encompassing data on appointments taken in 18 of the largest cities in Italy .[10] For each month and city, Tecnocasa provides the number of active agencies and the total number of appointments made, divided into three categories: buyer-agent, seller-agent, and unlabeled ones. We construct city-level proxies of physical search pressure from the demand (supply) side as the ratio of buyers' (sellers') appointments to the number of Tecnocasa agencies in the city. These measures complement indicators from Immobiliare.it in important ways. On one side, in-person appointments on the buyer side provide evidence on the part of the demand-side search that is directly exposed to hot temperatures. On the other side, sellers' appointments add a key piece of information as the announcements inventory on Immobiliare.it cannot provide by itself a direct measure of the supply of sellers in the market.[11] Figure 2 shows the geographical coverage of our indicators,

[10] With two exceptions, they correspond with Italian regional capitals.

[11] Indeed, ads are in most cases administered for sellers by real estate agents so, at the aggregate level, there may be relevant confounding factors in using variations in the ads stock as a proxy on the effects of hot temperatures on the sellers. Moreover, as agents usually have a larger set of ads than those they can make online on Immobiliare.it, they can easily fill their online space with other ads in case they have fewer houses to advertise, hiding possible effects on the extensive margin of the housing stock.

with red dots for cities in which data are only available from Immobiliare.it and blue ones for those that are available from both Immobiliare.it and Tecnocasa. The cities in which physical search indicators have been constructed also have data on online search, with no exception. Overall, our dataset covers the Italian peninsula fully, with no regions left out.

Figure 2: Cities

Notes: The figure depicts in red the municipalities only in the Immobiliare dataset, and in blue those also in the Tecnocasa dataset.

3.4 Housing transactions

Data on housing transactions are provided by the National Council of Notaries (or Notariat).[12] We obtain the monthly count of total transactions made in the municipalities of all provincial capitals, where months correspond to that of the deed and the location of the transaction refers to that of the transacted dwelling.[13] As for in-person appointments, these

[12]The National Council of Notaries is the reference institution of Italian notaries, who are public officials that certify transaction deeds, making them legally valid. More information at `https://www.notariato.it/en/`.

[13]The municipality of the dwelling can differ from that of the Notary's office. If a single deed concerns multiple dwellings located in different cities, one transaction is assigned to each of the concerned cities.

data have been provided to us for this project and are not available to the public. With respect to public transaction data from the Italian Revenue Agency, these data have a higher frequency (monthly instead of quarterly) and differ in the way transactions are counted: while the Revenue Agency constructs an index of transactions that weights them by the share of the housing unit involved, the Notariat dataset is a simple transaction count, which considers as single transactions even those made on portions of properties. For our purposes, the Notariat's measure is preferable, as it is one-to-one related to the number of buyer-seller matches found in the market. If temperatures impact housing search, this could translate into fewer housing transactions. According to Tecnocasa, the average lag between the first visit to a house made by a potential buyer and the day in which a transaction on the same house is finalized is of a few months (2 to 5 months). In Appendix, Table A.2 presents some descriptive statistics of all the data used in this paper: weather data, online search data, physical search data, and transaction data.

4 Online search

4.1 Empirical strategy

To shed light on the impact of extremely hot temperatures on online housing search, we adopt a fixed effects panel regression framework, which is common in the climate econometrics literature (see Dell et al., 2014). Data from Immobiliare.it is suitable to run the following advertisement-level estimates:

$$y_{it} = \alpha + \beta x_{c(i)t} + Controls'_{it}\Gamma + \mu_i + \nu_{r(i)t} + \epsilon_{it}. \tag{1}$$

where i indicates the advertisement, t the month, and $c(i)$ (or $r(i)$) is the city (or region) in which the advertised dwelling is located. The dependent variable y is a proxy for housing demand, defined either as the number of *clicks* (in logs), or as a dummy equal to one if at least one contact request has been registered for advertisement i in month t, and 0 otherwise ($\mathbf{1}(contacts > 0)$). For the second dependent variable, we thus estimate a linear probability model. Our main explanatory variable $x = r25$ is the $\log(\cdot + 1)$ transformation of the number of days with average daily temperature above 25°C in city $c(i)$ and month t, as described in Section 3.1.[14] *Controls* is a vector of characteristics at the announcement and city level. At announcement level, we include a series of climate-related factors that can have explanatory power for housing search: a dummy that equals one if the dwelling (or its building) has an energy class above C level (i.e., a low climate impact as it requires less energy to warm or cool); other dummies (one for each characteristic) for housing including amenities like a terrace, a balcony or a garden (private or shared) and the presence of an air conditioning system, all indicating a higher resilience to hot temperatures. At the city level, we consider monthly realized precipitations, categorized at four levels of intensity, and a dummy equal to 1 if at least one extreme weather event including avalanches, hails, lightning strikes, severe wind, and heavy snowfalls/snowstorms have occurred during the month. Equation 1, which illustrates the most demanding specification in terms of explanatory variables, also includes advertisement-level fixed effects, μ_i, and region $\times$ month fixed effects, $\nu_{r(i)t}$.

4.2 Results

Table 1 presents our baseline results, estimated over more than 9.5 million advertisement-month observations. We report the estimated elasticity of $r25$ on clicks (panel (a)) and on the probability of receiving at least one contact request (panel (b)). In panel (a), the first column shows a negative and significant correlation between $r25$ and clicks in the absence of any controls. This result is confirmed in the subsequent columns when we incrementally include control variables, starting from municipality fixed effects and month-year dummies (column 2) and advertisement- and city-level characteristics (column 3). Column 4 displays the final estimate made under the most demanding specification, which also includes ad-level fixed effects, region x month x year fixed effects, and other weather-related controls (precipitation categories and the extreme event dummy). Similarly, panel (b) shows that across all three reported specifications, an increase in the number of hot days in a month reduces the probability of receiving a contact request through the portal. In other words, buyers not only reduce the search activity made through the web, but they also appear to

[14] We use the log transformation to estimate β as a proper demand elasticity and the +1 correction to take into account the considerable amount of zeros.

refrain from requesting appointments to visit a house. This additional effect may indicate that experiencing unpleasantly hot temperatures also discourages future temperature exposure. While these patterns are found when temperatures become hotter, results are not just related to summer months: as holiday closures for real estate agencies and vacations for buyers and sellers might act as confounding factors, we repeat the specification in Column (4) by excluding the months of July and August from the sample, finding very similar results (see Table A.6).

The effects found on online housing search might be rationalized in different ways. First, online search is more and more carried out using mobile devices (possibly in outdoor or non-cooled places), so it too can be considered not immune to hot temperature episodes. Second, locating ads and visiting houses can be thought of as an integrated search process: in this perspective, peak temperatures might push potential buyers to postpone their housing search at large (i.e., both online and physical), preferring different leisure activities.

Table 1: Online search

	(1)	(2)	(3)	(4)
(a) Dep. var.:	clicks			
$r25$	-0.06736***	-0.01939***	-0.00953***	-0.02626***
	[0.00028]	[0.00080]	[0.00071]	[0.00124]
N	9,510,932	9,510,932	9,510,932	9,510,932
adj. R^2	0.006	0.187	0.497	0.501
(b) Dep. var.:	probability of contact requests			
$r25$	-0.01347***	-0.00660***	-0.00440***	-0.00872***
	[0.00012]	[0.00035]	[0.00034]	[0.00056]
N	9,510,963	9,510,963	9,510,963	9,510,963
adj. R^2	0.001	0.067	0.304	0.305
Municipality FE		Y		
Month x Year FE		Y	Y	
Ads characteristics		Y	Y	Y
Advertisement FE			Y	Y
Region x Month x Year FE				Y
Precipitations				Y
Extreme events				Y

Notes: This table reports the estimated coefficient for the variable $r25$ according to the specification in Equation 1. The variable $\log(clicks)_{it}$ is defined as the logarithm of the number of visits for ad i during month t. The variable $\mathbf{1}(contacts > 0)_{it}$ is an indicator variable equal to one if the seller has received at least one contact request for the announcement i in month t. Ads characteristics include energy class, terrace, balcony, air conditioning, and garden type variables described in Table A.1. We also consider as controls monthly realized precipitations, categorized at four levels of intensity, and a dummy equal to 1 if at least one extreme weather event including avalanches, hails, lightning strikes, severe wind and heavy snowfalls/snowstorms has taken place during the month. Standard errors clustered at ad-level are in parenthesis. Significance values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

According to the estimated coefficient of $r25$ in Column 4 of Table 1, the results can be quantified as follows: an increase by 1% in $r25$ causes the number of clicks to fall by 0.03%. As the average monthly value of $r25$ across cities is 4.3 days, one additional day with average temperatures above 25°C in one month leads monthly clicks to fall by around 1% in the same month. Tables A.4 and A.5 in the Appendix report robustness checks for the results in Table 1, made by experimenting with a different set of control variables in panel regressions. In Table A.4, the time fixed effects are multiplied with area and region dummies to capture variation in demand due to local factors. The estimated elasticities remain negative and significant and increase in magnitude in the most demanding specification with region-time fixed effects. Table A.5 displays the estimated elasticities of demand to temperatures when we control for other, potentially confounding climate related-factors, namely precipitations and the extreme weather events described above: as peak temperatures may be concomitant with those, still climate-related phenomena, it is important to disentangle the effect of high temperatures on housing search from them. Results show that including a dummy for the occurrence of at least one event in the city-month leaves coefficients mostly unchanged. This result is expected given the low frequency and intensity of such events within the municipality of provincial capitals in the time period under investigation.

4.3 Dynamic effects

Hot temperatures have been found to affect housing demand during the month in which the peak temperature event occurs. We here explore how this effect evolves over time to understand whether the implications on the housing searching process persist beyond the direct impact. We explore the dynamic effects of very hot temperatures by estimating impulse response functions (IRF) in our advertisement-level panel setting, following the local projections (LP) method of Jordà (2005).[15] By applying local projections to the framework in Equation 1 we get

$$y_{i,t+h} = \alpha + \beta x_{c(i)t} + Controls'_{it}\Gamma + Z'_{i,t-k}\Omega + \mu_i + \nu_{r(i)t} + \epsilon_{i,t+h}. \tag{2}$$

where $h \in [0, H]$ and $k \in [1, K]$. We estimate our projections 12 times, from the contemporaneous impact (h=0) up to 11 months ahead (H=11). Following the local projections literature, we augment our specification with an additional set of controls Z, including lags of $r25$. [16]

[15]The LP approach to IRFs consists in estimating a sequence of regressions to predict the dynamic response of a variable of interest on an initial shock for a multiple time horizons. While LPs have first been applied in the macroeconometric literature, they are now also popular when working with micro panels (see Rambachan and Shephard, 2019 and Montiel Olea and Plagborg-Møller, 2021 for a discussion).

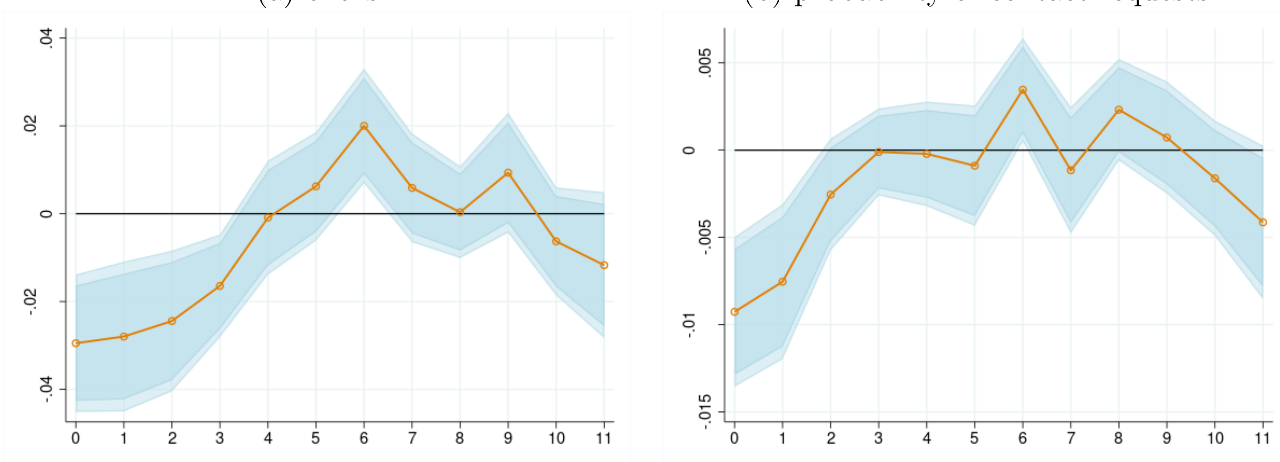
[16]Varying the lag structure, or including lags for the dependent variable does not significantly alter the estimates.

Figure 3 shows the dynamic response of advertisement clicks and the probability of web contacts to an increase in the number of hot days in a month. The impact effect is negative on both variables, consistent with the outcomes presented in the previous table. Estimates at longer horizons show that, while demand rebounds slightly a few months after the shock, the effects of temperature on online housing demand appear to be overall negative over a 12-month horizon.

Figure 3: Response of online clicks and contacts

(a) clicks

(b) probability of contact requests



Notes: The figure shows dynamic effects, in the current month and up to 11 months ahead, of the change in the number of days above 25C on the number of clicks per announcement (panel (a)) and of the probability of at least one web contact (panel (b)) during a month. The blue line represents the coefficient of the impulse response function estimated via the LP method according to the specification detailed in Section 4.3. The dark-blue shaded area represents the 90% confidence band. Light-blue shaded area represents the 95% confidence band.

5 In-person appointments

In this section, we explore the effects of temperature on physical search using data on appointments of both potential buyers and sellers with real estate agents.

5.1 Empirical strategy

In the spirit of Equation 1, we estimate the following city-level regression model

$$y_{ct} = \alpha + \beta x_{ct} + Controls'_{ct}\Gamma + \mu_c + \nu_t + \epsilon_{it}. \tag{3}$$

where c indicates the city and t the month. The dependent variables are the number of appointments taken by Tecnocasa agents by either buyers or sellers in each city for each month. We standardize this variable by the number of Tecnocasa agencies collecting the appointments in each city and transform them using the natural logarithm. In the same spirit of Equation 1, the explanatory variable is $r25$; $Controls$ is a vector of time-varying city-level controls, encompassing precipitation categories and the extreme weather event dummy. μ and ν are respectively city and time month-year fixed effects.

5.2 Results

Table 2 reports the results of the regression specified in Equation 3 and is divided into three panels, one for each dependent variable. The first panel shows that, as for online search, hot temperatures significantly reduce in-person appointments: this result shows up even when we include in the estimates the largest set of control variables, which encompasses city and year-month fixed effects (column (4)). Regarding buyers, the result is in line with the negative effects on clicks and web contacts found in the previous Section: in the housing market, online and physical search look to be complements, whereas high temperature is found to discourage housing search across the board. On the supply side, Panel (b) shows that sellers' appointments are also reduced when temperatures are too hot. This is consistent with the adverse consequences of extreme heat on human behavior, which limits the overall search-matching process.

To quantify these effects, consider that in the sample under investigation, the average number of days with temperatures above 25C is 3.3 (so the average of our regressor is 4.3): if this count increases by one single day, appointments taken with buyers and sellers in that month and city are both reduced by around 2%. In light of the increasing volatility in temperatures due to climate change, these effects can become more and more severe over time. By interpreting these results through the lens of a housing search model, a reduction of appointments – which for the buyers mostly relate to housing visits – on both sides of the market entails a reduction of market *thickness*, due to lower activity on both the demand and supply sides. Moreover, the estimates show that the impact is slightly stronger for the buyers, suggesting also a possible reduction in market *tightness*, i.e. the ratio of buyers to sellers.

Table 2: Physical search

	(1)	(2)	(3)	(4)
(a) Dep. var.:	Buyer-Agent appointments			
$r25_t$	-0.126***	-0.071**	-0.074**	-0.072**
	[0.023]	[0.031]	[0.030]	[0.030]
N	768	768	768	768
adj. R^2	0.072	0.803	0.814	0.815
(b) Dep. var.:	Seller-Agent appointments			
$r25_t$	-0.150***	-0.059**	-0.062**	-0.061**
	[0.025]	[0.025]	[0.025]	[0.024]
N	768	768	768	768
adj. R^2	0.074	0.878	0.885	0.885
Municipality FE		Y	Y	Y
Month × Year FE		Y	Y	Y
Cities charact			Y	Y
Precipitation quartiles				Y
Extreme events dummy				Y

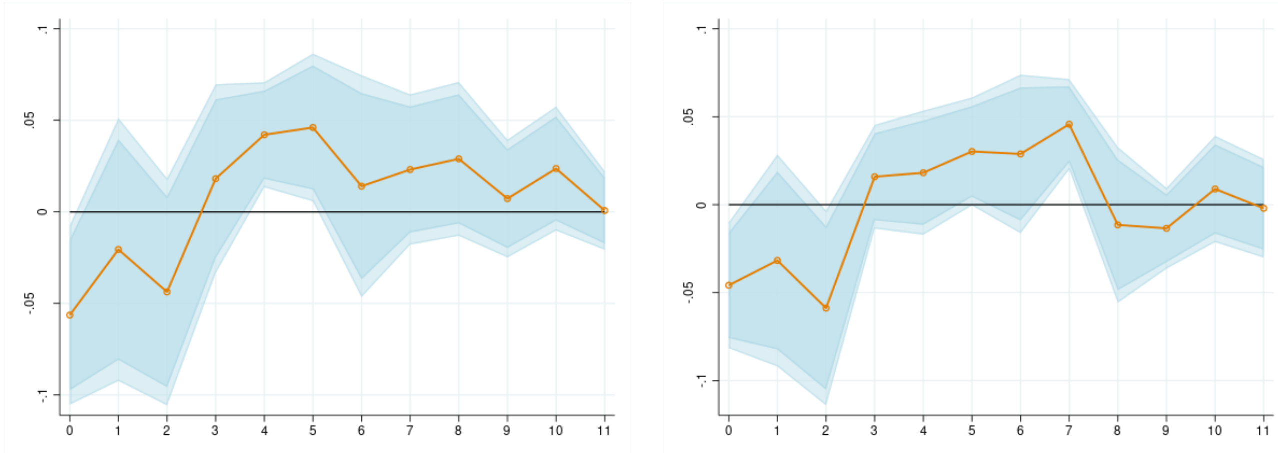
Notes: This table reports the estimated coefficient for the variable $r25$ according to the specification in Equation 3. In panels (a) and (b) the dependent variables are defined, respectively, as the logarithm of the number of per agency buyer-agent and seller-agent appointments in city c and month t. We consider as controls monthly realized precipitations, categorized at four levels of intensity, and a dummy equal to 1 if at least one extreme weather event including avalanches, hails, lightning strikes, severe wind, and heavy snowfalls/snowstorms have taken place during the month. Standard errors clustered at city-level are in parentheses. Significance values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.3 Dynamic effects

As we did in Section 4.3 for online search, here we quantify the dynamic response of in-person appointments by means of linear projections. Consistently with previous findings in Figure 3, the reduction in both buyer- and seller-agent appointments is temporary, with some rebound a few months after the shock (Figure 4). Overall, the dynamic response of in-person appointments is very similar to that of online clicks and web contacts. This additional result reinforces the evidence that hot temperatures are able to "cool" the housing market, reducing search volumes and sellers' activity.

Figure 4: Response of in-person appointments

(a) Buyer-agent appointments (b) Seller-agent appointments



Notes: The figure shows the reaction over 12 months of the average number of buyers' and sellers' appointments per agency (panels (a) and (b) respectively) to the change in the number of days above 25C during a month. The blue line represents the coefficient of the impulse response function estimated via the LP method according to the specification detailed in Section 5.3. The dark-blue shaded area represents the 90% confidence band. Light-grey shaded area represents the 95% confidence band.

6 Time on market, transactions and prices

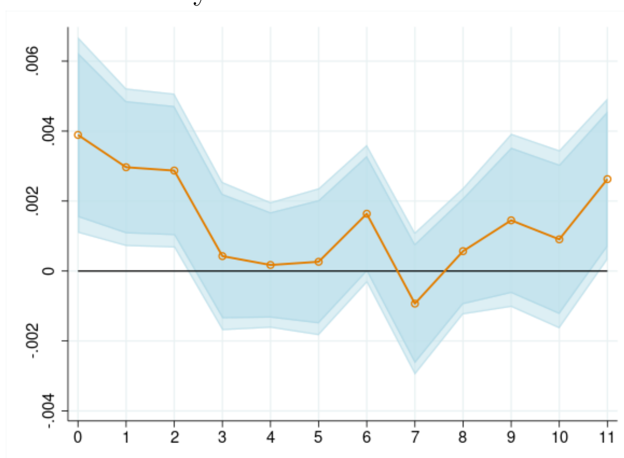
Up to this point, we have shown that high temperatures imply a reduction in both housing demand and supply, either physical or online. In this Section, we describe how these effects reverberate over housing sale quantities and prices. For this purpose, we explore the impact of temperatures on the time each ad publisher spends to sell a property through the online platform, on the number of realized housing transactions, and on prices.

6.1 Time on market

To explore how hot temperatures affect the time to sell a house, we rely on our data on online listings. At the advertisement level, we construct an indicator that values one if the advertisement does not disappear from the web portal in the current month (i.e., it is still present in month $t+1$) and 0 otherwise. Using a linear probability model, we test whether an increase in the number of days with temperatures over 25°C has an effect on the probability of an announcement to remain online. While clicks and contacts are a barometer of demand pressure, time on market tells whether this pressure translates into a matching for the target houses. Time on market can in principle be shaped not only by a lower number of potential buyers but also by composition effects on demand or by lower bid prices: for example, lower bids might also be due to behavioral effects of temperatures inducing unpleasant sensations and undervaluation of housing properties.

Figure 5: Response of the time on market

Probability that the ad remains online



Notes: : The figure shows the effect of hot temperatures on the time on market. The red line represents the coefficient of the impulse response function according to the specification detailed in Section 4.3. Dark-blue (light-blue) shaded areas represent the 90% (95%) confidence bands.

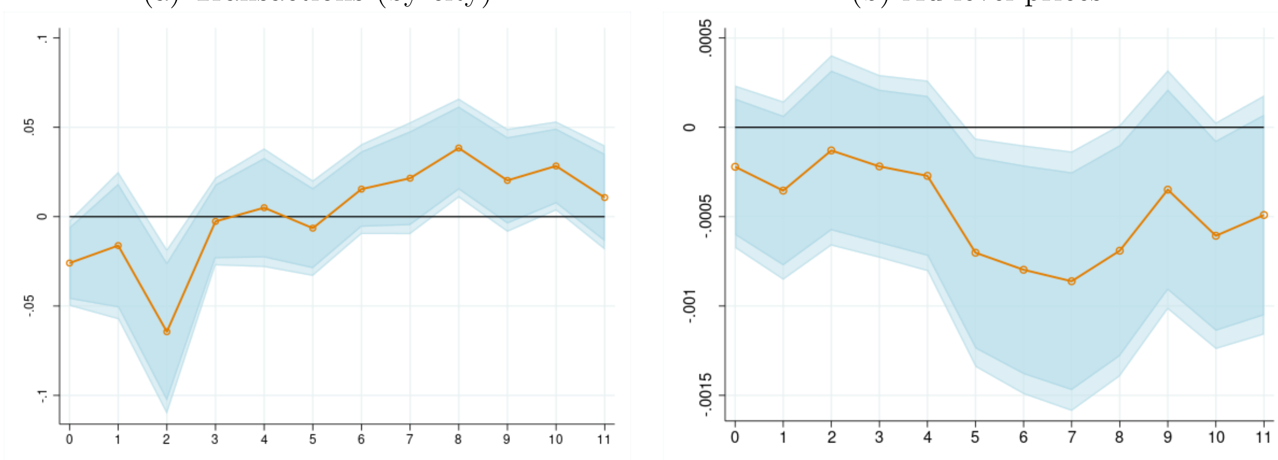
Figure 5 shows the dynamic effects of temperatures on the time on market, estimated according to the most demanding local projection specification in Equation 2. In line with what has been found for online search and in-person appointments, time on market increases following an increase in the share of very hot days in a month. Moreover, sales do not significantly speed up when demand revives.

6.2 The impact on transactions and posted prices

The previous section showed that an increase in the number of very hot days in a month raises the time to sale of a house. In turn, this might also reduce the number of realized housing transactions. To explore this issue, we re-run local projections on transaction counts at the city level using the Notariat dataset. As shown in panel (a) of Figure 6, transactions are also negatively impacted by hot temperatures. This effect is almost insignificant on impact and fully unfolds two months after the shock. This result is coherent with the evidence of a lag between the time in which buyers and sellers reach a deal on a housing unit and that in which the house is effectively sold.

Figure 6: Response of transactions and asking prices

(a) Transactions (by city) (b) Ad-level prices



Notes: The figure shows the reaction over 12 months of the number of transactions by city (panels (a)) and the asking price by ad (panel (b)) to the change in the number of days above 25C during a month. The red line represents the coefficient of the impulse response function estimated via the LP method according to the specification detailed in Sections 5.3 and 4.3. The dark-blue shaded area represents the 90% confidence band. Light-blue shaded area represents the 95% confidence band.

In the housing sector, variations in transactions are usually positively correlated with changes in realized sale prices. For the Italian real estate market, official sale prices are only surveyed semiannually so they cannot be directly used in this analysis, which exploits weather variations at higher frequency. However, we can rely on asking prices per square meter – available for each advertisement posted on Immobiliare.it – to get insights on where sale prices might go in response to hot temperature episodes. As we show in Figure A.1 in the Appendix, at the city level and annual frequency, average asking prices from our home listing dataset are highly positively correlated with sale prices, validating their use as a proxy for property-level sale prices (see also Pangallo and Loberto, 2018 and Benetton et al., 2022).[17] We compute impulse responses of ask prices to a temperature shock at the advertisement level. Results, reported in Panel (b) of Figure 6, show that home-level posted prices significantly decrease in response to the shock.

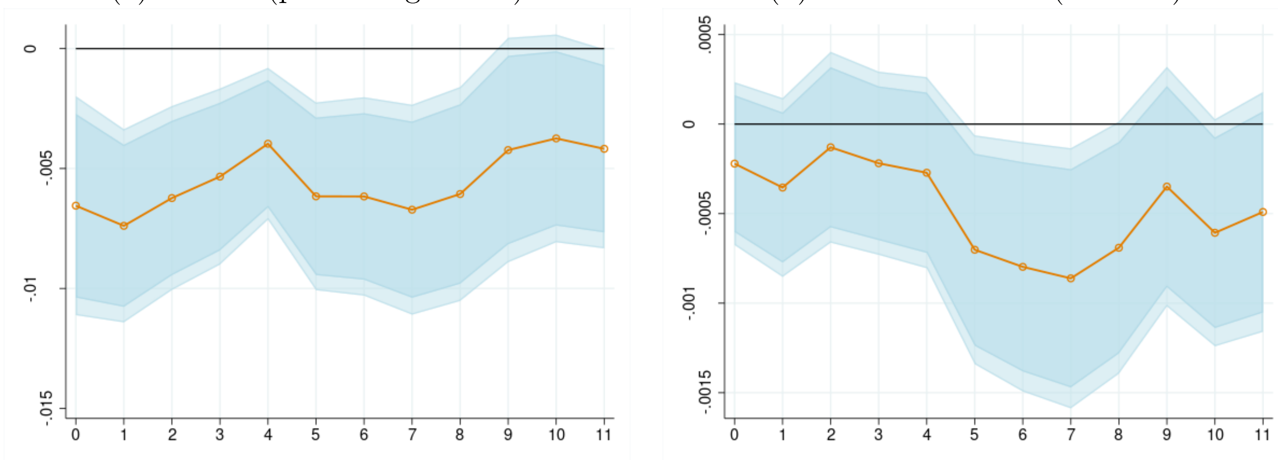
Because local projections in Equation 2 include advertisement-level fixed effects, the effect found on prices rests only on the impact *within* the same house – i.e., a repricing of the same housing unit. However, it is well possible that price effects unfold also *across* houses for sale. To explore potential effects on the extensive margin of the housing market, we re-estimate the local projections on house prices using a pooled OLS framework, i.e. by excluding advertisement-level fixed effects. Results, displayed in Figure 7, compare the price response previously obtained within the ads (Panel (b)), with that computed across all ads (Panel (a)). Panel (a) clearly shows that, by considering the full set of ads at each horizon, the results are much stronger. This finding is not surprising, for at least two reasons. First, the estimate using ad-level fixed effects excludes all advertisements which stay on the portal for just one month, i.e. the fast-selling ones. Provided that those ads cover a high share of the ads dataset, they can contribute largely to the overall price effect. Second, it is a common practice by ad publishers to replace ads over time with new ones for the same house for sale (but with lower prices) to avoid showcasing a downward price revision in the portal: for this reason, a house that is on the market for two months but under two different ads is excluded from the computation of the price effect when including ad-level estimates.

Overall, based on the effects found in panel (a), an increase in the share of hot days within a month induces prices to fall on average by 0.007%: this effect is about one-fifth of that found on the clicks, meaning that one additional day with average temperatures above 25°C in one month leads prices to contemporaneously fall by around 0.2%. Differently than in the case of demand and transactions, the response of prices persists for at least one year after the shock, indicating that hot temperature episodes are able to weigh on the housing market long after the temperature shock fades out.

[17] As proved by Han and Strange (2016), ask prices are able to significantly direct buyer search and shape final sale prices. This fits the case of the Italian real estate market, where asking prices represent a true ceiling for realized sale prices.

Figure 7: Response of prices – extensive vs intensive margin

(a) All ads (pooled regression) (b) Within-ad effect (baseline)



Notes: The figure shows the reaction over 12 months of the number of transactions by city (panels (a)) and the asking price by ad (panel (b)) to the change in the number of days above 25C during a month. The red line represents the coefficient of the impulse response function estimated via the LP method according to the specification detailed in Sections 5.3 and 4.3. The dark-blue shaded area represents the 90% confidence band. Light-blue shaded area represents the 95% confidence band.

7 Climate-safe housing

Our results indicate that, while the effects of temperature on housing transactions are temporary, those on prices are highly persistent. A natural question that arises is why the effects of temperature might have dynamic implications despite the temporary nature of hot temperature episodes. One possibility is that the impact found on housing search is coupled with a wake-up call effect on the risks related to increasingly hot temperatures, entailing a shift in household preferences. In this perspective, potential buyers may choose to adapt in different ways. For example, adaptation might entail a change in the type or location of the house to buy, or even the decision to renounce the purchase or postpone it to the medium run.

Table 3: Climatic safety

	(1)	(2)	(3)	(4)
(a) Dep. var.:		clicks		
$r25$	-0.030***	-0.026***	-0.033***	-0.025***
	[0.001]	[0.001]	[0.002]	[0.001]
$r25 \times \mathbf{1}(Climatic\ safety\ indicator)$	0.010***			
	[0.000]			
$r25 \times \mathbf{1}(Energy\ class\ over\ C)$		0.006***		
		[0.001]		
$r25 \times \mathbf{1}(Outdoor\ living\ space)$			0.009***	
			[0.001]	
$r25 \times \mathbf{1}(Air\ conditioning\ system)$				-0.002**
				[0.001]
N	7,363,133	7,363,133	7,363,133	7,363,133
adj. R^2	0.513	0.513	0.513	0.513
(a) Dep. var.:		probability of contact requests		
$r25$	-0.011***	-0.010***	-0.013***	-0.010***
	[0.001]	[0.001]	[0.001]	[0.001]
$r25 \times \mathbf{1}(Climatic\ safety\ indicator)$	0.004***			
	[0.000]			
$r25 \times \mathbf{1}(Energy\ class\ over\ C)$		0.002***		
		[0.000]		
$r25 \times \mathbf{1}(Outdoor\ living\ space)$			0.004***	
			[0.000]	
$r25 \times \mathbf{1}(Air\ conditioning\ system)$				0.002***
				[0.000]
N	7,363,151	7,363,151	7,363,151	7,363,151
adj. R^2	0.307	0.307	0.307	0.307
Region × Month × Year FE	Y	Y	Y	Y
Advertisement FE	Y	Y	Y	Y
Precipitations	Y	Y	Y	Y
Extreme events	Y	Y	Y	Y

Notes: This table reports the estimated coefficient for the variable $r25$ according to the specification in Equation 1. The variables $\log(clicks)_{it}$ and $\mathbf{1}(contacts > 0)_{it}$ are defined as in Table 1. $\mathbf{1}(Outdoor\ living\ space)$ is a binary variable equal to one if the dwelling i has a private garden, balcony, or terrace, zero otherwise or if the information about these characteristics is missing. $\mathbf{1}(Energy\ class\ over\ C)$ is a binary variable equal to one if the energy efficiency class of i is above C, zero otherwise, or if the information about these characteristics is missing. Since January 2012 it is mandatory in Italy to provide each building with an energy performance certificate that states the efficiency class. This class is represented by a scale of 10 levels ranging from A4 (the most efficient), A3, A2, A1, B, C, D, E, F to G (the least efficient). $\mathbf{1}(Air\ conditioning\ system)$ is a binary variable equal to one if i is equipped with an air conditioning system, zero otherwise, or if the information about these characteristics is missing. Weather controls are defined as in Table 1. Standard errors clustered at ad-level are in parenthesis. Significance values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Adaptation can have the form of substitution in favor of houses with specific characteristics within the city. We explore this possibility by investigating whether the effects on search are heterogeneous across houses with different climate-related characteristics. Indeed, houses have different energy efficiency classes, entailing different thermal performances and, as a consequence, a different energy consumption required to keep indoor temperature at specific levels; moreover, some houses have outdoor living spaces, which may offer shade and breeze in hot days. As those characteristics are unchangeable (or require too high expenditures to be modified), one could expect that hot temperatures can shape preferences towards more "climate-safe" dwellings. We construct a dummy indicator including houses featuring one or more outdoor living spaces of different types (private and shared gardens, balconies, and terraces) and a dummy for houses with energy efficiency class greater or equal to level C;[18] while it does not represent a structural housing feature as the other ones, we also include a dummy for the presence of an air conditioning system already installed in the house, which might also attract buyers searching for climate-safe houses. We summarize these features using a principal component analysis as in Table A.3, naming the first component (positively correlated with all variables) as *climatic safety indicator*, and use it to separate housing ads in two groups (climate-safe vs climate-unsafe houses).

Table 3 shows the results of the effects on clicks and on the probability of web contacts, either using the climatic safety indicator or the dummies referred to every single climatic characteristic as interaction terms with the main regressor. Results show that heterogeneity in housing supply matters: in response to hot temperatures, online search falls by less for climate-safe houses (Column (1)). This effect comes either from houses with high energy class (Column (2)) or from those featuring outdoor living spaces (Column (3)), indicating a preference shift that limits the negative effect of temperatures for those housing types.[19] These effects are visible in both the response of the number of clicks (Panel A) and on the probability of web contact requests (Panel B). On the contrary, no clear effect is detected based on the presence of air conditioning systems (positive in Column (4) of Panel B, negative in

[18]The energy efficiency classes according to the Italian system are (from the most to the least efficient): A4, A3, A2, A1, B, C, D, E, F, G. Houses with energy class greater or equal than C represent around one quarter of houses in the dataset.

[19]Results across energy efficiency levels hold even if highly efficient houses are defined as those with the class above B.

Column (4) of Panel A), suggesting that what matters are only the structural, unchangeable climate-related characteristics of the housing unit.

Table 4: Climatic safety - cheap vs expensive homes

	(1)	(2)	(3)	
Dep. var.:	clicks		Prob of contact requests	
	low price	high price	low price	high price
$r25$	-0.02869***	-0.03112***	-0.01035***	-0.01233***
	[0.00204]	[0.00199]	[0.00101]	[0.00088]
$r25 \times \mathbf{1}(climatic\ safety\ index)$	0.00819***	0.01106***	0.00289***	0.00508***
	[0.00068]	[0.00065]	[0.00039]	[0.00035]
N	3,640,446	3,698,433	3,640,450	3,698,447
adj. R^2	0.504	0.526	0.301	0.316
Region × Month × Year FE	Y	Y	Y	Y
Advertisement FE	Y	Y	Y	Y
Precipitations	Y	Y	Y	Y
Extreme events	Y	Y	Y	Y

Notes: This table reports the estimated coefficient for the variable $r25$ according to the specification in Equation 1. The variables $\log(clicks)_{it}$, $\mathbf{1}(contacts > 0)_{it}$, and weather controls are defined as in Table 1. Standard errors clustered at ad-level are in parenthesis. Significance values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

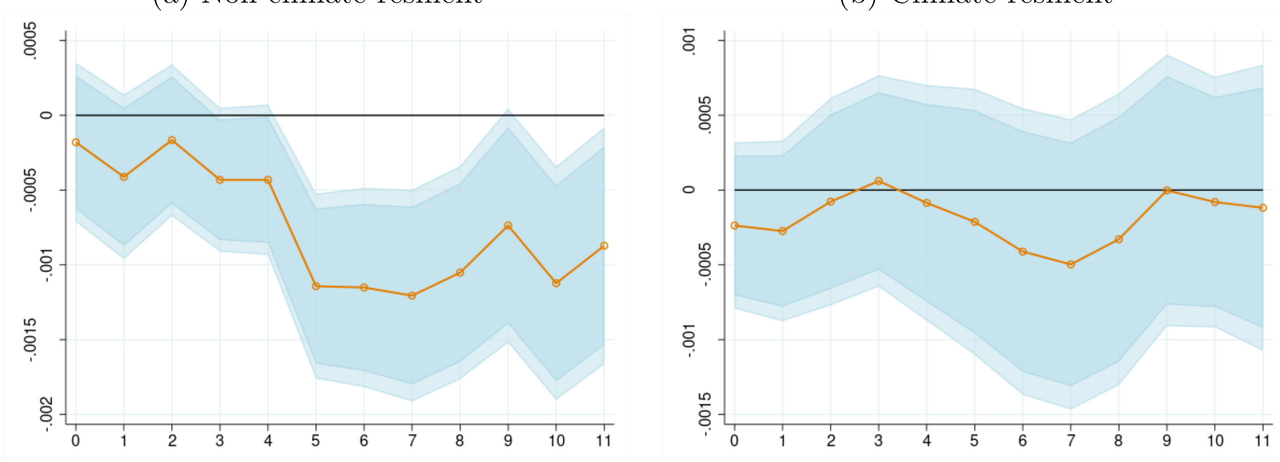
For their desirable characteristics, homes with the above-mentioned climate-resiliency features are also among the most expensive ones. To inspect whether our results are not confounded by other factors related to house prices, we re-run the estimates carried out in Table 3 within the subsets of houses with similar ask prices. We split the sample based on the median ask price per square meter, and repeat the estimates separately in the sub-samples of houses with below-median prices, and in that of houses with price equal to or above the median price within each city. Results, displayed in Table 3 for "low-price" and "high-price" homes, show two interesting results. First, an increase in the incidence of hot days within a month makes the number of clicks and the probability of contacts falling more for expensive houses than for less expensive ones. Second, climatic safety plays a larger role for expensive houses than for less expensive ones. This result might be related to the fact that housing demand is segmented across housing prices, connecting to other research on the topic (Piazzesi et al., 2020, among others). In this perspective, richer and possibly more educated buyers could be more aware of climatic risks, leading the preference shift towards climatic safe housing observed in the market.

7.1 Prices

To investigate the effects on the prices of climate-resilient and non-resilient houses, we re-run local projections for the two subsets of housing announcements. Results, displayed in Figure 8, clearly show that the effect on average asking prices comes entirely from a downward revision in the price of non-climate-resilient houses. Indeed, while the posted price of the latter category falls significantly after the high-temperature shock, this is not the case for the price of climate-resilient housing, which does not change significantly.

Figure 8: Asking prices

(a) Non-climate resilient (b) Climate resilient



Notes: The figure shows the reaction over 12 months of the prices of non-climate resilient houses (panels (a)) and those of the climate-resilient ones (panel (b)) to the change in the number of days above 25C during a month. The red line represents the coefficient of the impulse response function estimated via the LP method according to the specification detailed in Sections 5.3 and 4.3. The dark-blue shaded area represents the 90% confidence band. Light-blue shaded area represents the 95% confidence band.

8 Additional results

8.1 City-level heterogeneity

As argued in Section 2, high temperatures can be seen as a factor increasing the cost of housing search. To provide suggestive evidence for this mechanism, we run a heterogeneity analysis by exploiting two characteristics of local housing markets, namely their historical temperatures and the cities' surface extension. We define hotter cities as those with above-mean temperatures within the sample, and larger cities as those whose surface extension is above the average for the cities under investigation. These two characteristics are directly related to the costs of outdoor search: in hotter cities, search costs are normally higher than in colder ones, so buyers are more used to them and suffer less in case of peak temperature events. On the contrary, search costs can be higher in large cities, where buyers need to make longer trips to locate ads, visit dwellings and meet agents and sellers in person: in these places, the cognitive biases described in Section 2 can be magnified, leading to fewer visits and lower bids. To estimate these potentially heterogeneous effects by cities, we run equation 1 under our most demanding specification (i.e. as in column (3) of Table A.5) including the interaction between the main explanatory variable and a dummy denoting hotter and larger cities, one at a time.

Results for the effects on click and on the probability of contact requests are displayed in Table 5. Columns (1) and (3) show that the negative temperature elasticity of demand is lower for hotter cities when measured via $\log(clicks)$ and still positive (but not significant) for the probability of contacts, suggesting that adaptation to hot temperatures can be relevant for the housing search process. Columns (2) and (4) report a negative differential elasticity estimated for larger cities, for both clicks and contacts. As heat stress impacts housing search more in larger and colder cities, these findings add evidence to our intuition that temperature effects are transmitted mainly through an increase in individual search costs.

Table 5: **Online search - City heterogeneity**

	(1)	(2)	(3)	
Dep. var.:	$log(clicks)$		$\mathbf{1}(contacts > 0)$	
$r25$	-0.03334***	-0.02131***	-0.00896***	-0.00697***
	[0.00136]	[0.00127]	[0.00063]	[0.00058]
$r25 \times \mathbf{1}(Hotter\ city)$	0.01107***		0.00038	
	[0.00090]		[0.00043]	
$r25 \times \mathbf{1}(Larger\ city)$		-0.00988***		-0.00349***
		[0.00057]		[0.00029]
N	9510932	9510932	9510932	9510932
adj. R^2	0.501	0.501	0.305	0.305
Region × Month × Year FE	Y	Y	Y	Y
Advertisement FE	Y	Y	Y	Y
Precipitations	Y	Y	Y	Y
Extreme events	Y	Y	Y	Y

Notes: This table reports the estimated coefficient for the variable $r25$ according to the specification in Equation 1. The variables $\log(clicks)_{it}$ and $\mathbf{1}(contacts > 0)_{it}$ are defined as in Table 1. $\mathbf{1}(Hotter\ city)$ is a binary variable equal to one if the average annual temperature of the city $c(i)$ is above the median of the distribution across cities. $\mathbf{1}(Larger\ city)$ is a binary variable equal to one if city $c(i)$ extension above the median of the distribution across cities. Weather controls are defined as in Table 1. Standard errors clustered at ad-level are in parenthesis. Significance values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

8.2 Nonlinear effects of temperatures

The econometric evidence provided so far points to a negative effect of hot temperatures on the housing market. However, the climate economics literature has found that the effects of temperatures can be U-shaped, with both extremes having an impact (Schlenker and Roberts, 2009 and Barreca et al., 2016, among others). To explore the potential of the entire spectrum of temperatures to impact housing search, we follow the commonly used approach to construct temperature bins by counting, for each city and month, the number of days falling within consecutive temperature thresholds. Using these bins as a set of new explanatory variables, we re-investigate the effects of temperatures using the following panel specification

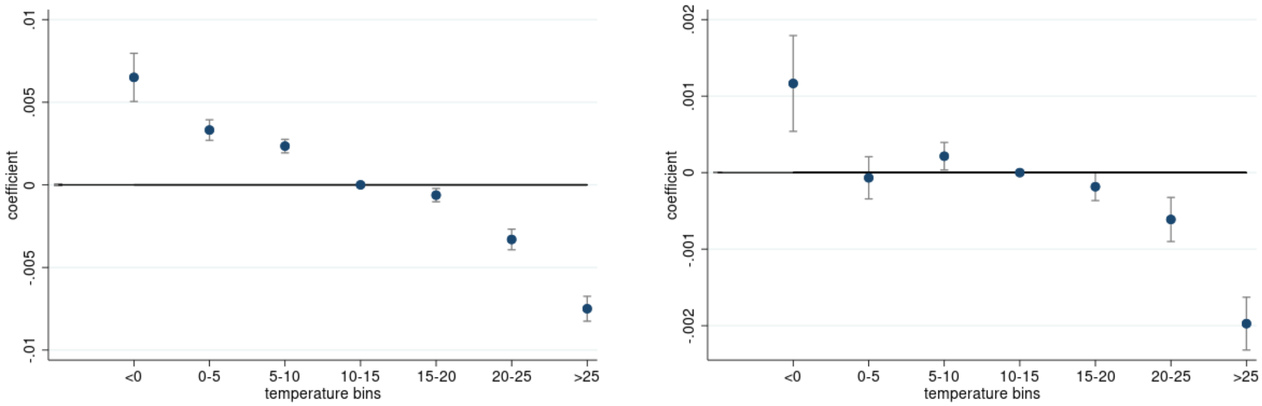
$$y_{it} = \alpha + \sum_k \beta_k T_{k,c(i)t} + Controls'_{it}\Gamma + \mu_i + \nu_r(i)t + \epsilon_i t. \qquad (4)$$

where the variables of interest $T_{k,c(i)t}$ include now all temperature bins. To disentangle temperature effects with a sufficient degree of granularity, we construct seven bins and thus seven variables T_k: the first one counts the number of days with average mean temperature below 0C, then between 0 and 5, 5-10, 10-15,15-20, 20-25 and above 25C. The estimates are carried out for online search variables (at the announcement level) and for in-person appointments (at the city level). To avoid multicollinearity, we take out the central temperature bin (10-15) from equation 4, so the estimated effects are intended to be deviations from the effects of the central bin.

Figure 9 displays the coefficients (with 95% bands) for clicks and contacts, and Figure 10 for buyers' and sellers' appointments. Results confirm that, compared to the average bin, an increase in very hot temperatures induces a negative and significant effect on online and physical search. Regarding physical search, these effects are U-shaped, in line with the effects found on human health by Barreca et al. (2016). On the contrary, online search is found to be positively affected by cold temperatures. These asymmetric effects of cold temperatures on online vs. physical search suggest that opposite temperature extremes can have profoundly different implications on housing search. One reason could be related to the existence of less attractive (and viable) leisure alternatives in case of extreme cold – with ice or snow reducing mobility – which may encourage buyers to substitute physical search with online search. We leave this investigation as an interesting avenue for future research.

Figure 9: Nonlinear effects - online search

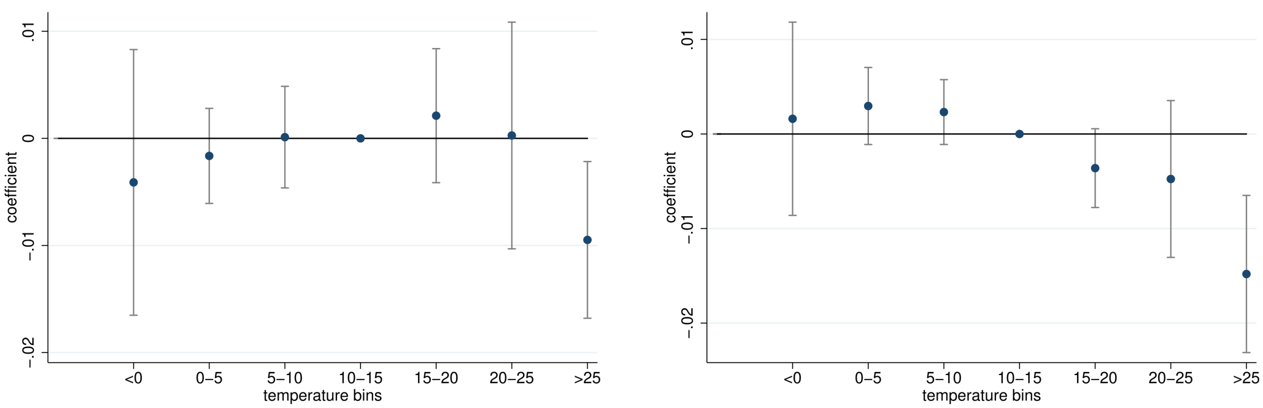
(a) $\log(clicks)$ (b) $\mathbf{1}(contacts > 0)$



Notes: The two panels in figure shows the coefficients β_k and the corresponding confidence intervals at 95% obtained by estimating Equation 4.The dependent variables are $\log(clicks)$ and $\mathbf{1}(contacts > 0)$ in panels (a) and (b) respectively.

Figure 10: Nonlinear effects - physical search

(a) Buyers' appointments (b) Sellers' appointments



Notes: The two panels in figure shows the coefficients β_k and the corresponding confidence intervals at 95% obtained by estimating Equation 4.The dependent variables are the logarithm of the average number of buyers' and sellers' appointments by agency, in panels (a) and (b) respectively.

8.3 Buying vs renting

As Immobiliare.it also contains ads of properties for rent, we here exploit this information and analyze how the incidence of hot temperatures can affect search when it comes to rental apartments. Such investigation is interesting for two reasons. First, it sheds light on the underlying channels at work: as hot temperatures might have a direct impact on the search for rental apartments as well, the wake-up call on future climatic risks may instead hardly influence the choice of a rental apartment, as renting is a temporary housing solution. Second, it provides some interpretation for the price effects found in Section 6. From an asset pricing perspective (Giglio et al., 2021b), following a climate-related shock, home sale prices may decline either because of a reduction in the flow utility of housing services (which is equally provided by purchased and rented houses) or due to an increase in the present discounted cost of climate risk – a longer-run component that might not vary substantially in case of renting. Evaluating the effects on demand for rent and comparing the impact on rent rates with that on sale prices are key to answering these two questions.

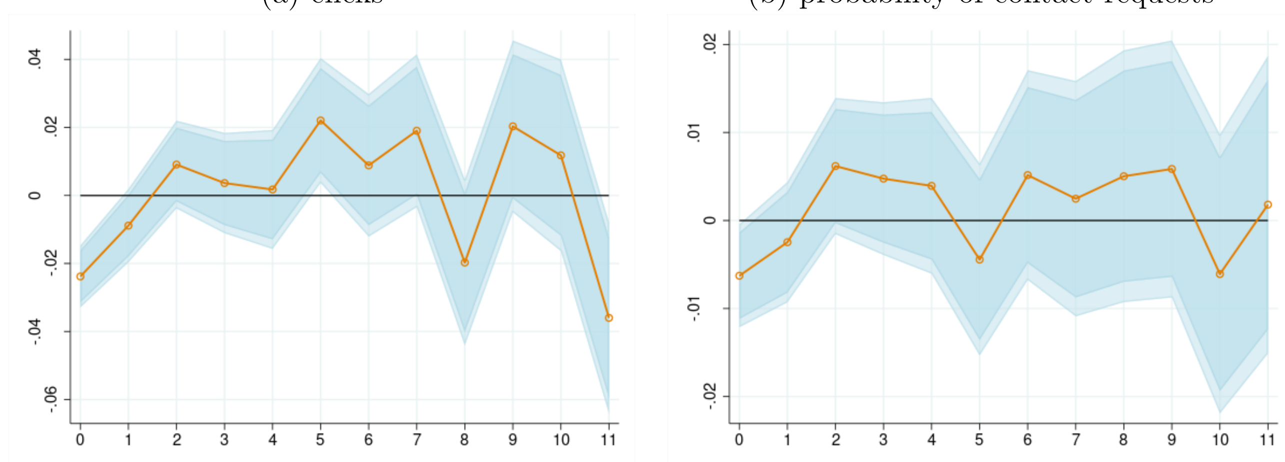
We repeat the impulse response analysis by focusing on clicks and contacts of rental apartments, and on rent rates. Figures 11 display the response of clicks (Panel a) and of the probability of contact requests (Panel b). An increase in the share of days with daily average temperatures above 25°C immediately reduces the number of clicks and the probability of contact requests through the web for rental apartments; the impacts – both in terms of size and dynamics – are very similar to those found on houses for sale (see Figure 3). This result confirms the importance of a direct effect of temperatures on search, which lowers market thickness and slows down the overall housing market.

Figures 12 display the impulse response of rent rates. Interestingly, Panel (a) shows that, while decreasing slightly over time, rent rates do not respond significantly to temperature shocks. This absence of a significant reaction confirms our intuition: because of the temporary nature of renting, the wake-up call effect induced by hot temperatures is switched off in the rental market, leading to lower downward price pressures on rent rates compared to sale prices. As an additional test of this claim, we re-run the IRFs on rental rates for the subset of rent ads that are not climate resilient, along the lines of what is done in Section 7. Panel (b) shows that, even for these kinds of apartments, there are no effects on rent rates in the months following the shock. Both results also imply that the impact previously found on house sale prices passes mainly through an increase in the present discounted cost of climate risk.

All in all, these findings suggest that the direct effects on search – due to the physical impacts of hot temperatures – and the wake-up call effects are distinct and relevant channels affecting housing search. The existence of a wake-up call effect is what makes the difference between the overall impact of temperatures on housing for sale vs housing for rent.

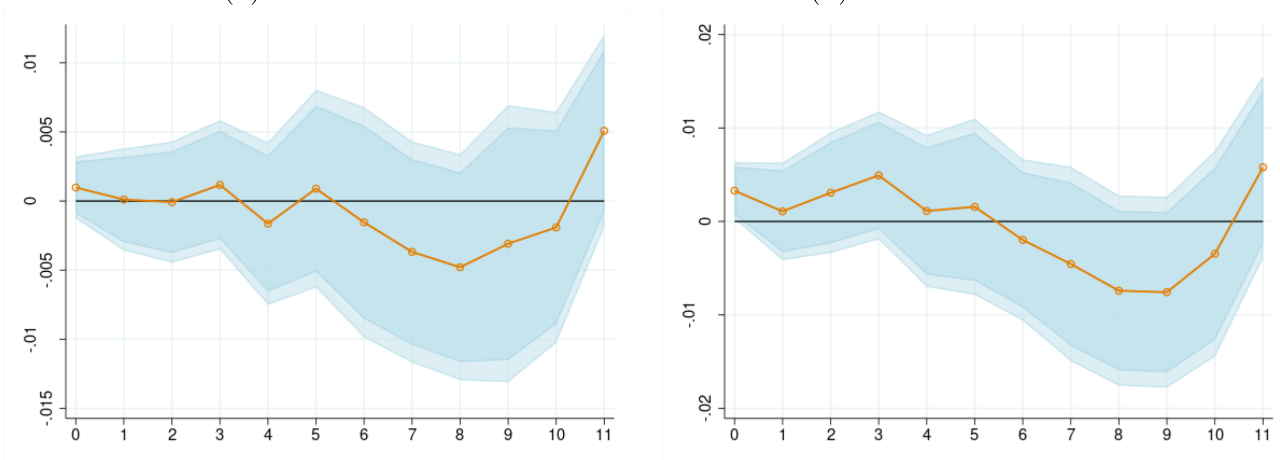
Figure 11: Apartments for rent - Response to hot temperatures

(a) clicks (b) probability of contact requests



Notes: The figure shows dynamic effects, up to 12 months ahead, of the change in the number of days above 25C on the number of clicks (panel (a)) and the probability of web contacts (panel (b)) for apartments for rent during a month. The red line represents the coefficient of the impulse response function estimated via the LP method according to the specification detailed in Section 4.3. The dark-blue shaded area represents the 90% confidence band. The light-blue shaded area represents the 95% confidence band.

Figure 12: Response of rent rates



Notes: The figure shows dynamic effects, up to 12 months ahead, of the change in the number of days above 25C on the asking price for sales (panel (a)) and rents (panel (b)) for square meter during a month. The red line represents the coefficient of the impulse response function estimated via the LP method according to the specification detailed in Section 4.3. The dark-blue shaded area represents the 90% confidence band. The light-blue shaded area represents the 95% confidence band.

9 Conclusions

We investigate the effects of climate change on the housing market. We find that an increase in the incidence of hot temperatures significantly affects housing search, both online and physical, increasing the time-on-market of housing advertisements. This in turn reduces housing transactions and prices, where the latter effect comes from houses that are not perceived as structurally climate-safe, i.e. resilient to future climatic risks. By focusing on the housing market, this paper sheds light on the effects of climate change on search activities and points to the role of temperature as a driver of house prices. Studying how climate change impacts other types of search activities or alters the connection between online and physical search can be promising avenues for future research.

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A Additional Tables and Figures

Table A.1: Immobiliare.it: summary of the available variables

Group	Data type	Variables
Property	geographical	longitude, latitude
	numerical	ask price, floor area
	categorical	property type, kitchen type, heating type, maintenance status energy class, garden type
	dummy	furniture, balcony, terrace, air conditioning, basement, utility room, garage
	textual	address, ad description
Building	numerical	property's floor number
	categorical	building category
	dummy	elevator, doorman
Contract	categorical	contract type
	dummy	foreclosure auction
Advertisement	numerical	pictures count, ash codes of the pictures n. of clicks, n. of contact requests
Ad publisher	categorical	publisher type
	textual	agency name, agency address

Table A.2: Descriptive statistics

	No. Obs.	Mean	St. dev.	p25	p50	p75
(a) ***Weather data*** ⊞						
$\#\{Days\ over\ 25C\}$	5,184	3.3	7.0	0	0	1
Precipitations	5,184	65.5	61.2	24.9	51.5	87.7
Avalanche	5,184	0	0.014	0	0	0
Large hail	5,184	0.005	0.072	0	0	0
Damaging lightning strikes	5,184	0.001	0.031	0	0	0
Severe wind	5,184	0.030	0.302	0	0	0
Heavy snowfall/snowstorm	5,184	0	0.014	0	0	0
(b) ***Housing data*** ⊠						
Clicks	10,028,861	310.6	585.0	97	180	341
Contacts	10,028,861	0.5	1.8	0	0	0
Price/m^2	9,525,729	2,419.2	1,409.7	1,432.4	2,102.9	3,072.9
(c) ***Housing data*** ⊞						
Buyers' appointments by agency	768	50.7	23.6	34.0	47.0	65.2
Sellers' appointments by agency	768	31.9	19.9	19.5	26.7	38
Nr. of agencies	768	45.0	62.3	8	20	67.5
(d) ***Transactions data*** ⊞						
Transactions	4,944	405.3	753.3	122	215	387

Notes: This table contains summary statistics for the main variables used in our analysis. The symbol ⊞ denotes city-level characteristics, ⊠ ad-level features. The variable $\#\{Days\ over\ 25C\}$ is defined as the number of days in a month-year with average temperature above 25 degrees Celsius in each city and each month. The variable *Precipitations* is defined as the sum of average precipitations in mm for each month in each city. The variables *Avalanche*, *Large hail*, *Damaging lightning strikes*, *Sever wind* and $Heavy\ snowfall/snowstorm$ are binary variables equal to one if an event of each kind has happened in a city in a month. in The variable *Clicks* is defined as the number of visits on the Ad page on the Immobiliare.it web portal for each month. The variable "*Contact* is a variable that counts for each ad in each month the number of direct contacts with the seller through the web portal. $Price/m^2$ is the posted price for each ad in each month for a squared meter. *Stay* is an indicator variable equal to one if the announcement still exists the following month. $Transaction$ denotes the number of transactions registered by the Notariat for each city in each month.

Table A.3: Principal Component Analysis

Component	Eigenvalue	Difference	Proportion	Cumulative
1st	1.34532	0.394413	0.3363	0.3363
2nd	0.950903	0.0623167	0.2377	0.5741
3rd	0.888586	0.0733909	0.2221	0.7962
4th	0.815195	.	0.2038	1.0000
Variable	**1st component**	**2nd component**	**3rd component**	**4th component**
Garden	0.5273	-0.2453	-0.6313	0.5131
Terrace	0.5780	-0.2339	-0.0598	-0.7795
Air conditioning system	0.3542	0.9321	-0.0755	-0.0113
Energy class over C	0.5123	-0.1279	0.7695	0.3592

Notes: This table contains summary statistics for the principal component analysis used to define the climatic safety indicator. This binary variable is defined as 1 when the 1st component is positive.

Table A.4: Online search - time dummies

	(1)	(2)	(3)
(a) Dep. var.:		$log(clicks)$	
$r25$	-0.00953***	-0.01711***	-0.02648***
	[0.00071]	[0.00086]	[0.00123]
N	9510932	9510932	9510932
adj. R^2	0.497	0.498	0.501
(b) Dep. var.:		$\mathbf{1}(contacts > 0)$	
$r25$	-0.00440***	-0.00971***	-0.00871***
	[0.00034]	[0.00041]	[0.00056]
N	9510963	9510963	9510963
adj. R^2	0.304	0.304	0.305
Month × Year	Y		
Macroarea × Month × Year		Y	
Region × Month × Year			Y
Advertisement FE	Y	Y	Y

Notes: This table reports the estimated coefficient for the variable $x_{it} = r25_{it} := \log(\#\{Days > 25C\}_{c(i),t} + 1)$ according to the specification in Equation 1. The variable $\log(clicks)_{it}$ is defined as the logarithm of the number of visits for ad i during month t. The variable $\mathbf{1}(contacts > 0)_{it}$ is an indicator variable equal to one if the seller has received at least one contact request for the announcement i in month t. Ads characteristics include energy class, terrace, balcony, air conditioning and garden type variables described in Table A.1. Standard errors clustered at ad-level are in parenthesis. Significance values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.5: Online search - precipitations and extreme events

	(1)	(2)	(3)
(a) Dep. var.:		$log(clicks)$	
$r25$	-0.02648***	-0.02629***	-0.02626***
	[0.00123]	[0.00124]	[0.00124]
N	9510932	9510932	9510932
adj. R^2	0.501	0.501	0.501
(b) Dep. var.:		$\mathbf{1}(contacts > 0)$	
$r25$	-0.00871***	-0.00872***	-0.00872***
	[0.00056]	[0.00056]	[0.00056]
N	9510963	9510963	9510963
adj. R^2	0.305	0.305	0.305
Region × Month × Year	Y	Y	Y
Advertisement FE	Y	Y	Y
Precipitations		Y	Y
Extreme events			Y

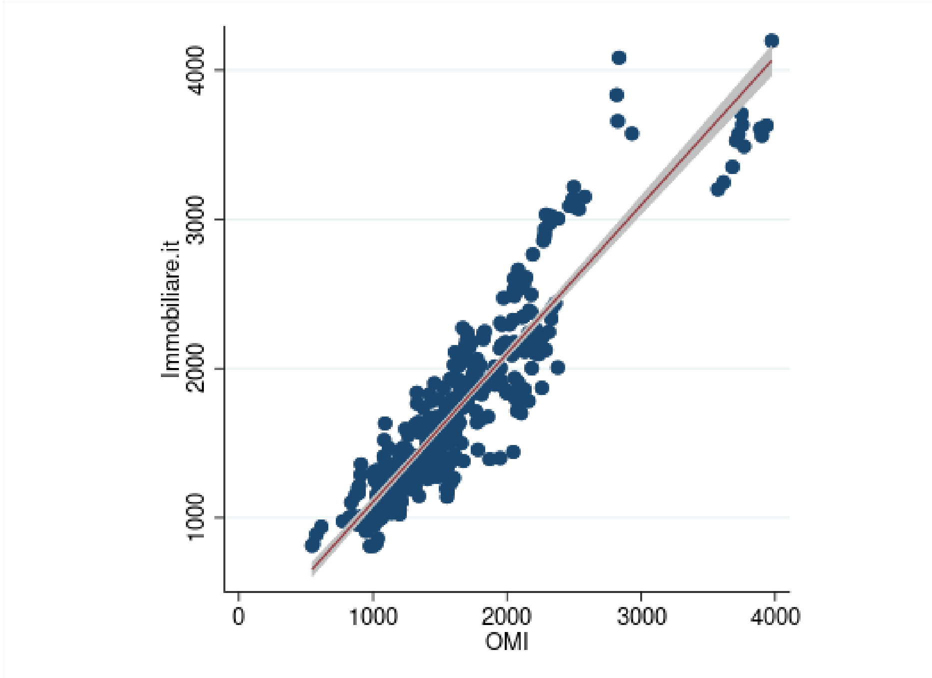
Notes: This table reports the estimated coefficient for the variable $x_{it} = r25_{it} := \log(\#\{Days > 25°C\}_{c(i),t} + 1)$ according to the specification in Equation 1. The variable $\log(clicks)_{it}$ is defined as the logarithm of the number of visits for ad i during month t. The variable $\mathbf{1}(contacts > 0)_{it}$ is an indicator variable equal to one if the seller has received at least one contact request for the announcement i in month t. We consider as controls monthly realized precipitations, categorized at four levels of intensity, and a dummy equal to 1 if at least one extreme weather event including avalanches, hails, lightning strikes, severe wind and heavy snowfalls/snowstorms has taken place during the month. Standard errors clustered at ad-level are in parenthesis. Significance values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.6: Online search - Excluding July and August

	(1)	(2)
Dep. var.:	$log(clicks)$	$\mathbf{1}(contacts > 0)$
$r25$	-0.009***	-0.005***
	[0.002]	[0.001]
N	6,104,698	6,104,711
adj. R^2	0.512	0.311
Ads characteristics	Y	Y
Advertisement FE	Y	Y
Region x Month x Year FE	Y	Y
Precipitations	Y	Y
Extreme events	Y	Y

Notes: This table reports the estimated coefficient for the variable $r25$ according to the specification in Equation 1 excluding from the sample the months of July and August. The variable $\log(clicks)_{it}$ is defined as the logarithm of the number of visits for ad i during month t. The variable $\mathbf{1}(contacts > 0)_{it}$ is an indicator variable equal to one if the seller has received at least one contact request for the announcement i in month t. Ads characteristics include energy class, terrace, balcony, air conditioning, and garden type variables described in Table A.1. We also consider as controls monthly realized precipitations, categorized at four levels of intensity, and a dummy equal to 1 if at least one extreme weather event including avalanches, hails, lightning strikes, severe wind and heavy snowfalls/snowstorms has taken place during the month. Standard errors clustered at ad-level are in parenthesis. Significance values: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure A.1: Posted and Transaction prices



Notes: The figure depicts a scatter plot of posted prices from Immobiliare.it against transaction prices from OMI averaged at city level in 2016-2019. The red line and gray dashed areas represent respectively the linear fit ($R^2 = 0.85$, $\beta = 0.995$, $\alpha = 111$) and 95 percent confidence band.

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