Distributional Consequences of Extreme Heat in Housing Markets*

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Abstract

Utilizing a unique dataset encompassing housing transaction prices, property viewing records, and listing price adjustments, we document a plausibly causal effect of abnormal exposure to contemporaneous extreme heat on wealth redistribution between home buyers and sellers. A one-standard-deviation increase in contemporaneous heat exposure is associated with a 1.48% increase in housing transaction prices that is unrelated to property fundamentals. Sellers are unaffected by extreme heat in both initial listing prices and subsequent adjustments. In contrast, buyers experiencing high temperatures engage in fewer in-person visits and pay more attention to online listings. Moreover, buyers do not negotiate commensurate price discounts, resulting in higher transaction prices. Collectively, our results suggest a redistribution of wealth from buyers experiencing cognitive impacts associated with elevated temperatures to sellers in the housing market. We also explore and report rich results concerning heterogeneity across, e.g., regions, market cycles, and demographic groups.

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1 Introduction

Climate change stands as one of today's most pressing global challenges, supported by an extensive body of evidence that underscores its far-reaching economic and societal impacts (Addoum et al., 2020; Hong et al., 2020; Barnett et al., 2020). Despite substantial global efforts, including endeavors toward carbon neutrality, global warming continue causing substantial losses and stunt economic growth (Kotz et al., 2021). Prior research has documented the multifaceted impact of extreme heat induced by climate change across diverse domains, encompassing areas such as electricity consumption (Auffhammer et al., 2017), business sales and worker productivity (Addoum et al., 2020, 2023; Somanathan et al., 2021), agricultural output (Moore et al., 2017), and even conflict incidence (Hsiang et al., 2013). High temperatures also impair individuals' cognitive functioning and performance (Ebi et al., 2021; Schlader et al., 2015), in turn negatively affecting decisions and behaviors that require mental effort, including individuals' trading behavior (Peillex et al., 2021), judges' court decisions (Heyes and Saberian, 2019), and patent examiners' biases (Kovács, 2017).

Despite the emergence of this body of literature, the impact of climate change-induced extreme heat on decision-making involving large real estate transactions remains largely unexplored. This lack of attention is surprising given the prominence of housing in household net worth. In particular, recent studies document that in both U.S. and international settings, primary real estate represents the majority of households' portfolio holdings across asset classes (Campbell, 2006; Badarinza et al., 2016). We fill this gap by investigating how extreme heat affects transaction prices in the housing market in ways orthogonal to property fundamentals, as well as the consequent implications for redistribution across wealth and demographic groups. We further illuminate the underlying mechanisms by considering both buyers' and sellers' (behavioral) responses to extreme heat.

Specifically, we utilize detailed granular data on housing transactions, spanning 24 major cities in China over the period between January 1, 2015 and December 31, 2019 and covering

over 600,000 transactions. This extensive dataset includes not only final transaction prices for individual resale housing units, but also provides detailed information on buyers' online attention metrics and on-site housing views, as well as sellers' listing behavior and price adjustments. Critically, these latter measures allow us to study and isolate the mechanisms underlying any price impacts. In our study, we link transactions with contemporaneous temperature and weather-related measures from the National Meteorological Administration. Following the climate literature (e.g., Baldauf et al., 2020), we run hedonic pricing regressions to estimate the impact of contemporaneous heat exposure on housing transaction prices.[1] Importantly, our estimates control for a full set of housing characteristics, and fixed effects accounting for unobservables at the time, location, and seasonal levels.

We begin by documenting that exposure to high temperatures generates a positive and significant effect on transaction prices.[2] In particular, controlling for an extensive set of characteristics (i.e., size, age, floor number, number of rooms, and proximity to both schools and subways) and holding city, year, and season fixed, we find that exposure to higher temperatures is immediately associated with a positive impact on housing prices that is both economically and statistically significant.[3] Furthermore, this relationship is highly non-linear, with the strongest effects occurring when ambient temperatures are highest. In particular, we find that after including a full set of hedonic controls and fixed effects, abnormal exposure to an additional day during the transaction week with a maximum temperature above 35°C increases housing transaction prices by approximately 0.54%.[4] This effect is sizable in economic terms, amounting to an RMB 13,007 ($1,858 USD) increase in transaction price for the average unit in our sample (Figure 1). Notably, this increase represents over 42.32%

[1]Although we do not focus on the impact of extreme cold given its lower relevance amid a warming global climate, we present estimation results for abnormally low temperatures in the seasonal heterogeneity analysis (see Appendix Section C10).

[2]To estimate the causal effect, our empirical specification leverages local contemporaneous temperature—a robust exogenous variable—as the independent variable.

[3]Specifically, a one-standard-deviation increase in local temperatures results in a 1.48% increase in housing transaction unit prices, *ceteris paribus*.

[4]Meanwhile, an additional day during the transaction week with a maximum temperature between 30°C and 35°C corresponds to an approximate 0.15% increase in housing prices.

of the average Chinese per capita income (RMB 30,733) at the end of our sample period.

These findings are surprising, given that Haggag et al. (2019) find evidence that people misattribute the influence of a temporary state to a stable quality of the good. If anything, buyers may misattribute the unpleasantness of the extreme heat and like the properties less. To say the least, it is unclear a priori whether transient extreme heat should be associated with higher transaction prices.[5] Moreover, from a welfare standpoint, a back-of-the-envelope analysis based on our estimates demonstrates that the wealth redistribution implied by extreme heat in the housing market exhibits significant variation across buyers with different demographic characteristics. Specifically, as shown in Figure 1, rich male buyers in the north experience the greatest impact from extreme heat, overpaying by about $4,343. In comparison, poor female buyers in the south are least affected, overpaying sellers by merely $645. Interestingly, we find that high temperatures have the unintended consequence of reducing the gender gap in housing investment returns between male and female buyers.[6]

We next turn to uncovering the underlying mechanisms driving our results. Our main conjecture is grounded in the general observation that temperature shocks affect cognitive functioning, mood, and productivity (Baylis, 2020; Ebi et al., 2021; Somanathan et al., 2021). For example, Danziger et al. (2011) document that cognitive shortcuts triggered by high temperatures can influence human decisions. Housing purchase decisions are complicated, often demanding significant cognitive effort and consideration of consumption commitments, mortgage decisions, and broader portfolio implications (Cocco, 2005; Yao and Zhang, 2005; Chetty and Szeidl, 2007; Hu and Lee, 2020).

To the extent that individuals use cognitive shortcuts when exposed to high temperatures, these shortcuts may manifest themselves among other observable behaviors and outcomes. Specifically, buyers subject to extreme heat may experience increased search costs. To avoid

[5] In the sections that follow, we provide a detailed analysis of the underlying drivers of this effect, including mechanisms such as a reduction in buyer search activities and weakened bargaining power.

[6] Goldsmith-Pinkham and Shue (2023) document that female buyers achieve significantly lower returns on housing investments compared to their male counterparts.

extreme heat, buyers may under-visit potential units, viewing only a limited set of properties and potentially relying on attention-grabbing online rankings and descriptions that are likely to present units in a positive light. As a result, increased information asymmetry between buyers and sellers may narrow the opportunity set of housing options available to buyers and bias their perceptions of housing units upward (i.e., the less buyers search, the more difficult it is to find a better priced home with comparable characteristics). In turn, the transaction price they pay may also become biased upward.

To test this idea, we examine weekly on-site housing viewing frequency as a proxy for buyers' search efforts.[7] Our results indicate that high temperatures have a negative and statistically significant impact on buyers' in-person housing viewing activities. In addition, we present evidence that high temperatures at the time of transaction are positively correlated with both the initial listing price and final listing price of properties chosen by buyers. Together, these findings imply that high temperatures lead buyers to consider a narrower set of more expensive properties than they would otherwise.

While our main conjecture is that extreme heat is likely to elicit a behavioral response from buyers (who travel more than the sellers and thus are more exposed), we acknowledge that a reduction in search efforts can also be consistent with a rational response to extreme heat. Moreover, when buyers reduce on-site viewings due to extreme heat, they naturally have less opportunities to negotiate with sellers, which mechanically implies that prices have a smaller chance of being lowered from initial listing values. However, we provide two pieces of evidence consistent with buyers in our sample overreacting to extreme heat when searching for a home. First, the economic magnitude of our results suggests that a behavioral interpretation is more appropriate; it is difficult to rationalize an average spike in transaction prices of RMB 13,007 ($1,858 USD) in response to extreme ambient temperatures. Furthermore, we conduct a survey of buyers, eliciting information on their willingness-to-pay under extreme

[7] On-site housing viewings are crucial for buyers to gather information about a property's interior. Only properties viewed on-site are likely to be included in a buyer's consideration set.

heat. Our survey results rule out the possibility that changes in buyers' search behavior and price adjustments are driven entirely by rational responses to extreme heat.

Next, we consider several tests directly aimed at examining the cognitive effects of heat, whereby extreme heat can affect cognitive functioning, mood, and productivity (Baylis, 2020; Ebi et al., 2021; Somanathan et al., 2021). First, we consider how sellers' actions contribute to the price effects we document. In particular, we examine how sellers' pricing behaviors on the supply side are affected by extreme heat. Our results indicate that high temperatures lead to a decrease in the frequency of sellers' price adjustments. However, we find no effect on sellers' initial listing prices and the total subsequent price adjustment. Taken together, these results imply that the impact of high temperatures on sellers' pricing behaviors does not substantially contribute to the overall impact of temperatures on transaction prices. Importantly, this result, combined with our earlier finding of a positive correlation between high temperatures and both the initial and final listing prices of transacted homes, suggests that it is buyers who drive our main result by narrowing their search under extreme heat.

We further consider how strategic interactions between buyers and sellers during price negotiations are affected by heat extremes. To the extent that both buyers' and sellers' cognitive function and decision-making are potentially affected by high temperatures, the resultant net impact on prices and other outcomes is dependent upon which group experiences a more pronounced decline. To answer this empirical question and better understand the bargaining power dimension, we compute two bargaining measures that compare initial and final listing prices against the final transaction price. We estimate how these measures are affected by abnormally high temperatures, and consistently find a significant relation indicative of net bargaining power shifting in the direction of sellers. Put another way, our results suggest that when buyers consider a subset of properties with higher listing prices amid high temperatures, they are unable to negotiate commensurate price discounts.[8]

[8]Oftentimes, buyers need repeated negotiations to bring down the price from the initially listed value. Reducing search activities and visits due to extreme heat reduces their opportunities for negotiation. This result is also consistent with buyers being at a relative disadvantage to sellers, since buyers are exposed to

Finally, we examine how high temperatures affect buyers' attention toward online listings. If extreme heat directs buyers' attention toward properties that are highly ranked online, then we would expect increased variability in online attention for properties. Using demand-side data, we calculate the standard deviation in online attention across listed properties in a given community. Our estimates indicate that high temperatures indeed lead to more pronounced variation in online attention for housing. In addition, we examine the correlation between the attention garnered by different communities in the current week compared to the previous week. Consistent with heightened attention, we find that high temperatures amplify this correlation.

Collectively, our results support that buyers experiencing extreme heat use cognitive shortcuts and that the resultant biases manifest through observable spikes in transaction prices plausibly unrelated to housing fundamentals. In our final set of tests, we explore heterogeneity and robustness in our baseline results. We first investigate the heterogeneity in market segment, i.e., the extent to which the price impact of extreme heat is concentrated in high- vs. low-end housing units. We include interaction terms and find a stronger effect of high temperatures on transaction prices for high-end apartments. Furthermore, we present additional evidence indicating that the impact of high temperatures on onsite housing viewings is also more pronounced for high-end apartments. We also explore and report heterogeneity on the dimensions of regional effects, housing market cycles, buyer characteristics, and seasons. Finally, we address the concern that especially extreme heat waves may lead residents to leave affected areas, generating a result counter to our main findings. We find that even the most extreme heat waves in our sample do not generate price declines.[9]

Our findings enrich the extensive literature exploring how environmental factors influence individual financial decision-making. This body of work primarily examines the impact on

extreme heat when traveling to view properties and conduct final on-site negotiations. In contrast, sellers are not subject to extreme heat ahead of on-site negotiations, because these proceedings are typically conducted at their own home and do not require travel.

[9]Maybe extreme heat waves in China just do not make living conditions intolerable for residents.

investor behavior, trading performance, and stock returns, of weather (Cortés et al., 2016; Dehaan et al., 2017; Goetzmann et al., 2015), sunlight intensity (Hirshleifer and Shumway, 2003), pollution (Huang et al., 2020; Li et al., 2021), etc.[10] Our work contributes by documenting the impact of climate-change-related heat extremes on housing prices, as well as buyers and sellers' behavior while exploring the potential mechanisms at play.[11]

Our study also contributes to the burgeoning field of climate finance, particularly the set of papers focusing on the implications of rising temperatures on business and financial outcomes. For instance, Pankratz et al. (2023) reveal that high temperatures negatively affect corporate performance; Addoum et al. (2020) find that extreme heat does not significantly impact the sales and productivity of the average U.S. firm or business establishment. Meanwhile, Addoum et al. (2023) explore the influence of extreme heat on profits across different industries, and their occasional manifestation in analyst earnings forecasts and stock prices. Studies involving the impact of climate change on housing prices focus on the long-term effects of climate risk beliefs, such as sea-level rise triggered by climate change (Bakkensen and Barrage, 2022; Baldauf et al., 2020; Bernstein et al., 2019; Giglio et al., 2021; Murfin and Spiegel, 2020). We consider individual behavioral responses triggered by temperature increases, focusing on the potential cognitive impact of heat extremes on buyers and sellers, and documenting the resultant effect on transaction prices, wealth transfers, and welfare

[10] In the context of general consumption, Haggag et al. (2019) document consumers' attribution biases.

[11] In comparison to the literature exploring the impact of weather-related conditions on cognitively demanding individual behaviors and performances, e.g., stock trading (Huang et al., 2020), analysts' forecasts (Dehaan et al., 2017; Dong et al., 2021), and outdoor ticket purchases (Buchheim and Kolaska, 2017), housing transactions possess three distinct and crucial characteristics. First, houses are both investment and consumption goods (Hu and Lee, 2020), subject to not only investment-related behavioral biases stemming from reduced cognitive functions, but also changes in subjective consumption preferences induced by environmental factors. Second, housing wealth constitutes approximately 70% of an average family's total wealth in China, rendering housing transactions the most significant decisions for most households. Consequently, individuals might exhibit fewer behavioral biases attributed to environmental conditions due to more meticulous considerations in housing purchase decisions. Whether environmental factors induce behavioral biases in individuals within the housing market and ultimately impact transaction prices remains an empirical question. Third, the heterogeneity in prices and returns within the housing market is influenced by variation in bargaining power and effort among buyers and sellers (Cvijanović and Spaenjers, 2021). Accordingly, how and the extent to which weather-related conditions affect housing transaction prices is also affected by bargaining power and efforts of both buyers and sellers.

redistribution in the housing market.

The third related strand of literature examines the impact of individual behavioral biases on transactional outcomes in the housing market. Such biases include superstitions (Andersen and Nielsen, 2017; Bhattacharya et al., 2021), conspicuous spending motives (He et al., 2020), discrimination (Christensen and Timmins, 2022), misinformation (Chinco and Mayer, 2016), stigma from exogenous auction failures (Cortés et al., 2022), sunk-costs-related effects (Ratnadiwakara and Yerramilli, 2022) and price-salience-related behavioral effects (Agarwal and Karapetyan, 2022).[12] Our paper adds by investigating the relationship between rising temperatures associated with climate change and individual behaviors in the housing market, and the underlying mechanisms.[13]

The rest of the article is organized as follows. Section 2 provides institutional details. Section 3 introduces the data, reports summary statistics, and describes the empirical strategy. Sections 4 and 5 present main empirical results and analyze the underlying mechanisms. Section 6 discusses heterogeneity, robustness and welfare analysis, before Section 7 concludes.

2 Institutional Background

For at least two decades in the new century, China's housing market became a primary driver of economic growth, due to a combination of factors including urbanization, economic expansion, and land/housing reforms (Sun et al., 2017). Per capita residential space for urban residents increased from 14.87 square meters in 2000 to 39.8 square meters in 2019.[14]

[12]For instance, Andersen and Nielsen (2017) provide empirical evidence demonstrating that forced sales resulting from sudden deaths of housing owners lead to fire sale discounts. Ratnadiwakara and Yerramilli (2022) find that sunk costs positively impact sellers' decisions regarding listing prices, thereby affecting transaction prices. Agarwal and Karapetyan (2022) illustrate how making debt and the total price salient for buyers mitigate mispricing caused by buyers' inattention, thereby alleviating unintentional borrowing.

[13]Our work is related to the study of Hu and Lee (2020), which explores the impact of sentiment on housing transactions, focusing on auction sales. Our research differs in that (i) we explore individuals' underlying cognitive functioning and behavioral biases, (ii) our sample covers most major cities in China (as opposed to focusing on a single city), with broad geographic distribution enabling us to explore regional heterogeneity and housing market cycles, and (iii) our unique datasets capture both house viewing activities—the demand side—and detailed sellers' price adjustments—the supply side, which is rare and not explored in prior studies.

[14]https://news.sina.com.cn/c/255505.html. Retrieved July 30, 2023

Meanwhile, housing prices experienced a significant surge from 2,000 yuan per square meter in 2000 to 9,307 yuan (RMB) per square meter in 2019—an increase of 365%.[15] In traditional Chinese culture, home-ownership holds profound significance, especially for young adults before marriage. As of 2019, housing assets accounted for about 70% of total assets among Chinese households,[16] contributing significantly to their wealth, with a homeownership rate reaching an impressive 96%.[17] Figure A1 in Appendix A illustrates the trend of average urban housing prices from 2000 to 2020 in four major Chinese cities, exhibiting marked increases from 2008 onward.

China's housing market is primarily comprised of two types of transactions: new property sales and resale (second-hand) transactions. In new property transactions, developers set standardized prices for completed properties. Buyers directly visit sales offices for inquiries, make deposits, and complete payments without a negotiation process, leading to highly standardized pricing. In contrast, the resale market involves homeowners setting an initial listing price and potentially making subsequent adjustments. During on-site viewings, buyers engage in price negotiations with homeowners that significantly shape final transaction prices. Our research focuses on resale housing transactions.

Our data is sourced from one of China's largest real estate agency platforms, which handles a variety of property transactions, including resale, new property sales, and rentals. By 2019, this company had expanded its operations to encompass over 30 major cities across China, boasting a network of over 8,000 branches and employing more than 100,000 real estate agents. It held a market share exceeding 50% in Beijing's real estate intermediary sector and ranked among the top two in market share in cities such as Tianjin, Qingdao, Nanjing, and Chengdu. The company introduced its website and app in 2014, facilitating online browsing of resale homes for potential buyers. This platform enables users to select

[15] https://baijiahao.baidu.com/s?id=1655968257643641934&wfr=spider&for=pc. https://baijiahao.baidu.com/s?id=1731063100820151774&wfr=spider&for=pc. Retrieved July 3, 2023

[16] https://baijiahao.baidu.com/s?id=1664955012368433005&wfr=spider&for=pc. Retrieved Oct 30, 2023.

[17] https://wlmq.jiwu.com/news/4018541.html. Retrieved Oct 30, 2023.

real estate agents and communicate with them directly. It also offers features such as community popularity rankings, accessible on both the website and app, which provide valuable assistance to buyers in neighborhood selection and other aspects of property acquisition.

The process and steps involved in resale property transactions are as follows: When buyers intend to purchase a resale property, they can contact real estate agents at a nearby real estate agency branch or browse various communities and property listings on the company's website or app. Each community or property listing is associated with specific agents, allowing potential buyers to establish online connections. Upon contact, buyers communicate their preferences, including location and property characteristics, to the agent. The agent then typically suggests approximately a dozen properties for consideration. Next, the buyer selects three to five preferred property listings for on-site viewings. The agent accompanies the buyers for property viewings and arranges a meeting between the buyer and the seller for direct price negotiations at the property.[18] On-site viewings are typically scheduled within two to four days, though some appointments are arranged on the same day buyers first contact the agents.

Alternatively, buyers can autonomously search and browse various communities and property listings available on the website or app. These listings are linked to different agents, thereby leading buyers to reach out to distinct agents to communicate, inspect properties, and explore additional listings. This allows buyers to identify a property that aligns more closely with their preferences and potentially at a lower price under comparable conditions. This process ensures that buyers receive personalized assistance while retaining the flexibility to independently explore and evaluate potential properties.

When buyers conduct on-site property viewings, they make decisions after carefully assessing the property and listing prices. There could be three scenarios: First, if the buyer is unhappy with the property, they can withdraw immediately. Second, if content with the

[18]Because on-site housing viewings and final price negotiations are conducted at the considered properties, buyers are typically more exposed to extreme heat than sellers, who are often at their own residence.

property but unable to reach an agreement with the seller on price, the buyer may opt to withdraw or engage in another round of price negotiations. This typically involves revisiting the property with the same seller within a few days for further on-site viewing and negotiations.[19] Third, if the buyer finds the property satisfactory and agrees upon a price with the seller, both parties will proceed to sign the contract on-site. Usually, the buyer initiates the transaction by paying a 5% deposit, with the remaining payment settled later. The transaction time recorded in the company's data system refers to the moment when the buyer signs the contract with the seller after concluding on-site negotiations and expressing satisfaction with the property.

For sellers, initiating the sale of a resale property involves reaching out to an agent responsible for their neighborhood, either through the company's physical branches or app. The agent facilitates the process by helping the seller upload pertinent property documents and other details. In addition, the agent arranges for a company photographer to capture images of the property, which are then uploaded onto the website for prospective buyers to browse. Meanwhile, sellers set an initial listing price, which they can subsequently adjust.

3 Data and Empirical Strategy

3.1 Data Description

We obtain a unique dataset on resale housing from one of China's largest real estate agency platforms, covering 24 major cities across China and spanning the period between January 1, 2015 and December 31, 2019. The list of cities included in the sample is presented in Table A1 of Appendix A. Compared with existing studies on housing transactions (Cvijanović and Spaenjers, 2021; Hu and Lee, 2020), a key advantage of our dataset lies in its

[19]Notably, we interviewed some agents and found that the bargaining process between buyers and sellers always occurs during on-site property viewings and requires the presence of an agent. This is because agency companies, in order to prevent "double-dealing" (i.e., bypassing the agent to complete transactions privately), do not allow buyers and sellers to contact each other directly.

extensive coverage. In addition to transaction prices on over 600,000 resale properties, our dataset includes a demand-side component capturing on-site housing viewing records and online attention metrics representing buyers' demand, comprising over 30 million records. In addition, a supply-side component details sellers' initial pricing and price adjustments, also totaling over 30 million records. The supply- and demand-side information offers a nuanced and dynamic understanding of buyers' and sellers' behaviors, thereby facilitating our analyses of underlying mechanisms such as search costs, attention-driven behaviors, etc.

The resale housing transaction dataset includes comprehensive information on apartment and transaction characteristics, such as number of rooms, building size, building age, floor level, proximity to school districts and subway stations, transaction prices and dates, buyer demographics, and initial and final listing prices of the sold properties. Notably, the transaction date refers to the specific time when buyers and sellers negotiate the transaction price with the assistance of agents and finalize the contract on-site. Summary statistics for transaction outcomes are detailed in Panel A of Table 1.[20] The average natural logarithm of the unit sale price stands at 10.265, corresponding to an average transactional unit price of 28,710 RMB/m^2 (approximately 4,081 USD/m^2). The average natural logarithm of the total transaction price is 5.41, equivalent to an average total price of 2.236 million RMB (approximately 320,000 USD). In addition, the average room count is 2.156, the average building size is 83.90, approximately 51.9% of apartments are situated within school districts, about 48.3% are in close proximity to subway stations, and 50.3% of buyers are male.

The dataset on buyers' housing demand is a panel that provides comprehensive details, including weekly on-site viewing counts and online attention metrics for each listed property, as well as detailed apartment characteristics such as building age, size, floor level, and number of rooms. The on-site viewing activities and online attention directed toward listed properties by buyers serve as key indicators of their demand and can be used to measure search frictions. These metrics play an important role in validating potential underlying

[20]The definitions of variables are provided in Table A2.

mechanisms. The summary statistics presented in Panel B of Table 1 indicate that the mean of weekly onsite viewings per property is 1.67. To explore the role of attention, we also compile a supplementary dataset capturing community-level online attention, reflecting individuals' subjective preferences for the community where the property is located. Summary statistics for this dataset, as reported in Panel B of Table 1, show that the average weekly online attention measure (i.e., number of online views) at the community level is approximately 11.

On the supply side, the dataset on sellers' pricing and price adjustments encompasses weekly data on price adjustment counts, magnitudes, directions, and initial pricing for each listed property, as well as apartment characteristics including building age, area, floor, and number of rooms. This dataset directly reflects sellers' dynamic pricing strategies, offering insights into their responses to high temperatures with respect to pricing behaviors. Summary statistics detailed in Panel C of Table 1 report an average weekly price adjustment count of 0.208 per listed property. On average, upward adjustments occur approximately 0.056 times, while downward adjustments take place around 0.146 times. In terms of adjustment magnitudes, the net effect averages -1.235%. The average magnitude for upward adjustments is around 4.45%, while downward adjustment magnitudes average 3.64%.

Following Huang et al. (2020), we source temperature and other weather-related data at the city level from the National Meteorological Administration. This dataset includes mean, maximum, and minimum temperatures, humidity, sunshine hours, wind speed, and precipitation. Aggregating to the city-week level, we merge these weather variables with the three housing market datasets. Given the potential influence of air pollution on individuals' cognitive performance and mood (Dong et al., 2021), we also incorporate data on two key pollutants—sulfur dioxide and PM2.5—at the city level from China's Ministry of Environmental Protection. These variables are included in additional robustness tests. Panel D of Table 1 provides summary statistics for these variables, such as the average mean

temperature of 15.24°C, an average maximum temperature of 20.4°C, an average minimum temperature of 11.31°C, and average precipitation of 23.9 (measured in tenths of a millimeter) in our sample. On average, there are approximately 0.24 days per week throughout the year when the daily maximum temperature reaches 35°C. Figure A2 shows the trend of the annual frequency of regional heatwave events from 1960 to 2018. We can see that over the past sixty years, the frequency of heatwaves in China has significantly increased. After 2000, the annual frequency of heatwaves is approximately twice that of the period before 1990.

3.2 Empirical Specification

Similar to Baldauf et al. (2020) and Chu et al. (2021), we run a hedonic pricing model to examine the contemporaneous impact of extreme heat on housing transaction prices. Our baseline regression model is as follows:

$$\ln P_{ijct} = \mu_0 + \mu_1 temp_{ct} + \mu_2 X_{it} + \mu_3 W_{ct} + \delta_j + \partial_{cys} + \varepsilon_{it}, \tag{1}$$

where the dependent variable, $\ln P_{ijct}$, is the natural logarithm of the unit or total transaction price for transaction i within business area j in city c during week t.[21] $temp_{ct}$ denotes the average temperature of city c during week t, the period in which transaction i takes place. In many tests, we replace $temp_{ct}$ with three key high-temperature bin variables: temp > 35, temp30_35, and temp25_30, which represent the number of days within the transaction week where the maximum temperatures are above 35°C, between 30°C and 35°C, and between 25°C and 30°C, respectively.[22][23] X_{it} encompasses various apartment characteristics and geographical factors, including number of floors, building age, number of rooms, building

[21] Note that in Eq. (1), since building size is included as a control variable, *lntotalprice* does not capture the size effect. Instead, it serves as an alternative dependent variable, functioning as a robustness check.

[22] We measure extreme heat exposure at the weekly level in our empirical specifications since this allows us to incorporate intensity of treatment into our non-linear effects by counting the number of days within a week that fall into different high-temperature bins, such as those exceeding 35°C.

[23] We do not include a temperature bin above 40°C because, even in southern Chinese cities, days exceeding 40°C are extremely rare (fewer than 2–3 per year), making the inclusion of such a bin econometrically problematic due to data sparsity.

size, decoration status, proximity to school districts, and adjacency to subway stations. δ_j represents location-specific fixed effects based on business area,[24] addressing concerns regarding neighborhood conditions' impact on prices. ∂_{cys} represents a city-year-season fixed effect, controlling for any citywide seasonal trends and policy shocks. Standard errors are clustered at the district level.[25]

To address the concern that other local weather conditions might confound the relationship between local temperatures and transaction prices, we include other city-wide weather-related variables, W_{ct}, capturing humidity, sunshine hours, precipitation, wind speed, etc., in city c during week t. Our coefficient of interest, μ_1, captures the impact of contemporaneous temperatures on housing transaction prices. A positive estimate for μ_1 would indicate that contemporaneous heat exposure has a positive impact on transaction prices.[26]

4 Main Results

4.1 Baseline Linear Specification

To understand the relationship between contemporaneous temperature increases and transaction prices, we first estimate Eq.(1) and report our baseline linear estimation results in Table 2. In Column (1), we include only city-year-season fixed effects and location-specific

[24]Business areas such as SanLiTun refer to geographical units within a city. A business area typically includes several dozen to a hundred communities, while an administrative district often encompasses ten to thirty business areas.

[25]In China, a typical city is comprised of 4-5 districts, with each district including around ten business areas. In Appendix C3, we show that our estimation results are robust to clustering standard errors at the city level, as well as two-way clustering at the district-week and city-week levels.

[26]Notably, it seems unlikely that our estimates would be driven by reverse causality or omitted variables. First, the independent variable of interest, local temperatures, stands as a robust exogenous variable. It is highly unlikely that negotiated housing prices or individual behaviors regarding housing investments exert influence on local temperatures. Second, our specification includes an extensive set of time-varying control variables and a comprehensive array of fixed effects. Third, as noted by Chen et al. (2019), unobservable time-varying confounders such as cultural characteristics, societal customs, and changes in individuals' preferences tend to evolve on longer timescales, often on yearly or semi-annual cycles, remaining relatively unchanged within shorter time-frames such as weeks or months. Hence, our empirical specification is likely to provide a robust strategy for addressing challenges posed by reverse causality and unobservable confounders.

fixed effects, which control for seasonal trends, city-level macroeconomic cycles, and time-invariant location-specific factors such as neighborhood conditions (e.g., proximity to a top school). The coefficient estimates on *temp* are positive and statistically significant, implying that housing prices are higher when the local temperature is high, beyond what is already captured or expected for that city in a particular season. In Column (2), we add controls related to apartment characteristics, such as size, building age, floor number, decoration, number of rooms, proximity to school districts, and proximity to subway stations. The results in Column (2) are similar to those in Column (1), showing that the positive relation between housing prices and local temperature persists after including hedonic controls.[27]

Finally, to address the potential concern that other weather-related factors confound the relationship between local temperature and housing prices, we follow Huang et al. (2020) and include additional local weather-related measures as control variables in our regressions. Specifically, we include measures of local humidity, sunshine hours, precipitation, and wind speed. Controlling for these weather-related factors, the coefficient estimate on temperature remains positive and statistically significant in Column (3) of Table 2. In particular, we find that the estimated coefficient on *temp* is 0.0148, indicating that a one-standard-deviation increase in contemporaneous temperatures is associated with a 1.48% (0.0148%*100.03) increase in housing transaction prices.[28] Furthermore, when we replace the dependent variable *lnprice* with *lntotalprice* and re-estimate Eq (1), the estimation results reported in Columns (4)-(6) of Table 2 remain quantitatively similar to those in Columns (1)-(3).

[27]Note that the influence of apartment characteristics on housing prices aligns with findings in existing literature. Attributes such as decoration status, room count, proximity to school districts, and accessibility to subway stations consistently demonstrate a positive impact on housing prices. Conversely, factors such as size, floor number, and building age exhibit negative correlations with housing prices. The negative relationship between size and housing prices might stem from larger apartments having lower unit prices per square meter, assuming other variables remain constant. During our sample period, many buildings in China's cities, especially those with six to eight stories, lacked installed elevators. Consequently, this situation potentially led to relatively lower prices for higher floor levels, all else being equal.

[28]Here, the unit of temperature is 0.1 degrees Celsius.

4.2 Nonparametric Tests

Our initial tests provide evidence that elevated contemporaneous temperatures are associated with higher transaction prices in the housing market. However, this relationship is not necessarily driven by extreme heat alone. It may be that moderate temperatures positively influence transaction prices, with potentially attenuated effects at the extremes. To further investigate the nonlinear relationship between high temperatures and pricing, we follow Barreca et al. (2016) and Hoffmann and Rud (2024) and define three key high-temperature bins: *temp>35*, *temp30_35*, and *temp25_30*, representing the number of days within the week of a transaction with maximum temperatures above 35°C, between 30°C and 35°C, and between 25°C and 30°C, respectively. We then replace *temp* with *temp>35*, *temp30_35*, and *temp25_30*, and re-estimate the baseline regression specified in Eq (1).

The estimation results reported in Table 3 show that nearly all estimates associated with the three high-temperature bins are positive and statistically significant, with the largest coefficients observed in the temp>35 bins. The estimation results align with those in Table 2, indicating a positive impact of high temperatures on transaction prices. For instance, focusing on column (3) of Table 3, the estimates indicate that an additional day during the transaction week with maximum temperature above 35℃ increases housing transaction prices by about 0.54%, while an additional day within the 30℃-35℃ range corresponds to an increase in housing transaction prices of about 0.15%.[29] Considering that the average unit price of apartments in our sample is RMB 28,710, with an average size of 83.9 square meters, an additional day with maximum temperature above 35℃ translates to an increase in housing transaction prices by about RMB 13,007 (0.54% * 28,710 * 83.9 sqm). Given that RMB 13,007 amounts to nearly 42.32% of China's per capita income in 2018 (which was RMB 30,733), the welfare implication of this effect is economically sizable.

[29]The expression "an additional day with a maximum temperature within high-temperature bins" refers to an additional day during the transaction week.

5 Economic Channels

Thus far, our tests have documented that exposure to high temperatures generates a positive and significant effect on housing prices. In particular, controlling for an extensive set of characteristics (i.e., size, age, floor number, number of rooms, and proximity to both schools and subways) and holding city, year, and season fixed, we find that exposure to higher temperatures is associated with a positive impact on housing prices that is both economically and statistically significant. We now turn to uncovering the underlying mechanisms.

5.1 Search Costs and Information Asymmetry Channel

Cvijanović and Spaenjers (2021) argue that heterogeneity in prices and returns can be attributed in part to individuals' search costs and information asymmetry. Specifically, buyers with relatively high search costs and information constraints may end up paying higher transaction prices and earning lower returns. When buyers face higher search costs and greater information asymmetry, a consequent reduction in opportunity set makes it more challenging to find a lower-priced housing option that meets their needs (all else being equal).

In our context, high temperatures may elevate buyers' search costs and information constraints by inducing fatigue and impairing their cognitive function and productivity, leading to reduced on-site housing views. To test this idea, we replace *lnprice* with *viewing* (i.e., the number of on-site housing viewings for each property within a week) as the dependent variable and re-estimate Eq (1).

Consistent with our predictions, the estimated coefficients on $temp > 35$ and $temp30_35$ in column (1) of Table 4 are both negative and statistically significant.[30] Notably, the coefficient estimates for $temp > 35$ are the most substantial, followed by $temp30_35$. The effects are economically significant: an additional day with maximum temperature above

[30]For brevity, we do not report the coefficient estimates for the weather-related or housing characteristic control variables in the subsequent analyses.

35°C results in a 1.38 percent decrease in on-site property viewings. Furthermore, replacing three high-temperature bins with *temp* and re-estimating Eq (1) yields a positive and statistically significant coefficient (see column (2) of Table 4), indicating that the linear effect is inconsistent with the nonparametric result. This discrepancy arises because low-temperature environments can also lead to a significant decrease in on-site property viewings by buyers.

Next, we further explore how high temperatures might elevate buyers' search costs by examining the extent to which buyers limit the set of properties they consider amid extreme heat. Specifically, we examine whether the initial and final listing prices of properties selected by buyers are higher during extreme heat episodes. Together with our earlier finding that buyers limit their on-site viewings when exposed to extreme heat, a finding that buyers ultimately choose more expensive properties, despite identical property characteristics, would suggest that increased search costs manifest through narrower consideration sets.

We test this conjecture by replacing the dependent variables *lnprice* and *lntotalprice* with *lnprice_last*, *lntotalprice_last*, *lnprice_initial*, and *lntotalprice_initial*, representing the last and initial listing prices of transacted properties, and re-estimate Eq (1).[31] The estimation results, reported in Table 5, show a positive and statistically significant relation between high temperatures and the final and initial listing prices of houses. In columns (1) and (2) of Table 5, the estimated coefficients on $temp > 35$ and *temp*30_35 are positive and statistically significant at the 1% level. Taking column (1) of Table 5 as an example, during the week of the transaction, an additional day with a maximum temperature above 35°C is associated with a 0.31% increase in the final listing price, while an extra day within the 30°C-35°C range corresponds to an increase in the final listing price by about 0.13%. In columns (3) and (4) of Table 5, the estimated coefficients on $temp > 35$ are both positive and statistically significant. Column (3) indicates that an additional day with a maximum

[31]Specifically, *lnprice_last* is the natural logarithm of the final listed unit price of the sold property; *lntotalprice_last* is the natural logarithm of the final listed total price of the sold property; *lnprice_initial* is the natural logarithm of the initial listed unit price of the sold property; and *lntotalprice_initial* is the natural logarithm of the initial listed total price of the sold property.

temperature above 35°C is associated with a 0.185% increase in the initial listing price.

One interpretation of these results could be that buyers rationally reduce their search behaviors due to heightened search costs during extreme heat episodes. If high temperatures make on-site viewings uncomfortable for buyers, it may be rational to reduce the search intensity to maximize overall utility, even if this results in higher transaction prices due to a smaller opportunity set.[32] Put another way, potential buyers may be willing to pay a certain price to avoid the discomfort of on-site viewings amid high temperatures. We rule out this rational interpretation by providing two pieces of complementary evidence. First, we note that it is unlikely that buyers would rationally reduce their search efforts and overpay as much as indicated in our previous results. In particular, we find that the average increase in transaction prices exceeds the typical buyer's average weekly wage. This economic magnitude is more likely to be the result of a behavioral response than a rational response to the discomfort of extreme heat.

To lend further support for a behavioral interpretation of our search cost results, we conduct a survey of potential buyers. Specifically, we ask buyers to evaluate the following statement: "Assuming that reducing in-person viewings would increase the total transaction price you pay, how much more would you be willing to pay in RMB to reduce one on-site home viewing on a day when the maximum temperature exceeds 35 degrees Celsius?" More specific details about the questionnaire can be found in Appendix B. Based on 169 valid responses, our survey results show that, on average, buyers are willing to pay 682 RMB (96 USD) to avoid one on-site home viewing during extreme heat. This willingness-to-pay (WTP) can be seen as a rational benchmark for the role of search costs. This benchmark is an order of magnitude lower than the 7,551 RMB (1,064 USD) indicated in Column (1) of Table 5.[33] That is, buyers' reported willingness-to-pay accounts for only 9% (682 ÷ 7551)

[32]Here, overall utility can be thought of as increasing in residential and investment returns from a successful home purchase and decreasing in transaction price paid, time and effort costs of searching, and discomfort from on-site home viewings in high temperatures.

[33]Taking Column (1) of Table 5 as an example, the average unit last listed price of the houses in our sample is RMB 29,349, with an average size of 83.9 square meters. An additional day with maximum temperatures

of the total amount paid by buyers that is attributable to search costs and information asymmetry.[34] Taken together, our evidence supports the conclusion that extreme heat leads buyers to irrationally consider a narrower set of more expensive properties.

Next, we consider the extent the total effect of extreme heat can be attributed to this channel. Our computations are motivated by the rationale that buyers' narrower consideration sets due to extreme heat directly affect the final listing prices of transacted properties, but do not affect subsequent events affecting transaction prices such as on-site bargaining. Thus, we approximate the proportion of the total effect of extreme heat attributable to search cost and information asymmetry channel by calculating the ratio of the increase in final listing prices of transacted properties to the increase in final transaction prices.

To calculate this ratio, we first consider the case where the maximum temperature during the week of the transaction exceeds 35°C. The estimated coefficient on temp>35 for transaction price in column (3) of Table 3 is 0.5424, and the estimated coefficient on temp>35 for last listing price in column (3) of Table 5 is 0.3109. The average natural logarithm of transaction price is 10.265, and the average natural logarithm of the last listing price is 10.287. Therefore, the search costs and information asymmetry channel can explain $\frac{0.3109 \times 10.287}{0.5424 \times 10.265} = 57.4\%$ of the total effect.

We also consider the case where the highest temperature during the week of the transaction falls between 30-35°C. The estimated coefficient on temp30_35 for transaction price in column (3) of Table 3 is 0.1505, and the estimated coefficient on temp30_35 for last listing price in column (3) of Table 5 is 0.1261. Thus, the search cost and information asymmetry channel explains $\frac{0.1261 \times 10.287}{0.1505 \times 10.265} = 84\%$ of the total effect in this case. Collectively, our estimates suggest that search costs and information asymmetry induced by extreme heat explain over half of the total price impact on transaction prices we document.

exceeding 35°C is associated with an increase in the last listed total prices of transacted houses by an average of RMB 7,551 (0.31% * 29,349 * 83.9 sqm).

[34]Here, we use the changes in the last listed prices of transacted homes as a proxy for the overpayment generated by search costs and information asymmetry channels, since searching behaviors directly affect the last listed prices of homes in buyers' consideration sets, all else being equal.

5.2 Strategic Interactions Between Buyers and Sellers

We next consider additional channels related to buyers' and sellers' interactions, and how they relate to the effects of extreme heat we document in the housing market. In particular, we examine the impact of sellers' responses to extreme heat, as well as bargaining interactions between buyers and sellers.

Supply-side responses to high temperatures. In our first set of tests, we examine how sellers' pricing behaviors on the supply side are affected by extreme heat. We examine three dimensions: the setting of initial listing prices, the frequency of price adjustments, and the magnitude of price adjustments. To understand how high temperatures impact initial listing prices, we replace the dependent variable in Eq (1) with *lnnew_list_price* for the natural logarithm of the unit listing price and *lnnew_list_totalprice* for the natural logarithm of the total listing price. We then re-estimate regression Eq (1) using three high-temperature bins. The estimation results presented in Table A3 indicate that the estimated coefficients on $temp > 35$ and $temp30_35$ are both insignificant.[35] While the coefficient for $temp25_30$ is significant, this category only reflects a relatively mild level of high temperatures. Therefore, this result does not provide evidence supporting the notion that extreme heat influences sellers' initial listing prices.[36]

Next, we explore the pricing adjustment strategies employed by sellers in response to high temperatures. We include a new variable, *total_adjusttimes*, representing the number

[35] In the dataset we utilize to capture sellers' pricing behaviors, there is no information provided regarding whether a property is in a school district or not. Consequently, school is not included in our set of control variables. However, we control for location-specific fixed effects, ensuring that the estimation results are not materially affected.

[36] The conclusion drawn here that high temperatures do not significantly affect sellers' initial listing prices is not contradictory to the positive and statistically significant relation between high temperatures and the listing price of transacted properties discussed in Section 5.1. The estimation results in Section 5.1 focus on the relationship between high temperatures and both the initial and final listing prices of transacted properties. This result, combined with the findings of the current section, indicates that sellers' initial price-setting behaviors on the supply side do not directly influence transaction prices. Instead, the primary effect stems from the increased difficulty buyers face in selecting a lower-priced property under similar conditions amid high temperatures.

of price adjustments for an apartment within a week. We then replace the dependent variable in Eq (1) with *total_adjusttimes* and re-estimate Eq (1). In Table A4, column (1) shows that the estimated coefficients on $temp > 35$ and $temp30_35$ are both negative and statistically significant. This suggests a decrease in the frequency of pricing adjustments by sellers in response to high temperatures. Furthermore, when examining the frequency of upward and downward price adjustments, the estimation results presented in columns (2) and (3) of Table A4 indicate that high temperatures reduce the frequency of both upward and downward price adjustments. Specifically, the estimation results suggest that within a given week, an additional day with maximum temperatures exceeding 35°C leads to an approximately 0.76% decrease in the total frequency of pricing adjustments by sellers. It also results in a 0.23% reduction in the frequency of upward pricing adjustments and a 0.48% decrease in the frequency of downward pricing adjustments. These findings align with our expectation that high temperatures impair sellers' productivity, leading to fewer pricing adjustments.

We further investigate how the magnitude of sellers' price adjustments changes in response to high temperatures. We introduce three dependent variables: *total_adjustmag* represents the net effect of the magnitude of price adjustments after accounting for both upward and downward adjustments; *up_adjustmag* reflects the absolute magnitude of upward adjustments; and *down_adjustmag* captures the absolute magnitude of downward adjustments.[37] Re-estimating Eq (1), the results in column (5) of Table A4 in Appendix A show statistically significant and negative coefficient estimates on $temp > 35$ and $temp30_35$, indicating a decrease in the magnitude of upward pricing adjustments due to high temperatures. Specifically, the result indicates that within a given week, an additional day above 35°C reduces the magnitude of upward pricing adjustments by 2.04%. In column (6) of Table A4, the estimated coefficient for $temp > 35$ is positive and statistically significant at the 5% level, suggesting that high temperatures significantly increase the magnitude of downward

[37]Note that *total_adjustmag* measures the net effect of upward and downward price adjustments. A positive and statistically significant coefficient estimate suggests that the magnitude of upward price adjustments increases relative to that of downward price adjustments during periods of high temperatures.

pricing adjustments. This may be because high temperatures weaken sellers' capabilities to rationally adjust pricing, driving both upward and downward adjustments to deviate from the norm. In addition, the decline in rational pricing adjustment ability may lead sellers to worry about extended sale periods (i.e., failing to complete the transaction within a particular amount of time), thereby adopting more conservative pricing strategies. This results in a decrease in the magnitude of upward price adjustments and an increase in the magnitude of downward price adjustments.

Regarding the total price adjustment, the estimation results in column (4) of Table A4 show that the estimated coefficient for $temp > 35$ is statistically insignificant.[38] Although the coefficient estimates for $temp25_30$ and $temp30_35$ are negative and statistically significant, considering their relatively lower temperature ranges compared to $temp > 35$, and the insignificant estimated coefficients for $temp > 35$, we remain cautious in concluding that high temperatures negatively affect the sellers' total price adjustments. However, it does suggest that high temperatures do not increase the total price adjustments (i.e., systematically raise listing prices).

Taken together, our estimation results indicate that while extreme heat negatively impacts the frequency of sellers' price adjustments, it does not significantly increase the pricing of newly listed properties or the total price adjustments for existing listings. Hence, the supply side impact of high temperatures on the pricing behaviors of sellers does not substantially contribute to the primary effects we document.

Bargaining power. We further explore how strategic interactions between buyers and sellers during price negotiations are affected by temperature extremes. Goldsmith-Pinkham

[38]While high temperatures have a negative impact on the magnitude of upward price adjustments and a positive impact on the magnitude of downward price adjustments, it is not surprising that high temperatures do not have a significant effect on the total price adjustment. This is because both the frequency of upward price adjustments and the frequency of downward price adjustments significantly decrease under the influence of high temperatures. As a result, the total price adjustment, which reflects the net effect, may not show a significant change.

and Shue (2023) and Cvijanović and Spaenjers (2021) argue that the dynamics of bargaining power between buyers and sellers significantly impact transaction prices and returns in the housing market. Specifically, in instances where buyers possess relatively low bargaining power, they tend to pay higher prices, *ceteris paribus*. The bargaining process in the housing market involves negotiations between buyers and sellers. Since extreme heat has the potential to weaken the bargaining power of both parties, the net impact on outcomes depends on whether buyers or sellers experience a more pronounced effect.

Empirically, we construct two variables to measure buyers' bargaining power:

$$bargain_last = \frac{totalprice_last - totalprice}{totalprice_last}, \tag{2}$$

$$bargain_initial = \frac{totalprice_initial - totalprice}{totalprice_initial}, \tag{3}$$

where *totalprice_last* denotes the last total listing price, *totalprice_initial* is the initial total listing price, and *totalprice* is the total transaction price. *bargain_last* assesses buyers' bargaining power by determining the difference between the last total listing price and the total transaction price, then dividing this by the last total listing price. Similarly, *bargain_initial* evaluates buyers' bargaining power by calculating the disparity between the initial total listing price and the total transaction price, then dividing this by the initial total listing price. We then include *bargain_last* and *bargain_initial* as dependent variables and re-estimate Eq (1) for each.[39] If the bargaining power channel contributes to the positive impact of high temperatures on housing prices, we would expect that the coefficient estimates on extreme temperatures are negative and statistically significant, since extreme heat would weaken buyers' bargaining power relative to that of sellers.

The estimation results are shown in Column (1) and Column (4) of Table 6. The coefficient estimates on $temp > 35$ are both negative and statistically significant for *bargain_last*

[39]Here, we include *bargain_initial* as a robustness check for our main measure of buyers' bargaining power, *bargain_last*.

and *bargain_initial*, indicating that the bargaining power channel is indeed an underlying mechanism through which high temperatures positively affect housing prices. Taking Column (1) of Table 6 as an example, we observe that the estimated coefficient on $temp > 35$ is -0.19 and is statistically significant at the 1% level. This indicates that during the week of a transaction, an additional day with maximum temperature above 35°C decreases the average buyers' bargaining power by approximately 6.55% relative to the mean ($0.19\% \div 0.029$).

This outcome might be attributed to the fact that buyers typically aim to negotiate a price below the most recent listing price, while sellers aim to maintain listing prices and use them as a reference point. As a result, buyers often need to exert significant effort to negotiate lower prices at the time of transaction. In contrast, the cognitive effort requirements for sellers are relatively low. Consequently, extreme heat may weaken the bargaining power of buyers more than that of sellers. Additionally, since on-site housing viewings and final price negotiations are conducted at the property under consideration, buyers are typically more exposed to extreme heat than sellers, who are often at their own residence. Moreover, extreme heat reduces opportunities for in-person negotiation between buyers and sellers, thereby lowering the buyers' ability to bring the price down from the anchoring values sellers initially list.

We also explore the effect of extreme heat on bargaining power on both the intensive and extensive margins. To examine the intensive margin, we focus on successfully negotiated transactions (i.e., transactions where *bargain_last* or *bargain_initial* is positive). The estimation results in Columns (2) and (5) of Table 6 show negative and statistically significant coefficient estimates on $temp > 35$ and *temp*30_35 for *bargain_last* (Intensive) and *bargain_initial* (Intensive). Similarly, when employing the linear variable *temp* as the independent variable of interest to investigate intensive margin effects, we obtain consistent results, as indicated in Columns (2) and (5) of Table A5 in Appendix A.

Turning to the extensive margin, we examine the extent to which the propensity for

buyers to successfully negotiate below-ask transaction prices is affected by extreme heat. Specifically, we replace values greater than 0 in the dependent variable *bargain_last* with 1, while values of 0 remain unchanged, and then re-estimate Eq (1). The estimation result in Column (3) of Table 6 shows a negative and statistically significant coefficient estimate on $temp > 35$ and *temp*30_35 for *bargain_last* (Extensive). Similarly, we construct and use *bargain_initial* (Extensive) as the dependent variable and then replace three high temperature bins with *temp* to further examine the extensive margin effects. The estimation results, shown in Column (6) of Table 6 and Columns (3) and (6) of Table A5 in Appendix A, yield consistent findings, confirming the existence of extensive margin effects in the weakening of buyers' bargaining power. In sum, the effect of extreme heat on bargaining power serves to diminish the ability of buyers to successfully negotiate below-ask transaction prices on both the intensive and extensive margins.

5.3 Attention Channel

In our final set of tests, we examine how high temperatures affect buyers' attention. These tests are motivated by prior studies documenting that individual investors often purchase attention-grabbing stocks, which subsequently generate suboptimal returns (Fang et al., 2014). Recently, Huang et al. (2020) demonstrate that air pollution limits trading capabilities, leading individuals to focus more on prominent stocks. This shift in focus leads to the acquisition of attention-grabbing stocks, driving worsening trade performance. Motivated by these findings, our conjecture is that high temperatures may lead buyers to focus on attention-grabbing apartments via limitations in their cognitive abilities and decision-making skills. In our context, home buyers may rely on attention-grabbing properties available on the websites or apps of real estate agency platforms when making housing choices. If buyers concentrate their attention on these attention-grabbing properties, this may reduce the likelihood of selecting a lower-priced home with similar features that also fulfills their needs.

To test this conjecture, we examine whether potential buyers direct increased attention toward properties that are more highly ranked online (or apartments located in more highly ranked communities). Figure A3 provides an example of an apartment's online ranking. To the extent that potential buyers are drawn toward attention-grabbing properties amid extreme heat, we would expect increased variability in online attention for properties. To investigate this, we construct a panel dataset at the community level and create a new variable, $sd(attention_community)$, which represents the standard deviation in the number of online views for each apartment within a week at the community level. We then replace *lnprice* with $sd(attention_community)$ as the dependent variable in Eq (1).

The estimation results reported in column (1) of Table 7 validate our predictions. We find that $temp > 35$ and $temp30_35$ both have a positive and statistically significant impact on $sd(attention_community)$. Specifically, during the week of the transaction, an additional day with a maximum temperature above 35°C increases $sd(attention_community)$ by approximately 0.61%, while an extra day within the 30°C-35°C range corresponds to an increase in $sd(attention_community)$ by about 0.31%. Moreover, upon replacing the three high temperature bins with *temp* and re-estimating Eq (1), the estimation results presented in column (2) of Table 7 remain consistent.

Next, we consider the fact that potential buyers may rely on online platforms for initial community selection and assessment. In turn, community rankings on such platforms can serve as a crucial reference point for decision-making among buyers subject to extreme heat. Figure A4 displays the user interface for our data provider's online platform, highlighting the community rankings available on the agency's website and app. To the extent that community rankings serve as an attention grabber for potential buyers subject to extreme heat, we expect high temperatures to amplify the week-to-week autocorrelation in community-level online views.

To test this conjecture, we define $attention_community(t-1)$, representing the total

online views a community received in the previous week, while the dependent variable, $attention_community(t)$, denotes the total online views received in the current week. We include $attention_community(t-1)$, three high temperature bins, and their interaction terms in Eq (1) and re-estimate the regression. The estimation results, presented in column (1) of Table 8, show positive and statistically significant coefficient estimates on $temp > 35 * attention_community(t-1)$ and $temp30_35 * attention_community(t-1)$, thereby supporting our conjecture. Specifically, during the week of the transaction, an additional day with maximum temperature above 35°C leads to about a 0.27% increase in the correlation between $attention_community(t)$ and $attention_community(t-1)$. Moreover, we incorporate the linear variable $temp$, along with its interaction terms with $attention_community(t-1)$, and re-estimate Eq (1). The results in column (2) of Table 8 demonstrate that the estimated coefficient on $temp * attention_community(t-1)$ is positive and statistically significant, which is consistent with our nonlinear estimation results. Taken together, our results suggest that buyers subject to extreme heat are prone to focusing on attention-grabbing properties and communities, suggesting that attention is an underlying mechanism through which high temperatures affect housing prices.

6 Robustness, Heterogeneity, and Welfare

6.1 Robustness Checks

We present additional robustness checks in Appendix C. In particular, we show that our main results are robust to the inclusion of additional control variables, alternative fixed effect specifications, and alternative methods of adjusting for clustered standard errors.[40] Furthermore, we demonstrate that our conclusions remain unchanged when accounting for the contemporaneous effects of precipitation, under alternative temperature measures, and

[40] Additional control variables include air pollution-related variables and buyers' demographic characteristics. Alternative fixed effect refers to city-year-month fixed effects.

when including leads and lags of temperature. An additional concern may be that if heat waves become significantly more severe in the future, housing prices would eventually decline as people might choose to leave the affected areas. However, extreme heat waves of such magnitude are highly unlikely to occur in major Chinese cities. Furthermore, within our sample, we find that prices do not decline even after the most extreme heat waves. The estimation results are displayed in Figure A6. For more details, please see Appendix C.

6.2 Understanding Heterogeneity

Heterogeneity in market segments. We first investigate whether the impact of high temperatures on housing transaction prices varies with market segments, using high-end apartments (versus low-end apartments) as a proxy for housing market segmentation. Prior studies document that individuals tend to seek compensatory consumption when experiencing negative emotions, thereby alleviating their negative feelings and achieving psychological compensation (Briers and Laporte, 2013; Sharma and Alter, 2012). High temperatures, as a negative environmental factor akin to air pollution, may negatively impact individuals' emotions and reduce their perceived quality of living spaces. As a result, buyers may prioritize evaluating quality attributes over merely considering prices to improve their living experience and attain psychological compensation.[41] Hence, buyers affected by high temperatures may exhibit increased subjective demand for promptly enhancing their living quality, potentially making them more willing to pay higher prices. We predict that the impact of high temperatures on housing transaction prices is more pronounced among high-end apartments. In addition, we also expect that high temperatures have a stronger positive impact on buyers' demand for high-end apartments compared to lower-end apartments. This stems from the notion that higher-end apartments are better suited to fulfill individuals' subjective demand

[41] That is, high temperatures may lead buyers to prioritize enhancing their living environment, potentially placing less weight on pricing in their housing decisions.

for improving their living environment.[42]

To test these conjectures, we include *area* (the building sizes), *room* (the numbers of rooms), and their interaction terms with three high temperature bins in Eq (1). We then use *viewing*, buyers' on-site property viewing activities, as a proxy for changes in subjective demand and replace the dependent variable with *viewing*. The estimation results are presented in Table 9. In column (1), the coefficient estimates on $temp > 35 * area$, $temp30_35 * area$, and $temp25_30 * area$ are all positive and statistically significant. Moreover, in column (2), the coefficient estimates on $temp > 35 * room$, and $temp30_35 * room$ are both positive and statistically significant. Taken together, these results suggest that high temperatures indeed generate a more pronounced positive impact on buyers' housing viewing activities for high-end apartments relative to lower-end apartments.

Additionally, we replace the dependent variable with *lnprice* and *lntotalprice*. The rationale is that if changes in subjective demand indeed serve as a driving factor behind heterogeneity in market segments, high temperatures would exert a stronger positive influence on housing prices for high-end apartments compared to lower-end apartments. The estimation results, reported in Table 10 across Columns (1) to (4), exhibit positive and statistically significant coefficient estimates on $temp > 35 * area$, $temp30_35 * area$, $temp > 35 * room$, and $temp30_35 * room$. Collectively, these findings support our predictions, indicating that high temperatures indeed exert a more pronounced effect on prices for high-end apartments.[43]

Regional heterogeneity. Next, we explore the heterogeneity in the main effect between cities located in the southern and northern regions, guided by the theory of acclimatization.[44] Given that individuals in southern Chinese cities are more consistently exposed to hot cli-

[42]Moreover, the buyers of high-end apartments are typically high-income individuals, who may be more sensitive to the negative impact of the external environment on their living experience. In contrast, low-income groups have limited choices due to financial constraints.

[43]The estimation results from the heterogeneity analysis are used to calculate the wealth loss of buyers across different demographic groups for the welfare analysis.

[44]Acclimatization is defined by the U.S. Centers for Disease Control and Prevention as "the beneficial physiological adaptations that occur during repeated exposure to a hot environment."

mates, they may have developed a degree of adaptation to high temperatures. This potential adaptation could weaken the contemporaneous impact of exposure to high temperatures on housing transaction prices.

To test this idea, we introduce a new variable, *south_city*, assigned a value of 1 for cities in the sample situated in the southern region and 0 otherwise. We incorporate *south_city* and its interaction terms with three high-temperature bins and re-estimate Eq (1). The results presented in Table 11 show that the estimated coefficients on $temp > 35 * south_city$ are negative and statistically significant, supporting our predictions. Specifically, the estimates in Column (1) suggest that during the week of a transaction, an additional day with maximum temperature above 35°C results in a decrease in transaction prices for housing in southern cities by 36.62% compared to that in northern cities. That is, the positive impact of high temperatures on housing transaction prices is 36.62% lower for properties in southern regions compared to those in the north. This finding suggests that individuals residing in China's southern regions might experience a mitigated impact of short-term exposure to high temperatures on housing transaction prices, possibly due to their adaptive responses to elevated temperatures.

Heterogeneity throughout housing market cycles. We examine how the influence of high temperatures on housing transaction prices varies over different phases of the housing market cycle. Our estimation result suggests that during boom periods, the positive impact of the $temp > 35$ high-temperature bin on housing transaction prices is 27.79% weaker compared to non-boom periods. This result indicates that housing market booms play a negative moderating role on the impact of extreme heat on housing transaction prices. The detailed results are presented in Appendix Section C8.

Demographic heterogeneity. We also explore how the impact of high temperatures on housing transaction prices varies across different buyer groups, with a particular focus on

two key demographics: gender and age. The estimation results show that male buyers, compared to female buyers, experience a 27.45% greater impact on housing transaction prices in the $temp > 35$ high-temperature bin. We also observe that the coefficient estimates on $temp * buyer_age$ are negative and statistically significant. This suggests that buyer age may negatively moderate the main effect due to the buffering role of personal experience in decision-making. Appendix Section C9 reports estimation results and findings.

Heterogeneity across seasons. Finally, we examine how the effect of high temperatures on housing transaction prices varies across seasons. Our estimation results indicate that in spring, summer, and autumn, high temperatures positively affect housing transaction prices through the behavioral mechanisms documented above. The detailed discussion of the estimation results can be found in Appendix Section C10.

6.3 Welfare Analysis

We conduct back-of-the-envelope calculations to quantify the wealth redistribution effects among different groups. From Section 4.2, the estimation results show that an additional day during the transaction week with maximum temperature above 35°C increases housing transaction prices by 0.54%. Given that the average unit price of apartments in our sample is RMB 28,710 and the average size is 83.9 square meters, an additional day with maximum temperature above 35°C leads to an average increase of RMB 13,007 (0.54% * 28,710 * 83.9 sqm) (approximately USD 1,858) in housing transaction prices. Consequently, on average, an additional day with maximum temperature above 35°C during the transaction week results in an unexpected wealth transfer of USD 1,858 from buyers to sellers.

Furthermore, our heterogeneity analyses provide more granular insights into how high temperatures differentially affect buyers across various groups. These estimation results can help us quantify the wealth redistribution across different groups and identify the specific groups of buyers who experience the largest and smallest losses in wealth redistribution

triggered by extreme heat. Specifically, we focus on three key characteristics of buyers: region (South vs. North), gender (male vs. female), and income level (rich vs. poor).[45]

To calculate the differences in wealth redistribution among these groups, we utilize the heterogeneous estimates from Section 6.2. Specifically, in Column (2) of Table 10, the estimated coefficients of interaction terms for temp>35 and temp30_35 with *room* are 0.1981 and 0.1109, respectively. In Column (1) of Table A19, the coefficients for temp>35*gender and temp30_35*gender are 0.2745 and 0.0898, respectively. In Column (1) of Table 11, the coefficient for temp>35*south_city is -0.3662.[46] Then, we use the nonparametric estimation results from Column (3) of Table 3, where the estimated coefficients on temp>35 and temp30_35 are 0.5424 and 0.1505, respectively. These serve as the baseline coefficients for general buyers' responses to high temperature. We calculate the wealth redistribution values for different groups of buyers by multiplying the heterogeneous estimated coefficients.[47]

The wealth redistribution values for the eight groups are presented in Figure 1. From Figure 1, we can see that the wealth redistribution values differ significantly across groups under the impact of high temperatures. Moreover, within each group, the redistribution values associated with extreme high temperatures (temp>35) are larger than those from moderate high temperatures (temp30_35). Among these groups, "male+rich+north" buyers

[45]Here, income level (rich vs. poor) is proxied by buyers of high-end vs. low-end apartments. Specifically, we classify buyers of properties with 4 or more rooms as the "rich" group, while others are classified as the "poor" group. This reflects the reality of China's housing market, where high-end properties typically have 4 or more rooms, while mid- and low-end properties rarely have more than three rooms.

[46]Note that the differences in wealth redistribution between rich and poor buyers are influenced not only by differences in their sensitivity to high temperatures, which can affect transaction unit prices, but also by the variation in the total price structure of the apartments they choose. Here, we use the 75th percentile of total transaction prices in our sample, which is $541,400, as a proxy for the total price structure of "rich" buyers. Similarly, we use the 25th percentile of total transaction prices, which is $187,100, as a proxy for "poor" buyers' prices.

[47]For example, when calculating the wealth redistribution for the "male+rich+south" group associated with an additional day during the transaction week with maximum temperature above 35°C, we use:

$$W_{\text{male+rich+south}} = 541,400 \times 0.5424 \times \left(1 + \frac{0.2745}{2}\right) \times \left(1 + \frac{0.1981}{2}\right) \times \left(1 - \frac{0.3362}{2}\right) = 2,998 \text{ USD}.$$

For interaction terms, such as temp>35*gender, the coefficient captures the difference in male buyers' responses relative to females. Thus, we use $1 \pm \frac{\text{coefficient}}{2}$ to approximate group-level differences.

are the most affected by extreme heat (temp>35), with a wealth redistribution value of $4,343 to sellers. In comparison, "female+poor+south" buyers are the least affected, with a wealth redistribution value of just $645. That is, an additional day with maximum temperatures above 35°C during the transaction week leads to high-income males living in the North to pay, on average, $4,343 more in total transaction prices, while low-income females in the South pay, on average, $645 more. In sum, our welfare analysis demonstrates that the high-temperature-induced wealth redistribution effect in the housing market exhibits significant variation across buyers with different demographic characteristics.

The above welfare analysis focuses on the wealth transfer from buyers to sellers under the assumption that transaction probabilities during high-temperature weather are homogeneous among different groups. However, different demographic groups may exhibit heterogeneous sensitivity to high temperatures, leading to differences in transaction probabilities. This heterogeneity can affect the total wealth transfer value among groups. To address this, we replace the dependent variable in Eq (1) with the weekly transaction volume for each group and re-estimate Eq (1).[48] The estimates, reported in Figure A7, reveal that low-income males and females living in northern regions are the most negatively affected by high temperatures in terms of transaction volumes, while high-income groups experience trivial impact.[49]

Finally, we use the statistically significant coefficient estimates from Figure A7 as discount factors for the wealth transfer values, as they reflect the reduced transaction probabilities for each group. We then multiply these discount factors with the welfare redistribution values for each group reported in Figure 1, thus obtaining the net wealth redistribution values among the eight buyer groups shown in Figure A8. We can see that high-income male buyers living in northern regions experience the largest wealth losses due to high temperatures, significantly exceeding the losses of other groups. In comparison, the wealth losses for low-income female buyers are minimal, amounting to no more than $1,000. Notably, within the same wealth

[48]Here, the transaction volume refers to the weekly number of transactions at the zipcode level.

[49]This may be because low-income groups in China are less likely to own cars, making it more difficult for them to travel during high-temperature periods.

bracket and region, female buyers consistently experience lower wealth losses than their male counterparts. This suggests that high temperatures may have the unanticipated effect of reducing the gender gap in buyers' housing investment returns.[50]

7 Conclusion

We investigate how extreme heat affects housing transaction prices as well as the underlying mechanisms. Leveraging a unique, detailed dataset of approximately 60 million observations, encompassing housing transaction data, buyers' demand data, and home seller pricing data, we find an economically and statistically significant positive relationship, arguably unexpected, between exogenous high temperatures (unrelated to house fundamentals in any foreseeable term) and housing transaction prices. Furthermore, we explore several underlying mechanisms, documenting the importance of behavioral biases stemming from exposure to extreme heat.

To our best knowledge, this paper is the first to explore the impact of high temperatures on transactions in the housing market and the underlying mechanisms linked to behavioral/cognitive biases. Overall, our findings add to the burgeoning climate finance literature and shed light on a novel financial impact of climate change. Considering the substantial financial costs buyers face, our findings offer practical guidance for buyers and inform policy-making. Interestingly, the wealth redistribution between buyers and sellers triggered by high temperatures may be less pronounced in southern regions compared to northern regions due to individual climate adaptability. As a result, our findings also highlight potential regional disparities in wealth distribution resulting from high temperatures. Moreover, our welfare analysis reveals substantial variation in the high-temperature-induced wealth redistribution effect within the housing market, depending on the demographic characteristics of buyers.

[50]Recent literature has documented that female buyers achieve significantly lower returns on housing investments compared to their male counterparts (Goldsmith-Pinkham and Shue, 2023).

For instance, we find that extreme heat unintentionally narrows the gender gap in housing investment returns between male and female buyers.

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Tables

Table 1: Summary Statistics

Variable	N	Mean	SD	P10	P50	P90
Panel A: Transaction						
lnprice	645,581	10.265	0.695	9.314	10.318	11.146
lntotalprice	645,581	5.411	0.734	4.419	5.442	6.333
lnprice_last	645,581	10.287	0.724	9.333	10.345	11.18
lnprice_initial	645,581	10.313	0.758	9.36	10.375	11.217
lntotalprice_last	645,581	5.433	0.758	4.431	5.464	6.373
lntotalprice_initial	645,581	5.461	0.782	4.454	5.505	6.399
bargain_last	645,581	0.029	0.036	0	0.024	0.063
bargain_initial	645,581	0.058	0.078	0	0.047	0.151
room	645,581	2.144	0.803	1	2	3
building age	645,581	3.491	1.396	1	2	2
decoration	645,581	1.483	0.639	0	1	2
floor	645,581	1.132	0.804	0	1	2
subway	645,581	0.519	0.500	0	1	1
school	645,581	0.485	0.500	0	1	2
area	645,581	83.90	36.15	47	79	129
buyer_age	645,581	0.098	0.298	0	0	0
gender	645,581	0.503	0.500	0	1	1
marriage	645,581	0.396	0.489	0	0	1
boom	645,581	0.235	0.424	0	0	1
Panel B: Demand side						
viewing	31,090,555	1.663	3.028	0	1	5
sd(attention_community)	4,388,974	1.670	1.741	0	1.155	3.844
attention_community(t)	5,091,979	10.804	19.328	0	4	28
area	31,090,555	1.658	1.354	0	1	4
room	31,090,555	2.397	0.899	1	2	3
building age	31,090,555	3.476	1.445	2	3	5
decoration	31,090,555	1.371	0.699	0	1	2
floor	31,090,555	1.094	0.825	0	1	2
subway	31,090,555	0.488	0.500	0	0	1

Continued on next page

Table 1 – Continued from previous page

Variable	N	Mean	SD	P10	P50	P90
school	31,090,555	0.468	0.499	0	0	1
Panel C: Supply side						
lnnew_list_price	4,515,755	10.171	0.729	9.210	10.159	11.141
lnnew_list_totalprice	4,515,755	5.422	0.795	4.357	5.425	6.471
total_adjusttimes	30,950,636	0.208	0.483	0	0	1
up_adjusttimes	30,950,636	0.056	0.231	0	0	0
down_adjusttimes	30,950,636	0.146	0.386	0	0	1
total_adjustmag	5,525,054	-1.235	4.277	-6.0	-1.87	4.65
up_adjustmag	1,746,144	4.449	3.164	1.18	3.45	10.34
down_adjustmag	4,152,014	3.641	2.650	1.01	2.94	7.53
area	30,950,636	1.655	1.353	0	1	4
room	30,950,636	2.395	0.899	1	2	3
building age	30,950,636	3.479	1.446	2	3	5
decoration	30,950,636	1.373	0.697	0	1	2
floor	30,950,636	1.095	0.825	0	1	2
subway	30,950,636	0.489	0.500	0	0	1
Panel D: Weather-related						
temp	31,090,555	152.41	100.034	4.286	168	274.429
temp>35	31,090,555	0.237	0.891	0	0	0
temp30_35	31,090,555	1.081	1.863	0	0	4
temp25_30	31,090,555	1.303	1.822	0	0	4
humidity	31,090,555	65.575	17.267	38.857	69.143	85.429
precipitation	31,090,555	23.889	42.170	0	5.571	71.429
sunlight	31,090,555	53.010	27.085	13	55	88.429
wind	31,090,555	21.306	6.878	13	20.571	30.571
so2	645,581	9.654	7.619	3	7.5	19.571
pm25	645,581	49.49	32.47	21.167	40.857	85.571
min_temp	645,581	113.1	100.5	-36.857	123.429	236.5
max_temp	645,581	204.0	100.1	52.143	223	321.571

Notes. In Panel A, this transaction-related dataset consists of resale homes transacted between January 2015 and December 2019. *lnprice*, *lnprice_last*, and *lnprice_initial* are measured in RMB per square meter. *lntotalprice*, *lntotalprice_last*, and *lntotalprice_initial*

are measured in 10,000 RMB. *room* is an indicator variable representing the number of rooms in the apartment, categorized into five groups: 1 for one bedroom, 2 for two bedrooms, 3 for three bedrooms, 4 for four bedrooms, and 5 for more than four bedrooms. *building age* is an indicator variable measuring the age of the building: 1 for 0-5 years, 2 for 5-10 years, 3 for 10-15 years, 4 for 15-20 years, 5 for 20-30 years, and 6 for over 30 years. *decoration* is an indicator variable reflecting the decoration status: 0 for unfinished, 1 for lightly decorated, and 2 for well-decorated. $floor$ denotes the apartment's floor level: 0 for low, 1 for mid, and 2 for high. *subway* is a binary variable indicating proximity to a subway: 1 for close, 0 otherwise. *school* is a binary variable indicating proximity to a school: 1 for close, 0 otherwise. *buyer_age* is a dummy variable for the buyer's age: 1 for elderly people aged 60 and above, and 0 for middle-aged and younger individuals under 60. *gender* is a dummy variable for the buyer's gender: 1 for male and 0 for female. *marriage* is a dummy variable for the buyer's marital status: 1 for married and 0 for unmarried. *boom* is a dummy variable indicating whether the housing market cycle in the city is in a boom phase. If the average monthly house price growth rate in the city has been positive for each of the past six months, the value is set to 1; otherwise, it is set to 0. Following Ratnadiwakara and Yerramilli (2022), all housing-price-related variables such as *lnprice*, *lnprice_last*, *lnprice_initial*, *lntotalprice*, *lntotalprice_last*, and *lntotalprice_initial* are winsorized at the 1st and 99th percentiles. Panel B presents the descriptive statistics of the demand-side dataset. *area* is an indicator variable indicating residential area size. If the area is less than 60 square meters, the value is 0. For areas between 60-90 square meters, the value is 1. For areas between 90-120 square meters, the value is 2. For areas between 120-140 square meters, the value is 3. For areas between 140-180 square meters, the value is 4. If area is greater than 180 square meters, the value is 5. $sd(attention_community)$ and $attention_community(t)$ is sourced from a panel dataset at the community level. *viewing*, $sd(attention_community)$, and $attention_community(t)$ are winsorized at the 1st and 99th percentiles. Panel C presents the descriptive statistics of the supply-side dataset. All variables related to pricing and price adjustment behavior of supply-side sellers, such as *lnnew_list_price*, are winsorized at the 1st and 99th percentiles. Panel D reports the descriptive statistics for weather-related variables. For simplicity, we primarily present the descriptive statistics from the demand-side dataset. *min_temp* represents the average daily minimum temperature of the week in which the transaction occurs, while *max_temp* represents the average daily maximum temperature of the week in which the transaction occurs. See Table A2 for a comprehensive definition of these variables.

Table 2: Preliminary Results (Linear)

VARIABLES	**lnprice**			**lntotalprice**		
	(1)	(2)	(3)	(4)	(5)	(6)
temp	0.0141***	0.0135***	0.0148***	0.0129***	0.0130***	0.0140***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
area		-0.1049***	-0.1049***		0.7351***	0.7351***
		(0.015)	(0.015)		(0.020)	(0.020)
building age		-5.2066***	-5.2067***		-6.7631***	-6.7632***
		(0.341)	(0.341)		(0.283)	(0.283)
floor		-1.1689***	-1.1689***		-1.2372***	-1.2372***
		(0.202)	(0.202)		(0.211)	(0.211)
decoration		4.5056***	4.5058***		5.5114***	5.5117***
		(0.176)	(0.176)		(0.195)	(0.195)
room		4.2545***	4.2534***		12.6738***	12.6728***
		(0.441)	(0.441)		(0.480)	(0.480)
school		16.7377***	16.7427***		13.6652***	13.6707***
		(3.745)	(3.744)		(4.270)	(4.269)
subway		1.9285***	1.9291***		1.5924***	1.5930***
		(0.486)	(0.486)		(0.516)	(0.516)
precipitation			-0.0015*			-0.0009
			(0.001)			(0.001)
humidity			-0.0211***			-0.0193***
			(0.005)			(0.005)
sunlight			-0.0054**			-0.0033
			(0.002)			(0.002)
wind			0.0255***			0.0277***
			(0.007)			(0.008)
Observations	645,581	645,581	645,581	645,581	645,581	645,581
Adjusted R^2	0.932	0.939	0.939	0.725	0.930	0.930
City*year-quarter FE	Y	Y	Y	Y	Y	Y
Location FE	Y	Y	Y	Y	Y	Y

Notes. This table shows linear effect of contemporaneous temperature increases on housing transaction prices. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the unit sale price, and *lntotalprice*, representing the natural logarithm of the total transaction price. The independent variable of interest in our analysis is *temp*, denoting the average temperature of city c during the week t corresponding to transaction i. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Baseline Results: Using Three High-Temperature Bins

VARIABLES	**lnprice**			**lntotalprice**		
	(1)	(2)	(3)	(4)	(5)	(6)
temp>35	0.6179***	0.5755***	0.5424***	0.4687***	0.5892***	0.5500***
	(0.048)	(0.048)	(0.048)	(0.068)	(0.050)	(0.050)
temp30_35	0.1665***	0.1522***	0.1505***	0.0749*	0.1317***	0.1297***
	(0.022)	(0.021)	(0.022)	(0.044)	(0.021)	(0.022)
temp25_30	0.1057***	0.0879***	0.0715**	0.0241	0.0825***	0.0626**
	(0.032)	(0.030)	(0.031)	(0.045)	(0.031)	(0.032)
area		-0.1048***	-0.1048***		0.7352***	0.7352***
		(0.015)	(0.015)		(0.020)	(0.020)
building age		-5.2069***	-5.2069***		-6.7632***	-6.7633***
		(0.341)	(0.341)		(0.283)	(0.283)
floor		-1.1723***	-1.1719***		-1.2405***	-1.2401***
		(0.202)	(0.202)		(0.211)	(0.211)
decoration		4.5063***	4.5063***		5.5122***	5.5122***
		(0.176)	(0.176)		(0.195)	(0.195)
room		4.2515***	4.2513***		12.6708***	12.6706***
		(0.441)	(0.441)		(0.481)	(0.481)
school		16.7338***	16.7387***		13.6593***	13.6647***
		(3.751)	(3.750)		(4.276)	(4.275)
subway		1.9285***	1.9284***		1.5924***	1.5923***
		(0.485)	(0.485)		(0.515)	(0.515)
precipitation			-0.0000			0.0004
			(0.001)			(0.001)
humidity			0.0038			0.0042
			(0.004)			(0.004)
sunlight			0.0055***			0.0066***
			(0.002)			(0.002)
wind			0.0220***			0.0243***
			(0.007)			(0.007)
Observations	645,581	645,581	645,581	645,581	645,581	645,581
Adjusted R^2	0.932	0.939	0.939	0.725	0.930	0.930
City*year-quarter FE	Y	Y	Y	Y	Y	Y
Location FE	Y	Y	Y	Y	Y	Y

Notes. This table reports the nonlinear effect of contemporaneous high temperatures on housing transaction prices. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the unit sale price, and *lntotalprice*, representing the natural logarithm of the total transaction price. The independent variables of interest in our analysis are *temp>35*, *temp*30_35, and *temp*25_30, denoting the number of days with temperatures above 35℃, between 30℃ and 35℃, and between 25℃ and 30℃, respectively, in city c during week t, corresponding to transaction i. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Search Cost and Information Asymmetry Channel

VARIABLES	**viewing**	
	(1)	(2)
temp>35	-0.0138***	
	(0.004)	
temp30_35	-0.0070***	
	(0.002)	
temp25_30	0.0026	
	(0.005)	
temp		0.0024***
		(0.000)
area	-0.2251***	-0.2249***
	(0.016)	(0.016)
building age	-0.0326***	-0.0319***
	(0.011)	(0.011)
floor	-0.0769***	-0.0767***
	(0.008)	(0.008)
decoration	-0.0725***	-0.0722***
	(0.010)	(0.010)
room	-0.1527***	-0.1528***
	(0.021)	(0.021)
school	0.0806	0.0788
	(0.068)	(0.068)
subway	0.0688***	0.0687***
	(0.014)	(0.014)
Observations	31,090,555	31,090,555
Adjusted R^2	0.114	0.115
Weather Controls	Y	Y
City*year-quarter FE	Y	Y
Location FE	Y	Y

Notes. This table presents the impact of high temperatures on on-site property viewing frequency. Our dependent variable is *viewing*, which represents the number of property viewings by buyers for each housing unit per week. The independent variable of interest in column (1) is *temp*, denoting the average temperature of city c during the week t corresponding to transaction i. The independent variables of interest in column (2) are *temp>35*, *temp*30_35, and *temp*25_30, denoting the number of days with temperatures above 35℃, between 30℃ and 35℃, and between 25℃ and 30℃, respectively, in city c during week t, corresponding to transaction i. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Correlation between High Temperatures and Listing Price of the Transacted Property: Using Three High-Temperature Bins

VARIABLES	**Final Listed Price**		**Initial Listed Price**	
	(1)	(2)	(3)	(4)
	lnprice_last	**lntotalprice_last**	**lnprice_initial**	**lntotalprice_initial**
temp>35	0.3109***	0.3216***	0.1853**	0.2063***
	(0.065)	(0.065)	(0.072)	(0.069)
temp30_35	0.1261***	0.1066***	0.0773*	0.0620
	(0.033)	(0.030)	(0.041)	(0.038)
temp25_30	0.0185	0.0126	-0.0308	-0.0310
	(0.046)	(0.045)	(0.052)	(0.049)
area	-0.1153***	0.7245***	-0.1025***	0.7360***
	(0.013)	(0.021)	(0.014)	(0.021)
building age	-5.3616***	-6.9137***	-5.1544***	-6.6985***
	(0.332)	(0.276)	(0.332)	(0.271)
floor	-1.2882***	-1.3528***	-1.1648***	-1.2239***
	(0.206)	(0.214)	(0.193)	(0.199)
decoration	4.3968***	5.4057***	4.1584***	5.1706***
	(0.177)	(0.193)	(0.179)	(0.195)
room	4.7572***	13.1792***	4.5217***	12.9704***
	(0.410)	(0.545)	(0.419)	(0.543)
school	16.8377***	13.7629***	16.5991***	13.4841***
	(3.847)	(4.364)	(3.782)	(4.299)
subway	2.0332***	1.6929***	1.9575***	1.6171***
	(0.503)	(0.532)	(0.536)	(0.554)
Observations	645,581	645,581	645,581	645,581
Adjusted R^2	0.892	0.892	0.822	0.843
Weather Controls	Y	Y	Y	Y
City*year-quarter FE	Y	Y	Y	Y
Location FE	Y	Y	Y	Y

Notes. This table displays the relationship between high temperatures and the final listed prices of the properties sold. We utilize four main dependent variables: *lnprice_last*, representing the natural logarithm of the final listed unit price of the sold property; *lntotalprice_last*, indicating the natural logarithm of the final listed total price of the sold property; *lnprice_initial*, representing the natural logarithm of the initial listed unit price of the sold property; and *lntotalprice_initial*, indicating the natural logarithm of the initial listed total price of the sold property. The independent variables of interest in our analysis are *temp>35*, *temp*30_35, and *temp*25_30, denoting the number of days with temperatures above 35℃, between 30℃ and 35℃, and between 25℃ and 30℃, respectively, in city c during week t, corresponding to transaction i. For ease of presentation, our dependent variables, *lnprice_initial*, *lntotalprice_initial*, *lnprice_last*, and *lntotalprice_last*, are multiplied by 100. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Effect on net Bargaining Power: Using Three High-Temperature Bins

VARIABLES	**bargain_last**			**bargain_initial**		
	(1) **(Total)**	(2) **(Intensive)**	(3) **(Extensive)**	(4) **(Total)**	(5) **(Intensive)**	(6) **(Extensive)**
temp>35	-0.1912***	-0.0985***	-0.0265***	-0.2331***	-0.1433***	-0.0137***
	(0.010)	(0.010)	(0.001)	(0.021)	(0.018)	(0.001)
temp30_35	-0.0036	-0.0077**	-0.0163***	-0.0281***	-0.0364***	-0.0015***
	(0.004)	(0.003)	(0.001)	(0.009)	(0.008)	(0.001)
temp25_30	0.0018	0.0002	-0.0006	-0.0288***	-0.0265***	-0.0005
	(0.005)	(0.004)	(0.001)	(0.011)	(0.010)	(0.001)
area	-0.0009	0.0087***	-0.0005***	0.0020	0.0183***	-0.0004***
	(0.002)	(0.001)	(0.000)	(0.003)	(0.001)	(0.000)
buliding age	-0.0033	0.0240	0.0024*	0.1543***	0.1942***	0.0050***
	(0.023)	(0.017)	(0.001)	(0.038)	(0.033)	(0.001)
floor	-0.0558***	-0.0326***	-0.0019***	0.0362	0.0760**	-0.0002
	(0.006)	(0.007)	(0.000)	(0.028)	(0.033)	(0.001)
decoration	-0.0637***	-0.1214***	0.0048***	-0.2212***	-0.4256***	0.0059***
	(0.024)	(0.018)	(0.001)	(0.054)	(0.035)	(0.002)
room	0.1222**	-0.0636*	0.0087***	0.1576*	-0.1356**	0.0060***
	(0.050)	(0.036)	(0.002)	(0.087)	(0.055)	(0.002)
school	0.0817	-0.0415	0.0167	-0.4994***	-0.5628***	-0.0065
	(0.145)	(0.067)	(0.017)	(0.181)	(0.156)	(0.012)
subway	0.0213	0.0002	0.0003	-0.0263	-0.0402	-0.0006
	(0.018)	(0.017)	(0.001)	(0.036)	(0.037)	(0.001)
Observations	645,581	583,980	645,581	645,581	566,040	645,581
Adjusted R^2	0.180	0.274	0.099	0.204	0.226	0.119
Weather Controls	Y	Y	Y	Y	Y	Y
City*year-quarter FE	Y	Y	Y	Y	Y	Y
Location FE	Y	Y	Y	Y	Y	Y

Notes. This table presents the effect of high temperatures on buyers' bargaining power. We employ two primary dependent variables: *bargain_last*, which assesses buyers' bargaining power by determining the difference between the last listed total prices and the total transaction prices, then dividing this by the last listed total prices; *bargain_initial*, which measures buyers' bargaining power by calculating the disparity between the initial listed total prices and the total transaction prices, and then dividing this by the initial listed total prices. The independent variables of interest in our analysis are *temp>35*, *temp*30_35, and *temp*25_30, denoting the number of days with temperatures above 35℃, between 30℃ and 35℃, and between 25℃ and 30℃, respectively, in city c during week t, corresponding to transaction i. Column (1) and (4) examine the total effect changes in bargaining power; Columns (2) and (5) show changes in bargaining power along the intensive margin, while Columns (3) and (6) show changes along the extensive margin. For ease of presentation, the dependent variables, $bargain_last(Total)$, $bargain_initial(Total)$, $bargain_last(Intensive)$, and $bargain_initial(Intensive)$, are multiplied by 100. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Attention-grabbing Channel: Standard Deviation of Online Attention

VARIABLES	**sd(attention_community)**	
	(1)	(2)
temp>35	0.6074***	
	(0.168)	
temp30_35	0.3148**	
	(0.149)	
temp25_30	-0.1994	
	(0.157)	
temp		0.1483***
		(0.005)
Observations	4,388,942	4,388,942
Adjusted R^2	0.220	0.221
Weather Controls	Y	Y
City*year-quarter FE	Y	Y
Location FE	Y	Y

Notes. This table presents the impact of high temperatures on the standard deviation of online attention received by housing units within the community level, used to verify the attention-grabbing channel. Our dependent variables: $sd(attention_community)$, signify the standard deviation of weekly online attention received by each housing unit within the community. The independent variables of interest in our analysis are $temp$, $temp>35$, $temp30_35$, and $temp25_30$, denoting the average temperatures and different temperature bins of city c during the week t corresponding to transaction i, respectively. For ease of presentation, the dependent variable $sd(attention_community)$ is multiplied by 100. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Attention-grabbing Channel: Path Dependence of Community Selection

VARIABLES	**attention_community(t)**	
	(1)	(2)
temp>35	-11.6151***	
	(1.346)	
temp30_35	2.7208**	
	(1.081)	
temp25_30	-1.8962*	
	(1.035)	
attention_community(t-1)	85.2746***	84.3025***
	(0.480)	(0.588)
temp>35*attention_community(t-1)	0.2662**	
	(0.119)	
temp30_35*attention_community(t-1)	0.1466***	
	(0.053)	
temp25_30*attention_community(t-1)	0.1803*	
	(0.099)	
temp		0.1084***
		(0.028)
temp*attention_community(t-1)		0.0092***
		(0.002)
Observations	5,091,952	5,091,952
Adjusted R^2	0.785	0.785
Weather Controls	Y	Y
City*year-quarter FE	Y	Y
Location FE	Y	Y

Notes. This table shows whether high temperatures amplify the correlation between the number of online attentions received by a community in week $t-1$ and the number of online attentions in week t, used to verify the attention-grabbing channel. The dependent variable is $attention_community(t)$, representing the number of online attentions received by the community in week t. The independent variables of interest in our analysis are $temp * attention_community(t)$, $temp > 35 * attention_community(t-1)$, $temp30_35 * attention_community(t-1)$, $temp25_30 * attention_community(t-1)$, capturing how high temperature moderates the relationship between the number of online attentions in week $t-1$ and week t for the community. For ease of presentation, our dependent variables $attention_community(t)$ are multiplied by 100. Robust standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Heterogeneity in Market Segment (housing viewings): Using Three High-Temperature Bins

VARIABLES	**viewing**	
	(1)	(2)
temp>35	-0.0268***	-0.0453***
	(0.004)	(0.006)
temp30_35	-0.0148***	-0.0032
	(0.003)	(0.008)
temp25_30	-0.0055	-0.0195***
	(0.007)	(0.006)
temp>35*area	0.0077***	
	(0.002)	
temp30_35*area	0.0047***	
	(0.001)	
temp25_30*area	0.0049***	
	(0.002)	
temp>35*room		0.0131***
		(0.002)
temp30_35*room		0.0052**
		(0.002)
temp25_30*room		0.0024
		(0.002)
Observations	31,090,555	31,090,555
Adjusted R^2	0.114	0.114
Housing Char.	Y	Y
Weather Controls	Y	Y
City*year-quarter FE	Y	Y
Location FE	Y	Y

Notes. This table presents how high temperatures affect on-site viewings of high-end properties compared to lower-end properties. The dependent variable is *viewing*, representing the total number of on-site property viewings by buyers for that housing unit within the week. The independent variables of interest in our analysis are *temp>35*area*, *temp30_35*area*, *temp25_30*area*, *temp>35*room*, *temp30_35*room*, and *temp25_30*room*, which capture how high temperatures affect the on-site viewings of properties with larger areas and more rooms relative to those with smaller areas and fewer rooms. Housing characteristics include area, building age, floor, decoration, room, school, and subway. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Heterogeneity in Market Segment (housing price): Using Three High-Temperature Bins

VARIABLES	**lnprice**		**lntotalprice**	
	(1)	(2)	(3)	(4)
temp>35	0.1791	0.1125	-0.2758	-0.0940
	(0.133)	(0.129)	(0.286)	(0.187)
temp30_35	-0.1488**	-0.0857	-0.0665	-0.1713*
	(0.063)	(0.056)	(0.125)	(0.087)
temp25_30	0.1360**	0.0993*	-0.0643	-0.2400**
	(0.060)	(0.057)	(0.239)	(0.101)
temp>35*area	0.0043***		0.0098***	
	(0.002)		(0.003)	
temp30_35*area	0.0036***		0.0024	
	(0.001)		(0.001)	
temp25_30*area	-0.0008		0.0015	
	(0.001)		(0.003)	
temp>35*room		0.1981***		0.2991***
		(0.058)		(0.081)
temp30_35*room		0.1109***		0.1410***
		(0.024)		(0.039)
temp25_30*room		-0.0119		0.1422***
		(0.027)		(0.048)
Observations	645,581	645,581	645,581	645,581
Adjusted R^2	0.939	0.939	0.930	0.930
Housing Char.	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
City*year-quarter FE	Y	Y	Y	Y
Location FE	Y	Y	Y	Y

Notes. This table presents how high temperatures affect housing transaction prices of high-end apartments compared to lower-end apartments. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the unit sale price, and *lntotalprice*, representing the natural logarithm of the total transaction price. The independent variables of interest in our analysis are *temp>35*area*, *temp30_35*area*, *temp25_30*area*, *temp>35*room*, *temp30_35*room*, and *temp25_30*room*, which capture how high temperatures affect housing prices of properties with larger areas and more rooms relative to those with smaller areas and fewer rooms. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. Housing characteristics include area, building age, floor, decoration, room, school, and subway. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

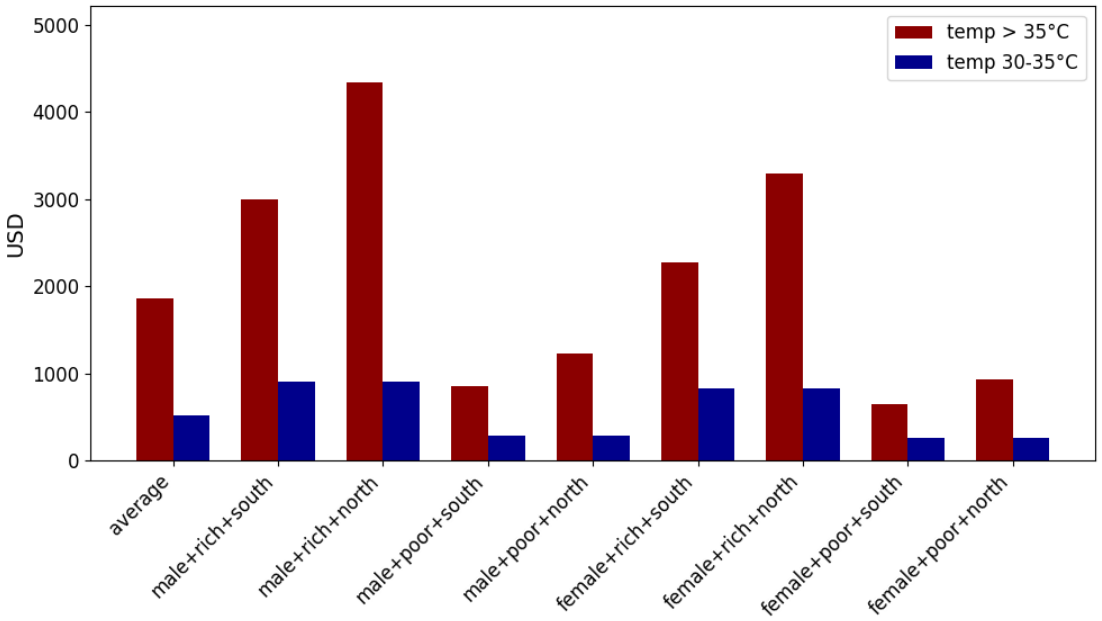
Table 11: Regional Heterogeneity (Adaptation Test): Using Three High-Temperature Bins

VARIABLES	**(1)** **lnprice**	**(2)** **lntotalprice**
temp>35	0.6987***	0.7136***
	(0.045)	(0.047)
temp30_35	0.1609***	0.1436***
	(0.026)	(0.025)
temp25_30	0.0814*	0.0736*
	(0.042)	(0.044)
temp>35*south_city	-0.3662***	-0.3835***
	(0.084)	(0.090)
temp30_35*south_city	-0.0329	-0.0423
	(0.044)	(0.045)
temp25_30*south_city	-0.0610	-0.0652
	(0.060)	(0.061)
Observations	645,581	645,581
Adjusted R^2	0.939	0.930
Housing Char.	Y	Y
Weather Controls	Y	Y
City*year-quarter FE	Y	Y
Location FE	Y	Y

Notes. This table presents whether there is a weaker relationship between high temperatures and housing prices in southern cities compared to northern cities. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the unit sale price, and *lntotalprice*, representing the natural logarithm of the total transaction price. The variable *south_city* is a binary variable that takes the value of 1 when the housing unit is located in a southern city and 0 otherwise. The independent variables of interest in our analysis are *temp>35*south_city*, *temp30_35*south_city*, and *temp25_30*south_city*, capturing how *south_city* moderates the relationship between temperature and housing transaction prices. Housing characteristics include area, building age, floor, decoration, room, school, and subway. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. Robust standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figures

Figure 1: Average Wealth Redistribution from Buyers by Demographic Groups



Notes. This figure presents the average incremental wealth loss from housing transactions experienced by buyers across different demographic groups during extreme heat.

Appendix A: Figures and Tables

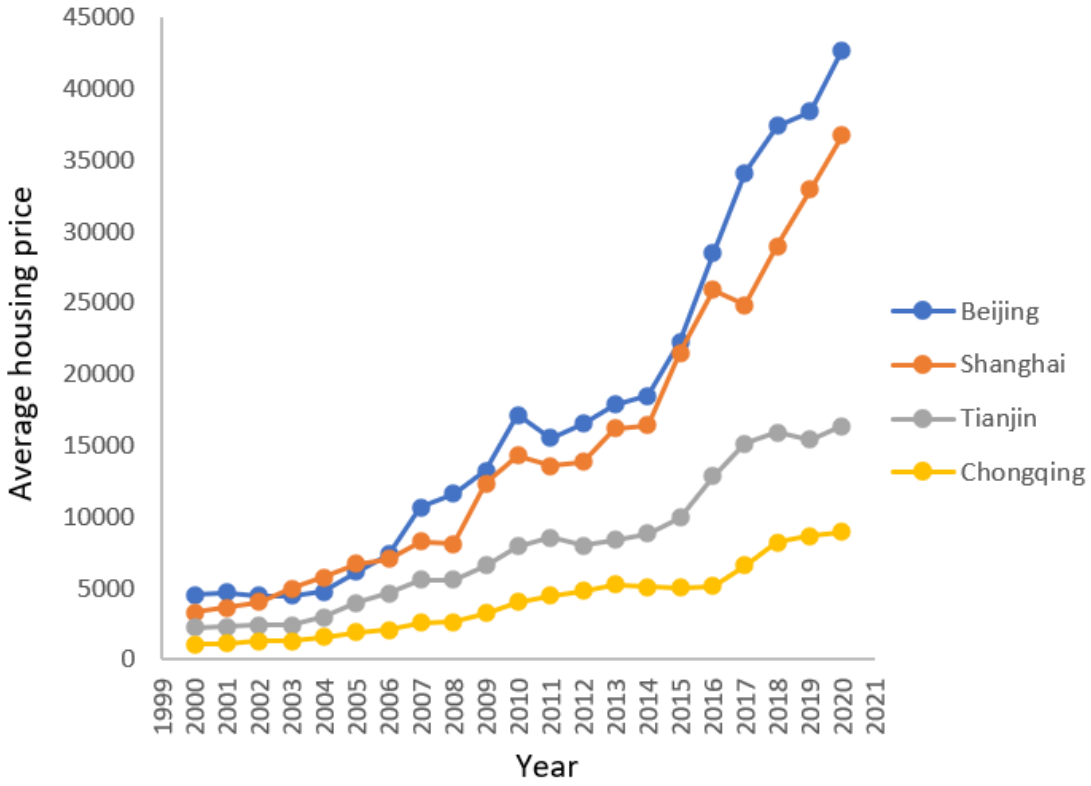


Figure A1: Average housing prices in four major cities, 2000 to 2020

Notes. This figure illustrates the changes in average housing prices in cities from 2000 to 2020, taking Beijing, Shanghai, Tianjin, and Chongqing as examples. These four cities are China's four major direct-administered municipalities. The data source is the National Bureau of Statistics of China.

Table A2: Variable Definition

Variable	**Definition**
	Panel A: Transaction
lnprice	The natural logarithm of unit sale price (CNY/m^2)
lntotalprice	The natural logarithm of total transaction price (10000 CNY)
lnprice_last	The natural logarithm of the last listing unit price (CNY/m^2)
lnprice_initial	The natural logarithm of the initial listing unit price (CNY/m^2)
lntotalprice_last	The natural logarithm of the last listing total price (10000 CNY)
lntotalprice_initial	The natural logarithm of the initial listing total price (10000 CNY)

Continued on next page

Variable	Definition
bargain_last	Bargaining power1: measured as (the last listed total price - total transaction price) / the last listed total price
bargain_initial	Bargaining power2: measured as (the initial listed total price - total transaction price) / the initial listed total price
room	Number of rooms
building age	Building age
decoration	Decoration condition
floor	Floor number
subway	Near subway stations
school	Within school districts
area	Size of property
buyer_age	buyer's age (Dummy variable)
gender	buyer's gender
marriage	Marital status of the buyer
boom	Boom cycle regarding housing market
	Panel B: Demand side
viewing	The number of times a property is viewed by buyers on-site during the week
sd(attention_community)	The standard deviation of online attention received by properties within the community during the week
attention_community(t)	The number of online attentions for each community during the current week and serving as a proxy for community popularity
area	Size of property
room	Number of rooms
building age	Building age
decoration	Decoration condition
floor	Floor number
subway	Near subway stations
school	Within school districts
	Panel C: Supply side
lnnew_list_price	The natural logarithm of unit listing price of newly listed properties
lnnew_list_totalprice	The natural logarithm of the total listing price of newly listed properties

Continued on next page

Variable	Definition
total_adjusttimes	The number of price adjustments made by sellers for a property within a week
up_adjusttimes	The number of upward price adjustments for a property within the week
down_adjusttimes	The number of downward price adjustments for a property within the week
total_adjustmag	The overall magnitude (net effect) of price adjustments for properties with changed prices
up_adjustmag	The magnitude of price increases for properties with raised prices
down_adjustmag	The magnitude of price decreases for properties with lowered prices
area	Size of property
room	Number of rooms
building age	Building age
decoration	Decoration condition
floor	Floor number
subway	Near subway stations
	Panel D: Weather-related
temp	Average temperature (0.1℃)
temp>35	The number of days within the week with the maximum temperature exceeding 35 degrees Celsius.
temp30_35	The number of days within the week with the maximum average temperature ranging from 30 to 35 degrees Celsius.
temp25_30	The number of days within the week with the maximum average temperature ranging from 25 to 30 degrees Celsius.
humidity	Average humidity (1%)
precipitation	Precipitation (mm)
sunlight	Sunshine hours (0.1h)
wind	Wind speed (m/s)
so2	Sulfur dioxide concentration
pm25	PM2.5 concentration
min_temp	Minimum temperature (0.1℃)
max_temp	Maximum temperature (0.1℃)

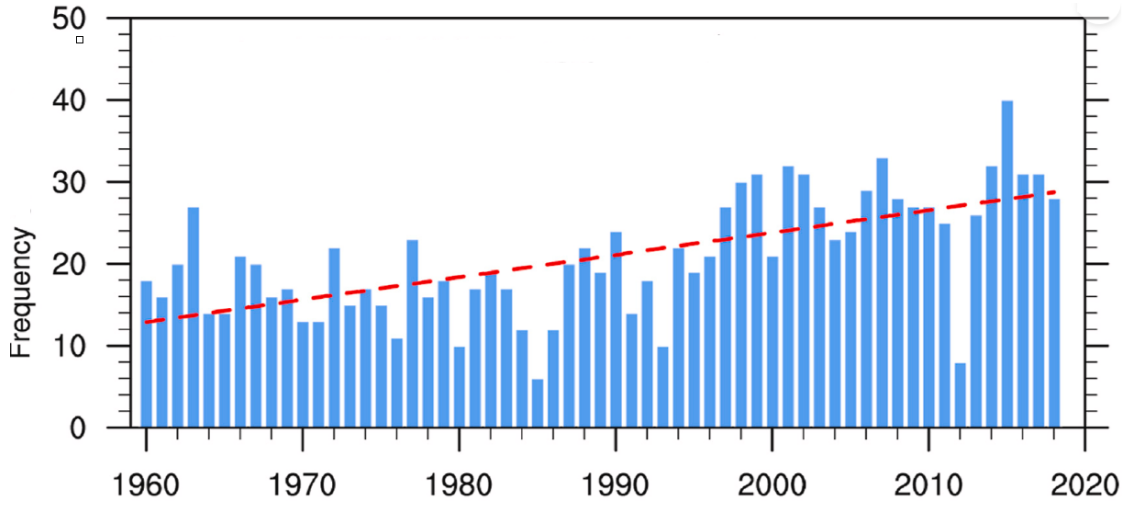


Figure A2: Annual Frequency of China's Regional Heat Wave

Source: Wang and Yan (2021)

Table A1: City List for Sample

All Sample City	Beijing, Shanghai, Chengdu, Dalian, Dongguan, Hangzhou, Hefei, Huizhou, Jinan Langfang, Nanjing, Qingdao, Xiamen, Shenzhen, Shenyang, Suzhou Tianjin, Wuxi, Wuhan, Xi'an, Yantai, Changsha, Zhengzhou, Chongqing
Southern City	Shanghai, Chengdu, Dongguan, Hangzhou, Hefei, Huizhou, Nanjing, Xiamen Shenzhen, Suzhou, Wuxi, Wuhan, Changsha, Chongqing
Northern City	Beijing, Dalian, Jinan, Langfang, Qingdao, Shenyang, Tianjin, Xi'an, Yantai, Zhengzhou

Notes. This table lists the cities included in the sample, categorized into All Sample City, Southern City, and Northern City.



Figure A3: An Example of Apartment's Online Ranking

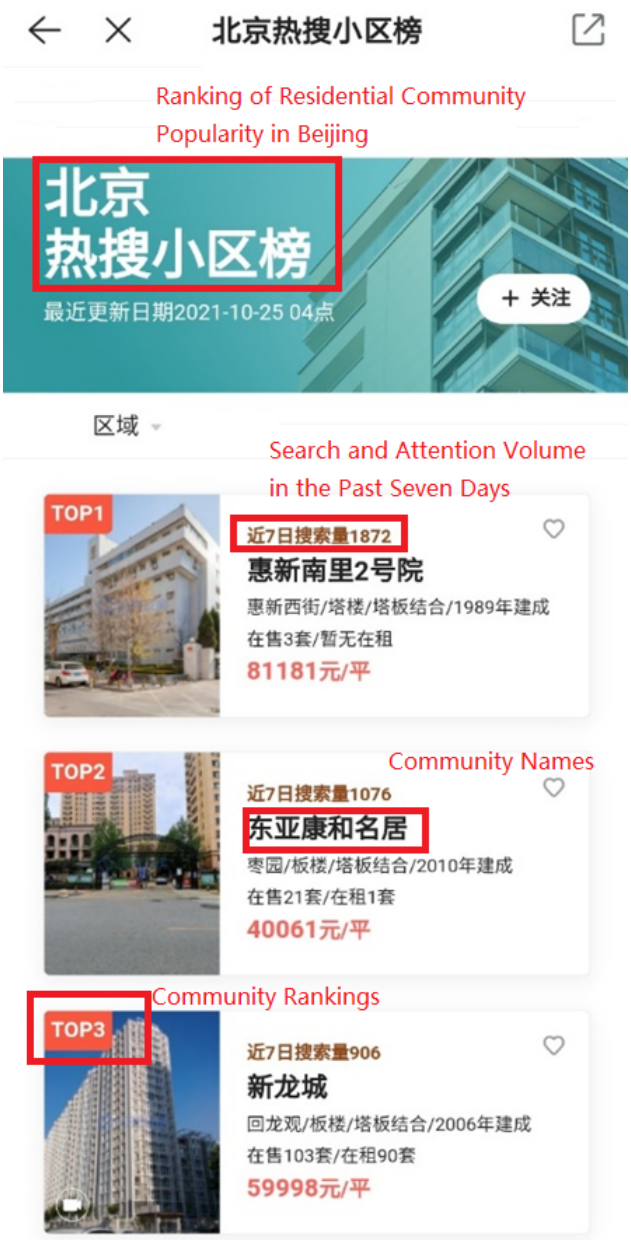
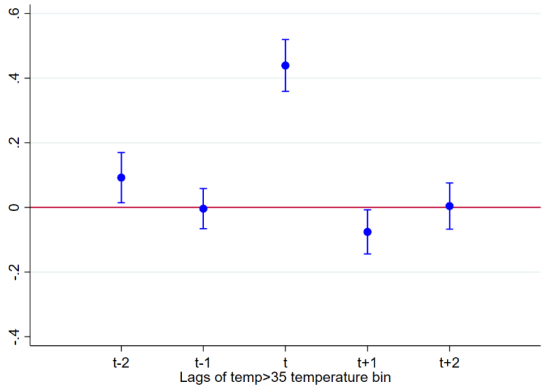
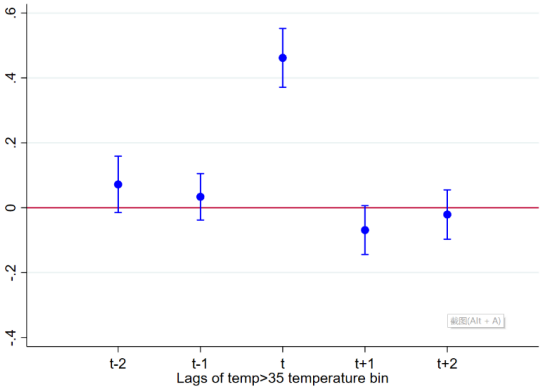


Figure A4: User Interface for Community Rankings

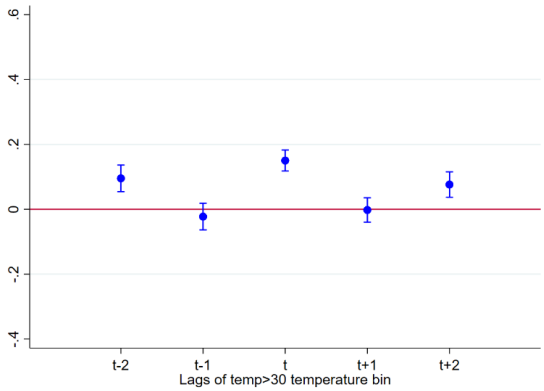
Figure A5: Impact of Contemporaneous, Lagged, and Lead High Temperatures on Housing Transaction Prices



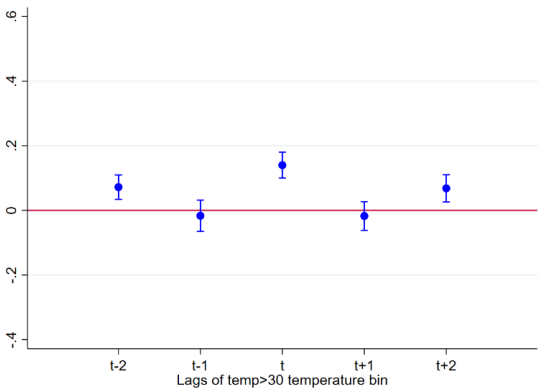
a. Impact of lags of $temp > 35$ on unit prices



b. Impact of lags of $temp > 35$ on total prices



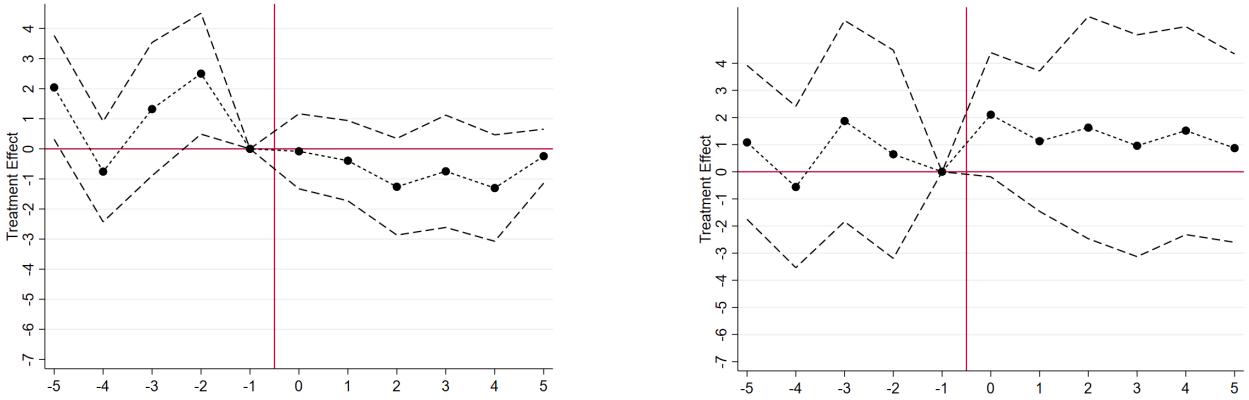
c. Impact of lags of $temp > 30$ on unit prices



d. Impact of lags of $temp > 30$ on total prices

Notes. Coefficients and 95% confidence intervals are plotted from Eq (1). t represents the current contemporaneous high temperature bin. The time units for lagged or lead periods are measured in weeks. All control variables, fixed effects, and clustering of standard errors are the same as in Table 3.

Figure A6: Fundamental Effects: housing prices for treated vs. control cities around the extreme heat events



(a) Transaction unit price (b) Transaction total price

Notes. This figure illustrates the dynamic trend in transaction-level housing price differences between the treatment group (i.e., those cities where transactions occurred that experienced extreme heat events within the sample window) and the control group (i.e., those cities that did not experience extreme heat events within the sample window). The housing transaction prices of the two groups do not exhibit significant trend differences either before or after the introduction of the extreme heat event. The dependent variable in Panel (a) is *lnprice*, representing the natural logarithm of the transaction unit price, while the dependent variable in Panel (b) is *lntotalprice*, representing the natural logarithm of the transaction total price. Both *lnprice* and *lntotalprice* are multiplied by 100. The vertical line marks the beginning of the extreme heat event. The unit of the horizontal axis is months. Refer to Table A2 for a comprehensive definition of control variables. All control variables and fixed effects used in column (2) of Table A17 are included. Reporting 95% confidence intervals. Standard errors are clustered at the district level.

Table A3: Change in Initial Listing Prices of Newly Listed Properties (Supply-side Response): Using Three High-Temperature Bins

VARIABLES	**lnnew_list_price**	**lnnew_list_totalprice**
	(1)	(2)
temp>35	-0.0150	-0.0116
	(0.030)	(0.028)
temp30_35	0.0181	0.0153
	(0.023)	(0.022)
temp25_30	0.0971***	0.0916***
	(0.019)	(0.019)
area	-1.7533***	21.2701***
	(0.284)	(0.342)
age	-5.0451***	-6.4585***
	(0.230)	(0.268)
floor	-1.5970***	-1.9285***
	(0.178)	(0.192)
decoration	4.3351***	4.8597***
	(0.163)	(0.171)
room	4.5942***	14.2802***
	(0.272)	(0.364)
subway	1.6059***	1.3305***
	(0.418)	(0.412)
Observations	4,515,722	4,515,722
Adjusted R^2	0.930	0.921
Weather Controls	Y	Y
City*year-quarter FE	Y	Y
Location FE	Y	Y

Notes. This table presents how high temperatures affect sellers' pricing of newly listed properties. We utilize two primary dependent variables: *lnnew_list_price*, indicating the natural logarithm of the unit listing price of newly listed properties, and *lnnew_list_totalprice*, representing the natural logarithm of the total listing price of newly listed properties. The independent variables of interest in our analysis are $temp > 35$, $temp30_35$, and $temp25_30$, denoting the number of days with temperatures above 35℃, between 30℃ and 35℃, and between 25℃ and 30℃, respectively, in city c during week t, corresponding to transaction i. For ease of presentation, our dependent variables, *lnnew_list_price* and *lnnew_list_totalprice*, are multiplied by 100. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A4: Changes in Pricing Adjustment Strategies for Existing Listed Properties (Supply side Response): Using Three High-Temperature Bins

VARIABLES	**total_adjusttimes**	**up_adjusttimes**	**down_adjusttimes**	**total_adjustmag**	**up_adjustmag**	**down_adjustmag**
	(1)	(2)	(3)	(4)	(5)	(6)
temp>35	-0.7558***	-0.2305***	-0.4820***	-1.6394	-2.0439**	0.8274**
	(0.075)	(0.039)	(0.064)	(1.461)	(1.023)	(0.408)
temp30_35	-0.6178***	-0.1973***	-0.3878***	-2.4606***	-2.6396***	0.1935
	(0.042)	(0.028)	(0.027)	(0.930)	(0.908)	(0.205)
temp25_30	-0.0109	-0.0406**	0.0310	-1.5838**	1.2995***	0.0832
	(0.049)	(0.019)	(0.036)	(0.629)	(0.381)	(0.239)
area	-0.0818	0.1231***	-0.1837***	2.4214***	20.0919***	16.3002***
	(0.096)	(0.027)	(0.070)	(0.702)	(1.240)	(1.295)
age	0.0778	-0.1388***	0.2593***	-9.7267***	7.9144***	8.5071***
	(0.066)	(0.017)	(0.051)	(0.502)	(0.743)	(0.745)
floor	0.8606***	0.1408***	0.6954***	-2.8169***	3.9555***	2.7407***
	(0.078)	(0.013)	(0.067)	(0.443)	(0.776)	(0.538)
decoration	2.2618***	0.4906***	1.6912***	-5.8844***	-18.4936***	-12.5787***
	(0.115)	(0.028)	(0.090)	(1.145)	(0.885)	(0.687)
room	-0.8561***	-0.1721***	-0.6430***	2.7402***	-6.0348***	-7.9121***
	(0.098)	(0.022)	(0.085)	(0.784)	(1.337)	(1.056)
subway	0.0288	0.0159	0.0030	1.4707	-2.2112	-2.6376**
	(0.100)	(0.026)	(0.074)	(0.918)	(1.420)	(1.253)
Observations	30,950,636	30,950,636	30,950,636	5,525,012	1,746,083	4,151,967
Adjusted R^2	0.033	0.040	0.039	0.173	0.077	0.083
Weather Controls	Y	Y	Y	Y	Y	Y
City*year-quarter FE	Y	Y	Y	Y	Y	Y
Location FE	Y	Y	Y	Y	Y	Y

Notes. This table presents how high temperatures affect sellers' behaviors in adjusting the listing prices of properties already on the market. We employ six primary dependent variables: *total_adjusttimes*, indicating the number of price adjustments made by sellers for a property within the week; *up_adjusttimes*, indicating the number of upward price adjustments made by sellers for a property within the week; *down_adjusttimes*, indicating the number of downward price adjustments made by sellers for a property within the week; *total_adjustmag* represents the overall magnitude of price adjustments for properties with changed prices; *up_adjustmag* indicates the extent of price increases when a property's price is adjusted upward; *down_adjustmag* denotes the extent of price decreases when a property's price is adjusted downward. The independent variables of interest in our analysis are $temp > 35$, $temp30_35$, and $temp25_30$, denoting the number of days with temperatures above 35℃, between 30℃ and 35℃, and between 25℃ and 30℃, respectively, in city c during week t, corresponding to transaction i. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 of Appendix A for a comprehensive definition of control variables. For ease of presentation, all dependent variables are multiplied by 100. Robust standard errors clustered at the district level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A5: Effect on net Bargaining Power (Linear)

VARIABLES	**bargain_last**			**bargain_initial**		
	(1) **(Total)**	(2) **(Intensive)**	(3) **(Extensive)**	(4) **(Total)**	(5) **(Intensive)**	(6) **(Extensive)**
temp	-0.0021***	-0.0016***	-0.0002***	-0.0067***	-0.0045***	-0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
area	-0.0008	0.0087***	-0.0005***	0.0021	0.0183***	-0.0004***
	(0.002)	(0.001)	(0.000)	(0.003)	(0.001)	(0.000)
building age	-0.0030	0.0240	0.0024*	0.1541***	0.1940***	0.0050***
	(0.023)	(0.017)	(0.001)	(0.038)	(0.033)	(0.001)
floor	-0.0563***	-0.0330***	-0.0020***	0.0347	0.0750**	-0.0003
	(0.006)	(0.007)	(0.000)	(0.028)	(0.033)	(0.001)
decoration	-0.0635***	-0.1213***	0.0048***	-0.2209***	-0.4254***	0.0059***
	(0.024)	(0.018)	(0.001)	(0.054)	(0.035)	(0.002)
room	0.1214**	-0.0636*	0.0088***	0.1563*	-0.1363**	0.0059***
	(0.050)	(0.036)	(0.002)	(0.087)	(0.055)	(0.002)
school	0.0762	-0.0436	0.0171	-0.5039***	-0.5654***	-0.0068
	(0.146)	(0.067)	(0.017)	(0.182)	(0.157)	(0.012)
subway	0.0212	0.0002	0.0003	-0.0267	-0.0407	-0.0006
	(0.018)	(0.017)	(0.001)	(0.036)	(0.037)	(0.001)
Observations	645,581	583,980	645,581	645,581	566,040	645,581
Adjusted R^2	0.179	0.273	0.095	0.205	0.226	0.120
Weather Controls	Y	Y	Y	Y	Y	Y
City*year-quarter FE	Y	Y	Y	Y	Y	Y
Location FE	Y	Y	Y	Y	Y	Y

Notes. This table shows the linear effect of high temperatures on buyers' bargaining power. We employ two primary dependent variables: *bargain_last*, which assesses buyers' bargaining power by determining the difference between the last listed total prices and the total transaction prices, then dividing this by the last listed total prices; *bargain_initial*, which measures buyers' bargaining power by calculating the disparity between the initial listed total prices and the total transaction prices, and then dividing this by the initial listed total prices. The independent variable of interest in our analysis is *temp*, denoting the average temperature of city c during the week t corresponding to transaction i. Columns (1) and (4) examine the total effect changes in bargaining power; columns (2) and (5) investigate the intensive effect changes in bargaining power; columns (3) and (6) assess the extensive effect changes in bargaining power. For ease of presentation, the dependent variables, *bargain_last* (Total), *bargain_initial* (Total), *bargain_last* (Intensive), and *bargain_initial* (Intensive), are multiplied by 100. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Alternative Fixed Effect (city-year-month): Linear

VARIABLES	**lnprice**	**lntotalprice**
	(1)	(2)
temp	0.0093***	0.0087***
	(0.001)	(0.001)
area	-0.1050***	0.7350***
	(0.015)	(0.020)
age	-5.2143***	-6.7703***
	(0.341)	(0.283)
floor	-1.1681***	-1.2362***
	(0.203)	(0.211)
decoration	4.5030***	5.5089***
	(0.176)	(0.194)
room	4.2591***	12.6770***
	(0.441)	(0.480)
school	16.7263***	13.6484***
	(3.736)	(4.266)
subway	1.9399***	1.6006***
	(0.486)	(0.516)
Observations	645,580	645,580
Adjusted R^2	0.940	0.931
Weather Control	Y	Y
City*year-month FE	Y	Y
Location FE	Y	Y

Notes. This table shows the linear effect of high temperatures on housing transaction prices, replacing the city-year-season fixed effects with city-year-month fixed effects. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the unit sale price, and *lntotalprice*, representing the natural logarithm of the total transaction price. The independent variable of interest in our analysis is *temp*, denoting the average temperature of city c during the week t corresponding to transaction i. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A7: Alternative Fixed Effect (city-year-month): Using Three High-Temperature Bins

VARIABLES	**lnprice**	**lntotalprice**
	(1)	(2)
temp>35	0.4836***	0.5018***
	(0.047)	(0.055)
temp30_35	0.0488**	0.0464*
	(0.020)	(0.024)
temp25_30	-0.0252	-0.0225
	(0.024)	(0.032)
area	-0.1050***	0.7350***
	(0.015)	(0.020)
age	-5.2138***	-6.7698***
	(0.341)	(0.283)
floor	-1.1679***	-1.2359***
	(0.203)	(0.211)
decoration	4.5028***	5.5087***
	(0.176)	(0.195)
room	4.2582***	12.6761***
	(0.441)	(0.480)
school	16.7208***	13.6424***
	(3.738)	(4.267)
subway	1.9391***	1.5998***
	(0.486)	(0.516)
Observations	645,580	645,580
Adjusted R^2	0.940	0.931
Weather Controls	Y	Y
City*year-month FE	Y	Y
Location FE	Y	Y

Notes. This table shows the nonlinear effect of high temperatures on housing transaction prices, replacing the city-year-season fixed effects with city-year-month fixed effects. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the unit sale price, and *lntotalprice*, representing the natural logarithm of the total transaction price. The independent variables of interest in our analysis are $temp > 35$, $temp30_35$, and $temp25_30$, denoting the number of days with temperatures above 35℃, between 30℃ and 35℃, and between 25℃ and 30℃, respectively, in city c during week t, corresponding to transaction i. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A8: Additional Control Variables: Air-pollution-related Variables (Linear)

VARIABLES	**lnprice**			**lntotalprice**		
	(1)	(2)	(3)	(4)	(5)	(6)
temp	0.0155***	0.0154***	0.0152***	0.0146***	0.0146***	0.0144***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
pm25	0.0080***		0.0091***	0.0076***		0.0087***
	(0.001)		(0.002)	(0.001)		(0.001)
so2		0.0229*	-0.0126		0.0213	
		(0.012)	(0.011)		(0.013)	
area	-0.1049***	-0.1049***	-0.1049***	0.7351***	0.7351***	0.7351***
	(0.015)	(0.015)	(0.015)	(0.020)	(0.020)	(0.020)
age	-5.2070***	-5.2066***	-5.2071***	-6.7634***	-6.7630***	-6.7636***
	(0.341)	(0.341)	(0.341)	(0.283)	(0.283)	(0.283)
floor	-1.1692***	-1.1693***	-1.1691***	-1.2375***	-1.2375***	-1.2373***
	(0.202)	(0.202)	(0.202)	(0.211)	(0.211)	(0.211)
decoration	4.5061***	4.5059***	4.5060***	5.5119***	5.5118***	5.5119***
	(0.176)	(0.176)	(0.176)	(0.195)	(0.195)	(0.195)
room	4.2531***	4.2533***	4.2531***	12.6725***	12.6726***	12.6725***
	(0.441)	(0.441)	(0.441)	(0.480)	(0.480)	(0.480)
school	16.7393***	16.7417***	16.7394***	13.6675***	13.6697***	13.6675***
	(3.746)	(3.745)	(3.746)	(4.271)	(4.270)	(4.271)
subway	1.9291***	1.9291***	1.9291***	1.5930***	1.5930***	1.5930***
	(0.487)	(0.486)	(0.487)	(0.517)	(0.516)	(0.517)
Observations	645,581	645,581	645,581	645,581	645,581	645,581
Adjusted R^2	0.939	0.939	0.939	0.930	0.930	0.930
Weather Controls	Y	Y	Y	Y	Y	Y
City*year-quarter FE	Y	Y	Y	Y	Y	Y
Location FE	Y	Y	Y	Y	Y	Y

Notes. This table presents the linear impact of high temperatures on housing transaction prices after incorporating sulfur dioxide and PM2.5 as control variables. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the unit sale price, and *lntotalprice*, representing the natural logarithm of the total transaction price. The independent variable of interest in our analysis is *temp*, denoting the average temperature of city c during the week t corresponding to transaction i. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A9: Additional Control Variables (Air-pollution-related Variables): Using Three High-Temperature Bins

VARIABLES	**lnprice**			**lntotalprice**		
	(1)	(2)	(3)	(4)	(5)	(6)
temp>35	0.5413***	0.5359***	0.5252***	0.5490***	0.5437***	0.5336***
	(0.047)	(0.049)	(0.046)	(0.049)	(0.051)	(0.048)
temp30_35	0.1568***	0.1411***	0.1498***	0.1355***	0.1206***	0.1287***
	(0.023)	(0.022)	(0.023)	(0.022)	(0.022)	(0.022)
temp25_30	0.0767**	0.0648**	0.0735**	0.0674**	0.0562*	0.0643**
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
pm25	0.0032*		0.0098***	0.0029		0.0092***
	(0.002)		(0.002)	(0.002)		(0.002)
so2		-0.0329***	-0.0699***		-0.0318***	-0.0666***
		(0.008)	(0.009)		(0.010)	(0.010)
area	-0.1048***	-0.1048***	-0.1048***	0.7352***	0.7352***	0.7352***
	(0.015)	(0.015)	(0.015)	(0.020)	(0.020)	(0.020)
age	-5.2071***	-5.2070***	-5.2076***	-6.7634***	-6.7634***	-6.7639***
	(0.341)	(0.341)	(0.341)	(0.283)	(0.283)	(0.283)
floor	-1.1721***	-1.1713***	-1.1711***	-1.2402***	-1.2394***	-1.2393***
	(0.202)	(0.202)	(0.202)	(0.211)	(0.211)	(0.211)
decoration	4.5064***	4.5061***	4.5062***	5.5123***	5.5120***	5.5121***
	(0.176)	(0.176)	(0.176)	(0.194)	(0.195)	(0.195)
room	4.2512***	4.2516***	4.2516***	12.6705***	12.6709***	12.6708***
	(0.441)	(0.441)	(0.441)	(0.481)	(0.481)	(0.481)
school	16.7378***	16.7395***	16.7378***	13.6640***	13.6655***	13.6639***
	(3.751)	(3.749)	(3.751)	(4.276)	(4.274)	(4.275)
subway	1.9284***	1.9285***	1.9285***	1.5923***	1.5924***	1.5924***
	(0.485)	(0.485)	(0.486)	(0.515)	(0.515)	(0.516)
Observations	645,581	645,581	645,581	645,581	645,581	645,581
Adjusted R^2	0.939	0.939	0.939	0.930	0.930	0.930
Weather Controls	Y	Y	Y	Y	Y	Y
City*year-quarter FE	Y	Y	Y	Y	Y	Y
Location FE	Y	Y	Y	Y	Y	Y

Notes. This table presents the nonlinear impact of high temperatures on housing transaction prices after incorporating SO2 (sulfur dioxide) and PM2.5 as control variables. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the unit sale price, and *lntotalprice*, representing the natural logarithm of the total transaction price. The independent variables of interest in our analysis are $temp > 35$, $temp30_35$, and $temp25_30$, denoting the number of days with temperatures above 35℃, between 30℃ and 35℃, and between 25℃ and 30℃, respectively, in city c during week t, corresponding to transaction i. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A10: Additional Control Variables: Variables related to Buyer Demographics (Linear)

VARIABLES	**lnprice**	**lntotalprice**
	(1)	(2)
temp	0.0147***	0.0140***
	(0.001)	(0.001)
gender	-0.4631***	0.5509***
	(0.081)	(0.120)
buyer_age	-0.6652***	-0.0599
	(0.205)	(0.238)
marriage	0.2638	0.6861***
	(0.249)	(0.213)
area	-0.1045***	0.7351***
	(0.015)	(0.020)
building age	-5.2077***	-6.7790***
	(0.341)	(0.282)
floor	-1.1783***	-1.2382***
	(0.201)	(0.211)
decoration	4.5026***	5.5150***
	(0.175)	(0.195)
room	4.2549***	12.6213***
	(0.440)	(0.482)
school	16.6828***	13.6249***
	(3.738)	(4.256)
subway	1.9302***	1.5990***
	(0.486)	(0.517)
Observations	645,581	645,581
Adjusted R^2	0.939	0.930
Weather Controls	Y	Y
City*year-quarter FE	Y	Y
Location FE	Y	Y

Notes. This table illustrates the linear impact of high temperatures on housing transaction prices after including three additional control variables for buyer characteristics: gender, age, and marital status. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the unit sale price, and *lntotalprice*, representing the natural logarithm of the total transaction price. The independent variable of interest in our analysis is *temp*, denoting the average temperature of city c during the week t corresponding to transaction i. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A11: Additional Control Variables (buyer Demographics): Using Three High-Temperature Bins

VARIABLES	**lnprice**	**lntotalprice**
	(1)	(2)
temp>35	0.5409***	0.5521***
	(0.048)	(0.050)
temp30_35	0.1496***	0.1313***
	(0.022)	(0.021)
temp25_30	0.0701**	0.0630**
	(0.031)	(0.032)
gender	-0.4661***	0.5480***
	(0.081)	(0.120)
buyer_age	-0.6606***	-0.0552
	(0.204)	(0.238)
marriage	0.2639	0.6863***
	(0.249)	(0.214)
area	-0.1044***	0.7352***
	(0.015)	(0.020)
building age	-5.2079***	-6.7791***
	(0.341)	(0.282)
floor	-1.1812***	-1.2410***
	(0.201)	(0.212)
decoration	4.5030***	5.5155***
	(0.175)	(0.195)
room	4.2530***	12.6193***
	(0.440)	(0.482)
school	16.6792***	13.6195***
	(3.744)	(4.262)
subway	1.9295***	1.5984***
	(0.485)	(0.516)
Observations	645,581	645,581
Adjusted R^2	0.939	0.930
Weather Controls	Y	Y
City*year-quarter FE	Y	Y
Location FE	Y	Y

Notes. This table illustrates the nonlinear impact of high temperatures on housing transaction prices after including control variables for three buyer characteristics: gender, age, and marital status. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the unit sale price, and *lntotalprice*, representing the natural logarithm of the total transaction price. The independent variables of interest in our analysis are $temp > 35$, $temp30_35$, and $temp25_30$, denoting the number of days with temperatures above 35℃, between 30℃ and 35℃, and between 25℃ and 30℃, respectively, in city c during week t, corresponding to transaction i. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A12: Alternative Clustering of Standard Errors (Linear)

VARIABLES	**lnprice**			**lntotalprice**		
	(1)	(2)	(3)	(4)	(5)	(6)
temp	0.0148***	0.0148***	0.0148***	0.0140***	0.0140***	0.0140***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	645,581	645,581	645,581	645,581	645,581	645,581
Adjusted R^2	0.939	0.939	0.939	0.930	0.930	0.930
Weather Control	Y	Y	Y	Y	Y	Y
City*year-quarter FE	Y	Y	Y	Y	Y	Y
Location FE	Y	Y	Y	Y	Y	Y
Standard Errors:						
District-Week	Y	-	-	Y	-	-
City	-	Y	-	-	Y	-
City-Week	-	-	Y	-	-	Y

Notes. This table shows the linear effect of contemporaneous temperature increases on housing transaction prices with two-way clustering: on district-week for columns 1 and 4, and on city-week for columns 3 and 6, while standard errors are clustered by city in columns 2 and 5. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the unit sale price, and *lntotalprice*, representing the natural logarithm of the total transaction price. The independent variable of interest in our analysis is *temp*, denoting the average temperature of city c during the week t corresponding to transaction i. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A13: Alternative Clustering of Standard Errors: Using Three High-Temperature Bins

VARIABLES	**lnprice**			**lntotalprice**		
	(1)	(2)	(3)	(4)	(5)	(6)
$temp > 35$	0.5424***	0.5424***	0.5424***	0.5500***	0.5500***	0.5500***
	(0.077)	(0.092)	(0.105)	(0.078)	(0.088)	(0.101)
temp30_35	0.1505***	0.1505***	0.1505***	0.1297***	0.1297***	0.1297***
	(0.034)	(0.031)	(0.040)	(0.033)	(0.026)	(0.035)
temp25_30	0.0715*	0.0715	0.0715	0.0626*	0.0626	0.0626
	(0.039)	(0.043)	(0.049)	(0.036)	(0.039)	(0.045)
Observations	645,581	645,581	645,581	645,581	645,581	645,581
Adjusted R^2	0.939	0.939	0.939	0.930	0.930	0.930
Housing Char.	Y	Y	Y	Y	Y	Y
Weather Control	Y	Y	Y	Y	Y	Y
City*year-quarter FE	Y	Y	Y	Y	Y	Y
Location FE	Y	Y	Y	Y	Y	Y
Standard Errors:						
District-Week	Y	-	-	Y	-	-
City	-	Y	-	-	Y	-
City-Week	-	-	Y	-	-	Y

Notes. This table reports the nonlinear effect of high temperatures on housing transaction prices with two-way clustering: on district-week for columns 1 and 4, and on city-week for columns 3 and 6, while standard errors are clustered by city in columns 2 and 5. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the unit sale price, and *lntotalprice*, representing the natural logarithm of the total transaction price. The independent variables of interest in our analysis are *temp>35*, *temp*30_35, and *temp*25_30, denoting the number of days with temperatures above 35℃, between 30℃ and 35℃, and between 25℃ and 30℃, respectively, in city c during week t, corresponding to transaction i. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A14: Excluding Rainy Days (Linear)

VARIABLES	**lnprice**	**lntotalprice**
	(1)	(2)
temp	0.0154***	0.0146***
	(0.001)	(0.001)
area	-0.1130***	0.7399***
	(0.016)	(0.022)
age	-5.1630***	-6.8245***
	(0.353)	(0.299)
floor	-1.2389***	-1.2973***
	(0.233)	(0.236)
decoration	4.4838***	5.4301***
	(0.183)	(0.197)
room	4.2190***	12.2548***
	(0.445)	(0.504)
school	16.6680***	13.5690***
	(3.772)	(4.315)
subway	1.8965***	1.5719***
	(0.521)	(0.556)
Observations	484,215	484,215
Adjusted R^2	0.940	0.933
Weather Controls	Y	Y
City*year-quarter FE	Y	Y
Location FE	Y	Y

Notes. This table presents the impact of high temperatures on housing transaction prices after excluding rainy days. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the unit sale price, and *lntotalprice*, representing the natural logarithm of the total transaction price. The independent variable of interest in our analysis is *temp*, denoting the average temperature of city c during the week t corresponding to transaction i. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A15: Excluding Rainy Days: Using Three High-Temperature Bins

VARIABLES	**lnprice**	**lntotalprice**
	(1)	(2)
temp>35	0.4753***	0.4908***
	(0.067)	(0.064)
temp30_35	0.1519***	0.1353***
	(0.027)	(0.027)
temp25_30	0.1147***	0.1062***
	(0.029)	(0.030)
area	-0.1129***	0.7400***
	(0.016)	(0.022)
age	-5.1623***	-6.8238***
	(0.353)	(0.299)
floor	-1.2431***	-1.3014***
	(0.233)	(0.236)
decoration	4.4847***	5.4311***
	(0.183)	(0.197)
room	4.2158***	12.2517***
	(0.445)	(0.504)
school	16.6675***	13.5663***
	(3.778)	(4.321)
subway	1.8956***	1.5711***
	(0.519)	(0.554)
Observations	484,215	484,215
Adjusted R^2	0.940	0.933
Weather Controls	Y	Y
City*year-quarter FE	Y	Y
Location FE	Y	Y

Notes. This table illustrates the nonlinear impact of high temperatures on housing transaction prices after excluding rainy days. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the unit sale price, and *lntotalprice*, representing the natural logarithm of the total transaction price. The independent variables of interest in our analysis are $temp > 35$, $temp30_35$, and $temp25_30$, denoting the number of days with temperatures above 35℃, between 30℃ and 35℃, and between 25℃ and 30℃, respectively, in city c during week t, corresponding to transaction i. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A16: Alternative Measures of Independent Variable (Linear)

VARIABLES	**lnprice**		**lntotalprice**	
	(1)	(2)	(3)	(4)
max_temp	0.0134***		0.0127***	
	(0.001)		(0.001)	
min_temp		0.0128***		0.0122***
		(0.001)		(0.001)
area	-0.1051***	-0.1051***	0.7299***	0.7299***
	(0.015)	(0.015)	(0.020)	(0.020)
building age	-5.2036***	-5.2036***	-6.8327***	-6.8326***
	(0.341)	(0.341)	(0.281)	(0.281)
floor	-1.1684***	-1.1686***	-1.2538***	-1.2540***
	(0.202)	(0.202)	(0.213)	(0.213)
decoration	4.5068***	4.5069***	5.5755***	5.5756***
	(0.176)	(0.176)	(0.196)	(0.196)
room	4.2187***	4.2186***	12.7365***	12.7364***
	(0.440)	(0.440)	(0.491)	(0.491)
school	16.7206***	16.7185***	13.6479***	13.6459***
	(3.744)	(3.746)	(4.279)	(4.281)
subway	1.9289***	1.9278***	1.5863***	1.5852***
	(0.486)	(0.486)	(0.517)	(0.517)
Observations	645,581	645,581	645,581	645,581
Adjusted R^2	0.939	0.939	0.929	0.929
Weather Controls	Y	Y	Y	Y
City*year-quarter FE	Y	Y	Y	Y
Location FE	Y	Y	Y	Y

Notes. This table presents the effect of linear high temperatures on housing transaction prices, replacing the measurement of temperature with the daily average maximum and minimum temperatures. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the unit sale price, and *lntotalprice*, representing the natural logarithm of the total transaction price. The variables of interest in our analysis are the mean of daily maximum temperatures within the week (i.e., *max_temp*) and the mean of daily minimum temperatures within the week (i.e., *min_temp*) in city c corresponding to transaction i. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A17: Examination of Alternative Explanation

VARIABLES	**lnprice**		**lntotalprice**	
	(1)	(2)	(3)	(4)
treatpost	-0.0032	-0.2403	0.1668	0.2831
	(0.613)	(0.538)	(1.038)	(0.663)
area		-0.1048***		0.7351***
		(0.015)		(0.020)
age		-5.2091***		-6.7654***
		(0.341)		(0.283)
floor		-1.1718***		-1.2398***
		(0.202)		(0.211)
decoration		4.5065***		5.5123***
		(0.176)		(0.194)
room		4.2514***		12.6708***
		(0.441)		(0.481)
school		16.7467***		13.6745***
		(3.750)		(4.275)
subway		1.9281***		1.5920***
		(0.485)		(0.515)
Observations	645,581	645,581	645,581	645,581
R-squared	0.932	0.939	0.725	0.930
Weather Control	Y	Y	Y	Y
City*year-month FE	Y	Y	Y	Y
Location FE	Y	Y	Y	Y

Notes. This table investigates whether there is a systematic change in housing prices for cities after experiencing high-temperature events compared to properties of similar characteristics in cities that did not undergo such events using a staggered DiD approach. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the transaction unit price, and *lntotalprice*, representing the natural logarithm of the transaction total price. The independent variable of interest in our analysis is *treatpost*, acting as a DiD estimator. Its value is 1 when observations are within the period following a high-temperature event in the corresponding cities and 0 otherwise. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. Robust standard errors clustered at the district level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A18: Heterogeneity Throughout Housing Booms: Using Three High-Temperature Bins

VARIABLES	**(1)** **lnprice**	**(2)** **lntotalprice**
temp>35	0.6470***	0.6483***
	(0.066)	(0.067)
temp30_35	0.1271***	0.1133***
	(0.030)	(0.029)
temp25_30	0.0851**	0.0622*
	(0.037)	(0.036)
boom	1.5415***	1.2722***
	(0.280)	(0.277)
temp>35*boom	-0.2779***	-0.2491**
	(0.096)	(0.109)
temp30_35*boom	0.0656	0.0488
	(0.063)	(0.065)
temp25_30*boom	0.0075	0.0745
	(0.073)	(0.072)
Observations	645,581	645,581
Adjusted R^2	0.939	0.930
Housing Char.	Y	Y
Weather Controls	Y	Y
City*year-quarter FE	Y	Y
Location FE	Y	Y

Notes. This table presents whether there is a weaker relationship between high temperatures and housing transaction prices during boom periods in the housing market compared to other periods. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the unit sale price, and *lntotalprice*, representing the natural logarithm of the total transaction price. The variable *boom* is a binary variable that takes the value of 1 when the housing market trend in the city where the property is sold is in a boom state, and 0 otherwise. The independent variables of interest in our analysis are *temp>35*boom*, *temp30_35*boom*, and *temp25_30*boom*, capturing how *boom* moderates the relationship between high temperature and housing transaction prices. Housing characteristics include area, building age, floor, decoration, room, school, and subway. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. Robust standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A19: Demographic Heterogeneity: Using Three High-Temperature Bins

VARIABLES	**lnprice**		**lntotalprice**	
	(1)	**(2)**	**(3)**	**(4)**
temp>35	0.4008***	0.5598***	0.4093***	0.5703***
	(0.046)	(0.047)	(0.050)	(0.050)
temp30_35	0.1048***	0.1505***	0.0712**	0.1311***
	(0.028)	(0.022)	(0.030)	(0.023)
temp25_30	0.0500	0.0630*	0.0320	0.0527
	(0.034)	(0.032)	(0.037)	(0.034)
gender	-0.6829***		0.2847**	
	(0.083)		(0.115)	
temp>35*gender	0.2745***		0.2767***	
	(0.057)		(0.056)	
temp30_35*gender	0.0898***		0.1194***	
	(0.028)		(0.033)	
temp25_30*gender	0.0410		0.0614*	
	(0.026)		(0.034)	
buyer_age		-0.6597***		-0.0681
		(0.228)		(0.238)
temp>35*buyer_age		-0.1986**		-0.2197**
		(0.095)		(0.101)
temp30_35*buyer_age		-0.0051		-0.0167
		(0.050)		(0.056)
temp25_30*buyer_age		0.0820*		0.1059*
		(0.048)		(0.057)
Observations	645,581	645,581	645,581	645,581
Adjusted R^2	0.939	0.939	0.930	0.930
Housing Char.	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
City*year-quarter FE	Y	Y	Y	Y
Location FE	Y	Y	Y	Y

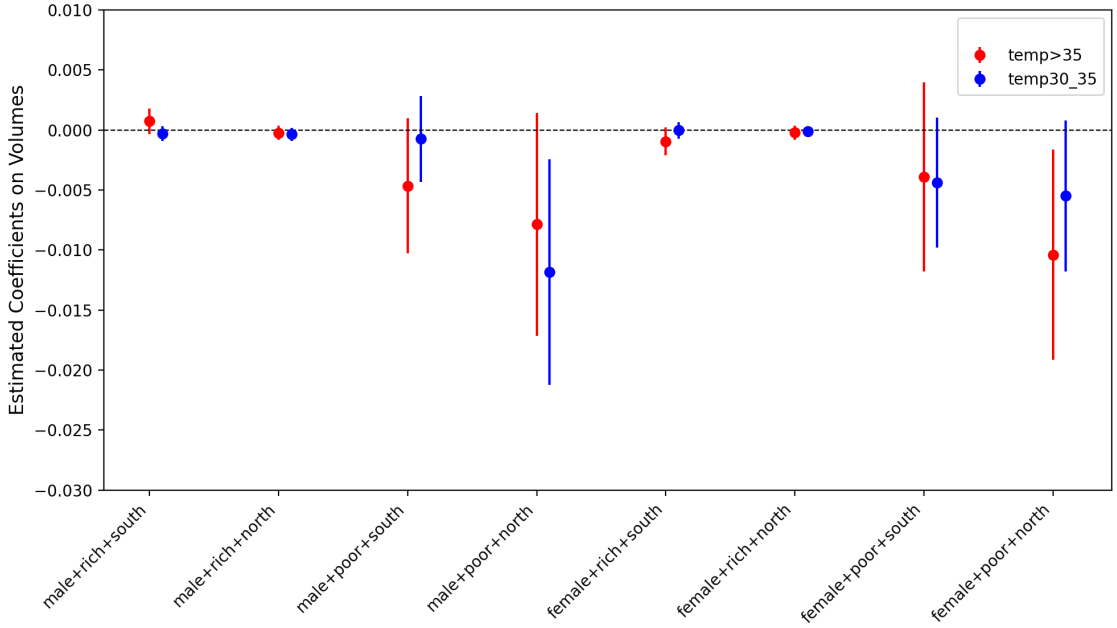
Notes. This table presents how the relationship between high temperatures and housing transaction prices varies across different genders and age groups of buyers. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the unit sale price, and *lntotalprice*, representing the natural logarithm of the total transaction price. *gender* is a binary variable, taking the value 1 if the buyer is male and 0 otherwise. *buyer_age* represents age groups of buyers, with larger values indicating older age groups. The independent variables of interest in our analysis are *temp>35*gender*, *temp30_35*gender*, *temp25_30*gender*, *temp>35*buyer_age*, *temp30_35*buyer_age*, and *temp25_30*buyer_age*, capturing how gender and *buyer_age* moderate the relationship between high temperature and housing transaction prices. Housing characteristics include area, building age, floor, decoration, room, school, and subway. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. Robust standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A20: Heterogeneity across Seasons: Using Three High-Temperature Bins

VARIABLES	**lnprice**				**lntotalprice**			
	Spring	**Summer**	**Fall**	**Winter**	**Spring**	**Summer**	**Fall**	**Winter**
temp>35	0.7928***	0.4462***	0.4964***		0.7074***	0.4818***	0.6556***	
	(0.251)	(0.066)	(0.153)		(0.235)	(0.074)	(0.181)	
temp30_35	0.1773***	-0.0148	0.0621		0.1385***	0.0378	0.0577	
	(0.026)	(0.049)	(0.040)		(0.031)	(0.057)	(0.044)	
temp25_30	0.1194**	-0.0474	-0.0385		0.0972*	-0.0071	-0.0483	
	(0.048)	(0.053)	(0.056)		(0.054)	(0.059)	(0.069)	
temp5_10				0.0640				0.0811*
				(0.040)				(0.047)
temp0_5				-0.1025**				-0.0661
				(0.044)				(0.047)
temp<0				-0.0720				-0.0593
				(0.050)				(0.057)
Observations	207,421	151,884	142,380	143,556	207,421	151,884	142,380	143,556
Adjusted R^2	0.938	0.940	0.940	0.941	0.929	0.931	0.932	0.932
Housing Char	Y	Y	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y	Y	Y
City*year-quarter FE	Y	Y	Y	Y	Y	Y	Y	Y
Location FE	Y	Y	Y	Y	Y	Y	Y	Y

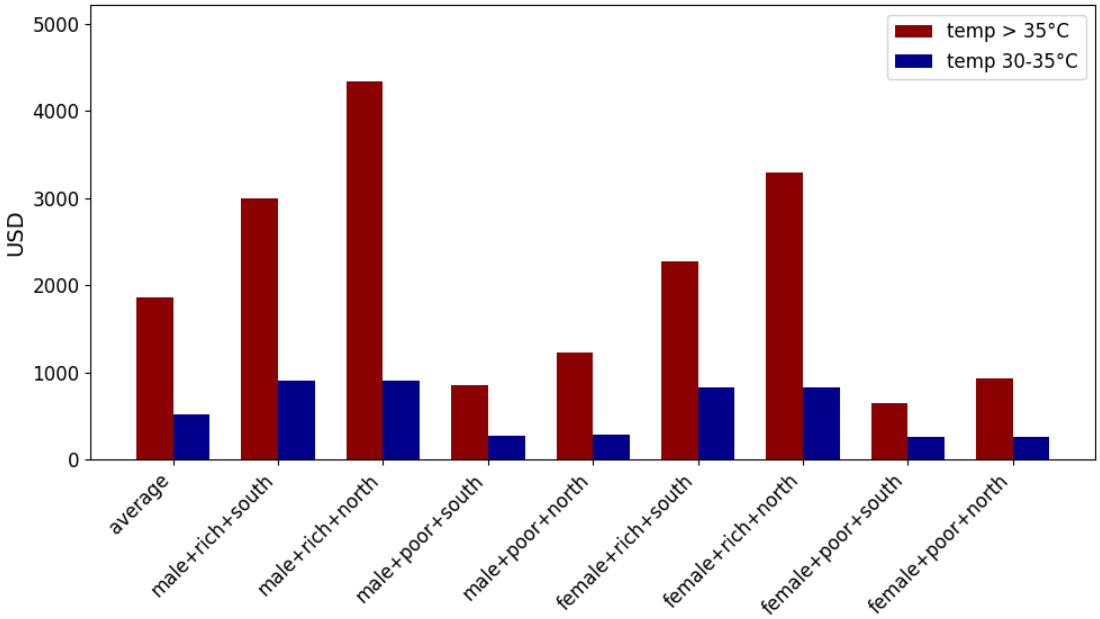
Notes. This table presents how the linear impact of high temperatures on housing transaction prices varies across four seasons, using different temperature bins. We employ two primary dependent variables: *lnprice*, which denotes the natural logarithm of the unit sale price, and *lntotalprice*, representing the natural logarithm of the total transaction price. Weather-related controls include sunshine, wind speed, humidity, and precipitation. See Table A2 for a comprehensive definition of control variables. For ease of presentation, our dependent variables, *lnprice* and *lntotalprice*, are multiplied by 100. Robust standard errors clustered at the district level reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure A7: Effects of High Temperatures on Transaction Volumes across Different Groups



Notes. Coefficients and 95% confidence intervals are plotted from Eq (1).

Figure A8: Average Wealth Redistribution from Buyers by Demographic Groups (After Accounting for Sensitivity in Transaction Volumes)



Notes. This figure illustrates the average additional wealth loss from housing transactions incurred by buyers across different demographic groups during periods extreme heat, after accounting for group-specific sensitivity in transaction volumes.

Appendix B: Survey

B1 Survey Description

The goal of our survey is to measure buyers' willingness to pay (WTP) for reducing one on-site home viewing during high-temperature weather, which serves as a proxy for buyers' rational search costs. Thus, we designed a short survey consisting of only three questions. The first question is: "Assuming that reducing on-site home viewings would increase the total transaction price you pay, how much more would you be willing to pay in RMB to reduce one on-site home viewing on a day when the maximum temperature exceeds 35 degrees Celsius?" Question 2 asks for gender, and question 3 asks for age. The survey targets buyers. With the assistance of local real estate agency managers, we selected five stores in Beijing for the distribution of the questionnaire, which was conducted from October 10 to October 15, 2024. The five stores are located in five districts of Beijing: Dongcheng District, Xicheng District, Haidian District, Chaoyang District, and Fengtai District. Our target respondents were buyers coming to the stores for housing consultations or planning to view properties. After the consultation, our research assistants asked if they could complete a short questionnaire. A total of 181 buyers were approached for the questionnaire, of which 12 declined for various reasons, resulting in 169 completed surveys.

B2 Survey Respondent Characteristics

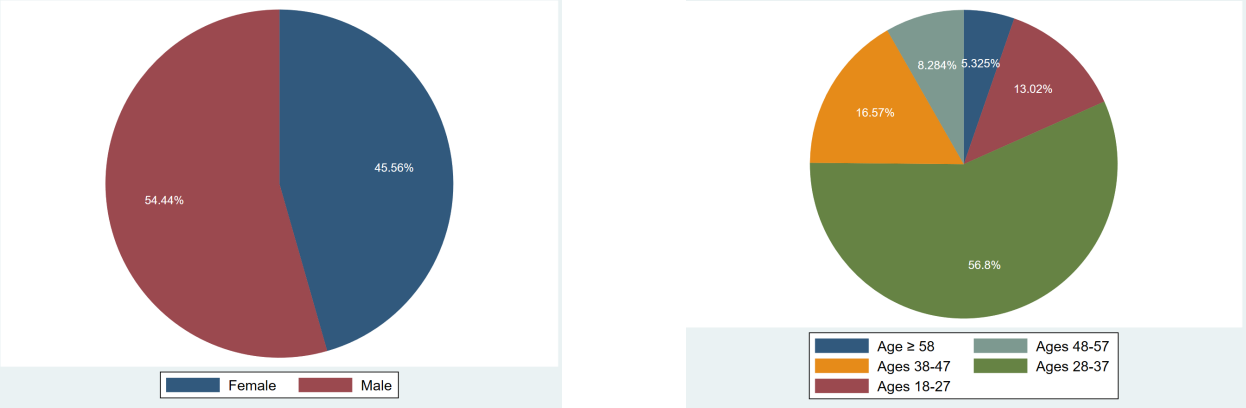
We first conducted a statistical analysis of the demographic characteristics of the 169 valid responses. Figure B1 presents pie charts that illustrate the distribution of respondents' demographics in terms of gender and age. In Panel A, we see that 54.44% of respondents are male, while 45.56% are female. In Panel B, the age distribution reveals that 13.02% of respondents are aged 18-27, 56.8% are aged 28-37, 16.57% are aged 38-47, 8.284% are aged 48-57, and 5.325% are aged 58 and older. The demographic characteristics of the respondents are similar to the overall sample, suggesting that our survey has good representativeness.

B3 Survey Results

Finally, we conducted descriptive statistical analysis on our variable of interest, WTP, which refers to respondents' (buyers') WTP for reducing one on-site home viewing on days when the maximum temperature exceeds 35 degrees Celsius. The sample mean of WTP is 681.83 RMB (approximately 96 USD). The maximum value is 5000 RMB (approximately 704 USD), while

the minimum is 0, and the standard deviation is 585.32. This indicates that, on average, buyers are willing to pay 96 USD to reduce one on-site home viewing in high temperatures. Figure B2 illustrates the distribution of respondents' (buyers') WTP for reducing one on-site home viewing in high temperatures. We can see that most buyers are unwilling to pay more than 1000 RMB (141 USD) for this.

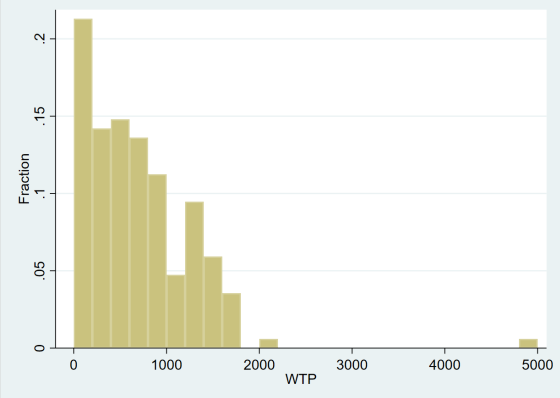
Figure B1: Respondents' Demographics



(a) Gender (b) Age

Notes. The pie charts show the distribution of respondents' demographics in terms of gender and ages.

Figure B2: Distribution of Respondents' (Buyers') WTP for Reducing One On-site Home Viewing during High Temperatures



Notes. The unit of WTP on the horizontal axis is RMB yuan.

Appendix C: Robustness Tests and Additional Heterogeneous Analyses

C1 Alternative Fixed Effects

In our baseline estimates, to account for the city-level confounding factors such as seasonal characteristics, time-varying housing demand, and policy shocks, we include city-year-season fixed effects. In this section, following Chu et al. (2021), we replace city-year-season fixed effects with city-year-month fixed effects and re-estimate Eq (1). The coefficient estimates on *temp*, reported in Column (1) and (2) of Table A6 of Appendix A, suggest that we obtain qualitatively similar results. Furthermore, when we replace *temp* with *temp>35*, *temp30_35*, *temp25_30*, and re-estimate Eq (1), the estimations presented in Table A7 of Appendix A remain robust.

C2 Additional Control Variables

Although we controlled for weather-related variables such as precipitation, sunshine, and humidity in the baseline results, one may be concerned that air pollution, as a confounding factor, may affect our main effect. Hence, we introduce two air pollution-related variables, *PM2.5* and *SO2*, as additional control variables and re-estimate Eq (1). The estimation results, as shown in Table A8, indicate that our results remain robust. Similarly, we replace *temp* with the three high-temperature bins and rerun Eq (1). The estimation results presented in Table A9 of Appendix A align qualitatively with those in Table A8.

One may also be concerned that buyers' population characteristics play a confounding role in the relationship between high temperatures and negotiated prices. The rationale behind this concern is that high temperatures might alter buyers' participation rates based on diverse demographic factors, consequently impacting negotiated prices. That is, the impact of high temperatures on negotiated prices may only reflect differences in buyers' demographic characteristics rather than individual behavioral biases. To address this concern, we include three control variables—buyers' gender, age, and marital status—and re-estimate the baseline regression model specified in Eq (1). The coefficient estimates on *temp* in Table A10 and the coefficient estimates on *temp>35*, *temp30_35*, and *temp25_30* in Table A11 of Appendix A indicate that the estimation results remain qualitatively unchanged.

C3 Alternative Clustering of Standard Errors

In the main body, we clustered standard errors at the district level. Here, we follow Huang et al. (2020) and first use two-way clustering at the district-week level, then cluster at the city level, and finally apply two-way clustering at the city-week level, re-estimating Eq (1). The estimation results are reported in Table A13. We can see that the estimated coefficients on $temp > 35$ and $temp30_35$ remain positive and statistically significant, except that the estimated coefficients on $temp25_30$ become insignificant. Similarly, the linear estimation results reported in Table A12 are consistent with those in Table 2. Altogether, our estimation results remain robust when using alternative clustering of standard errors.

C4 Excluding Rainy Days

According to Hu and Lee (2020), inconveniences in individual travel induced by rainy days, such as hindering buyers from conducting housing viewings and transactions, could influence behavioral biases in buyers. To mitigate this concern, we exclude observations related to rainy days and re-estimate our baseline regression. Specifically, we categorize samples where precipitation ranks in the top quarter of the dataset as rainy day samples. The estimation results reported in Column (1) and (2) of Table A14 of Appendix A show that the coefficient estimates on *temp* remain positive and statistically significant. Furthermore, we replace *temp* with *temp>35*, *temp30_35*, *temp25_30*, exclude rainy day samples, and then re-estimate Eq (1). The estimation results presented in Table A15 of Appendix A consistently support our findings.

C5 Alternative Measures of Independent Variable

In our baseline estimates, we use average temperatures (i.e., *temp*) as the primary independent variable of interest. Now, we follow Barreca et al. (2016) and consider alternative independent variables: the mean of daily maximum temperatures within the week (i.e., *max_temp*) and the mean of daily minimum temperatures within the week (i.e., *min_temp*). We then re-estimate our baseline regression Eq (1). The estimation results, reported in Table A16 of Appendix A, indicate that the coefficient estimates on *max_temp* and *min_temp* are both positive and statistically significant. These findings align qualitatively with our baseline estimate results, reinforcing the robustness of our baseline results.

C6 Dynamic Results: Leads and Lags of Temperature

Next, we investigate whether the main effect is primarily driven by contemporaneous high temperature or if it is influenced by recent high temperatures by augmenting our baseline specification to include lagged and lead high-temperature bin measures. Following Huang et al. (2020), including contemporaneous high temperature along with lagged and lead high temperatures as additional controls also allows us to verify whether the impact of contemporaneous high temperatures in our main effect remains robust.

We first select the high-temperature bin $temp > 35$ and introduce its lagged and lead variables, then re-estimate Eq(1). The estimation results are reported in panels (a) and (b) in Figure A5. We can see that the impact of current high temperatures on housing transaction prices is much more pronounced than that of lagged and lead high temperatures. High temperatures at $t-1$ and $t-2$ only have a weak effect on housing transaction prices. Then, we replace the high-temperature bin with $temp > 30$ as the threshold and re-estimate Eq(1); the estimation results are reported in panels (c) and (d) in Figure A5. Similarly, we observe that current high temperatures have a more pronounced impact on housing transaction prices compared to that of lagged and lead high temperatures.[51] Taken together, our dynamic estimation results indicate that the main effect is primarily driven by contemporaneous high temperatures, with only a weak influence from recent high temperatures. The estimation results further support the robustness of the main effect.

C7 Exploring Alternative Explanation: Long-term Preferences

In contrast to the primary focus of this paper, which examines the contemporaneous effects of high temperatures on housing transaction prices and the decision-making of buyers and sellers from a behavioral perspective, this section aims to explore an alternative fundamental-based explanation. Specifically, we examine whether extreme heat can impact future housing transaction prices in the aftermath of extreme high-temperature events by potentially altering the long-term preferences of buyers and homeowners in the local area.

Intuitively and rationally, we would expect that local housing transaction prices would systematically decline following such extreme heat events. This could happen because (i) extreme heat damages the houses and thus their valuation, and (ii) extreme heat events make buyers update their beliefs about the utility they derive living in this region (i.e.,

[51] However, high temperatures at $t+2$ also have a statistically significant and positive effect on housing transaction prices, which may be related to autocorrelation in extreme heat.

extreme heat causes discomfort among local residents, leading to a decrease in their long-term preferences for living in that area). These are in sharp contrast to the behavioral channels we have focused on thus far.

For our analysis, we define extreme high-temperature events as the occurrence of the maximum temperature in the city since 1990. If this event falls within our sample period, the observations in the city are labeled as '1' for the subsequent period; otherwise, they are labeled as '0'. We identified a total of six such extreme heat events. Cities experiencing these events constitute the treatment group, while the remainder comprise the control group. Based on this definition, we construct a new variable, *Treat_Post*. Similar to Tian and Xu (2022), we employ a staggered Difference-in-Differences analysis to study the long-term effects of experiencing these high-temperature events on housing transaction prices.

$$\ln P_{ijct} = \beta_0 + \beta_1 \mathit{Treat_Post}_{ct} + \beta_2 X_{it} + \beta_3 X_{ct} + \delta_j + \partial_{cys} + \epsilon_{it} \tag{4}$$

$$\ln P_{ijct} = \beta_0 + \sum_{l=-5}^{5} \beta_l \mathit{Treat}_{ct} \times 1[k = l] + \beta_2 X_{it} + \beta_3 X_{ct} + \delta_j + \partial_{cys} + \epsilon_{it} \tag{5}$$

We replace the independent variable *temp* with *Treat_Post*, the staggered DiD estimator, and re-estimate Eq (4). The estimation results are reported in Table A17. In column (1), we only include city*year-month fixed effects and location fixed effects without any control variables, and we find that the coefficient estimates on *Treat_Post* are statistically insignificant. Furthermore, in column (2), we include apartment characteristics and weather-related controls and find that the coefficient estimates on *Treat_Post* remain statistically insignificant. In columns (3) and (4), when replacing the dependent variable *lnprice* with *lntotalprice*, the coefficient estimates on *Treat_Post* continue to be statistically insignificant. Hence, the estimation results show that extreme heat events do not systematically alter residents' long-term preferences, consequently having no significant impact on housing transaction prices.

Figure A6 shows visual evidence of the dynamic trend of the effect of extreme heat events on housing transaction prices in the treatment group relative to the control group by estimating Eq (5), a more flexible version of Eq (4).[52] Panel A of Figure A6 shows little difference in *lnprice* between the trends of the treatment group and the control group, both before and after the extreme heat events. Similarly, Panel B of Figure A6 shows no statistically significant difference in *lntotalprice* between the trends of the treatment group and the control group. Taken together, our analysis rules out the existence of fundamental effects of extreme heat on housing prices.

[52]The pre-shock month (k = -1) is used as the omitted category.

C8 Heterogeneity throughout Housing Market Cycles

We examine how the influence of high temperatures on housing transaction prices varies over different phases of the housing market cycle. The rationale is that housing market boom may positive sentiment among buyers, which may counteract the negative impact of high temperatures on their cognitive abilities and productivity. Consequently, we predict that a housing market boom exerts a negative moderating effect on the positive impact of high temperatures on housing transaction prices. To test this conjecture, we construct a new variable, *boom*, which takes a value of 1 if the local housing market exhibits significant upward trends and 0 otherwise.[53] Specifically, *boom* is set to 1 if the average housing prices in the city have consistently increased over the past six months.[54] Next, we include *boom* and the interaction term between *boom* and three high-temperature bins in Eq (1), and then re-estimate Eq (1). The estimation results presented in Table A18 suggest that the estimated coefficient on $temp > 35 * boom$ is negative and statistically significant. This suggests that during boom periods, the positive impact of the $temp > 35$ high-temperature bin on housing transaction prices is 27.79% weaker compared to non-boom periods. This result indicates that the housing market boom indeed plays a negative moderating role in the impact of extreme heat on housing transaction prices.

C9 Demographic Heterogeneity

We explore how the impact of high temperatures on housing transaction prices varies across different segments of buyers, with a particular focus on two key demographics: gender and age. For gender, we designate a value of 1 if the buyer is male and 0 otherwise. For buyers' age, we include a dummy variable *buyer_age*: it takes the value of 1 for elderly individuals aged 60 and above, and 0 for middle-aged and younger individuals under 60. We then include interaction terms between the two demographic characteristics (i.e., *gender* and *buyer_age*) and three high temperature bins, respectively, and re-estimate Eq (1). The estimation results presented in Columns (1) and (3) of Table A19 show positive and statistically significant coefficient estimates on $temp > 35 * gender$ and $temp30_35 * gender$. This indicates that male buyers, compared to female buyers, experience a 27.45% greater impact on housing transaction prices in the $temp > 35$ high-temperature bin. This finding aligns with the existing

[53] The city-level housing price trend data is sourced from https://m.fang.com/fdc/index/ershoufangindex.html.

[54] Our rationale is based on the perspective of buyers' perception. If buyers observe a continuous upward trend in housing prices in the city over the past six months, they are likely to perceive the local real estate market as being in a boom state. Conversely, if there are certain months where prices did not rise, they may question the boom status of the local real estate market.

psychological studies indicating that adverse environmental factors such as air pollution may have a more severe effect on males' cognitive abilities compared to females (Zhang et al., 2018).

In Columns (2) and (4) of Table A19, we include *buyer_age* and its interaction terms with $temp > 35$, $temp30_35$, and $temp25_30$ and re-estimate Eq (1). We observe that the coefficient estimates on $temp * buyer_age$ are negative and statistically significant. This suggests that buyers' ages might negatively moderate the main effect. This may be because, while older individuals are more physically vulnerable to high temperatures than younger individuals, their experience in negotiation and other stages of the housing transaction process could serve as a buffer, counterbalancing or even outweighing the physical effects.

C10 Heterogeneity across Seasons

Next, we examine how the effect of high temperatures on housing transaction prices varies across seasons. We expect that in spring, summer, and fall, high temperatures will positively affect housing transaction prices through the behavioral mechanisms documented above. However, in winter (i.e., December, January, and February), it is almost impossible to experience temperatures that fall into our defined high-temperature bins (i.e., daily maximum temperatures above 25°C). Therefore, we introduce three bins representing low temperatures to see if low temperatures in winter affect housing transaction prices: $temp5_10$, $temp0_5$, and $temp < 0$, which indicate the number of days in a week with daily maximum temperatures between 5-10°C, 0-5°C, and below 0°C, respectively. Notably, we choose to use the daily maximum temperature in winter to examine the effect of low temperatures on transaction prices because buyers and sellers usually negotiate and transact from 10 AM until around 3 PM, a period during which the temperature is close to the daily maximum. We then split the sample into different seasons and re-estimate Eq (1) separately. The estimation results are reported in Table A20 of Appendix A.

In Column (1) of Table A20, we observe that in spring, all three high-temperature bins have a positive and statistically significant impact on housing transaction prices, with the extreme heat bin (i.e., $temp > 35$) having the largest impact. Specifically, during the week of the transaction, an additional day with a maximum temperature above 35°C increases housing transaction prices by approximately 0.79%, while an extra day within the 30°C-35°C range corresponds to an increase in housing transaction prices of about 0.18%. In summer and fall, as shown in columns (2) and (3), the estimation results indicate that only the extreme high-temperature bin, $temp > 35$, has a positive and statistically significant impact on housing transaction prices. This may be because average temperatures in summer are

already high, so only extreme heat significantly affect individuals' cognition and productivity. In fall, high temperatures mainly occur in early September, and individuals may have developed short-term adaptability to general high temperatures after the summer, translating to only extreme high temperatures having a significant impact on housing transaction prices. Column (4) shows that in winter, the low-temperature bin $temp0_5$ has a negative and statistically significant impact on housing transaction prices. This result is consistent with existing studies, which concludes that low temperatures negatively affect individuals' moods, thereby lowering their valuation expectations for housing (Hu and Lee, 2020).