High Temperature, Climate Change and Real Estate Prices

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Abstract

Combining granular data on temperatures across the continental United States with comprehensive listing-level data for residential properties and survey data on beliefs about climate change from 2000 to 2021, we examine the impact of exposure to local heat shocks on residential real estate prices. We first show that abnormally high local temperature leads to elevated belief in climate change. We find that exposure to local heat shocks results in a significant decrease in house prices, and this effect is more pronounced in communities concerned about global warming, during periods of increasing public attention to climate change and among counties heavily exposed to the risk of sea level rise. In contrast to the transaction price regression, we find no relation between abnormal temperature exposure and rental prices, suggesting that the observed temperature exposure discount is driven by concerns about long-horizon climate risks. Taken together, our results highlight the importance of uncertainty about climate change in affecting the real estate market.

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We benefited from the comments of the seminar participants at Baruch College.

1 Introduction

A growing body of scientific study is providing evidence to support the existence of climate change. Notably, Intergovernmental Panel on Climate Change (IPCC) reports that global temperatures in each of the previous three decades have been higher than the last.[1] Global warming is likely to reach 1.5°C between 2030 and 2052 if it continues to increase at the current rate.[2] In addition, extreme weather events are becoming more common. Scientific experts warned that heat waves that previously may have occurred once every 50 years can now be expected every 10 years.[3] According to a survey by Redfin, nearly two-thirds of people surveyed by them said they would be hesitant to buy a home in an area with extreme temperatures, suggesting that climate risk is a concern for U.S. home buyers.[4] Despite the survey evidence of increased concern about climate risks among home buyers, it is unclear how climate risks affect the real estate market. In this paper, we aim to provide direct evidence of how exposure to abnormal temperatures affects residential real estate markets in the United States. Specifically, we empirically estimate how location-specific temperature shocks affect listing-level house prices.

We begin by building a detailed dataset of abnormal temperature exposures for properties across the continental United States. We use granular weather data covering daily temperatures and precipitation across 4,940 weather stations in the United States from 1980 to 2021. We obtain these data from National Oceanic and Atmospheric Administration (NOAA) Global Historical Climatology Network-Daily (GHCN-Daily).[5] We then combine the weather data with a comprehensive

[1] See IPCC report.Under a warming scenario of 2°C, economic damage from climate change could reach $69 trillion by the year 2100.

[2] In Figure 2, we plot a heat map of temperature anomaly in the United States from 2000 to 2021, which is defined as the deviation of average monthly temperature from the average long-run historical temperature. It is worth noting that consistent with global warming, the abnormal temperatures are positive in general, suggesting that the recent two decades is on average warmer than the pre-2000 period in the United States.

[3] In response, increasing numbers of researchers are trying to understand and quantify a broad array of economic costs related to climate change. See Related Literature.

[4] See report from Redfin.

[5] The Global Historical Climatology Network daily (GHCNd) is an integrated database of daily climate summaries from land surface stations across the globe. GHCNd is made up of daily climate

listing-level dataset of 32 million transactions over the 2000-2021 period from Multiple Listing Service (MLS) platforms collected by CoreLogic to generate measures of zipcode-level temperature exposure for each property. By exploiting information on time (year-month) and location (at the zip code level) of each property, we can measure the weather conditions on the transaction (closing) date of the property. Following Addoum, Ng and Ortiz-Bobea (2020) and Choi, Gao and Jiang (2020), we construct several measures of temperature exposure using the matched NOAA weather and MLS listings data.[6] The first measure is the average abnormal temperature experienced at each property location in the transaction month, which is defined as the difference between monthly temperature (in Celsius degrees) and the historical average temperature in the same calendar month and same location over the last twenty years. Second, to capture exposure to extremes that may be masked in the deviations to historical average measure, we count the number of extreme hot (cold) days in the transaction month when the temperatures exceed 30°C (fall below 0°C).[7] Third, we calculate the abnormal number of extreme hot (cold) days in a similar way to abnormal temperatures. Using these measures, we empirically estimate a model controlling for housing characteristics, average precipitation, zip code fixed effects, and time fixed effects to ask how location-specific abnormal temperature exposure affects house prices in the United States. Our identification relies on exogenous variation in the temperature distribution for a given zip code in any given calendar month.

records from numerous sources that have been integrated and subjected to a common suite of quality assurance reviews.

[6]The measures of temperature exposure are proxies that correlate with public belief about climate change over time and across regions. Although local weather fluctuations may not be scientifically informative about the global warming trend, public beliefs about climate change do increase significantly after people personally experience unusually warm weather. See Li, Johnson and Zaval (2011), Lang (2014), Myers, Maibach, Roser-Renouf, Akerlof and Leiserowitz (2013), Akerlof, Maibach, Fitzgerald, Cedeno and Neuman (2013), Konisky, Hughes and Kaylor (2016), and Howe, Markowitz, Lee, Ko and Leiserowitz (2013). An additional advantage of using abnormal temperature exposure (temperature anomaly) is that it is plausibly exogenous to the local economic conditions and thus helps in making causal inferences (Dell, Jones and Olken, 2014).

[7]Because the definition of temperature extremes is likely to vary across geographies, we also define location and time-specific extreme temperature exposure variables. Specifically, we calculate the number of days that max (min) temperatures are above (below) the 90th (10th) percentile of the zipcode specific temperature distribution in a given month.

We obtain the local climate change belief and risk perception measures from Yale Climate Opinion Maps.[8] Using the temperature anomaly measures (abnormal temperature and the abnormal number of hot days) , we first verify that abnormally high local temperatures lead to elevated belief in climate change in that region. Next, we examine whether the effect of abnormally high temperature extends beyond climate change belief to have any effect on house prices. Rising global temperatures have a domino effect, causing other climate change events, such as sea-level rise, more frequent and intense droughts, severe wildfires, more frequent extreme weather events, and more heat waves. Our hypothesis is that due to the immobility of the residential properties, they are vulnerable to the impacts of the aforementioned physical climate risks. At the same time, higher local abnormal temperature leads to elevated concern about the negative impacts of climate change on the housing market. Thus, home buyers would demand a price discount due to their rising concern about the potential collateral damage brought by future climate change. For all three temperature exposure measures, we find that the average effect of abnormal temperature exposure on house prices is significantly negative, which suggests that people do take into account the long-run risks of climate change when purchasing a house, especially after they experience unusually hot temperatures. Specifically, a 1-standard deviation increase in abnormal temperature corresponds to a decrease of 0.07 percentage points in house prices. When we break the abnormal temperature into quintile ranks, we find that the negative impact is concentrated in the top quintiles when unusually warm weather takes place. Compared to the historical average number of days with high temperatures, 1 extra day spent above 30°C is associated with a statically significant

[8] Specifically, we use the percentage of the population who think global warming is happening and who are somewhat/very worried about global warming in a county as the measure of local climate change belief. The original survey questions are "Recently, you may have noticed that global warming has been getting some attention in the news. Global warming refers to the idea that the world's average temperature has been increasing over the past 150 years, may be increasing more in the future, and that the world's climate may change as a result. What do you think: Do you think that global warming is happening?", "How worried are you about global warming?". For the question measuring how worried respondents are about global warming, "very worried" and "somewhat worried" were combined into a single measure of "worried". See Section 2.3 for data detail.

0.04-percentage-point decrease in house prices. Compared to months with no days above 30°C, the negative effect on house prices is the strongest in months with more than 20 extremely hot days, which is a 2.0 percentage points drop at 1% significance level.

To further test our conjecture that the effect of abnormal temperature exposure on house prices should be more pronounced in regions where people have stronger beliefs in climate change, and during periods of increasing public attention to climate change[9], we identify to what extent the abnormal temperature discounts vary across communities with different levels of belief in climate change and periods of varying levels of public awareness of climate change. Consistent with this conjecture, first, we find that belief in climate change plays a significant role in the pricing of properties, in areas with more believers in climate change, abnormal temperature exposure has a much larger negative impact on house prices. Second, using the publication of Stern Review[10] as a quasi-natural experiment, we conduct difference-in-differences tests to identify how abnormal temperature exposure affects house prices as people become more aware of the potential risks of climate change. Since the Stern Review is unlikely to change the likelihood or physical risk of climate change other than through increased awareness of climate change risk, we find that the effect of abnormal temperature exposure on house prices is greater after the release of the Stern Review.

In addition, we replicate our main analyses using rental market information to determine whether any observed abnormal temperature exposure discount is due to current property characteristics or the pricing of long-run climate risk. We find that the same discount does not exist in rental prices, reinforcing the idea that this discount is due to expectations of potential future collateral damage, not current property

[9] The key assumption is that home buyers are able to connect higher local temperatures to a larger narrative of climate change. Also, it is more likely when the public, on the whole, becomes more aware of climate risks.

[10] On October 30, 2006, economist Nicholas Stern published a report detailing the costs of damages that climate change is expected to have on the world economy. The "Stern Review" is one of the earliest and most thorough analyses of the economics of climate change and also one of the most well known, providing a detailed description of the potential costs triggered by global warming (Stern and Stern, 2007). As shown by Painter (2020), the Stern Review significantly increased the market attention (measured by Google search volume) toward climate change.

quality.

In our next set of tests, we examine heterogeneity in the relation between abnormal temperature exposure and house prices. We find stronger significant negative effects in the South, West and Midwest relative to the Northeast areas[11], and for properties above the median house price. For abnormal temperature exposure discounts in markets with different liquidity, our results suggest that the abnormal temperature exposure discount we document over the full sample is economically meaningful in all but the most liquid markets. In addition, consistent with supply elasticity theory, the abnormal temperature exposure discount is more pronounced in relatively inelastic locations. For counties exposed to sea level rise (SLR) risk, we find that the negative impact of abnormal temperature exposure on house prices is much stronger than that on counties not exposed to the risk of SLR.

Related Literature

In recent years, the idea that that climate may substantially influence economic performance has gained increasing attention. A rapidly growing body of research examine the impacts of weather on a variety of economic outcomes such as economic growth (Dell, Jones and Olken, 2009, 2012; Addoum, Ng and Ortiz-Bobea, 2020; Hsiang, 2010), labor supply (Graff Zivin and Neidell, 2014), consumer decisions (Conlin, O'Donoghue and Vogelsang, 2007; Busse, Pope, Pope and Silva-Risso, 2015; Gilchrist and Sands, 2016) and other societal outcomes.[12]

For example, prior work documents a negative effect on output using exogenous variation in location-specific temperature. In particular, Dell et al. (2009) use a panel

[11]Northeast includes New England and the Middle Atlantic regions, Midwest includes East North Central and West North Central, South includes South Atlantic, East South Central and West South Central, and West includes the Mountain and Pacific regions. See Census Regions and Divisions of the United States.

[12]For instance, prior work studies the impact of weather on Agriculture (Fisher, Hanemann, Roberts and Schlenker, 2012), Crime and Mortality (Barreca, Clay, Deschenes, Greenstone and Shapiro, 2016; Hsiang, Kopp, Jina, Rising, Delgado, Mohan, Rasmussen, Muir-Wood, Wilson, Oppenheimer et al., 2017), Morbidity (Agarwal, Qin, Shi, Wei and Zhu, 2021; White, 2017; Mullins and White, 2019; Karlsson and Ziebarth, 2018; Bobb, Obermeyer, Wang and Dominici, 2014), Migration (Bohra-Mishra, Oppenheimer and Hsiang, 2014; Deschenes and Moretti, 2009) and Political Stability (Miguel, Satyanath and Sergenti, 2004). See Dell et al. (2014) for a comprehensive review.

of annual country-level observations to show that a 1°C increase in mean temperature reduces per capita income by 1.4 percentage points among developing countries. Moreover, Jones and Olken (2010), Hsiang (2010), and Dell et al. (2012) find that temperature shocks negatively affect manufacturing exports and reduce output in the industrial and service sectors. Addoum et al. (2020) extend this literature to account for the effects of temperature on establishment sales by building a detailed panel of temperature exposures for economic establishments across the United States. They estimate how location-specific temporary temperature shocks affect establishment-level sales and productivity and find that the population average effects on sales and productivity of these shocks are close to zero. Jin, Li, Lin and Zhang (2021) show that higher local temperatures lead to reduction in local employment and the number of establishments. Besides economic growth, studies also show that the negative impacts of extreme temperatures extend to labor supply. For instance, linking the American Time Use Survey to regional weather data, Graff Zivin and Neidell (2014) find that extremely hot temperatures reduce hours worked across several heat sensitive industries. Custodio, Ferreira, Garcia-Appendini and Lam (2021) exploit variation in local temperature across suppliers of the same client to find that suppliers experiencing a 1°C increase in average daily temperature decrease their sales by 2%. The effect is more pronounced among suppliers in manufacturing and heat-sensitive industries, which is consistent with lower labor productivity and supply when temperatures are higher.

A strand of literature establishes the link between temperatures and consumer decisions. Conlin, O'Donoghue and Vogelsang (2007) show that cold-weather clothing purchasing depends on the weather at the time of purchase, which suggests that people's decisions are over-influenced by the current weather. This finding is echoed by Busse, Pope, Pope and Silva-Risso (2015), they also find that the choice to purchase warm-weather or cold-weather car types depends on the weather at the time of purchase. Gilchrist and Sands (2016) find the weather shocks to opening weekend viewership has impacts on movie consumption.

More broadly on the relation between climate change and financial and real estate markets, a more recent literature is emerging that assesses risks associated with climate change in these markets such as the impacts of extreme weather and physical climate risk factors like floods, rising sea levels and wildfires.[13] Choi, Gao and Jiang (2020) find that local high-temperature shocks are associated with people's attention and belief to climate change, which triggers carbon-intensive listed firms to perform worse in the stock market. Jiang, Li and Qian (2019) find that firms with high adjustment costs to seal level risk pay higher costs to obtain long-term loans. Painter (2020) and Goldsmith-Pinkham, Gustafson, Lewis and Schwert (2021) show that municipal bonds have begun responding to the sea level rise risks. Using sea level rise risk as a proxy for climate risk, Giglio, Maggiori, Rao, Stroebel and Weber (2021b) find that climate risk is priced in housing markets, with increased climate risk leading to relatively lower prices for more exposed properties. Bernstein, Gustafson and Lewis (2019), and Baldauf, Garlappi and Yannelis (2020) show that house prices of homes exposed to sea level rise sell are significantly lower than observably equivalent unexposed properties equidistant from the beach. They also show that differences in beliefs about climate change play an important role in affecting house prices. In contrast, Murfin and Spiegel (2020) find limited price effects for houses based on their inundation threshold under projections of sea level rise.

Deng, Han, Li and Riddiough (2021) identify a significant high temperature-mortgage default relation using granular weather information and comprehensive loan performance data. Issler, Stanton, Vergara-Alert and Wallace (2020) find a significant increase in mortgage delinquency and foreclosure after a fire. Nguyen, Ongena, Qi and Sila (2022) find that lenders charge higher interest rates for mortgages on properties exposed to a greater risk of sea level rise. Duan and Li (2021) study the climate change concern and loan officers' mortgage lending decisions. They find that abnormally high local temperature leads to elevated belief in climate change, and loan officers approve fewer mortgage applications and originate lower amount of loans in

[13] See Hong, Karolyi and Scheinkman (2020), and Giglio, Kelly and Stroebel (2021a) for a comprehensive review.

abnormally warm weather. Cvijanovic and Van de Minne (2021) find that exposure to extreme temperatures significantly reduces average realized total returns in commercial real estate, and there is substantial variation in sensitivity to temperature shocks across property types. In this paper, we focus on the relationship of temperature exposures and residential real estate prices. Our study adds to the existing literature by identifying statistically and economically significant negative effects of abnormally high temperature on house prices.

The rest of the paper proceeds as follows. Section 2 describes our data and present summary statistics for variables of interest. We then present our empirical methodology and results in Section 3 and Section 4, respectively. Finally, Section 5 concludes.

2 Data

To examine the relationship between abnormal temperature exposure, belief in climate change and house prices, we combine data from several sources. In this section, we describe our data sources and various sample restrictions that we use. We then discuss how we measure temperature exposure and summarize our matched sample.

2.1 Housing Data

Our housing data is from a comprehensive listing-level dataset on residential properties for sale collected by CoreLogic. The data come from MLS platforms operated by regional real estate boards. Each MLS varies in size but, on average, has real estate agent representation in it's geographical area. Each observation in the data represents a listing on its associated MLS platform, with many variables describing very detailed characteristics of the property as well as the status of the listing. These variables include the date when the property is listed, the original listing price, the last observed listing price, and a host of property-specific characteristics such as the size of living area, number of bedrooms and bathrooms, the age of the structure, that we use both as controls and as determinants of the amenity value of a property. If the property sells, we observe the date of sale and the transaction price. If the property fails to sell, we also observe when the property is pulled from the market. Figure 1 displays the locations of the properties in our sample. Each MLS platform in the full CoreLogic MLS dataset begins at different times, we restrict our analysis to the subsample of MLS whose data begins in 2000, which results in the final sample from 2000 to 2021.

2.2 Weather Data

We obtained the weather data from the National Climatic Data Center (NCDC) Global Historical Climatology Network-Daily, which collects daily observations of maximum and minimum temperature, precipitation amount from 4940 weather stations across the contiguous United States. Throughout our analysis, we construct the daily temperature as the midpoint of the maximum and minimum temperatures. In addition, NCDC maintains a database containing the longitude and latitude of each weather station, which allows us to match the listing level data with weather data by identifying nearest weather stations for each five-digit zip code.

Specifically, we also obtain from the US Census the longitude and latitude for the centroid of each five-digit zip code for each property in our MLS data for the contiguous United States. Next, we calculate the distances of the centroid of each zip code to every weather station and identify the three nearest weather stations. Following Conlin et al. (2007), for each zip code, if the nearest weather station has weather information, then we assign those daily weather conditions to that zip code. If there is missing weather information from the nearest weather station, then we consider the second-nearest weather station; and if there is missing weather information from the second-nearest weather station, then we consider the third-nearest weather station.[14] After merging the weather information with the listing information using the five-digit zip code, we drop observations for properties whose housing characteristics and transaction price are missing.

[14]The average distance between a zip code and the closest weather station is less than 16.8 km (10.4 miles).

In Figure 2, we plot a heat map of temperature anomaly in the United States from 2000 to 2021, which is defined as the deviation of average monthly temperature from the average long-run historical temperature.[15] The x-axis is from January to December, and the y-axis is from 2000 to 2021. Each cell's number stands for the departure of each monthly average temperature from its corresponding long-run average temperature. And each cell's color indicates the magnitude of the deviation in the corresponding cell range from -2.5°C to 5°C, with larger positive (negative) deviations associated with warmer (cooler) colorings. For example, in March 2012, the average monthly temperature was 4.95°C higher than the long-term average temperature in March. In June 2021, the average monthly temperature was 2.28°C higher than the long-term average temperature in June. It is worth noting that consistent with global warming, the abnormal temperatures are positive in general, suggesting that the recent two decades is on average warmer than the pre-2000 period in the United States.

2.3 Yale Climate Change Option Maps Data

We also obtain the annual climate change belief measures at U.S. county and State level from Yale Climate Opinion Maps (Howe, Mildenberger, Marlon and Leiserowitz, 2015).[16] Their study provides, at both the county and state level, survey evidence on how respondents answer questions regrading their climate change belief and risk perceptions, which includes but not limited to (1) whether they believe that climate change is happening; (2) whether they believe they will be personally affected by climate change; (3) whether they believe global warming will harm future generations; and (4) whether they are somewhat or very worried about global warming. Specifi-

[15]The base period for the long-run historical temperature calculations is from 1901 to 2000.

[16]These data are not based on surveys conducted in every U.S. county, city, and state; they are statistically modeled estimates of the percentage of the adult population who agree/support a particular belief or attitude in a particular geographic area. The statistical model used to estimate opinions incorporates original survey data and combines it with additional information such as the percentage of people in each geographic area who voted for a particular presidential candidate, along with economic, demographic and geographic population characteristics that predict Americans' climate attitudes. Also, smaller geographic areas have higher uncertainty than larger areas.

cally, we use two measures from the survey to proxy for people's belief about climate change. Importantly, we see significant variation in both measures. The first measure, Happening, is the fraction of population in a county (state) who think global warming is happening. The second measure, Worried, is the fraction of population in a county (state) who are somewhat/very worried about global warming. The data on climate change belief is available annually from 2014 to 2021 at county level, and from 2008 to 2021 at state level. Figure 3 (A) and (B) plot the fraction of adults at county-level who think global warming is happening and who are somewhat/very worried about global warming in year 2021, respectively.

2.4 Data Construction and Summary Statistics

Following Choi et al. (2020) and Addoum et al. (2020), we construct several temperature exposure variables for each weather station in every month. We calculate 1) the temperature deviation from long-run historical zipcode-monthly average temperature, 2) the number of extreme hot (cold) days during each month when the temperature is above 30°C and below 0°C [17], 3) and the deviation of the number of extreme hot (cold) days from historical mean. See Section 3 for details.

Table 1 reports summary statistics for key variables in the matched sample of property and weather exposure variables. It shows the mean, standard deviation, minimum, median and maximum values for the house prices and housing characteristics, as well as our temperature exposure, precipitation measures and climate change belief measures. Temperatures are reported in degrees Celsius, time-based temperature exposures are measured in days, and precipitation is reported in millimeters. For the period of 2000-2021 in our sample, the monthly average (median) temperature increased by 0.29-Celsius degrees (0.3-Celsius degrees) relative to the average temperature in the same calendar month over the last twenty years. This demonstrates that most regions in the U.S. experienced rising temperatures over the last two decades, consistent with the trend of global warming. Figure 4 displays the dis-

[17] 30° Celsius is equal to 86° Fahrenheit, 0° Celsius is equal to 32° Fahrenheit.

tribution of the deviation of the monthly average temperature from long-run average in our matched sample data. The blue (red) curve is the distribution of the deviation of monthly average temperature from the historical mean in the same calendar month in the past twenty (ten) years. The average (median) number of extreme hot days in a calendar month is 7 (1) days. The average (median) house price in our sample is $260,530 ($200,000). According to Yale Climate Opinion Maps, on average 68% of the population believe global warming is happening, and 58% of the population are somewhat/very worried about global warming at the state level.

3 Methodology

To test the effects of the temperature exposure on house prices in a given zip code in any given month, we estimate a linear model relating the house prices and the temperature exposure variables:

$$y_{i,j,t} = \alpha + \beta\, Temperature_{j,t} + \gamma\, Precipitation_{j,t} + \delta\, P_{i,t} + \theta_j + \theta_{y,m} + \epsilon_{i,j,t} \tag{1}$$

where $y_{i,j,t}$ is the natural logarithm of transaction price for listing i in time t and location j, $Temperature_{j,t}$ and $Precipitation_{j,t}$ are the temperature exposure and precipitation variables in year-month t and zip code j, respectively. Following Giglio, Maggiori and Stroebel (2015), we include a vector of property-specific controls $P_{i,t}$ such as the property size, number of bedrooms and bathrooms, and the age of the property. [18]

To help isolate the causal effect of temperature exposures, our specification includes the zip code fixed effects θ_j and the year-by-month fixed effects $\theta_{y,m}$. They control for unobserved time-invariant zip code level house price factors and time-varying house price trends, respectively. These fixed effects help ensure that our model is identified given the exogenous random fluctuations in the distribution of temperatures for a given zip code region in any calendar month. $\epsilon_{i,j,t}$ is the error

[18] We censor the top 1 percent of values in some of our controls to account for outliers.

term that contains additional factors that can impact house prices. Standard errors are clustered at zip code level to account for correlation between temperature exposure measures and unobservable shocks.

The main coefficient of interest is β, which is the coefficient on temperature exposure measures $Weather_{j,t}$. Following Choi et al. (2020) and Addoum et al. (2020), we use three main temperature exposure variables at the zip code level: 1) The abnormal temperature in a given region is the difference between monthly temperature (in Celsius degrees) and the last twenty-year historical average temperature in that region. Specifically, given a zipcode region and a calendar month, we first calculate the local monthly temperature by taking the average of the daily average temperatures in our data, and then minus the average temperature in the same zipcode region and in the same calendar month over the last twenty years.[19] 2) Second, to capture exposure to extremes that may be masked in the deviations to historical average measure, we define absolute extreme temperature thresholds. Our second measure is the abnormal number of extreme hot (cold) days, which is defined as the difference between the number of days when the temperatures exceed 30°C (fall below 0°C) in the current month and the historical long-run extreme hot (cold) days in the same calendar month over the past twenty years. Also, because the definition of temperature extremes is likely to vary across geographies, we define location and time-specific extreme temperature exposure variables. Specifically, we calculate the number of days that max (min) temperatures are above (below) the 90th (10th) percentile of the zipcode specific temperature distribution in a given month, and then calculate the deviations from the historical mean in a similar way. 3) Third, we also use the number of extreme hot (cold) days in the current month to examine the effect of prolonged periods of high temperature on house prices. Following the climate economy literature closely (Dell et al., 2014), we also control for the average monthly rainfall amount. Our identification relies on exogenous variation in the temperature distribution for a given zip code in any given calendar month.

[19] We also use deviation from the last ten-year historical monthly average temperature, main results remain unchanged and are not shown in the results to save space.

4 Results

4.1 Belief in Climate Change and Abnormal Temperature Exposure

In order to investigate whether people's attention varies with local temperatures, Choi et al. (2020) use international data find that monthly change in the Google Search Volume Index on the topic of "Global warming" in a city increases significantly when the city experienced unusually warm weather, which suggests that people pay more attention to global warming when they are experiencing an abnormally high temperature. Similarly, results of Duan and Li (2021) based on regional variation within U.S. are broadly consistent with their finding. Following their approach, we examine whether abnormal temperature in the local area leads to elevated public climate beliefs and risk perception in that region.

We test how local temperature exposures influence climate change beliefs, where we obtain the local climate change belief and risk perception measures from Yale Climate Opinion Maps. Table 2 Panel (A) reports the results on the effect of abnormal temperature on Americans' climate change beliefs, risk perceptions at the county level. In column (1) and column (3), the dependent variables are Happening and Worried, which measure the estimated fraction of adult population in a county who think that global warming is happening and who are somewhat/very worried about global warming, respectively. The unit of beliefs and risk perception in climate change is county-year level, and the sample period is from 2014 to 2021. Standard errors in parentheses are clustered at the state and year level. In both columns, the coefficients on the abnormal temperature are both positive and significant at 5% level. This indicates that both measures of climate change belief and risk perception increase after experiencing abnormally high local temperature.

In column (2) and column (4), we rank all months into quintiles based on abnormal temperature in a zip code region and use these quintile dummies (Q2-Q5) in the regression instead of the abnormal temperature. The coefficients of the quintile dummies indicate that the temperature effect is nonlinear: the coefficients of quintiles 2, 3, and 4 in column (2) and the coefficients of quintiles 2 and 4 in column (4) and are not significantly different from zero, while the coefficients of quintile 5 are significant at 5% and 1%, respectively. Based on the estimation in Column (3), a 1°C increase in the average temperature anomaly increases the fraction of population who are somewhat/very worried about global warming by 0.11 percentage points, which is about 1.6% of the sample standard deviation. In column (4), compared to the 20% abnormally coolest months, in the 20% abnormally warmest months more population are worried about the climate change. It shows that both measures of climate change belief are positively affected by local temperature anomalies, and the effect manifests when the abnormal temperature is in top quintiles. Thus, our results suggest that people's climate change belief increases with the highest abnormal local temperatures, which are the most salient. Panel (B) use abnormal number of hot days as explanatory variable, and the conclusion remains the same.

4.2 Effect of Abnormal Temperature Exposure on Real Estate Prices

We next examine whether the effect of abnormally high temperature extends beyond climate change belief to have any effect on house prices. Rising global temperatures have a domino effect, causing other climate change events, such as sea-level rise, more frequent and intense droughts, more severe wildfires, and more frequent extreme weather events. These can cause dangerous, destructive storms with wind damage, a higher risk of flooding and erosion, and more heat waves. Our hypothesis is that due to the immobility of the residential properties, they are vulnerable to impacts of aforementioned physical climate risks. At the same time, higher local abnormal temperature leads to elevated concern about the negative impacts of climate change in the housing market. Thus, home buyers would demand a price discount due to their rising concern about the potential collateral damage brought by future climate change. Table 3 , 4 and 5 present our estimates from regressions of the form outlined in equation 1. In all regressions, the dependent variables are the natural logarithm of the transaction (closing) price. Following Giglio et al. (2015) and Dell et al. (2014), we control for several property characteristics (i.e. Property size, Number of bedrooms and bathrooms, and the Age of the property) and the average monthly precipitation level. We control for zip code fixed effects and year-by-month fixed effects in all regressions to control time-invariant zip code level characteristics and time-varying economic fundamentals. Standard errors are clustered at the zip code level.

In Table 3 column (1) and (2), the explanatory variable is *Abnormal Temperature*, measured as the difference between the average temperature in closing month and the average temperature in the same zip code region and same calendar month over the last twenty years in zip code j and on closing date t. Without controlling for monthly average precipitation and housing characteristics, the estimated coefficient on abnormal temperature is -0.0007, significant at 1% level. After including the controls, the estimated coefficient is still significant at 10% level. The results indicate that higher abnormal temperature is associated with significant lower house prices. A 1-standard-deviation increase in *Abnormal Temperature* corresponds to a decrease of 0.07 percentage points (= 0.0004×1.64) in house prices.[20] In column (3) and (4), we replace abnormal temperature with the quintile dummies based on local abnormal temperature. In column (4), the coefficients on these quintile dummies indicate a strong monotonic effect of local temperature abnormalities on house prices. To show the monotonic effect of temperature anomalies on house prices, in Figure 5 we plot the coefficients on quintile dummies of abnormal temperature, along with the 95% confidence intervals. It shows that the negative effect on house prices is the strongest in the highest abnormal temperature quintile, consistent with our results in Table 2. The estimates show that with a change from temperature quintile 1 (coolest) to quintile 5 (warmest), it is corresponding to a drop of 0.4 percentage points at 1% significance level. The effect is smaller for mildly warm temperatures.

We next present the estimates of the effects of extreme temperature exposure on house prices. In Table 4 column (1), we include a measure of abnormal extremely hot days for which temperatures exceed an upper limit of 30°C, as well as a measure of

[20] In other words, a 1°C increase in abnormal temperature exposure is associated with a 0.04-percentage-point decrease in house prices.

extremely cold days for which the temperature drops below 0°C. As with the abnormal temperature measure, we also find evidence of a significant negative relation between a property's exposure to extreme temperature and the house price. In particular, compared to the historical average number of days with high temperatures, 1 extra day spent above 30°C is associated with a statically significant 0.04-percentage-point decrease in house prices. In column (2), we adopt relative measures of temperature extremes and define extremely hot days as the number of days for which the maximum temperature exceeds the 90th percentile of the historical monthly distribution of daily temperatures in a zip code region. Similarly, extremely cold days are defined as the number of days that are colder than the 10th percentile in the historical distribution. The regression results show that house prices are significantly negative related to extremely hot days. In column (3), we rank all months into quintiles based on abnormal number of extremely hot days (temperatures exceed 30°C) in a zip code region and use abnormal hot days quintile dummies (Q2-Q5) as explanatory variables. The extreme temperature effect on house prices is non-monotonic, the coefficient on quintile 5 suggests that for properties located in regions experiencing the most frequent hot days, there is a 0.51-percentage-point drop in house prices compared with those located in regions with the least frequent hot days.

In Table 5, we repeat the same analysis using the number of extreme hot (cold) days in the current transaction (closing) month to examine the effect of prolonged periods of high temperature on house prices. Again, we find evidence that house prices are negatively related to extremely hot days. In column (3), we replace the explanatory variables with dummies indicating periods with different number of hot days. The coefficients suggest that the negative effect on house prices is the strongest in months with more than 20 extremely hot days, which is a 2.0 percentage points drop at 1% significance level compared to months with no days above 30°C.

Taken together, the results in Tables 3—5 show that the average effect of abnormal temperature exposure on house prices is significantly negative, which suggests that people do take into account the long-run risks of climate change when purchasing a house, especially after they experience unusually hot temperatures.[21]

4.3 Belief in Climate Change and Real Estate Prices

4.3.1 The Role of Climate Change Belief and Risk Perception

Prior studies (Choi et al., 2020; Duan and Li, 2021) and our Section 4.1 have documented that high-temperature shocks are associated with increased awareness of climate change risks. We therefore hypothesize that the effect of abnormal temperature exposure on house prices should be more pronounced in regions where people have stronger beliefs in climate change.

To test our conjecture, in Table 6 column (1) and (2), we regress the house prices on *Abnormal Temperature* and its interaction with *Happening* and *Worried*, standardized measures of the level of concern regarding climate change risk in the county housing the property.[22]In both columns, the coefficients of the interaction terms are negative at 1% significance level, which suggests that a state's reported level of concern over future climate change does significantly affect the abnormal temperature exposure discount. These effects are considerably larger than what is observed in the full sample. Similarly, we add a term that interacts *Abnormal Number of Hot Days* with *Happening* and *Worried* in Table 6 column (3) and (4). The results show that the negative relation between abnormal temperature exposure and a property's price is significantly negative related to an area's beliefs in climate change. Overall, we find that belief in climate change plays a significant role in the pricing of properties, in areas with more believers in climate change, the abnormal temperature exposure has a much larger negative impact on house prices.

4.3.2 Difference-In-Differences Analysis around the Stern Review

Painter (2020) documents that public awareness of climate change risks has increased

[21] The key assumption is that home buyers are able to connect higher local temperatures to a larger narrative of climate change.

[22] One caveat is that we only know the belief about climate change in the county housing the property, but not the county of the buyer's address.

significantly since the release of "Stern Review" on October 30, 2006. We use this publication event as a quasi-natural experiment to identify how climate change concerns interact with abnormal temperature exposure to affect house prices.[23] After the release of the Stern Review, it is likely that home buyers became more aware of the potential risks future climate change poses on their real estate investments. On the other hand, the Stern Review is unlikely to change the likelihood or physical risk of climate change other than through increased awareness of climate change risk. As a result, we expect that the effect of abnormal temperature exposure on house prices should be greater after the release of the Stern Review.

To examine whether increased awareness of climate change risks leads to a greater effect of abnormal temperature exposure on house prices, we employ a difference-in-differences framework. In Table 7, we create a dummy variable Stern Review *Stern*, which is equal to one if the transaction date is after the Stern Review was released, and equal to zero if the date is before the Stern Review was released. In column (1), the results reveal that home buyers began to account for climate change risks after the release of the Stern Review, as the coefficient on the interaction terms is negative and significant. We restrict the sample to three years, and one year before and after the release of the Stern Review in column (2) and (3), respectively. The narrower time frames help mitigate the possibility of pre-existing trends confounding the results. For the three-year window, the interaction term remains statistically significant negative. For the one-year window, the interaction term is smaller and statistically insignificant. The results using the abnormal number of hot days are similar.

[23]It is beyond the scope of this paper to determine precisely which reports result in an increase in abnormal temperature exposure discount over time. Bernstein et al. (2019) used 2014 as their event year to study the effect of new information about expected Sea-Level-Rise on exposed properties, as a number of scientific reports and popular media articles published around that time documented predictions of an increasingly dire global coastline.

4.4 Robustness and Heterogeneity in the Abnormal Temperature Exposure Discount

In this section we explore further by region, property value level and market liquidity. We also provide the rental placebo checks, and show the negative effects are stronger in areas with low housing supply elasticity, for counties exposed to SLR risk than counties not exposed to the risk of SLR.

4.4.1 Regional and Affordability Heterogeneity

In this subsection, we explore further heterogeneity by region, and property value level. Table 8 repeats the main analysis from Table 3 for subsets of our data for which variations in amenity are likely to be smaller. Specifically, we split the sample (a) by geography—Northeast, Midwest, South, and West; (b) by property value—above and below $200,000 (median house price in our sample). Columns (1) through (8) split the sample by regions: Northeast, Midwest, South, and West. We find stronger effects in the South, West and Midwest relative to the Northeast areas, with the coefficients of abnormal temperature of being negative and significant. The estimates of the quintile dummies present similar results. We do not find a statistically significant effect on the Northeast region.[24] We hypothesize that the abnormal temperature exposure discounts are likely to differ in less or more expensive housing. For example, due to climate change impacts, the need to modify and maintain existing homes and higher insurance premiums could directly affect the costs of homeownership. This could be of particular concern to the extent it affects the availability of less expensive housing. Columns (9)—(12) split the sample by properties below the median house price and above the median house price in our sample. We find that the effect of the abnormal temperature is stronger for properties above the median house price. In fact, we only find statistically significant effects for these properties.

[24]One potential hypothesis is that effects may be weaker in areas where we expect more climate change mitigation.

4.4.2 Market Liquidity Heterogeneity

If housing markets were highly liquid with enough transactional buyers, then the abnormal temperature exposure discounts may not occur frequently (Bernstein et al., 2019). However, recent evidence indicates that housing markets are highly illiquid (Piazzesi, Schneider and Stroebel, 2020). In hot housing markets where each seller has a huge number of bids, we might expect the abnormal temperature exposure related discount to dissipate. To test our predictions, we examine the relation between market liquidity and the abnormal temperature exposure discount. Specifically, we interact *Abnormal Temperature* with indicators for highly liquid markets using four market liquidity measures—days on market, average sale price to list ratio, inventories, as well as absorption rate that is calculated by dividing the number of properties sold in a given period by the total number of properties available for sale. The above argument suggests that the coefficient on the interaction term between abnormal temperature exposure and periods of extremely high liquidity will be positive, negating the abnormal temperature exposure discount in these settings.

Table 9 presents the results from interacting the abnormal temperature exposure with indicators for a market in the top 10% in terms of each liquidity measure. In column (1) we see the coefficient on the interaction between abnormal temperature exposure and "Low days on market" is 0.0023 and significant at the 1% level, suggesting that the abnormal temperature exposure discount attenuates in the most liquid markets. We confirm this by constraining our sample to just markets at or above the 90th percentile of liquidity and see an insignificant negative coefficient. Columns (3) through (8) repeat this analysis with the other three normalized measures of liquidity, and yield similar results. Overall, the results suggest that the abnormal temperature exposure discount we document over the full sample is economically meaningful in all but the most liquid markets.

4.4.3 Rental Placebo Tests and Heterogeneity by housing stock supply

It is possible there is unobservable determinants of property value that covary with the abnormal temperature exposure.[25] We examine this possibility by conducting a placebo test, we utilize residential rents as outcome variable and regress the rental prices on abnormal temperature in a specification similar to Equation 1. These tests are predicated on the idea that both renters and buyers care about property quality, but, the rental market is subject to more turnover, unlike buyers, renters are unlikely to care about long-run climate change risks in decision-making. Thus, if the relation between abnormal temperature exposure and sale prices that we observe is related to the pricing of long-run climate change risks due to rising temperatures, we expect no significant relation between rental prices and abnormal temperature exposure. If instead the relation between exposure and sale prices that we observe is due to omitted property characteristics or amenities, then we expect a negative relation between abnormal temperature exposure and rental prices. Table 10 presents estimates for regressions of rental prices on abnormal temperature exposure. Column (1), (2) and (3) replicate the specification of column (2) of Table 3, column (1) of Table 4 and column (2) of Table 4, respectively. Different from the residential real estate purchase market, we do not find evidence of a significant negative association between abnormal temperature exposures and rental prices.

We next explore if and in what ways the effect of abnormal temperature exposure on house prices differed across zip codes in Metropolitan Statistical Area (MSA) with different supply elasticity. According to supply elasticity theory, we would expect

[25] The concern with the estimates presented in the residential real estate purchase market is that they might not just capture the pricing of future climate change risk, but that our estimates might also be picking up changes in the flow-utility of climate risk-exposed properties that could be correlated with abnormal temperature exposure. For example, it could be that abnormal temperature exposure rises after severe wildfires that have a particularly strong direct effect on the utility of living in properties located in areas at very high risk of destructive wildfires. To show that such a confounding story is not driving our results, we present that estimates of rental prices of properties on abnormal temperature exposures are not statistically significant and negative. It suggests that our findings for transaction prices are not the result of a decline in the flow utility of these properties when abnormal temperature exposure increases. Instead, the decline in transaction prices most likely results from the increased present discounted cost of future climate change risk.

abnormal temperature exposure to matter more for house prices in areas with lower supply elasticity (where it is relatively hard to build). We examine this possibility by taking into account the Saiz (2010) measure of local housing supply elasticity.[26] To explore the effect of real estate supply elasticity and segmented real estate markets, in Table 11, we split the sample based on the Saiz (2010) measure of supply elasticity. Panel (A) and (B) repeats the main analysis as in Table 3 and 4, splitting the sample below and above the median level of housing supply elasticity. Consistent with theory, the abnormal temperature exposure discount is more pronounced in relatively inelastic locations.[27]

4.4.4 Abnormal Temperature Exposure Discount and Sea Level Rise Risk

The rise in the local abnormal temperatures is a "wake-up call" that makes home buyers aware of the risks of climate change. One of the most salient climate risks that matters for residential real estate is sea level rise (SLR). Due to the vulnerability to the effect of potential sea level rise, people of coastal areas may be more sensitive to the effects of high temperatures. To test this conjecture, we take into account the Hallegatte, Green, Nicholls and Corfee-Morlot (2013) measure of sea level rise risk.[28] Appendix Table 1 reports the SLR risk of all U.S. cities included in Hallegatte et al. (2013) and their associated counties and states. The city (county) with the highest SLR risk is New Orleans, LA, which is expected to have an annual loss of 1.48% GDP due to sea level rise. Consistent with our conjecture, for counties exposed to SLR risk, Table 12 displays that the negative impact of abnormal temperature exposure on

[26]While this measure of elasticity is widely used as an instrumental variable for house prices (Mian and Sufi, 2011), not all authors agree it is ideal, the measure of local housing supply is correlated with other demand factors (Davidoff, 2015). We do not use elasticity as an instrument, but as a source of heterogeneity. Not all homes in our data are located within an MSA, and the Saiz (2010) measure is available at the MSA level for 269 MSAs, and does not vary over time in the sample.

[27]The effect was smaller in elastic locations (where it is relatively easy to build).

[28]Hallegatte et al. (2013) report the SLR risk for major coastal cities across the world. SLR risk is measured as predicted annual loss relative to the local GDP based on a 40 cm rise in sea level and assuming cities attempt to adapt to the rise in sea level (e.g., upgrading dikes and sea walls). In this paper, we use the SLR risk at the county level by assigning the risk value of a city to its associated county.

house prices is much stronger than that on counties not exposed to the risk of SLR. Our finding thus complements several recent studies (Bernstein et al. (2019), Baldauf et al. (2020), Murfin and Spiegel (2020), Painter (2020), Goldsmith-Pinkham et al. (2021)) documenting that the sea level rise risk is priced in real estate and municipal bonds price.

5 Conclusion

In this paper, we investigate how exposure to local heat shocks affects residential real estate prices in the United States. Motivated by climate scientists' projections of continued increases in average and extreme temperature frequency, we build a dataset of listing-level temperature exposures. We find that exposure to abnormal temperatures leads to a significant decrease in house prices, and this effect is more pronounced in communities concerned about global warming, during periods of increasing public attention to climate change and among counties heavily exposed to the risk of sea level rise. In contrast to the transaction price regression, the placebo rental tests show that there is no relation between abnormal temperature exposure and rental prices, suggesting that the observed temperature exposure discount is driven by concerns about long-horizon potential future collateral damage, not current property quality. We document substantial variations in sensitivity to heat shocks across regions and markets with different liquidity and housing supply elasticity. Overall, our results highlight the importance of uncertainty about climate change in affecting the real estate market.

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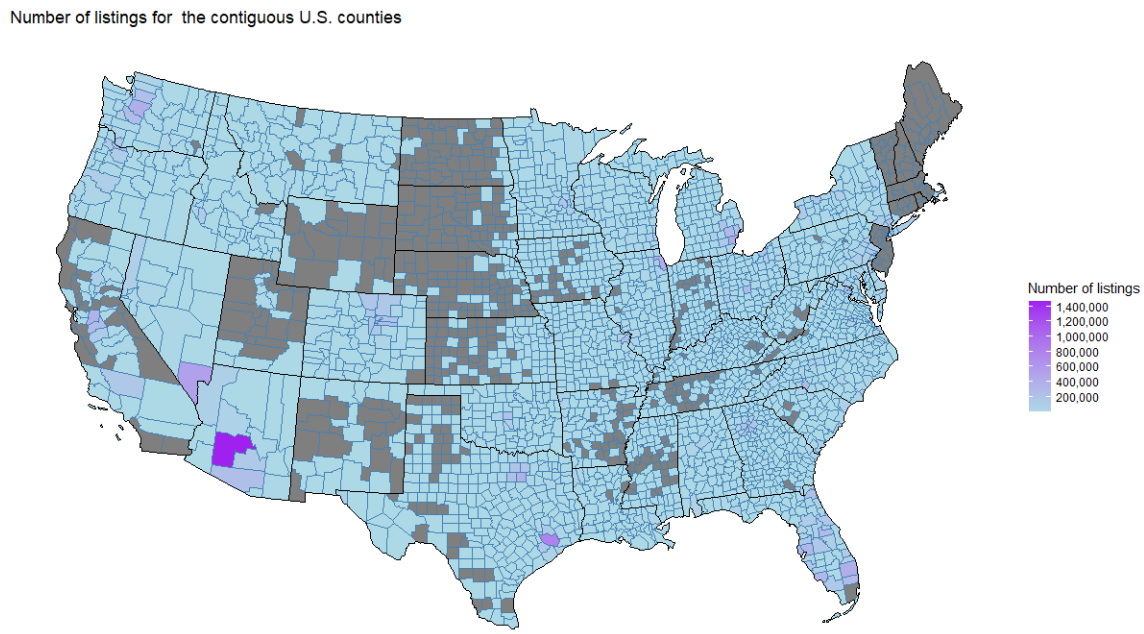
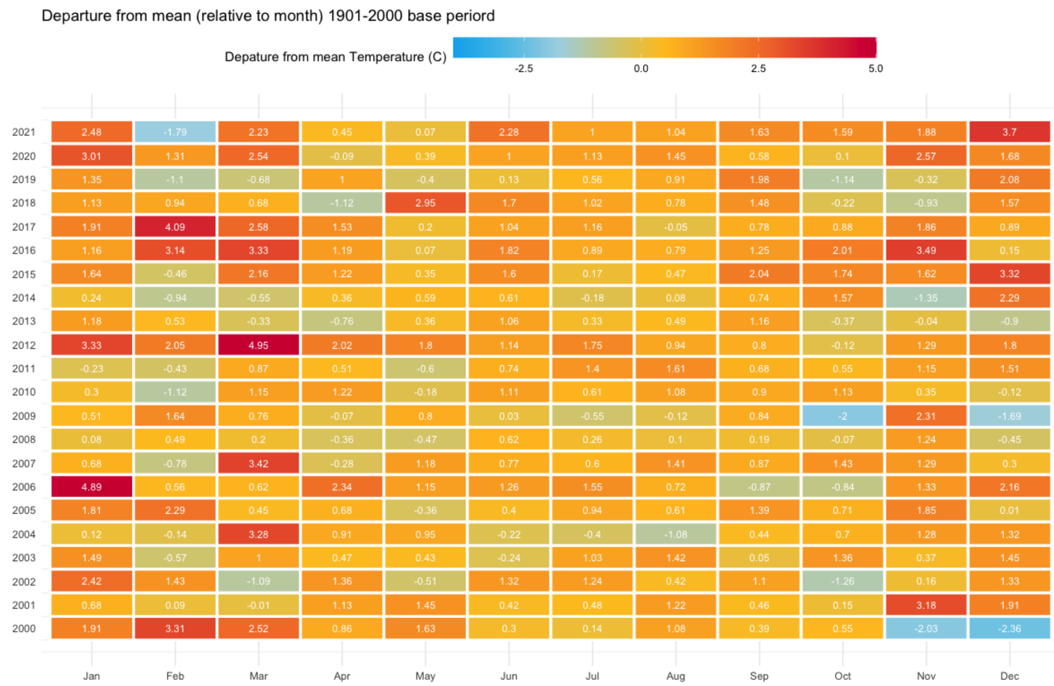
Figures

Figure 1. Coverage



This figure plots the number of listings for U.S. counties in the sample.

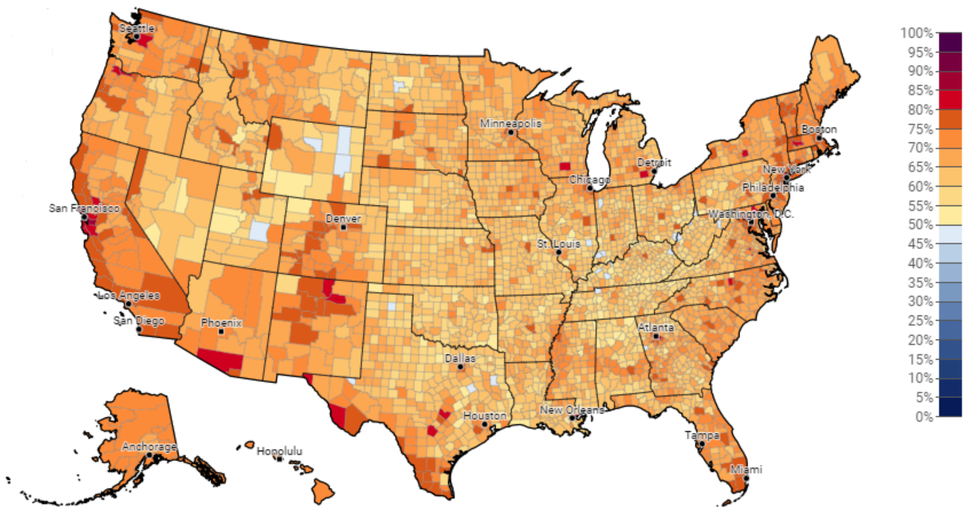
Figure 2. National Time Series Weather Data



This heat map depicts the deviation of average monthly temperature from the average long-run historical temperature in the United States from 2000 to 2021. The base period for the long-run historical temperature calculations is from 1901 to 2000. The x-axis is from January to December, and the y-axis is from 2000 to 2021. Each cell's number stands for the departure of each monthly average temperature from its corresponding long-run average temperature. And each cell's color indicates the magnitude of the deviation in the corresponding cell range from -2.5°C to 5°C, with larger positive (negative) deviations associated with warmer (cooler) colorings. We see a number of warm colorings in general, suggesting consistent with global warming, recent two decades is on average warmer than the pre-2000 period in the United States.

Figure 3. Americans' Climate Change Beliefs and Risk Perceptions

(A) Estimated % of adults who think global warming is happening, 2021



(B)

Estimated % of adults who are worried about global warming, 2021

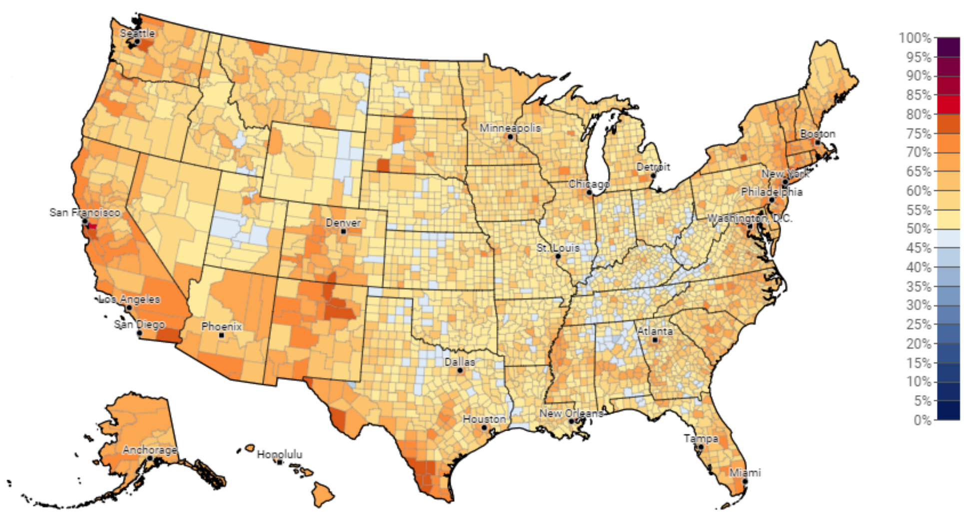
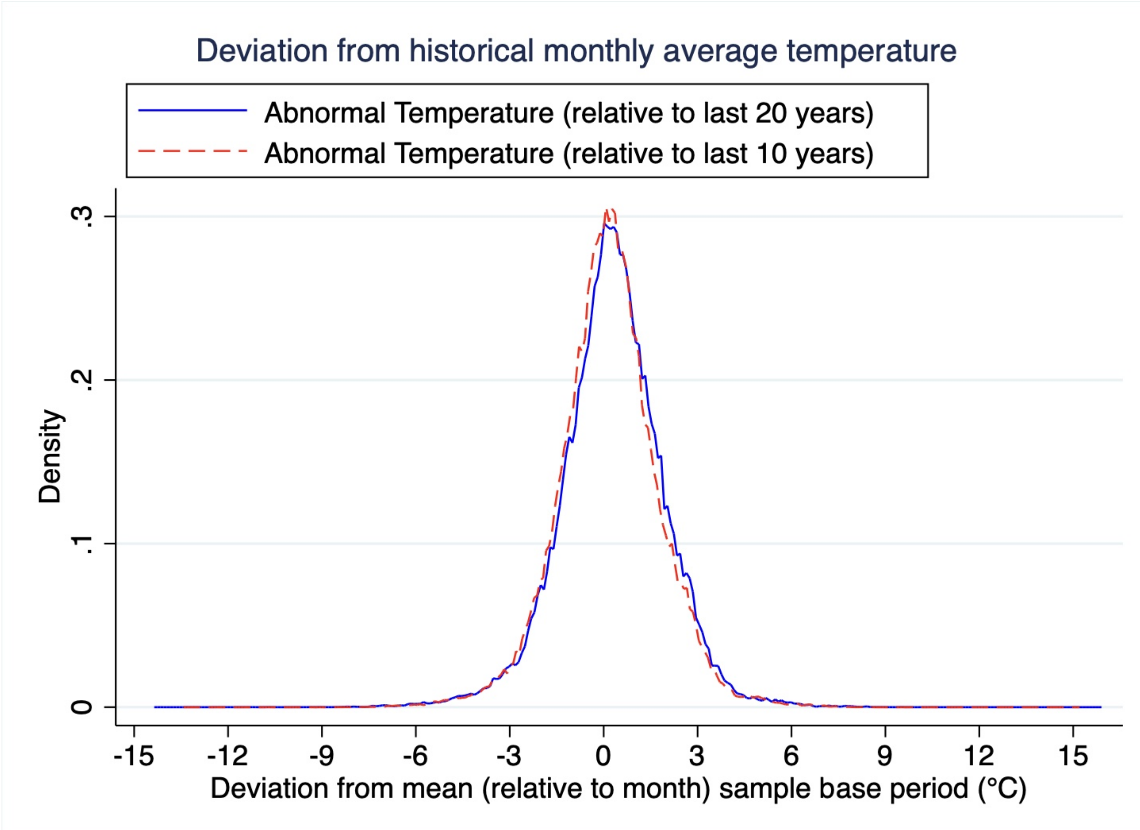


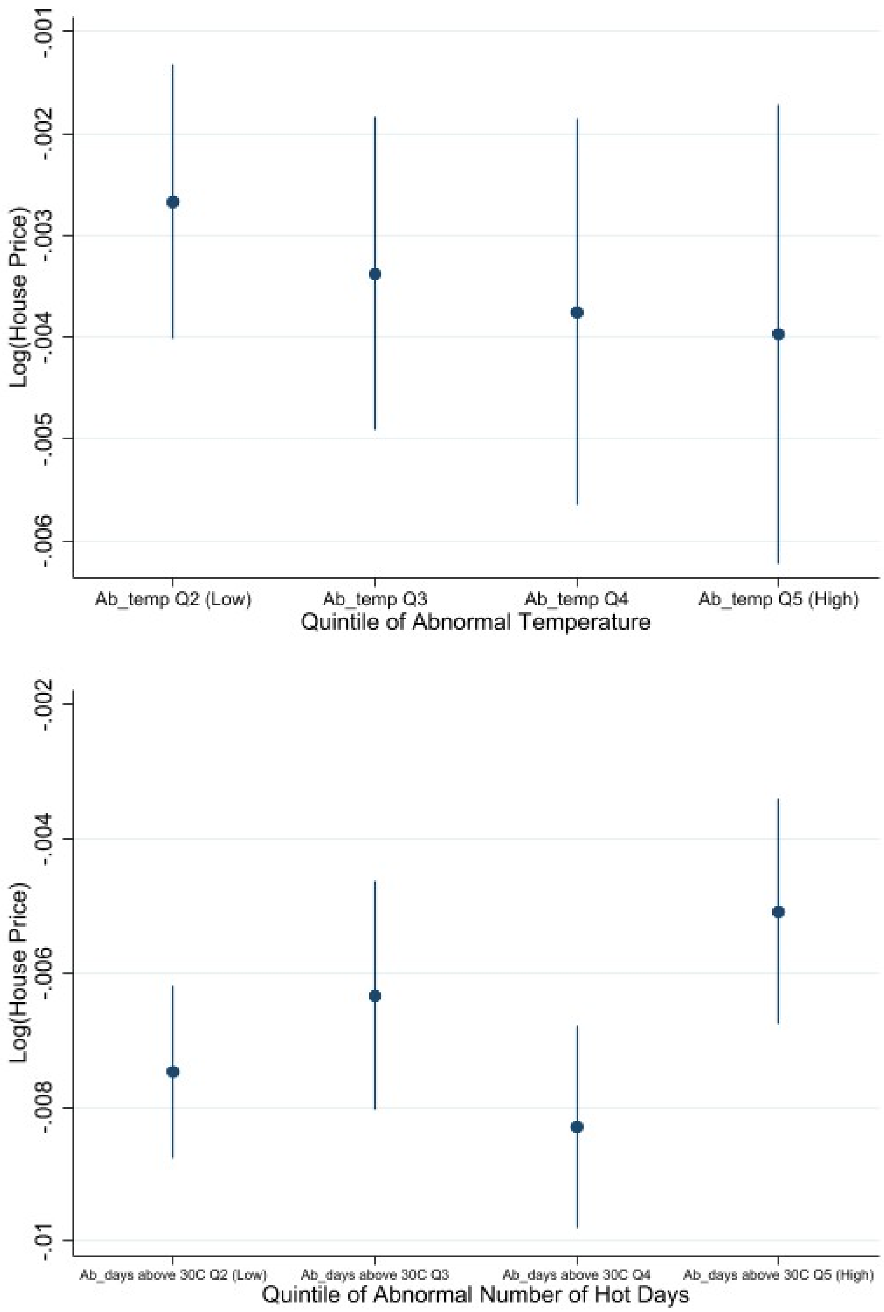
Figure 3(A) shows the fraction of adults at U.S. counties who think global warming is happening in 2021. Figure 3(B) shows the fraction of adults at U.S. counties who are somewhat/very worried about global warming in 2021. The data is from Yale Climate Opinion Maps. The original survey questions are "Recently, you may have noticed that global warming has been getting some attention in the news. Global warming refers to the idea that the world's average temperature has been increasing over the past 150 years, may be increasing more in the future, and that the world's climate may change as a result. What do you think: Do you think that global warming is happening?", "How worried are you about global warming?". For the question measuring how worried respondents are about global warming, "very worrie" and "somewhat worried" were combined into a single measure of "worried".

Figure 4. Sample Weather Data



This figure plots the distribution of the deviation of the monthly average temperature from long-run average in our matched sample data. The blue and red curve is the distribution of the deviation of monthly average temperature from the historical mean in the same calendar month in the past twenty and ten years, respectively.

Figure 5. Abnormal Temperature Exposure and House Prices



This figure plots the coefficient estimates from the Table 3 regression (4) and Table 4 regression (3). The dependent variable is the natural logarithm of house price. The independent variables are quintile dummies that equal to one if a given calendar month in a particular zip code region belongs to quintile 2 to quintile 5 of temperature anomalies measures (abnormal temperature and abnormal number of hot days. We control for housing characteristics, average precipitation level, and zip-code and year-by-month fixed effects in the regression. Standard errors are clustered at zip code level. The sample period is from 2000 to 2021.

Tables

Table 1. Summary Statistics

	U.S.				
	Mean	Std.Dev.	Min	Median	Max
House price	260530	281555	1000	200000	86625000
Weather variables					
Abnormal Temperature	0.29	1.64	-14.36	0.30	15.91
Abnormal Days above 30°C	0.30	3.15	-25.80	0	28.25
Abnormal Days below 0°C	-0.15	2.42	-28.30	0	20.20
Mean temperature	16.58	9.14	-23.63	18.09	44.89
Abnormal Days above 90th pctl	-0.02	0.72	-2.85	0.25	1.80
Abnormal Days below 10th pctl	-0.01	0.69	-2.85	0.25	1.85
Days above 30°C	7.55	10.24	0	1.00	31.00
Days below 0°C	4.33	8.12	0	0	31
House controls					
Number of bedrooms	3.22	0.90	0	3	6
Size	1912	879.79	419	1711	5367
Number of bathrooms	2.18	0.94	0	2	5
Year built	1979	28.26	1005	1986	2021
Other variables					
Global warming is happening	0.68	0.05	0.52	0.68	0.85
Worried about global warming	0.58	0.06	0.42	0.58	0.76

This table presents summary statistics of main variables used in our regression analysis. The sample period is from 2000 to 2021. *House price* is the transaction price in the MLS data. Temperatures are reported in degrees Celsius, time-based temperature exposures are measured in days.*Abnormal Temperature* in a particular month and a given zip code region is the difference between monthly average temperature (in Celsius degrees) and the historical average temperature in the same calendar month over the last twenty years in the same region. *Abnormal Days above 30°C* and *Abnormal Days below 0°C* are the abnormal number of extreme hot (cold) days, which is defined as the difference between the number of days when the temperatures exceed 30°C (fall below 0°C) in the current month and the historical long-run extreme hot (cold) days in the same calendar month over the past twenty years. *Abnormal Days above 90th pctl* is deviations of the number of days that max (min) temperatures are above (below) the 90th (10th) percentile of the zipcode specific temperature distribution in a given month from the historical mean. *Global Warming is happening* is the percentage of population who think global warming is happening. *Worried about global warming* is the percentage of population who are somewhat/very worried about global warming.

Table 2. Belief in Climate Change and Abnormal Temperature

	Happening		Worried	
	(1)	(2)	(3)	(4)
Panel A: Abnormal Temperature				
Abnormal Temperature	0.1058**		0.1067**	
	(0.0349)		(0.0313)	
Ab_temp Q2 (Low)		-0.0396		0.0457
		(0.0620)		(0.0473)
Ab_temp Q3		0.0756		0.1982***
		(0.0577)		(0.0391)
Ab_temp Q4		0.0475		0.1140
		(0.0854)		(0.0784)
Ab_temp Q5 (High)		0.1926**		0.2346***
		(0.0725)		(0.0496)
State-by-Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.4122	0.4118	0.5161	0.5157
Observations	15208638	15208638	15208638	15208638
Panel B: Abnormal Hot Days				
Abnormal Days above 30°C	0.0466**		0.0556**	
	(0.0154)		(0.0139)	
Ab_days above 30°C Q2 (Low)		0.2332**		0.2474*
		(0.0789)		(0.1123)
Ab_days above 30°C Q3		-0.1405		-0.0020
		(0.2458)		(0.2973)
Ab_days above 30°C Q4		0.1303		0.3329*
		(0.2609)		(0.1334)
Ab_days above 30°C Q5 (High)		0.1428*		0.2596**
		(0.0596)		(0.0669)
State-by-Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.4121	0.4120	0.5161	0.5159
Observations	15208638	15208638	15208638	15208638

This table presents the regression results of abnormal temperature exposure on the public belief in climate change. The dependent variables *Happening* and *Worried* are the percentage of population in a county who think global warming is happening, and who are somewhat/very worried about global warming, respectively. The independent variables in panel (A) and (B) are Abnormal Temperature and Abnormal Temperature_Q2-Q5, Abnormal number of hot days when temperatures are above 30°C and Abnormal number of hot days_Q2-Q5. *Abnormal Temperature* in a particular month and a given zip code region is the difference between monthly average temperature and the historical average temperature in the same calendar month over the last twenty years in the same region. We rank all months into quintiles based on abnormal temperature in a given zip code region and use these quintile dummies (Q2-Q5) in the regression. *Abnormal Day above 30°C* is defined in a similar way. Standard errors in parentheses are clustered at the state and year level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Abnormal Temperature and House Prices

	Log(House price)			
	(1)	(2)	(3)	(4)
Abnormal Temperature	-0.0007***	-0.0004*		
	(0.0003)	(0.0002)		
Ab_temp Q2 (Low)			-0.0024***	-0.0027***
			(0.0007)	(0.0007)
Ab_temp Q3			-0.0022***	-0.0034***
			(0.0008)	(0.0008)
Ab_temp Q4			-0.0035***	-0.0038***
			(0.0010)	(0.0010)
Ab_temp Q5 (High)			-0.0048***	-0.0040***
			(0.0012)	(0.0011)
Precipitation	No	Yes	No	Yes
House Char.	No	Yes	No	Yes
Zipcode FE	Yes	Yes	Yes	Yes
Year-by-Month FE	Yes	Yes	Yes	Yes
Adj. R^2	0.5348	0.7525	0.5348	0.7525
Observations	32073046	32072132	32073046	32072132

This table presents the regression results of abnormal temperature exposure on house price. The dependent variable is the natural logarithm of house price. The independent variables are Abnormal Temperature and Abnormal Temperature_Q2-Q5. *Abnormal Temperature* in a particular month and a given zip code region is the difference between monthly average temperature and the historical average temperature in the same calendar month over the last twenty years in the same region. We rank all months into quintiles based on abnormal temperature in a given zip code region and use these quintile dummies (Q2-Q5) in the regression. Precipitation is the average rainfall amount in a given month. House characteristics include property size, number of bedrooms and bathrooms, and the age of the structure. Standard errors in parentheses are clustered at the zip code level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Abnormal Hot Days Deviation and House Prices

	Log(House price)		
	(1)	(2)	(3)
Abnormal Days above 30°C	-0.0004***		
	(0.0001)		
Abnormal Days above 90th pctl		-0.0014***	
		(0.0003)	
Ab_days above 30°C Q2 (Low)			-0.0075***
			(0.0007)
Ab_days above 30°C Q3			-0.0063***
			(0.0009)
Ab_days above 30°C Q4			-0.0083***
			(0.0008)
Ab_days above 30°C Q5 (High)			-0.0051***
			(0.0009)
Abnormal Days below 0°C	-0.0002*		
	(0.0001)		
Abnormal Days below 10th pctl		-0.0004	
		(0.0003)	
Precipitation	Yes	Yes	Yes
House Char.	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes
Year-by-Month FE	Yes	Yes	Yes
Adj. R^2	0.7525	0.7525	0.7525
Observations	32072132	32072132	32072132

This table presents the regression results of abnormal temperature exposure on house price. The dependent variable is the natural logarithm of house price. The independent variables are Abnormal number of hot (cold) days, Abnormal number of hot days_Q2-Q5, Abnormal Days above (below) 90th (10th) pctl. *Abnormal Days above 30°C* and *Abnormal Days below 0°C* are the abnormal number of extreme hot (cold) days, which is defined as the difference between the number of days when the temperatures exceed 30°C (fall below 0°C) in the current month and the historical long-run extreme hot (cold) days in the same calendar month over the past twenty years. *Abnormal Days above 90th pctl* and *Abnormal Days below 10th pctl* are deviations of the number of days that max (min) temperatures are above (below) the 90th (10th) percentile of the zipcode specific temperature distribution in a given month from the historical mean. We rank all months into quintiles based on abnormal number of days above 30C in a given zip code region and use these quintile dummies (Q2-Q5) in the regression. Precipitation is the average rainfall amount in a given month. House characteristics include property size, number of bedrooms and bathrooms, and the age of the structure. Standard errors in parentheses are clustered at the zip code level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Abnormal Current Hot Days and House Prices

	Log(House price)		
	(1)	(2)	(3)
Days above 30°C	-0.0004***		
	(0.0000)		
Days above 90th pctl		-0.0002	
		(0.0003)	
Temperature above 30°C			
Less than 10 days			-0.0052***
			(0.0007)
Between 10 and 20 days			-0.0146***
			(0.0009)
More than 20 days			-0.0199***
			(0.0012)
Days below 0°C	-0.0008***		
	(0.0001)		
Days below 10th pctl		0.0011***	
		(0.0003)	
Precipitation	Yes	Yes	Yes
House Char.	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes
Year-by-Month FE	Yes	Yes	Yes
Adj. R^2	0.7526	0.7525	0.7525
Observations	32072132	32072132	32072132

This table presents the regression results of abnormal temperature exposure on house price. The dependent variable is the natural logarithm of house price. The independent variables Number of hot (cold) days, Number of days above (below) 90th (10th) pctl. *Days above 30°C* and *Days below 0°C* are the number of extreme hot (cold) days, which is defined as the number of days when the temperatures exceed 30°C (fall below 0°C) in the current transaction (closing) month. *Days above 90th pctl* is the number of days that max (min) temperatures are above (below) the 90th (10th) percentile of the zipcode specific temperature distribution in the current transaction (closing) month. We also use dummies that indicate periods with different number of hot days in the regression, such as the number of hot days in the transaction month is "Less than 10 days", "Between 10 and 20 days" and "More than 20 days". Precipitation is the average rainfall amount in a given month. House characteristics include property size, number of bedrooms and bathrooms, and the age of the structure. Standard errors in parentheses are clustered at the zip code level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Beliefs and the Price of Abnormal Temperature Exposure

	Log(House price)			
	(1)	(2)	(3)	(4)
Abnormal Temperature	0.0003	0.0001		
	(0.0011)	(0.0011)		
Ab_temp*Happening	-0.0087***			
	(0.0025)			
Ab_temp*Worried		-0.0066***		
		(0.0019)		
Abnormal Days above 30°C			-0.0049***	-0.0036***
			(0.0006)	(0.0006)
Ab_hot*Happening			-0.0160***	
			(0.0015)	
Ab_hot*Worried				-0.0090***
				(0.0010)
Precipitation	Yes	Yes	Yes	Yes
House Char.	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes
Year-by-Month FE	Yes	Yes	Yes	Yes
Adj. R^2	0.7637	0.7637	0.7637	0.7637
Observations	23241642	23241642	23241642	23241642

This table presents the regression results of the role of the climate belief in the relation between abnormal normal temperature exposure and house price. The dependent variable is the natural logarithm of house price. For independent variables, *Happening* and *Worried* are the percentage of population who think global warming is happening, and who are somewhat/very worried about global warming, respectively. *Abnormal Temperature* in a particular month and a given zip code region is the difference between monthly average temperature and the historical average temperature in the same calendar month over the last twenty years in the same region. *Abnormal Days above 30°C* is the abnormal number of extreme hot days, which is defined as the difference between the number of days when the temperatures exceed 30°C in the current month and the historical long-run extreme hot days in the same calendar month over the past twenty years. Standard errors in parentheses are clustered at the zip code level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Difference-in-differences of the Price of Abnormal Temperature Exposure around the Stern Review

	Log(House price)					
	(1)	(2)	(3)	(4)	(5)	(6)
Abnormal Temperature	0.0023	-0.0075***	-0.0015***			
	(0.0017)	(0.0012)	(0.0004)			
Ab_temp*Stern	-0.0171***	-0.0093***	-0.0002			
	(0.0055)	(0.0016)	(0.0006)			
Abnormal Days above 30°C				0.0008	-0.0039***	0.0004
				(0.0006)	(0.0004)	(0.0009)
Ab_hot*Stern				-0.0060***	-0.0018***	-0.0004
				(0.0019)	(0.0005)	(0.0013)
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes
House Char.	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Three years	One year	Full	Three years	One year
Adj. R^2	0.7526	0.7556	0.7993	0.7526	0.7555	0.7993
Observations	32072132	8204708	3770053	32072132	8204708	3770053

This table presents the regression results of the role of the increased public awareness in climate change in the relation between abnormal normal temperature exposure and house price. The dependent variable is the natural logarithm of house price. For independent variable, *Stern* is a dummy variable equals one if the transaction date is after the Stern Review was released, and equals zero if the transaction date is before the Stern Review was released. *Abnormal Temperature* in a particular month and a given zip code region is the difference between monthly average temperature and the historical average temperature in the same calendar month over the last twenty years in the same region. *Abnormal Days above 30°C* is the abnormal number of extreme hot days, which is defined as the difference between the number of days when the temperatures exceed 30°C in the current month and the historical long-run extreme hot days in the same calendar month over the past twenty years. Standard errors in parentheses are clustered at the zip code level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Abnormal Temperature Exposure and House Prices: Regional Characteristics

	Northeast		Midwest		South		West		Below Median		Above Median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Abnormal Temperature	0.0003		-0.0034***		-0.0058***		-0.0054***		0.0010		-0.0017***	
	(0.0014)		(0.0008)		(0.0006)		(0.0008)		(0.0016)		(0.0002)	
Ab_temp Q2 (Low)		-0.0001		0.0019		-0.0160***		-0.0187***		-0.0000		-0.0038***
		(0.0021)		(0.0017)		(0.0012)		(0.0016)		(0.0008)		(0.0005)
Ab_temp Q3		0.0021		-0.0031		-0.0214***		-0.0176***		0.0003		-0.0053***
		(0.0030)		(0.0021)		(0.0016)		(0.0021)		(0.0009)		(0.0006)
Ab_temp Q4		-0.0029		-0.0021		-0.0287***		-0.0290***		0.0031***		-0.0082***
		(0.0037)		(0.0027)		(0.0020)		(0.0024)		(0.0012)		(0.0007)
Ab_temp Q5 (High)		-0.0023		-0.0103***		-0.0286***		-0.0240***		0.0014		-0.0077***
		(0.0048)		(0.0035)		(0.0023)		(0.0029)		(0.0013)		(0.0009)
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
House Char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.7939	0.7939	0.7461	0.7461	0.7264	0.7265	0.7777	0.7778	0.4932	0.4932	0.7057	0.7057
Observations	2706599	2706599	7219948	7219948	14058926	14058926	8086615	8086615	16159577	16159577	15910824	15910824

This table presents the regression results of the heterogeneity in the abnormal temperature exposure discount. The dependent variable is the natural logarithm of house price. *Abnormal Temperature* in a particular month and a given zip code region is the difference between monthly average temperature and the historical average temperature in the same calendar month over the last twenty years in the same region. Northeast includes New England and the Middle Atlantic regions, Midwest includes East North Central and West North Central, South includes South Atlantic, East South Central and West South Central, and West includes the Mountain and Pacific regions. Standard errors in parentheses are clustered at the zip code level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Abnormal Temperature Exposure Discount in Highly Liquid Market

	Low Days on Market		High Sale to List		Low Inventories		High Absorption	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Abnormal Temperature	-0.0007**	-0.0017	-0.0192***	-0.0005	-0.0015***	-0.0013	-0.0091***	0.0039*
	(0.0003)	(0.0016)	(0.0007)	(0.0004)	(0.0002)	(0.0012)	(0.0008)	(0.0022)
Ab_temp*Low days on market	0.0023***							
	(0.0003)							
Ab_temp*High sale to list			0.0187***					
			(0.0007)					
Ab_temp*Low inventories					0.0040***			
					(0.0011)			
Ab_temp*High absorption rate							0.0184***	
							(0.0010)	
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
House Char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Low DOM	Full	High Sales/List	Full	Low Inventories	Full	High Absorption
Adj. R^2	0.7525	0.7507	0.7522	0.7861	0.7528	0.7765	0.7529	0.7695
Observations	32072132	3259046	31074480	3105668	31842333	3147736	31842333	3183945

This table presents the regression results of the heterogeneity in the abnormal temperature exposure discount. The dependent variable is the natural logarithm of house price. *Abnormal Temperature* in a particular month and a given zip code region is the difference between monthly average temperature and the historical average temperature in the same calendar month over the last twenty years in the same region. Liquidity measures include Days on market, Average sales to list, Inventories and Absorption rate. "Highly liquid market" takes a value of one if any liquidity measure is in the most liquid decile. Standard errors in parentheses are clustered at the zip code level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10. Robustness: Rent Placebo Test

	Log(Rent price)		
	(1)	(2)	(3)
Abnormal Temperature	-0.0005		
	(0.0004)		
Abnormal Days above 30°C		0.0002	
		(0.0002)	
Abnormal Days below 0°C		0.0011***	
		(0.0003)	
Abnormal Days above 90th pctl			0.0005
			(0.0005)
Abnormal Days below 10th pctl			-0.0006
			(0.0005)
Precipitation	Yes	Yes	Yes
House Char.	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes
Year-by-Month FE	Yes	Yes	Yes
Adj. R^2	0.4686	0.4686	0.4686
Observations	5435208	5435208	5435208

This table presents the regression results of abnormal temperature exposure on rental price. The dependent variable is the natural logarithm of rental price. *Abnormal Temperature* in a particular month and a given zip code region is the difference between monthly average temperature and the historical average temperature in the same calendar month over the last twenty years in the same region. *Abnormal Days above 30°C* and *Abnormal Days below 0°C* are the abnormal number of extreme hot (cold) days, which is defined as the difference between the number of days when the temperatures exceed 30°C (fall below 0°C) in the current month and the historical long-run extreme hot (cold) days in the same calendar month over the past twenty years. *Abnormal Days above 90th pctl* and *Abnormal Days below 10th pctl* are deviations of the number of days that max (min) temperatures are above (below) the 90th (10th) percentile of the zipcode specific temperature distribution in a given month from the historical mean. Precipitation is the average rainfall amount in a given month. House characteristics include property size, number of bedrooms and bathrooms, and the age of the structure. Standard errors in parentheses are clustered at the zip code level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11. Abnormal Temperature Exposure and House Prices: Heterogeneity by Housing Supply Elasticity

	Below Median		Above Median	
	(1)	(2)	(3)	(4)
Panel A: Abnormal Temperature				
Abnormal Temperature	-0.0009**		-0.0006*	
	(0.0004)		(0.0003)	
Ab_temp Q2 (Low)		-0.0053***		-0.0007
		(0.0009)		(0.0011)
Ab_temp Q3		-0.0074***		-0.0005
		(0.0012)		(0.0011)
Ab_temp Q4		-0.0071***		-0.0045***
		(0.0014)		(0.0014)
Ab_temp Q5 (High)		-0.0046**		-0.0056***
		(0.0019)		(0.0016)
Precipitation	Yes	Yes	Yes	Yes
House Char.	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes
Year-by-Month FE	Yes	Yes	Yes	Yes
Adj. R^2	0.7210	0.7210	0.7774	0.7774
Observations	17892519	17892519	14179613	14179613
Panel B: Abnormal Hot Days				
Abnormal Days above 30C	-0.0005***		-0.0003*	
	(0.0001)		(0.0002)	
Ab_days above 30C Q2 (Low)		-0.0090***		-0.0055***
		(0.0009)		(0.0010)
Ab_days above 30C Q3		-0.0092***		-0.0022*
		(0.0011)		(0.0013)
Ab_days above 30C Q4		-0.0130***		-0.0042***
		(0.0012)		(0.0010)
Ab_days above 30C Q5 (High)		-0.0050***		-0.0063***
		(0.0012)		(0.0013)
Precipitation	Yes	Yes	Yes	Yes
House Char.	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes
Year-by-Month FE	Yes	Yes	Yes	Yes
Adj. R^2	0.7210	0.7774	0.7774	0.7210
Observations	17892519	14179613	14179613	17892519

This table presents the regression results of the heterogeneity in the abnormal temperature exposure discount. The dependent variable is the natural logarithm of house price. *Abnormal Temperature* in a particular month and a given zip code region is the difference between monthly average temperature and the historical average temperature in the same calendar month over the last twenty years in the same region. *Abnormal Days above 30°C* is the abnormal number of extreme hot days, which is defined as the difference between the number of days when the temperatures exceed 30°C in the current month and the historical long-run extreme hot days in the same calendar month over the past twenty years. We split the sample according to the Saiz (2010) measure of the elasticity of housing supply, into above and below median, respectively. Standard errors in parentheses are clustered at the zip code level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12. Abnormal Temperature Exposure Discount and Sea Level Rise Risk

	SLR risk		No SLR risk		SLR risk		No SLR risk	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Abnormal Temperature	-0.0062***		-0.0004***					
	(0.0008)		(0.0001)					
Ab_temp Q2 (Low)		-0.0092***		-0.0023***				
		(0.0021)		(0.0007)				
Ab_temp Q3		-0.0203***		-0.0015*				
		(0.0029)		(0.0008)				
Ab_temp Q4		-0.0286***		-0.0029***				
		(0.0029)		(0.0010)				
Ab_temp Q5 (High)		-0.0195***		-0.0041***				
		(0.0033)		(0.0012)				
Abnormal Days above 30°C					-0.0023***		-0.0003***	
					(0.0004)		(0.0001)	
Ab_days above 30°C Q2 (Low)						0.0053***		-0.0084***
						(0.0015)		(0.0007)
Ab_days above 30°C Q3						-0.0039*		-0.0064***
						(0.0022)		(0.0009)
Ab_days above 30°C Q4						-0.0038*		-0.0083***
						(0.0019)		(0.0008)
Ab_days above 30°C Q5 (High)						-0.0132***		-0.0053***
						(0.0029)		(0.0009)
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
House Char.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.7591	0.7592	0.7523	0.7523	0.7591	0.7591	0.7523	0.7523
Observations	3032628	3032628	29039465	29039465	3032628	3032628	29039465	29039465

This table presents the regression results of the heterogeneity in the abnormal temperature exposure discount. The dependent variable is the natural logarithm of house price. *Abnormal Temperature* in a particular month and a given zip code region is the difference between monthly average temperature and the historical average temperature in the same calendar month over the last twenty years in the same region. *Abnormal Days above 30°C* is the abnormal number of extreme hot days, which is defined as the difference between the number of days when the temperatures exceed 30°C in the current month and the historical long-run extreme hot days in the same calendar month over the past twenty years. We split the sample according to the Hallegatte et al. (2013) measure of the sea level rise risk. Standard errors in parentheses are clustered at the zip code level. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix

Appendix Table 1. Counties With Sea Level Risk

City, State	County	State	FIPS	Mean annual Loss	SLR risk
New Orleans, LA	Orleans	LA	22071	1940	1.479%
Miami, FL	Miami Dade	FL	12086	2964	0.420%
Tampa/St. Petersburg, FL	Hillsborough	FL	12057	948	0.324%
Tampa/St. Petersburg, FL	Pinellas	FL	12103	948	0.324%
Virginia Beach, VA	Virginia Beach	VA	51810	328	0.173%
Boston, MA	Suffolk	MA	25025	849	0.149%
Baltimore, MD	Baltimore	MD	24005	299	0.104%
LA/Long Beach/Santa Ana, CA	Los Angeles	CA	6037	217	0.097%
LA/Long Beach/Santa Ana, CA	Orange	CA	6059	217	0.097%
New York, NY/ Newark, NJ	Bronx	NY	36005	2159	0.089%
New York, NY/ Newark, NJ	Kings	NY	36047	2159	0.089%
New York, NY/ Newark, NJ	New York	NY	36061	2159	0.089%
New York, NY/ Newark, NJ	Queens	NY	36081	2159	0.089%
New York, NY/ Newark, NJ	Richmond	NY	36085	2159	0.089%
New York, NY/ Newark, NJ	Essex	NJ	34013	2159	0.089%
New York, NY/ Newark, NJ	Essex	NY	36031	2159	0.089%
Providence, RI	Providence	RI	44007	135	0.083%
Philadelphia, PA	Philadelphia	PA	42101	309	0.044%
San Francisco/Oakland, CA	San Francisco	CA	6075	185	0.042%
San Francisco/Oakland, CA	Alameda	CA	6001	185	0.042%
Houston, TX	Walker	TX	48471	214	0.038%
Houston, TX	Montgomery	TX	48339	214	0.038%
Houston, TX	Liberty	TX	48291	214	0.038%
Houston, TX	Waller	TX	48473	214	0.038%
Houston, TX	Austin	TX	48015	214	0.038%
Houston, TX	Harris	TX	48201	214	0.038%
Houston, TX	Chambers	TX	48071	214	0.038%
Houston, TX	Colorado	TX	48089	214	0.038%
Houston, TX	Wharton	TX	48481	214	0.038%
Houston, TX	Fort Bend	TX	48157	214	0.038%
Houston, TX	Galveston	TX	48167	214	0.038%
Houston, TX	Brazoria	TX	48039	214	0.038%
Houston, TX	Matagorda	TX	48321	214	0.038%
Washington, D.C.	Washington	DC	11001	91	0.016%
Seattle, WA	King	WA	53033	90	0.023%
San Diego, CA	San Diego	CA	6073	14	0.004%
Portland, OR	Multnomah	OR	41051	4	0.002%
San Jose,CA	Santa Clara	CA	6085	2	0.001%
San Jose,CA	Santa Clara	CA	6085	2	0.001%

This table presents U.S. cities (counties) subject to climate change risk arising from rising sea level, estimated by Hallegatte et al. (2013). Details can be find from the supplement information provided by the authors. See Nature Climate Change . The mean annual loss is the optimistic bound calculated assuming a 40 centimeter rise in sea level and assuming that cities attempt to adapt to the rise in sea level. SLR risk is the expected mean annual loss as a percentage of a city's GDP ((MM$)). All counties not included in this table are assigned a SLR risk of zero.