Rotterdam School of Management - Erasmus University

Master Thesis - MSc. Finance and Investments

Climate risk and house prices: Is the US market ready for climate change?

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Preface

Acknowledgments

I would like to express my gratitude to my coach, Florian Madertoner, for his invaluable time, investment in this thesis, and his excellent taste in Warhammer books. My thanks also go to my co-reader, Lingtian Kong, for the insightful feedback on my proposal. Most importantly, I am deeply grateful to my sister, Margaux, for her constant support and presence. Finally, I extend my appreciation to my family and friends, with a special mention to a certain guest speaker from England.

Abstract

This study investigates the relationship between climate risk and house prices in US cities. Utilizing cross-sectional regression analysis and an index that compiles future risks of wildfires, hurricanes, and floods, the research reveals that climate risk impacts house prices only when a city's exposure is extreme. Additionally, positive emotions provoked by seasides significantly moderate the impact of climate risk on house prices and directly influences them. Furthermore, recent exposure to natural disasters increases the discount on house prices only in cities within Republican states, suggesting that political beliefs may outweigh perception. However, this study is limited by its sample size and the simplification of natural disaster exposure, indicating the need for further research.

Contents

1. Introduction

Four decades ago, the first-ever meeting of the "Ad Hoc Group on Carbon Dioxide and Climate" took place and led to an important conclusion: the Earth's atmosphere would undergo an increase in temperature over the coming decades. Initially, both governments and individuals remained largely indifferent to this situation. However, with the increasing frequency of natural disasters and extreme weather events, societal concerns began to arise. Despite the increasing importance of climate change in international relations and the daily life of many, not all countries have accepted that the earth is getting warmer.

In the present-day United States, only 63% of adults believe global warming affects the weather (Yale, 2023). In states such as Wyoming, West Virginia, and North Dakota, these percentages fall below 50%, contrasting with top-ranking western states like California (Yale, 2023). This divide in beliefs is not trivial as it has been shown that Republican states tend to have higher levels of climate change deniers compared to Democrat-led States (Gregersen, 2020). With the upcoming 2024 presidential elections, this distinction in beliefs is likely to be featured in numerous presidential debates.

Nevertheless, climate change relevance surpasses the political sphere. In 2018, California experienced its deadliest wildfire season, claiming almost 100 lives and destroying more than $25 billion worth of property (Nic Querolo, 2019). Over time, natural disasters like the California fires have spread concern beyond climate scientists and over to the financial world. Growing climate change uncertainty has raised concerns regarding assets potentially at risk for investors and companies. Most investors have concluded that the assets most at risk of natural disasters are the ones without any mobility (Paprotny, 2020). These include production and power plants, agricultural properties, infrastructures, and most importantly, real estate. Particularly, real estate's role as a primary good and not simply an investment has made it of highest importance.

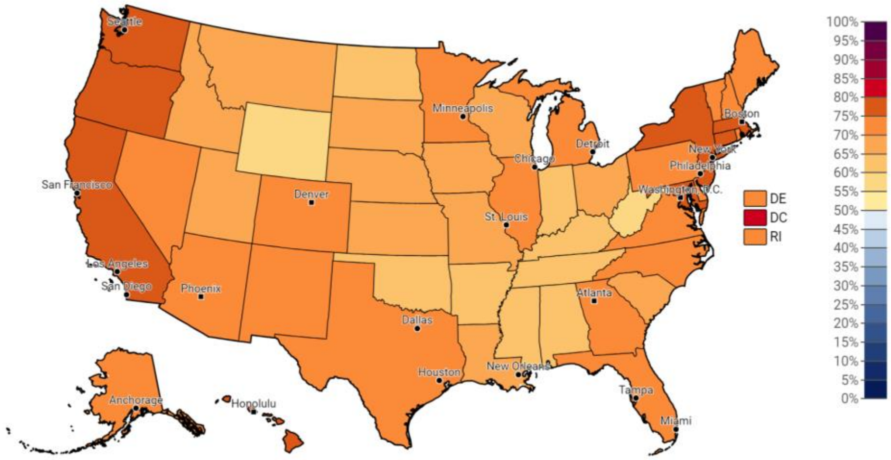

Figure 1: Estimated % of adults who think global warming is real. Midwest and portions of the South have the lowest rates of belief while Western states like California have the highest rates of belief. Source: *Yale Climate Opinion Maps 2023.*

Turning to the literature, three types of natural disasters have been shown to affect house prices in a significant manner. Floods, being the most studied disaster in the literature, are believed to hurt house prices (Skantz, 1987; Speyrer, 1991). Hurricane studies display similar characteristics stemming from their heavy correlation with floods. The economic intuition behind both these phenomena is that as properties are exposed to climate risk, they become less desirable for home buyers and renters alike. In turn, this decreases both the income generated from rental agreements and the potential sale price of the house. It's important to note that while rent and property value may decrease, building occupancy doesn't change with the increased risk from floods or hurricanes (Addoum, 2021).

In spite of this intuition, recent findings suggest a positive relationship between flood occurrences, hurricanes, and house prices (Tobinand, 1988; Fuerst, 2021). The literature suggests that floods decrease house supply, making climate risk indirectly increase prices through supply and demand equilibrium (Murphy, 2009). Less popular but still relevant to the literature are wildfires, with many studies finding that houses decrease in price the closer they are to a wildfire and the more intense it is (Huang, 2024). From this divergence in results and the increasing number of studies, it's possible to conclude that the topic is still in its infancy. Yet, even with its relatively young age, deep connections with psychological concepts and politics have been established.

Indeed, psychological heuristics have always had a major role in moderating any relationships related to markets and businesses. As seen with speculative behaviors, pricing mechanisms are inherently bound by such heuristics. One of the most important biases is the salience heuristic[1] which states that the more an individual remembers an event the more likely it is to influence his/her/their decision-making (Mullen, 1992). For example, the reversal effect observed in house prices following floods may stem from a shift in memory, wherein the fading memory of a natural disaster leads to prices reverting close to their original state. Secondly is the affect bias which finds that the more an individual is attracted to an object, such as a house with beach-side features, the less objective their decisions are regarding that object (Park, 2000).

However, within this broader cognitive framework, perception is often intertwined with belief and personal identity. Notably, political affiliation stands as a potent identity driver in contemporary United States. Yet, the impact of political affiliation on house prices and climate risk remains largely unexplored, showing a gap in the literature (Baldauf et al, 2020). Given the intrinsic connection between beliefs, house prices, and climate risk, it is plausible that political affiliation acts as a moderator. In this context, this thesis aims to investigate the incorporation of climate risk in US house prices.

To answer this question, this thesis develops its own climate risk index using a personally modified version of the open-source Python model CLIMADA. The index consists of the exposure to the three most frequent natural disasters in the US: floods, hurricanes, and wildfires. Each natural disaster utilizes several datasets, from the NASA FIRM to the International Best Track Archive for Climate Stewardship. To make the index as forward-looking as possible, I created synthetic events for wildfires and hurricanes. For hurricanes, this entails reproducing the path of prior cyclones and adding a random walk to account for the unpredictability of climate change. Next, I use Knutson et al.’s (2015) work to change the intensity and probability of tropical cyclones according to a moderate climate change scenario. For wildfires, similar enhanced synthetic events were created, albeit with some limitations as the synthetic events cannot burn areas that haven’t previously experienced a wildfire (Arca, 2012). The last component of the climate risk index comes from

[1] First popularized by Shelley Taylor and Susan Fiske (1978), the term is interchangeable with the availability heuristic.

floods. Here, the forward element was found by using next-century geospatial projection of floods. All these elements are then scaled to create a city ranking of climate risk exposure. After controlling for outliers and overfitting, this data, alongside some other control variables, is used in an OLS regression. Although time series are popular for this kind of study, the static and forward-looking nature of the climate index makes it impossible to evaluate the effect of climate risk through time. Thus, I opt for a cross-sectional analysis with state clustering and a robust standard error.

Overall, the results showed mixed support for the various hypotheses. Only extreme Climate risk exposure was found to affect house prices. Affect was found to play a significant role in both increasing house prices and moderating the effect of climate risk. Inversely, Salience and its interaction term displayed an unexpected lack of significance which may be due to mechanisms like the gambler fallacy. Lastly, political affiliation seems to be the strongest moderator, implying that belief takes priority on perception in the order of economic mechanisms established in this study.

2. Literature Review

2.1. Natural disasters & house prices

With the increased intensity of natural disasters caused by global warming, financial actors have been exponentially pressured to factor climate change in their activities. Indeed, many are attempting to find new ways of making their future investments climate-risk-proof as more than 66% of global companies have at least one asset at risk of climate change (S&P Global, 2021). Correspondingly, ESG-related investments are projected to increase to a volume of $34 trillion in 2026 (PricewaterhouseCoopers, 2022). It’s important to differentiate between types of climate risks, as companies affected by climate change face two different threats. Transition risk refers to the economic consequences of climate policies, shifts in consumer preferences, and the adoption of greener technologies. On the other hand, physical risk encompasses all acute and chronic natural disasters resulting from and amplified by climate change. In the context of this thesis, only the physical aspect of climate risk will be considered. Moreover, climate risk will be limited to any physical danger caused by natural disasters that impact consumers and society. Natural disasters affected by climate change can vary wildly from region to region but for the US, the main concerns are tropical cyclones, wildfires, and flooding, all of which are projected to increase in the next decades in both intensity and frequency (NOAA, 2024; Banholzer S, 2014).

With over 40% of the US population residing in coastal regions, floods have historically accounted for 90% of the damage caused by natural disasters (Homeland Security, 2024). Initially, it was commonly thought that floods had a direct and adverse impact on house prices. As far back as 1987, MacDonald et al. found a statistically significant price difference, noting that houses within the floodplains of Monroe, Louisiana, were 6% lower than those located outside of this region. Later, similar results were found with a 4% price impact in Houston Texas, and a 4.2% change in New Orleans (Skantz, 1987; Speyrer, 1991). On average, the decline in prices not only scale with the distance from the event's epicenter but also the extent of the building damage (Fang, 2021; Ortega, 2018). Correspondingly, in Northern Australia, Fuerst et al. (2021) came to observe the same phenomenon but while homes susceptible to flooding were selling at a discount, those facing sea rising risks did not see any changes.

Yet, what makes floods unique is that they often result from tropical cyclones, as they elevate water levels in rivers, establishing a close interconnection. Tropical cyclones exhibit similar decreasing price patterns like with Ewing, Kruse, and Wang (2007) who suggested extreme winds caused a 1.5 to 2% decrease in housing value. This connection is also reciprocal as regions experiencing frequent windstorms are more likely to be perceived at a heightened risk of flooding. This phenomenon is seen with a significant 0.2 % difference in areas susceptible to flooding affected by windstorms compared to areas not affected by flooding but impacted by windstorms (Kim, 2020). The negative direction of the sign is supposedly driven by asset capitalization rates and not building occupancy (Addoum, 2021). To put it another way, following a natural disaster, both the property operating income and asset value decrease leading to lower property value.

Nonetheless, wildfires are significantly more detached from other natural disasters like tropical cyclones and floods. The lack of correlation between the disasters mainly comes from their geographical settings. While wildfires are found on the west coast of the US, river floods and hurricanes are more likely to occur on the east coast. Additionally, the interest surrounding wildfires is very recent, as one of the earliest studies was ordered by the Federal Emergency Management Agency's Office of Cerro Grande Fire Claims in 2001. The study found that houses affected by the Cerro Grande fire of May 2000, decreased in price from 3 to 11%. A crucial pattern in understanding the impact of wildfires on house prices is the catastrophe's geographical characteristics. For example, Huang et al. (2024) suggested that depending on whether a house was uphill or downhill of wind currents the price impact diverged significantly. In recent times, studies have started to investigate the proximity effect of fires on housing prices and found that, on average, if the distance separating the house and fire is greater than 2.8km, there won't be a significant price impact (Rossi, 2016). The extent of the price decline also appears to escalate in areas previously susceptible to wildfires (Athukorala, 2016). This raises questions about the enduring relevance of global warming effects on the association between wildfires and housing prices. As new areas become affected, substantial price drops may not be as pronounced in the future.

Overall, it's possible to link these studies' claims back to the fundamental principle of risk-return trade-off within finance and economics (Farma, 1968). The house rate of return is calculated by subtracting the buying price from the selling price and then dividing it by the buying price. This rate implies lower asset prices scales with increased price volatility and risk. When considering climate risk, it aligns with this risk-return relationship: a house selling at a discount yields a higher rate of return and entails a higher risk of exposure to natural disasters. I thus formulate the first hypothesis based on the results of the literature and the risk-return trade-off:

H1: Relative to other real estate markets, those exposed to higher climate risk exhibit lower property prices.

Nevertheless, with increasingly complex methods and theories, many have come to find a surprising reversal of prices following exposure to climate risk. Indeed, many have come to the same conclusion; that a weak reversal effect may exist between flooding depth and house prices (Tobin, 1988; Fuerst, 2021; Morgan, 2007). Similar disasters like windstorms tend to share this reversal pattern, implying high levels of correlation (Ewing, 2007). Due to its recent discovery, the mechanism behind this effect has yet to be fully explored, although several theories have been proposed.

Firstly, according to Tobinand and Fuerst (1988; 2021), repair and renovation costs serve as the main drivers, as flood-affected houses require enhanced structural integrity, in turn increasing both the cost and value of the property in preparation for future events. A more general theory was proposed by Murphy et al. (2009) in which better preparedness and limited housing supply caused lagging pricing of risk. Finally, recent studies suggest that the stabilization of house prices following natural disasters stems from inadequate pricing of flooding risks. Consequently, following natural disasters only partially affect house prices (Gourevitch, 2023; Fridgen, 1999). However, there are limitations to these findings. For instance, Morgans's study (2007), modelled floodplain as a categorical variable that combined flooding risk and waterfront amenities into one, making it harder to distinguish the effect of flooding on house prices.

Beyond theories, this heterogeneity of results can also be explained by the structural limitations of the methodology. For example, while Lamond and Proverbs (2006) found a non-statistically significant price impact, their sample size was only comprised of 159 observations. With such a small sample, the probability of a type II error is very high. In other words, there is a high likelihood that Lamond and Proverbs's (2006) results were found by chance and the effect is not significant. Contributing to the discourse, Daniel et al. (2009) affirm there is a systematic omission of variables such as house age and maintenance level; both are believed to strongly bias results towards a negative sign. In conclusion, the different theories and research limitations have led to varying findings, indicating that more investigation is needed to fully understand the relationship. That is why, I decide to formulate the second hypothesis:

H2: Following exposure to natural disasters, real estate market prices tend to return to pre-disaster levels.

Although I expect a reversal effect after a few months or years, the possibility of a momentum effect cannot be ruled out since real estate has historically been shown to continuously increase in value (Beracha, 2011).

2.2. Perception & biases: Affect and salience

While a majority of the theoretical framework focuses on exclusively house prices and climate risk, there exists a wider array of studies on the effects of perception. As real estate markets are bound by mechanisms such as demand and supply, aggregate price movements can often be caused by outside factors like perception (Byrne, 2013). As seen with investor speculation and the 2008 housing bubble, these mechanisms have demonstrated significant price impacts.

One of the main drivers of these aggregate price movements is the salience heuristic. It refers to the "systematic tendency of individuals to allocate disproportionate significance to information that is vivid, emotionally charged, or readily available, while potentially overlooking less conspicuous but equally relevant data in decision-making processes" (Mullen, 1992). In the context of this study, the stakeholders affected by this bias are the house buyers and consumers. Perception and salience have demonstrated their importance by exacerbating the price impact of wildfires in two distinct manners: through the proximity and visibility of the wildfire. Yet, after a few months, a reversal effect occurs, indicating that information loses saliency over time (McCoy, 2018). These results are further supported by Nie et al. (2023) who observed that repeated wildfires led to changes to the status quo and caused houses to appreciate at a slower rate than adjacent regions. Other natural disasters have also been linked to perception. Examining the impact of Hurricane Sandy, Cohen et al. (2021) discovered that while NYC residents reassessed their beliefs regarding future damage, the price influence appeared to fade over time. The type of information is also crucial, as studies have found that hurricanes exert a more significant impact on prices compared to floodplain maps and insurance premiums. Despite carrying similar implicit information, hurricanes appear to have a more pronounced effect on pricing dynamics, most likely because they are more 'salient' (Gibson, 2020). This is further confirmed by the fact that stronger hurricanes have a higher effect on both prices and memory availability (Kim, 2022). Based on these elements I establish two more hypotheses:

H3: Relative to unaffected real estate markets, properties recently impacted by natural disasters show lower prices.

H4: Relative to unaffected real estate markets, properties recently impacted by natural disasters demonstrate higher price sensitivity to climate risk.

Affecting pricing dynamics in tandem with salience is the affect heuristic. In this cognitive process, consumers rely on the positive or negative emotions associated with a stimulus to assess risks. When feelings toward an object are positive, individuals tend to perceive the risks as low and the benefits as high (Park, 2000). Conversely, negative feelings lead to an inclination to view risks as high and benefits as low. Additionally, positive emotions like affect enhance individuals' reliance on employing heuristics in their judgments (Park, 2000). Supporting this idea, Samarasinghe et al.

(2010) showed that desirable houses with a water view had a 28% premium on average. The identical houses also enjoyed a discounted decrease when in flooding territory. Bin & Kruse (2008) used a different method where instead, they had a dummy variable for houses near water amnesties and showed that high levels of collinearity existed between floods and seaside views. To combat this, other studies have used the distance to water amenities instead of dummies to model the affect heuristic and sea-side premium (Atreya, 2013; Bin, 2013). In conclusion, discussion on the topic of affect seems to be homogenous which is why I add these two hypotheses:

H5: Real estate markets near seaside show higher prices.

H6: Relative to unaffected real estate markets, properties closer to seaside demonstrate lower price sensitivity to climate risk.

2.3. Political perception & beliefs

While perception plays a decisive role in aggravating the effect of climate risk through salience and affect, these factors do not solely exist in a vacuum as they often intersect with the notion of beliefs, particularly within the realm of politics. For example, Baldauf, Garlappi, and Yannelis (2020) analyzed US housing data and found that houses projected to be underwater in "believer" counties (higher percentage of people accepting climate change) had lower prices compared to "denier" counties, implying the importance of beliefs. Ratnadiwakara et al. (2019) furthered this claim by supporting that Republican flood “deniers” terminated their insurance more often and thus decreased their house value. Regarding climate change, Tyson et al. (2020) discovered that, on average, Republican supporters tend to deny the human responsibility in climate change, whereas Democrats acknowledge the necessity of acting.

This large divide can be generally simplified as democrats being climate change activists while republicans are more akin to climate change deniers. While no study has directly approached the issue, a link can be made between political beliefs, perception, and the way we relate house prices with climate risk. Significantly, persistent challenges remain regarding the interaction of biases with political beliefs. Javeline et al (2019) showed that regardless of political affiliation, coastal houses in the United States are not significantly reinforced for natural disasters. On the other hand, Bruine et al., (2014) suggest that regardless of climate change opinions, a majority recognize the increasing risk of floods in Pittsburgh and Pennsylvania. This raises some critical questions, as there is the possibility that while Republicans deny the existence of climate change, they may still recognize the growing danger of natural disasters enabled by climate change. On the contrary, it is also possible that none of the two parties fully acknowledges the price impact of climate risk on house prices.

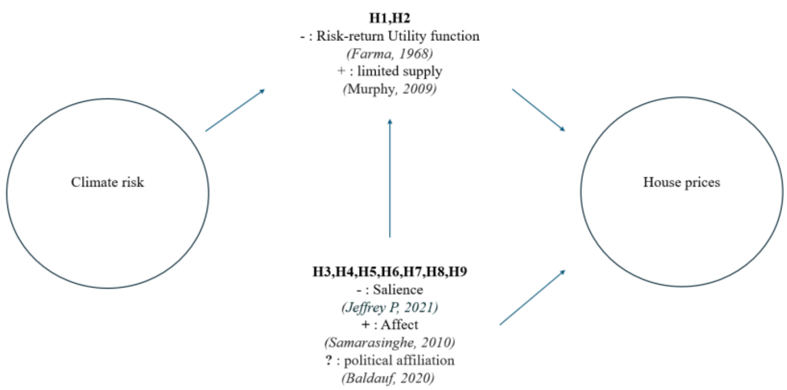

Figure 2: Visual representation of the conceptual framework. This figure shows a summary of literature mechanisms. As shown here and in the hypotheses, salience, affect and political affiliation are all assumed to have some level of interaction with the main relationship. Climate risk is believed to affect house prices negatively house prices through the risk-return framework or positively with a limited supply.

As political partisanship may be related to climate risk and climate change beliefs, I assume some moderation may occur with the main relationship. Since Democrat supporters are more climate risk-aware than Republican supporters, it's possible that their aggregate preferences would cause house prices to incorporate a climate risk discount. As a result, there's a strong likelihood that states aligned with the Democrat Party exhibit lower prices than those aligned with the Republican Party, influenced by the inclinations of their residents towards climate change policies and beliefs. This relationship may also interact with the salience and affect heuristic as regardless of political affiliation, an experience as strong as a natural disaster is likely to shift beliefs. It is for this reason that I add the final set of hypotheses to this thesis body:

H7: Relative to Democrat real estate markets, Republican properties show higher prices.

H8: Relative to Democrat real estate markets, Republican properties show lower price sensitivity to climate risk.

H9: Relative to Democrat real estate markets, Republican properties recently affected by natural disasters show the same price sensitivity to climate risk.

3. Methodology

A few assumptions and questions arise when decomposing the mechanisms through which house prices factor in climate risk. Indeed, there are various ways of modelling climate risk such as with global climate models (GCMs) which incorporate simulations of the earth's climate for projections of temperature changes, rise in sea levels, or probabilistic catastrophe events. Instead, I opt to model the climate risk of US cities as the average present and future exposure to natural disasters. Assuming a simpler definition allows for straightforward results interpretation and a more transparent understanding of how natural disasters are calculated and quantified.

In addition to climate risk, I operationalize house prices as the average city house price for 2021. Although more granular options, such as individual house prices, may be available, they entail calculating climate risk at a much smaller scale. Even if the accuracy of the relationship increased, the number of control variables required, such as borough socio-economic indicators, would pose a severe threat to the robustness of the results. Lastly, since this study's definition of climate risk incorporates forward and backward-looking elements, the index is static through time. As such, the scope of the methodology is restricted to a cross-sectional analysis of 2021. The selection of the year is driven by the dual purpose of ensuring temporal relevance and obtaining access to control variables, often published with a one-to-two-year lag.

3.1. Data & sample

House price data for 2022 and 2021 was sourced through Redfin, a brokerage company offering house price information for US cities. Redfin also gives access to valuable control information such as the number of newly listed and sold houses. For the scope of this thesis, the median house price per city is used to operationalize the notion of house prices. Furthermore, this study only considers the average median house price of ‘major’ cities with a population of more than 80,000 inhabitants.

Certain limitations become apparent in this thesis's primary independent variable, the climate risk index. On the one hand, forward-looking climate indexes already exist but are not publicly available, such as with Risk Factor, a private company specialized in categorizing future natural disaster risk for houses. Conversely, backward-looking climate risk indexes are publicly available; however, their effectiveness is constrained as they are unable to encompass climate change measures found in forward-looking data. To solve this issue, I create a climate risk index for each city which incorporates three natural disasters and forward-looking measures.

3.2. Variables & model

All hypotheses are tested through a standard OLS cross-sectional regression, robust standard error, and state-level clustering. Control variables include crime rate, house demand and supply, population, population density, recent natural disaster information, median household income, state policitical party affiliation, state unemployment rate, distance to nearest shore, and county social resilience. The description and source of each variable is given in Table 3.1. Additionally, all data except crime rates have been sourced from 2021. Although crime rate doesn't coincide with the year of the cross-sectional analysis, it has been shown to have a lagged effect on house prices of 1 to 3 years (de Graaff, 2022). The BRIC index is another important variable used to control the impact of climate risk. The index describes the resilience of a community to natural disasters and has six different categories, which all range from 0 to 1: social, community capital, institutional, infrastructural, economic, and environmental. From these categories only economic is excluded as it includes elements such as population and income which would create strong collinearity with this regression's control variables. Data regarding city unemployment rates was also found to be scarce. To counter this limitation, I make the very broad assumption that state-level unemployment rates can be used as a proxy.

Taking inspiration from Samarasinghe et al. (2010) the affect heuristic is modelled by calculating the nearest shore distance for each city in degrees. On the other hand, the salience heuristic is a binary variable representing whether a city was affected by a natural disaster in 2021. Although this method of quantifying saliency may initially suggest collinearity with the climate risk variable, the time horizon considered in the index should negate any problem. For instance, when utilizing flooding risk estimates for 2065, any collinearity should be nullified by the more than extensive time frame, introducing a temporal separation between the two variables. Lastly, each state's voting percentage from the 2020 elections was used to determine whether they were a Democrat or Republican state. For outliers, because of the relatively small sample, only control variables are winsorized at 5% and 95% intervals. The reasoning behind this decision is that extreme values found in the climate risk index are vital to determine the hypothesis's significance since they provide crucial data points that highlight the potential impact and severity of climate-related events.

Following data being winsorized, I analyze the distribution of all variables to check for skewness or kurtosis. Conclusively I find that demand, supply, house prices, crime rate, BRIC, and income all need to be converted into logarithmic scales. However, some variables should not be converted. This is the case for nearest distance to shore, party affiliation, unemployment rate, and climate risk. Distance to shore is skewed because most of the United States' large cities are near coastal areas. Logging distance to shore would mean prioritizing statistical soundness over real-world accuracy. State unemployment rate follows a similar idea; since the sample size is limited to 50 states, it will always have distribution problems. Lastly, I expected climate risk not to follow a normal distribution. As climate change affects natural disasters, city exposure will likely be skewed and present fatter tails. This phenomenon is a natural consequence of climate change exacerbating extreme events and like distance to shore, using a logarithmic conversion would skew the reality of this distribution. Instead of taking the logarithm of the variable, I choose to square it in the subsequent regressions. This decision is based on the understanding that the impact of climate risk on house prices should become increasingly pronounced as a city's level of danger escalates.

$$house\ price_{i,t} = \beta_0 + \beta_1 Climate\ risk^2{}_{i,t} + \delta_1 recent\ natural\ disaster_{i,t} + \delta_2 recent\ natural\ disaster_{i,t} * climate\ risk^2{}_{i,t} + \beta_2 distance\ to\ shore_{i,t} + \delta_3 distance\ to\ shore * (hurricane + flood\ index)^2{}_{i,t} + Control\ variables_{i,t} + \mu \quad (1)$$

This first model is aimed at testing the various hypotheses related to perception. The inclusion of two interaction terms is justified by the influence of perception on climate risk and house prices. Therefore, the individual variables serve the purpose of preventing omitted variable bias. At the same time, the interaction terms aim to assess whether aggregate perception alters how individuals interpret the connection between climate risk and house prices. Moreover, the salience variable is reported at a state level since natural disasters tend to affect the perception of more than just city residents. The same logic is applied to distance to shore where it is assumed that cities located on shorelines experience a different climate risk-house price relationship. When paired with distance to shores, climate risk is restricted to water-related variables since the inclusion of wildfires may bias the interaction.

$$house\ price_{i,t} = \beta_0 + \beta_1 Climate\ risk^2{}_{i,t} + \delta_1 state\ party\ afilitation_{i,t} + \delta_2 state\ party\ afilitation_{i,t} * Climate\ risk^2{}_{i,t} + Control\ variables_{i,t} + \mu \quad (2)$$

$$house\ price_{i,t} = \beta_0 + \beta_1 Climate\ risk^2{}_{i,t} + \delta_1 recent\ natural\ disaster_{i,t} + \delta_2 recent\ natural\ disaster_{i,t} * climate\ risk^2{}_{i,t} + \beta_2 distance\ to\ shore_{i,t} + \delta_3 distance\ to\ shore_{i,t} * (hurricane + flood\ index)^2{}_{i,t} + \delta_4 state\ party\ afilitation_{i,t} + \delta_5 state\ party\ afilitation_{i,t} * Climate\ risk^2{}_{i,t} + \delta_6 recent\ natural\ disaster_{i,t} * climate\ risk^2{}_{i,t} * state\ party\ afilitation_{i,t} + + Control\ variables_{i,t} + \mu \quad (3)$$

$$house\ price_{i,t} = \beta_0 + \beta_1 Climate\ risk^2{}_{i,t} + \beta_2 house\ price_{i,t+1} + \delta_1 salience * house\ price_{i,t+1} + Control\ variables_{i,t} + \mu \quad (4)$$

Two different models are used to test the effect of political affiliation; the first one omits perception variables as there might be heavy interaction with political affiliation. The other model includes everything to control for a maximum of effects and get the most accurate and unbiased coefficients. Republicans might change their opinion post-natural disaster since they leave such a strong impression, thus, an interaction between salience and party affiliation was included. To thoroughly test if there is a reversal effect I also create a separate model to avoid biasing static variables like climate risk. The interaction term is included to test if following a natural disaster, a reversal effect occurs in affected states. If the interaction sign is positive this will show signs of momentum but if the sign is negative and significant it will confirm the reversal effect.

Table 3.1: Variables. This table provides a summary of all variables used in this study as well as their origin Climate Risk Index

Variable	*description*	*source*
	Housing Market variables	
House prices	Average median price per city for the years 2021 and 2022	Redfin
House demand	Average monthly number of sold houses	Redfin
House offer	Average monthly number of newly listed houses	Redfin
	City level variables	
Climate risk	Sum of all scaled risk indicators	Various
Crime rate	(Total violent crimes/population)	FBI Crime Report 2020
Population	Population per city	Simple maps
Population density	Population per square kilometer	Simple maps
Distance to water	City distance to nearest coast in degrees	Natural earth
Income per household	Average yearly household income	US census bureau
	State level variables	
Political affiliation	Binary variable, 1 if Republican and 0 if Democrat	US census bureau
Unemployment rate	% of Labor force unemployed	Bureau of Labor Statistics
Salience	Binary variable, 1 if affected in 2021 by a natural disaster	EM-DAT
	County-level variable	
BRIC index	Baseline resilience factor for communities in 2020 (minus economical)	University of South Carolina

3.3. Climate Risk Index

The climate risk index was developed through CLIMADA, an open-source Python software used to model natural catastrophes and their impact. Due to the recurring occurrence of floods, wildfires, and windstorms in the United States, these three have been prioritized for this index. All three natural disasters use their own datasets and have some forward-looking elements associated with them. This climate index aims to incorporate the intensity and probability at which a city is at risk of wildfires, tropical cyclones, and floods.

3.3.1 Tropical cyclones & hurricanes

The data for Tropical cyclones comes directly from the International Best Track Archive for Climate Stewardship. This dataset contains all the historical tracks of tropical cyclones with their respective intensity through time for a specific basin. For instance, in Figure 3, I loaded the track and intensity for Hurricane IRMA.

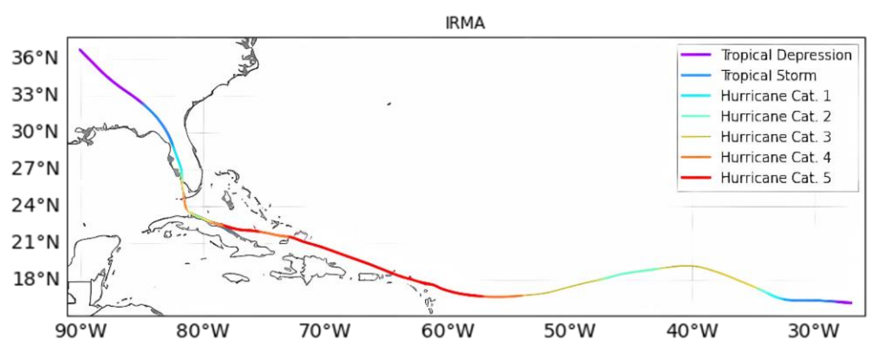

Figure 3: Visual representation of the path of hurricane IRMA in CLIMADA. This figure shows the historical direction and intensity of the track for Hurricane IRMA.

In this case, the probabilistic element is achieved through the generation of synthetic events. These events are random walks of the same hurricane's path and can be modulated to have their intensity and windspeed decay over time. In Figure 4, I have generated 5 synthetic tracks for the IRMA hurricane for demonstration. This partially encompasses the unpredictability of climate change, considering the possibility of new regions being impacted by hurricanes. The utilization of a random walk helps capture this dynamic effectively.

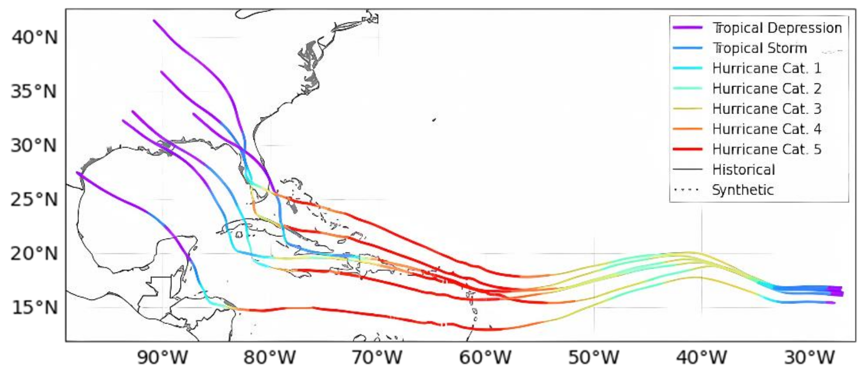

Figure 4: Visual representation of the path of the synthetic tracks of IRMA in CLIMADA. This figure shows the direction and intensity of the different tracks for Hurricane IRMA.

Furthermore, another step can be taken to model climate change. In CLIMADA, I use a function to incorporate the effects of a moderate climate change scenario outlined in the study by Knutson et al. This function allows for the modification of both the intensity and probability of hurricanes (2015).

Utilizing tropical cyclone tracks spanning from 2015 to 2022, alongside generating two synthetic tracks for each event and amplifying their intensity and probability, 456 cyclone tracks were simulated. Next, hurricane intensity was extracted for each city, consolidating all hurricane tracks. These averages undergo min-max scaling, ensuring that they fall within the range of 0 to 1. In this scale, a value of 1 indicates that the city is most susceptible to the tropical cyclone tracks, while 0 signifies the least vulnerability. It's noteworthy that many cities in the western US were unaffected by such tropical cyclones, and thus, they were assigned a value of 0.

3.3.2 Wildfires

The data used for computing wildfires comes from the NASA Fire Information for Resource Management System (FIRM) and compiles historical fires with their heat from 2000 to 2022 but was limited to 2015-2022 as the original dataset was too large for the following method. In CLIMADA, wildfires work similarly to tropical cyclones with fire seasons being comparable to hurricane IDs. The area used to compute the intensity of the wildfires was made larger compared to those used in tropical cyclones, as wildfires typically do not originate within a city but rather in its periphery. Unlike hurricanes, however, there are some notable limitations. For instance, if no data within an area is found for a specific year, the model breaks down and no value is returned.

Fortunately, even with all these limitations, CLIMADA allows for the creation of synthetic wildfire events. These synthetic fire seasons are created by taking 4 steps:

1) A map of potential fire propagation is created, where each point is assigned a probability of the fire spreading. While only previously burned points can spread fire, the user can increase the probability of the spreading.
2) An amount of fire specified by the user is started.
3) These fires start by burning a random point on the map and spread based on the assigned probability.
4) These fires are compiled in one new historical fire season called synthetic fire season.

Using Arca et al.'s (2012) research on climate change and wildfires, I decided to increase the probability of a fire spreading by almost 100% to represent the effect of a moderate global warming scenario. Unfortunately, because of the high computational power required, it was only increased by 20%. Following the creation of one synthetic fire season for each city, the same logic of min-maxing employed for tropical cyclones was applied here.

3.3.3 River floods

Among the three types of natural disasters, river floods present the most challenges. First, the flood index uses two different datasets covering the period 2010-2100. While both datasets are from the ISIMIP (Inter-Sectoral Impact Model Intercomparison Project), one has spatial information regarding flood depth while the other has information about the fraction of the flooded area. Only the years from 2024 to 2065 were used as this was the limit before hardware limitations. As these datasets are already forward looking, there is no need for any modulation and the same process of intensity extraction is used. This approach comes with notable limitations as this data only covers river floods but not sea floods. For example, Miami, a city prone to flooding, exhibits gaps in data for certain years, raising concerns about the reliability of the information. Nevertheless, consistent min-max scaling is applied to standardize these values within the 0 to 1 range. The purpose of this scaling is to amalgamate the three variables for each city. Consequently, a city with the highest risk in all categories would receive a climate risk score of 3, while a city with no risk would be assigned a score of 0.

3.4. Descriptive Statistics

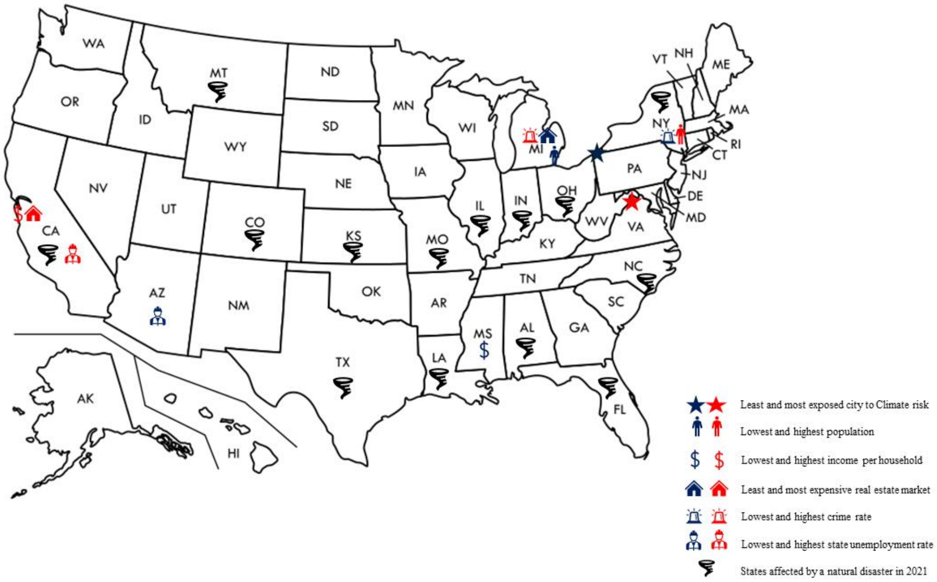

Figure 5: visual representation of the city max and min statistics. In the figure, it's possible to see that California concentrates many maxima including, highest household income, highest unemployment, and highest house prices.

Figure 5 provides a simplified representation of the geographical distribution of the sample, highlighting California as distinctive with the highest household income, unemployment rate, and real estate prices. For the past decade, Sunnyvale California has been the most expensive city in the US, mainly stemming from its proximity to the Silicone Valley, home of large technology companies. Furthermore, the neighboring state of Arizona has the lowest unemployment rate. Unintuitively, a higher unemployment rate doesn't always entail a worse economy. It signifies that state residents can afford transition periods between their jobs. To further investigate this claim, I calculate the average state income and find that California's is higher by almost 20,000 dollars, coinciding with the reality that Republican states like Arizona have worse economic performance than Democrat states. Consistent with this observation, Table 3.2 reveals a tendency for Democrat-controlled states to encompass cities with the highest median income.

Surprisingly, the resilience of Democrat states is roughly the same as Republicans. This means that in the case of a natural disaster, both parties are equally well prepared for these events. Because Republicans disregard climate risk, I expected them to show less interest in allocating resources to natural disasters. However, governmental legislation may force regions to allocate resources regardless of political affiliation.

Table 3.2: Descriptive statistics. The number in parentheses refers to the standard error of each variable. Demand and supply represent the average monthly newly listed and sold houses in thousands. Average Median house price is also reported in thousands of dollars for both 2021 and 2022. Population as well as population density is reported in thousands. Population density represents the average amount of people living per square kilometer. Median income represents the income per household hence why the maximum value is quite high. Crime rate was calculated by taking the total number of violent crimes in 2020 and dividing it by the city's population. Nearest coast distance is represented in degrees while salience and unemployment rate are both reported at the state level. BRIC score is the resilience index to natural disasters of every county, the economic factor was removed since it included variables like population and median income. Included is also summary statistics for cities within Republican and Democrat states.

	Standard statistics					Political dependent statistics	
Variables	N	Mean	Std. Dev.	Min	Max	Republicans mean	Democrats mean
Demand	267	2.0296	1.55047	0.0173	8.416	2.312 (1.67)	1.883 (1.46)
Supply	267	2.09532	1.46942	0.0165	7.825	2.405 (1.63)	1.93 (1.355)
Home prices	267	439.379	289.161	58	1662.3	269.2 (104)	527.34 (313)
Future home price	267	478.503	311.534	63.583	1854.917	300.1 (122)	570.32 (339.09)
CLR index	267	1.129	.319	.227	1.845	1.124 (0.381)	1.131 (0.282)
Population	267	586.135	1591.822	93.932	18713.220	444.54 (738)	660.8 (1885)
Density	267	1.62	1.2317	0.269	10.715	0.943 (0.34)	1.969 (1.373)
Median income	267	70.905	22.783	35.070	156.059	61.79 (18.29)	75.61 (23.48)
Crime rate	267	.004	.003	0	.027	0.004 (0.003)	0.004 (0.003)
Nearest coast	267	3.236	3.876	0	13.83	4.73 (3.57)	2.46 (3.8)
Political party	267	.341	.475	0	1	NA	NA
Salience	267	.921	.27	0	1	0.967 (0.17)	0.897 (0.3)
Unemployment	267	6.878	1.547	3	9	5.61 (1.13)	7.53 (1.31)
BRIC	267	2.11	.113	1.817	2.376	2.17 (0.1)	2.11 (0.116)

Yet, as seen in Figure 5, the state with the lowest house prices is Michigan, with the city of Flint. In the sample, Flint is found to have the highest crime rate and is only safer than 13% of the cities in the US (NeighborhoodScout, 2024). In Michigan, crime rate has been historically high because of Detroit, a city ridden with homicide, poverty, and gang violence. Over time, this influence has spread over to neighboring cities like Flint due to increasing income inequalities. Additionally, crime rates were calculated based on 2020 data, a year characterized by the COVID-19 pandemic. In Detroit and Flint, police redeployment became disorganized, with many officers in quarantine, significantly reducing law enforcement presence in the city. As seen in the sample, this diminished police presence created opportunities for crime to increase.

Focusing on the climate index variable, most values are between 0.806 and 1.446 which falls in line with prior expectations. Indeed, in the very rare case that the average city index is above 1.5, it would imply either extreme exposure to one natural disaster or moderate exposure to all of them.

Lastly, the political party mean is 0.341, showing that 34.1% of cities in the sample are part of a Republican state. In conjunction, the population variable has an incredibly high standard error. Looking at the political dependent statistics, I observe that Democrat states have a higher population and a higher associated standard deviation. The high standard deviation in the sample is likely caused by Democrat states being over-dominant over Republican states. Beyond the statistical implications of this study, this disparity aligns with the reality that Republican states tend to be more rural and less concentrated in cities, hence the lower standard deviation.

Table 3.3: Correlation matrix. Provided is a correlation matrix of all variables. Most correlations are in line with the literature except unemployment and house prices, supply or demand and population.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) House supply	1.000													
(2) Average current house price	-0.053	1.000												
(3) Average future house price	-0.052	0.996	1.000											
(4) House Demand	0.971	-0.091	-0.089	1.000										
(5) Risk index	-0.074	0.014	0.012	-0.079	1.000									
(6) Population	-0.028	0.125	0.110	-0.026	0.100	1.000								
(7) Density	-0.142	0.440	0.420	-0.175	0.217	0.470	1.000							
(8) Median income	0.023	0.795	0.797	-0.000	0.011	-0.010	0.170	1.000						
(9) Crime rate	-0.236	-0.373	-0.378	-0.239	0.143	-0.193	-0.063	-0.501	1.000					
(10) Affect	0.120	-0.392	-0.387	0.151	-0.442	-0.101	-0.320	-0.208	0.044	1.000				
(11) Political party	0.131	-0.424	-0.411	0.152	-0.010	-0.065	-0.396	-0.288	0.014	0.278	1.000			
(12) Salience	-0.062	-0.014	-0.015	-0.044	-0.062	0.001	-0.132	0.004	-0.039	0.088	0.122	1.000		
(13) Unemployment	-0.136	0.527	0.518	-0.145	0.037	0.078	0.373	0.361	-0.116	-0.538	-0.588	0.035	1.000	
(14) BRIC	-0.001	-0.180	-0.202	-0.013	0.141	-0.072	0.045	-0.157	0.265	0.231	-0.016	-0.165	-0.243	1.000

Moreover, I calculate a correlation matrix to see if any variables show abnormal correlation patterns. An important correlation of 0.5 can be seen between house prices and unemployment rate which is surprising considering the theory supports that an increase in unemployment is related to a decrease in house prices (Dvorkin, 2016). This phenomenon might be the product of economic mechanisms, as many studies have pointed out a positive correlation between unemployment and income inequality (Cysne, 2009). Given the relationship between rising house prices and the exclusion of most middle and lower-class families from homeownership, higher-income households likely dominate the housing market demand. Under this assumption, higher house prices may be a sign of high-income inequality which in turn leads to a higher unemployment rate.

Table 3.3 also reveals an important detail, demand and supply aren't correlated with population or density. Both variables should scale along with one another as an increase in the size of a city entails more housing. A reason for this unconventional correlation may be that these variables are very simple proxies of the real mechanisms. Alternatively, the response of US cities to population growth may diverge from initial expectations. Typically, large cities are designed with commuting patterns in mind, where residents travel from suburbs and neighboring areas. Consequently, while an increase in population may not directly boost demand for in-city real estate, it could increase demand in suburbs and adjacent regions. This puts in perspective that demand and supply proxies may not be needed, which will be assessed in the robustness section.

3.5. Assumption testing

Before interpreting the models, I decide to test for two assumptions: multicollinearity, and standard error normality. As seen in Table 1 of the Appendix, no important variables exhibit high VIF values, suggesting multi-collinearity won’t be an issue in interpreting the models. Median income and future house prices are the only variables showing a moderate level of multicollinearity, which is unsurprising as future house prices are expected to correlate with current ones through either a momentum or reversal effect.

Next, I test for normality of the Standard-Error through Shapiro-Wilk tests, the results of which are reported in Table 2 of the Appendix. In the Table, it’s possible to see that only model 1’s standard error is significantly different from a normal distribution. A non-linear relationship could bias the distribution but given that most variables are transformed through logarithmic processes, and that salience is binary, only affect could exhibit such a phenomenon. After testing various nonlinear relationships such as exponential or quadratic and comparing their AIC and R-squared, no significant improvement was found in the normality of the standard error. Moreover, out of all the specifications, model 4 displays the highest level of normality, which is attributed to the importance of past prices in real estate. Often, houses will continuously appreciate through a momentum effect, the omission of which likely biases the distribution of the standard error.

4. Results & Robustness check

4.1. Results & Interpretation

Table 4.1: Model 3 results. The dependent variable is the logged house prices of US cities in 2021. The main independent variables are the climate risk index, political affiliation, salience, and affect. Climate risk is a composite index of exposure to various natural disasters while political affiliation is a binary variable that is equal to 1 if the state was Republican during the 2020 elections. Salience is a binary variable that is equal to 1 if a state has been affected by a natural disaster in 2021. Affect is the distance in degrees to the nearest shore.
"-" interactions, "***" 1% significance, "**" 5% significance, "*" 10% significance

	(1)		*(2)*		*(3)*	
Variables	*Coefficients*	*P-values*	*Coefficients*	*P-values*	*Coefficients*	*P-values*
Climate risk squared	-0.146	0.224	-0.146	0.261	-0.146*	0.085
Political party	-0.24***	0.005	-0.24	0.106	-0.24***	0.008
Salience	-0.141	0.428	-0.141	0.485	-0.141	0.281
Affect	-0.018**	0.014	-0.018	0.294	-0.018**	0.050
Political-risk	0.248**	0.017	0.248**	0.014	0.248***	0.004
Salience-risk	0.11	0.352	0.11	0.379	0.11	0.196
Affect-risk	-0.042***	0.000	-0.042***	0.001	-0.042***	0.000
Salience-political-risk	-0.19**	0.049	-0.19**	0.015	-0.19**	0.012
Affect-political-risk	0.026*	0.063	0.026**	0.028	0.026**	0.046
Log of Demand	-0.01	0.636	-0.01	0.651	-0.01	0.565
Log of Supply	0.008	0.776	0.008	0.811	0.008	0.749
Log of crime rate	-0.014	0.632	-0.014	0.704	-0.014	0.628
Log of population	-0.006	0.779	-0.006	0.779	-0.006	0.782
Log of pop density	0.225***	0.000	0.225***	0.000	0.225***	0.000
Log of income	1.278***	0.000	1.278***	0.000	1.278***	0.000
Unemployment rate	0.002	0.894	0.002	0.911	0.002	0.873
Log of BRIC score	-0.783**	0.023	-0.783*	0.090	-0.783**	0.025
State clustering	No		Yes		No	
Robust S-E	No		No		Yes	
R^2	0.8163		0.8280		0.8280	
N	267		267		267	

Table 4.1 extends the first and second models by including political affiliation and its interaction terms. The model is subject to either a robust or state-clustered standard error to get the least amount of bias. Alongside these standard errors, including affect, salience, and political affiliation reduces omitted variable bias and makes model 3 the best fit for estimating the effect of climate risk on house prices.

Findings reveal that only income, population density, and BRIC score are significant amongst control variables at the 0.01 and 0.05 thresholds. In the table, supply and demand have little impact on house prices, directly contradicting the law of demand and supply (Mankiw, 2021; Hubbard, 2020). Apart from these variables, crime rate has a negative effect, yet its high standard error makes it hard to generalize. Conceptually, the negative sign aligns with the variable's concept: a higher crime rate makes a city less desirable to live in. I also record populations' lack of significance, likely caused by the inclusion of population density as they share a strong correlation. Lastly, unemployment rate shows an extremely small coefficient, possibly due to the limited number of observations.

Focusing on the climate risk index, the size and significance of the coefficient lend significant support to hypothesis 1. This evidence indicates that the relevance of climate risk has increased as future and present natural disasters appear to be partially reflected in house prices. The somewhat significant 14.6% decrease shows climate change awareness is growing in the US, a notable shift in the country's history. The increasing importance of climate change in popular discourse has been so influential that it has spurred reactions from the US government, leading to significant impacts on the real estate market. In 2022, the US Senate achieved a historical milestone by passing the Inflation Reduction Act, which aims to reduce greenhouse gas emissions and promote clean green energy. From this project, future and current green real estate projects are expected to benefit from extended tax credits and direct allocations from the government (Contopoulos, 2024).

These results align with previous literature and bolster Farma's theory's credibility, thereby providing a credible signaling mechanism in the US (1968). Signaling occurs through the risk-return trade-off proposed by Farma, where a property exposed to heightened climate volatility requires a lower sale price to attract buyers seeking higher returns in compensation for the elevated risk. This price adjustment is necessary for the property to remain competitive in the market and will likely create major shifts in real estate. In the future, real estate agencies will have to diversify their investment to hedge climate risk volatility to stay competitive and financially stable. On the other hand, the discount may incentivize some investors to increase their exposure to properties at risk from climate change. Farma's theory shows that while these properties carry higher risks, they also offer potentially higher returns.

Even so, the index results are still insufficient in representing the risks of climate change. This inadequacy becomes evident when considering the objective of the index. In the methodology, a one-unit increase signifies a substantial leap in exposure to natural disasters, akin to transitioning from a minor inconvenience to an existential threat that recurs seasonally. This relationship between the independent variable and the dependent variable fundamentally differs from other discount factors like crime rates or undesirable views, as it can render a property completely uninhabitable, void of future cash flows, and endanger the homeowner's safety. Thus, a 14.6% discount in house prices seems insufficient in reflecting climate change's imminent, extreme, and inevitable danger. Since the current index design doesn't fully capture the severity of climate risk, I believe the lack of impact functions is reducing the size of the discount. In climate risk modeling, impact functions allow to convert the intensity and damage of a natural disaster to monetary terms which depend on the physical integrity of cities. The inclusion of an impact function might lead to more extreme discounts as the exposure to natural disasters will be more accurate.

Practically, climate risk is still underestimated in the US. Historically, the US has always lagged in recognizing the climate threat compared to Europe and even China, which have shown greater interest (Eib, 2019). This lack of concern, combined with the moderate discount may asymmetrically affect investors over house consumers. Research suggests that house consumers suffer from limited mobility compared to real estate companies, often due to factors like mortgage constraints, restricted housing availability, and inadequate information about alternative properties (Fannie Mae, 2020). Consequently, market signaling becomes less relevant for the general population, while insurance coverage grows more critical.

Table 4.2: Model 4 results. The dependent variable is logged house prices. The main independent variables are climate risk and future house prices. Climate risk is a composite index of exposure to various natural disasters while future house prices are the prices for the year 2022.
"-" interactions, "***" 1% significance, "**" 5% significance, "*" 10% significance

	(1)		*(2)*		*(3)*	
Variables	*Coefficients*	*P-values*	*Coefficients*	*P-values*	*Coefficients*	*P-values*
Climate risk squared	-0.008*	0.058	-0.008	0.174	-0.008*	0.085
Political party	-0.018**	0.019	-0.018	0.153	-0.018**	0.023
Salience	0.028	0.888	0.028	0.891	0.028	0.929
Affect	-0.001	0.251	-0.001	0.220	-0.001	0.169
Log of future house prices	0.976***	0.000	0.976***	0.000	0.976***	0.000
Future-salience	-0.003	0.926	-0.003	0.929	-0.003	0.954
Log of Demand	-0.002	0.651	-0.002	0.420	-0.002	0.562
Log of Supply	-0.002	0.623	-0.002	0.489	-0.002	0.604
Log of crime rate	0.007	0.137	0.007	0.228	0.007	0.182
Log of population	0.006*	0.080	0.006	0.126	0.006*	0.098
Log of pop density	0.011*	0.065	0.011	0.148	0.011*	0.086
Log of income	0.037**	0.036	0.037*	0.068	0.037*	0.062
Unemployment rate	0.002	0.356	0.002	0.417	0.002	0.291
Log of BRIC score	0.177***	0.002	0.177**	0.033	0.177***	0.001
State clustering	No		Yes		No	
Robust S-E	No		No		Yes	
R^2	0.9956		0.9956		0.9956	
N	267		267		267	

In Table 4.2, the results of model 4 do not support the second hypothesis, which presupposes that house prices return to their original levels after a natural disaster. Thus, the momentum effect found in real estate appears robust to natural disasters, although the literature suggests that an underlying issue could be biasing these results. For future house prices, on the condition that a state experienced a natural disaster in 2021, a 1% increase in future house prices will lead to current house prices rising by 0.973%. Moreover, other variables such as affect, salience, income, and population density have all drastically decreased in significance. BRIC score is the only variable where significance remained constant, but its sign is now positive. From the sudden changes in significance and the extremely high R squared, I conclude that overfitting might be an issue for this model.

These results suggest that houses continuously appreciate regardless of whether a natural disaster occurred in the region. In truth, real estate assets have always been highly sought after for their resilience and potential to appreciate over time, making them a popular choice for both individual investors and large financial institutions (Block, 2011). In the context of this study, the lack of a reversal might imply that the momentum of house prices is also robust to natural disasters. To illustrate, New York, a city projected to be at a heightened risk of floods and hurricanes in the following decades, has seen its house prices increase by 43% since 2005 (Porter 2024).

Despite the significant lack of a reversal, evidence from the literature suggests that another mechanism might bias the results (Murphy, 2009). Distinct regions may react differently to natural disasters, with some states showing a reversal effect within a year and others in six months. Thus, price efficiency might be affected by numerous variables, such as the online presence of an event, the severity and type of natural disaster, the resilience and adaptive capacity of the local community, and the availability of insurance coverage. For example, disasters with extensive internet coverage may trigger faster reversals in house prices than those that received less attention. This theory is especially relevant as price reversals are intrinsically linked to the limited memory availability as seen with Hurricane Sandy (Addoum, 2021). In this regard, a time series analysis becomes more valuable as it allows to validate the existence of a reversal and analyze how the mechanism relates to attention.

Table 4.3: Model 1 results. The dependent variable is the logged house prices of US cities in 2021. The main independent variables are the climate risk index, salience, affect, and their interactions. Climate risk is a composite index of exposure to various natural disasters while salience is a binary variable that is equal to 1 if a state has been affected by a natural disaster in 2021. Affect is the distance in degrees to the nearest shore.
"-" interactions, "***" 1% significance, "**" 5% significance, "*" 10% significance

	(1)		*(2)*		*(3)*	
Variables	*Coefficients*	*P-values*	*Coefficients*	*P-values*	*Coefficients*	*P-values*
Climate risk squared	-0.089	0.453	-0.089	0.473	-0.089	0.296
Salience	-0.16	0.373	-0.16	0.399	-0.16	0.218
Affect	-0.02***	0.005	-0.02	0.257	-0.02**	0.030
Salience-risk	0.073	0.526	0.073	0.510	0.073	0.372
Affect-risk	-0.03***	0.000	-0.03**	0.011	-0.03***	0.001
Log of Demand	-0.01	0.666	-0.01	0.637	-0.01	0.596
Log of Supply	0.01	0.711	0.01	0.744	0.01	0.678
Log of crime rate	-0.013	0.632	-0.013	0.701	-0.013	0.623
Log of population	-0.009	0.697	-0.009	0.717	-0.009	0.692
Log of pop density	0.242***	0.000	0.242***	0.000	0.242***	0.000
Log of income	1.317***	0.000	1.317***	0.000	1.317***	0.000
Unemployment rate	0.018	0.260	0.018	0.491	0.018	0.246
Log of BRIC score	-0.766**	0.028	-0.766*	0.076	-0.766**	0.027
State clustering	No		Yes		No	
Robust S-E	No		No		Yes	
R^2	0.8183		0.8183		0.8183	
N	267		267		267	

In Table 4.3, climate risk does not have the same significance level as in model 3, highlighting the importance of political affiliation and perceptions as control variables. Aside from the climate risk variable, a comparison of model 1 and model 3 reveals remarkably similar coefficients and significance levels. The perception-related independent variables are somewhat significant with

Affect displaying high levels of significance and a strong economic effect of 2%, indicating direct support for hypothesis 5. The existence of such a premium was expected as it has been a historic factor in determining house prices. Seaside locations have always been popular, as being near the water and outdoors has been shown to boost happiness and quality of life (MacKerron, 2013).

The table also reveals that results align with hypothesis 6, as positive emotions seem to exert sufficient influence to moderate the effect of climate risk on house prices. This is directly supported by the affect interaction term which follows a pattern of high significance but low economic impact. With a mere -4% impact, this small effect can be understood in two ways. Firstly, in the presence of affect, the influence of an additional unit of climate risk is decreased to 4%. Second, when combined with climate risk, the premium for beachside properties is heightened, a phenomenon that could be attributed to the increased sensitivity of lower-valued houses to premiums. In either scenario, the impact of a one-unit rise in climate risk diminishes, indicating that strong emotions can bias the effect of risk on assets. For real estate investors, this means they can benefit by selling sea-side houses at a historic premium and not suffer from any climate risk-related discount. However, this relationship only holds for the year 2021 and as climate risk becomes more apparent to home buyers in subsequent decades, the relationship may become less significant. In fact, with the rising sea levels, beach-side locations may transition from a premium to a discount.

The two models also refute hypothesis 3 where I expected recent natural disasters to decrease house prices significantly. Instead, I observe a strong but non-significant negative effect of 14% to 16%. Similarly, results clash with hypothesis 4, where climate risk was supposed to be exacerbated by recent natural disasters. I find a positive sign where, on the condition that a state experiences a natural disaster in 2021, a one-unit increase in climate risk will escalate house prices by 11%. This comes as a surprise since natural disasters are one of the most recurrent, destructive, and documented events in the US. Thus, fear should make disasters readily available in the memory of state residents and strengthen the association between climate risk and house prices. This is furthered by the literature where natural disasters were shown to be heavily associated with a short-term negative sign (McCoy, 2018; Gibson, 2020; Kim, 2022).

From these unexpected outcomes, I have identified three possible explanations for the discrepancy with existing literature. The first explanation involves the gambler's fallacy, a cognitive bias where individuals mistakenly believe past random events influence future ones. Research has shown that individuals in China and the US often make suboptimal real estate decisions based on the assumption that a natural disaster cannot occur repeatedly in the same area (Yin, 2016). Following a natural disaster, house prices in areas exposed to climate risk may increase as investors mistakenly believe that the same event will not occur repeatedly in the region. In reality, natural disasters result from the accumulation of various meteorological factors, and in the context of climate change, the intensification of these factors is likely to increase their occurrence, contradicting the gambler's fallacy's reasoning.

Secondly, I hypothesize that access to information may be a decisive factor in why salience is not entirely significant. Like the reversal effect, the price impact of a natural disaster might depend on its internet presence. If an event is not widely reported or discussed online, potential buyers and sellers may remain unaware of the damage, or the long-term risks associated with the affected area. In opposition, constant reminders of the disaster's devastation could amplify the event's salience, leading to slower price adjustments and a more prolonged impact on property values.

Lastly, political affiliation may act as a moderator. This is partially confirmed when looking at the three-way interaction term between political affiliation, climate risk, and salience in model 3. On the condition that the state is Republican and has recently been affected by a natural disaster, a one-unit increase in climate risk will further decrease house prices by 19%. When excluding the gambler fallacy, this would indicate that salience depends on political affiliation to affect house prices.

Table 4.4: Model 2 results. The dependent variable is the logged house prices of US cities in 2021. The main independent variables are the climate risk index and political affiliation. Climate risk is a composite index of exposure to various natural disasters while political affiliation is a binary variable that is equal to 1 if the state was Republican during the 2020 elections.
"-" interactions, "***" 1% significance, "**" 5% significance, "*" 10% significance.

	(1)		*(2)*		*(3)*	
Variables	*Coefficients*	*P-values*	*Coefficients*	*P-values*	*Coefficients*	*P-values*
Climate risk squared	-0.036	0.337	-0.036	0.537	-0.036	0.379
Political party	-0.177*	0.052	-0.177	0.230	-0.177**	0.041
Political-risk	0.078	0.143	0.078	0.319	0.078	0.127
Log of Demand	-0.000	0.981	-0.000	0.982	-0.000	0.977
Log of Supply	-0.01	0.741	-0.01	0.772	-0.01	0..697
Log of crime rate	0.000	0.985	0.000	0.977	0.000	0.985
Log of population	0.004	0.870	0.004	0.877	0.004	0.867
Log of pop density	0.255***	0.000	0.255***	0.000	0.255***	0.000
Log of income	1.345***	0.000	1.345***	0.000	1.345***	0.000
Unemployment rate	0.043	0.008	0.043	0.102	0.043	0.002
Log of BRIC score	-1.297***	0.000	-1.297**	0.028	-1.297***	0.000
State clustering	No		Yes		No	
Robust S-E	No		No		Yes	
R^2	0.7745		0.7838		0.7838	
N	267		267		267	

As opposed to model 3, model 2's climate risk index does not have economic or statistical significance. Control variables show very similar significance levels to model 1 and 3 except for crime rate and demand, both of which have coefficients close to 0.

In model 2 and 3, being part of a Republican state significantly decreases house prices by 14 to 17%, directly contradicting hypothesis 7. The negative sign directly clashes with prior expectations and implies that another phenomenon is responsible for this price gap. Most likely, Republican states have just and all-around poorer economic performance in this sample. In recent decades, Republican states have shown lower household incomes, higher poverty rates, and less investment in education and infrastructure compared to Democratic-leaning states (Gelman, 2005). This disparity is also seen in the summary statistics, with Republican states having lower economic performance than Democrat states.

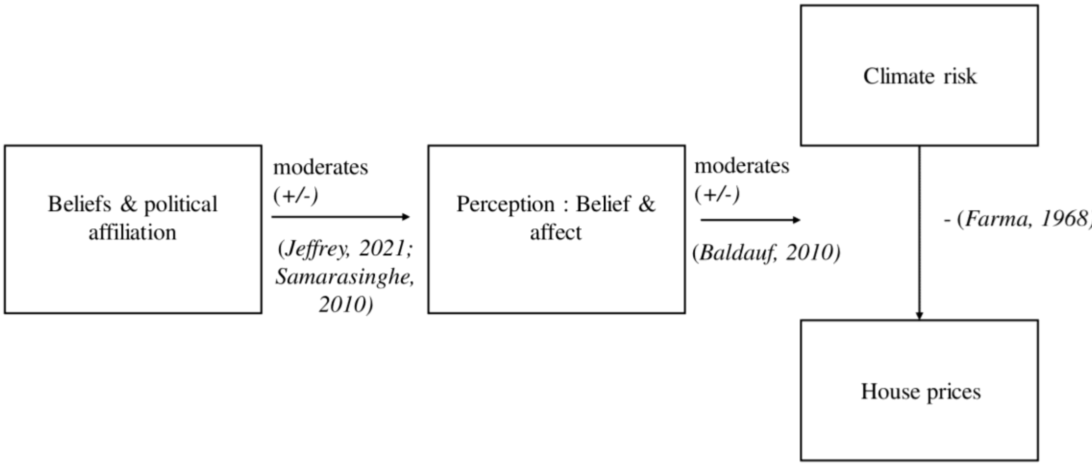

Figure 6: visual representation of the order of mechanisms. Beliefs have been identified as the primary determinant of whether perception significantly influences climate risk.

Beyond hypothesis 7, I also established that Republican towns suffering from climate risk may observe a less extreme discount than Democrats. Per Hypothesis 8, I find a positive and significant term for the interaction term in model 3. This means that if a state is Republican, the climate discount is reduced. The variable's robustness suggests that Republicans experience no price discounts when climate risk increases, which presumably comes from their tendency to disregard all forms of climate risk. As shown by their lack of trust in most news sources, Republicans are more likely to follow a narrative and disregard the truth compared to Democrats (Mark, 2020). Because of this, climate risk and global warming are often overlooked as “fake news” by many Republicans. Coinciding with this reality, the literature also showed that Republican climate change deniers display higher house prices (Baldauf, 2020).

The last interaction term established in hypothesis 9 relates to how salience interacts with climate risk on the condition of whether the state is Democrat or Republican. As previously mentioned, on the condition that the city is part of a Republican state and it has recently experienced a natural disaster, a one-unit increase in climate risk will further decrease house prices by 19%. The strong economic and statistical sign of the variable indicates no support hypothesis 9. What’s important to add in the context of these results is that belief seems like a direct moderator of perception. The strength of belief cannot be understated as it has been shown to enable perception variables like salience to become highly significant. In Figure 6, I represent the potential order of mechanisms. This coincides with the rising importance of political beliefs in the US. In the last 20 years, politics have become polarizing, and individuals have increasingly been defining themselves off of them (Iyengar, 2012). Seemingly, this trend is bleeding out into this study and how climate risk affects house prices.

4.2. Robustness check

Table 4.5: Model 3 AIC & BIC criterion. The model considered here is climate risk alongside control variables regressed on house prices.

Model 3	*BIC*	*AIC*	R^2
With log demand & log supply	141.9226	106.05	0.8163
Without	130.997	102.3017	0.8165

In model 3, overfitting was predominantly observed in the variables of offer and demand. The decision to remove these variables was based on their lack of contribution to the R squared and the significant improvement of the AIC and BIC criteria. Following the removal of both demand and supply, I conduct a robustness check by dividing the climate risk index in quartiles and changing salience to include the online attention of natural disasters.

This first change was motivated by the indifference of the US population towards climate risk which likely moderates the discount to only occur in areas exposed to extreme climate risk. The second change was made in response to the earlier discussion on the importance of internet salience. The greater the internet presence of a natural disaster, the more efficiently price mechanisms will function. To operationalize the concept, I begin by taking the average interest from Google Trends for each named natural disaster in 2021. Next, I aggregate the interest levels for each disaster at the state level. Additionally, in Table 4.6, I re-calculate a simpler model that excludes the interaction terms.

Table 4.6: robust model. The dependent variable is logged house prices. The main independent variables are the quartiles of climate risk and internet salience. Climate risk is a composite index of exposure to various natural disasters. The first quartile wasn't included because of collinearity issues.

"***" 1% significance, "**" 5% significance, "*" 10% significance.

	(1)		*(2)*		*(3)*	
Variables	*Coefficients*	*P-values*	*Coefficients*	*P-values*	*Coefficients*	*P-values*
Climate risk 50th	0.084	0.328	0.084	0.201	0.084	0.279
Climate risk 75th	0.047	0.642	0.047	0.437	0.047	0.608
Climate risk 100th	-0.1	0.291	-0.1	0.241	-0.1	0.234
Political party	0.078	0.306	0.078	0.260	0.078	0.420
Google interest	0.035***	0.002	0.035***	0.004	0.035***	0.01
Affect	-0.004	0.720	-0.004	0.830	-0.004	0.647
Log of crime rate	-0.036	0.316	-0.036	0.374	-0.036	0.311
Log of population	-0.023	0.336	-0.023	0.235	-0.023	0.382
Log of pop density	0.31***	0.000	0.31***	0.000	0.31***	0.000
Log of income	1.2***	0.000	1.2***	0.000	1.2***	0.000
Unemployment rate	0.063*	0.098	0.063*	0.053	0.063	0.209
Log of BRIC score	-0.017	0.969	-0.017	0.964	-0.017	0.973
State clustering	No		Yes		No	
Robust S-E	No		No		Yes	
R^2	0.82699		0.8699		0.8699	
N	267		267		267	

Table 4.6 shows that only the fourth quartile is found to have a negative, albeit non-significant, effect. Climate risk is thus partially incorporated in house prices in the US only on the condition that the exposure is extreme. The lack of uniformity has consequences not only for investors but also for policy interventions. Firstly, real estate investors cannot rely on a discount signal unless the house is exposed to extreme climate risk, which in this case, the strong salient nature of extreme natural disasters makes signaling useless. Secondly, the need for government intervention is

reinforced by this lack of signaling. Since market forces have not adequately reflected all available information, governments should step in and develop climate risk labels for houses, similar to those used for energy consumption.

On the topic of salience, it's clear that scaling the variable with internet attention has led to a more significant and more substantial effect. Now for every point of interest manifested through Google searches, house prices will increase by 3.5%. Although this increase might seem counterintuitive, as previously mentioned on the topic of reversal, an increase in internet attention may correlate with a heightened price efficiency. In turn, if the price efficiency of a state is sufficiently high, a reversal effect could occur in less than a year, hence the positive coefficient.

5. Limitations

Firstly, the sample size is too small, a consequence of combining several sources into one. As seen with the high standard error of many variables, the limited number of observations has likely led to precision issues. This core limitation is furthered by the arbitrary city threshold which has concentrated observations in California and North-eastern states. On the contrary, the challenge lies in finding these missing observations, as the cut-off was set to include cities large enough to react dynamically to climate risk. In future studies, it may be useful to further investigate where the optimal population cut-off lies to maximize precision and robustness.

On the topic of variables, climate risk, supply, demand, affect and salience all could have used more advanced methods. Regarding the main independent variable, the index could have benefited from converting the risk exposure in monetary terms or including biomass in wildfire synthetic events. Adding new natural disasters could also make the index more complete. In CLIMADA, it's possible to model hail, landslides, and winter storms, although there, the challenge lies in the creation of synthetic events. Using these elements would likely have led to more precise results, albeit harder to interpret than the current index iteration. Furthermore, the index should be validated for robustness by comparing it with other relevant indexes or climate exposure datasets. In the context of supply and demand, certain cities may only attract out-of-state residents, in turn, these residents may have different expectations and perceptions of climate risk. Thus, future studies may need to delve deeper into the price impact of the different types of demand.

Besides demand and supply, salience is another variable that could benefit from more refined data. While Google Trends roughly approximates internet attention, social media often serves as a better proxy. Further research on the topic may involve using X or Instagram developer accounts to retrieve aggregate data and perform sentiment analysis. Alternatively, the affect variable could have been expanded to include additional distances to attractive locations such as mountains and forests or attractive features like weather quality.

Lastly, given more time, a rolling index based on yearly natural disaster projections could have been incorporated. This approach not only considers the impact of evolving information but also creates a straightforward comparison to the existing literature, as all studies utilize panel data. Using a time-series approach would also have led to a more precise estimation of the salience bias since only a few major natural disasters occurred during the year 2021.

6. Conclusion

The main objective of this thesis was to find whether the US housing market incorporated climate risk into its prices. The topic has been heavily debated since the early 1980s, and with the increasing importance of climate change, its popularity is only growing. Many natural disasters such as floods, wildfires, and hurricanes have been shown to negatively impact house prices (Skantz, 1987; Speyrer, 1991; Huang, 2024; Kim, 2020). Most believed that house prices would decrease as risk increased to allow for greater asset sale returns and better risk compensation (Farma, 1968). Later, it was found that there may exist a reversal effect of prices 1 to 3 years following a natural disaster (Morgan, 2007). The theory proposes that as demand returns to its original state, property numbers stay the same, increasing house prices. Nevertheless, these discounts heavily intertwine with concepts like perception and beliefs.

Both these notions have been operationalized in the literature through salience, affect, and political affiliation. While affect has been shown to increase house prices through mechanisms such as beach-side premiums, several studies have displayed its potential to lessen climate risk effect on house prices (Samarasinghe, 2010). Salience is similar in the fact that it has garnered a large consensus where, on average, recent natural disasters decrease the property value of houses (Cohen, 2021). In the literature, both concepts heavily intersect with political affiliation, although there, the links with climate risk are less direct.

This thesis incorporated elements from literature but also contributed by taking a new approach to modelling natural disasters. Instead of taking a single category, I incorporated wildfires, hurricanes, and floods in one index to take the most holistic approach. This index was made using the open-source software CLIMADA and employed several datasets to model future changes brought by global warming. Additionally, it was paired with a robust and clustered standard error in a cross-sectional regression of house prices for the year 2021.

Following a robustness check, climate risk was found to potentially discount house prices on the condition that the exposure was extreme. This observation is quite worrying as it shows climate risk is not incorporated in house prices unless natural disasters are already close to occurring. I theorize that the lack of belief in climate risk in the US causes only the most vivid predictions to be reflected in house prices. This idea is also supported with salience, where on the condition they experience a natural disaster in their states, Republicans are found to experience a climate risk discount similar to Democrats. Given these results, beliefs and political affiliation seem to have a stronger effect on perception than previously thought, hinting that an order of magnitude exists. Looking at the methodology, it’s hard to generalize and relate these results to the literature. The main divide comes from the use of a cross-sectional regression compared to a time series or difference in difference. Trends like reversal or salience are harder to analyze only using a cross-sectional analysis as they differ over time.

For future studies, focusing on a specific mechanism or psychological component identified in this research will be pivotal to further advance the topic. For example, the attention given to an event online could be further developed using platforms like X and natural language processing models. Affect would benefit from the inclusion of the distance to other desirable locations like mountains. On the other hand, certain real-estate mechanisms were not accounted for. Although demand and offer were removed because of overfitting, better proxies would likely lead to more significant results. As shown with summer or vacation houses, demand is not restricted to being in-state but often is an amalgamation of many different streams. Thus, future studies should establish finer mechanisms for supply and demand.

7. Appendix

Table 1: VIF for model 4. No noticeable multi-collinearity problem can be observed. The largest VIF value is only 5.11 and is a lag of the main dependent variable, making the large VIF value fit within the study framework.

0<VIF<5 small effect, 5<VIF<10 medium effect, 10<VIF strong effect.

Variables	*VIF*
Future house prices	5.11
Median Income	4.50
Demand	2.88
Supply	2.72
Crime rate	2.58
Unemployment rate	2.36
Affect	2.28
Population density	1.96
Political party	1.95
Population	1.86
Risk index squared	1.49
BRIC	1.37
Salience	1.10

Table 2: Shapiro-Wilk test. A significant value indicates normality of error. Only model 1 exhibits non-normal results. "***" 1% significance, "**" 5% significance, "*" 10% significance.

Models	*p-values*
Model 1	0.397
Model 2	0.052*
Model 3	0.072*
Model 4	0.020**

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