WORKING
PAPER
SERIES

Title

Does Climate Change Affect Investment Performance? Evidence From Commercial Real Estate

Authors

Dragana Cvijanovic

Alex van de Minne

Date

December 2021

MIT Center for Real Estate

MIT Center for
Real Estate Research
Paper No.
21/15

MIT CENTER FOR REAL ESTATE

Does Climate Change Affect Investment Performance? Evidence From Commercial Real Estate
Dragana Cvijanovic, Alex van de Minne
MIT Center for Real Estate Research Paper No. 21/15
December 2021

Abstract

Combining granular data on temperatures across the continental US with micro-level com-mercial real estate (CRE) data from 1980 to 2020, we study the impact of exposure to extreme temperature shocks on investment performance of CRE at the individual asset level. We find that exposure to extreme temperatures significantly reduces average realized total returns in CRE. This result is driven by reduction in asset returns. We do not observe a significant ef-fect on income return. We document substantial variation in sensitivity to temperature shocks across property types. Our results are driven by shocks to time-varying CRE risk premium due to decreased predictability of future rental income.

Dragana Cvijanovic
Cornell University

Alex van De Minne
University of Connecticut

1 Introduction

Commercial real estate (CRE) is an important asset class (Ghent, Torous, and Valkanov, 2019). As of 2020, MSCI Inc. estimated that roughly US$10.5 trillion in global real estate assets were held for investment purposes under professional institutional management, while Nareit estimates that the 2018 total dollar value of commercial real estate in the U.S. was $16 trillion. According to the Mortgage Bankers Association, total commercial debt outstanding was $3.98 trillion at the end of the second quarter of 2021,[1] with banks accounting for 24.3% of total commercial loan volume.[2] As of 2019, pension, endowment, and foundation funds control over $9 trillion in total assets, with nearly $800 billion invested in real estate.[3] Despite the significance of CRE as an asset class, and its importance in the overall institutional portfolios, little is yet known about how climate risks affect the performance of commercial real estate.

This lack of understanding can have significant implications. It is widely known in the scientific community that climate change is one of the greatest risks facing humanity. According to the Intergovernmental Panel on Climate Change[4] temperatures in each of the previous three decades have been higher than the last. Moreover, extreme weather events are becoming more prevalent. Scientific evidence suggests that in some locations, the frequency of heat waves has more than doubled and is expected to increase by a factor of almost five over the next 50 years (Lau and Nath, 2012).

In this paper we aim to address this question by conducting one of the first studies to provide direct evidence on how exposure to extreme temperatures affects U.S. commercial real estate performance at the individual asset level. We analyze how exposure to location-specific temperature shocks affects CRE total returns and its components, namely asset returns (or capital gains) and income returns (property yields).

In our analysis we use granular climate data that documents daily temperatures across 481,631 16-square-kilometer (i.e., 4×4 km) grids covering the continental United States from 1980 to 2020, available from the PRISM Climate Group, the U.S. Department of Agriculture's official climatological database. We combine the PRISM climate data with detailed property-level CRE data from the National Council of Real Estate Investment Fiduciaries (NCREIF). Data consist of quarterly

[1] See https://www.mba.org/2021-press-releases/september/commercial/multifamily-mortgage-debt-increased-15-percent-in-the-second-quarter-of-2021

[2] See www.globest.com.

[3] See www.reit.com.

[4] See Pachauri, Allen, Barros, Broome, Cramer, Christ, Church, Clarke, Dahe, Dasgupta, et al. (2014).

financial and accounting information reported by member funds between 1980Q1 and 2020Q4. For each commercial property transaction, data set contains acquisition dates and transaction prices, rental income, property capital and operating costs, as well as hedonic characteristics (such as age, ownership structure, location etc.).

In our analysis, we employ a (total return) repeated sales framework (Case and Shiller, 1987; Geltner and Goetzmann, 2000) to estimate the impact of location-specific extreme temperature shocks on individual CRE asset total returns, asset and income returns, and holding costs. To do this we follow Addoum, Ng, and Ortiz-Bobea (2020) and define several measures of temperature exposure using the matched PRISM weather and NCREIF property-level data. As our first proxy, we compute the average temperature experienced at each property-location over the holding period. Since the first measure only captures average temperatures, as our second proxy, we define absolute extreme temperature thresholds. In particular, we calculate the number of days that (max) temperatures exceed 30°C (86 °F) and (min) temperatures fall below 0°C (32 °F) over the holding period. Using these measures, we estimate a series of repeated-sales (cross-sectional) OLS regressions, controlling for location-specific precipitation levels. We include MSA-(purchase *minus* sale) year fixed effects to control for MSA-specific changes in demand, as well as property type-(purchase *minus* sale) year fixed effects to account for the fact that different property types may have been subject to different economic trends over our sample period. Since ours is a difference estimation, exploring within property variation between year of purchase and year of sale, this allows us to identify the causal effect of temperature exposure using random and exogenous variation in the distribution of heat around each property's mean exposure over a holding period (Blanc and Schlenker, 2017; Dell, Jones, and Olken, 2014).

We find that exposure to extreme temperatures significantly reduces average realized total returns in CRE. Our estimates suggest that for every full year (or 356 days) the property was exposed to (max) temperatures over 30°C during its holding period, total returns reduced by approximately 6.9 percentage points. At the same time, for every full year (or 365 days) the property was exposed to (min) temperatures below 0°C during the holding period, total returns reduced by approximately 11.8 percentage points.

When we decompose total returns into asset and net income return (Chambers, Spaenjers, and Steiner, 2021; Eichholtz, Korevaar, Lindenthal, and Tallec, 2021), we find that this result is mostly driven by reduction in asset returns. Exposure to extreme temperatures does not seem to affect net income return in a statistically significant way. Given the richness of our data set, we are able to further decompose net income return into three components: (gross) income, capital expenditures (CapEx) and operating expenditures (OpEx).[5] Unsurprisingly, we do not find statistically significant results on average, with the exception of extremely negative temperatures, which seem to have a significantly (but economically low) negative effect on CapEx.

Intuitively, real estate assets can be thought of claims to cash flows (or net income) at different horizons. Standard valuation models state that there are three sources of variation in real estate asset returns (Fama, 1990): (a) shocks to expected net rental income, (b) predictable return variation due to variation in risk-free rate, and (c) shocks to discount rate (time-varying risk premium) due to unpredictability of future net rental income. In our analysis we control for time-period specific variation, suggesting that the lower total returns cannot be attributed to the differences in the risk-free rate. Likewise, we analyse 40 years of data, and we do not find evidence that net income was affected by exposure to extreme temperatures.[6] Assuming that investor expectations were in line with the realized income on average, this suggests that the main driver of lower total returns, and lower asset returns, is due to the fact that future income is harder to predict (and consequently more risky). To test this conjecture empirically, we analyze the effect of extreme temperature exposure on net income predictability. We find positive and statistically significant relationship between both extremely hot temperatures and extremely cold temperatures, and (net) income volatility. These results suggest that net income (cash flows) of real estate assets exposed to extreme temperatures exhibit higher volatility, which makes future income harder to predict, resulting in higher risk premium in areas with more extreme temperatures. In line with Giglio et al. (2021) these findings suggest that commercial real estate prices directly reflect climate risk, as proxied by exposure to extreme temperatures.[7]

While our baseline results paint an interesting picture, they obscure the fact that different CRE property types might exhibit different return sensitivity to extreme temperatures. When re-estimating our baseline analysis by property type, we find that the negative effect of extremely hot temperatures on asset returns is attenuated for industrial and office properties. At the same time, the negative effect of extremely cold temperatures on asset returns is amplified for hotel,

[5]We define *net income* as: Net Income = Income - CapEx - OpEx.

[6]Giglio, Maggiori, Rao, Stroebel, and Weber (2021) use a universe of housing transactions to study how the residential real estate prices and rents in flood zones vary with households' perceptions of the risk of future climate change on the net income (cash flows) from real estate in those locations. They find that annual rents of exposed and non-exposed properties do not vary differentially with movements in those perceptions.

[7]Favilukis, Ludvigson, and Van Nieuwerburgh (2017) find that, in the context of residential real estate, the observed boom in house prices at the beginning of this century was entirely the result of a decline in the housing risk premium.

office and retail properties. As before, we do not find significant variation across property types when it comes to income return. However, hotels tend to generate higher (lower) gross rental income when exposed to extremely hot (cold) temperatures, with a similar pattern observed in their operating and capital expenditures. Industrial properties seem to generate lower (higher) gross rental income when exposed to extremely hot (cold) temperatures, with a similar pattern observed in their operating expenditures. Office buildings seem to have significantly higher gross rental income, but also operating and capital expenditures when exposed to extremely cold temperatures, while retail properties seem to generate lower gross rental income and pay lower operating expenses when exposed to extremely hot temperatures.

When analyzing the effect of *average* temperatures on total returns and its components, we find a null result, which is line with the existing literature (Addoum et al., 2020). To the extent that exposure to extreme temperatures affects predictability of future real estate cash flows, this should be well understood by all market participants: external appraisers, buyers and sellers. We empirically test this conjecture, by studying the effect of extreme temperatures on *appraisal* returns. Our results remain unchanged. Next, we explore the inter temporal differences in our results. We assign to each property a value on a {0-1} scale, based on the time of purchase and time of sale, relative to year 2000, the year after the Kyoto agreement was signed. For example, if the property was bought in year 1998 and sold in year 2008, the classification variable will have value 0.8 (as in 80% of its "exposure" was after 2000). We then re-estimate our baseline specification by interacting measure of extreme temperatures with this classification variable. We find that average total return results are mostly driven by properties that were transacted after year 2000, suggesting that the observed patterns are a more recent phenomenon, coinciding with an increase in public attention to climate change in the recent years.

Since historically global warming resulted in both (1) higher number of warm days (negative impact on total returns) and in (2) fewer days below 0°C (resulting in positive impact on total returns), we next quantify the total net effect of climate change on total returns on a selection of cities located in the north (Portland, Chicago, and Boston), and in the south (Los Angeles, Houston and Miami) of the U.S. Cities located in the northern parts of the U.S. lost enough cold days to offset the impact of an increase in warm days, and have thus been the net beneficiaries of the global warming so far. On average, these cities enjoyed a total return increase of 3 percentage points over the average holding period in our sample (6 years). In contrast, southern cities have seen a net loss in total returns of approximately 3 percentage points over the same period.

We also conduct several important robustness checks. First, we ask whether investment performance of real estate that is located in relatively warmer areas of the US is more sensitive to extreme temperatures than that of its peers located in cooler parts of the country. We find limited evidence in support of this adaptation story. Second, a potential concern in our baseline analysis is that the further away from the centroid of the weather subgrid a real estate asset is, the more inaccurate the temperature reading for that property will be. Since PRISM weather data is available by 4x4 km grid locations, this implies that the properties that are located close or on the grid border might be allocated less precise temperature readings. To address this concern, we estimate a Weighted Repeated Sales Model that (inverse) weighs observations (properties) based on their distance from the centroid of the 4x4 km grid. We obtain almost identical results, suggesting that this measurement issue is not of first-order concern. To address a potential concern with our baseline analysis in that there might be an omitted variable that is correlated with both our (total) return outcome variables and exposure to extreme temperatures that can be driving our results, we run an additional set of tests in which we also include 4x4 km grid-location random effects. This test allows us to compare the performance of two otherwise identical properties located at the same 4x4 km grid-location which were transacted at different points in time. Results remain almost identical. Finally, to address a potential issue that capital expenditures made in the first couple of years can have a significant effect on asset returns (Sagi, 2021), we exclude all properties that were held for less than two years. We also re-estimate our baseline analysis using *net asset* returns, where we adjust property asset return by deducting the (sum of) capital expenditures incurred over the holding period. Our results remain similar.

This paper contributes to the literature on the economic costs of climate change. Early cross-sectional studies show that countries with higher mean temperature exhibit lower levels and growth in per capita income (Gallup, Sachs, and Mellinger, 1999; Dell, Jones, and Olken, 2009). Temperature extremes have also been shown to affect sales and labor productivity. Specifically, Graff Zivin and Neidell (2014) show that extremely hot temperatures reduce hours worked across several heat-sensitive industries. Moreover, Jones and Olken (2010), Hsiang (2010), and Dell, Jones, and Olken (2012) find that temperature shocks negatively affect manufacturing exports and reduce output in the industrial and service sectors. Addoum et al. (2020) find no evidence that local average temperatures affect sales, productivity, and profitability using establishment-level or firm-level data in the United States. Custodio, Ferreira, Garcia-Appendini, and Lam (2020) analyze the effects of climate change on firm value by focusing on the effect of changes in temperature on firm sales. Exploiting variation in local temperatures across suppliers of the same client they find that suppliers experiencing a 1°C increase in average daily temperature decrease their sales by 2%.

The effect of climate change on real estate has thus far mainly focused on housing prices and risk. Using flood risk as a proxy for climate risk, Giglio et al. (2021) 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) show that homes exposed to sea level rise (SLR) sell for approximately 7% less than observably equivalent unexposed properties equidistant from the beach. Baldauf, Garlappi, and Yannelis (2020) investigate the link between differences in expectations about future risks and real estate prices by focusing on changes in flood risk associated with rising sea levels due to climate change. They show that differences in beliefs about climate change significantly affect house prices.[8] Our paper contributes to this literature by examining the sensitivity of investment performance of commercial real estate with respect to exposure to extreme temperature shocks.

Our study aims to inform the debate about the economic impact of climate change. We provide evidence that exposure to extreme temperature shocks has a significant negative impact on CRE performance. Having in mind the large pension fund allocations to this asset class,[9] these findings suggest that exposure to extreme weather events has significant negative effect on both the investment community and individual households through negative impact on the size of their retirement savings.

The paper is structured as follows: in Section 2 we describe the data used in this study. Section 3 describes the empirical methodology, while Section 4 shows the main results. Robustness tests are discussed in Section 5, followed by a more general discussion of the results in Section 6. Finally, we conclude in Section 7.

2 Data

To examine the relationship between temperature exposure and CRE performance, we start by using property-level CRE data from NCREIF. Data consist of quarterly financial and accounting information reported by member funds between 1980Q1 and 2020Q4. For each property transaction,

[8] There is a growing literature in finance that has documented the exposure of real estate to physical climate risk factors, such as rising sea levels and wildfires: Hallstrom and Smith (2005), McKenzie and Levendis (2010), Bakkensen and Barrage (2017), Eichholtz, Steiner, and Yönder (2019), Bernstein, Billings, Gustafson, and Lewis (2020), Ortega and Taspınar (2018), among others.

[9] American workers had an average of $95,600 in their 401(k) plans at the end of 2018.

data set contains acquisition dates and transaction prices. If a sale (or partial sale) took place, the sale date and net/gross prices (excluding/including selling expenses) are typically reported.[10] In addition to transaction prices, for each property we have information about market value appraisals and net operating income (NOI), as well as about quarterly capital expenditures (CapEx), operating expenses (OpEx) and hedonic characteristics of the property (property location, age, property type, leverage, ownership structure, owning fund, and type of fund). The locations of our properties are mapped in Figure 1.

[Place Figure 1 about here]

We obtain daily temperature and precipitation data from the PRISM Climate Group. The PRISM data capture the daily mean (= (min + max)/2), minimum, and maximum temperature, as well as level of precipitation in millimeters (mm), in each of 481,631 16-sq-km (or 4×4 km) grid-locations covering the continental United States. Following Addoum et al. (2020) we compute several temperature exposure variables for each grid location in each quarter: the average quarterly temperature, the number of days during each quarter between 1980 and 2020 where the high temperature exceeded 30°C and where the low temperature fell below 0°C, and average quarterly precipitation in millimeters. This procedure yields a balanced panel of weather data for continental United States. Figure 2 shows a map of our temperature exposure variables at the grid-level, using historical averages between 1980 and 2010

[Place Figure 2 about here]

We match the property level data with weather data by geocoding the addresses in the NCREIF data first, using the Google API. Next, we calculate the distance of every individual NCREIF property to the centroid of every 4×4 km grid in the PRISM data. Subsequently, we match the NCREIF property to the grid which has the closest centroid. Finally, we calculate the relevant temperature and precipitation statistics by using the date of purchase and date of sale of the individual asset. In particular, we calculate the mean temperature and precipitation between the purchase and sale date, and the number of days above 30°C and below 0°C during the holding period.

[Place Table 1 about here]

[10] The NCREIF data contributor manual states that "selling expenses are directly attributable to the sale which are the seller's responsibility including, but not limited to, items such as commissions, disposition fees, legal fees, title insurance, escrow fees, etc."

Summary statistics are shown in Table 1. On average we find that CRE investors earned a total return of 48%, while holding the property for an average of 5.6 years. Note that the CRE investments with a holding period of less than 2 years are filtered out, following the existing literature (Clapp and Giaccotto, 1999; Sagi, 2021).[11] Net income generated the largest share of the total return, with close to 30% income return, whereas the asset values "only" increased by approximately 18% on average. We are further able to observe individual components of net income return: (gross) income, operating expenses and capital expenditures. Note that we have slightly fewer observations for the rental income (which is defined as potential gross income (PGI) minus any vacancy allowances), and operating expenses. The total income as a fraction of the purchase value during the holding period was 60% on average. The total costs (OpEx and CapEx) amounted to approximately 37% as a fraction of purchase value. In terms of breakdown by property type, out of 6,782 observations in total, over two thousand are industrial properties. We also observe relatively many apartments (1,917 observations) and offices (1,744 observations). The lowest number of observations is available for retail (822 observations) and hotel properties (172 observations).

[Place Figure 3 about here]

In Figure 3 we compute 5-year average temperature and precipitation variables for our matched data sample.

The average mean temperature between 1980 and 2020 was 16°C (see Table 1). The top panel of Figure 3 shows that average temperatures have increased from 14.5°C between 1980 – 1985 to over 16°C between 2015 – 2020. Similarly, the percentage of days above 30°C (below 0°C) increased (decreased) from 18% (18%) to 20% (13.5%) during the same time period (see middle panel of Figure 3). Average precipitation increased from an all time low during the period 1985 – 1990 of 2.3mm, to an all time high in the final period of 2015 – 2020 of almost 2.8mm.

3 Methodology

3.1 Repeat sales total returns

Measuring total returns in real estate is fraught with difficulties, since real estate assets are highly heterogeneous and illiquid. We follow Bailey, Muth, and Nourse (1963) and Case and Shiller (1989)

[11] The reason being that holding a property for less then 2 years is atypical as there are considerable transaction costs associated with acquiring real estate. Thus, either (1) there was an extremely motivated buyer willing to offset the transaction costs, or (2) the property was a "flip", meaning it was renovated/redeveloped and sold immediately. Both cases to not reflect "normal" market circumstances, hence such observations are omitted.

in setting up a repeated sales framework to solve this issue. First, we start by providing the full cash flow as enjoyed by a CRE investor investing in a real estate asset i:

$$O_i = -V_{i,t=0} + \sum_{t=1}^{T} \frac{CF_{i,t}}{(1+r_t)^t} + \frac{V_T}{(1+r_t)^T}. \tag{1}$$

A close inspection of the cash flows presented in Equation (1) yields two observations. First, note that we only observe asset values (V) at two – not adjacent – periods periods in time: one is the purchase price at $t = 0$, and the other is the sales price at time is T.[12] In between those two dates we only observe cash flows (CF). As a result, it is impossible to estimate a model in a standard (balanced) panel setup (see for example Dell et al., 2012, 2014; Addoum et al., 2020), as we do not know the full evolution of V over the holding period. Second, note that while Equation (1) is nonlinear in the periodic returns, it is linear in the inverse of the accumulated value level of the compounded returns. Thus, we can use linear regression to filter out noise and idiosyncratic effects to estimate a total return index level for the population of NCREIF properties.

In particular, we set up a repeat sales framework in which each observation in the database consists of a consecutive pair of repeat sales of the same property (together with the intermediate cumulative cash flows between those two dates). The repeat sales model is now defined as:

$$TotalReturn_{i,m,j,t,s} = \mu_{m,t,s} + \theta_{j,t,s} + \epsilon_{i,m,j,t,s}, \tag{2}$$

where $TotalReturn_{i,m,j,t,s}$ captures total return (%) from investing in property i, located in Metropolitan Statistical Area (MSA) m, of property type j, between the year of purchase s and the year of sale t.[13] To guard against spurious inference, we control for a host of influences. To capture property-type specific trends, we include property type-(buy minus sell) year fixed effects $\theta_{j,t,s}$. Since property values will be affected by changes in local demand at the time of purchase and sale, we start by controlling for time-varying location-specific factors by using (geographical) division-year fixed effects. In this set up, continental U.S. is divided into 8 (geographical) divisions[14], thus

[12]It is possible to obtain appraisals for these properties in the intermediate time periods, however, as explained in Geltner (1991), such appraisals lag true values, and are too smooth and sometimes biased. Nonetheless, in Section 6.1 we make use of the appraised values in our analysis.

[13]It should be noted that most standard repeat sales literature looks at the log difference between the purchase and sales price. However, our data sample may contain negative values for income return (see discussion further below), in cases when investors paid more in expenses than they received in rent for a specific property during the holding period resulting in negative net rental income. Driven by these considerations, we keep total return as a %.

[14]These divisions are Pacific (CA,OR,WA), Mountain (MT,ID,WY,NV,UT,CO,NM,AZ), West North Central (ND,SD,MN,NI,IA,KS,MO), Southwest (TX,OK,AM,LA), East North Central (WI,IL,IN,OH,MI), Southeast

allowing us to take into account broad location-specific changes in demand that might be driving our results. We further refine this approach by including MSA-(buy minus sell) year fixed effects $\mu_{m,t,s}$. As shown in Figure 4 in the case of Atlanta–Sandy Springs–Alpharetta, GA Metropolitan Statistical Area, within-MSA variation in the number of extreme temperature days in our sample is substantial,[15] and not necessarily driven by the "urban heat island (UHI)" effect.[16] Thus the additional inclusion of the MSA-year fixed effects $\mu_{m,t,s}$ allows for comparison between two assets of the same property type, transacted at the same point in time, located in the same MSA, but in different 4x4 km temperature grid locations.

[Place Figure 4 about here]

Both selection matrices $\theta_{j,t,s}$ and $\mu_{m,t,s}$ are "differenced." More specifically, we subtract a dummy matrix with the year of sale ($\theta_{j,t}$ and $\mu_{m,t}$) with a dummy matrix with the year of purchase ($\theta_{j,s}$ and $\mu_{m,s}$). As a result, selection matrices $\theta_{j,t,s}$ and $\mu_{m,t,s}$ will have a value of -1 in the year of purchase (s), and a 1 at the year of sale (t), and zero otherwise.[17]

Our empirical strategy also allows for less saturated models, where in Specification 2 we either do not explicitly control for MSA-specific heterogeneity, or where we replace MSA-year fixed effects $\mu_{m,t,s}$ with and MSA $\times$ time trend, such that the MSA-specific slope parameter absorbs unobserved variation in CRE returns in each MSA.

As in the case of Case and Shiller (1987) and Geltner and Goetzmann (2000), the interpretation of Equation 2 is then as follows: the total return between the purchase (s) and sale (t) of the property is expected to be the difference in the total return index level between the time of purchase and the time of sale. The residuals (ϵ) are assumed to be normally distributed with zero mean and standard error σ, and the model is estimated by OLS.

Note that the repeat sales model does not contain any control variables, other than the year of purchase and the year of sale. This is motivated by the fact that as long as the property did not change between the year of purchase and the year of sale, the property characteristics are

(FL,GA,AL,MS,TN), Mideast (SC,NC,VA,WV,KY,MD), and Northeast (NY,CT,MA,NJ,DE,PA,VT,NH,ME).

[15] Moran's I does not reveal any significant spatial auto-correlation between our temperature variables, indicating a random pattern. The $N \times N$ weight matrix needed to calculate Moran's I is defined as 1/(distance between all properties). However, we do find a (non-spatial) correlation between T $>$ 30°C and T $<$ 0°C of -0.48. Thus, if a property has more warm days, it will - on average - also have less cold days. This correlation is more pronounced for moderate cities like Atlanta. The correlation is less pronounced in cities like Boston (cold) and San Diego (hot).

[16] Urban areas are known to have a local climate different from that of surrounding rural areas, and the temperature difference constitutes an urban heat island, or UHI (Heinl, Hammerle, Tappeiner, and Leitinger, 2015).

[17] For conciseness, we will refer to MSA-(buy minus sell) year fixed effects $\mu_{m,t,s}$ (property type-(buy minus sell) year fixed effects $\theta_{j,t,s}$) as MSA-year (property type-year, respectively) fixed effects in the rest of the paper.

"differenced out."[18] Thus, our repeat sales model is effectively equivalent to modeling price levels (plus any accumulated income in the meantime), with property fixed effect included, controlling for the unobserved time-invariant individual asset level heterogeneity in the process.

3.2 Adding climate variables to the repeat sales model

The main goal of this study is to analyze how exposure to extreme temperatures affects performance of (commercial) real estate assets. To this end we include climate variables to our repeat sales regression:

$$TotalReturn_{i,m,j,t,s} = \beta X_{i,t,s} \times (t_i - s_i) + \mu_{m,t,s} + \theta_{j,t,s} + \epsilon_{i,m,j,t,s}, \tag{3}$$

where $X_{i,t,s}$ contains the climate variables, more precisely the temperature exposure (percentage of days above/below a certain threshold) as defined in Section 2 and precipitation at the property sub-grid location level between the purchase and sale of the property with corresponding (vector of) parameters β. In our baseline regression, we cluster standard errors by MSA and year of sale.[19]

The temperature and precipitation variables (in vector $X_{i,t,s}$) are multiplied (i.e. "scaled") with the holding period in years $(t - s)$. As a result, all our estimates are annualized, with the following interpretation: for every full year (or 365 days) that a property is exposed to X, the total return changes by β.

We further explore how different components of $TotalReturn_{i,t,s}$ from individual property investment are related to temperature exposure. Following Chambers et al. (2021) and Eichholtz et al. (2021) total return from investing in property $TotalReturn_{i,t}$ is defined as:

$$TotalReturn_{i,t,s} = \underbrace{\frac{V_{i,t} - V_{i,s}}{V_{i,s}}}_{\text{Asset return}} + \underbrace{\frac{\sum_s^t CF_{i,s,t}}{V_{i,s}}}_{\text{Net Income return}}, \tag{4}$$

where $V_{i,t}$ $(V_{i,s})$ denotes the transaction price of property i at time t (s). $\sum_s^t CF_{i,s,t}$ is the sum of the free cash flow (net income) between the purchase and sale of the property. The first part of Equation (4) denotes price appreciation (or *asset return*), while the second term denotes *net*

[18] One exception is the age variable. A property will be older when it is sold compared to when it was bought. However, standard repeat sales literature still omits age for two reasons. First, it is perfectly co-linear with time of sale (Francke and Van de Minne, 2017): If a property is sold two years later, it will also have aged by two years. And second, the fact that a property ages is part of the investor experience, and should therefore not be controlled for.

[19] We also consider an alternative approach whereby we take into account that the further away from the centroid of the climate grids a property is, the more inaccurate the temperature reading for that property will be. Our results remain similar. See Section 5.2 for details.

income return. Further, the sum of the free cash flow (or net income) consists of the following elements (Geltner, Miller, Clayton, and Eichholtz, 2014):

$$\frac{\sum_s^t Net\ Income_{i,s,t}}{V_{i,s}} = \frac{\sum_s^t Income_{i,s,t}}{V_{i,s}} - \frac{\sum_s^t OpEx_{i,s,t}}{V_{i,s}} - \frac{\sum_s^t CapEx_{i,s,t}}{V_{i,s}}, \tag{5}$$

where $\sum_s^t Income_{i,s,t}$ is the (gross) rental income generated[20] by property i between the year of purchase s and year of sale t, $\sum_s^t OpEx_{i,s,t}$ is the (sum of) Operating Expenses, which are costs associated with keeping the property running on a day-to-day basis (like insurance, utilities, cleaning, day-to-day maintenance, and management fees), and $\sum_s^t CapEx_{i,s,t}$ is (the sum of) Capital Expenditures, which are discretionary costs like substantial renovations, or fees to brokers to attract tenants.[21]

4 Results

4.1 Effect of extreme temperatures on property total returns

We begin our analysis by estimating Equation (3). Results are shown in Table 2. Our dependent variable is property total return, which we regress on a measure of extreme temperature in the property location. Following Addoum et al. (2020) we use a measure of extremely hot days for which high temperatures exceed an upper limit of 30°C, as well as a measure of extremely cold days for which the low temperature drops below 0°C. We also include a measure of grid-location precipitation. In Column 1, we do not control for MSA-specific time trends at the time of purchase and sale, nor for the property-type specific time-varying unobserved heterogeneity. Interestingly, the estimated coefficient on extreme temperatures, both over 30°C and below °0C, as well as for precipitation are positive and statistically significant at the 99% level.

[Place Table 2 about here]

However, once we control for time-period specific shocks at the time of purchase and sale that are shared across the regions by including (buy minus sell) year fixed effects (Column 2), the estimated coefficients on both extreme hot and extreme cold temperatures become negative and highly significant. Similar estimates are also obtained when we take into account property-type specific time-varying trends, for example, that office buildings are performing better in a particular

[20]Gross rental income is defined as the potential gross income (PGI) minus any vacancy allowance.

[21]In Section 5.4 we discuss an alternative treatment of capital expenditures for the computation of total returns.

time period relative to other property types, as shown in Column 3. In Column 4, we explicitly control for both time-varying property-type specific trends and time-varying location specific trends, as captured by (geographical) division-year fixed effects, and the estimated coefficients on both extreme hot and extreme cold temperatures remain negative and highly significant. In Column 5, we replace (geographical) division-(buy minus sell) year fixed effects with an MSA $\times$ time trend, to allow for the MSA-specific slope parameter to absorb unobserved variation in CRE returns in each MSA. In our most saturated model, as specified in Equation 3, we control for property-type specific time-varying trends and for location-specific time-varying trends (for example changes in local demand that might be driving the attractiveness of commercial real estate in a particular MSA), as captured by the MSA-year fixed effects $\mu_{m,t,s}$ (Column 6). This also yields negative and highly significant coefficients on extreme temperatures. The estimated coefficient on Temperatures over 30°C is -0.071. With an average holding period of 5.6 years and average percentage of days over 30°C of 20% (see Table 1), this suggest hot weather has resulted in a $(5.6 \times 0.2 \times -0.071 =)$ 8 percentage point decrease in total return on average for CRE investors during our analysed period. Similarly, the estimated coefficient on Temperatures below 0°C is -0.125, suggesting total return drop of $(5.6 \times 0.15 \times -0.125 =)$ 10 percentage points. Interestingly, the estimated coefficient on precipitation is -0.003, however, it is not statistically different from zero.

4.2 Effect of extreme temperatures on total return components

Our baseline specifications control for unobserved, time-variant and time-invariant (through differencing) demand-side factors, allowing us to plausibly attribute the estimated difference in total returns to supply-side factors. These factors might include reductions in (net) income yield due to rent concessions to entice demand for space, or increases in operating costs and capital expenditures that cannot be passed on to tenants (e.g., energy or investment costs for air conditioning, equipment cooling or heating systems, insulation installation costs etc). In addition, extreme temperatures can adversely affect the demand for real estate in the asset markets, because of lower income expectations, or due to lower predictability of future cash flows (i.e. higher risk). In this section, we exploit the heterogeneity in our data to analyze the channels through which extreme temperature exposure might affect property returns.

4.2.1 Effect of extreme temperatures on asset returns

We first explore whether the negative effect of extreme temperature exposure documented in Table 2 is driven by changes in its market value over the holding period (or asset return). In particular, we re-estimate Equation 3 by using asset return, as defined in Equation 4 as our dependent variable. As shown in Table 3, the estimated coefficients on extreme temperature are negative and statistically significant at 99% level, suggesting that properties more exposed to extreme temperatures (both above 30°C and below 0°C), tend to realize lower asset returns. Interestingly, this is more pronounced in case of temperatures below 0°C. More specifically, on average high temperatures over 30°C resulted in $5.6 \times 0.20 \times$-0.079 = -9 percentage point drop in asset values and low temperatures below 0°C resulted in $5.6 \times 0.15 \times$ -0.149 = -12 percentage point drop in asset values. Similar to our baseline results, precipitation does not seem to affect asset level returns (the estimated coefficient in Column 6 -0.002, and it is not statistically different from zero).

[Place Table 3 about here]

4.2.2 Effect of extreme temperatures on net income return

Next, we analyze if the estimated relationship between property returns and extreme temperatures is driven by changes in the net income generating ability of the property. In Table 4 we show the results of estimating Equation 3, with net income return as the dependent variable. Interestingly, we do not find a statistically significant relationship between extreme temperatures and net income return in any of the specifications (estimated coefficients are positive, however, they are not statistically different from zero).

[Place Table 4 about here]

Given the richness of our data, we are able to further disentangle individual components of net income return. In particular, we are able to tease out which channel is driving our results: whether it is a reduction in rent collections (rental *income*), or increase in operating or capital expenditures. Results shown in Table 5 suggest that this finding is driven by reduction in income (Column 1) and in capital expenditures (Column 3), although the estimated coefficient on temperatures above 30°C is imprecisely estimated in both cases. The estimated coefficient on extremely low temperatures, those below 0°C is negative in case of all income, operating expenditures and capital expenditures, with the latter one being the only coefficient that is statistically significant and different from zero, although the impact is economically small.

[Place Table 5 about here]

4.2.3 Drivers of total returns

As shown above, decomposing total returns into asset and net income return (Chambers et al., 2021; Eichholtz et al., 2021), we find that this result is mostly driven by reduction in asset returns. Exposure to extreme temperatures does not seem to affect income return in a statistically significant way. Standard valuation models state that there are three sources of variation in real estate asset returns (Fama, 1990): (a) shocks to expected cash flows or net income, (b) predictable return variation due to variation in risk-free rate, and (c) shocks to discount rate (time-varying risk premium) due to unpredictability of future rental income. In our analysis we explicitly control for time-period specific variation that is shared across all assets/regions, suggesting that the lower total returns cannot be attributed to the differences in the risk-free rate. Likewise, we analyse 40 years of data, and we do not find evidence that net income was affected by exposure to extreme temperatures. Assuming that investor expectations were in line with the realized income on average, this suggests that the main driver of lower total returns, is due to the fact that future income is harder to predict (and consequently carries a higher risk premium) in areas with more extreme temperatures. To test this conjecture empirically, we analyze the effect of extreme temperature exposure on cash flow predictability by estimating the following specification:

$$\frac{SD(\text{Income Component})_{i,m,j,t,s}}{V_{i,m,j,s}} = \beta X_{i,t,s} + \mu_{m,t,s} + \theta_{j,t,s} + \epsilon_{i,m,j,t,s}. \tag{6}$$

where SD(Income Component) denotes income volatility, as proxied by standard deviation of real estate income components. Note that we divide the income components by the purchase price (V_s) so as to normalize the results, as we have done throughout the paper. In contrast to our previous findings we do not "scale" the right-hand side of the equation anymore, because by taking the standard deviation of our dependent variables, we already scaled the left-hand side of the equation. Results are shown in Table 6.

The estimated coefficients on extreme temperatures above 30°C are positive and significant at 95% confidence level for (rental) income (Column 1) and net income (Column 4). Similarly, the estimated coefficients on extreme temperatures below 0°C are positive and significant at 95% confidence level for net income (Column 4) and all net income components (Columns 1–3). These results suggest that cash flows of real estate assets exposed to extreme temperatures exhibit higher volatility, which makes future income harder to predict, resulting in higher risk premium for real estate assets located in areas with more extreme temperatures.

[Place Table 6 about here]

4.3 Effect of extreme temperatures per property type

Results presented in previous sections offer an important insight into how extreme temperatures affect total returns and its components for CRE on average. In this subsection we further explore these results by analyzing how those results vary by property type. In particular, we estimate the following specification:

$$TotalReturn_{i,m,j,t,s} = \beta X_{i,t,s} \times (t_i - s_i) + \gamma X_{i,t,s} \times P_j \times (t_i - s_i) + \mu_{m,t,s} + \theta_{j,t,s} + \epsilon_{i,m,j,t,s}, \quad (7)$$

where P_j denotes property type $\{Office, Retail, Industrial, Hotel, Apartments\}$. Results of this estimation are shown in Table 7. In Column 1 we see that while the baseline coefficient β is significant for both temperatures above 30°C and below 0°C, estimated coefficients on the interaction term γ with different property types is not statistically different from zero. In case of asset return (Column 2), picture becomes more interesting. While estimated coefficient β is negative and statistically significant for both extreme warm and extreme cold temperatures, coefficient γ on the interaction term is positive and significant in case of industrial and office properties for extremely warm temperatures, suggesting that this negative effect of extremely warm temperatures on asset returns is attenuated for industrial and office property types. In case of extremely cold temperatures, we find an opposite result. Estimated coefficient γ is negative for hotel, office and retail properties, indicating that the negative effect of extremely cold temperatures on asset returns is most pronounced in case of these property types. As presented earlier, we see no effect on total income return (Column 3). However, when we break income return down into its different components, an interesting picture emerges. Industrial and retail properties seem to witness significantly lower rental income in case of extremely warm temperatures, while hotels seem to enjoy higher rent collections. Similar pattern is also observed in case of operating expenditures (OpEx):

while hotels seem to spend more on OpEx, industrial and retail properties seem to spend less in case of extremely warm temperatures. When it comes to CapEx, we see a significantly positive correlation between extremely warm temperatures and CapEx in case of hotel and office properties. Extremely low temperatures are significantly negatively correlated with OpEx and CapEx, while this relationship gets attenuated and even switches sign in case of office buildings.

[Place Table 7 about here]

4.4 Effect of *average* temperatures on total returns

Our analysis so far has focused on the effect of exposure to extreme temperatures on CRE investment performance. In this subsection, we ask a related question: if and how *average* temperatures affect CRE total returns. In Table 8 we re-estimate Equation 3, where now the dependent variable is average temperature in the 4x4 km grid location. While in Column 1 we see a significant positive relationship between average temperatures and property total returns, this result becomes insignificant when we include our full set of controls and fixed effects. This suggest, unsurprisingly, that properties located in on average warmer locations do not generate significantly different total returns. Taken together with our findings in previous sections, this result indicates that it is the exposure to *extreme* temperatures, rather than warm temperatures themselves, that is being priced in the cross-section of CRE (total) returns.

[Place Table 8 about here]

5 Robustness

5.1 Adaptation

In the first set of robustness tests, we explore the heterogeneity of our results based on the property location. In particular, we consider the possibility that properties located in (historically) relatively hotter areas of the country may exhibit different temperature sensitivity from otherwise identical properties located in cooler parts of the country. To the extent that real estate investors have an incentive to adapt to local conditions, we may find differential effects associated with exposure to extreme heat and cold among properties in locations that are generally hotter or colder.[22] To test this conjecture, we follow Addoum et al. (2020) and split our sample into two subsamples based on average temperatures. Specifically, we calculate the average annual temperature in the PRISM data. We then define a warmer location indicator variable that equals 1 for the set of properties in the top half of average temperatures experienced and include this variable as an interaction with each of our temperature exposure variables. Table 9 presents the results of these tests.

[Place Table 9 about here]

The estimated coefficient in our most saturated model (Column 6) for temperatures over 30°C is negative (-0.174) and statically significant at the 10% level. The coefficient of the interaction between high temperatures and warm locations is positive and economically large (+0.106). This could indicate that there are indeed levels of adaptions, where properties in historic warm locations are not affected by warm temperatures as much as their counterparts in colder locations. However, the effect is not statistically significant. In Table 15 in the Appendix we interact both cold locations and warm locations with the climate variables, which allows us to check if the interaction of warm locations with high temperatures is statistically different from zero. From Table 15 we find that the effect (as compared to zero) is -0.067 (-0.174) in warm (cold) locations and that the coefficient is statistically significant. Thus there is some weak evidence of adaption, but the estimates are not significantly different from each other. Likewise, we also do not find evidence that there is adaption in the case of cold weather or precipitation. The coefficients on the interacted terms in warm or cold locations are very similar to each other (see Table 15 in the Appendix).

5.2 Weighted repeat sales model

A potential concern in our baseline analysis is that of a measurement bias: the further away from the centroid of the climate grid a property is, the more inaccurate the temperature reading for that property will be. Since PRISM weather data is available by 4x4 km grid locations, this implies that the properties that are located close or on the grid border might be allocated less precise temperature readings. A second related concern is that the variance of total returns could positively co-vary with the holding period. For example, a lack of ongoing maintenance could accumulate over a long period resulting in large discounts at the time of sale, in particular compared to a property

[22] An alternative form of adaptation would be through endogenous location choice. For example, investors may want to invest in to properties that are spread across the country to benefit from geographical diversification of weather shocks.

that was well maintained (Case and Shiller, 1989).[23] To address these issues, we run a robustness test that (inverse) weighs observations based on the distance of the property from the grid centroid and the holding period.[24] In particular, the estimation procedure consists of the following steps:

- Step 1: We estimate Equation 3 by ordinary least squares (OLS).
- Step 2: The squares of the residuals ($\hat{\epsilon}$) from Step 1 are subsequently regressed on a constant (c_0), the distance to the centroid (d), and the time between the two consecutive sales ($t-s$), using Ordinary Least Squares (OLS) as well. This Eq. is given by;

$$\hat{\epsilon}_i^2 = c_0 + \alpha d_i + \delta(t_i - s_i) + \eta_i, \tag{8}$$

  where η are the residuals from this second stage, which are assumed to be mean zero with standard error σ_η.
- Step 3: Re-estimate Equation 3 by generalized / weighted least squares, where the weights are provided by: $\left(\hat{c_0} + \hat{\alpha} d_i + \hat{\delta}(t_i - s_i)\right)^{1/2}$.

Results of this estimation are shown in Table 10. They are almost identical to our baseline results in Table 2. Results from the second stage of the WLS procedure described above shown in the bottom panel of Table 10 suggest that (log) distance from the centroid of the climate subgrid is not significantly different from zero when explaining the error term (Column 6), while the holding period is.

5.3 Unobserved location-grid heterogeneity

Another potential concern with our baseline analysis is that there is an omitted variable that is correlated with both our (total) return outcome variables and exposure to extreme temperatures that can be driving our results. Since our analysis is based on cross-sectional data, in the following test we add 4x4 km grid-location random trend $\tau_{i,k}$, which allow us to identify the causal effect of temperature exposure by comparing otherwise identical properties (due to differencing implied by the repeated sales methodology) that are located in the same grid-location, but which were transacted at a different point in time. Inclusion of grid-location random trends also helps us

[23] In general, if a property was held for a long time "something" could have happened to it that is unobservable to the econometrician.

[24] This (inverse) Weighted Repeat Sales Model is a workhorse methodology used by S&P and FHFA in their index methodologies.

account for the unobserved heterogeneity at the grid-location level, which might be driving our results. This is given by;

$$TotalReturn_{i,m,j,t,s} = \beta X_{i,t,s} \times (t_i - s_i) + \tau_{i,k} \times (t_{i,k} - s_{i,k}) + \mu_{m,t,s} + \theta_{j,t,s} + \epsilon_{i,m,j,t,s}, \quad (9)$$

$$\tau_{i,k} \sim \mathcal{N}(0, \sigma_\tau), \quad (10)$$

where k is the sub-grid identifier, which we suppressed in the remainder of the Equation for brevity. Our random effect is normally distributed with mean zero and standard deviation σ_τ (Equation 9. Our choice of random effects relative to fixed effects is driven by the fact that there is a high number of sub-grids in our data sample (2,621), which can result in a significant loss of degrees of freedom when employing fixed effects (Francke and Van de Minne, 2020). Further, the sub-grids are by definition a subset of the MSA m, resulting in potential identification concerns in the time fixed effects and trend estimates. The model is estimated using the restricted maximum likelihood (REML).

Results of this estimation are shown in Table 11. As we can see in Column 1, the estimated coefficient on total return is almost identical to the one in Column 6 of Table 2. Result for asset return (Column 2) and income return (Column 3) are also almost identical to the baseline estimation shown in Table 3 and Table 4 respectively.

5.4 Alternative treatment of capital expenditures

In our baseline analysis presented in Section 4, we follow Chambers et al. (2021) and Eichholtz et al. (2021) and deduct (the sum of) capital expenditures (CapEx) to arrive at *net income return.* CapEx spending is lumpy and averages roughly 2% per year for sold properties in our sample. Using NCREIF data between 1978 and 2017, Sagi (2021) finds that around 10% of transacted properties experience CapEx spending of 10% or more of initial appraisal value in the first two years, and the standard deviation of total CapEx in the first two years is about 9%. This suggests that, consistent with Goetzmann and Spiegel (1995), CapEx can have a sizeable impact on a property's gross market value appreciation in the first two years after acquisition. We address this issue by excluding properties with holding periods shorter than two years from our analysis. In addition, motivated by these stylized facts, we re-estimate the effect of extreme temperatures on asset returns shown in Table 3, by defining *net asset return* as the asset return minus (the sum of) CapEx over the holding period as a fraction of the purchase price. This is given by:

$NetAssetReturn_{i,s,t} = \frac{V_{i,t} - V_{i,s}}{V_{i,s}} - \frac{\sum_s^t CapEx_{i,s,t}}{V_{i,s}}$, where V are transaction prices at time of buy (s) and sale (t), for property i, $CapEx$ are the capital expenditures. Results shown in Table 12 are consistent with our baseline analysis.

[Place Table 12 about here]

6 Discussion

Our results suggest that real estate assets exposed to extreme temperatures realize lower total returns and that this is driven by increases in asset risk premium stemming from lower (net) cash flow predictability. This suggests that investors are wary of higher cash flow volatility for more exposed properties, and are willing to pay *less*, resulting in the observed price discounts at the time of sale. In this section we provide more color to how these changes in fundamentals affect realized returns. We proceed by discussing the following topics: (1) how well understood are these changes by market observers, such as real estate appraisers; and (2) do we see any temporal variation in the observed evidence. Finally, we analyze (3) what has been the economic *net effect* of climate change on real estate total returns.

6.1 Evidence from appraisal data

For their NPI-qualifying properties,[25] NCREIF members are required to report quarterly appraisal values where at least once every three years the appraisal is done by an independent (external) appraiser. Using NCREIF data Sagi (2021) finds that roughly one-third of the transaction prices reported in the NCREIF data correspond to external appraisals. To the extent that exposure to extreme temperatures affects predictability of future real estate cash flows, this should be well understood by all market participants: external appraisers, buyers and sellers. In this section, we empirically test this conjecture, by studying the effect of extreme temperatures on *appraisal* returns. Specifically, we estimate Equation 3, whereby we compute total returns using appraised values. Our results remain unchanged (Table 13), suggesting that the extreme temperature imposed changes in cash flow predictability are well understood by all market participants.

[25]The NCREIF Property Index (NPI) provides returns for institutional grade real estate held in a fiduciary environment in the U.S. Managers must have at least $100 million of properties under management that are at least partially held in tax exempt accounts such as open end funds, closed end funds or separate accounts, to qualify for index inclusion.

[Place Table 13 about here]

6.2 Inter-temporal variation

In this section we seek to understand if the observed evidence of climate change risk being priced in CRE is a more recent phenomenon. In particular, we explore the inter temporal variation in our results. We assign to each property a value on a {0-1} scale, based on the time of purchase and time of sale, relative to year 2000, the year after the Kyoto agreement was signed.[26] For example, if the property was bought in year 1998 and sold in year 2008, the classification variable will have value 0.8 (as in 80% of it's "exposure" was after 2000). We then re-estimate our baseline specification by interacting measure of extreme temperatures with this classification variable. Results are shown in Table 14. We find that our average total return results are mostly driven by properties that were transacted after year 2000, suggesting that the observed patterns are a more recent phenomenon, coinciding with an increase in public attention to climate change in the recent years following the adoption of the Kyoto agreement.

[Place Table 14 about here]

6.3 Economic implications

Results presented in Table 2 suggest that exposure to both extreme positive (above 30°C) and extreme negative temperatures (0°C) reduces total returns from CRE. Since historically global warming resulted in both (1) higher number of warm days (negative impact on total returns) and in (2) fewer days below 0°C (resulting in positive impact on total returns), it is important to quantify the total net effect of climate change on total returns.

To do this, we first calculate the centroid of a selection of cities (Portland, Chicago, Boston, Los Angeles, Houston, and Miami). We then use the PRISM data to compute the percentage of days where the high (low) temperature was above 30°C (0°C) in the last 6 years, which is the average holding period in our sample (1980 – 2020). In the final step we use the estimates from our main model (Table 2) to compute the combined effect of climate change on total returns.

The results are plotted in Figures 5 – 6.

[26] Kyoto protocol was first adopted 11 September 1997 in Kyoto, Japan. Over the following two years, 1998-99, 84 signatories were added to the agreement. The agreement commits state signatories to reduce greenhouse gas emissions, based on the scientific consensus that (part one) global warming is occurring and (part two) that human-made CO2 emissions are driving it. It came into force on 16 February 2005. See: www.unfccc.int.

[Place Figure 5 about here]

[Place Figure 6 about here]

Figure 5 plots the results for the three northern cities: Portland, Chicago, and Boston. Interestingly, these cities lost enough cold days to offset the impact of an increase in warm days, and are thus net beneficiaries of the global warming so far. On average, these cities enjoyed a total return increase of 3 percentage points over 6 years by simply holding their properties during the period of increasing temperatures. In contrast, Figure 6 shows the results for southern cities (Los Angeles, Houston and Miami). As predicted, these cities have seen a net loss in total returns of approximately 3 percentage points during the period of increasing temperatures. Hence, in the case of southern cities the decrease in the number of cold days was not sufficient to offset the impact of the increase in the number of warm days on average.

Taken together, the evidence presented in this section suggests that the economic impact of climate change is significant, and that so far locations in the north of the US have been net beneficiaries of this phenomenon. With the ever changing climate conditions, and time-variation in sensitivity of CRE returns to extreme temperatures, it leaves to be seen if this will continue to be the case in the future.

7 Conclusion

In this paper we conduct one of the first studies to provide direct evidence on how exposure to extreme temperatures affects U.S. commercial real estate performance at the individual asset level. We analyze how exposure to location-specific temperature shocks affects CRE total returns and its components, namely asset returns (or capital gains) and income returns (property yields). We find that exposure to extreme temperatures significantly reduces average realized total returns in CRE. We find that this result is mostly driven by reduction in asset returns. Exposure to extreme temperatures does not seem to affect income return in a statistically significant way. Given the richness of our data set, we are able to further decompose income return into three components: rental income, capital expenditures (CapEx) and operating expenditures (OpEx). Unsurprisingly, we do not find statistically significant results on average.

To understand the potential mechanism driving our results, we analyze the effect of extreme temperature exposure on cash flow predictability. We find positive and statistically significant relationship between both extremely hot temperatures and extremely cold temperatures, and (net) cash flow volatility. These results suggest that cash flows of real estate assets exposed to extreme temperatures exhibit higher volatility, which makes future income harder to predict, resulting in higher risk premium for real estate assets located in areas with more extreme temperatures.

We further document that different CRE property types exhibit different return sensitivity to extreme temperatures. When analyzing the effect of *average* temperatures on total returns and its components, we find a null result. To the extent that exposure to extreme temperatures affects predictability of future real estate cash flows, this should be well understood by all market participants: external appraisers, buyers and sellers. We empirically test this conjecture, by studying the effect of extreme temperatures on *appraisal* returns, and obtain similar results.

Finally, we quantify the total net effect of climate change on total returns on a selection of cities located in the north (Portland, Chicago, and Boston), and in the south (Los Angeles, Houston and Miami). We find that cities located in the north of the country on average enjoyed a total return increase of 3 percentage points over a sample holding period, and have thus been the net beneficiaries of the global warming so far. In contrast, southern U.S. cities have seen a net loss in total returns of approximately 3 percentage points during the period of increasing temperatures.

References

Addoum, J. M., D. T. Ng, and A. Ortiz-Bobea, 2020, Temperature shocks and establishment sales, *The Review of Financial Studies* 33, 1331–1366.

Bailey, M. J., R. F. Muth, and H. O Nourse, 1963, A regression method for real estate price index construction, *Journal of the American Statistical Association* 58, 933–942.

Bakkensen, L. A., and L. Barrage, 2017, Flood risk belief heterogeneity and coastal home price dynamics: Going under water?, Technical report, National Bureau of Economic Research.

Baldauf, M., L. Garlappi, and C. Yannelis, 2020, Does climate change affect real estate prices? only if you believe in it, *The Review of Financial Studies* 33, 1256–1295.

Bernstein, A., S. B. Billings, M. Gustafson, and R. Lewis, 2020, Voting with their sandals: Partisan residential sorting on climate change risk, Technical report, National Bureau of Economic Research.

Bernstein, A., M. T. Gustafson, and R. Lewis, 2019, Disaster on the horizon: The price effect of sea level rise, *Journal of Financial Economics* 134, 253–272.

Blanc, E., and W. Schlenker, 2017, The use of panel models in assessments of climate impacts on agriculture, *Review of Environmental Economics and Policy* 11, 258–279.

Case, K. E, and R. J. Shiller, 1987, Prices of single family homes since 1970: New indexes for four cities, *New England Economic Review* 45–56.

Case, K. E, and R. J. Shiller, 1989, The efficiency of the market of single-family homes, *The American Economic Review* 79, 125–137.

Chambers, D., C. Spaenjers, and E. Steiner, 2021, The rate of return on real estate: Long-run micro-level evidence, *The Review of Financial Studies* 34, 3572–3607.

Clapp, J. M., and C. Giaccotto, 1999, Revisions in repeat-sales price indexes: Here today, gone tomorrow, *Real Estate Economics* 27, 79–104.

Custodio, C., M. A. Ferreira, E. Garcia-Appendini, and A. Lam, 2020, Economic costs of climate change, *Available at SSRN 3724940* .

Dell, M., B. F. Jones, and B. A. Olken, 2009, Temperature and income: Reconciling new cross-sectional and panel estimates, *American Economic Review* 99, 198–204.

Dell, M., B. F. Jones, and B. A. Olken, 2012, Temperature shocks and economic growth: Evidence from the last half century, *American Economic Journal: Macroeconomics* 4, 66–95.

Dell, M., B. F. Jones, and B. A. Olken, 2014, What do we learn from the weather? the new climate-economy literature, *Journal of Economic Literature* 52, 740–98.

Eichholtz, P., M. Korevaar, T. Lindenthal, and R. Tallec, 2021, The total return and risk to residential real estate, *The Review of Financial Studies* 34, 3608–3646.

Eichholtz, P., E. Steiner, and E. Yönder, 2019, Where, when, and how do sophisticated investors respond to flood risk?, *Available at SSRN 3206257* .

Fama, E. F., 1990, Stock returns, expected returns, and real activity, *The Journal of Finance* 45, 1089–1108.

Favilukis, J., S. C. Ludvigson, and S. Van Nieuwerburgh, 2017, The macroeconomic effects of housing wealth, housing finance, and limited risk sharing in general equilibrium, *Journal of Political Economy* 125, 140–223.

Francke, M. K., and A. M. Van de Minne, 2017, Land, structure and depreciation, *Real Estate Economics* 45, 415–451.

Francke, M. K., and A. M. Van de Minne, 2020, Modeling unobserved heterogeneity in hedonic price models, *Real Estate Economics* .

Gallup, J. L., J. D. Sachs, and A. D. Mellinger, 1999, Geography and economic development, *International Regional Science Review* 22, 179–232.

Geltner, D. M., 1991, Smoothing in appraisal-based returns, *The Journal of Real Estate Finance and Economics* 4, 327–345.

Geltner, D. M., and W. Goetzmann, 2000, Two decades of commercial property returns: A repeated-measures regression-based version of the NCREIF index, *The Journal of Real Estate Finance and Economics* 21, 5–21.

Geltner, D. M., N. G. Miller, J. Clayton, and P. M. A. Eichholtz, 2014, *Commercial Real Estate, Analysis & Investments*, third edition (OnCourse Learning).

Ghent, A. C., W. N. Torous, and R. I. Valkanov, 2019, Commercial real estate as an asset class, *Annual Review of Financial Economics* 11, 153–171.

Giglio, S., M. Maggiori, K. Rao, J. Stroebel, and A. Weber, 2021, Climate change and long-run discount rates: Evidence from real estate, *The Review of Financial Studies* 34, 3527–3571.

Goetzmann, W. N., and M. Spiegel, 1995, Non-temporal components of residential real estate appreciation, *The Review of Economics and Statistics* 199–206.

Graff Zivin, J., and M. Neidell, 2014, Temperature and the allocation of time: Implications for climate change, *Journal of Labor Economics* 32, 1–26.

Hallstrom, D. G., and V. K. Smith, 2005, Market responses to hurricanes, *Journal of Environmental Economics and Management* 50, 541–561.

Heinl, M., A. Hammerle, U. Tappeiner, and G. Leitinger, 2015, Determinants of urban–rural land surface temperature differences–a landscape scale perspective, *Landscape and Urban Planning* 134, 33–42.

Hsiang, S. M., 2010, Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America, *Proceedings of the National Academy of sciences* 107, 15367–15372.

Jones, B. F., and B. A. Olken, 2010, Climate shocks and exports, *American Economic Review* 100, 454–59.

Lau, N., and M. Nath, 2012, A model study of heat waves over North America: Meteorological aspects and projections for the twenty-first century, *Journal of Climate* 25, 4761–4784.

McKenzie, R., and J. Levendis, 2010, Flood hazards and urban housing markets: The effects of Katrina on New Orleans, *The Journal of Real Estate Finance and Economics* 40, 62–76.

Ortega, F., and S. Taspınar, 2018, Rising sea levels and sinking property values: Hurricane Sandy and New York's housing market, *Journal of Urban Economics* 106, 81–100.

Pachauri, R. K., M. R. Allen, V. R. Barros, J. Broome, W. Cramer, R. Christ, J. A. Church, L. Clarke, Q. Dahe, P. Dasgupta, et al., 2014, *Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change* (Ipcc).

Sagi, J. S., 2021, Asset-level risk and return in real estate investments, *The Review of Financial Studies* 34, 3647–3694.

8 Tables

Table 1. Descriptive statistics. *Total Return* is defined as *Asset Return* plus *Net Income Return* (see Equation 4). *Net Income Return* is defined in Equation 5. The return and expense variables (operating and capital) are expressed as a percentage of the purchase price. *Temperature (°C):* gives the daily average mean (= (max + min)/2) temperature in °C during the holding period. *Temperature over 30°C (%):* gives the percentage of days during the holding period where the max temperature exceeded 30°C. *Temperature below 0°C (%):* gives the percentage of days during the holding period where the min temperature was below 0°C. *Precipitation (mm):* denotes the average daily precipitation during the holding period in millimeters. *MSA:* denotes Metropolitan Statistical Area. The *within* statistics are based on the corresponding variable which is first demeaned per MSA.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Total Return (%)	6,782	0.476	0.501	−0.857	0.155	0.723	3.239
- Asset Return (%)	6,782	0.179	0.389	−0.714	−0.069	0.387	1.881
- Net Income Return (%)	6,782	0.296	0.264	−0.445	0.128	0.419	1.384
- Income Return (%)	6,172	0.608	0.496	−0.019	0.287	0.783	8.496
- Operating Expenses (%)	6,178	0.266	0.319	−0.088	0.102	0.322	6.939
- Capital Expenditures (%)	6,782	0.116	0.150	−0.797	0.023	0.153	1.937
Holding period (years)	6,782	5.598	3.356	2	3	7	25
Temperature (°C)	6,782	15.629	4.503	5.197	11.782	18.848	25.650
- within MSA	6,782	0.000	1.317	−10.230	−0.476	0.475	9.597
Temperature over 30°C (%)	6,782	0.200	0.141	0.000	0.081	0.321	0.655
- within MSA	6,782	0.000	0.055	−0.300	−0.021	0.019	0.436
Temperature below 0°C (%)	6,782	0.150	0.138	0.000	0.007	0.272	0.541
- within MSA	6,782	0.000	0.045	−0.335	−0.012	0.011	0.453
Precipitation (mm)	6,782	2.594	1.155	0.046	1.522	3.434	5.620
- within MSA	6,782	0.000	0.403	−2.656	−0.194	0.168	2.671
Distance to centroid (m) of climate subgrid	6,782	1,631	606	36	1,213	2,091	3,005
Property Types							
Apartment	1,917						
Hotel	172						
Industrial	2,127						
Office	1,744						
Retail	822						

Table 2. Effect of extreme temperature on total returns in commercial real estate. Estimates are based on Equation (3). The temperature variables are expressed as a percentage of days over (under) 30°C (0°C) of the holding period. *MSA:* Metropolitan Statistical Area, *Division:* is a multi-state clustering as defined by our data provider NCREIF. There are 8 of such divisions. The dependent variable is Total Return, defined as: income return + asset return (Equation 4). Standard errors are clustered by MSA and year of sale. *Buy Yr FE:* are dummies for the year of buy, and *Sell Yr FE:* are dummies for year of sale. Given that we difference our Equation (3), we also difference the set of dummies.

	Dependent variable:					
	Total Return (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature over 30°C (%)	0.056***	−0.036***	−0.054***	−0.057***	−0.074***	−0.071***
	(0.012)	(0.011)	(0.010)	(0.019)	(0.021)	(0.027)
Temperature below 0°C (%)	0.025*	−0.057***	−0.057***	−0.079***	−0.094***	−0.125***
	(0.014)	(0.012)	(0.010)	(0.022)	(0.030)	(0.039)
Precipitation (mm)	0.009***	−0.001	−0.003**	0.002	−0.003	−0.003
	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)
Constant	0.264***	0.086***	0.061***	0.058***	0.056***	0.044***
	(0.021)	(0.014)	(0.013)	(0.012)	(0.013)	(0.013)
(Buy - Sell) Yr FE	no	yes	no	no	no	no
(Buy - Sell) Yr FE × property type FE	no	no	yes	yes	yes	yes
(Buy - Sell) Yr FE × division FE	no	no	no	yes	no	no
Trend × MSA FE	no	no	no	no	yes	no
(Buy - Sell) Yr FE × MSA FE	no	no	no	no	no	yes
Observations	6,782	6,782	6,782	6,782	6,782	6,782
R^2	0.090	0.355	0.440	0.502	0.463	0.619
Adjusted R^2	0.089	0.350	0.425	0.469	0.444	0.517
Residual Std. Error	0.478	0.404	0.380	0.365	0.374	0.348

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 3. Effect of extreme temperature on asset returns in commercial real estate. Estimates are based on Equation (3). The temperature variables are expressed as a percentage of days over (under) 30°C (0°C) of the holding period. *MSA:* Metropolitan Statistical Area, *Division:* is a multi-state clustering as defined by our data provider NCREIF. There are 8 of such divisions. The dependent variable is asset return, defined as total return - income return (Equation 4). Standard errors are clustered by MSA and year of sale. *Buy Yr FE:* are dummies for the year of buy, and *Sell Yr FE:* are dummies for year of sale. Given that we difference our Equation (3), we also difference the set of dummies.

	Dependent variable:					
	Asset Return (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature over 30°C (%)	−0.007	−0.036***	−0.048***	−0.063***	−0.077***	−0.079***
	(0.010)	(0.010)	(0.009)	(0.017)	(0.018)	(0.023)
Temperature below 0°C (%)	−0.041***	−0.067***	−0.066***	−0.091***	−0.112***	−0.149***
	(0.011)	(0.010)	(0.009)	(0.021)	(0.025)	(0.031)
Precipitation (mm)	0.002*	−0.001	−0.002**	0.001	−0.003	−0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)
Constant	0.190***	0.098***	0.082***	0.081***	0.077***	0.071***
	(0.017)	(0.012)	(0.011)	(0.010)	(0.011)	(0.011)
(Buy - Sell) Yr FE	no	yes	no	no	no	no
(Buy - Sell) Yr FE × property type FE	no	no	yes	yes	yes	yes
(Buy - Sell) Yr FE × division FE	no	no	no	yes	no	no
Trend × MSA FE	no	no	no	no	yes	no
(Buy - Sell) Yr FE × MSA FE	no	no	no	no	no	yes
Observations	6,782	6,782	6,782	6,782	6,782	6,782
R^2	0.008	0.206	0.294	0.368	0.322	0.514
Adjusted R^2	0.007	0.201	0.275	0.325	0.298	0.384
Residual Std. Error	0.388	0.348	0.331	0.320	0.326	0.305

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4. Effect of extreme temperature on net income returns in commercial real estate. Estimates are based on Equation (3). The temperature variables are expressed as a percentage of days over (under) 30°C (0°C) of the holding period. *MSA:* Metropolitan Statistical Area, *Division:* is a multi-state clustering as defined by our data provider NCREIF. There are 8 of such divisions. The dependent variable is net income return, defined as total return - asset return (Equation 4). Standard errors are clustered by MSA and year of sale. *Buy Yr FE:* are dummies for the year of buy, and *Sell Yr FE:* are dummies for year of sale. Given that we difference our Equation (3), we also difference the set of dummies.

	Dependent variable:					
	Net Income Return (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature over 30°C (%)	0.064***	0.0002	−0.005	0.007	0.002	0.008
	(0.005)	(0.004)	(0.004)	(0.007)	(0.011)	(0.013)
Temperature below 0°C (%)	0.066***	0.010**	0.009**	0.011	0.019	0.024
	(0.006)	(0.004)	(0.004)	(0.008)	(0.015)	(0.016)
Precipitation	0.007***	−0.0002	−0.001	0.001	0.001	−0.0003
	(0.001)	(0.0005)	(0.0004)	(0.001)	(0.002)	(0.002)
Constant	0.074***	−0.012**	−0.021***	−0.023***	−0.021***	−0.027***
	(0.009)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
(Buy - Sell) Yr FE	no	yes	no	no	no	no
(Buy - Sell) Yr FE × property type FE	no	no	yes	yes	yes	yes
(Buy - Sell) Yr FE × division FE	no	no	no	yes	no	no
Trend × MSA FE	no	no	no	no	yes	no
(Buy - Sell) Yr FE × MSA FE	no	no	no	no	no	yes
Observations	6,782	6,782	6,782	6,782	6,782	6,782
R^2	0.359	0.600	0.650	0.675	0.661	0.739
Adjusted R^2	0.359	0.598	0.640	0.653	0.649	0.670
Residual Std. Error	0.212	0.168	0.159	0.156	0.156	0.152

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 5. Effect of extreme temperature on subcategories of income return. Estimates are based on Equation (3). The temperature variables are expressed as a percentage of days over (under) 30°C (0°C) of the holding period. *MSA:* Metropolitan Statistical Area. The dependent variables are: rental income (column 1), operating expenses (OpEx, column 2) and capital expenditures (CapEx, column 3), scaled by the purchase price. Standard errors are clustered by MSA and year of sale. *Buy Yr FE:* are dummies for the year of buy, and *Sell Yr FE:* are dummies for year of sale. Given that we difference our Equation (3), we also difference the set of dummies.

	Dependent variable:		
	Income	OpEx	CapEx
	(1)	(2)	(3)
Temperature over 30°C (%)	−0.005	0.003	−0.006
	(0.018)	(0.016)	(0.009)
Temperature below 0°C (%)	−0.015	−0.019	-0.018^{*}
	(0.019)	(0.015)	(0.010)
Precipitation (mm)	0.003	0.001	0.001
	(0.002)	(0.002)	(0.001)
Constant	-0.029^{***}	−0.010	0.008^{*}
	(0.009)	(0.007)	(0.004)
(Buy - Sell) Yr FE × property type FE	yes	yes	yes
(Buy - Sell) Yr FE × MSA FE	yes	yes	yes
Observations	6,172	6,178	6,782
R^2	0.845	0.815	0.541
Adjusted R^2	0.806	0.768	0.418
Residual Std. Error	0.218	0.154	0.114
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 6. Effect of extreme temperature on the predictability of income. Predictability is measured by taking the standard deviation of the different income variables. Estimates are based on Equation (6). Predictability of income is defined by (first) taking the standard deviation of the income component and (second) dividing it by the purchase price to normalize said standard deviations. This is given by: $\frac{SD(\text{Income Component})_{i,t,s}}{V_{i,s}}$, where V is the purchase price at time s for property i. Income components are the following: *Income:* Gross rental income (potential gross income (PGI) minus any vacancy allowance), *OpEx:* operating expenses, *CapEx:* capital expenditures, *Net Income:* is defined as *Income - OpEx - CapEx*. The temperature variables are expressed as a percentage of days over (under) 30°C (0°C) of the holding period. *MSA:* Metropolitan Statistical Area. Standard errors are clustered by MSA and year of sale. *Buy Yr FE:* are dummies for the year of buy, and *Sell Yr FE:* are dummies for year of sale. Given that we difference our Equation (3), we also difference the set of dummies. *SD:* standard deviation.

	Dependent variable:			
	SD(Income)	SD(OpEx)	SD(CapEx)	SD(Net Income)
	(1)	(2)	(3)	(4)
Temperature over 30°C (%)	0.012**	0.014	0.005	0.022**
	(0.005)	(0.010)	(0.003)	(0.010)
Temperature below 0°C (%)	0.017***	0.043***	0.008**	0.045***
	(0.006)	(0.012)	(0.003)	(0.012)
Precipitation (mm)	−0.001	0.0002	−0.001*	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.024***	0.025***	0.013***	0.035***
	(0.002)	(0.003)	(0.001)	(0.004)
(Buy - Sell) Yr FE × property type FE	yes	yes	yes	yes
(Buy - Sell) Yr FE × MSA FE	yes	yes	yes	yes
Observations	6,172	6,552	6,178	6,782
R^2	0.639	0.297	0.536	0.304
Adjusted R^2	0.548	0.103	0.420	0.117
Residual Std. Error	0.020	0.054	0.015	0.055
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7. Effect of extreme temperature on different property types. Estimates are based on Equation (7). The temperature variables are expressed as a percentage of days over (under) 30°C (0°C) of the holding period. The dependent variables are total return (column 1), asset return (column 2), net income return (column 3), gross income (column 4), operating expenses (OpEx, column 5) and capital expenditures (CapEx, column 6). Variables in columns 4–6 are scaled by the purchase price. Net Income is defined in Equation 5. Standard errors are clustered by MSA and year of sale. The model includes property type times buy minus sale year fixed effects and MSA times buy minus sale year fixed effects. The baseline property type in all regressions is *Apartments*.

	Dependent variable:					
	Total	Asset	Net Income =	Income -	OpEx -	CapEx
	(1)	(2)	(3)	(4)	(5)	(6)
Temp $\geq$ 30°C	−0.080***	−0.101***	0.021	0.007	0.004	−0.014
	(0.031)	(0.012)	(0.027)	(0.018)	(0.013)	(0.010)
Hotel	−0.021	0.046	−0.067	0.224*	0.256**	0.041**
	(0.062)	(0.028)	(0.048)	(0.127)	(0.107)	(0.020)
Industrial	0.039	0.045***	−0.007	−0.034**	−0.026***	0.002
	(0.024)	(0.009)	(0.021)	(0.014)	(0.010)	(0.008)
Office	−0.007	0.028***	−0.034	−0.020	0.004	0.015**
	(0.025)	(0.009)	(0.022)	(0.014)	(0.010)	(0.007)
Retail	0.012	0.012	−0.0005	−0.036**	−0.025**	−0.0004
	(0.038)	(0.019)	(0.030)	(0.016)	(0.012)	(0.012)
Temp $\leq$ 0°C	−0.096**	−0.129***	0.034	−0.031	−0.038**	−0.029***
	(0.043)	(0.016)	(0.036)	(0.021)	(0.016)	(0.010)
Hotel	−0.192	−0.123***	−0.069	−0.292*	−0.181	−0.031
	(0.080)	(0.038)	(0.059)	(0.159)	(0.140)	(0.022)
Industrial	−0.010	0.002	−0.012	0.021	0.018*	0.014
	(0.025)	(0.010)	(0.023)	(0.016)	(0.010)	(0.012)
Office	−0.056	−0.036***	−0.020	0.050***	0.052***	0.024***
	(0.026)	(0.010)	(0.023)	(0.017)	(0.012)	(0.008)
Retail	−0.051	−0.040**	−0.011	0.014	0.015	0.014
	(0.036)	(0.016)	(0.030)	(0.017)	(0.012)	(0.012)
Precipitation (mm)	−0.004	−0.002	−0.002	0.006***	0.005**	0.003*
	(0.004)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)
Hotel	−0.017	−0.011***	−0.006	−0.034**	−0.028**	−0.001
	(0.009)	(0.004)	(0.007)	(0.015)	(0.013)	(0.002)
Industrial	0.001	−0.002	0.003	−0.005***	−0.005***	−0.003**
	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Office	0.008	0.005***	0.003	−0.001	−0.002*	−0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Retail	0.001	−0.001	0.002	−0.004**	−0.004***	−0.002**
	(0.004)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
Constant	0.043***	0.070***	−0.028**	−0.027***	−0.007	0.009*
	(0.013)	(0.006)	(0.011)	(0.009)	(0.007)	(0.004)
Observations	6,782	6,782	6,782	6,172	6,178	6,782
R^2	0.623	0.519	0.743	0.857	0.835	0.546
Adjusted R^2	0.521	0.388	0.673	0.820	0.793	0.423
Residual Std. Error	0.347	0.304	0.151	0.210	0.145	0.114

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8. Effect of *average* temperature on total returns. Estimates are based on Equation (3). The temperature variable is the mean temperature in °C during the holding period. *MSA:* Metropolitan Statistical Area, *Division:* is a multi-state clustering as defined by our data provider NCREIF. There are 8 of such divisions. The dependent variable is Total Return, defined as income + asset return. Standard errors are clustered by MSA and year of sale. *Buy Yr FE:* are dummies for the year of buy, and *Sell Yr FE:* are dummies for year of sale. Given that we difference our Equation (3), we also difference the set of dummies.

	Dependent variable:					
	Total Return (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature in °C	0.003***	0.001*	0.0001	0.001**	0.0003	0.001
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.001)	(0.001)
Precipitation (mm)	0.004**	−0.003**	−0.005***	0.004*	−0.003	−0.004
	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)
Constant	0.195***	0.087***	0.064***	0.060***	0.057***	0.046***
	(0.019)	(0.014)	(0.013)	(0.012)	(0.013)	(0.013)
(Buy - Sell) Yr FE	no	yes	no	no	no	no
(Buy - Sell) Yr FE × property type FE	no	no	yes	yes	yes	yes
(Buy - Sell) Yr FE × division FE	no	no	no	yes	no	no
Trend × MSA FE	no	no	no	no	yes	no
(Buy - Sell) Yr FE × MSA FE	no	no	no	no	no	yes
Observations	6,782	6,782	6,782	6,782	6,782	6,782
R^2	0.131	0.348	0.432	0.501	0.460	0.616
Adjusted R^2	0.130	0.344	0.416	0.467	0.441	0.513
Residual Std. Error	0.468	0.406	0.383	0.366	0.375	0.350
Note:				*p<0.1; **p<0.05; ***p<0.01		

Table 9. Adaptation: Effect of extreme temperatures in warm locations. Estimates are based on Equation (3). We include an interaction of our climate variables with historic warm locations. Locations with temperatures above the long-run average in the PRISM data are considered "warm locations." The temperature variables are expressed as a percentage of days over (under) 30°C (0°C) of the holding period. *MSA:* Metropolitan Statistical Area. The dependent variable is total return. Standard errors are clustered by MSA and year of sale. *Buy Yr FE:* are dummies for the year of buy, and *Sell Yr FE:* are dummies for year of sale. Given that we difference our Equation (3), we also difference the set of dummies.

	Dependent variable:					
	Total Return (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature over 30°C (%)	0.021	0.035	0.028	0.041	−0.075	−0.174*
	(0.112)	(0.075)	(0.063)	(0.061)	(0.080)	(0.103)
Temperature below 0°C (%)	0.074*	−0.066**	−0.080***	−0.090***	−0.127***	−0.114**
	(0.040)	(0.030)	(0.026)	(0.030)	(0.041)	(0.046)
Precipitation (mm)	0.002	−0.004	−0.004*	−0.0004	0.001	−0.001
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.005)
Temperature over 30°C (%) × warm location	0.027	−0.077	−0.085	−0.099*	0.001	0.106
	(0.113)	(0.075)	(0.062)	(0.058)	(0.078)	(0.102)
Temperature below 0°C (%) × warm location	−0.044	0.027	0.046	−0.010	0.054	−0.017
	(0.044)	(0.034)	(0.030)	(0.029)	(0.046)	(0.052)
Precipitation (mm), warm location	0.008**	0.003	0.001	0.003	−0.005	−0.002
	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)
Constant	0.265***	0.085***	0.060***	0.059***	0.055***	0.044***
	(0.021)	(0.014)	(0.013)	(0.012)	(0.013)	(0.013)
(Buy - Sell) Yr FE	no	yes	no	no	no	no
(Buy - Sell) Yr FE × property type FE	no	no	yes	yes	yes	yes
(Buy - Sell) Yr FE × division FE	no	no	no	yes	no	no
Trend × MSA FE	no	no	no	no	yes	no
(Buy - Sell) Yr FE × MSA FE	no	no	no	no	no	yes
Observations	6,782	6,782	6,782	6,782	6,782	6,782
R^2	0.092	0.357	0.442	0.503	0.463	0.619
Adjusted R^2	0.092	0.352	0.426	0.469	0.444	0.517
Residual Std. Error	0.478	0.403	0.380	0.365	0.374	0.348

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 10. Effect of extreme temperature on total returns in commercial real estate using Weighted Least Squares. Estimates are based on Equation (3) and Equation (8). The temperature variables are expressed as a percentage of days over (under) 30°C (0°C) of the holding period. In the second stage we regress holding period and distance to the centroid of subgrid our climate data. *MSA:* Metropolitan Statistical Area, *Division:* is a multi-state clustering as defined by our data provider NCREIF. There are 8 of such divisions. The dependent variable is total return. Standard errors are clustered by MSA and year of sale. *Buy Yr FE:* are dummies for the year of buy, and *Sell Yr FE:* are dummies for year of sale. Given that we difference our Equation (3), we also difference the set of dummies.

	Dependent variable:					
	Total Return (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature over 30°C (%)	0.054***	−0.036***	−0.055***	−0.058***	−0.074***	−0.071***
	(0.013)	(0.012)	(0.010)	(0.019)	(0.021)	(0.027)
Temperature below 0°C (%)	0.022	−0.057***	−0.056***	−0.080***	−0.094***	−0.125***
	(0.014)	(0.012)	(0.010)	(0.023)	(0.030)	(0.039)
Precipitation (mm)	0.009***	−0.001	−0.003**	0.003	−0.003	−0.003
	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)
Constant	0.284***	0.081***	0.053***	0.052***	0.056***	0.044***
	(0.025)	(0.017)	(0.014)	(0.013)	(0.013)	(0.013)
(Buy - Sell) Yr FE	no	yes	no	no	no	no
(Buy - Sell) Yr FE × property type FE	no	no	yes	yes	yes	yes
(Buy - Sell) Yr FE × division FE	no	no	no	yes	no	no
Trend × MSA FE	no	no	no	no	yes	no
(Buy - Sell) Yr FE × MSA FE	no	no	no	no	no	yes
Observations	6,777	6,782	6,782	6,782	6,782	6,782
R^2	0.087	0.354	0.450	0.515	0.463	0.619
Adjusted R^2	0.087	0.350	0.436	0.482	0.444	0.517
Residual Std. Error	0.346	0.268	0.240	0.223	0.374	0.348
Results from second stage						
lln distance to centroid of grid	0.022**	0.010	0.012*	0.007	0.011*	0.005
	(0.011)	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)
ln holding period	0.203***	0.143***	0.103***	0.083***	0.095***	0.051***
	(0.009)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)
Constant	−0.246***	−0.135**	−0.110**	−0.053	−0.096**	−0.017
	(0.079)	(0.055)	(0.048)	(0.043)	(0.046)	(0.035)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 11. Effect of extreme temperature on total returns, using random effect trends per (4x4 km) weather subgrid. Estimates are based on Equation (9). The temperature variables are expressed as a percentage of days over (under) 30°C (0°C) of the holding period. *MSA:* Metropolitan Statistical Area, *Division:* is a multi-state clustering as defined by our data provider NCREIF. There are 8 of such divisions. The dependent variables are total return (column 1), asset return (column 2) and income return (column 3). Standard errors are clustered by MSA and year of sale. *Buy Yr FE:* are dummies for the year of buy, and *Sell Yr FE:* are dummies for year of sale. Given that we difference our Equation (3), we also difference the set of dummies.

	Dependent variable:		
	Total Return (%)	Asset Return (%)	Net Income Return (%)
	(1)	(2)	(3)
Temperature over 30°C (%)	-0.069^{***}	-0.077^{***}	0.008
	(0.017)	(0.015)	(0.007)
Temperature below 0°C (%)	-0.101^{***}	-0.126^{***}	0.024^{***}
	(0.022)	(0.019)	(0.009)
Precipitation (mm)	-0.003	-0.003	-0.0003
	(0.003)	(0.003)	(0.001)
Constant	0.037^{***}	0.062^{***}	-0.026^{***}
	(0.011)	(0.010)	(0.005)
(Buy - Sell) Yr FE × property type FE	yes	yes	yes
(Buy - Sell) Yr FE × MSA FE	yes	yes	yes
Trend per 4x4km subgrid	yes	yes	yes
Observations	6,782	6,782	6,782
Log Likelihood	-2,972.196	-2,273.795	1,434.137
Akaike Inf. Crit.	8,818.392	7,421.590	5.726
Bayesian Inf. Crit.	18,621.650	17,224.840	9,808.979
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 12. Effect of extreme temperature on net asset returns in commercial real estate. Estimates are based on Equation (3). Net asset return is defined as the asset return, minus any capital expenditures (CapEx). More specifically: Net Asset Return$_{i,s,t}$ = $\frac{V_{i,t}-V_{i,s}}{V_{i,s}} - \frac{\sum_s^t CapEx_{i,s,t}}{V_{i,s}}$, where V are transaction prices at time of buy (s) and sale (t), for property i, $CapEx$ are the capital expenditures. The temperature variables are expressed as a percentage of days over (under) 30°C (0°C) of the holding period. *MSA:* Metropolitan Statistical Area, *Division:* is a multi-state clustering as defined by our data provider NCREIF. There are 8 of such divisions. Standard errors are clustered by MSA and year of sale. *Buy Yr FE:* are dummies for the year of buy, and *Sell Yr FE:* are dummies for year of sale. Given that we difference our Equation (3), we also difference the set of dummies.

	Dependent variable:					
	Net Asset Return (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature over 30°C (%)	−0.034***	−0.039***	−0.057***	−0.058***	−0.073***	−0.073***
	(0.010)	(0.010)	(0.009)	(0.017)	(0.018)	(0.024)
Temperature below 0°C (%)	−0.064***	−0.070***	−0.070***	−0.080***	−0.093***	−0.131***
	(0.011)	(0.011)	(0.009)	(0.020)	(0.025)	(0.033)
Precipitation (mm)	−0.0004	−0.001	−0.003***	0.001	−0.003	−0.003
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)
Constant	0.162***	0.095***	0.075***	0.075***	0.070***	0.063***
	(0.016)	(0.012)	(0.011)	(0.010)	(0.010)	(0.010)
(Buy - Sell) Yr FE	no	yes	no	no	no	no
(Buy - Sell) Yr FE × property type FE	no	no	yes	yes	yes	yes
(Buy - Sell) Yr FE × division FE	no	no	no	yes	no	no
Trend × MSA FE	no	no	no	no	yes	no
(Buy - Sell) Yr FE × MSA FE	no	no	no	no	no	yes
Observations	6,782	6,782	6,782	6,782	6,782	6,782
R^2	0.043	0.216	0.345	0.411	0.376	0.552
Adjusted R^2	0.043	0.211	0.327	0.371	0.354	0.432
Residual Std. Error	0.376	0.342	0.315	0.305	0.309	0.290

Note: *p<0.1; **p<0.05; ***p<0.01

Table 13. Effect of extreme temperature on *appraised* values in commercial real estate. Estimates are based on Equation (3). The temperature variables are expressed as a percentage of days over (under) 30°C (0°C) of the holding period. *MSA:* Metropolitan Statistical Area, *Division:* is a multi-state clustering as defined by our data provider NCREIF. There are 8 of such divisions. The dependent variable is the appraised value of our properties 6 months before the transaction divided by the purchase price. The dependent variable include both "stale"/ internal and external appraised values. Standard errors are clustered by MSA and year of sale. *Buy Yr FE:* are dummies for the year of buy, and *Sell Yr FE:* are dummies for year of sale. Given that we difference our Equation (3), we also difference the set of dummies.

	Dependent variable:					
	Appraisal Return (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature over 30°C (%)	−0.006	−0.030***	−0.041***	−0.055***	−0.056***	−0.063***
	(0.008)	(0.008)	(0.007)	(0.015)	(0.015)	(0.019)
Temperature below 0°C (%)	−0.028***	−0.048***	−0.046***	−0.065***	−0.076***	−0.108***
	(0.009)	(0.008)	(0.007)	(0.017)	(0.019)	(0.025)
Precipitation (mm)	0.003***	0.0002	−0.001	0.002	−0.003	−0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Constant	0.103***	0.029***	0.015	0.013	0.012	0.008
	(0.013)	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)
(Buy - Sell) Yr FE	no	yes	no	no	no	no
(Buy - Sell) Yr FE × property type FE	no	no	yes	yes	yes	yes
(Buy - Sell) Yr FE × division FE	no	no	no	yes	no	no
Trend × MSA FE	no	no	no	no	yes	no
(Buy - Sell) Yr FE × MSA FE	no	no	no	no	no	yes
Observations	6,781	6,781	6,781	6,781	6,781	6,781
R^2	0.007	0.204	0.296	0.362	0.323	0.503
Adjusted R^2	0.006	0.199	0.277	0.319	0.299	0.369
Residual Std. Error	0.327	0.293	0.279	0.270	0.274	0.260

Note: *p<0.1; **p<0.05; ***p<0.01

Table 14. Effect of temperature on total, asset and income returns, before and after year 2000. Estimates are based on Equation (3), with interaction of post 2000 exposure. The post 2000 exposure variable takes on a value between 0 and 1, depending on the percentage of the holding period that was after 2000. The temperature variables are expressed as a percentage of days over (under) 30°C (0°C) of the holding period. *MSA:* Metropolitan Statistical Area. The dependent variables are total return (column 1), asset return (column 2) and net income return (column 3). Standard errors are clustered by MSA and year of sale. *Buy Yr FE:* are dummies for the year of buy, and *Sell Yr FE:* are dummies for year of sale. Given that we difference our Equation (3), we also difference the set of dummies.

	Dependent variable:		
	Total Return (%)	Asset Return (%)	Net Income Return (%)
	(1)	(2)	(3)
Temperature over 30°C (%)	0.018	−0.040	0.058***
	(0.044)	(0.038)	(0.019)
Temperature below 0°C (%)	−0.165**	−0.178***	0.013
	(0.068)	(0.060)	(0.030)
Precipitation (mm)	−0.006	−0.009	0.003
	(0.008)	(0.007)	(0.003)
Temperature over 30°C (%) × Exposure after 2000	−0.110**	−0.048	−0.062***
	(0.050)	(0.044)	(0.022)
Temperature below 0°C (%) × Exposure after 2000	0.042	0.032	0.010
	(0.074)	(0.065)	(0.032)
Precipitation (mm) × Exposure after 2000	0.004	0.008	−0.004
	(0.009)	(0.008)	(0.004)
Constant	0.044***	0.071***	−0.027***
	(0.011)	(0.010)	(0.005)
(Buy - Sell) Yr FE × property type FE	yes	yes	yes
(Buy - Sell) Yr FE × MSA FE	yes	yes	yes
Observations	6,782	6,782	6,782
R^2	0.620	0.515	0.740
Adjusted R^2	0.517	0.384	0.670
Residual Std. Error	0.348	0.305	0.152

Note: *p<0.1; **p<0.05; ***p<0.01

9 Figures

Figure 1. Geographical locations of the NCREIF commercial real estate property universe.

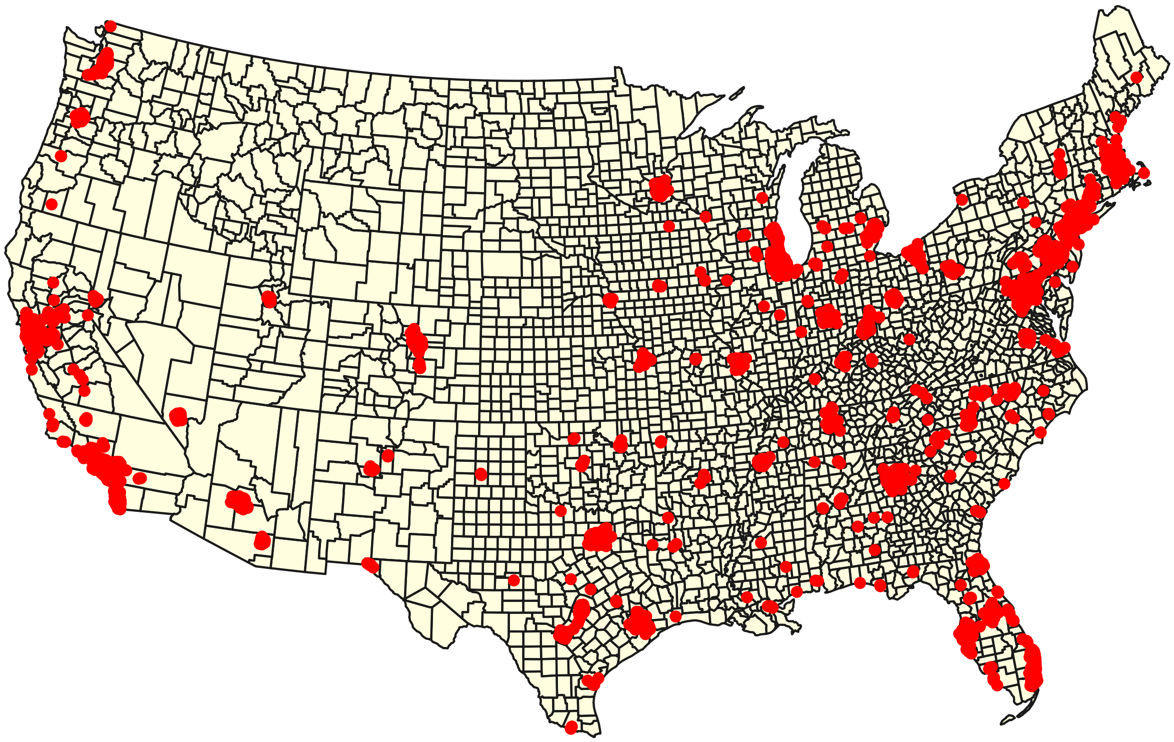
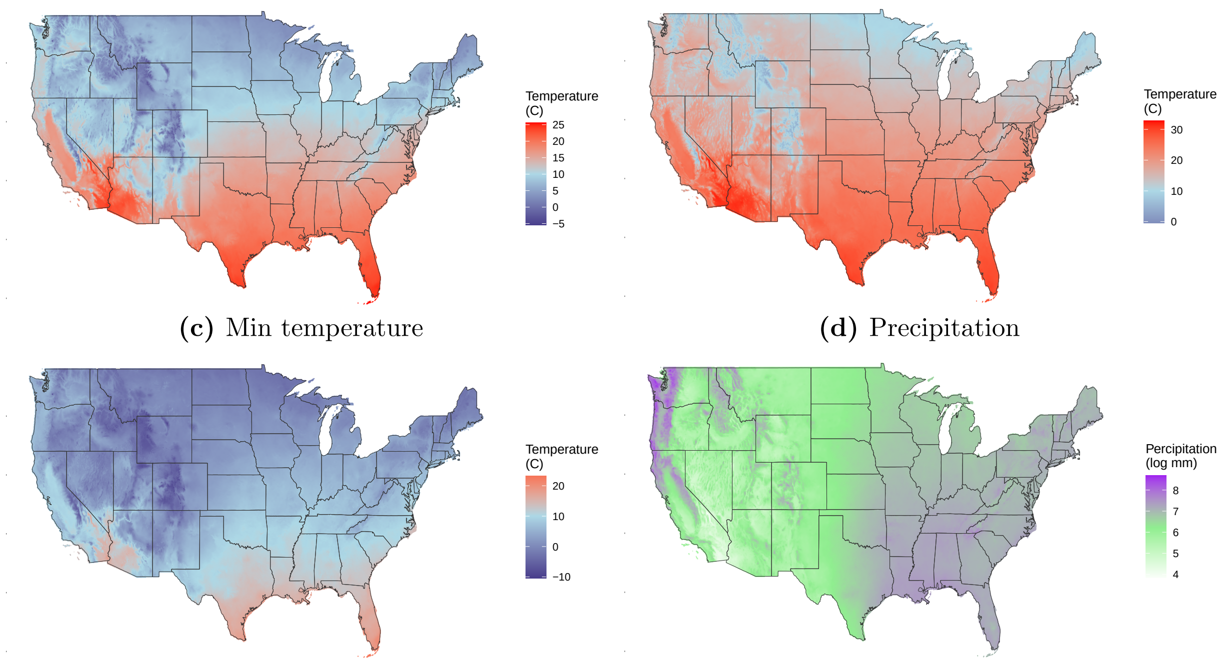


Figure 2. Temperature data from PRISM. Normalized data between 1980 and 2010.



(a) Mean temperature

(b) Max temperature

(c) Min temperature

(d) Precipitation

Figure 3. Time series averages of our temperature variables merged with NCREIF data per 5 year intervals.

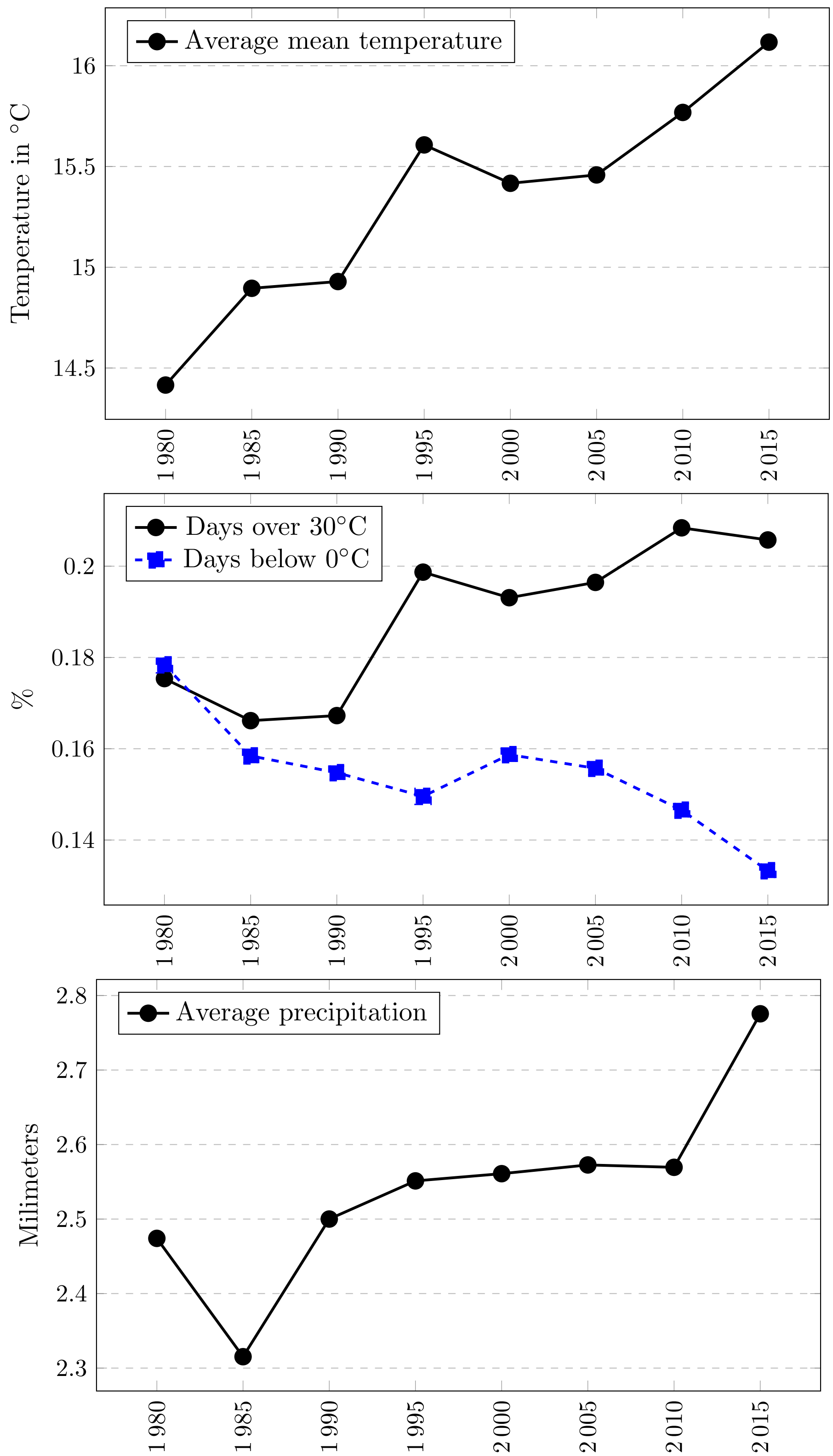
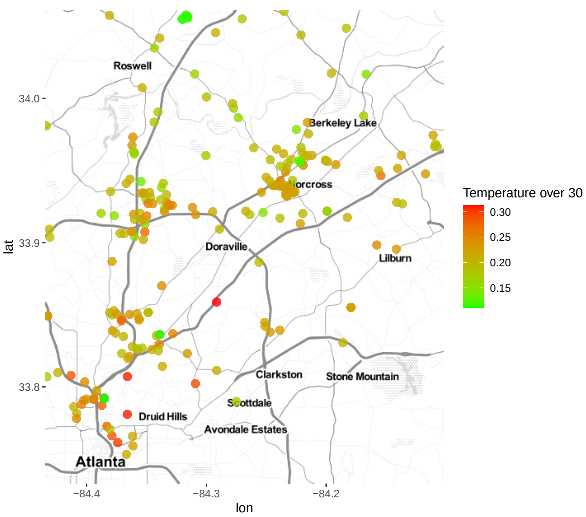
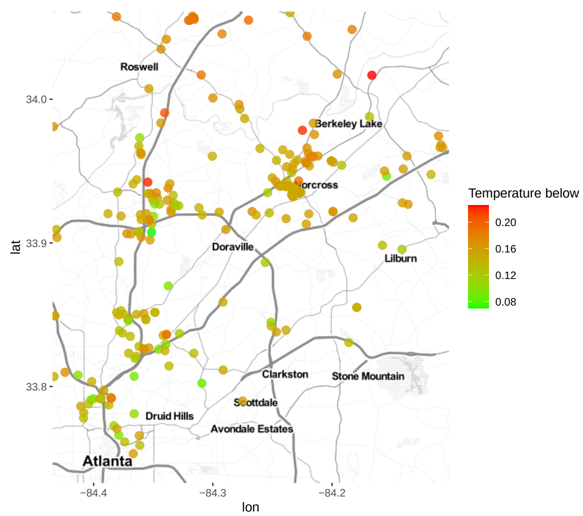


Figure 4. Example of within city differences in the main temperature variables in Atlanta–Sandy Springs–Alpharetta, GA Metropolitan Statistical Area.

(a) Temperature over 30°C



(b) Temperature below 0°C



(c) Precipitation (mm)

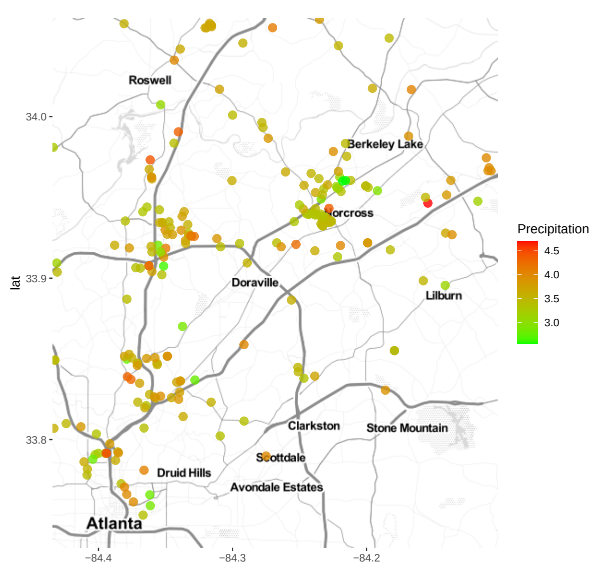


Figure 5. Total effect (warm and cold days) of holding and selling a property for 6 years between 1987 and 2020. The effect is computed by $\hat{\beta} \times \hat{X}_{t-6\times 4,t}$, or the estimated coefficient times the amount of days above (below) 30 °C (0 °C) of the previous 6 years in the centroid of the presented cities. Northern cities. Estimates are from Table 2.

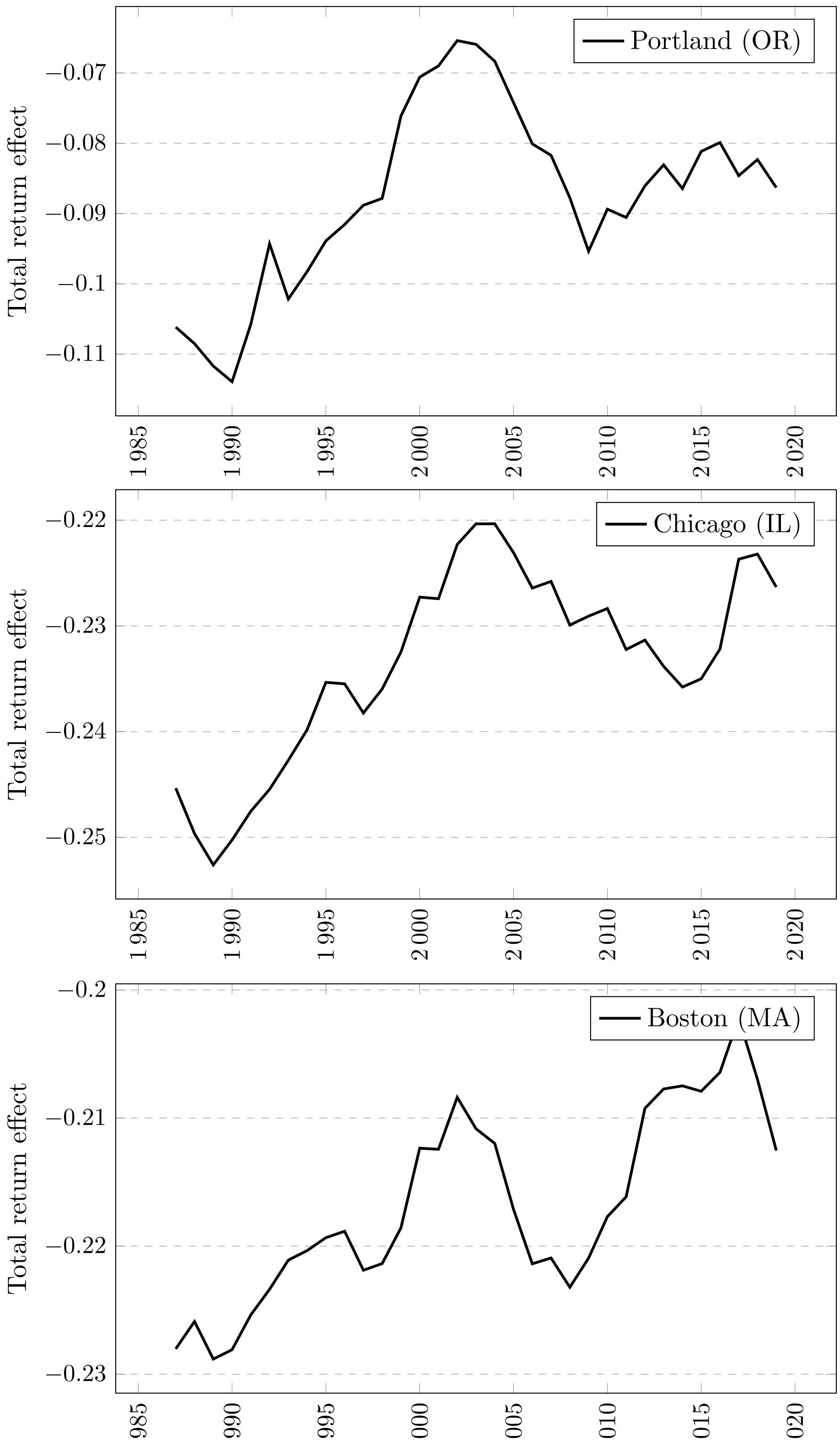


Figure 6. Total effect (warm and cold days) of holding and selling a property for 6 years between 1987 and 2020. The effect is computed by $\hat{\beta} \times \hat{X}_{t-6\times4,t}$, or the estimated coefficient times the amount of days above (below) 30 °C (0 °C) of the previous 6 years in the centroid of the presented cities. Southern cities. Estimates are from Table 2.

A Appendix

Table 15. Adaptation levels. Effect of extreme temperatures in warm locations. Alternative specification to Table 9. Estimates are based on Equation (3). We include an interaction of our climate variables with historic warm locations and cold locations. Locations with temperatures above the long-run average in the PRISM data are considered "warm locations" and vice verse. The temperature variables are expressed as a percentage of days over (under) 30°C (0°C) of the holding period. *MSA:* Metropolitan Statistical Area. The dependent variable is total return. Standard errors are clustered by MSA and year of sale. *Buy Yr FE:* are dummies for the year of buy, and *Sell Yr FE:* are dummies for year of sale. Given that we difference our Equation (3), we also difference the set of dummies.

	Dependent variable:					
	Dependent variable: Total Return (%)					
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature over 30°C (%) × cold location	0.021	0.035	0.028	0.041	−0.075	−0.174*
	(0.112)	(0.075)	(0.063)	(0.061)	(0.080)	(0.103)
Temperature below 0°C (%) × cold location	0.074*	−0.066**	−0.080***	−0.090***	−0.127***	−0.114**
	(0.040)	(0.030)	(0.026)	(0.030)	(0.041)	(0.046)
Precipitation (mm) × cold location	0.002	−0.004	−0.004*	−0.0004	0.001	−0.001
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.005)
Temperature over 30°C (%) × warm location	0.048***	−0.042***	−0.057***	−0.058***	−0.074***	−0.067**
	(0.013)	(0.012)	(0.011)	(0.019)	(0.021)	(0.027)
Temperature below 0°C (%) × warm location	0.030	−0.038**	−0.034**	−0.099***	−0.073**	−0.131***
	(0.021)	(0.016)	(0.015)	(0.025)	(0.037)	(0.049)
Precipitation (mm) × warm location	0.010***	−0.001	−0.003**	0.003	−0.004	−0.003
	(0.002)	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)
Constant	0.265***	0.085***	0.060***	0.059***	0.055***	0.044***
	(0.021)	(0.014)	(0.013)	(0.012)	(0.013)	(0.013)
(Buy - Sell) Yr FE	no	yes	no	no	no	no
(Buy - Sell) Yr FE × property type FE	no	no	yes	yes	yes	yes
(Buy - Sell) Yr FE × division FE	no	no	no	yes	no	no
Trend × MSA FE	no	no	no	no	yes	no
(Buy - Sell) Yr FE × MSA FE	no	no	no	no	no	yes
Observations	6,782	6,782	6,782	6,782	6,782	6,782
R^2	0.092	0.357	0.442	0.503	0.463	0.619
Adjusted R^2	0.092	0.352	0.426	0.469	0.444	0.517
Residual Std. Error	0.478	0.403	0.380	0.365	0.374	0.348
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 16. Effect of temperature on total, asset and income returns, before and after year 2000. Alternative specification to Table 14. Estimates are based on Equation (3), with interaction of post and pre 2000 exposure. The post (pre) 2000 exposure variable takes on a value between 0 and 1, depending on the percentage of the holding period that was after (before) 2000. The temperature variables are expressed as a percentage of days over (under) 30°C (0°C) of the holding period. *MSA:* Metropolitan Statistical Area. The dependent variables are total return (column 1), asset return (column 2) and income return (column 3). Standard errors are clustered by MSA and year of sale. *Buy Yr FE:* are dummies for the year of buy, and *Sell Yr FE:* are dummies for year of sale. Given that we difference our Equation (3), we also difference the set of dummies.

	Dependent variable:		
	Total Return (%)	Asset Return (%)	Net Income Return (%)
	(1)	(2)	(3)
Temperature over 30°C (%) × Exposure before 2000	0.018	−0.040	0.058***
	(0.044)	(0.038)	(0.019)
Temperature over 30°C (%) × Exposure after 2000	−0.092***	−0.088***	−0.004
	(0.019)	(0.016)	(0.008)
Temperature below 0°C (%) × Exposure before 2000	−0.165**	−0.178***	0.013
	(0.068)	(0.060)	(0.030)
Temperature below 0°C (%) × Exposure after 2000	−0.122***	−0.146***	0.024**
	(0.023)	(0.020)	(0.010)
Precipitation (mm) × Exposure before 2000	−0.006	−0.009	0.003
	(0.008)	(0.007)	(0.003)
Precipitation (mm) × Exposure after 2000	−0.002	−0.001	−0.001
	(0.003)	(0.003)	(0.001)
Constant	0.044***	0.071***	−0.027***
	(0.011)	(0.010)	(0.005)
(Buy - Sell) Yr FE × property type FE	yes	yes	yes
(Buy - Sell) Yr FE × MSA FE	yes	yes	yes
Observations	6,782	6,782	6,782
R^2	0.620	0.515	0.740
Adjusted R^2	0.517	0.384	0.670
Residual Std. Error	0.348	0.305	0.152
Note:			*p<0.1; **p<0.05; ***p<0.01