University of Pretoria
Department of Economics Working Paper Series

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Working Paper: 2022-36
August 2022

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The Heterogeneous Impact of Temperature Growth on Real House Price Returns across the US States

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Abstract

This paper investigates the impact of temperature growth on real returns of US housing markets at the state level. Using the 1-month, 3-month, and 12-month horizons for the period 1975:01 to 2021:06 and heterogeneous random coefficients panel data model, we find that increased temperature growth rates negatively affect real house price returns across all horizons. The effects intensify when the media refers more to climate change news. While most states experience a decline in real house price returns at a 3-month horizon, the largest relative negative impacts are registered over the 12-month horizon, suggesting that climate risk is a long-run risk. Geographically, the rising temperatures have the most negative effect on real house returns in the US West Coast states of California, Arizona, Nevada, and Idaho, and the Sun Belt states, most notably Florida, Georgia, Texas, Tennessee, and Alabama. The results remain robust after controlling for state-level leading economic indicators and state- and national-level economic uncertainty arising from policy changes.

Keywords: Climate Risks; Temperature Growth; Panel Random Coefficient Model; US States

JEL Codes: C33; D80; Q54

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1. Introduction

Homeowners, regulators, policymakers, academicians, providers of capital, investors, and a host of other market players are becoming increasingly conscious of the impact of climate-related risks on the pricing of physical and financial assets (Baldauf et al., 2020; Faccini et al., 2021), economic performance (Kim et al., 2021)[1], cost of raising capital by the public sector (Painter, 2020)[2], commodity currency and terms of trade (Gupta et al., 2019; and Kapfhammer et al., 2020) and financial stability (Flori et al., 2021; Battiston et al., 2021).

Recent studies by Battiston et al. (2021) and Flori et al. (2021) point out that the occurrence of rare disasters necessitates nearly every future investment setting to incorporate climate-related financial risks. However, the form and level of the source of climate-related uncertainty may vary across investment opportunities. The real estate market faces climate-related physical and transition risks. Physical risk refers to damage to real estate (land, homes, and supporting infrastructure) caused by climate change, causing a rise in the frequency and severity of storms, flooding, wildfires, sea levels, and average temperatures. Transition risk relates to technological, regulatory[3], consumer behavior, and economic and social responses to climate change. Examples of such responses include the decarbonization of buildings, the use of low-emissions, heat- and fire-resistant construction materials, and changes in insurance underwriting and lending models to price climate-related risks (Clapp et al., 2017).

In this study, we investigate the state-level impact of climate change on real house price returns across the US states. Our motivation for state-level analysis stems from the need to use

[1] Kim et al. (2021) find that an increase in extreme weather conditions in the US negatively impacts US macro variables by persistently reducing aggregate industrial production growth while increasing aggregate unemployment and inflation.

[2] Painter (2020) finds that US Counties more vulnerable to climate risk pay higher underwriting fees and initial yields in issuing long-term municipal bonds compared to counties less likely to be affected by climate risk. Since climate risk and non-climate risk counties have the same issuance cost and initial yield for short-term bonds, it seems the market prices climate change risks for long-term securities only.

[3] A survey by Stroebel and Wurgler (2021) identifies regulatory risk as the primary climate risk to businesses and investors over the next five years, while the physical risk is viewed as the top risk over the next 30 years. The respondents believe that asset prices overwhelmingly underestimate climate risks.

localized house prices and weather information relative to regional-level analysis. In particular, we focus on the effects of rising temperature on housing returns since increasing temperatures might affect the housing market through multiple channels. First, rising temperatures trigger large-scale climate-related events such as massive wildfires, droughts, hurricanes, flooding, gale-force storms, precipitation, rising sea level, and destructive winds. Second, rising temperatures increase the annual costs of managing owner-occupied and rental properties. For example, higher electricity and water usage due to more cooling and stress on electrical grids erodes the financial resources of local governments. Third, an upsurge in the intensity and frequency of climate risk due to increasing temperatures presents a high risk of structural damage, especially to coastal properties. Residential properties in weather-plagued locales under constant danger of destructive natural disasters become less appealing and are sold at low profit or loss. Contemporarily, discounted valuations and higher insurance premiums are used to indirectly account for risks from natural disasters such as fires, floods, and earthquakes that may affect real estate valuation. Overall, worsening physical and transition climate risks force real estate players to consider new residential buildings' physical and environmental features.

Using one-, three- and twelve-month time aggregations and a heterogeneous random coefficients panel data model in our analysis, we find that increased temperature growth rates negatively impact real house price returns across all horizons. While a plurality of states experiences a decline in real house price returns in response to temperature increases at a 3-month horizon, the largest negative impacts are registered over the 12-month horizon. US West Coast states and the US Sun Belt region, notably Florida, Arizona, Georgia, Nevada, Texas, California, Tennessee, Idaho, and Alabama, are most negatively impacted by temperature increases. The foregoing overwhelming evidence supports the need to price climate risk and the documented multiplier effects of climate risk on physical and financial assets. Furthermore,

our results remain robust after controlling for state-level leading economic indicators and state- and national-level economic policy uncertainties.

The media significantly influences how people understand and react to climate change. It is shown that media attention to climate change has a considerable effect on policy agenda setting related to climate risks (Keller et al., 2020), public discourses about climate change (Nisbet, 2009), and public awareness and beliefs regarding climate change (Baldauf et al., 2020). Therefore, in the next step, we examine whether the impact of temperature growth on housing returns amplifies when media attention to climate change increases. Using the (negative) climate change news indexes proposed by Engle et al. (2020), we find that the negative effect of temperature growth on real housing returns intensifies at all forecast horizons when the media refers more to negative climate change news. Furthermore, the negative effect greatly increases when looking at longer time horizons, suggesting that investors heavily price the climate risk in the real estate market over the long run.

We have several reasons to focus on the real estate market. Among the physical assets, real estate is an exciting asset class for any study due to its duration and importance to households and the overall economy. First, Baldauf et al. (2020) argue that the long-duration nature of a real estate asset exposes it to long-run risks emerging from climate change. Second, the 2019 Survey of Consumer Finance (SCF)[4] shows primary residences represent 62% of the median homeowners' total assets and 42% of the median homeowners' wealth. Furthermore, 65% of US households owned a primary residence, compared to 50.5% with a retirement account and 30.5% with financial assets (bonds, stocks, certificate of deposit, and savings bonds). Therefore, a primary residence is the most widely held asset. Third, as collateral to secure debt

[4] The SCF is a triennial cross-sectional survey that provides detailed information on the finances (balance sheets, pensions, income, and demographic characteristics) of US households.

for consumption and investment purposes, real estate becomes a valuable source of household debt that fuels overall economic production and activities.

Our work is related to the burgeoning and developing literature focusing on the effects of climate change on asset markets. Bernstein et al. (2019) show that homes in coastal counties exposed to extreme climate risk sell at an 8.5% discount, broadly consistent with the 7% discount documented by Baldauf et al. (2020). Livy (2020) finds that aberrant increases in heating and cooling degree days negatively impact housing prices, with cooling degree days having a larger negative impact. Gourley (2021) affirms that home prices are negatively affected by temporary summer and winter weather conditions. Real estate values decline more in local housing markets with higher vulnerability to climate-related risks. Local housing market prices decline as perceptions of climate-related sea-level rises (Giglio, et al., 2015, 2021), flooding risk (Bernstein, et al., 2019 and Baldauf, et al., 2020), and wildfire risk (McCoy and Walsh, 2018; Garnache and Guilfoos, 2019) increases. Further, Keenan et al. (2018) find that high-value housing markets with a high climate-related risk of flooding (e.g., Miami) will experience slower property price appreciation than lower flooding-risk properties. These studies provide evidence of pricing perceptions of climate-related risk in some real estate markets. An empirically unexplored question is how long-run risks associated with extreme weather and climate change[5] affect real estate returns across heterogeneous regional housing markets. Hence, our results contribute to the enlarging literature on how investors price long-run risk in the real estate market.

Climate risk affects the real estate market in several aspects. Real estate markets facing high climate risks will experience steep insurance premiums increase as insurers realize that they cannot shoulder home losses at current insurance premium rates. In extreme cases, insurers

[5] Climate change, a long-run risk, refers to the shift in the statistical distribution of future weather patterns.

will drop the homeowners or deny renewals for homes in high-risk neighborhoods, fearing increasing losseses irrespective of the insurance premium they charge[6]. Ultimately, insurers will free high climate risk housing markets to avoid filing for bankruptcy (Chiglinsky and Chen, 2020).[7] Uninsurable, high-risk homes near the oceans and high-risk flood and wildfire zones may force mortgage providers to charge high-interest rates or deny mortgages altogether if they cannot price future climate risk. For example, extreme weather events such as hurricanes can result in prolonged job losses, resulting in mortgage default. Issler et al. (2020) find that households living in high-risk wildfires and flooding zones exhibit increased residential mortgage default rates.

Furthermore, climate risk can severely impact the demand and value of homes and property taxes. For example, Shi and Varuzzo (2020) note that land values get significantly depressed as climate-related physical risks directly reduce the demand and value of real estate due to high repair and maintenance costs and infrastructure and transportation disruptions caused by weather disasters. Reduced demand and home values in real estate markets vulnerable to climate-related risks, stresses, and shocks, reduce household wealth, spending, and local economic activities.[8] However, it may increase the demand and value of inland homes facing low frequency and severity of climate risk.[9] As homeowners relocate from the waterfront to inland homes (or from high climate- to low climate-risk zones), there will be fewer households in the coastal community, a smaller tax base, and potentially higher property and sales taxes to

[6] According to an October 2020 report compiled by California's insurance regulator, insurers in California refused to renew 235,250 homeowners' insurance policies in 2019, a 31% increase from 2018. This compares to 61% increase (between 2018 and 2019) in non-renewals for homes in ZIP codes assessed to have a moderate to very high fire risk.

[7] See https://www.insurancejournal.com/news/west/2020/12/04/592788.htm

[8] This emerges from past studies (See for example, Stroebel and Vavra (2019) and Mian et al. (2013)), which show that housing wealth represents the largest portion of US household wealth. Since US household spending varies with housing wealth, reduced real estate values (borrowing collateral) will reduce household wealth, borrowing capacity, spending, and local economic activity.

[9] A study by Wolf and Klaiber (2017) shows that warmer weather around Buckeye Lake and Grand Lake resulted in excessive algae affecting the lakefront homes, resulting in an estimated $152 million reduction in combined lakefront property values between 2009 and 2015.

maintain and support community infrastructures (Shi and Varuzzo, 2020). Further, such climate-risk-induced relocations cause economic losses for investors and households.

Our results contribute to established literature on the determinants of real estate investment returns (Piazzesi et al., 2007; Chambers et al., 2021) and the more targeted literature on how climate risks can change the valuations of asset prices (Choi et al., 2020; Duan et al., 2021; Bolton and Kacperczyk, 2021; Ilhan et al., 2021). Although there is some evidence to suggest that the stock market is already pricing the risks associated with climate change, there is a lack of evidence in the housing market. Yi and Choi (2020) investigate the impact of the devastating Iowa flood of 2008 on housing values and find that unexpected inundation during the flood causes to drop in house prices. Fang et al. (2021) use a dataset of residential transactions in Miami-Dade County to study whether the local housing markets may be impacted by a large-scale but distant storm incident without experiencing direct damage. Similarly, Votsis and Perrels (2016) show a significant decrease in the prices of homes in flood-prone zones following the dissemination of the flood risk maps. Hence, our study differs from previous event study-based approaches focusing on a specific region with a shorter horizon by examining the heterogeneous impacts of climate risks on the housing market across the US states and providing implications of climate risks for the housing market in a broader content. In this regard, our paper is in line with the US Metropolitan Statistical Areas (MSAs)-based study of Donadelli et al. (2020) on the negative impact of tornado activity on house prices, particularly in the South and Midwest census regions. Though we study the less granular, state-level housing markets, our study still provides the state-specific impact of climate change, as captured by growth in temperature, at various investment horizons, on real house price returns.

The remainder of the paper is organized as follows: Section 2 presents the data and methodology. Section 3 discusses the results, while Section 4 concludes.

2. Data and methodology

2.1 Data and model specification

We use an unbalanced panel dataset covering the monthly period from 1975:01 to 2021:06, based on availability at the time of writing. The dataset includes data on the 49 US states, barring Hawaii. For the house price data, we use nominal house prices of the states derived from Freddie Mac,[10] with the indices based on an ever-expanding database of loans purchased by either Freddie Mac or Fannie Mae. Real house prices were generated by deflating the nominal values by the national Consumer Price Index (CPI). The CPI data was obtained from the FRED database of the Federal Reserve Bank of St. Louis.[11] We use real house price log returns (*rhr1*) and construct 3-month (*rhr3*) and 12-month (*rhr12*) rolling sums series of log returns to capture the effect of climate risk at shorter and longer horizons. The corresponding average temperature (in degrees Fahrenheit) data for each state is obtained from National Oceanic and Atmospheric Administration (NOAA).[12] From the raw data, we compute month-on-month growth in temperature (*temp_g*) to model the impact of climate change on the US housing market. We also use a state-specific leading indicator to account for the influence of economic cycles in the estimated model.[13] The data, originally created by the Federal Reserve Bank of Philadelphia, was sourced from the FRED database. Finally, given the importance of the role of uncertainty in driving house price movements (van Eyden et al., forthcoming), we also consider three metrics of newspaper-based economic policy uncertainty (*epu*) separately, derived from the work of Baker et al. (2022).[14] To construct the state-level measures of *epu*,

[10] The data is available for download from: http://www.freddiemac.com/research/indices/house-price-index.page.
[11] https://fred.stlouisfed.org/series/CPIAUCSL.
[12] See: https://www.ncdc.noaa.gov/cag/statewide/time-series.
[13] The leading index for each state predicts the six-month growth rate of the state's coincident index, with the latter including four indicators: nonfarm payroll employment, the unemployment rate, average hours worked in manufacturing and wages and salaries. In addition to the coincident index, the leading indicator also includes other variables that lead the economy: state-level housing permits, state initial unemployment insurance claims, delivery times from the Institute for Supply Management (ISM) manufacturing survey, and the interest rate spread between the 10-year Treasury bond and the 3-month Treasury bill.
[14] The data is available for download from: http://policyuncertainty.com/state_epu.html.

these authors use around 3,500 daily and weekly newspapers for every state in the US (as well as Washington DC), but exclude national papers published in a given state (such as the New York Times or Wall Street Journal). Baker et al. (2022) construct three state-level *epu* indexes by recording the fraction of articles that contain terms from term sets regarding the economy, uncertainty, and policy, with the three indexes distinguished only by variations in their policy term sets, i.e., for inclusion in each index, an article must contain the word: "economic" or "economy" as well as, 'uncertainties,' or 'uncertainty.' The nation-level epu index (*epu_national*) measures the level of uncertainty within a state that stems from specifically national policy-related sources.[15] Then the index *epu_state* looks to measure the level of uncertainty within a state that comes from state and local policy issues.[16] Finally, the third index, *epu_composite*, is composed of articles that contain terms related to the economy and uncertainty and a term from a composite set of terms that contains state-specific policy terms and national policy terms.

To capture the effect of climate risk on the US housing market at various horizons, we specify the following model:

$$rhrh_{i,t} = \beta_{0i} + \beta_{1i} temp\_g_{i,t-1} + \beta_{2i} lead_{i,t-1} + \beta_{ji} epu\_j_{i,t} + \varepsilon_{i,t} \quad (1)$$

where $rhrh_{i,t}$ is state-level real house price log-returns at horizon *h*, where *h*=1, 3 and 12, *i*=1, 2,…, 49; *t*=1975:01 to 2021:06 (i.e., the maximum coverage) at a monthly frequency, as the model with the leading indicator covers 1982:01 to 2020:02. When *epu*'s are included, the coverage runs from 1985:01 to 2020:02. We use *h*-period rolling sums of real house price log

[15] It includes terms related to national elections, elected officials, federal agencies, departments, and regulators.

[16] Each state-specific policy term set includes terms that describe the names of their executive positions and legislative bodies at both state and local levels as well as terms that note policy initiatives put to a direct vote by citizens. Also included are the names of the state bodies that deal with regulations spanning the environment, labor and unemployment, gambling, transportation, banking, energy and utilities, and other financial services. As a result, this set of terms is unique to each state, since the names and titles of officials and regulators and departments vary across states.

returns to measure cumulative returns to capture the effect of climate risk at various horizons. The primary variable of interest is temperature growth lagged by one period. We also include a leading indicator lagged by one period and economic policy uncertainty measures as control variables. Three different *epu_j* measures are separately included (*j*=state, national or composite).[17] The β's in Eq. (1) capture the cross-section-specific (state-level) parameters, and the idiosyncratic error term ($\varepsilon_{i,t}$) is distributed with mean zero and variance $\sigma_{ii,t}I$.

2.1. Methodology

Fixed- and random-effects models incorporate panel-specific heterogeneity by including a set of nuisance parameters that provide each panel with its own constant term. However, all panels share common slope parameters, which is undesirable in the current context. Random-coefficients (RC) models (Swamy, 1970) are more general, allowing each panel to have its vector of randomly drawn slopes from a distribution common to all panels. The implementation of the estimator ensures the best linear unbiased predictors of the panel-specific draws from said distribution (Poi, 2003).

Consider a general random-coefficients model, with *y* being the dependent variable and *X* being the predictor, of the form:

$$y_i = X_i\beta_i + \varepsilon_i \tag{2}$$

In the case of RC, each panel specific β_i is related to an underlying common parameter vector β:

$$\beta_i = \beta + v_i \tag{3}$$

[17] The metrics of uncertainty being newspapers-based is expected to be available in a timely-manner, and hence enter the model without being lagged by a period.

where $E\{v_i\} = 0, E\{v_i v_i'\} = \Sigma, E\{v_i v_j'\} = 0$ for $j \neq i$, and $E\{v_i \epsilon_j'\} = 0$ for all i and j. We may combine equations (2) and (3) to get:

$$y_i = X_i(\beta + v_i) + \varepsilon_i$$

$$= X_i\beta + u_i$$

with $u_i \equiv X_i v_i + \varepsilon_i$. Furthermore:

$$E\{u_i u_i'\} = E\{(X_i v_i + \varepsilon_i)(X_i v_i + \varepsilon_i)'\}$$

$$= X_i \Sigma X_i' + \sigma_{ii} I$$

$$\equiv \Pi_i$$

We can stack the P panels:

$$y = X\beta + u \tag{4}$$

where:

$$\Pi \equiv E\{u_i u_i'\} = \begin{bmatrix} \Pi_1 & 0 & \cdots & 0 \\ 0 & \Pi_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \Pi_P \end{bmatrix}$$

Estimating the parameters in equation (3) is a standard problem, which can be solved with generalized least squares (GLS):

$$\hat{\beta} = (X'\Pi^{-1}X)^{-1}X'\Pi^{-1}y$$

$$= \left(\sum_i X_i'\Pi_i^{-1}X_i\right)^{-1} \sum_i X_i'\Pi_i^{-1}y_i$$

$$= \sum_i W_i b_i \tag{5}$$

with W_i the GLS weight and $b_i = (X_i'X_i)^{-1}X_i'y$. The resulting $\hat{\beta}$ for the overall (national) result is therefore a weighted average of the state-specific OLS estimates. For more details on GLS weight and $\hat{\beta}$ variance specification, the reader can refer to Poi (2003).

To obtain the state-specific $\widehat{\beta_i}$ vectors, Judge et al. (1985) suggest that if attention is restricted to the class of estimators $\{\beta_i^*\}$ for which $E\{\beta_i^*|\beta_i\} = \beta_i$, then the state-specific OLS estimator b_i is appropriate. Following Green's (1997) suggested method of obtaining the variance of $\widehat{\beta_i}$, it follows that $\hat{\beta}$ is both consistent and efficient; and although inefficient, b_i is also a consistent estimator of β.

Poi (2003) also suggests a test to determine whether the panel-specific β_is are significantly different from one another. The null hypothesis is stated as:

$$H_0: \beta_1 = \beta_2 = \cdots = \beta_P \tag{6}$$

and the test statistic is defined as:

$$T \equiv \sum_{t=1}^{P} (b_i - \beta^\dagger)' \{\hat{\sigma}_{ii}^{-1}(X_i X_i)\} (b_i - \beta^\dagger) \tag{7}$$

where $\beta^\dagger = \{\sum_{t=1}^{P} \hat{\sigma}_{ii}^{-1}(X_i X_i)\}^{-1} \sum_{t=1}^{P} \hat{\sigma}_{ii}^{-1}(X_i X_i) b_i$.

The test statistic T is distributed as χ^2 with $k(P-1)$ degrees of freedom.

The next section presents the empirical results for equation (1).

3. Empirical findings

3.1 The effect of temperature growth on housing returns

Tables 1 to 3 present the random coefficient (Swamy, 1970) estimation results for equation (1) for all states combined, while the state-specific results of the impact of temperature growth on real house price log returns are depicted in Figure 1.

[INSERT TABLES 1 TO 3]

Overall, temperature growth, lagged by one period across all horizons, gives rise to a statistically significant decline in real house price log-returns. The negative impact is also increasing over the 3-month and 12-month horizons. Based on the final models (column (5)) in Tables 2 and 3, the effect can be quantified as follows: on average, a one percentage point increase in temperature growth leads to a 0.003 percentage points decrease in real house price log returns, ceteris paribus.[18]

The leading indicator reflecting housing market conditions is statistically significant at the one percent level across all model specifications and at all horizons, with an increasing effect at longer horizons. For example, at the 12-month horizon (refer to Table 3), a one-unit increase in the leading indicator translates to between a 0.017 and 0.018 percentage points increase in real house price returns.

The negative temperature-house price relationship is also robust after including economic policy uncertainty (epu) indicators, measuring policy uncertainty at the state and national levels. Economic policy uncertainty exerts a negative impact on real house price log returns. It appears that the uncertainty takes time to filter through to house price returns as the impact of changes in economic policy uncertainty increases in magnitude and significance at a longer horizon. The same holds for the composite indicator for economic policy uncertainty.

3.2 Heterogeneous impact of temperature growth on local housing markets

[18] We also analyzed the role of stochastic volatility associated with temperature growth, based on the model of Kastner and Früwirth-Schnatter (2014), following the suggestion of Alessandri and Mumtaz (2021) in terms of modelling climate-related risks, and found that it does not have any significant impact on real house price log returns across any of the three horizons considered, with complete details of these results available upon request from the authors. When we used realized volatility instead, i.e., sum of squared growth in daily temperatures (with the underlying data derived from Bloomberg) over a month, our (insignificant) findings, available upon request, did not change. It may be argued that it is a consistent upward and increasing trend in temperatures that are negatively perceived by potential homeowners when making housing investment decisions, rather than fluctuating temperatures, since increased temperatures have a utility cost implication for owning a property, as well as maintenance cost of and insurance premiums.

To consider and compare the heterogeneous impact of climate change on the housing market across the different US states, we again use the random coefficient estimator to obtain state-specific heterogeneous slope parameters for the independent variables in the model specification. We report the results for the model specification in column (5) across all horizons in Figures (1) and (2). The specification is chosen as it includes all independent variables, including the composite indicator for the state- and national-level economic policy uncertainty. It is also the model with the lowest root mean square error (RMSE) for each horizon. Figure 1 reveals the impact of increased temperature growth across all 49 US states included in the study on real house price log returns, ordered by the magnitude of the 12-month horizon impact. The statistically insignificant coefficient estimates are restricted to zero in the graphical representation.

At the 1-month horizon, the immediate impact of temperature growth on real housing returns appears to be limited and smaller in magnitude. At the 3-month horizon, real house price log returns are negatively affected by rising temperature growth in most states, while the extent of the impact increases at the 12-month horizon. Across all states and all horizons, the impact of increased temperature growth on log real house price returns is negative.[19]

[INSERT FIGURE 1]

We make three important inferences from the results presented in Figure 1. First, it is evident that for most states (38 out of 49 states), the negative impact is also statistically significant at the 3-month horizon. For the rest of the states, the coefficients are negative but statistically immaterial at conventional significance levels (except Alaska, for which a positive but insignificant impact is recorded). Second, the negative effect of temperature growth on real

[19] The exceptions for which we observe a small positive, yet statistically insignificant impact include Alaska at the 3-month horizon and New York, New Hampshire, Vermont, and Pennsylvania at the 12-month horizon. These states may have different housing market dynamics, with demand-side factors counteracting the negative impact of climate change. New York City metro remains the largest real estate market by value in the US.

house returns increases at longer horizons, even though fewer states have a statistically significant change in real house price log returns at the 12-month horizon. However, for those states that do experience a decline in real house price returns, the impact is more pronounced. Third, West Coast States (notably, Arizona, Nevada, California, and Idaho) and US Sun Belt states (notably, Florida, Georgia, Texas, Tennessee, Alabama, and South- and North Carolina) experience the largest negative impact of rising temperatures. The Sun Belt states are more severely impacted relative to West Coast states. This is also evident from the spatial depiction of the impact of temperature increases on house price returns in Figure 2. The most significant negative impacts are registered for Florida and Georgia on the East Coast and Arizona and Nevada on the West.

We also note that at the longer 12-month horizon, Michigan and Ohio rank amongst the top ten states regarding the negative impact of increased temperature growth, with Illinois ranking 13th. These Midwestern states are part of the Great Lakes region, with the lakes being the largest supply of fresh water on earth. This result may suggest that being close to water bodies in the face of increasing temperatures may also negatively impact house price returns in the longer term. These findings are consistent with the findings of Wolf and Klaiber (2017), which show that warmer weather around Buckeye Lake and Grand Lake resulted in excessive algae affecting the lakefront homes, resulting in an estimated $152 million reduction in combined lakefront property values between 2009 and 2015. It may be noteworthy that the result for Michigan, Ohio, and Illinois only arises when *epu_composite* is included in the model. For the model specification with only state-level economic policy uncertainty, we do not see any impact at the 12-month horizon for these three states. At the same time, Michigan is the only state with a significant negative impact at the 3-month horizon, but with a low rank of 28.

A few shifts are registered when comparing the magnitude of the effects at the 3-month horizon with the longer 12-month horizon. Notably, California, which only ranks 11th at the 3-

month horizon, ranks 6th at the 12-month horizon. Tennessee ranks 12th at the 3-month horizon and moves into 7th position. On the other hand, Delaware ranks 4th at the 3-month horizon and only ranks 18th at the 12-month horizon.

[INSERT FIGURE 2]

Figure 2 depicts the *absolute value* of the state-specific coefficients of lagged temperature growth. The darker shaded states are predicted to experience a larger *negative* impact in real house price returns because of accelerated increases in temperature. Apparently, the mega-drought that has been gripping the American West, fuelled by climate change, may be responsible for the negative impact on the housing market in the West Coast states of California, Washington, and Oregon, and the desert states of Nevada, Arizona, and Idaho. The North American deserts span large portions of Nevada, Utah, parts of Idaho, and Oregon and extend into eastern California. Rising temperatures, which cause heat waves and heightened risks of wildfires, notwithstanding the increasing cooling utility bills and water restrictions from prolonged droughts, may depress the house values in these states. This explanation is consistent with Livy's (2020) findings that aberrant increases in heating and cooling degree days negatively impact housing prices, with cooling degree days having a larger negative impact.

Apart from the West Coast, the Sun Belt states are also affected across all horizons, but with an increasing impact over the 12-month horizon. Across all horizons, Florida ranks first as the state for which the housing market has been most negatively impacted by climate change and temperature increases, followed by neighboring Georgia at the 3-month horizon and Arizona at the 12-month horizon. Housing market dynamics in the Sun Belt region may have been driven both by demographic shifts boosting Sun Belt populations and heat waves in a warming climate experienced in these states. Sun Belt states most severely negatively impacted

include Florida, Georgia, Arizona, Texas, Alabama, Tennessee, North Carolina, and South Carolina. The negative impact is notable since increases in Sun Belt populations should increase housing demand, which would support housing prices and counteract the negative impact of climate change. However, the impact of increasingly rising temperatures seems to cause a net negative effect on real house price log returns. The results support the conjecture that using costly heat- and fire-resistant construction materials to counter the increased long-run climate risk to real estate (caused by high temperatures in these states) may reduce the equity in real estate markets. Further, consistently prolonged summer heat waves burden air conditioners, increasing utility costs and the prevalence of wildfires, restricting water usage due to lengthy droughts, and ultimately causing severe and increasingly frequent hurricanes. These may depress the house prices and real returns of the Sun Belt's housing market.

Finally, a significant negative impact is observed at longer horizons for the states of Michigan, Ohio, and Illinois, all in the Great Lakes region. This is consistent with the idea that climate change is a long-run risk and shows that warm weather around the Great Lakes can cause excessive algae and repair costs for residential and commercial buildings, causing a reduction in real estate values.

3.3 Attention to climate change and housing returns

The news media significantly influence the public's knowledge and understanding of the effects of climate change. Put differently, the media affect the concerns about climate change via the channel of agenda-setting, thereby changing people's beliefs, attitudes, and assessments about climate change. For instance, Bernstein et al. (2019) indicate that people's beliefs about the effects of climate change significantly impact the prices of owner-occupied coastal homes. They find that houses in areas where agents are most concerned about climate change sell at an 8.5% discount. Duan and Li (2022) show that when public attention is focused on climate

change, mortgage lenders are less likely to grant loans for homes in areas at high risk of sea level rise. Hence, we expect that greater media attention to climate risks may amplify the effect of temperature growth on housing returns since a surge in the threat posed by climate change causes investors to cut down on their consumption and future investment prospects.

To formally test this hypothesis, we modify our panel regression model as the following:

$$rhrh_{i,t} = \beta_{0i} + \beta_{1i} temp\_g_{i,t-1} + \beta_{2i} temp\_g_{i,t-1} * attention_t + \beta_{2i} lead_{i,t-1} + \beta_{ji} epu\_j_{i,t} + \varepsilon_{i,t} \quad (8)$$

where $attention_t$ alternatively represents the Crimson Hexagon's[20] negative climate change news index (*chneg*) and its innovation part (*chneg_innovation*) capturing unexpected changes in the negative climate change index, which is computed as the residuals from autoregressive processes of order 1 (AR(1)), as developed by Engle et al. (2020).[21] Again, based on data availability, we consider forecast horizons of h = 1, 3, and 12 months for the 2008:06-2018:04 period.

Tables 4 to 6 present the estimation results of the equation (8). In all tables, column 1 provides results for the *chneg*, column 2 for *chneg_innovation*. The findings in Columns 1 and 2 of Tables 4 to 6 show that the estimated coefficients of interaction terms are statistically significant and negative across all forecast horizons, implying that the negative effect of temperature growth on real housing returns intensifies when the media attention to climate change increases. Considering that *chneg* and *chneg_innovation* are designed to capture the negative news on climate change, they might directly impact 'people's perceptions about the likelihood of climate change occurring and its consequences, which in turn affect the home

[20] Crimson Hexagon has collected a massive corpus of over one trillion news articles and social media posts. The underlying news sources cover over 1,000 outlets, including the WSJ, The New York Times, The Washington Post, Reuters, BBC, CNN, and Yahoo News.

[21] The data is available for download from the website of Professor Johannes Stroebel at: https://pages.stern.nyu.edu/~jstroebe/.

buying behavior of households. In addition, the negative impact is considerably amplified when looking at longer time horizons, suggesting that investors aggressively price the climate risk that is associated with the real estate market over the long term. As a robustness check, we estimate equation (8) also using the climate change risk indices introduced in Engle et al. (2020), which captures the number of climate change news in The Wall Street Journal (WSJ) without doing any sentiment analysis on the content of the information.[22] The findings in Columns 3 and 4 of Tables 4 to 6, estimated over 1984:01-2017:06, indicate that the climate attention measures (*wsj* and *wsj_innovation*) have a negative and statistically significant coefficient for all forecast horizons except for h=12. The insignificant coefficient of the interaction term for h=12 suggests that investors' attention to climate change is short-lived. This is in line with the findings of Nguyen et al. (2022), who find that sea level rise premium is larger in the wake of a hurricane or a time of heightened media attention to climate change, but these effects fade away by the end of the second quarter. Overall, our results are robust to alternative measures of climate attention and show that the investors consider more the content of the climate news at the long horizon, and only negative climate change news has a significant effect on housing returns at longer horizons.

[INSERT TABLES 4 TO 6]

4. Conclusion

We provide evidence supporting the notion of a negative impact of climate change and climate risk on the US housing market. Estimation results suggest that increased growth in temperature exerts a negative impact on real house price returns with an increased impact over a 12-month

[22] This index is calculated as the correlation between the text content of The WSJ each month and a fixed climate change vocabulary, which Engle et al. (2020) construct from a list of authoritative texts published by various governmental and research organizations. In the process, the *wsj* associates increased climate change reporting with news about elevated climate risk, based on the idea that climate change primarily rises to the media's attention when there is a cause for concern. The data on the index and its innovation are downloadable from: https://pages.stern.nyu.edu/~jstroebe/.

horizon. Our panel estimation results, based on a random coefficients model which allows for obtaining heterogeneous slope coefficients, suggest that states on the West Coast and the US Sun Belt region are most negatively impacted by increasing temperature growth. On average, the largest negative impact is documented on the housing markets in Florida[23], Arizona, Georgia, Nevada, Texas, California, Tennessee, Idaho, and Alabama. As part of future analysis, it would be interesting to extend our analysis to out-of-sample forecasting of the impact of climate change on the US housing market.

Our findings have important policy implications. Decreasing real estate values due to the increased risk of climate change will affect the collateral values of outstanding mortgages. Mortgage lenders would risk suffering losses if borrowers defaulted on their mortgage payments after the outstanding loan amounts reached a level greater than the collateral's value. Depending on the proportion of such mortgages that are still due on banks' balance sheets, this may be a factor that contributes to the instability of the financial system. Hence, it is essential that financial institutions consider the potential dangers posed by climate change in their risk management procedures to maintain an adequate level of preparedness. Due to their role in protecting the financial system's resilience, central banks and bank regulators should conduct climate change-related financial risk monitoring as a part of their prudential supervisory procedures. Our findings underline the significance of this matter by revealing that the risks associated with climate change have a significant effect on the housing market.

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[23] With an average elevation of only six feet and higher than global average sea levels caused by typical wind and ocean current patterns, an increasing number of properties in Florida are becoming exposed to the risks of frequent flooding damage. Further, sunny day flooding, which occurs sans any precipitation, has accelerated in recent years due to lunar tides.

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TABLES AND FIGURES

Table 1. Random coefficient estimation results for real house price log returns at a 1-month horizon, 1975M01 to 2021M06

Dependent variable: *rhr1*

	rhr1 (1)	*rhr1* (2)	*rhr1* (3)	*rhr1* (4)	*rhr1* (5)
l_temp_g	-0.000612***	-0.00135***	-0.000883***	-0.000900***	-0.000834***
	(-2.82)	(-6.04)	(-5.95)	(-5.83)	(-5.52)
l_lead		0.00106***	0.00144***	0.00143***	0.00144***
		(7.15)	(8.16)	(8.01)	(7.99)
epu_state			-0.00000142*		
			(-1.72)		
epu_national				-0.00000117*	
				(-1.80)	
epu_composite					-0.00000154
					(-1.22)
_cons	0.000717***	-0.000789***	-0.00106***	-0.00101***	-0.00111***
	(9.78)	(-3.28)	(-3.21)	(-2.98)	(-3.18)
# observations	27244	22442	16316	16316	16316
# states	49	49	49	49	49
Par constancy χ^2	271.2	1083.8	1375.2	1387.1	1366.5
d.o.f	96	144	192	192	192
prob	0.0047	0.0000	0.0000	0.0000	0.0000
RMSE	0.007129	0.006628	0.005531	0.005535	0.005520

Note: *t* statistics in parentheses; *t* statistics based on robust (bootstrapped) standard errors; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; *l* stands for first-lag of the specific variable. Analysis is based on 49 US states (excluding Hawaii); Sample period: Model (1) 1975:01-2021:06; Model (2) 1982:01-2020:02; Model (3) to (5): 1985:01-2020:02.

Table 2. Random coefficient estimation results for real house price log returns at a 3-month horizon, 1975M01 to 2021M06

Dependent variable: *rhr3*

	rhr3 (1)	*rhr3* (2)	*rhr3* (3)	*rhr3* (4)	*rhr3* (5)
l_temp_g	-0.00240***	-0.00424***	-0.00356***	-0.00357***	-0.00325***
	(-4.01)	(-9.35)	(-8.12)	(-7.86)	(-7.57)
l_lead		0.00347***	0.00432***	0.00428***	0.00434***
		(7.78)	(7.95)	(7.81)	(7.86)
epu_state			-0.00000794***		
			(-2.96)		
epu_national				-0.00000610***	
				(-3.03)	
epu_composite					-0.00000705*
					(-1.80)
_cons	0.00213***	-0.00285***	-0.00277***	-0.00261**	-0.00319***
	(9.76)	(-3.92)	(-2.78)	(-2.55)	(-2.97)
# observations	27195	22442	16306	16306	16306
# states	49	49	49	49	49
Par constancy χ^2	328.4	1273.3	1737.3	1751.9	1739.1
d.o.f	96	144	192	192	192
prob	0.0001	0.0000	0.000	0.000	0.000
RMSE	0.020109	0.020145	0.015553	0.015557	0.015451

Note: *t* statistics in parentheses; *t* statistics based on robust (bootstrapped) standard errors; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; *l* stands for first-lag of the specific variable. Analysis is based on 49 US states (excluding Hawaii); Sample period: Model (1) 1975:01-2021:06; Model (2) 1982:01-2020:02; Model (3) to (5): 1985:01-2020:02.

Table 3. Random coefficient estimation results for real house price log returns at a 12-month horizon, 1975M01 to 2021M06

Dependent variable: *rhr12*

	rhr12 (1)	*rhr12* (2)	*rhr12* (3)	*rhr12* (4)	*rhr12* (5)
l_temp_g	0.000473**	-0.00319***	-0.00451***	-0.00507***	-0.00305***
	(-1.99)	(-4.33)	(-4.91)	(-5.91)	(-4.95)
l_lead		0.0179***	0.0171***	0.0166***	0.0170***
		(11.73)	(8.11)	(7.89)	(7.97)
epu_state			-0.0000726***		
			(-5.77)		
epu_national				-0.0000653***	
				(-7.37)	
epu_composite					-0.0000930***
					(-5.68)
_cons	0.00859***	-0.0179***	-0.00696*	-0.00394	-0.00779**
	(12.54)	(-7.09)	(-1.86)	(-1.07)	(-1.99)
# observations	26754	22442	16207	16207	16207
# states	49	49	49	49	49
Par constancy χ^2	26754	22442	2281.5	2289.2	2297.6
d.o.f	394.2	1579.5	192	192	192
prob	0.0463	0.000	0.0000	0.0000	0.0000
RMSE	0.058980	0.055176	0.052609	0.052610	0.052562

Note: *t* statistics in parentheses; *t* statistics based on robust (bootstrapped) standard errors; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; *l* stands for first-lag of the specific variable. Analysis is based on 49 US states (excluding Hawaii); Sample period: Model (1) 1975:01-2021:06; Model (2) 1982:01-2020:02; Model (3) to (5): 1985:01-2020:02.

Table 4. Random coefficient estimation results for real house price log returns at a 1-month horizon, controlling for climate risk

Dependent variable: *rhr1*

	rhr1 (1)	*rhr1* (2)	*rhr1* (3)	*rhr1* (4)
l_temp_g	0.0106***	-0.00166***	0.00458***	-0.000459***
	(10.53)	(-8.08)	(7.34)	(-3.43)
*l_temp_g*chneg*	-5.987***			
	(-11.29)			
*l_temp_g*chneg_innovation*		-2.978***		
		(-6.24)		
*l_temp_g*wsj*			-0.880***	
			(-8.48)	
*l_temp_g*wsj_innovation*				-0.805***
				(-8.13)
l_lead	0.00123***	0.00117***	0.00145***	0.00146***
	(7.80)	(7.61)	(7.93)	(7.96)
epu_composite	-0.0000129***	-0.0000127***	-0.00000120	-0.00000134
	(-5.05)	(-4.78)	(-0.82)	(-0.91)
_cons	-0.000940***	-0.000648**	-0.00130***	-0.00129***
	(-2.96)	(-2.01)	(-3.40)	(-3.37)
# observations	5880	5831	14758	14758
# states	49	49	49	49
Par constancy χ^2	1527.5	1105.4	1415.8	1376.7
d.o.f	240	240	240	240
prob	0.0000	0.0000	0.0000	0.0000

Note: *t* statistics in parentheses; *t* statistics based on robust (bootstrapped) standard errors; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; *l* stands for first-lag of the specific variable. Analysis is based on 49 US states (Hawaii excluded); Sample period: Model (1) 1984:01-2017:06; Model (2) 1984:02-2017:06; Model (3) 2008:06-2018:04; Model (3) 2008:07-2018:04.

Table 5. Random coefficient estimation results for real house price log returns at a 1-month horizon, controlling for climate risk

Dependent variable: *rhr3*

	rhr3 (1)	*rhr3* (2)	*rhr3* (3)	*rhr3* (4)
l_temp_g	0.0306***	-0.00655***	0.00522***	-0.00266***
	(10.92)	(-10.45)	(3.42)	(-6.40)
*l_temp*g_chneg*	-17.91***			
	(-12.49)			
*l_temp_g*chneg_innovation*		-8.194***		
		(-7.00)		
*l_temp_g*wsj*			-1.380***	
			(-5.83)	
*l_temp_g*wsj_innovation*				-1.083***
				(-4.48)
l_lead	0.00370***	0.00368***	0.00440***	0.00442***
	(7.18)	(7.30)	(7.89)	(7.90)
epu_composite	-0.0000392***	-0.0000367***	-0.00000652	-0.00000667
	(-5.02)	(-4.49)	(-1.49)	(-1.52)
_cons	-0.00305***	-0.00260**	-0.00375***	-0.00375***
	(-2.89)	(-2.43)	(-3.24)	(-3.23)
# observations	5880	5831	14758	14758
# states	49	49	49	49
Par constancy χ^2	2125.3	1467.5	1717.3	1697.6
d.o.f	240	240	240	240
prob	0.0000	0.0000	0.0000	0.0000

Note: *t* statistics in parentheses; *t* statistics based on robust (bootstrapped) standard errors; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; *l* stands for first-lag of the specific variable. Analysis is based on 49 US states (Hawaii excluded); Sample period: Model (1) 1984:01-2017:06; Model (2) 1984:02-2017:06; Model (3) 2008:06-2018:04; Model (3) 2008:07-2018:04.

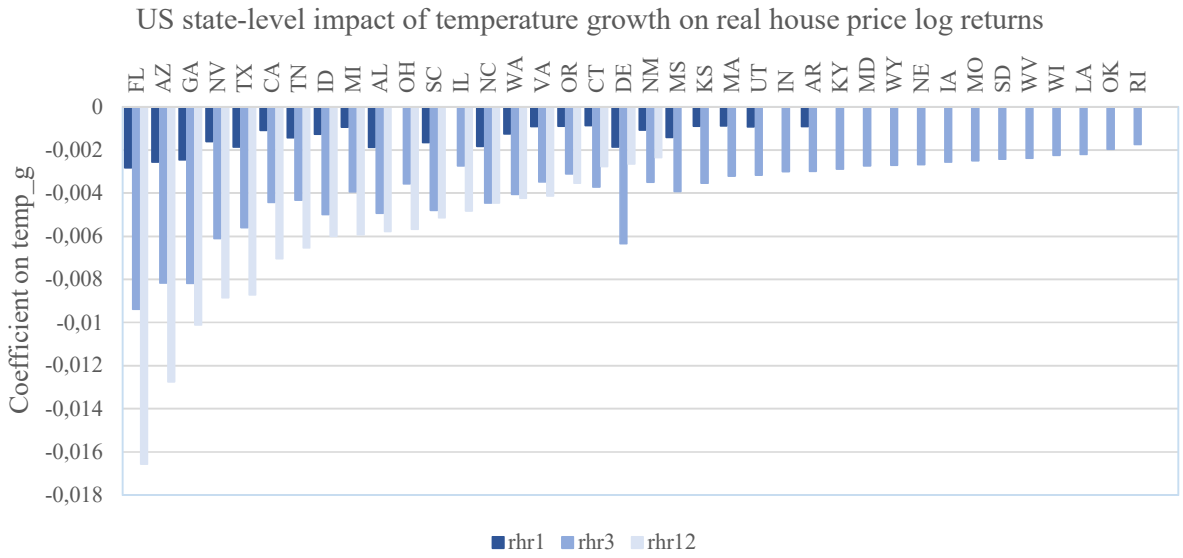
Table 6. Random coefficient estimation results for real house price log returns at a 1-month horizon, controlling for climate risk

Dependent variable: *rhr12*

	rhr12 (1)	*rhr12* (2)	*rhr12* (3)	*rhr12* (4)
l_temp_g	0.0407***	-0.00585***	-0.00929	-0.00213**
	(7.18)	(-6.23)	(-1.60)	(-2.47)
*l_temp*g_chneg*	-21.90***			
	(-8.10)			
*l_temp_g*chneg_innovation*		-17.76***		
		(-6.48)		
*l_temp_g*wsj*			1.164	
			(1.32)	
*l_temp_g*wsj_innovation*				0.329
				(0.29)
l_lead	0.0182***	0.0178***	0.0175***	0.0175***
	(8.01)	(7.97)	(8.07)	(8.07)
epu_composite	-0.000206***	-0.000208***	-0.0000935***	-0.0000931***
	(-6.61)	(-6.66)	(-5.28)	(-5.25)
_cons	-0.0173***	-0.0156***	-0.0103**	-0.0103**
	(-3.99)	(-3.61)	(-2.41)	(-2.39)
# observations	5880	5831	14758	14758
# groups	49	49	49	49
Par constancy χ^2	2291.6	2183.1	2267.6	2268.0
d.o.f	240	240	240	240
prob	0.0000	0.0000	0.0000	0.0000

Note: *t* statistics in parentheses; *t* statistics based on robust (bootstrapped) standard errors; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; *l* stands for first-lag of the specific variable. Analysis is based on 49 US states (Hawaii excluded); Sample period: Model (1) 1984:01-2017:06; Model (2) 1984:02-2017:06; Model (3) 2008:06-2018:04; Model (3) 2008:07-2018:04.

Figure 1. US state-level coefficient values of temperature growth sorted by results with dependent variable 12-period rolling sum of real house price log returns (*rhr12*)



Note: All coefficients statistically significant at conventional levels are depicted on graph.

Figure 2. Impact of temperature growth on real house price log returns at different horizons

Figure 2a. *horizon*=1: *rhr1*

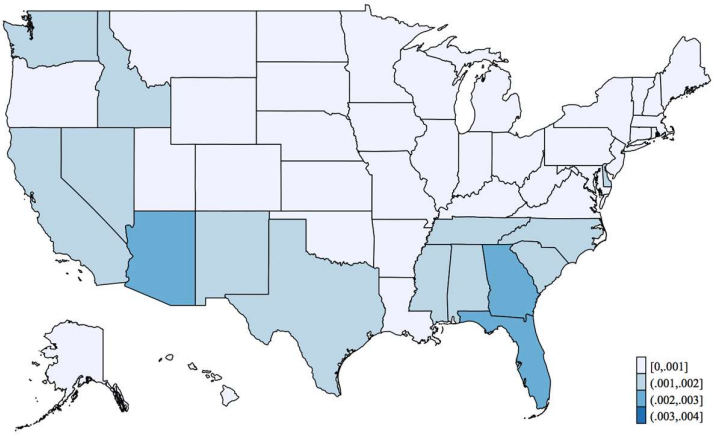


Figure 2b. *horizon*=3: *rhr3*

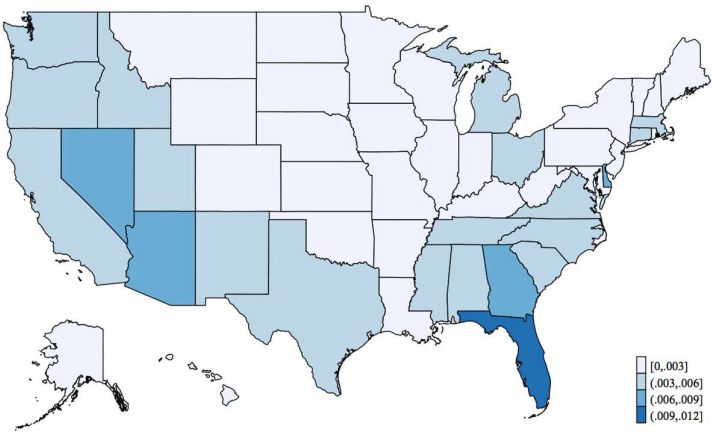
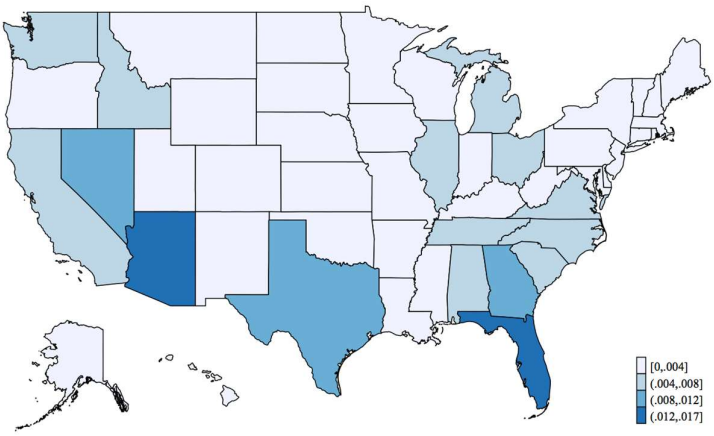


Figure 2c. *horizon*=12: *rhr12*



Note: The relative impact of increased temperature growth on real house price log returns at different horizons are displayed. Coefficient values are depicted in *absolute terms*, implying that a darker shaded state experienced a *larger negative impact*.