PERCEPTION VS REALITY: HOW CLIMATE RISK AWARENESS AFFECTS HOUSEHOLD DECISIONS IN THE UNITED STATES

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ABSTRACT

This thesis investigates the dynamic interplay between climate risk perception and household economic decisions concerning housing values, affordability, and residential mobility in the United States. Utilizing county-level panel data (2014–2022) from the Climate Change in the American Mind survey and American Community Survey, the study develops a comprehensive Climate Perception Index through principal component analysis. Two-way fixed-effect regression models reveal that counties with heightened climate risk awareness significantly correlate with lower housing values, elevated price-to-income ratios, and increased migration rates, demonstrating capitalization of perceived climate risks into housing markets. These relationships exhibit notable heterogeneity contingent upon homeownership rates, income levels, and coastal proximity. Dynamic panel models incorporating lagged dependent variables confirm the temporal persistence and path-dependency of market responses, underscoring the robustness. These findings highlight the critical role climate awareness plays in household adaptation behaviors and carry implications for climate-resilient urban policy development.

Keywords: Climate change; Risk awareness; Household decision-making; Risk capitalization; Climate adaptation.

BIOGRAPHICAL SKETCH

Yuxuan Jiang was born in Beijing, China. Before coming to Cornell, she earned a Bachelor of Science degree in Economics and Finance from the Hong Kong University of Science and Technology (HKUST). Her research interests lie at the intersection of climate change and sustainable development, with a particular focus on how environmental and economic systems interact with human behavior, social vulnerability, and adaptive capacity.

Dedicated to my grandparents and parents.

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CHAPTER 1 INTRODUCTION

Climate change represents one of the most pressing and complex challenges of the 21st century, with profound and far-reaching implications for economies, ecosystems, and societies worldwide. In the United States, the effects of climate change have become increasingly tangible, resulting in rising temperatures, altered precipitation patterns, and increasing frequency and intensity of extreme weather events. These changes are not merely environmental concerns but also carry significant economic, financial, and social consequences. Understanding how these climate-driven disruptions cascade through systems and influence human decision-making is critical to designing effective adaptation strategies and policies.

In recent decades, the frequency and severity of climate-related disasters in the U.S. have shown a concerning upward trajectory. According to the National Oceanic and Atmospheric Administration (NOAA), the average number of billion-dollar disasters has risen sharply from 7.1 events per year between 1980 and 2013, to 13.8 per year from 2014 to 2022, and a five-year average of 23.0 events from 2020 to 2024. These events span droughts, floods, freezes, severe storms, hurricanes, and wildfires. Such disasters not only escalate direct losses, but also create substantial indirect costs related to infrastructure damage, disrupted supply chains, displacement, and volatility in insurance and housing markets.

The impacts of climate change should not be underestimated. Studies by Burke et al. (2015) and Hsiang et al. (2017) estimate that each 1°C increase in global temperature could reduce U.S. GDP by approximately 1.2%, with projected national economic damages reaching up to 8% of GDP under high-emissions scenarios. However, these effects are not uniform. At the county level, the southern and coastal counties are expected to experience disproportionately higher losses, exacerbating regional economic inequality (Hsiang et al., 2017). At the household level, the impacts can be various, including disruptions and income losses (Deryugina et al., 2018), reduced labor productivity under extreme heat (Behrer & Park, 2022), and rising insurance costs that disproportionately burden vulnerable communities (USGCRP, 2018; Fellowes-Granda et al., 2023; United States Environmental Protection Agency, 2025).

Table 1: Billion-dollar Disaster Events in the United States, 1980-2025

Disaster Type	Events	Events /Year	% Frequency	Total Costs	% of Total Costs	Cost/ Event	Cost/ Year	Deaths	Deaths /Year
Drought	32	0.7	7.9%	372.1	12.6%	11.6	8.1	4658	101
Flooding	45	1.0	11.2%	205.7	7.0%	4.6	4.5	742	16
Freeze	9	0.2	2.2%	37.6	1.3%	4.2	0.8	162	4
Severe Storm	203	4.4	50.4%	520	17.6%	2.6	11.3	2145	47
Tropical Cyclone	67	1.5	16.6%	1558.8	52.8%	23.3	33.9	7211	157
Wildfire	23	0.5	5.7%	150.1	5.1%	6.5	3.3	537	12
Winter Storm	24	0.5	6.0%	105.4	3.6%	4.4	2.3	1463	32
Total	**403**	**8.8**	**100.0%**	**2949.7**	**100.0%**	**7.3**	**64.1**	**16918**	**368**

Note: The unit of Total Costs, Cost/Event, and Cost/Year is Billion USD. Values are CPI-adjusted.

Table 2: Comparisons of Billion-dollar Disaster Events in the United States, 1980-2025

Time Period	Billion-Dollar Disasters	Events/ Year	Cost	% of Total Cost	Cost/ Year	Deaths	Deaths/ Year
1980s (1980-1989)	33	3.3	221.8	7.5%	22.2	2994	299
1990s (1990-1999)	57	5.7	338.9	11.5%	33.9	3075	308
2000s (2000-2009)	67	6.7	628	21.3%	62.8	3102	310
2010s (2010-2019)	131	13.1	1005.2	34.1%	100.5	5227	523
Last 5 Years (2020-2024)	115	23	755.8	25.6%	151.2	2520	504
Last 3 Years (2022-2024)	73	24.3	466.8	15.8%	155.6	1534	511
Last Year (2024)	27	27	184.8	6.3%	184.8	568	568
All Years (1980-2025)	**403**	**8.8**	**2,949.7**	**100.0%**	**64.1**	**16918**	**368**

Note: The unit of Cost and Cost/Year is Billion USD. The types of disasters are drought, flooding, freeze, severe storm, tropical cyclone, wildfire, and winter storm. Values are CPI-adjusted.

The influences of climate change are heavily reflected in individual and collective behavior. Households respond to climate risks through various channels, such as migration, investment in protective infrastructure, insurance uptake, or changes in consumption patterns. These responses are shaped by objective risk and subjective perceptions (Lo, 2013), yet misperceptions can lead to both maladaptive decisions and under-preparation. For instance, perceived risk can significantly predict migration intentions (Hauer et al., 2020), However, another evidence from a Swiss Re survey revealed a wide ‘protection gap’ driven by misinformation. 43% of U.S. homeowners mistakenly believed their standard insurance covers flood damage, while only around 15% indeed have flood insurance (Moorcraft, 2021). These dynamics highlight the pivotal role of risk communication and public awareness in shaping adaptive capacity.

As financial resilience performs as the core component of climate resilience (Hallegatte et al., 2016), households are encouraged to adopt proactive strategies such as purchasing extreme weather event-related insurance (Hudson et al., 2016; Botzen et al., 2019; Tesselaar et al., 2020), reinforcing structures, or relocating away from high-risk areas. However, such actions remain uneven across demographic groups and geographies (Shu et al., 2023), partly due to varying access to information (Azeez et al., 2024), resources (Birkmann et al., 2022), and institutional support (Chhetri, 2012).

At the systemic level, the increasing unpredictability and severity of climate disasters pose growing risks to financial markets and macroeconomic stability. The Financial Stability Report (2023) by the Federal Reserve Board identifies climate-related events as an emerging class of systemic shocks capable of triggering disruptions in real estate markets, credit availability, and public finance. Market signals have begun incorporating climate risk information, but often imperfectly and heterogeneously (Bernstein et al.,2019), and response vary due to factors such as belief in climate change (Baldauf et al., 2020), perceived risk (Bakkensen and Barrage, 2017), and experience with past climate events (Atreya et al., 2013).

Furthermore, infrastructure systems face mounting stress: over 60,000 miles of coastal roads are already at risk from sea-level rise (USGCRP, 2018), and weather-related power outages have doubled since 2003 (Kenward et al., 2021). The American Society of Civil Engineers (2021) estimates that bridging the climate adaptation infrastructure gap will require over $2.6 trillion in investment over the next decade.

Given these converging pressures, this thesis aims to investigate how households respond to climate risk in the United States, specifically their decisions on housing and mobility choices. In addition, the study aggregated data at the county level to explore how household responses vary by regional exposure and perception of risk, while adding controls for socioeconomic status. By synthesizing insights from urban economics and risk perceptions, this study contributes to a more comprehensive understanding of climate adaptation at the micro level, offering insights for improving resilience and narrowing the adaptation gap under the increasing climate uncertainty.

The rest of this thesis is organized as follows: Chapter 2 is the literature review; Chapter 3 introduces the method, data, variables and hypotheses; Chapter 4 presents the empirical results and analysis; Chapter 5 discusses the robustness of results; and Chapter 6 summarizes the conclusions and limitations, with further implications on urban policies and markets.

CHAPTER 2 LITERATURE REVIEW

2.1 Effects of Climate Change

Climate change imposes heterogeneous impacts on households, influencing housing markets and social structures across geographic and socioeconomic dimensions. Three key channels through which it shapes household decisions are rising social inequality, shifting migration patterns, and evolving property market dynamics.

2.1.1 Social Inequality

Climate change increasingly acts as an amplifier of socioeconomic inequality, particularly within housing markets. It is projected to increase both the uncertainty and spatial inequality of economic damages across U.S. counties. Hsiang et al. (2017) discovered that under RCP8.5 (the highest baseline emissions scenario), climate damages are disproportionately borne by poorer U.S. counties, with losses rising by 0.93% of income per decile decrease. While wealthier regions may even experience net benefits, the poorest counties face potential losses of up to 27.8% of income, highlighting the limitations of nationally averaged damage estimates of masking the distributional effects. These disparities call for damage functions that incorporate aversion to inequality and risk. At the urban level, such inequality manifests through 'climate gentrification' (Keenan et al., 2018), as properties at higher elevations in Miami-Dade County appreciate at accelerated rates compared to similar properties at lower elevations, indicating that climate risk is driving shifts in real estate investment patterns that displace lower-income residents from historically affordable areas.

2.1.2 Migration and Population Displacement

Climate change is reshaping migration patterns through both acute and chronic environmental pressures. Hauer (2017) quantified the potential magnitude of sea-level rise displacement, projecting that up to 13 million Americans could be displaced by 2100. His county-level analysis identifies likely migration hotspots and suggested that climate-induced migration will fundamentally alter population distributions across the country. The spatial heterogeneity of these migration responses emerges in the model developed by Fan et al. (2018). Their analysis demonstrated that climate migration patterns depend on both push factors (climate risks in origin locations) and pull factors (economic opportunities and amenities in destination locations). These findings suggest that climate migration will accelerate existing urbanization trends while potentially creating new growth centers in climate-resilient regions.

2.1.3 Property Market Dynamics

Climate change also affects directly in real estate markets via price signals and changing risk premiums. Bernstein et al. (2019) quantified how flood risk affects residential property values. They explored that properties exposed to flood risk sell for approximately 7% less than comparable unexposed properties, with this discount increasing over time as climate risk awareness grows. Their longitudinal analysis suggests evolving market responses to climate information. In wildfire-prone areas, McCoy and Walsh (2018) analyzed how wildfire events affect housing prices and development patterns. Their research found that large wildfires reduce property values by 15-20% in affected areas, but these effects diminish over time. The study also implied that incomplete risk perception and disaster memory decay may undermine market signals that could otherwise discourage development in high-risk areas.

2.2 Perceptions and Awareness of Climate Risk

People take climate change and its associated risks differently. Understanding how individuals perceive and respond to climate risks is pivotal to inform better adaptation plans and implementation. The following section explores both the conceptual framework of climate risk perception and the empirical patterns observed across different contexts.

2.2.1 Theoretical Framework for Understanding Climate Risk

The analysis of household climate risk perception requires robust theoretical frameworks that capture deviations from perfectly rational decision-making. Botzen et al. (2021) synthesized behavioral economic perspectives on climate risk perception, highlighting the roles of cognitive biases, social influences, and cultural worldviews in shaping how individuals understand and respond to this type of low-probability-high consequence (LP-HC) risk. Their framework emphasizes that systematic deviations from perfect rationality significantly impact climate policy design and risk communication effectiveness. Integrating economic and psychological perspectives, Alló and Loureiro (2014) conducted a meta-analysis of willingness-to-pay for climate mitigation policies. Their analysis demonstrates that risk perception variables explain significant variation in willingness-to-pay, with perceived vulnerability to climate impacts serving as a particularly robust predictor. These findings carry implications for both climate policy design and adaptation planning, particularly in housing markets.

2.2.2 Empirical Views on Climate Risk

Direct experience with climate events powerfully shapes risk perception. Bergquist et al. (2020) conducted a meta-analysis examining climate risk perception, finding that personal experience with climate-related weather events increases climate concern by approximately 23%. This type of ‘experiential learning’ frequently outweighs political ideology or socioeconomic factors in determining risk perception. Climate experiences also modify risk preferences. Bernstein et al. (2019) documented increased risk aversion following hurricane exposure, with affected households subsequently reducing equity investments by approximately 8%. Ballew et al. (2019) documented the temporal evolution of U.S. climate risk perceptions, noting increasing public concern in recent years. Their analysis identifies key drivers of changing risk perceptions, including extreme weather events, improved climate science communication, and shifting political dynamics, while noting persistent partisan gaps in climate risk perception.

These changing perceptions influence behavioral intentions and policy preferences. The Yale Climate Opinion Maps (YCOM) documented steady increases in climate concern across all U.S. regions since 2014, with particularly marked increases in regions experiencing extreme events (Leiserowitz et al., 2018). Their time-series data reveals that the proportion of Americans who felt 'very worried' about climate change increased from 19% in 2014 to 35% in 2023, with the steepest increases in regions directly affected by hurricanes, wildfires, or flooding. Additionally, from the housing market perspective, Atreya et al. (2013) analyze how flood experience affects risk perception and property values. Their research revealed that floods increase risk perception and reduce property values, but these effects diminish over time as event memory fades. The decay of risk perception carried significant implications for housing markets and adaptation planning in flood-prone areas.

2.3 Responses to Climate Risk

Households respond to climate risks through different channels, and this section mainly underlined two: migration decisions and housing market participation. These responses reflect both rational adaptation strategies and behavioral biases in risk assessment.

2.3.1 Migration Response

Risk perceptions directly influence household migration decisions in climate-vulnerable areas. Hauer et al. (2020) found that perceived flood risk significantly predicted migration intentions in coastal communities, after controlling for objective risk and socioeconomic factors. These suggest that perceptions may trigger migration before physical impacts occur, with important implications for adaptation policy and managed retreat. However, the decision to migrate in response to climate risks involves complex trade-offs. Koerth et al. (2017) examine planned relocation intentions among coastal residents, finding that risk perception, place attachment, and adaptive capacity interact in forming migration decisions. Households with high risk perception but strong place attachment often invest in structural adaptation measures rather than relocating, highlighting the complex interplay between perception and migration behavior.

The migration behavior can also be examined from the frameworks of urban economics, which offers an understanding of how climate risks affect spatial equilibrium patterns. Desmet and Rossi-Hansberg (2015) develop a dynamic spatial model incorporating climate change impacts, and results show that migration functions as a key adaptation mechanism but faces constraints from moving costs and information limitations. Climate change significantly alters the spatial distribution of economic activity in the United States, with potential growth in cooler regions and decline in areas facing severe heat impacts.

2.3.2 Housing Market Response

Heterogeneous climate risk perceptions create observable market segmentation. Bakkensen and Barrage (2017) developed a framework to understand climate risk capitalization in coastal property markets and discovered evidence of both risk capitalization and belief heterogeneity. Households with higher flood risk perceptions sort into lower-risk properties, while those with lower risk perceptions occupy higher-risk areas, creating potential for market inefficiencies and selective retreat patterns. Furthermore, climate change beliefs influence housing market outcomes through impacts on price formation. Baldauf et al. (2020) examined how climate change beliefs affect house prices and found that houses exposed to sea level rise sell at a discount only in census tracts where residents believe in climate change. People who believe in climate change tend to discount the value of properties potentially vulnerable to its effects. The study implies that heterogeneous climate change beliefs create spatial sorting in housing markets, potentially on market discrepancies and volatilities.

These market dynamics reflect the complex interaction between objective climate risks, subjective risk perceptions, and adaptive behavior. Although markets incorporate climate-related information, this process is imperfect and exhibits substantial heterogeneity across space, time, and demographic subgroups.

CHAPTER 3 METHODS

3.1 Variables

The multi-dimensional dataset is constructed using sources from the Climate Change in the American Mind (CCAM) survey and public data provided by the United States Census Bureau. All data are aggregated at the county level, with a period ranging from 2014 to 2022. Below lists all variables to be further applied in statistical models.

Table 3: List of Variables

Variable	Description
HP	The median house value (log).
PTI	The house price to income ratio.
MR	The in-migration rate in the year prior to taking the survey (%).
CPI	The constructed Climate Perception Index.
Income (INC)	The median income level (thousand USD).
Ownership (HO)	The house is owned by the household (%).
Distance (CD)	The distance from the county to the nearest coast lines (thousand km).
Age65	Elderly people over 65 years old (%).
Poverty	People with income below the poverty level (%).
New	The building is newly constructed after 2010 (%).
INC*HO	The interaction term between Income and Ownership.
CPI*CD	The interaction term between Climate Perception Index and Distance.
CPI*HO	The interaction term between Climate Perception Index and Ownership.
County (Cty FE)	All counties within 50 states and Washington D.C. in the United States, excluding the minor outlying islands.
Year (Yr FE)	Each year from 2014 to 2022.

Dependent Variables (HP, PTI, MR)

Housing value (HP), Price-to-income ratio (PTI), and Migration rate (MR) are three dependent variables to be investigated in the study, with data retrieved from American Community Survey (ACS). ACS is the annual demographics survey program conducted by the United States Census Bureau, providing detailed information about social, economic, and housing characteristics of the U.S. population. Regarding the dependent variables, Housing value (HP) reflects the market valuation of real estate (Grether & Mieszkowski, 1974; Breuer & Steininger, 2020), revealing asset revaluation mechanisms under climate change (Bernstein et al., 2019). Additionally, the Price-to-income ratio (PTI) evaluates housing affordability, measuring the proportional relationship between house prices and household income. This indicates how climate change affects differences in housing affordability across regions (Kahn & Walsh, 2015). Lastly, the Migration rate (MR) indicates population mobility, measuring the proportion of households that moved from a different place within the U.S. to the current house in the last year, divided by the total county population. This variable identifies how economic factors drive migration (Stawarz et al., 2021; Frost, 2024) and reflects households' adaptive responses to environmental changes in this study (Hauer, 2017).

Climate Perception Index (CPI)

CCAM is a nationally representative survey conducted by the Yale Program on Climate Change Communication and the George Mason University Center for Climate Change Communication (Howe et al., 2015; Marlon et al., 2022), examining public opinions and concerns related to climate change among the American people. To capture climate change perception at the county level, I constructed a **Climate Perception Index (CPI)** based on ten indicators from CCAM, as they comprehensively reflect cognitive (belief in scientific consensus, human causation, future impact), affective (concern, worry, perceived personal harm), and temporal (perceived timing of impact) dimensions of public climate perception. These variables have high relevance to the conditions of participants and related households, which are the targeted scope of our study.

Table 4 shows the ten selected variables that encompass key dimensions of climate perception. Given the conceptual overlap among these indicators and their observed strong pairwise correlations (shown in Table 5), the study applied the Principal Component Analysis (PCA) to reduce dimensionality and construct a single composite to capture the shared variation among them (Johnson & Wichern, 2002; Jolliffe & Cadima, 2016). This approach had been adopted and tested in previous research (Abson et al., 2012; Burck et al., 2022). Prior to PCA, all variables were standardized (z-scores) to ensure comparability and equal weighting across differing measurement scales.

Table 4: Indicators Related to Climate Perception Index

Variable	Description
affectweather	Estimated percentage who somewhat or strongly agree that global warming is affecting the weather in the United States
consensus	Estimated percentage who believe that most scientists think global warming is happening
futuregen	Estimated percentage who think global warming will harm future generations a moderate amount or a great deal
happening	Estimated percentage who think that global warming is happening
harmplants	Estimated percentage who think global warming will harm plants and animal species a moderate amount or a great deal
harmus	Estimated percentage who think global warming will harm people in the US a moderate amount or a great deal
human	Estimated percentage who think that global warming is caused mostly by human activities
personal	Estimated percentage who think global warming will harm them personally a moderate amount or a great deal
timing	Estimated percentage who think global warming will start to harm people in the United now or within 10 years
worried	Estimated percentage who are somewhat or very worried about global warming

After computing the eigenvalues and eigenvectors of the correlation matrix, the first principal component (PC1) was retained and interpreted as the Climate Perception Index, as it explains the largest share of the total variance across the selected indicators. Specifically, PC1 was found to account for approximately 85.97% of the total variance, indicating that it effectively summarizes the underlying patterns of climate risk awareness, concern, and perceived impact in the population. The high proportion of explained variance justifies the use of PC1 as a valid proxy for the multidimensional construct of climate perception. Furthermore, table 6 shows loadings of each variable on PC1, indicating how strongly each indicator contributes to the overall index. Variables such as *consensus, harmus, human*, and *worried* exhibit relatively high positive loadings, reinforcing the interpretation of PC1 as a unified factor of climate belief and perception. By summarizing complex attitudinal data into a single index, this approach allows for more parsimonious modeling in regression analysis while mitigating issues of multicollinearity. CPI performs as the key independent variable in modelling.

Table 5: Correlation Matrix of Indicators Related to Climate Perception Index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) affectweather	1.000									
(2) consensus	0.880	1.000								
(3) futuregen	0.880	0.983	1.000							
(4) happening	0.953	0.986	0.996	1.000						
(5) harmplants	0.911	0.974	0.999	0.995	1.000					
(6) harmus	0.816	0.985	0.995	0.996	0.993	1.000				
(7) human	0.905	0.986	0.996	0.997	0.994	0.994	1.000			
(8) personal	0.728	0.977	0.983	0.989	0.975	0.994	0.986	1.000		
(9) timing	0.778	0.982	0.982	0.990	0.972	0.993	0.985	0.992	1.000	
(10) worried	0.894	0.988	0.994	0.997	0.991	0.997	0.996	0.995	0.992	1.000

Table 6: Weights of PC1

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Weight	0.092	0.120	0.109	0.109	0.104	0.119	0.120	0.027	0.079	0.120

Distance to Coastline (CD)

Distance to coastline (CD) directly relates to the physical vulnerability of households and reflects the differential effects across geographic locations. Coastal zones are particularly susceptible to climate change impacts not only through sea-level rise (Baldauf et al., 2020; Tarui et al., 2023), but also through interannual and long-term changes in winds, storm surges, and wave action (Griggs et al., 2021). The calculation of CD is based on the annual county boundary shapefiles provided by the Census Bureau's Topologically Integrated Geographic Encoding and Referencing (TIGER) dataset. Given the number of counties (over 3,000) and the complexity of the coastline geometries, I utilized a nearest neighbor approximation to enhance efficiency rather than calculating the full pairwise distance matrix between county centroids and all coastal geometries. By identifying the single closest point on the coastline to each county centroid, the actual geodesic distance can be retrieved and converted to thousand km. This approach yields results that are effectively equivalent to those obtained by scanning all possible distances.

Other Variables

Several other variables are included to perform as independent variables and control variables. All these variables are extracted based on the American Community Survey. Income (I) is the median income level of households in the same county each year. Ownership (HO) means the percentage of houses owned by the household. 'Age65', 'Poverty', and 'New' are three control variables. 'Age65'measures the percentage of elderly people compared to the total county population, 'Poverty' measures the percentage of households with incomes below the income level, and 'New' measures the percentage of newly built buildings within the county with construction year after 2010. In addition, interaction terms such as I*HO (Household income and home ownership), CPI*CD (Climate Perception Index and Distance to coastlines), and CPI*HO (Climate Perception Index and home ownership) are created to be further employed. Factors of county and year are used to construct fixed-effect models.

Table 7: Descriptive Statistics

	N	Mean	St. Dev.	Median	Min	P25	P75	Max	t value
HP	28,255	11.80	0.48	11.74	9.84	11.46	12.07	14.18	4151.07
PTI	28,255	2.80	1.07	2.58	0.54	2.15	3.16	11.88	441.70
MR	28,255	86.10	4.33	86.60	47.16	83.86	88.90	100.00	3344.27
CPI	28,255	19.19	10.66	19.20	-1.94	10.26	24.08	65.01	302.73
INC	28,255	52.52	14.94	50.43	17.11	42.41	59.47	170.46	590.92
HO	28,255	71.80	8.23	72.99	18.97	67.76	77.36	96.99	1467.13
CD	28,255	0.58	0.43	0.54	0.00	0.19	0.92	1.61	228.03
Age65	28,255	1.24	0.45	1.18	0.00	0.96	1.44	7.55	469.87
Poverty	28,255	14.96	6.11	14.11	1.04	10.62	18.28	57.99	411.82
New	28,255	1.15	1.67	0.60	0.00	0.14	1.52	46.14	116.35

Table 8: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) HP	1.00									
(2) PTI	0.82	1.00								
(3) MR	-0.16	-0.19	1.00							
(4) CPI	0.35	0.28	-0.03	1.00						
(5) INC	0.76	0.33	-0.02	0.33	1.00					
(6) HO	-0.14	-0.32	0.54	-0.23	0.09	1.00				
(7) CD	-0.22	-0.33	0.02	-0.14	0.01	0.19	1.00			
(8) Age65	-0.01	0.04	0.23	0.01	-0.07	0.31	0.06	1.00		
(9) Poverty	-0.51	-0.11	-0.03	-0.06	-0.72	-0.33	-0.24	-0.09	1.00	
(10) New	0.17	0.10	-0.10	0.12	0.16	-0.01	-0.07	-0.05	-0.10	1.00

3.2 Hypotheses

According to the previous elaboration in the literature review and variable construction section, three hypotheses are listed below to investigate the influence of climate perception and objective risk on three dependent variables, respectively. The hypotheses are:

H1 (House Value): Counties with higher levels of climate change perception tend to have lower house values, possibly reflecting climate risk pricing in local housing markets.

H2 (Price-to-Income Ratio): Stronger climate change perception is correlated with lower price-to-income ratios, as heightened risk perception might reduce relative housing demand.

H3 (Migration Rate): Greater climate change awareness is linked to higher residential mobility, potentially reflecting increased sensitivity to environmental risk or climate-related relocation preferences.

3.3 Model

The study estimates a two-way fixed-effect model where the outcome variables regressed on Climate Perception Index, Income, Ownership, Distance to coastlines, controlling for elderly share, poverty rate, and the proportion of newly built houses, along with county and year fixed effects to remove the time-invariant heterogeneity of different counties and years from the error terms. The baseline model includes the following terms:

$$Y_{c,t} = \beta_0 + \beta_1 CPI_{c,t} + \beta_2 INC_{c,t} + \beta_3 HO_{c,t} + \beta_4 CD_{c,t} + \beta_5 Age65_{c,t} + \beta_6 Poverty_{c,t} + \beta_7 New_{c,t} + \alpha_c + \delta_t + \varepsilon_{c,t}\,, \quad (1)$$

$Y_{c,t}$ indicates dependent variables HP, PTI, MR respectively. α_c implies the county-fixed effect, and δ_t implies year-fixed effects. $\varepsilon_{c,t}$ denotes the error terms.

To further examine the conditional effects and potential heterogeneity in household responses, interaction terms $INC \cdot HO, CPI \cdot CD, CPI \cdot HO$ are introduced into various models. $INC \cdot HO$ captures whether the influence of income on outcome variables varies across different levels of homeownership. $CPI \cdot CD$ allows the model to assess whether the impact of climate awareness is stronger or weaker depending on geographic exposure to risk. Similarly, $CPI \cdot HO$ investigates whether relationships between climate perception and dependent variables are moderated by housing tenure status. These interaction terms help to create a more nuanced understanding of how demographic and spatial characteristics shape behavioral responses to climate risk.

In the end, the full model is shown below:

$$Y_{c,t} = \beta_0 + \beta_1 CPI_{c,t} + \beta_2 INC_{c,t} + \beta_3 HO_{c,t} + \beta_4 CD_{c,t} + \beta_5 Age65_{c,t} + \beta_6 Poverty_{c,t} + \beta_7 New_{c,t} + \theta_1 INC_{c,t} \cdot HO_{c,t} + \theta_2 CPI_{c,t} \cdot CD_{c,t} + \theta_3 CPI_{c,t} \cdot HO_{c,t} + \alpha_c + \delta_t + \varepsilon_{c,t}, \quad (2)$$

CHAPTER 4 RESULTS ANALYSIS

Based on the above model specifications, I empirically tested the regression models in R Studio with the result tables attached below.

4.1 Housing Price

Table 9: Results of Two-way Fixed Effects Model (HP)

	Dependent variable: HP (log median house price)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CPI	-0.0005***	-0.0005***	-0.001***	-0.0005***	-0.001***	-0.0005***	-0.001***	-0.001***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
INC	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
HO	-0.001**	-0.006***	-0.001**	-0.004***	-0.006***	-0.006***	-0.003***	-0.007***
	(0.0005)	(0.0020)	(0.0004)	(0.0010)	(0.0020)	(0.0020)	(0.0010)	(0.0020)
CD	-6.345***	-6.357***	-6.906***	-6.326***	-6.922***	-6.341***	-6.888***	-6.905***
	(1.8630)	(1.8630)	(1.8610)	(1.8630)	(1.8600)	(1.8630)	(1.8600)	(1.8600)
Age65	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Poverty	0.0002	0.0002	0.0002	0.0002	0.0001	0.0002	0.0002	0.0001
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
New	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
INC*HO		0.0001***			0.0001***	0.0001**		0.0001**
		(0.0000)			(0.0000)	(0.0000)		(0.0000)
CPI*CD			0.001***		0.001***		0.001***	0.001***
			(0.0001)		(0.0001)		(0.0001)	(0.0001)
CPI*HO				0.0001***		0.0001**	0.0001***	0.0001**
				(0.0001)		(0.0001)	(0.0001)	(0.0001)
Cty FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	28,135	28,135	28,135	28,135	28,135	28,135	28,135	28,135
F-Stat	319.239*** (df = 7; 24990)	280.506*** (df = 8; 24989)	291.407*** (df = 8; 24989)	280.392*** (df = 8; 24989)	260.174*** (df = 9; 24988)	249.825*** (df = 9; 24988)	259.961*** (df = 9; 24988)	234.570*** (df = 10; 24987)

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

Table 9 presents the results of 8 different models with HP (log-transformed median house values) as the dependent variable. All models consistently suggest that the Climate Perception Index (CPI) negatively impacts house prices, statistically significant at the 1% level. Specifically, since HP takes the logarithmic form and CPI is expressed in levels, a one-unit increase in CPI results in approximately 0.05% to 0.1% lower house value, after controlling for various socioeconomic factors. This aligns with previous research that awareness of flood risks and natural disasters negatively affects property values (Bernstein et al., 2019; Michaels et al., 2020).

Additionally, Income has a positive and highly significant coefficient (0.006), indicating that a $1,000 increase in median household income is associated with approximately a 0.6% increase in housing values, which is intuitively expected since higher-income areas mostly have higher property value. The negative coefficients on Distance suggest coastal proximity significantly increases house prices, implying the 'coastal premium' (Major & Lusht, 2004; Conroy & Milosch, 2011). Control variables show that areas with higher proportions of elderly populations are associated with lower housing values, while newly built houses have a consistently positive impact, reflecting modern amenities or improved resilience against climate risks.

The positive interaction between income and ownership (0.0001, significant at the 5% level) further suggests that the negative effect of homeownership on housing price is mitigated in higher-income areas. Similarly, the positive interaction between CPI and distance to coast (0.001, significant at the 1% level) indicates that the negative impact of climate risk perception diminishes with increasing distance from coastal areas, aligning with theoretical expectations that coastal regions are more sensitive to climate change concerns. Furthermore, the CPI and HO interaction (0.0001, significant at the 5% level) further suggests that areas with higher homeownership rates experience less negative impact from climate risk perception on housing values. Overall, these findings robustly support Hypothesis 1, confirming that the risk of climate is incorporated into house prices to some extent.

4.2 Price-to-Income Ratio

Table 10: Results of Two-way Fixed Effects Model (PTI)

	Dependent variable: PTI (price to income ratio)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CPI	0.003***	0.003***	0.002***	0.003***	0.002***	0.003***	0.002***	0.002***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
INC	-0.019***	-0.020***	-0.018***	-0.019***	-0.019***	-0.020***	-0.019***	-0.019***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
HO	-0.003*	-0.071***	-0.002*	-0.019***	-0.072***	-0.074***	-0.019***	-0.074***
	(0.0010)	(0.0050)	(0.0010)	(0.0030)	(0.0050)	(0.0050)	(0.0030)	(0.0050)
CD	0.346	0.151	-1.204	0.472	-1.438	0.201	-1.076	-1.387
	(5.8560)	(5.8310)	(5.8510)	(5.8510)	(5.8250)	(5.8300)	(5.8460)	(5.8250)
Age65	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Poverty	0.016***	0.015***	0.016***	0.016***	0.015***	0.015***	0.016***	0.015***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
New	0.031***	0.031***	0.031***	0.031***	0.032***	0.031***	0.031***	0.032***
	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
INC*HO		0.001***			0.001***	0.001***		0.001***
		(0.0001)			(0.0001)	(0.0001)		(0.0001)
CPI*CD			0.003***		0.003***		0.003***	0.003***
			(0.0003)		(0.0003)		(0.0003)	(0.0003)
CPI*HO				0.001***		0.0003*	0.001***	0.0003*
				(0.0001)		(0.0001)	(0.0001)	(0.0001)
Cty FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	28,135	28,135	28,135	28,135	28,135	28,135	28,135	28,135
F-Stat	328.134*** (df = 7; 24990)	316.451*** (df = 8; 24989)	296.421*** (df = 8; 24989)	292.294*** (df = 8; 24989)	290.124*** (df = 9; 24988)	281.747*** (df = 9; 24988)	268.084*** (df = 9; 24988)	261.502*** (df = 10; 24987)

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

Table 10 investigates the price-to-income ratio (PTI). CPI shows consistent positive significance across all specifications (0.002, significant at the 1% level), contradicting Hypothesis 2 that a higher climate perception translates into a higher PTI. This somewhat counters the intuition that higher risk perception might reduce housing demand, but empirically implies housing prices rise at a faster rate than local incomes. A plausible explanation is that climate-conscious households prioritize safer and more climate-resilient areas, thus competing intensely for the limited local housing stock and driving up prices disproportionately relative to incomes. Households may decide to trade off higher housing costs for perceived safety, resulting in higher PTI. Such dynamics align with the concept of 'climate gentrification' in recent literature (Keenan et al., 2018), denoting the phenomenon where rising costs of living in areas facing climate change impacts drive out low-income residents and attract wealthier people seeking safer or more resilient housing options. Baldauf et al. (2020) further illustrate that areas with higher belief in climate change experience stronger price premiums, reinforcing that housing price escalation under heightened climate consciousness surpasses local income growth, thereby raising affordability pressures.

Regarding other explanatory variables, Income exhibits a robust negative effect (-0.019, significant at the 1% level) across all models. A $1,000 increase in median household income is associated with approximately a 1.9% decrease in PTI, showing improved housing affordability. Ownership demonstrates a significant negative relationship with PTI (-0.002 to -0.074, significant at the 10% level), also suggesting that areas with higher homeownership tend to have lower affordability issues. Control variables reveal that areas with higher poverty rates are associated with worse affordability (0.015, significant at the 1% level), and areas with more newly built housing stock also show higher PTI (0.032, significant at the 1% level). Notably, the Distance variable is not statistically significant across any models.

Interaction terms still underscore important nuances. The interaction between Income and HO (0.001, significant at the 1% level) suggests that the affordability benefits of homeownership diminish in higher-income areas, while the interaction between CPI and CD (0.003, significant at the 1% level) implies the negative impact of climate risk perception on affordability strengthens with increasing distance from coastal areas. CPI and ownership interaction (0.0003 to 0.001, significant at the 10% level) further explains that areas with higher ownership experience stronger negative impacts from climate risk perception on affordability. Overall, this table implies that the perceived environmental safety concerns significantly inflate property values beyond income growth rates.

4.3 Migration Rate

Table 11 explores the impacts on migration rates (MR). CPI is positively and significantly correlated with MR (0.004 to 0.006, significant at the 10% level), supporting Hypothesis 3. Areas with higher climate risk awareness experience more population turnover, possibly due to households actively relocating in anticipation of climate risks or as a reaction to heightened risk perception (Hauer et al., 2020). This also reconfirms the study of Boustan et al. (2020) that climate disasters increase migration rates. Negative and significant coefficients on Income (-0.020, significant at the 1% level) suggest wealthier counties have lower migration, possibly due to better local adaptation capacity and resilience. Ownership significantly increases MR (0.263 to 0.361, significant at the 1% level), indicating an increase in migration decisions among homeowner-dominated counties. The CD variable is not statistically significant across any models. For control variables, areas with higher elderly populations show lower mobility (-0.034 to -0.035, significant at the 1% level), higher poverty rates are associated with decreased mobility (-0.122 to -0.124, significant at the 1% level), and areas with more newly built housing stock has a negative coefficient estimate (-0.087, significant at the 1% level), indicating that newer infrastructure decreases household incentives to relocate. The CD variable is not statistically significant across any models.

Table 11: Results of Two-way Fixed Effects Model (MR)

	Dependent variable: MR (migration rate)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CPI	0.006***	0.006***	0.004*	0.006***	0.004*	0.006***	0.004**	0.004**
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
INC	-0.021***	-0.020***	-0.021***	-0.021***	-0.020***	-0.020***	-0.021***	-0.020***
	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)
HO	0.263***	0.349***	0.263***	0.299***	0.348***	0.361***	0.300***	0.360***
	(0.0120)	(0.0410)	(0.0120)	(0.0250)	(0.0410)	(0.0420)	(0.0250)	(0.0420)
CD	-3.505	-3.261	-7.059	-3.782	-6.769	-3.477	-7.344	-7.001
	(48.4050)	(48.4010)	(48.4260)	(48.4040)	(48.4220)	(48.4020)	(48.4240)	(48.4230)
Age65	-0.034***	-0.034***	-0.035***	-0.034***	-0.035***	-0.034***	-0.035***	-0.035***
	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)
Poverty	-0.124***	-0.122***	-0.124***	-0.124***	-0.123***	-0.123***	-0.124***	-0.123***
	(0.0130)	(0.0140)	(0.0130)	(0.0130)	(0.0140)	(0.0140)	(0.0130)	(0.0140)
New	-0.088***	-0.089***	-0.087***	-0.088***	-0.088***	-0.089***	-0.087***	-0.087***
	(0.0240)	(0.0240)	(0.0240)	(0.0240)	(0.0240)	(0.0240)	(0.0240)	(0.0240)
INC*HO		-0.002**			-0.002**	-0.001*		-0.001*
		(0.0010)			(0.0010)	(0.0010)		(0.0010)
CPI*CD			0.006**		0.006**		0.006**	0.006**
			(0.0030)		(0.0030)		(0.0030)	(0.0030)
CPI*HO				-0.002		-0.001	-0.002*	-0.001
				(0.0010)		(0.0010)	(0.0010)	(0.0010)
Cty FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	28,143	28,143	28,143	28,143	28,143	28,143	28,143	28,143
F-Stat	94.868*** (df = 7; 24998)	83.645*** (df = 8; 24997)	83.679*** (df = 8; 24997)	83.351*** (df = 8; 24997)	74.929*** (df = 9; 24996)	74.469*** (df = 9; 24996)	74.687*** (df = 9; 24996)	67.546*** (df = 10; 24995)

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

For interaction terms, the interaction between income and HO (-0.001, significant at the 10% level) suggests that the mobility-increasing effect of homeownership diminishes in higher-income areas, while the negative impact of interaction between CPI and HO marginally significant in model (7) (-0.002, significant at the 10% level), suggesting that areas with higher ownership rates may experience slightly weaker impacts from climate risk perception on migration.

Overall, these results consistently demonstrate that climate risk perception significantly shapes housing market outcomes and household mobility patterns. The negative capitalization of climate risks incorporated into house prices (H1), positive association with price-to-income ratios (H2), and increased migration rates (H3) correspond to three hypotheses and collectively underscore the critical importance of climate awareness in urban economic decisions.

CHAPTER 5 ROBUSTNESS CHECKS

The previous three regression tables have shown rigorous robustness checks through the process by incrementally introducing interaction terms from the baseline model (1) to the full model (8). The negative relationship between CPI and HP, the positive relationship between CPI and PTI, and the positive relationship between CPI and MR all remain consistently significant across various model configurations. This confirms that the robustness of the main findings is effectively verified.

Panel Models with Lagged Variables

The study also introduced another robustness check to account for temporal autocorrelation and omitted dynamic effects within the panel data framework by including a one-year lag of the dependent variable as a regressor. Lagging was performed within the panel data structure in R, ensuring that values are appropriately lagged across county (distinguished by unique GEOID) and time (year) dimensions.

This approach is particularly relevant in panel settings with path dependence. (e.g., Arellano & Bond, 1991; Angrist & Pischke, 2009). In the context of this study, present outcomes might be inherently dependent on past values. Current median house values (HP), housing affordability (PTI), and migration rates (MR) may be influenced by their historical realizations due to persistent local trends, gradual price adjustments, or inertia in household decisions. Adding $Y_{c,t-1}$ as an explanatory variable on the right-hand side of equations enables the models to capture dynamic effects and ensures the estimated impacts of CPI and other explanatory variables are not confounded by serial correlation in the dependent variable. In addition, this approach could strengthen the identification of causal patterns by controlling for unobserved and time-varying county-level factors that influence both current and past values of the dependent variables. The intuition is that if the coefficient estimates of key regressors remain statistically significant and consistent after adding the lagged dependent variable, then the robustness of baseline findings is reinforced.

Now, with the lagged variable, the baseline model includes the following terms:

$$Y_{c,t} = \beta_0 + \mu Y_{c,t-1} + \beta_1 CPI_{c,t} + \beta_2 INC_{c,t} + \beta_3 HO_{c,t} + \beta_4 CD_{c,t} + \beta_5 Age65_{c,t} + \beta_6 Poverty_{c,t} + \beta_7 New_{c,t} + \alpha_c + \delta_t + \varepsilon_{c,t}\,, \quad (3)$$

And the full model becomes:

$$Y_{c,t} = \beta_0 + \mu Y_{c,t-1} + \beta_1 CPI_{c,t} + \beta_2 INC_{c,t} + \beta_3 HO_{c,t} + \beta_4 CD_{c,t} + \beta_5 Age65_{c,t} + \beta_6 Poverty_{c,t} + \beta_7 New_{c,t} + \theta_1 INC_{c,t} \cdot HO_{c,t} + \theta_2 CPI_{c,t} \cdot CD_{c,t} + \theta_3 CPI_{c,t} \cdot HO_{c,t} + \alpha_c + \delta_t + \varepsilon_{c,t}, \quad (4)$$

In such a setting, μ captures the degree of path dependence of $Y_{c,t-1}$on $Y_{c,t}$, measuring how strongly $Y_{c,t}$ is associated with its own past realization. β_1 to β_7 as the coefficients of contemporaneous independent variables now estimate the short-run marginal effect, which is how much $Y_{c,t}$ is expected to change in response to a one-unit change in regressors, controlling for the persistence captured by $Y_{c,t-1}$. This setup allows for isolating the immediate (within-period) impact of regressors, disentangled from dynamic feedback embedded in the models. With new specifications, results are summarized in three more tables below.

5.1 Housing Price

Table 12 demonstrates the robustness check results for log-transformed median house values with a lagged variable included. The coefficient estimate of $HP_{c,t-1}$ is strongly positive across all specifications (0.739, statistically significant at the 1% level), showing approximately 74% of the previous year's price level carrying over, and confirms path dependence in housing prices as the market adjusts gradually to conditional changes.

Table 12: Results of Robustness Check with Lagged Variable (HP)

	Dependent variable: HP (log median house price)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HP (t-1)	0.739***	0.739***	0.739***	0.739***	0.739***	0.739***	0.739***	0.739***
	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)
CPI	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
INC	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
HO	-0.0005	-0.001	-0.0005	-0.002**	-0.001	-0.002*	-0.002**	-0.002*
	(0.0003)	(0.0004)	(0.0003)	(0.0010)	(0.0004)	(0.0010)	(0.0010)	(0.0010)
CD	-0.0001	-0.0001	-0.001	-0.0001	-0.001	-0.0001	-0.001	-0.001
	(0.0004)	(0.0004)	(0.0010)	(0.0004)	(0.0010)	(0.0004)	(0.0010)	(0.0010)
Age65	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Poverty	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
New	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
INC*HO		0.0004			0.0004	0.0003		0.0003
		(0.0004)			(0.0004)	(0.0004)		(0.0004)
CPI*CD			-0.00004		-0.00004		-0.00004	-0.00004
			(0.00004)		(0.00004)		(0.00004)	(0.00004)
CPI*HO				-0.0001		-0.00005	-0.0001	-0.00005
				(0.00003)		(0.00004)	(0.00003)	(0.00004)
Cty FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	25,000	25,000	25,000	25,000	25,000	25,000	25,000	25,000
R^2	0.529	0.529	0.529	0.529	0.529	0.529	0.529	0.529
Adj R^2	0.461	0.461	0.461	0.461	0.461	0.461	0.461	0.461
F-Stat	3,069.622*** (df = 8; 21856)	2,728.705*** (df = 9; 21855)	2,728.709*** (df = 9; 21855)	2,728.993*** (df = 9; 21855)	2,455.977*** (df = 10; 21854)	2,456.090*** (df = 10; 21854)	2,456.234*** (df = 10; 21854)	2,232.938*** (df = 11; 21853)

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

The coefficient estimate of CPI remains negative (-0.0002, significant at the 1% level), indicating that after controlling for past house prices, higher climate awareness consistently exerts downward pressure on house values, although the impact becomes modest. Income retains its positive impact (0.014, significant at the 1% level), indicating the robustness of income's positive influence on housing prices. HO now shows a weak negative effect that becomes significant only in models with interaction terms. Control variables like Poverty and New remain broadly consistent with the original models, highlighting stability in the estimated relationships.

Notably, interaction terms become insignificant, suggesting the primary explanatory variables sufficiently capture the dynamics without significant conditional effects. The moderating effects of CD and HO become less pronounced. Overall, the stability of the negative effect of CPI on HP across all 8 models is strengthened.

5.2 Price-to-Income Ratio

The results of price-to-income ratio is shown in Table 13. $PTI_{c,t-1}$ exhibits positive persistence (0.692, significant at the 1% level). CPI consistently demonstrates a positive coefficient (0.001, significant at the 1% level), affirming previous findings that higher climate awareness correlates with rising housing affordability pressures, after controlling for past affordability levels.

Income's negative relationship with PTI remains robust (-0.141, significant at the 1% level), reinforcing that higher median income areas alleviate affordability issues. HO also exhibits a significant negative relationship with PTI (-0.002 to -0.010, significant at the 5% level), confirming that areas with higher homeownership tend to have better affordability. Distance to coastlines is insignificant across all panels. Controls maintain consistent patterns, with the elderly population showing a slight positive effect on PTI (0.002, significant at the 10% level), and newly built housing associated with worse affordability (0.019, significant at the 1% level).

Table 13: Results of Robustness Check with Lagged Variable (PTI)

	Dependent variable: PTI (price to income ratio)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PTI (t-1)	0.692***	0.692***	0.692***	0.692***	0.692***	0.692***	0.692***	0.692***
	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)
CPI	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
INC	-0.141***	-0.141***	-0.141***	-0.141***	-0.141***	-0.141***	-0.141***	-0.141***
	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
HO	-0.002**	-0.003**	-0.002**	-0.010***	-0.003**	-0.009***	-0.010***	-0.009***
	(0.0010)	(0.0010)	(0.0010)	(0.0020)	(0.0010)	(0.0020)	(0.0020)	(0.0020)
CD	-0.001	-0.001	0.002	-0.001	0.001	-0.001	0.001	0.001
	(0.0010)	(0.0010)	(0.0030)	(0.0010)	(0.0030)	(0.0010)	(0.0030)	(0.0030)
Age65	0.002*	0.002*	0.002*	0.002*	0.002*	0.002*	0.002*	0.002*
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Poverty	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
New	0.019***	0.019***	0.019***	0.019***	0.019***	0.019***	0.019***	0.019***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
INC*HO		0.002*			0.002*	0.001		0.001
		(0.0010)			(0.0010)	(0.0010)		(0.0010)
CPI*CD			-0.0001		-0.0001		-0.0001	-0.0001
			(0.0001)		(0.0001)		(0.0001)	(0.0001)
CPI*HO				0.0003***		0.0003***	0.0003***	0.0003***
				(0.0001)		(0.0001)	(0.0001)	(0.0001)
Cty FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	24,998	24,998	24,998	24,998	24,998	24,998	24,998	24,998
R^2	0.555	0.555	0.555	0.555	0.555	0.555	0.555	0.555
Adj R^2	0.491	0.491	0.491	0.491	0.491	0.491	0.491	0.491
F-Stat	3,402.958*** (df = 8; 21854)	3,025.639*** (df = 9; 21853)	3,024.888*** (df = 9; 21853)	3,027.364*** (df = 9; 21853)	2,723.105*** (df = 10; 21852)	2,724.794*** (df = 10; 21852)	2,724.661*** (df = 10; 21852)	2,477.114*** (df = 11; 21851)

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

Interaction terms also reflect consistent trends. The interaction between CPI and HO remains positive (0.0003, significant at the 1% level), indicating areas with higher ownership rates exhibit amplified negative impacts of climate risk perception on affordability. This dynamic panel model robustly confirms the climate-driven premium and affordability patterns.

5.3 Migration Rate

Lastly, Table 14 reveals the results for MR. The coefficient estimate of $MR_{c,t-1}$ indicate significant positive temporal dependence (0.670, significant at the 1% level), suggesting migration patterns strongly reflect past trends. However, unlike in static models, now CPI loses statistical significance after adding $MR_{c,t-1}$. This can be explained as the immediate impact of climate perception on mobility is somewhat absorbed by historical migration behaviors. This indicates climate perception may affect population movement gradually rather than instantaneously. HO remains to affect MR positively (coefficient estimate between 0.155-0.203, significant at the 1% level), while Income and CD remain statistically insignificant. Control variables maintain consistent impacts. The coefficient estimate is -0.019 for Age65, -0.061 for poverty, and -0.073 for newly built housing, all show negative associations with migration at the 5% significance level.

The impact of interaction between Income and HO is significantly negative (-0.019 to -0.024, significant at the 5% level), implying the mobility-enhancing effect of homeownership diminishes as income rises, reflecting slight income-dependent behavioral patterns. In addition, the interaction of CPI and HO has a negative coefficient (-0.002, significant at the 10% level), suggesting that the relationship is consistently weaker in areas with higher homeownership rates. This interaction effect is robust across both static and dynamic models.

Table 14: Results of Robustness Check with Lagged Variable (MR)

	Dependent variable: MR (migration rate)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MR (t-1)	0.670***	0.670***	0.670***	0.670***	0.670***	0.670***	0.670***	0.670***
	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)
CPI	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
INC	-0.024	-0.024	-0.024	-0.024	-0.023	-0.024	-0.024	-0.024
	(0.0230)	(0.0230)	(0.0230)	(0.0230)	(0.0230)	(0.0230)	(0.0230)	(0.0230)
HO	0.155***	0.161***	0.155***	0.203***	0.161***	0.199***	0.203***	0.199***
	(0.0090)	(0.0100)	(0.0090)	(0.0220)	(0.0100)	(0.0220)	(0.0220)	(0.0220)
CD	0.01	0.01	0.039	0.01	0.039	0.01	0.039	0.039
	(0.0100)	(0.0100)	(0.0240)	(0.0100)	(0.0240)	(0.0100)	(0.0240)	(0.0240)
Age65	-0.019**	-0.019**	-0.019**	-0.019**	-0.019**	-0.019**	-0.019**	-0.019**
	(0.0090)	(0.0090)	(0.0090)	(0.0090)	(0.0090)	(0.0090)	(0.0090)	(0.0090)
Poverty	-0.061***	-0.061***	-0.061***	-0.061***	-0.061***	-0.061***	-0.061***	-0.061***
	(0.0110)	(0.0110)	(0.0110)	(0.0110)	(0.0110)	(0.0110)	(0.0110)	(0.0110)
New	-0.073***	-0.073***	-0.073***	-0.073***	-0.073***	-0.073***	-0.073***	-0.073***
	(0.0220)	(0.0220)	(0.0220)	(0.0220)	(0.0220)	(0.0220)	(0.0220)	(0.0220)
INC*HO		-0.024**			-0.024**	-0.019*		-0.019*
		(0.0110)			(0.0110)	(0.0110)		(0.0110)
CPI*CD			-0.001		-0.001		-0.001	-0.001
			(0.0010)		(0.0010)		(0.0010)	(0.0010)
CPI*HO				-0.002**		-0.002*	-0.002**	-0.002*
				(0.0010)		(0.0010)	(0.0010)	(0.0010)
Cty FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	25,010	25,010	25,010	25,010	25,010	25,010	25,010	25,010
R^2	0.457	0.457	0.457	0.457	0.457	0.457	0.457	0.457
Adj R^2	0.379	0.379	0.379	0.379	0.379	0.379	0.379	0.379
F-Stat	2,298.158*** (df = 8; 21866)	2,043.751*** (df = 9; 21865)	2,043.069*** (df = 9; 21865)	2,043.911*** (df = 9; 21865)	1,839.617*** (df = 10; 21864)	1,839.964*** (df = 10; 21864)	1,839.756*** (df = 10; 21864)	1,672.913*** (df = 11; 21863)

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

To sum up, incorporating lagged dependent variables effectively controls for potential temporal autocorrelation and omitted dynamic effects. New findings suggest that climate risk perception has a modest negative effect on housing values, worsens affordability, and has a limited direct relationship with mobility after controlling for past patterns. The interaction effects between CPI and socioeconomic factors (particularly HO) demonstrate varying degrees of robustness but overall are consistent with the impact direction of key variables in original findings. This lagged-form approach highlights the persistent and path-dependent nature of housing market and migration decisions, further reinforcing the validity of insights in the previous section.

CHAPTER 6 CONCLUSION

This study provides empirical evidence on the complex relationship between climate risk perceptions and household economic decisions in the United States. By constructing and implementing an index on climate awareness and analyzing its impact on three critical dimensions of household behavior and social mobility, the research offers several important insights into climate adaptation at the micro level.

First, the findings confirm that climate risk perception is incorporated into housing markets, with higher climate awareness associated with lower property values. This negative capitalization effect varies spatially, diminishing with distance from coastal areas, and is moderated by socioeconomic factors such as homeownership rates and income levels. The results align with the emerging literature on climate risk pricing in real estate markets (Bernstein et al., 2019; Baldauf et al., 2020) while offering a more nuanced understanding of its conditional effects across geographic and demographic dimensions. In addition, contrary to the initial hypothesis, heightened climate risk awareness correlates with higher price-to-income ratios, suggesting increased affordability challenges in climate-conscious counties. This finding potentially reflects a 'climate gentrification' phenomenon (Keenan et al., 2018), where climate risk perception drives competition for safer or more resilient properties, bidding up prices beyond local income growth. The robustness of this relationship across model specifications highlights the potential for climate awareness to exacerbate housing affordability pressures, particularly in vulnerable coastal communities. Lastly, the positive association between climate perception and migration decision supports the theory that households actively respond to perceived environmental risks through relocation decisions. This mobility response appears most pronounced in areas with lower homeownership rates, suggesting that housing tenure may constrain adaptive capacity through mobility. The findings contribute to our understanding of climate-induced migration (Hauer et al., 2020) by emphasizing the role of subjective risk perception in driving population movements, rather than just physical exposure.

The dynamic panel models further reveal that these responses exhibit strong path dependence, with current outcomes significantly influenced by historical patterns. The incorporation of lagged dependent variables confirms the persistence impact of climate risk perception, particularly on housing values and affordability, while suggesting that migration responses may emerge more gradually over time.

These empirical findings carry several policy implications. First, it should be acknowledged that climate risk potentially carries distributional consequences on housing markets, as information disparities may exacerbate spatial inequality through differential price impacts. Shi et al. (2016) argue that climate adaptation planning must explicitly address equity concerns to avoid reinforcing existing socioeconomic vulnerabilities, particularly in disadvantaged communities. Additionally, climate-vulnerable communities are worth the attention of housing programs, since risk perception can drive disproportionate price increases relative to incomes. Furthermore, the empirical findings on risk perception's incorporation into property values offer valuable insights for climate risk disclosure policies. Understanding how effective risk communication can help real estate markets accurately price risks of climate hazards in aggregate is pivotal (Hino & Burke, 2021), which potentially addresses issues of systematic over- or under-valuation in vulnerable areas. Well-designed disclosure requirements could enhance market efficiency while promoting more equitable climate adaptation. Lastly, the findings of this study provide insights on a broader level towards managed retreats for climate-related disasters. The managed retreat policies should consider both physical and perceptual risk factors, which could influence household mobility decisions. A successful managed retreat requires approaches that integrate social justice considerations alongside technical evaluations of physical vulnerability (Siders et al., 2019). This means addressing not only the physical risks posed by climate change, but also the potential for relocation to exacerbate existing social inequalities and create new ones.

This study still has limitations that could be addressed further. First, while the Climate Perception Index captures important dimensions of climate awareness, the availability of data constrains it from fully reflecting the complexity of risk perception or distinguishing between different types of climate hazards. As Slovic et al. (2013) argue in *The Feeling of Risk*, risk perception is multidimensional and culturally embedded, incorporating elements of dread, familiarity, and perceived control that simple indices may overlook. Future research could develop more precise measures that differentiate between perceptions of various climate threats (e.g., flooding, wildfires, heat waves) and capture dimensions such as risk salience and perceived adaptive capacity. Second, the county-level analysis provides valuable insights into aggregate patterns but cannot capture within-county heterogeneity (Howe et al., 2015). Neighborhood-level data could enable more direct examination of how climate perceptions influence specific decisions, potentially revealing mechanisms that are masked in aggregated data. Third, the temporal scope of the analysis (from 2014 to 2022) covers a period of increasing climate awareness but may not capture longer-term adaptation processes or responses to specific catastrophic events. Extending the time horizon and incorporating event-study methodologies could provide further insights. Finally, this study focuses primarily on housing markets and migration as adaptation channels, but households may respond to climate risks through numerous other mechanisms, such as insurance uptake, energy consumption patterns, or investments in protective infrastructure, etc. A more comprehensive examination of these alternative adaptation strategies would provide a more complete picture of household climate resilience.

Despite these limitations, this research contributes to the understanding of climate adaptation at the household level by empirically demonstrating how subjective risk perceptions influence crucial economic decisions. As climate change continues to reshape environmental conditions across the United States, understanding these behavioral responses becomes increasingly vital for designing effective adaptation policies and building community resilience in the face of growing climate uncertainty.

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