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CLIMATE CHANGE IMPACTS ON HOUSEHOLD LOCATION CHOICES IN THE U.S. AND ECONOMIC CONSEQUENCES

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by

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ABSTRACT

This research starts with an empirical analysis on household location choices under changes in climate extremes. It follows with a modeling component that simulates the welfare impacts of climate change on US households by linking a random utility model (RUM) with a computable general equilibrium (CGE) model. Linking these models enables feedbacks resulting from climate change-induced migration by simultaneously updating regional labor supply in the CGE model while changing labor wages in the empirical RUM model.

A residential sorting model is used to estimate household location choices and to reveal household marginal willingness to pay (MWTP) to reduce frequency of extreme weather in the United States. A two-stage random utility model (RUM) is used for estimation. The first-stage discrete choice model employs a multinomial logit specification to recover heterogeneous parameters associated with metropolitan statistical area (MSA) specific variables, migration costs, and the mean indirect utility of each MSA. The second stage of this model decomposes the mean indirect utility obtained from the first stage into its MSA-specific attributes controlling for unobservables using region fixed effects and an instrumental variable (IV). The estimated coefficients obtained from the sorting model are compared to results from a conventional wage-hedonic model to evaluate the relative performance of these two models.

Additionally, a recursive dynamic inter-regional computable general equilibrium (CGE) model is developed to simulate regional economic impacts. The model is calibrated to the IMPLAN 2010 state-level social accounting matrices (SAMs) for the U.S. and it solves at 1-year steps from 2010 to 2065 across 30 industrial sectors and 5 different regions in the US. An important innovation of this research is the coupling of the RUM with the CGE model to

endogenize labor wages. Coupling these two models through the labor market influences household location choices in the RUM and allows for changes in the industrial size and sectoral composition of regional economies in the CGE model. This approach allows for both preference heterogeneity and sectoral interactions in the regional economies based on an iterative process.

In the empirical component, we find that extreme temperatures and extreme precipitation reduce utility. People's preferences for temperature extremes are heterogeneous. The climate of one's place of birth and demographic characteristics such as age, climate of birth region, and educational attainment are significant factors that lead to preference heterogeneity. We also find that the conventional wage-hedonic model underestimates values of amenities.

In the modeling component, we find that population share in the Northeast increases due to an moderate increase in frequency of warm weather reflected in the climate change scenario used in the analysis, while population share in the Midwest drops due to significant increases in extreme weather days. After considering the feedback from the labor market, population share in the West increases but shares in the Northeast, Midwest, and South drop relative to the business as usual (BAU) scenario without climate change. While climate amenity and job opportunities are both important factors in households' location decisions, wage effects tend to dominate climate effects on location choices for the working-age population, and retirees place a higher value on climate amenities compared to workers. In the high-emission A2 scenario, the percentage decrease in gross regional product (GRP) is 1.66% for the Northeast, 3.20% for the Midwest, 2.30% for the South, and 0.68% for California while comparing the climate change-induced migration scenario to the BAU scenario in 2065. In contrast, GRP in the West increases by 12.93% in the climate change-induced migration scenario relative to the business as usual

(BAU) scenario. Our findings suggest that different mitigating policies should target different regions based on heterogeneous regional impacts. In addition, we find that endogenizing labor wages dampens regional economic impacts from climate change-induced migration. The results suggest that ignoring feedbacks from the equilibrium labor market will overstate the economic impacts of climate-induced migration.

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Chapter 1

Introduction

1.1 Background and Motivations

The Intergovernmental Panel on Climate Change (IPCC) projected that average surface air temperature has increased by $0.74^{\circ}C$ since 1900 and that sea level will rise by 0.6-1.6m by 2100 (IPCC, 2010). While mean temperatures are one measure of climate change, the IPCC expects that extreme temperatures and weather are also likely to occur (IPCC, 2011). These changes in weather extremes may include increased numbers of both extremely hot and cold days as well as extreme weather events such as tornados, floods, and droughts that may occur with a higher probability each year. As changes in weather extremes are likely to be perceived readily by households, understanding how people perceive existing extreme climate events is an important input into climate change policy.

For households and businesses, increasing frequencies of extreme weather are likely to result in significant economic losses. Extreme heat and the natural disasters associated with high temperatures (e.g. the 2012 drought across much of the interior United States) are likely to lead to large economic costs across multiple sectors of the economy including transportation, agriculture, energy, and public health. Similarly, increases in extremely cold weather have been found to result in significant costs due to long-lasting impacts on public health. Deschenes and Moretti (2007) found that the mortality rate attributable to extreme cold accounts for approximately 1.3% of the average annual deaths in the U.S. over their sample period, while an increase in mortality rate attributable to extreme heat is lower and the impact is short-lived.

For households, a large body of research has shown that individuals are both aware of and respond to differences in climate. Rappaport (2007) uses a model of steady state growth and county level data from 1970 to study the impact of climate on household migration decisions and finds that households appear to migrate to locations that on average have warmer winters, cooler summers and less humidity. In a structural location choice model applied to Brazilian households, Timmins (2007) finds that households sort on the basis of differences in climate across regions as well as endogenous labor market outcomes. Despite a considerable amount of research showing clear linkages between climate and household migration, modeling the impacts of changes in weather extremes, such as extreme temperatures and extreme events have not been as heavily studied in the existing literature. Understanding household valuation of climate change in terms of extremes can provide important insights needed for analyzing the cost effectiveness of relevant climate change policies, particularly those aimed at reducing economic costs resulting from the negative impacts of climate extremes.

Heterogeneity in regional impacts is a key component in studying the effect of weather extremes on residential location choices, since climate change impacts are likely to be heterogeneous across both regions and individuals. Hot regions in the U.S. that experience significant increases in frequency of extreme weather may be negatively affected, while moderate increase in hot weather may be beneficial to cold regions. Factors such as different climates of individuals' prior locations, age and mobility choices may also lead to preference heterogeneity. For example, people born in regions that have exposure to extreme weather are potentially more sensitive to climate extremes. The flow of retired individuals to southern states also provides strong evidence that different segments of the population may be more or less sensitive to temperature extremes than other segments of the population.

In addition to heterogeneity, factors that influence location choices are of great importance in the literature of regional science. There are different groups of researchers who focus on different drivers in people's migration decisions. For example, amenity including amenable climate is found to be a significant and the dominant driver in migration decisions in developed countries such as the U.S. (Graves, 1976, 1979, 1980; Deller et al, 2001; Partridge, 2010). On the other hand, the new economic geography (NEG) literature highlights the importance of economic activities in people's migration decisions. These two primary factors—climate amenity and economic activities—may play different roles in people's migration decisions for people with different demographics. Working age-population may place a high value on job opportunities, while retirees may value climate amenities to a larger extent. In addition, multiple factors may have mutual impacts for location choices. For example, as households relocate to different locations in response to changes in climate extremes, there are economic consequences from changes in local labor supply. As population and labor supply increases (decreases) in one region, labor wages are likely to change in the opposite direction. In this sense, endogenizing labor wages may dampen economic impacts from amenity-driven migration. Previous studies lack further exploration on multiple factors and their mutual effects on migration and location decisions for different demographics.

Beyond economic consequences in the labor market, there are economic impacts on other markets as well due to climate change-induced migration. As population and labor supply shift across regions, the spatial distribution and sectoral composition of firms are likely to change, which generates a ripple effect across sectors. Changes in labor supply lead to changes in firms' location and production decisions, thus leading to changes in the size and composition of industries. Previous studies that focus on limited markets (e.g. the housing and labor markets) cannot fully capture these impacts. In a general equilibrium framework, we can capture both direct and indirect effects. For example, labor-intensive sectors are directly affected by climate change-induced migration yet are indirectly affected through markets and prices. Prices of inputs and outputs in one sector might change as a result of impacts on other sectors from climate change-induced migration. Changes in prices induce the substitution of higher-priced commodities with lower-priced goods.

In terms of methodology, there are a few studies that couple a CGE model with a micro-simulation model to simulate welfare impacts of policy instruments (e.g. Peichil, 2008; Bohringer and Rutherford, 2006; Aaberge, 2004). These studies, however, are limited to a reduced-form empirical analysis. Timmins and Schlenker (2009) argue that a structural model should be employed in the case where feedback matters and endogeneity exists. In the framework of sorting, labor wages are endogenous. As more (less) working-age people relocate into a region, labor supply is likely to increase (decrease). Labor wages correspond to changes in labor supply. Given the problem of endogeneity of labor wages, previous studies that completely ignore feedbacks from the labor market or address feedback from the scope of a partial equilibrium model may lead to biased results.

To address these limitations discussed above, this research starts with a structural empirical Tiebout sorting model that has been widely used to analyze the demand for public goods that vary across space. The equilibrium sorting model used in this study models the way households sort into local jurisdictions to maximize utility and obtain an optimal level of local public goods given prices and location choices of other households.

This empirical component is coupled with a computable general equilibrium (CGE) model, which simulates economic activities across 30 aggregated industrial sectors and 5 regions under different scenarios. The CGE model allows for the reallocation of factors including labor and capital across sectors and regions and captures interactions across different sectors through general equilibrium effects. Coupling these two models together, we can better simulate the regional economic impacts from climate change-induced migration through endogenizing labor wages. The linkage of the empirical structural model and the CGE model relies on estimated coefficients from the empirical component that predicts population shares by region in the US under changes in climate extremes. Population shares across regions can adjust for regional population and distribution of laborers, and are further used to calculate regional labor supply. Shifts in labor supply from the empirical model are used as inputs into the CGE model. The CGE model solves for the equilibrium wage at the regional level in response to changes in regional labor supply. These variables are disaggregated at the Metropolitan Statistical Area (MSA)-level and are fed back into the empirical model. Iterations continue between these two models until convergence criteria are satisfied: 1) locational equilibrium is achieved in the RUM, which means nobody has an incentive to move given others' location choices; 2) the wage rates that clear the labor market are determined by the CGE model and stay almost unchanged over iterations. This coupling process enables us to examine the effect on location decisions from two important factors--climate amenity and job opportunity for different demographics.

1.2 Objectives and Dissertation Outline

To summarize the research objectives, this dissertation aims to answer the following questions:

1) What are the effects of climate extremes on household location choices in the U.S.?

2) What are the differences in estimating values of climate (dis)amenities between the residential sorting model and the conventional wage-hedonic model?

3) How would changes in residential locational choices affect regional economies in the U.S.?

4) What are the differences in simulating economic impacts between the model with endogenized labor wages and the model that assumes exogenous wages?

The dissertation is structured as follows. Chapter 2 conducts a thorough literature review on residential location choices and regional economic impacts of climate change, followed by an introduction of a research approach that links the sorting model with a detailed model of regional economic activity to allow for feedbacks from re-sorting behaviors under changes in climate. Chapter 3 describes different datasets used for the empirical and modeling components of this study. The process of creating climate extremes from both observed and projected climate datasets is discussed in this section. Chapter 4 provides an empirical analysis that examines the effects of climate change on residential location choices in the U.S. in terms of extremes. In this chapter, results from the residential sorting model are compared to these from the conventional wage-hedonic model to evaluate the model performance while estimating implicit values of climate amenities. Chapter 5 describes the model structure of a recursive dynamic inter-regional CGE model, followed by Chapter 6 that describes the coupling process to endogenize labor wages. Economic impacts from climate change-induced migration are discussed in this section in terms of economic indicators such as regional GDP, total consumption, investment, government spending, and net exports. Two counterfactual scenarios—one with endogenized labor wages, the other without—are conducted in this section to analyze the biasness of ignoring feedbacks from the general equilibrium markets. The last chapter summarizes main findings and concludes with future directions.

Chapter 2

Literature Review and Research Approach

2.1 Literature Review

A substantial body of existing literature has employed reduced form models to measure household preferences for non-market goods, including climate. Both Rosen's (1979) first-stage hedonic and Roback's (1982) model have been commonly employed to uncover marginal valuations of (dis) amenities by exploiting housing and wage equilibria to estimate preferences. As these models rely on equilibria to reveal preferences, they do not directly model the maximizing behavior that leads to the observed equilibria. Despite their use in recovering marginal valuation for a wide-range of bundled non-market amenities, the use of reduced form models raise several challenges that are especially relevant in the study of climate change. First, by modeling the equilibrium outcome itself, reduced form models are largely unable to account for migration costs. As discussed by Timmins(2007), this presents a serious source of potential bias if these migration costs are large and it is an empirical question as to how large this potential bias may be. Second, reduced form models depend directly on assumptions about existing equilibria and are ill-suited for valuation of non-marginal changes that could result in changes in market equilibria (Bayer and Timmins, 2005). Finally, it is difficult to recover heterogeneous preferences for amenities, although semi-parametric and non-parametric techniques may alleviate some of this concern (see e.g. Crooker and Herriges, 2004; Huang, Nychka, and Smith, 2008), which are likely to play an important role in the evaluation of climate impacts.

Despite these challenges, reduced form models do provide important insights into household behavior related to climate. Recent work on the quality of life has uncovered households' implicit values for climate. Costa and Kahn (2003) estimate wage and house price hedonics and found warmer winters and cooler summers increase housing prices while increased rainfall lowers prices. Cross-sectional hedonic approaches provide additional support for climate amenities driving location choices, even across relatively small spatial areas. For example, urban heat island effects (Brazel et al., 2007) are characterized by increasing temperatures, in particular nighttime temperatures, as a result of urbanization and the conversion of open areas to heat retaining concrete and asphalt and have been shown to influence housing prices (Klaiber and Smith, 2011).

Although there are some studies that examine impacts of climate change in terms of weather extremes on agricultural output (Deschenes and Greenstone, 2007) and public health (Deschenes and Moretti, 2007), there are few studies that examine impacts of climate extremes on migration and household location choice. Poston et al. (2009) is one of the few examples. This paper examines the effects of climate extremes on three migration variables (in-migration, out-migration, and net-migration) by incorporating eleven climate variables including extreme heat days and extreme cold days. They use factor analysis to define a temperature measure which accounts for the variance in correlated climate variables. They find that this climate amenity is positively correlated with in-migration and net-migration rates and is negatively correlated with out-migration rate. However, this study does not consider preference heterogeneity and ignores migration costs.

Tiebout's insight that location choices are akin to observing households shopping for bundles of spatially provided goods provides the conceptual foundation underlying structural models of household location choice. In recent years, econometric methods have been developed to model this utility maximizing location choice and provide new insights into household behavior that complements the existing reduced form literature while providing the potential to overcome some of the inherent challenges facing reduced form approaches (Epple, et. al. 2001; Walsh, 2006; Timmins, 2007; Bayer et. al. 2009). The foundation for structural models is the linking of Tiebout's insights with discrete choice models characterizing the way households sort into local jurisdictions to maximize utility. Structural sorting models begin by defining mappings between the public goods of interest, such as climate measures, and local jurisdictions over which households sort. For climate extremes, which are unlikely to vary significantly over small areas, it seems reasonable to define jurisdictions broadly in terms of regions or metropolitan statistical areas. A further empirical question surrounds the treatment of idiosyncratic unobservables that lead to observed outcomes. The pure characteristics model omits an idiosyncratic error term while another line of structural models assumes an idiosyncratic error, often a Type I extreme value term, and gives rise to random utility models (RUM) characterizing location choice (Klaiber and Kuminoff, 2013).

One implication of this choice is the degree to which heterogeneity in rankings for location is modeled. The pure characteristics model of Epple (1987) and Epple and Sieg (1999) assumes that all households rank jurisdictions in the same order, although they may have different preferences for public goods. Random utility models along the lines of Bayer et al (2009) and Bayer and Timmins (2005) allow household rankings of jurisdictions to vary over households. For studying climate change, this added flexibility may be important if we suspect that different households perceive the bundles of goods provided by jurisdictions quite differently.

By modeling the optimizing decision process directly, it is relatively straight-forward to account for migration costs in structural models. Bayer et al. (2009) use a sorting model to estimate MWTP for air quality by using dummy variables that indicate whether an individual moves out of one's birth place and a similar approach is employed by Timmins (2007) in the case of migration in Brazil. In a working paper, Sinha and Cropper (2013) model household location choice of municipalities across the United States and include measures of mean temperature and precipitation, as opposed to extremes, as components of the bundle of goods associated with each MSA while controlling for migration costs. The authors find that migration costs are important determinants of location choice and that households prefer moderate weather outcomes. Unlike the vast majority of existing structural work, their analysis explicitly considers only a subset of households who are working-age (e.g. not retirees) and further focuses on households who have recently moved. This limited sample of households implies that preference measures are reflective of a subset of the population rather than the entire population as a whole and limits the ability to tease out potential heterogeneity in the omitted population segments.

In addition to literature on household location choices, there are many studies that examine climate change impacts on a global level (Hope, 2006; Nordhaus et al., 2000; Nordhaus W., 2008; Bosello, 2006). A number of recent international reports highlight the importance of studying the consequences of climate change-induced migration (Barnett et al., 2010). These reports focus on international migration between developing and developed countries, and examine whether migration can improve community adaptive capacity under climate change. To understand regional heterogeneity on a national level, it is necessary to examine the impacts at a finer scale (Partridge and Olfert, 2011). For example, recent studies have developed regional- and state-level general equilibrium models using the IMPLAN state-level social accounting matrices (SAMs) to capture heterogeneous impacts across regions and states (Rausch et al., 2011; Ross et al, 2008; Sue Wing, 2007). These studies examine climate change impacts on different sectors, such as human health, agricultural production, land-use patterns, and international trade. None of these regional studies, however, examine impacts from climate change-induced migration. In this research, we incorporate climate change-induced migration in the CGE model and examine the heterogeneous economic impacts at the regional level in the United States. Migration into or out of the U.S. in response to climate change is not captured in our analysis.

On a regional scale, there are both direct and indirect impacts. The labor market is one of the markets that are directly affected by climate change-induced migration. Changes in labor supply as a result of climate change-induced migration lead to changes in wage rates. There are a number of studies that employ a general equilibrium approach to study the impacts of labor migration on different sectoral wages (Grossmann, 1992; Manacorda, 2006; Dustmann, 2005; Brucker, 2011). These studies, however, have not considered climate change as a specific driver of migration. In this paper, we examine wage responses to changes in labor supply resulted from climate change-induced migration.

Beyond the impacts on labor market, multiple markets and industries are simultaneously affected by changes in labor supply as a result of climate change-induced migration. Labor migration across regions may lead to an uneven distribution of labor supply over space. Population loss due to out-migration directly reduces labor supply in that specific region. If the regional economy comprises labor-intensive producing sectors, there may be negative consequences from dramatic labor outflows. In contrast, labor-intensive firms may benefit from an increase in labor in-migration. Correspondingly, the industrial size and sectoral composition of regional economies are likely to change in response to changes in laborers (Timmins, 2007). Our model captures changes in the size and composition of industries due to climate change-induced migration. Business may shrink in one region, and may grow in another region. Regions that face a dramatic loss in labor supply may change industry composition by switching high-labor-intensive industries to less labor-intensive industries (Kohler, 1997). In addition to the supply side of the laborers, we also capture changes in demands for goods and services due to changes in population size.

To capture heterogeneous climate change impacts, previous studies explore the methodology of linking a CGE model with a micro-simulation model (Peichil, 2008; Bohringer and Rutherford, 2006; Aaberge, 2004). This method combines the strengths of the two models. A CGE model can capture inter-industrial interactions when simulating the macroeconomic impacts, while a micro-simulation model (e.g. an empirical model) can account for household heterogeneity and is therefore able to estimate and simulate disaggregate effects at the individual level. These studies, however, are based on a reduced-form approach. While combining environmental systems (e.g. climate and natural amenities) with human behavior (e.g. migration), structural models, as opposed to reduced-form approaches, exhibit the advantages in addressing feedbacks and endogenizing key variables (e.g. population share or wage rates) to simulate welfare effects (Timmins C., and Schlenker, 2009). Unlike previous studies, our paper links a structural sorting model to a CGE model to endogenize labor wages across regions in the U.S.

2.2 Research Approach

A coupling process is developed in this study to link the RUM of location choices with a CGE model of economic activities. The RUM is in the framework of residential sorting model and allows for a detailed set of preference parameters. This empirical method models the way households sort into different locations where they maximize utility given every other's location choice. The CGE model is used to simulate economic impacts by allowing for interactions across different sectors in the regional economies. The flowchart in Figure 2.1 shows the iterative process to simulate regional economic impacts by linking the CGE model with the empirical RUM. Five steps below summarize the process.

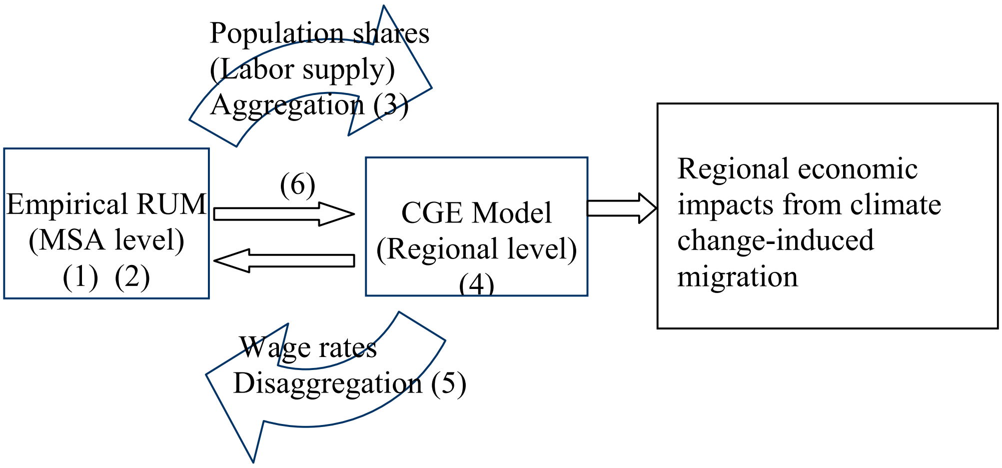

Figure 2. 1 Coupling a CGE model with the Empirical RUM

1) Estimate the empirical RUM and obtain the coefficients that are used for predicting the population shares across regions in the next step;

2) Predict the probability that the decision maker of household *i* chooses MSA *j*, based on a multinomial logit specification of the empirical RUM model. Predicted average of extreme temperatures and precipitation from 2056 to 2065 is used to predict the choice probabilities;

3) Aggregate the predicted probability obtained from step 2) to the regional level (Northeast, Midwest, South, West, and California) to obtain population shares by region. Compute regional labor supply as a product of working age population (those who are less than 65 years old) and labor productivity. Labor productivity is assumed to increase by 2.5 percent annually (Abler, Fisher-Vanden, et al., 2009). Working age population in 2065 is calculated as the product of predicted regional share of working-age population obtained from the RUM and total population projections acquired from the U.S. Census;

4) Input labor supply at the regional level obtained from step 3) into the CGE model to solve for equilibrium wage rates in response to changes in labor supply;

5) Assume the MSAs within the same region experience the same changes in labor wages, and feed the wage information back into the empirical RUM to re-predict the new probability of location choices in response to the updated wages;

6) Repeat steps 2)-5) until wage rates become stable in the CGE model, and the empirical RUM achieves the locational equilibrium—no one has incentive to move given others' location choices.

This process combines strengths of two models: it not only captures individual-level preference heterogeneity but also considers interactions across different industrial sectors. This approach is used to simulate regional economic impacts from climate change-induced migration by endogenizing labor wages. More details will be discussed in Chapter 6.

Chapter 3

Data

3.1 Data Used for the Empirical Model

The main dataset used for the empirical analysis is obtained from Integrated Public Use Microdata Sample (IPUMS), which comprise a 5% microdata sample from the 2000 US Population Census. This data contains detailed information on house prices and housing attributes, along with household demographic characteristics and migration information. Location-specific variables including sectoral wages, natural amenities, and entertainment opportunities at the metropolitan statistical area (MSA) level, are acquired from multiple sources. Climate extreme data (i.e. annual number of days with daily maximum temperature over 90F, annual number of days with daily minimum temperature below 32F, and annual number of days with daily maximum precipitation over 1 inch) are derived from the National Climate Data Center (NCDC). In this section, we describe our choice set followed by details of individual, household, and location-specific characteristics in our sample. We then describe how we aggregate the historical weather observations at the station level to the MSA level, followed by discussions on generating process for climate projections at the MSA level.

3.1.1 Choice Set

Households choose the location that is a bundle of housing service and public goods associated with this location among a discrete set of location alternatives.

Figure 3.1 shows the choice set that consists of 281 MSAs identified by the IPUMS dataset. The lowest geographic unit in the dataset is the Public Use Microdata Area (PUMA) that contains at least 100,000 people. The 281 MSAs are those that match the boundary of the aggregated PUMA units within each MSA. Considering that climate does not significantly vary at a small level (e.g. census district), it is reasonable to define MSA as a choice unit, and then aggregate the sorting outcomes to different regions that closely match climate zones (regions defined in this study are discussed in section 3.1.4). There are significant variations in extreme weather across MSAs. For example, annual extreme cold days with daily minimum temperature below 32F range from zero (e.g. Miami in Florida) to 164 days (e.g. Yakima, Washington). The annual extreme hot days with daily maximum temperature over 90F range from zero (e.g. Canton, OH) to 151 days (e.g. Yuma, Arizona). The annual number of days with daily maximum precipitation over one inch ranges from one (e.g. Yuma, AZ) to 22 days (e.g. Bellingham, WA). It is shown from Figure 3.2 to 3.4 that spatial variation is significant across MSAs and regions. The southern and western MSAs experience more extreme hot days, while the northeastern and western MSAs have relatively higher exposure to extreme cold days. MSAs by coastline and in southern region receive heavy rainfall.

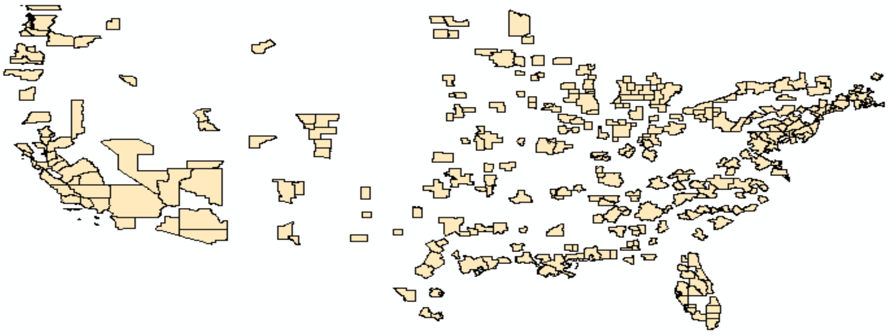

Figure 3. 1 281 MSAs Identified by IPUMS data

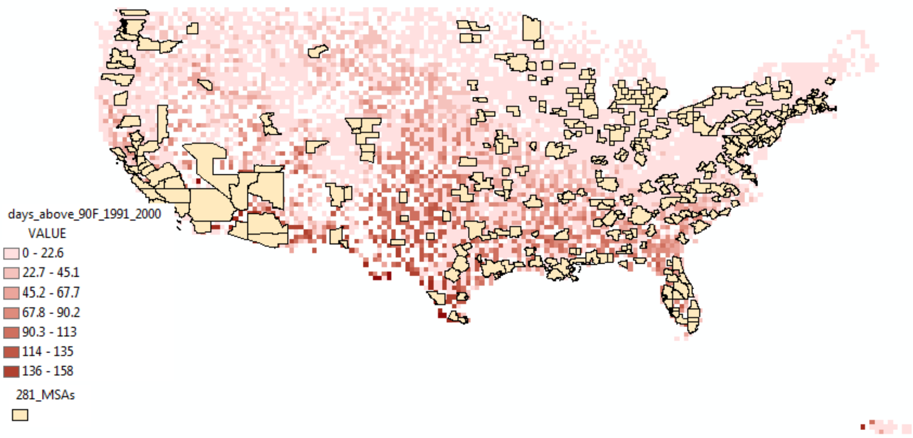

Figure 3. 2 Extreme Hot Days across MSAs and Regions (1991-2000)

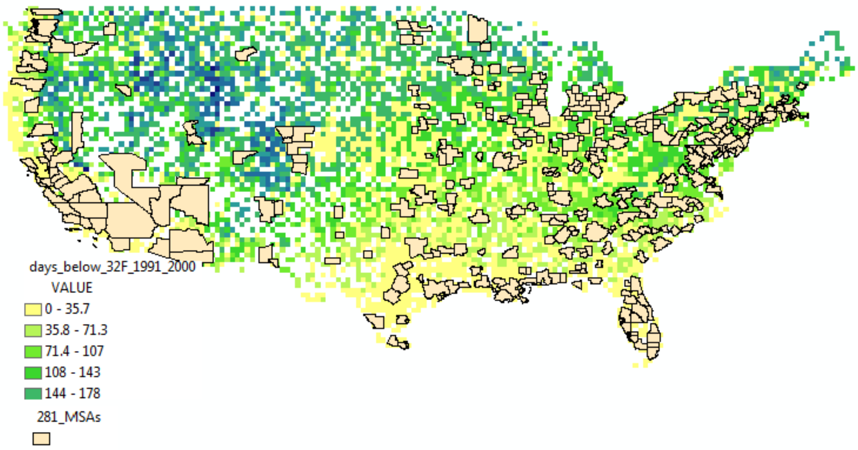

Figure 3. 3 Extreme Cold Days across MSAs and Regions (1991-2000)

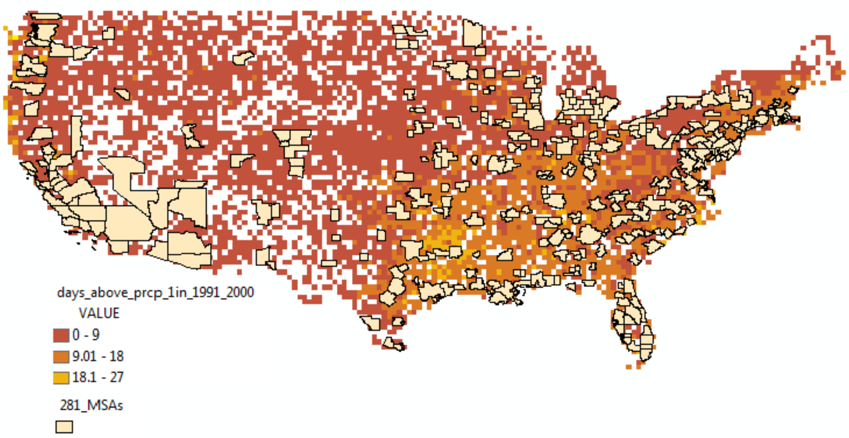

Figure 3. 4 High Precipitation Days across MSAs and Regions (1991-2000)

3.1.2 IPUMS data

Different from the U.S. Census data, the IPUMS data provide unique geographic variables including PUMA, MSA, and migration origins and destinations of each individual. Our sample comprises 1,820,691 households who lived in the 281

Metropolitan Statistical Areas (MSAs) of the U.S. (immigrants and those with zero household income are excluded). Assuming the head of household is the decision maker, we focus on his/her demographic factors. The main dataset contains housing attributes (Table 3.1) and demographic characteristics of the decision maker (Table 3.2). The dataset used in the first-stage sorting model requires a two-dimension matrix for each variable: the row dimension has 1,820,691observations that represent households, while the column dimension has 281 observations that represent MSAs. In order to capture preference heterogeneity among different population segments, we include households with different income sources including wages, people's own businesses, and retirement benefits. One reason of including retirees is that we believe this population segment values climate amenity differently than working-age population. Job opportunities may play a major role in the location decisions of working-age population while retirees may place a higher value on climate amenity and retirement benefits that vary by local jurisdiction. The geographic variables in the IPUMS dataset identify migration information. Since the dataset provides the birth state for each individual, we create a migration dummy variable that indicates whether MSA *j* is out of one's birth region to capture the migration costs of moving away from family roots. One's birth region, defined by matching climate zones with economic regions, is interacted with temperature extremes to reveal preference heterogeneity associated with adaptive behavior in response to changes in extreme weather. Those born in regions that have higher exposure to extreme weather may be more sensitive to extreme weather. They may not want to experience more of the climate extremes as they are familiar with the adverse effects.

The IPUMS data provides detailed information on housing prices and housing attributes, which allows us to obtain a comparable housing price index across MSAs by netting out the effect of housing characteristics on housing prices. Housing characteristics include lot size, bedrooms, facilities, the age of a house, etc. Only housing units that were owned in the year 2000 are included in the regression to keep the price index consistent with property value. The mean value of housing service by netting out implicit values of housing attributes is $168,988.

3.1.3 Other MSA-Specific Attributes Data

MSA-specific amenity and disamenity data are obtained from a variety of sources. Annual labor wages by sector including construction, production, and service are obtained from the U.S. Bureau of Labor Statistics (BLS). Service wage is calculated as a weighted average of business wage, health wage, sales wage, and transportation wage. Total number of establishments of businesses in arts, entertainment and recreation is obtained from the U.S. Census. This variable is divided by land area to serve as an index that indicates how abundant the cultural establishment is. Water area at the MSA level is also obtained from the U.S. Census and is considered as a measure for natural amenity. Climate data is acquired from National Climate Data Center (NCDC), and more details of observed climate extremes are provided in the next section. Summary statistics of the MSA-specific attributes are listed in Table 3.3.

Table 3. 1 Data Summary for Hedonic Housing Price Regression

	Mean	Description
valueh	168,988	The value of housing units ($)
acre_9	0.1535	Acreage of property 1-9 acreages
acre_10	0.0276	Acreage of property 10+ acreages
room2	0.0073	2 rooms in dwelling
room3	0.0269	3 rooms in dwelling
room4	0.0748	4 rooms in dwelling
room5	0.1943	5 rooms in dwelling
room6	0.2386	6 rooms in dwelling
room7	0.1852	7 rooms in dwelling
room8	0.1354	8 rooms in dwelling
room9	0.136	9 rooms in dwelling
bed2	0.0279	1 bedroom dwelling
bed3	0.1862	2 bedroom dwelling
bed4	0.5078	3 bedroom dwelling
bed5	0.2262	4 bedroom dwelling
bed6	0.0485	5 or more bedroom dwelling
unit2	0.001	Boat, tent, van, other
unit3	0.8284	1 family house, detached
unit4	0.061	1 family house, attached
unit5	0.015	2 family building
unit6	0.0088	3-4 family building
unit7	0.0076	5-9 family building
unit8	0.0057	10-19 family building
unit9	0.0057	20-49 family building
unit10	0.0095	50+ family building
Noplumb	0.002	Dwelling does not contain complete kitchen facilities
Nokitch	0.0027	Dwelling does not contain complete plumbing facilities
yr1	0.0255	0-1 year-old dwelling
yr2	0.0855	2-5 year-old dwelling
yr3	0.0852	6-10 year-old dwelling
yr4	0.1592	11-20 year-old dwelling
yr5	0.1703	21-30 year-old dwelling
yr6	0.1336	31-40 year-old dwelling
yr7	0.1416	41-60 year-old dwelling

Table 3. 2 Summary statistics for decision maker of the household

Variable	Description	Mean	Std. Dev.	Min	Max
Household demographics (I = 1,820,691)					
Estimated income in natural log term $	Estimated income for the head of household I possibly living in one of the MSA j	10.46	0.75	6.19	12.79
Whether j is out of I's birth region	Whether MSA j is out of individual I's birth region (Yes = 1; No = 0)	0.75	0.42	0.00	1.00
birth region in CA	Individual I was born in California (Yes = 1; No = 0)	0.07	0.26	0.00	1.00
birth region in West	Individual I was born in West (Yes = 1; No = 0)	0.06	0.23	0.00	1.00
birth region in Midwest	Individual I was born in Midwest (Yes = 1; No = 0)	0.27	0.45	0.00	1.00
birth region in Northeast	Individual I was born in Northeast (Yes = 1; No = 0)	0.27	0.45	0.00	1.00
birth reigon in South	Individual I was born in South (Yes = 1; No = 0)	0.32	0.47	0.00	1.00
Age above 65	Whether individual I is over 65 years old (Yes = 1; No = 0)	0.17	0.38	0.00	1.00
College graduates	Whether individual I is college graduate	0.34	0.47	0.00	1.00

Table 3. 3 Summary statistics for selected variables

MSA-specific variables (J = 281)					
Hot days	Mean annual number of days with maximum temp 90 degrees F or more in MSA j from 1991-2000 (NCDC)/10	2.60	2.64	0.00	15.10
Cold days	Mean annual number of days with minimum temp 32 degrees F or less in MSA j from 1991 to 2000 (NCDC)/10	5.60	4.04	0.00	16.40
Ln (Construction wage) ($000s)	Natural log of construction wage ($000s) (BLS)	3.46	0.19	2.87	3.95
Ln(production wage) ($000s)	Natural log of production wage ($000s) (BLS)	3.24	0.25	0.87	3.77
Ln(service wage) $000s	Natural log of service wage ($000s) (BLS)	3.44	0.12	2.97	3.92
Annual snowfall (in)	Annual snowfall (inches) from (NCDC)	17.97	23.59	0.00	115.60
High precip days	Annual days of precipitation with daily maximum over 1 inch from 1991 to 2000 (NCDC)	10.03	4.76	1.00	23.00
Annual tornado watches	Annual number of tornado watches (NCDC)	8.50	5.34	0.00	40.00
Cultural establishments	Total number of establishments in business patterns such as arts, entertainment& recreation/land are (square miles) (U.S. Census)	0.14	0.31	0.00	4.23
Water area (square miles) (00s)	Water area (area in square miles/100) (U.S. Census)	2.47	5.13	0.01	39.55
July Humidity (morning %)	July humidity (morning monitoring value in %)	86.48	11.00	28.00	100.00

3.1.4 Observed Climate Data

Daily minimum and daily maximum temperatures, daily precipitation and snowfall from 1991 through 2000 are obtained from the National Climate Data Center (NCDC). The dataset used in our analysis is acquired from the Global Historical Climatology Network (GHCN)-Daily, which covers daily maximum and minimum temperatures, precipitation, and snow records over global and regions from historical observations[1]. Each record in the dataset represents observations for a given weather station and day. Particularly for our research needs, we acquire daily observations for the United States across all weather stations. Daily data are used to compute variables such as extreme hot days (annual number of days with daily maximum temperature above 90F), extreme cold days (annual number of days with daily minimum temperature below 32F), and extreme precipitation days (annual number of days with daily maximum precipitation over 1 inch). The daily extreme observations for each year are imported into ArcGIS as shown in Figure. 3.5 (data for the year 2000 is used as an example). The attributes of each point include extreme hot days, extreme cold days, and annual number of days with extreme precipitation observed by each weather station. We then intersect point data with MSA polygons, and arithmetic mean values of exceedance days are calculated for each MSA by taking averages of point data within each MSA (the map is shown in Figure. 3.6). A similar generating process is conducted for other years. A ten-year average is calculated using the dataset from 1991 to 2000.

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[1]http://gis.ncdc.noaa.gov/map/viewer/#app=cdo&cfg=cdo&theme=daily&layers=111&node=gis

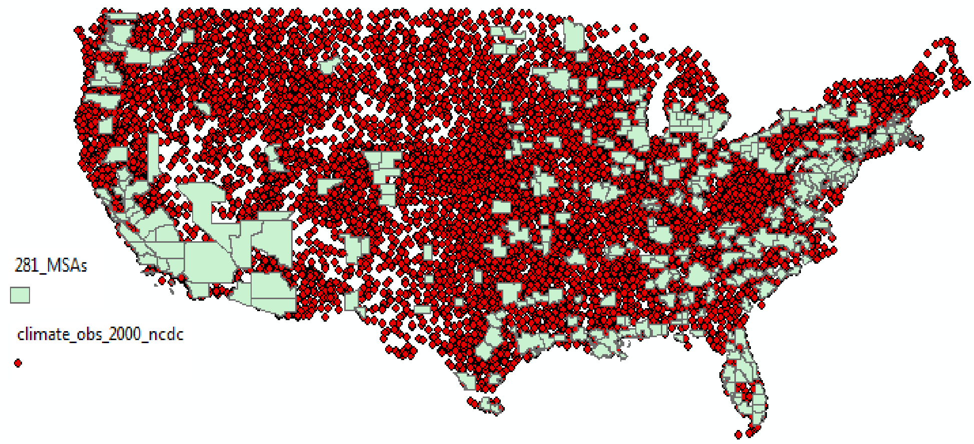

Figure 3. 5 Observed Climate Data by Weather Station in the U.S.

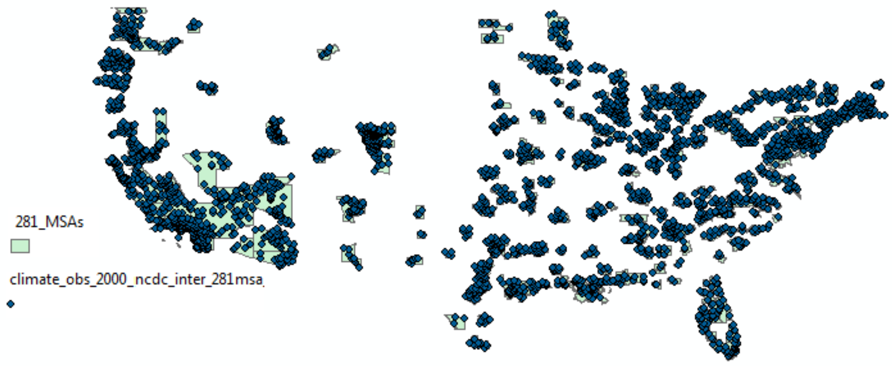

Figure 3. 6 Generating MSA-Level Climate Data

Summary statistics of the observed climate variables are listed in Table 3.4. Similar to the discussion in the section 3.1.1, the summary statistics shows that the South, West, and California experience relatively higher frequency of extreme hot days, while the Northeast, Midwest, and West are exposed to higher frequency of extreme cold days. Heavy rainfall is distributed mainly in the South. The definition of five regions will be discussed in the next section.

Table 3. 4 Summary Statistics of Observed Climate Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
		Northeast			
hot_1991_2000	46	5.778744	4.34925	0.8	18
cold_1991_2000	46	75.56691	25.12982	30.6	141.5
pr_1991_2000	46	9.696618	2.221853	5.4	13.4
		Midwest			
hot_1991_2000	72	8.586265	5.76265	0	27
cold_1991_2000	72	82.66698	34.18113	0	158.2
pr_1991_2000	72	7.657716	2.12552	0.9	14.1
		South			
hot_1991_2000	111	41.74092	25.31929	4.9	125.9
cold_1991_2000	111	28.77618	25.8419	0	149.5556
pr_1991_2000	111	13.75415	4.039845	1.6	22.2
		West			
hot_1991_2000	30	27.95667	35.96124	1.5	150.7
cold_1991_2000	30	88.68037	43.55548	3.7	164.2
pr_1991_2000	30	5.612963	5.397197	0.7	23.4
		CA			
hot_1991_2000	22	39.02929	23.58001	12.6	87
cold_1991_2000	22	21.24798	18.82663	3.9	86.9
pr_1991_2000	22	5.680303	3.191352	1.4	12.2

3.1.5 Five Regions and Climate Projections

There are four economic regions defined by the U.S. Census: Northeast, Midwest, South, and West. In order to examine whether people born in different climate zones have different tolerance and adaptive capacity towards extreme weather, we define five regions by matching four economic regions with the U.S. Department of Agriculture (USDA) Plant Hardiness Zones. As shown in Figure 3.7, different colors represent scales that increase with average annual minimum winter temperature. Plant hardiness zones are chosen as climate zones that are directly connected to temperature extremes. Different from economic regions defined by the U.S. Census, California is separate from the western region due to a relatively higher minimum winter temperature. Montana and Wyoming are separate from the West and are included in the Midwest due to the relatively colder winters in these two states compared to the western region. The division of five regions captures climate variation across climate zones while reflecting differences in regional economic activities.

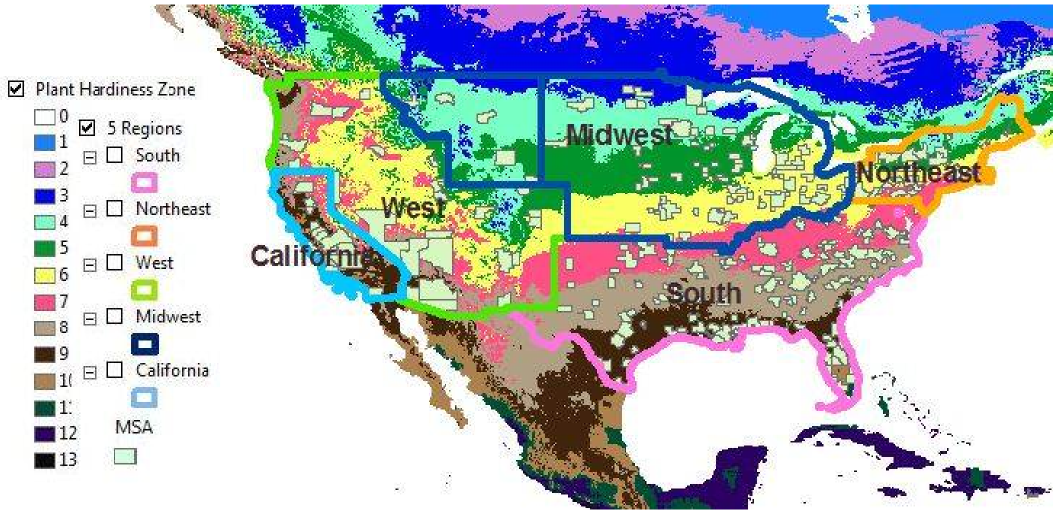

Figure 3. 7   Plant Hardiness Zones and Five Regions

Note: regions include 1) Northeast (CT, ME, MA, NH, RI, VT, NJ, NY, PA); 2) Midwest (IA, MN, NE, SD, ND, MT, WY, IL, IN, MI, OH, WI); 3) South (FL, GA, AR, MD, NC, SC, VA, WV, AL, KY, MS, TN, LA, KS, MO, OK, AR, TX); 4) West (NV, AZ, CO, NM, UT, OR, WA, ID); and 5) California

This dataset of climate projections in the United States is acquired from Ed Maurer's website (Maurer, 2010)[2]. The climate projections are derived from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multimodel dataset. It accounts for bias-correction and uses spatial downscaling technique. The daily bias-correction and constructed analogs (BCCA) downscaling technique are applied to climate projections, and this dataset contains BCCA downscaled general circulation model (GCM) projections. The model projections provide daily versions of the gridded observations that have relatively finer resolution at 1/8 degree (approximately 12kmx12km). Daily projections for the time period from 2056 to

2http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/dcpInterface.html#Projections:%20Subset%20Request

2065 are acquired respectively for precipitation, daily maximum temperature, and daily minimum temperature. The data include projections from 7 different climate models: Canadian Center for Climate Modeling and Analysis (CCCMA) Coupled Global Climate Model (CGCM3), the Centre National de Recherches Météorologiques Coupled global climate Model (CNRM-CM3), two versions of NOAA's Geophysical Fluid Dynamics Laboratory Coupled Model (GFDL-CM2.0 and –CM2.1), Institute Pierre Simon Laplace Climate Model (IPSL-CM4.1), Model for Interdisciplinary Research on Climate (MIROC-medres), Meteorological Institute University of Bonn (MIUB), ECHO-G Model. Projections from seven climate models for both IPCC emission scenarios A1B and A2 are acquired. A1B scenario assumes a homogenous world with balanced emphasis on all energy sources, while A2 scenario assumes a heterogeneous world that has a relatively higher emission path compared to the A1B scenario (ESS, 2013). The average of simulated values from 7 different models is used to minimize uncertainty from climate model structures respectively for the A1B and A2 emission scenarios. The total annual number of days with extreme weather (annual number of days with a maximum temperature over 90F, annual number of days with a minimum temperature below 32F, and annual number of days with a maximum precipitation over 1 inch) is computed.

Spatial distributions of extreme weather days are displayed in Figures 3.8, 3.9, and 3.10, respectively, for extreme hot days, extreme cold days, and days with heavy rainfall. Consistent with our expectation, at the end of 2056 (take the year 2056 as an example), extreme hot days are concentrated in California and the South, while extreme cold days are mainly concentrated in the Midwest and Northeast. The southern region and California experience a larger number of days with heavy rainfall than other regions.

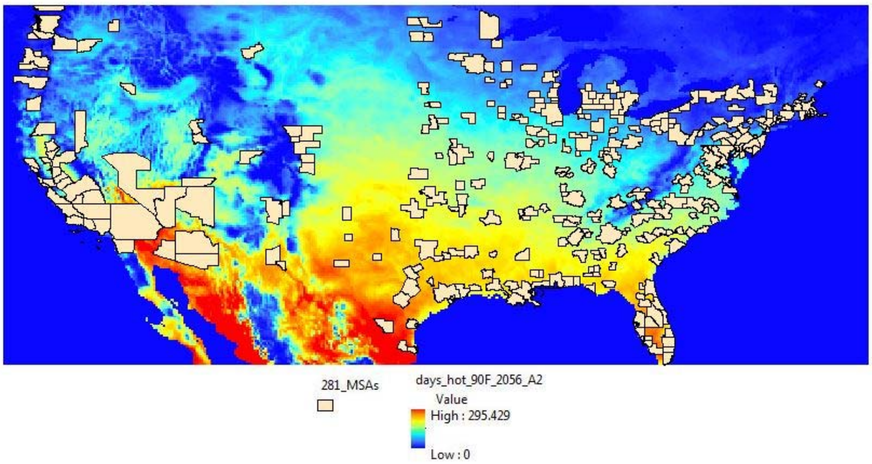

Figure 3. 8 Distribution of Projected Extreme Hot Days in 2056 (A2 Scenario)

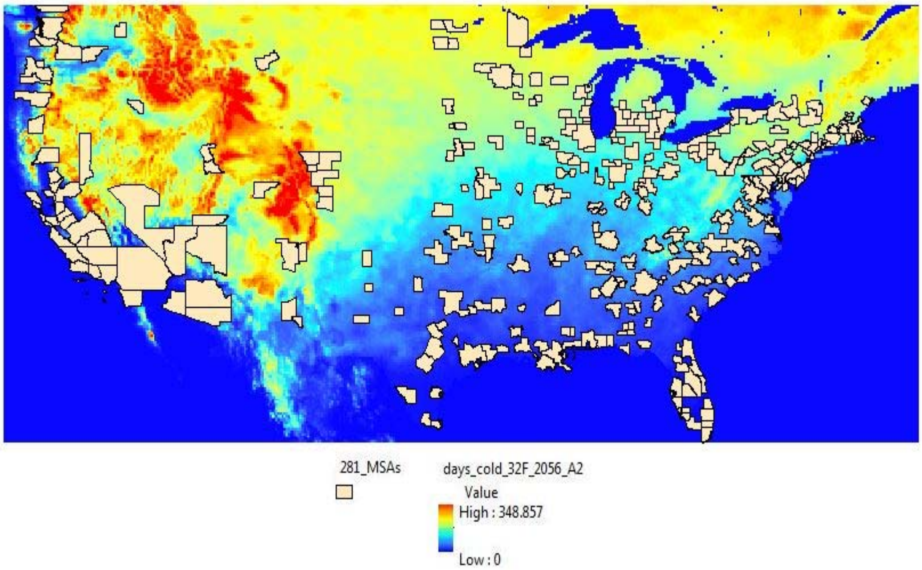

Figure 3. 9 Distribution of Projected Extreme Cold Days in 2056 (A2 Scenario)

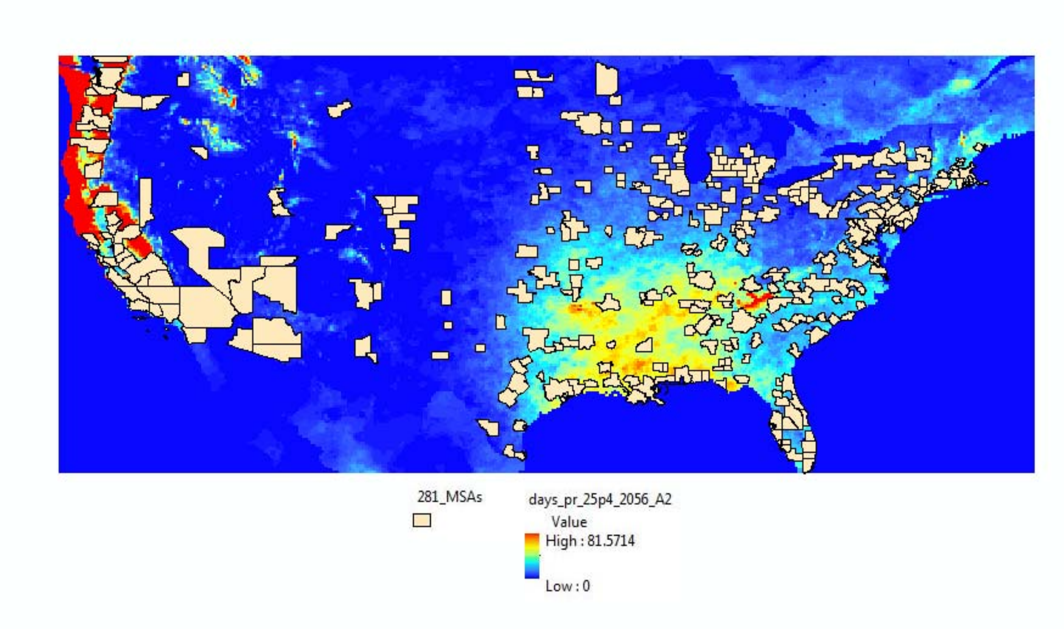

Figure 3. 10 Distribution of Projected Heavy Rainfall Days in 2056 (A2 Scenario)

In order to obtain MSA-level projected climate data, we apply the same approach as used for observed climate data. The gridded data is intersected with MSA polygons on ArcGIS and the mean values of extreme days are then computed for each MSA. The distribution of extreme cold days for each MSA in the year 2056 is shown in Figures 3.11. and 3.12.

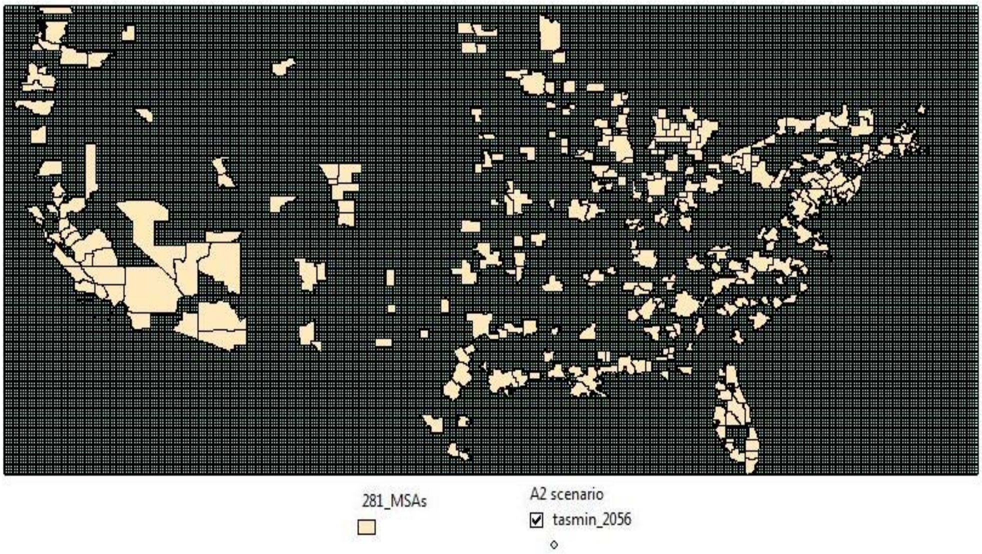

Figure 3. 11 Extreme cold days for the year 2056

(1/8 degree daily BCCA CMIP3 Climate Projections-A2 scenario)

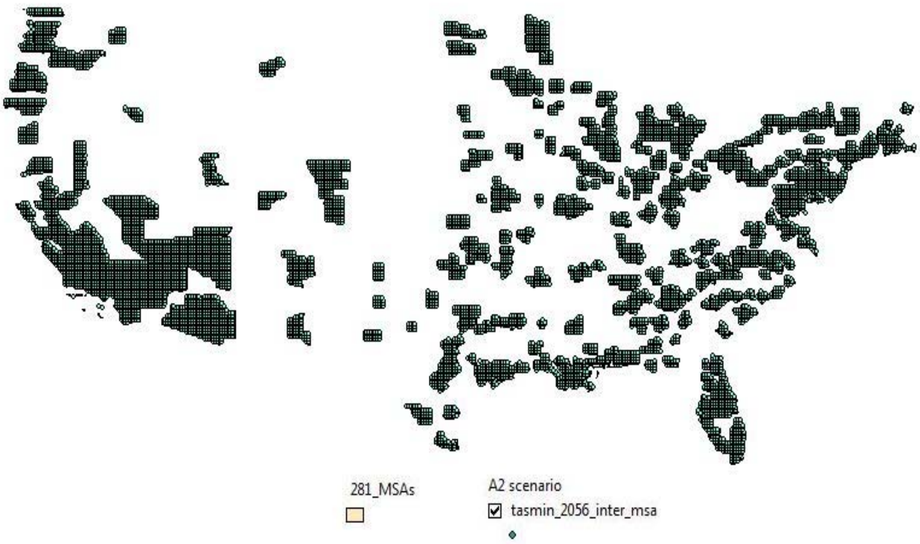

Figure 3. 12 Extreme cold days interacted with MSAs for the year 2056

(1/8 degree daily BCCA CMIP3 Climate Projections-A2 scenario

The same generating process is applied to each year from 2056 to 2065, and a 10-year average of climate projections is calculated to predict choice probabilities and to simulate economic impacts at the end of 2065. Summary statistics of climate projections for the A1b and A2 IPCC Special Report Emission Scenario (SRES) scenarios are shown respectively in Table 3.5 and Table 3.6. The Southern region experiences the largest number of extreme hot days, while the Northeast is highly exposed to extreme cold weather.

Table 3. 5 Summary Statistics of Climate Projections (A1b scenario)

Variable	Observation	Mean	Std. Dev.	Min	Max
		Northeast			
hot_2056_2065	46	31.07391	12.05645	4.5	57.7
cold_2056_2065	46	96.14565	22.04556	47.2	132.5
pr_2056_2065	46	3.486957	1.424174	1	6.4
		Midwest			
hot_2056_2065	72	59.07361	19.19449	22.3	105.7
cold_2056_2065	72	98.82639	22.34109	57.2	160.2
pr_2056_2065	72	1.829167	0.742557	0.9	4.1
		South			
hot_2056_2065	111	108.5649	28.15138	32.1	183.4
cold_2056_2065	111	29.69369	24.30432	0.4	139.3
pr_2056_2065	111	4.169369	1.953868	0.6	8.5
		West			
hot_2056_2065	30	59.32667	48.97951	3.9	179
cold_2056_2065	30	93.76	49.33734	3.2	184.8
pr_2056_2065	30	4.85	6.816954	0	25.3
		CA			
hot_2056_2065	22	68.83182	37.18132	9.8	139
cold_2056_2065	22	24.58636	25.65142	3.8	91.1
pr_2056_2065	22	4.572727	3.360014	1	11.5

Table 3. 6 Summary Statistics of Climate Variables (A2 scenario)

Variable	Observation	Mean	Std. Dev.	Min	Max
		Northeast			
hot_2056_2065	46	29.54565	13.00435	2.4	59
cold_2056_2065	46	98.10435	21.57763	48.9	134
pr_2056_2065	46	3.341304	1.347191	1	6.3
		Midwest			
hot_2056_2065	72	59.59306	21.08829	20.4	112.1
cold_2056_2065	72	101.2292	21.78874	59.7	161
pr_2056_2065	72	1.765278	0.788859	0.9	4.5
		South			
hot_2056_2065	111	117.2739	32.93072	30.2	203.8
cold_2056_2065	111	31.04505	25.109	0.5	139.6
pr_2056_2065	111	4.176577	1.865863	0.3	8.7
		West			
hot_2056_2065	30	63.65	54.15513	1.6	196.1
cold_2056_2065	30	95.49667	50.11996	3	186.7
pr_2056_2065	30	4.566667	6.433765	0	24.5
		CA			
hot_2056_2065	22	73.64091	40.96573	8.5	151.6
cold_2056_2065	22	24.87727	26.13348	3.6	92.2
pr_2056_2065	22	4.740909	3.25469	1	11.2

3.2 Data Used for the CGE Model

The main dataset used for the recursive dynamic inter-regional CGE model is obtained from the Minnesota IMPLAN group (MIG). The 2010 IMPLAN (IMpact analysis for PLANning) data contains social accounting matrices (SAM) for 440 industrial sectors at the state level. In order to examine economic impacts on aggregated industries across five regions as defined in the previous section, state-level SAMs over

440 sectors are aggregated into region-level SAMs across 30 aggregate sectors. Table 3.7 shows the aggregate industrial sectors.

Table 3. 7 Aggregated Industrial Sectors and Commodities

Food	Grains and oilseeds
	Fruits, vegetables, and nuts
	Greenhouse products
	Other crops
	Beef
	Dairy
	Poultry and eggs
	Other animal production
	Food and tobacco
	Forestry
\	Other agricultural products
Energy commodity	Oil and gas
	Coal
	Electricity
	Natural gas distribution
	Petro products
Housing	Construction
	Wood products
	Furniture
	Insurance
Others (non-energy, non-food, and non-housing)	Pulp paper
	Water and sewage
	Chemicals
	Other mining
	Rubber plastics
	Nonmetallic metals
	Primary metals
	Heat and air conditioning
	Other manufacturing
	Services
	Insurance

Beyond industrial sectors, IMPLAN data provides receipts and payments for institutions including households, governments, and corporations. Households are grouped into nine types based on annual household income: annual household income less than 5K, 5-10K, 10-15K, 15-20K, 20-30K, 30-40K, 40-50K, 50-70K, and above 70K. There are six types of governments including federal government nondefense, federal government defense, federal government investment, state local government non-education, state local government education, and state local government investment. Corporate institutions include enterprise, gross private fixed investment, and inventory addition deletions. These three institutions along with the foreign sector that deals with international trade comprise the four major economic agents in the CGE model.

IMPLAN data provides social accounting matrices (SAMs) of 50 states and Washington DC for the year 2010, which are used to calibrate the CGE model. We include only the SAMs of 48 states of the U.S. and Washington D.C. (Alaska and Hawaii are excluded due to the unavailability of projected climate data). The matrices display commodity and payment flows by different institutional groups and types. The column of the matrices represents payments, and the row represents receipts of income. The highest aggregated level of SAM structure consists of industry, commodity, institutions, trade (both intra-national and international), and factors. Factors in the IMPLAN data include employee compensation, proprietary income, other property income, and indirect business taxes. An example of the SAM structure is shown in Table 3.8. In this table, the column represents payments from industry, commodity, factors, institutions, and trade, while the row represents receipts of these five elements.

Table 3. 8 The Aggregated Level of SAM Structure in IMPLAN

	Industry	Commodity	Factors	Institutions	Trade
Industry		Make			Exports
Commodity	Use			Consumption	Exports
Factors	Value added				Exports
Institutions		Sales	Transfers	Transfers	Exports
Trade	Imports		Factor trade	Imports	

Source: Tools for Building National Economic Models Using State-Level IMPLAN Social Accounts (Rausch and Rutherford, 2007)

One important exogenous variable in the CGE model is population which serves as one of the key drivers of economic growth. Population projections are obtained from the U.S. Census. These projections provide state-level population to 2030 at 5-year steps (Table 3.9). State-level population projections are aggregated to the regional level. We take the annualized growth rate that is calculated from an average over the period 2025 to 2030 to project regional population from 2035 to 2065. The annual growth rate is assumed to be the same within a 5-year period.

Table 3. 9 Population Projections at Regional Level from 2010 to 2065

Regions	2010	2015	2020	2025	2030
NE	56,669,521	57,493,069	58,098,646	58,461,007	58,683,726
MW	62,957,839	64,027,547	64,808,976	65,292,509	65,635,002
SO	118,621,350	125,582,364	132,807,492	140,485,558	148,686,852
WE	26,793,958	29,008,155	31,435,502	34,098,929	36,966,356
CA	38,067,134	40,123,232	42,206,743	44,305,177	46,444,861

Chapter 4

Residential Sorting Model and Estimation Results

4.1 Introduction

The residential sorting model roots in Tiebout's insight that households sort into different locations where they maximize utility that consists of commodity bundles along with location-specific attributes including public goods. In recent years, econometric methods have been developed to overcome potential challenges of modeling location choices using reduced form approaches. Structural sorting models begin by defining a choice set that can map between the public goods of interest and local jurisdictions over which households sort. In the framework of structural sorting models, the pure characteristics model does not consider an idiosyncratic error term that varies by individual and location, while random utility model (RUM) includes an idiosyncratic error term to capture randomness of preferences (Klaiber and Kuminoff, 2013). The details of the error term will be discussed in section 4.2. Pure characteristics models assume that all households rank jurisdictions in the same order. In contrast, RUM captures preference heterogeneity across individuals. For example, Bayer et al (2009) use a RUM to estimate marginal willingness to pay (MWTP) to reduce 1 unit of PM2.5 by allowing different households to have different preferences for a bundle of goods including air quality associated with a jurisdiction. In our study, the RUM is preferred as we believe that different households perceive climate amenity provided by local jurisdictions differently.

4.2 Econometric Model

Random utility models of household location choice begin by defining the jurisdictions, j, over which households sort. A key consideration in the construction of jurisdictions is to ensure that the variables of interest to the researcher are meaningfully captured at the specified spatial level of aggregation defining a choice element facing households. Having chosen a jurisdiction, households are assumed to be utility maximizers who obtain a bundle of goods and services through their selection of jurisdiction while facing tradeoffs between the costs or wages associated with choosing that location. Following closely the model outlined by Timmins (2007), the utility realized by household i choosing to live in location j is given as

$$(4.1)\quad U_{ij} = b_i^{\beta_c} H_i^{\beta_h} Z_j^{\beta_z} e^{\beta_m M_{ij} + \sum_{q=1}^{Q} \beta_{qz}(HH_i^q \times Z_j) + \xi_j + \eta_{ij}}$$

where b_i represents numeraire consumption, H_i is the quantity of housing services demanded, Z_j captures attributes associated with choosing a particular location including measures of climate extremes associated with each location, M_{ij} is an individual and location specific measure of migration costs, HH_q^i contains individual demographics (e.g. age, birth region, and educational attainment). Preference heterogeneity is accounted for by inclusion of demographic interactions, indexed by q, with elements of Z_j. Error terms capturing unobservable attributes of location j are contained in ξ_j while an idiosyncratic term is given by η_{ij}.

To operationalize this model, households are assumed to maximize utility subject to a budget constraint given by $b_i + \rho_j H_i = I_{ij}$ where I_{ij} is household income, which accounts for potential wage differentials associated with the same individual observed locating in different locations, and ρ_j is a measure of housing price in location j. Utility maximization proceeds by choosing optimal levels of numeraire consumption and housing services and substituting those into a logged version of equation (4.1) to obtain indirect utility as

$$(4.2) \quad \ln V_{ij} = \beta_I \ln \hat{I}_{ij} + \sum_{q=1}^{Q} \beta_{qz} (HH_i^q \times Z_j) + \beta_m M_{ij} + \hat{\Theta}_j + \eta_{ij} \ ,$$

where

$$(4.3) \quad \hat{\Theta}_j = -\beta_\rho \ln \hat{\rho}_j + \beta_z \ln Z_j + \xi_j$$

The expressions for indirect utility given in equations (4.2) and (4.3) highlight the role of both location specific unobservables and idiosyncratic unobservable terms which will guide empirical implementation. Estimation will proceed in two stages. The first estimates a discrete choice model of location choice and includes location specific unobservables, ξ_j which are captured along with variables varying only across location in the fixed effect $\hat{\Theta}_j$. The second stage of estimation decomposes the estimated fixed effects $\hat{\Theta}_j$ into observable and unobservable components.

In the 1st stage, we obtain predicted income $\hat{I}_{ij}$ as denoted in equation (4.2) from an income regression as shown in section 4.3. This is because households are observed in only one location. In order to obtain income for household *i* possibly living in one of the 281 MSAs, we must estimate the income they would receive had they chosen to locate in a different location. Similarly, the housing price index associated with location *j* in the second stage denoted as $\hat{\rho}_j$ must be estimated as we observe many individual prices which must be aggregated to form a common price facing all households choosing a particular location. Details of each of these regressions are shown in the following section.

To obtain the discrete choice model in stage one, the idiosyncratic term in equation (4.2) is specified as a type I extreme value which gives rise to the well-known multinomial logit model. This model has a closed form expression for the probability of household i choosing location j given by

$$(4.4)\quad P(V_{ij} > V_{ik}\ \forall j \neq k) = \frac{V_{ij}}{\sum_{k=1}^{J} V_{ik}}$$

and is estimated via maximum likelihood

$$(4.5)\quad ll = \sum_j \sum_i Y_{ij} \ln P_{ij}\,.$$

The inclusion of a complete set of $(J-1)$ location specific fixed effects was shown by Berry (1994) to result in perfect prediction of observed shares in a multinomial logit model. In our case, observed shares denoted as W_j are the observed choice probability for location MSA *j*. As such, we employ a computational trick to estimate each of these parameters—coefficients of MSA-specific constants denoted as Θ_j—using a contraction mapping as shown below. This process iteratively updates the estimates for each Θ_j nested within the maximum likelihood routine until observed and predicted choice probabilities converge (i.e. $W_j = \sum_i \hat{P}_{ij}$). This algorithm allows one to solve for the alternative specific constants (ASCs) from a numerical trick instead of estimating them numerically from a gradient search within the maximum likelihood routine. In this sense, contraction mapping greatly reduces computational burden. The details are shown below.

The contraction mapping is defined as:

$$(4.6)\quad \Theta_j^{t+1} = \Theta_j^t - \ln\left(\sum_i \frac{\hat{P}_{ij}(\beta, \Theta_j^t)}{W_j} \right)$$

where *t* represents iteration, Θ_j is an ASC for MSA *j*, $\hat{P}_{ij}$ is the probability that household *i* chooses MSA *j*, which is a function of parameter β and Θ_j, W_j is the observed share of choosing MSA *j*.

The estimation step that solves for ASCs from a contraction mapping can be summarized as follows:

i. Start with an initial guess of Θ_j^t;

ii. Given Θ_j^t, maximize the log-likelihood function with respect to β:

$$ll = \sum_j \sum_i Y_{ij} \ln(P(\ln V_{ij} > \ln V_{ik} \ \forall j \neq k))$$

$$\text{where} \quad P(\ln V_{ij} > \ln V_{ik} \ \forall j \neq k) = \frac{e^{\beta'_k X_{ijk} + \Theta_j}}{\sum_{q=1}^{J} e^{\beta'_k X_{iqk} + \Theta_q}}$$

where x_{ijk} represents variables in the 1st stage of the sorting model, *i* represents household, *j* represents MSA, and *k* represents different categories of variables.

iii. Given the estimates of β, solve for Θ_j^{t+1} using the contraction mapping in equation (4.6);

iv. Repeat step ii and iii until the convergence of Θ_j is achieved.

Having obtained maximum likelihood estimates for the Θ_j parameters, the second stage of estimation decomposes them following equation (4.3) with the addition of a constant term capturing the arbitrary normalization of one of the J fixed effects to zero as only $(J-1)$ are identified in a discrete choice model.[3] Challenges arise in this decomposition as it is likely that correlation between parameters and the error term, ξ_j exists leading to biased OLS estimates. Of particular concern are the parameter on price as well as parameters in Z_j that arise due to the sorting process itself, such as population share, which are likely endogenous. To avoid complications associated with price, we move it to the left hand side of equation (4.3). We also separate the endogenous variable population share, S_j. The updated equation (4.3) is given as:

(4.7) $\hat{\Theta}_j + \hat{\beta}_h \ln \hat{\rho}_j = \beta_z \ln Z_j + \beta_s S_j + \xi_j$

where we estimate $\hat{\beta}_h$ as shown in appendix 4.A using $\beta_h = \beta_I(\hat{\rho}_j H_i / \hat{I}_{ij})$.

[3] The choice of normalization has no impact on the estimated results.

Population share is correlated with the residual in equation (4.7) by construction as shown by

$$(4.8)\quad \hat{S}_j = \frac{1}{N}\sum_{i=1}^{N}\frac{\exp(V_{ij})}{\sum_{k=1}^{J}\exp(V_{ik})}.$$

Because people are likely to choose to locate in a place where attributes are more desirable, and some of these attributes are unobserved to the analyst, instruments are needed to correct for this potential endogeneity. To account for this source of endogeneity, we further augment equation (4.7) by including region fixed effects and employ the instrumental variable (IV) strategy used by Bayer and Timmins (2006)[4]

$$(4.9)\quad IV_j = \frac{1}{N}\sum_{i=1}^{N}\tilde{P}_{ij} = \frac{1}{N}\sum_{i=1}^{N}\frac{\tilde{V}_{ij}}{\sum_{k=1}^{J}\tilde{V}_{ik}}$$

where the tildes indicate that additional variables from nearby metropolitan areas have been included in the regression and the instrument derives its power from distant sources of residual variation (variation in utilities that are defined only by exogenous variables), which are unlikely to be correlated with unobservables in a more proximate location. With these modifications equation (4.2) is estimated via multinomial logit while equation (4.7) is estimated using instrumental variables.

4.3 Predicted income

[4] Following the method of Bayer and Timmins (2007), predicted income is excluded while generating the instrumental variable (IV). The predicted income may be correlated with unobservable MSA-specific attributes. Wage rates by sector are also taken out of the model due to the same reason.

To predict the income each household would receive if they were to locate in different MSAs, we estimate an income equation similar to Bayer et al (2009) and use this model to predict income $\hat{I}_{ij}$, which is included in the first-stage of the sorting model shown in equation (4.2). We estimate the following income equation:

$$(4.10)\quad \ln I_i = \alpha_j + \sum_{m=1}^{M} \tau_{m,j} D_i^m + \varepsilon_{ij}$$

where I_i represents individual income earned from wages, earnings from people's own businesses, and retirement income including pensions and retirement income from social security , α_j represents MSA fixed effects that capture economic activity and retirement benefits at the MSA level, D_i^m denotes demographic characteristics and occupation information associated with individual *i*, where *m* indicates different types of demographics including age, gender, educational attainment, race, and occupation. Summary statistics are shown in Table 4.1.

Regression results are shown in Table 4.2 and indicate that households earn more as age increases, perhaps due to gains in knowledge and experience with age. Age squared is negatively significant. One reason might be that income falls after retirement. In addition, males appear to earn more than females, whites have relatively higher incomes than other demographics, and people with higher education levels have higher incomes. Managerial and professional occupations have relatively higher salaries than other occupations. Using these results, we predict income for each household by summing over all individuals within a household for each MSA. This reveals an overall mean value of predicted household income of $34,718. This estimated income is lower than the median income reported by the U.S. Census in the year 2000 ($41,994) because of the inclusion of retirees in our study.

Table 4. 1 Demographic Variable Description

Variable	Observation	Mean	Std. Dev.	Min	Max	Description
Age	3428583	45.13687	16.08084	15	93	Age
High school drop	3428583	0.0197822	0.1392512	0	1	High school dropout
High school grad	3428583	0.4506824	0.4975619	0	1	High school graduate
College	3428583	0.418351	0.4932885	0	1	Completed some college (not four year degree)
College grad	3428583	0.1111844	0.3143604	0	1	College graduate
Male	3428583	0.5275276	0.4992417	0	1	Male
Age square	3428583	2295.93	1569.715	225	8649	Age square
Married	3428583	0.629698	0.4828856	0	1	Married or not
White	3428583	0.8693475	0.33702	0	1	Race = white
Black	3428583	0.089607	0.2856179	0	1	Race = black
Native	3428583	0.0048227	0.069278	0	1	Race = American Indian or Alaska Native
Asian	3428583	0.0064881	0.080287	0	1	Race = Asian
Hispanic and others	3428583	0.0297347	0.1698546	0	1	Hispanic and other race
Manage production	3428583	0.2991472	0.4578845	0	1	Managerial and Professional occupation
Tech, sales, and Admin	3428583	0.29909	0.4578594	0	1	Technical, Sales, and Administrative occupation
Service	3428583	0.1065846	0.3085844	0	1	Service occupation
Farm, forest, and fish	3428583	0.0128584	0.1126634	0	1	Farming, forestry, and fishing occupation
production	3428583	0.0941733	0.2920697	0	1	Precision Production, Craft, and Repairers occupation
Operatives laborers	3428583	0.0992812	0.2990393	0	1	Operatives and Laborers occupation
Other occupation	3428583	0.0888653	0.2845492	0	1	other occupation

Inc	3428583	37117.43	46356.83	4	680000	income including wage income, business income (if self-employed), and retirement income)

Table 4. 2 Results from Income Regression

Variables	Estimate	Std. Err.	T	P>|t|
Dependent variable: ln(income)				
Age	0.1458083	0.0001817	802.52	0
Age square	-0.0014907	1.97E-06	-758.19	0
Male	0.5472341	0.0011467	477.23	0
High school grad (high school dropout is left out)	0.2073457	0.0039559	52.41	0
College	0.5482908	0.0040278	136.13	0
College graduate	0.8154107	0.0043296	188.34	0
Black (white is left out)	-0.0976465	0.0019529	-50	0
Native	-0.1178957	0.007783	-15.15	0
Asian	-0.1526193	0.0067441	-22.63	0
Hispanic and others	-0.0629044	0.0032476	-19.37	0
Tech, sales, and admin (Managerial and Professional is left out)	-0.2341183	0.0014967	-156.42	0
Service	-0.6231083	0.002064	-301.9	0
Farm, forest, and fish	-0.7065591	0.0049102	-143.9	0
Production	-0.1549971	0.0022003	-70.44	0
Operatives laborers	-0.3228336	0.0021818	-147.96	0
Other occupation	-0.3764964	0.0027089	-138.98	0
Observation: 3,428,583				
R-square: 0.9902				

Notes: 281 coefficients of MSA-specific constants (MSA fixed effects) are not listed in the table

4.4 Housing price index

A hedonic housing price model is used to obtain the housing price index (denoted as ρ_j) for each MSA. The hedonic housing price model is defined as:

(4.11) $\ln P_{ij} = \ln \rho_j + \beta_{ij} X_{ij} + e_{ij}$

where P_{ij} is the housing price (only homeowners are included in the regression), ρ_{ij} is the estimated housing price in MSA j (MSA fix effects), and X_{ij} are housing attributes reported in Table 4.3 that include variables such as the acreage of the property, the number of rooms in the house, and number of years since the house was built.

Table 4. 3 Summary Statistics for Housing Price Regression

Variables	Mean	Description
valueh	168,988	The value of housing units ($)
acre_9	0.1535	Acreage of property 1-9 acreages
acre_10	0.0276	Acreage of property 10+ acreages
room2	0.0073	2 rooms in dwelling
room3	0.0269	3 rooms in dwelling
room4	0.0748	4 rooms in dwelling
room5	0.1943	5 rooms in dwelling
room6	0.2386	6 rooms in dwelling
room7	0.1852	7 rooms in dwelling
room8	0.1354	8 rooms in dwelling
room9	0.1360	9 rooms in dwelling
bed2	0.0279	1 bedroom dwelling
bed3	0.1862	2 bedroom dwelling
bed4	0.5078	3 bedroom dwelling
bed5	0.2262	4 bedroom dwelling
bed6	0.0485	5 or more bedroom dwelling
unit2	0.0010	Boat, tent, van, other
unit3	0.8284	1 family house, detached
unit4	0.0610	1 family house, attached
unit5	0.0150	2 family building
unit6	0.0088	3-4 family building
unit7	0.0076	5-9 family building
unit8	0.0057	10-19 family building
unit9	0.0057	20-49 family building
unit10	0.0095	50+ family building
Noplumb	0.0020	Dwelling does not contain complete kitchen facilities
Nokitch	0.0027	Dwelling does not contain complete plumbing facilities
yr1	0.0255	0-1 year-old dwelling
yr2	0.0855	2-5 year-old dwelling
yr3	0.0852	6-10 year-old dwelling
yr4	0.1592	11-20 year-old dwelling
yr5	0.1703	21-30 year-old dwelling
yr6	0.1336	31-40 year-old dwelling
yr7	0.1416	41-60 year-old dwelling

The estimated MSA price levels provide a consistent measurement of the price of a homogeneous unit of housing services in a particular MSA as heterogeneity in housing characteristics is purged through the inclusion of X_{ij} attributes. By netting out the implicit values of housing attributes, housing price indices are comparable across MSAs. We take the exponential of the MSA fixed effects and obtain the mean housing price index of approximately $16,445. The scattered graph in Figure 4.1 shows that California has a relatively high price index, which is consistent with our expectation. Results of hedonic housing price regression are shown in Table 4.4.

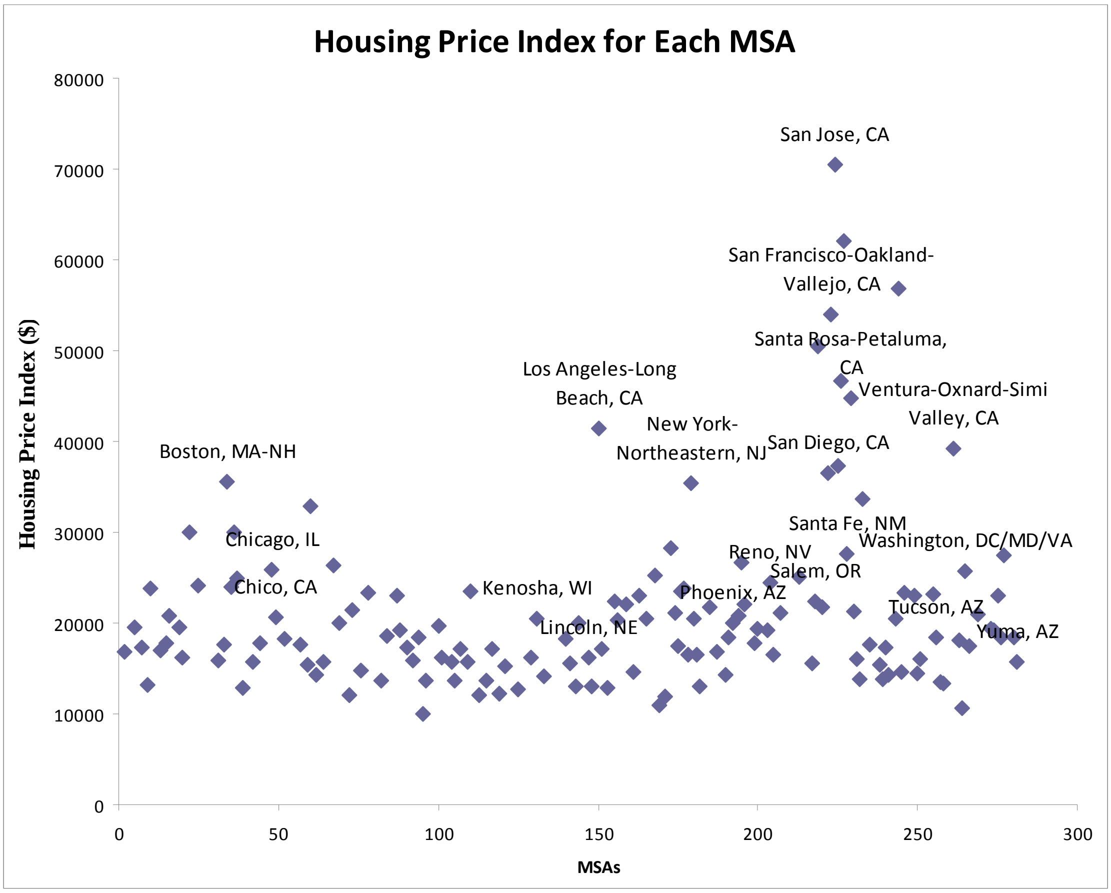

Figure 4. 1 Housing Price Regression Results

Table 4. 4 Hedonic Housing Price Regression to Obtain Housing Price Index

Dependent Variable: ln(house value in $)		
Variables	Coef.	Std. Err.
acre_9	0.2293447	0.0011204
acre_10	0.484376	0.0024098
room2	0.2601556	0.013702
room3	0.3645938	0.013633
room4	0.3399202	0.0138909
room5	0.4874492	0.0139123
room6	0.6201583	0.0139388
room7	0.7581641	0.0139573
room8	0.8844172	0.0139831
room9	1.094642	0.0140053
bed2	-0.0730917	0.0089261
bed3	0.0277223	0.0091637
bed4	0.0868816	0.0092378
bed5	0.1580952	0.0093004
bed6	0.2489188	0.0094754
unit2	-0.0357068	0.0128017
unit3	1.270124	0.0018044
unit4	1.116853	0.0023586
unit5	1.304594	0.0036758
unit6	1.289461	0.0044703
unit7	1.159725	0.0047681
unit8	1.129175	0.0054227
unit9	1.274372	0.0054686
unit10	1.418334	0.0044319
Noplumb	-0.1511751	0.0083232
Nokitch	-0.1768996	0.0095663
yr1	0.5237983	0.0026198
yr2	0.4621991	0.0016635
yr3	0.3713441	0.0016547
yr4	0.2462994	0.0013837
yr5	0.1101696	0.0013366
yr6	0.0707313	0.0013979
yr7	0.0487925	0.0013637
Constant	9.3902	0.0147
	Observation: 1,820,691	
	R-square: 0.9981	

4.5 Roback model

Using the estimated price indices from the previous section, the Roback model shows the relationship between wage, rents, and local amenities in a locational equilibrium framework (Rosen, 1979; Roback, 1982). Rosen (1979) and Roback (1982) argue that a higher housing price reflects a higher wage rate, higher quality of amenities or both. Following this logic we estimate the MWTP for the climate attribute using the Roback model. This model considers both the household's utility and firms' cost equations that are functions of climate attribute. It also assumes that the equilibrium levels of wages and rents are determined by the intersection of the two sides in the market. As such, we sum the coefficients from the housing price regression and income regression with respect to a specific attribute (e.g. extreme temperatures and precipitation). Equation (4.12) provides the specification of the housing price regression, where we have explicitly separated the climate variables from other elements of Z_j as given by

$$\ln \hat{\rho}_j = \beta_z \ln Z_j + \beta_c CLIMATE_j + \xi_j \tag{4.12}$$

where $\hat{\rho}_j$ is the predicted housing price index for a specific MSA *j* derived from the MSA fixed effects in equation (4.11); Z_j is the site-specific attributes, including sectoral labor wages, natural amenity, arts and entertainment; $CLIMATE_j$ represent extreme heat days, extreme cold days, days with extreme precipitation, and extreme weather events (e.g. number of tornado watches). The wage hedonic is given by

(4.13) $\ln I_j = \beta_z \ln Z_j + \beta_c CLIMATE_j + \xi_j$

where I_j is the year 2000 median family income in a specific MSA obtained from the U.S. Census; other variables are the same as in equation (4.12).

Results for both equations (4.12) and (4.13) are shown in Tables 4.5 and 4.6. We find from Table 4.5 that housing price rises as we reduce extreme weather days. We ignore the results from the income regression, and compute MWTP from only the housing price regression[5]. These results largely conform to our expectations and reveal that entertainment opportunity and labor wages positively affect housing prices. Turning to our climate variables, we find that extreme weather including days with extreme heat, extreme cold, heavy snowfall, and tornado watches reflects a lower housing price. Using this model can recover marginal willingness to pay (MWTP) associated with climate extremes. MWTP will be discussed in the next section.

Although the results based on the assumption that migration is costless provide a rough understanding in WTP for climate extremes in reality, migration is not costless and is likely to constrain location choices in the case of moderate improvements in climate. If migration costs are significant, people are less likely to relocate to a place for the sake of moderate improvements in climate. In order to capture migration costs, we conduct a valuation analysis using the residential sorting model, where these results from the Roback wage-hedonic model serve as a base of comparison to the sorting model.

[5]The signs of climate variables in the wage regression are negative, which is not consistent with expectation. Bayer et al. (2009) find similar results and ignore the coefficient from income regression. This is a conservative approach, since excluding the coefficient from the income regression inflates estimates of MWTP.

Table 4. 5 Wage-Hedonic Regression (wage regression)

Dependent variable: $\ln\rho_j$ (Coefficients of MSA-specific constant in Hedonic housing price regression)

	OLS (robust std. error.)	Region fixed effects	Region fixed effects w/ population density from the data sample
	(1)	(2)	(3)
Hot days	-0.00712	-0.0077	-0.0080
	(0.0079)	(0.0069)	(0.0069)
Cold days	-0.0180***	-0.0003	-0.00079
	(0.0069)	(0.0047)	(0.0047)
Ln(Construction wage) ($000s)	0.5797***	0.3541***	0.3658***
	(0.1266)	(0.1075)	(0.1082)
Ln(Production wage) ($000s)	-0.1510	-0.0631	-0.0652
	(0.0732)	(0.0529)	(0.0529)
Ln(Service wage) ($000s)	0.9929***	0.8382***	0.8538***
	(0.2471)	(0.1280)	(0.1291)
High precip days	-0.0161***	0.00016	0.0001
	(0.0048)	(0.0040)	(0.0040)
Annual snowfall (in)	-0.0138**	-0.0098*	-0.0098*
	(0.0008)	(0.0053)	(0.0053)
Annual tornado watches	-0.0159***	-0.0103***	-0.0110***
	(0.0038)	(0.0025)	(0.0027)
Water area (square miles) (00s)	0.0040*	0.0027	0.0028
	(0.0023)	(0.0025)	(0.0025)
Cultural establishments	0.1429	0.1672***	0.2620**
	(0.1180)	(0.0468)	(0.1086)
July Humidity (morning %)	0.0007	0.0023	0.0022
	(0.0016)	(0.0014)	(0.0014)
Population density*100000			-0.1016
			(0.1050)
R-square	0.5424	0.7010	0.7021

Table 4. 6 Wage-Hedonic Regression continued (hedonic regression)

Dependent variable: lnIj (2000 median household income in a specific MSA

	OLS (robust std. error.)	Region fixed effects	Region fixed effects w/ population density from the data sample
	(1)	(2)	(3)
Hot days	-0.0029	-0.0046	-0.0045
	(0.0030)	(0.0031)	(0.0031)
Cold days	-0.0050***	-0.0025	-0.0023
	(0.0018)	(0.0021)	(0.0021)
Ln(Construction wage) ($000s)	0.2089***	0.2291***	0.2235***
	(0.0497)	(0.0489)	(0.0492)
Ln(Production wage) ($000s)	-0.0138	-0.0092	-0.0082
	(0.0256)	(0.0240)	(0.0241)
Ln(Service wage) ($000s)	0.4472***	0.4390***	0.4315***
	(0.1163)	(0.0582)	(0.0587)
High precip days	-0.0019	-0.0025	-0.0023
	(0.0013)	(0.0018)	(0.0018)
Annual snowfall (in)	-0.0057**	-0.0025**	-0.0058**
	(0.0024)	(0.0024)	(0.0024)
Annual tornado watches	-0.0013	-0.0025**	-0.0022*
	(0.0013)	(0.0012)	(0.0012)
Water area (square miles) (00s)	0.0011	0.0011	0.0011
	(0.0014)	(0.0011)	(0.0011)
Cultural establishments	0.0430	0.0364*	-0.0090
	(0.0334)	(0.0212)	(0.0493)
July Humidity (morning %)	0.00020	-0.0005	-0.0005
	(0.0006)	(0.0006)	(0.0006)
Population density*100000			0.0487
			(0.0477)
R-square	0.5343	0.5592	0.5611

4.6 First-Stage Sorting Model

Results in Table 4.8 show the parameter estimates from the first stage of the sorting model. We find that the marginal utility of income is 1.00. This coefficient is used to calculate the coefficient on the housing price index at the MSA level, which is denoted as ρ_j. (See equation 4.A.11 in Appendix 4.A). Results from the same table show that people over 65 years old are more averse to extreme cold temperatures than younger people. College graduates are more sensitive to both extreme cold and hot temperatures. The intuition is that college graduates are expected to be more mobile and have more options to move than people without college degrees. Highly mobile individuals are more sensitive to temperature extremes than less mobile people. People born in the south are more sensitive to extreme heat than those born in other regions, while those born in California, the South, and the Northeast are more sensitive to extreme cold than people born in the West and the Midwest. One reason may be that people who are familiar with discomfort of weather extremes are most likely to react strongly to the extremes.

The migration dummy variable that indicates whether location *j* is out of an individual *i*'s birth region is significant. The coefficient of this variable recovers migration costs in terms of utility. Specifically, there is a significant utility cost associated with leaving one's birth region, which is -2.071. The mean indirect utility recovered from the 1st stage sorting model in terms of the coefficients of MSA specific constants are displayed in the scatter plot in Figure 4.2 (selected MSAs). The mean indirect utility of residing in Los Angeles ranks top one, which indicates that quality of life in Los Angeles ranks the highest, and this utility comprises all of the MSA-specific attributes in Los Angeles that are common to all households. The top 10 MSAs ranked by the mean indirect utility are listed in Table 4.7.

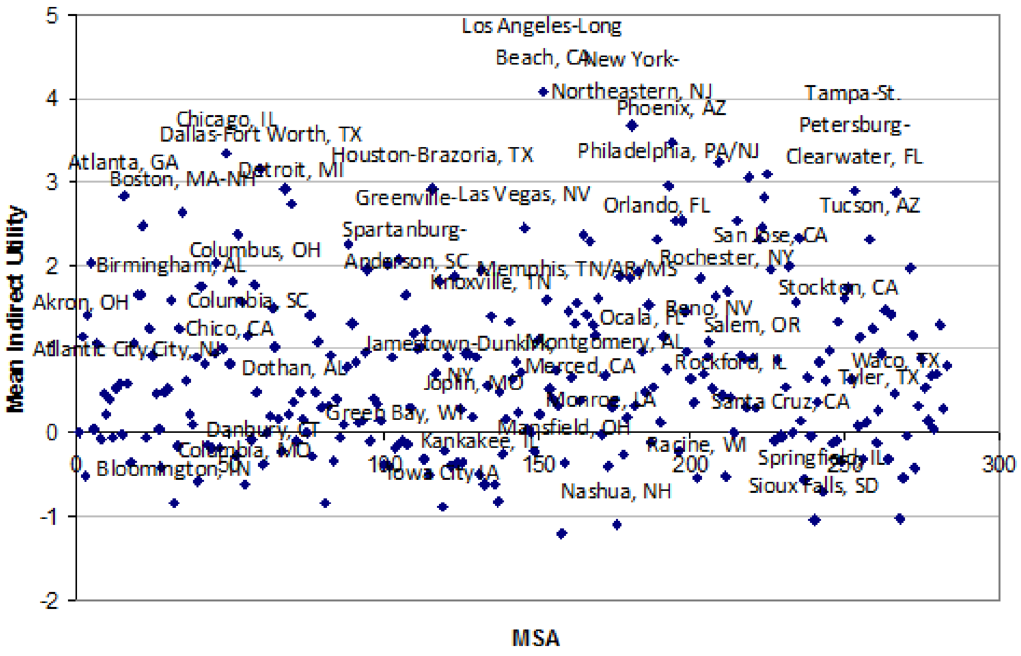

Figure 4. 2 Mean Indirect Utility for 281 MSAs

Table 4. 7 Top 10 MSAs Ranked by Mean Indirect Utility

Ranking	MSAs
1	Los Angeles-Long Beach, CA
2	New York-Northeastern, NJ
3	Chicago, IL
4	St. Luis, MO-IL
5	San Francisco-Oakland-Vallejo, CA
6	Philadelphia, PA/NJ
7	Dallas-Fort Worth, TX
8	Washington, DC/MD/VA
9	Phoenix, AZ
10	Portland, OR-WA

Table 4. 8 Parameter Estimates from First-Stage Sorting Model

Dependent variable: MSA location choice (I=1,820,691; J=281)	
Variable	Coefficient
Ln(predicted income)	1.0000***
	(0.0081)
Collgrad*Service_wage	1.6427***
	(0.0112)
MSA Outside Birth Macro Region	-2.0710***
	(0.0019)
Age 65 –x- Hot Days	0.0244***
	(0.0009)
Age 65 –x- Cold Days	-0.0247***
	(0.0007)
College –x- Hot Days	-0.0082***
	(0.0008)
College –x- Cold Days	-0.0315***
	(0.0005)
Born Northeast –x- Hot Days (South is left out)	0.0403***
	(0.0008)
Born West –x- Hot Days	0.0362***
	(0.0011)
Born Midwest –x- Hot Days	0.1067***
	(0.0008)
Born CA –x- Hot Days	0.0666***
	(0.0011)
Born CA –x- Cold Days (Northeast is left out)	-0.0377***
	(0.0009)
Born South -x- Cold Days	-0.0111***
	(0.0005)
Born West -x- Cold Days	0.0789***
	(0.0008)
Born Midwest -x- Cold Days	0.0538***
	(0.0005)

Notes: MSA fixed effects for 281 MSAs are omitted.

4.7 Second-Stage Sorting model

In the second stage of the sorting model, the mean indirect utility for each MSA is added to an additional term computing the housing price index for each MSA to form the dependent variable. (See equation 4.7). The second-stage results in Table 4.9 show that extreme cold and extreme hot are negatively significant, which is consistent with our expectation. The aggregate effects of both extreme heat and extreme cold are negative after we combine coefficients from both the1st and 2nd stages. Sectoral wages (tax inclusive) are used to measure the impacts of job opportunities. Service wage is positively significant, and job opportunity tends to be a significant driver in people's location decisions. The proximity to bodies of water is positively significant. One explanation is that people prefer to live near bodies of water, such as lakes, rivers, and oceans. Total establishments of business patterns in arts, entertainment, and recreation per square mile are positively significant, and people generally value entertainment and recreation. Humidity in July negatively affects household location choice, and people tend to move away from places with humid summers. The indirect utility effect with respect to population share provides a measurement of agglomeration effects or congestion effects. The negative sign indicates a congestion effect.

The first column in Table 4.9 reports OLS estimation results using robust standard errors. In order to address the unobservable effects across locations, a region fixed-effects model is used (column (2) to (4)). Results from an IV regression that include region fixed effects are listed in column (4), which addresses the endogeneity of population density (population share from equation (4.8) divided by land area of MSA *j*).

Table 4. 9 Second-Stage Sorting Model Results (N = 281)

Dependent variable: MSA mean indirect utility+0.386lnp

Variables	OLS	Region Fixed Effects	Region fixed effects with population density	Region fixed effects and IV regression
	(1)	(2)	(3)	(4)
Hot days	-0.0441	-0.0559*	-0.0530*	-0.0675*
	(0.0296)	(0.0297)	(0.0295)	(0.0382)
Cold days	-0.0552***	-0.0503**	-0.0457**	-0.0812***
	(0.0174)	(0.0201)	(0.0201)	(0.0247)
Ln(Construction wage) ($000s)	0.5142	0.9273**	0.8170*	1.3310**
	(0.4151)	(0.4613)	(0.4609)	(0.5865)
Ln(Production wage) ($000s)	-0.1432	-0.0655	-0.046	-0.1945
	(0.1975)	(0.2269)	(0.2255)	(0.2912)
Ln(Service wage) ($000s)	2.4201***	2.2105***	2.0635***	3.0627***
	(0.7276)	(0.5494)	(0.5498)	(0.7288)
High precip days	-0.0023	-0.0113	-0.0108	-0.0082
	(0.0131)	(0.0171)	(0.0170)	(0.0209)
Annual snowfall (in)	-0.0114	0.0148	0.0141	0.0230
	(0.0220)	(0.0227)	(0.0114)	(0.0280)
Annual tornado watches	0.0026	0.0153	0.0225**	-0.025
	(0.0102)	(0.0109)	(0.0114)	(0.0153)
Water area (square miles) (00s)	0.0515***	0.0477***	0.046***	0.0547***
	(0.0114)	(0.0107)	(0.0106)	(0.0137)
Cultural establishments	0.3925	0.4566**	-0.4359	5.1739***
	(0.3197)	(0.2006)	(0.4626)	(1.4173)
July Humidity (morning %)	-0.0306***	-0.0245***	-0.0242***	-0.0262***
	(0.0059)	(0.0060)	(0.0060)	(0.0074)
Population density*100000			0.9565**	-5.0037***
			(0.4474)	(1.4673)
R-square	0.4138	0.4493	0.4593	0.852

4.8 Discussion

When mobility is costly, the tradeoff between avoiding weather extremes and real wages is likely to be underestimated in a model that assumes free mobility. The magnitude of WTP to reduce additional extreme days (e.g. weather extremes, extreme precipitation, and tornado frequency) in a model that captures migration costs is likely to be higher.

In order to identify whether the conventional hedonic model that assumes free mobility underestimates values of weather extremes, results of marginal valuations from both the wage-hedonic model and sorting model are shown in Table 4.10 for comparison. The results from this table suggest that the MWTP to reduce one extreme weather day in the RUM is substantially higher than results from the conventional wage-hedonic model.

Table 4. 10 Estimated Marginal Willingness to Pay (MWTP)
for Extreme Temperature (Hedonic vs. RUM)

	Roback			RUM			
Climate Measure	OLS (robust std. error)	Region fixed effects	Region fixed effects w/ population density from the data sample	OLS (robust std. error)	Region fixed effects	Region fixed effects w/ population density from the data sample	Region fixed effects and IV for populatio n density
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hot days	$11	$12	$12	$18	$30	$18	$76
Cold days	$28	$0	$1	$232	$212	$193	$337
High precipitation days	$251	$0	$0	$93	$456	$436	$331
Annual tornado watches	$248	$160	$171	$105	$618	$909	$1,010

4.9 Conclusion

This empirical study employs a random utility model (RUM) that incorporates migration costs and allows for preference heterogeneity while valuing temperature extremes. Results show that people born in different regions have different preferences for temperature extremes. For example, people born in regions that have relatively high exposure to extreme weather (such as the Northeast, South, and California) are more averse to extreme weather than people born in other regions. Other demographic characteristics also have significant impacts on individuals' location decisions. We find that highly educated people (e.g. college graduates) are more averse to extreme temperatures than individuals without college degrees. This finding potentially reflects the fact that college graduates have more job opportunities and are more mobile than people with lower education levels. People over 65 years old are more averse to extreme cold weather and factor that in making location decisions. One reason might be that older retirees relocate to new places for the sake of pleasant amenities including warm weather. This finding is consistent with the retiree flows to southern states in early 2000s. We find that migration costs are significant. If migration costs are high, people are not willing to relocate to another region for the sake of a moderate improvement in climate.

Besides climate, other factors such as labor wages, natural amenities (e.g. water area), arts and entertainment are significant factors in household location choice. Service wages are positively significant in one's location choice. In particular, college graduates have stronger preferences for higher service wages. College graduates may have a higher probability of pursuing a business-related job with higher wages, and business-related jobs are categorized into the service sector. Proximity to water as an index of natural amenity is positively related to household location choice. The total number of arts, entertainment, and recreation establishments per square mile, as a measurement of abundance of recreational opportunities, has a positive effect on residential location choice.

One contribution of this study is that it captures preference heterogeneity, which allows us to better understand climate change impacts on migration and household location choice. This paper shows that it is not the case that all individuals have homogenous preferences, and they do not have the same preferences for weather extremes. In contrast, our results show that highly mobile people are more averse to extreme temperatures, while retirees are more sensitive to extreme cold weather than younger people. Individuals who are familiar with extreme weather are more sensitive to it thus are trying to avoid more of it. Besides preference heterogeneity, we capture mobility costs while estimating MWTP. Another advantage of the sorting model compared to the conventional hedonic model is that the former controls for location-specific unobservables. All these factors discussed above are ignored in the wage-hedonic model, which might lead to biased results. Our empirical findings show that the wage-hedonic model underestimates MWTP for climate extremes compared to RUM.

Appendix 4.A
Derive the Second-Stage Sorting Model
and the Coefficient of Housing Price Coefficient

Maximize utility subject to budget constraint, set up the Lagrangian expression

$$\underset{C_i, H_i, X_j}{Max} \ell = b_i^{\beta_c} H_i^{\beta_h} Z_j^{\beta_x} e^{\sum_{q=1}^{Q} \beta_{qz}(HH_q^i \times Z_j) + \beta_m M_{ij} + \xi_j + \eta_{ij}} + \lambda(I_{ij} - C_i + \rho_j H_i)$$

Individuals choose their location j, along with consumption of C_i and H_i to maximize their utility subject to a budget constraint.

F.O.C. with respect to C_i and H_i

$$\begin{cases} \dfrac{\partial \ell}{\partial C_i} = \beta_c C_i^{\beta_c - 1} H_i^{\beta_h} Z_j^{\beta_x} e^{\sum_{q=1}^{Q} \beta_{qz}(HH_q^i \times Z_j) + \beta_m M_{ij} + \xi_j + \eta} - \lambda = 0 & (4.A.1) \\ \dfrac{\partial \ell}{\partial H_i} = \beta_h H_i^{\beta_h - 1} C_i^{\beta_c} Z_j^{\beta_x} e^{\sum_{q=1}^{Q} \beta_{qz}(HH_q^i \times Z_j) + \beta_m M_{ij} + \xi_j + \eta_{ij}} + \lambda \rho_j = 0 & (4.A.2) \\ \dfrac{\partial \ell}{\partial \lambda} = I_{ij} - C_i + \rho_j H_i = 0 & (4.A.3) \end{cases}$$

In equilibrium, individuals must be indifferent among locations. If not, they would prefer to move. Hence, I can write H_i, C_i, and I_{ij} as H_{ij}, C_{ij}, and I_{ij}.

From (4.A.1)/(4.A.2) $\quad \dfrac{\beta_c}{\beta_h} \dfrac{H_{ij}}{C_{ij}} = \dfrac{1}{\rho_j}$

From (4.A.3) $\quad C_{ij} + \rho_j H_{ij} = I_{ij}$

$$H_{ij} = \frac{\beta_h C_{ij}}{\beta_c \rho_j} = \frac{\beta_h (I_{ij} - \rho_j H_{ij})}{\beta_c \rho_j} = \frac{\beta_h I_{ij} - \rho_j \beta_h H_{ij}}{\beta_c \rho_j}$$

$$(\beta_c \rho_j + \beta_h \rho_j) H_{ij} = \beta_h I_{ij}$$

$$H_{ij} = \frac{\beta_h}{\beta_c + \beta_h} \frac{I_{ij}}{\rho_j} \tag{4.A.4}$$

Substituting H_{ij} into equation (4.A.3), $C_{ij} = \frac{\beta_c}{\beta_h + \beta_c} I_{ij}$ (4.A.5)

Plugging (4.A.4) and (4.A.5) into the utility function, the indirect utility function is obtained:

$$\begin{aligned} V_{ij} &= \left(\frac{\beta_c}{\beta_c + \beta_h} I_{ij}\right)^{\beta_c} \cdot \left(\frac{\beta_h}{\beta_c + \beta_h} \frac{I_{ij}}{\rho_j}\right)^{\beta_h} \cdot Z_j^{\beta_x} e^{\sum_{q=1}^{Q} \beta_{qz} (HH_q^i \times Z_j) + \beta_m M_{ij} + \xi_j + \eta_{ij}} \\ &= \left(\frac{\beta_c}{\beta_c + \beta_h}\right)^{\beta_c} \cdot \left(\frac{\beta_h}{\beta_c + \beta_h}\right)^{\beta_h} \cdot I_{ij}^{\beta_c + \beta_h} \cdot \rho_j^{-\beta_h} Z_j^{\beta_x} e^{\sum_{q=1}^{Q} \beta_{qz} (HH_q^i \times Z_j) + \beta_m M_{ij} + \xi_j + \eta_{ij}} \\ &\cong I_{ij}^{\beta_c + \beta_h} \cdot e^{\sum_{q=1}^{Q} \beta_{qz} (HH_q^i \times Z_j) + \beta_m M_{ij} + \xi_j + \eta_{ij}} \end{aligned} \tag{4.A.6}$$

Let $\beta_I = \beta_c + \beta_h$, $\Theta_j = -\beta_h \ln \rho_j + \beta_x \ln Z_j + \xi_j$, $I_{ij} = \hat{I}_{ij} + \varepsilon_{ij}^I$, and $v_{ij} = \beta_I \varepsilon_{ij} + \eta_{ij}$

and take the log of indirect utility, equation (4.A.6) becomes the following

$$\begin{aligned} \ln V_{ij} &= \beta_I \ln I_{ij} + \sum_{q=1}^{Q} \beta_{qz} (HH_q^i \times Z_j) + \beta_m M_{ij} + \Theta_j + v_{ij} \\ &= \beta_I \ln \hat{I}_{ij} + \sum_{q=1}^{Q} \beta_{qz} (HH_q^i \times Z_j) + \beta_m M_{ij} + \Theta_j + \eta_{ij} \end{aligned} \tag{4.A.7}$$

Recall $\Theta_j = -\beta_h \ln \rho_j + \beta_x \ln Z_j + \xi_j$, in the second stage sorting model, MSA fixed effects Θ_j can be decomposed according to this equation. In this case, predicted income for every location j is entered into indirect utility function as a standalone measure.

In the second stage, the regression equation is:

$$\Theta_j = -\beta_h \ln \rho_j + \beta_x \ln Z_j + \xi_j \tag{4.A.8}$$

Now move $-\beta_h \ln \rho_j$ to the LHS of equation (4.A.7), regression equation becomes the following ($CLIMATE_j$ is included in z_j):

$$\Theta_j + \beta_h \ln \rho_j = \beta_x \ln Z_j + \xi_j \tag{4.A.9}$$

From equation (4.A.4) $H_{ij} = \dfrac{\beta_h}{\beta_c + \beta_h} \dfrac{I_{ij}}{\rho_j}$

$$\beta_h = \beta_I (\rho_j H_i / I_{ij}) \tag{4.A.10}$$

The parameter β_I is estimated in the first stage of sorting model, and set $\rho_j H_i / I_{ij}$ (the share of housing expenditure in income) equal to its median value in the sample.

From our regression results, $\beta_I = 1.00$, and the median values $\rho_j = 15{,}568$ $I_{ij} = 40380$,

$\beta_h = \beta_I (\rho_j H_i / I_{ij}) = 1.00 * (15{,}568 * 1) / 40380 = 0.386$ (4.A.11)

Appendix 4.B

The regression coefficient for extreme cold days is calculated as the following by combining results from both 1st and 2nd stage (column (4) in Table 4.10):

e.g. Coefficient of extreme heat (overall effect):

$$
\begin{aligned}
\beta_{heat} &= \frac{\partial \ln V}{\partial HEAT} = \beta_{heat\_1st\_stage} + \beta_{heat\_2nd\_stage} \\
&= \beta_{age\_g\_65\_heat} \times \overline{AGE} + \beta_{collgrad\_heat} \times \overline{COLLGRAD} + \beta_{northeast\_heat} \times \overline{NE} \\
&\quad + \beta_{midwest\_heat} \times \overline{MW} + \beta_{west\_heat} \times \overline{WE} + \beta_{CA\_heat} \times \overline{CA} + \beta_{heat\_2nd\_stage} \\
&= -0.0247 * 0.1726 - 0.0315 * 0.341 - 0.0111 * 0.3222 + 0.0538 * 0.273 + 0.0789 * 0.057 - 0.0377 * 0.074 - 0.0552 \\
&= -0.0573
\end{aligned}
$$

Median value of household income is \$40,380, and extreme heat days and extreme cold days are measure in 10 days. Coefficient of marginal utility of income is $\beta_I = 1.00$. MWTP to reduce additional extreme heat day = (0.0573/1)*40,380/10 = \$232.

Chapter 5

Recursive Dynamic Inter-Regional CGE Model

5.1 Introduction

The recursive dynamic inter-regional computable general equilibrium (CGE) model is developed based on the IMPLAN regional modeling framework of Rausch and Rutherford (2008) and Sue Wing (2007). The recursive dynamic CGE model is a multi-period model, in which results are computed one period at a time from the base year 2010 through the year 2065. The inter-regional CGE model is calibrated using regional social accounting matrices (SAMs) in the year 2010 that are aggregated from the IMPLAN state-level social accounts.

There are four economic agents including consumers, producers, governments, and foreign sector in the model. Consumers are endowed with a supply of labor and capital, which are the input factors for producers. The consumer's objective is to maximize utility that is a function of consumption goods (e.g. food, housing, energy, and others) constrained by the consumer's budget: earnings minus total savings. In our model, we assume a nested constant elasticity of substitution (CES) function that allows for different elasticities of substitution across different nests of commodities within the same utility function (Figure 5.1). Similar to the consumers' objectives, producers maximize their profits by choosing optimal levels of capital, labor, energy, and materials (KLEM). A nested Cobb-Douglas-CES production function is used in the model. The nesting structure of the production function allows for different elasticities of substitution across factor nests. For example, the elasticity of substitution between energy and materials is

0.7, which is different from the elasticity of substitution between capital and labor which is set at 1 (Figure 5.2). The government spends money and purchases goods and services using tax revenues to maximize utility. The foreign sector—a representative of rest of the world (ROW)—trades commodities in the international market.

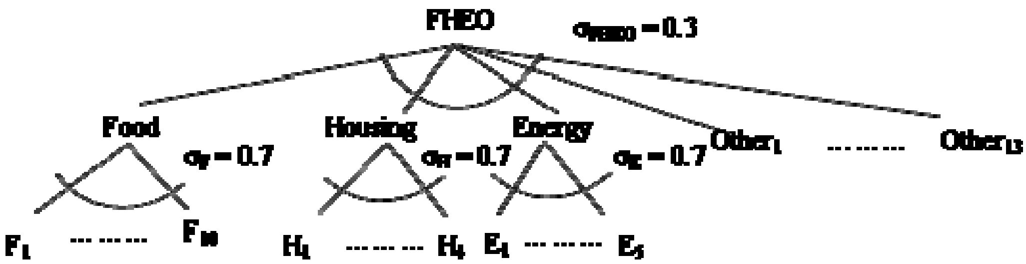

Figure 5. 1 Nested Structure for CES Utility Function

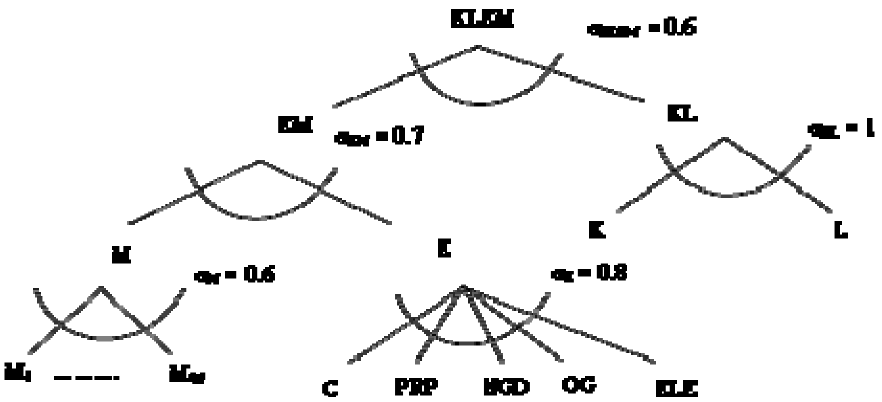

Figure 5. 2 Nested Structure for CES Production Function

Source: Abler, D., K. Fisher-Vanden, M. McDill, R. Ready, J. Shortle, I. Sue Wing, T. Wilson (2009). Economic Impacts of Projected Climate Change in Pennsylvania. *Report to the PA Department of Environmental Protection.*

A competitive equilibrium is achieved when four conditions hold: 1) market clearing—i.e., supply equals demand; 2) zero profits—i.e., producers cannot earn excess profit; 3) income balance—i.e., consumers purchase commodities based on their budget, which equals total income net savings; 4) total investment is equal to total savings. Details on the objectives of economic agents are shown in Section 5.2.

Two scenarios are simulated in the CGE model. The first is the baseline scenario the "business as usual" (BAU) scenario, which assumes no climate change. In this scenario, the economic model is simulated forward in time given assumptions of key exogenous variables. These variables include region-level projected population that is obtained from the U.S. Census, saving rates, depreciation rates, multifactor productivity growth rates, the rate of energy efficiency improvement, and rates of improvement in capital and labor quality. The second is the counterfactual scenario, which assumes that the regional population in the year 2065 is adjusted by regional population shares predicted by the RUM. There are two cases in this scenario: the 1st is the one where labor wages are assumed to be exogenous (the 1st iteration between the RUM and the CGE model without achieving equilibria in these two models), and the 2nd is the case that requires iterations between the RUM and the CGE models until convergence criteria are satisfied—equilibria is achieved in both the RUM and the CGE models. This case endogenizes labor wages by accounting for re-sorting decisions under changes in climate and resulting changes in wages and allowing for general equilibrium feedbacks.

5.2 Model Structure

- **Consumers**

Households maximize a utility function with a nested CES functional form subject to a budget constraint. Utility is a function of different commodity bundles, such as food, housing property, energy, and others.

The income of a consumer in region *r* and time period *t* ($Y_{r,t}$) comprises labor income ($YL_{r,t}$) and capital income ($YK_{r,t}$):

(5.1) $$Y_{r,t} = YL_{r,t} + YK_{r,t}$$

Labor income ($YL_{r,t}$) is the product of wage rates ($PL_{r,t}$) and labor supply ($LS_{r,t}$) (equation (2)), where labor supply is the product of working-age population ($POP_{r,t}$) and labor quality ($q^{L}_{r,t}$) (equation (5.3))

(5.2) $$YL_{r,t} = PL_{r,t} \times LS_{r,t}$$

(5.3) $$LS_{r,t} = POP_{r,t} \times q^{L}_{r,t}$$

Total savings ($S_{r,t}$) is the residual after we deduct consumption ($VCC_{r,t}$) from total income ($Y_{r,t}$) (equation (5.4)). A fixed savings rate, $s_{r,t}$, is assumed and determines the level of savings based on total income.

(5.4) $$S_{r,t} = s_{r,t} Y_{r,t} = Y_{r,t} - VCC_{r,t}$$

- **Producers**

Producers maximize profits subject to a constant return to scale (CRS) technology. We assume a nested CES functional form. Production for sector *j* in region *r* and time period *t* ($Q_{j,r,t}$) is function of capital ($K_{j,r,t}$), labor ($L_{j,r,t}$), productivity ($A_{j,r,t}$), and the growth in productivity in time period *t* ($g(t)$).

(5.5) $$Q_{j,r,t} = f(K_{j,r,t}, L_{j,r,t}, A_{j,r,t}, g(t))$$

- **Government**

The government collects taxes as the source of government revenues. Taxes include taxes on capital and labor paid by producers, sales tax paid by consumers, and household income tax. The government purchases commodities and services subject to government budget constraint, based on utility maximization.

- **Trade Sector**

An Armington approach is used to model intra-national trade flows where domestic goods are assumed to be imperfect substitutes for traded commodities. A nested CES function is used to represent total commodity supply. The total supply of commodity *i* in region *r* and time period *t* ($QS_{i,r,t}$) is represented in equation (5.6), where $D_{i,r,t}$ represents domestic goods, and $M_{i,r,t}$ represents traded goods:

(5.6) $$QS_{i,r,t} = A_0[\alpha^d D_{i,r,t}^{\rho} + \alpha^m M_{i,r,t}^{\rho}]^{\frac{1}{\rho}}$$

- **Investment**

Total investment supply associated with region *r* and time *t* ($I_{r,t}$) is equal to the product of investment supply for each product in region *r* and time *t* as shown in equation (5.7). In the equation, investment share for each product *n* is indicated as $\alpha^{I}_{n,r}$.

$$(5.7)\quad I_{r,t} = I_{1,r,t}^{\alpha^{I}_{1,r}} I_{2,r,t}^{\alpha^{I}_{2,r}} \ldots I_{n,r,t}^{\alpha^{I}_{n,r}}$$

Capital stock in region *r* and time period *t* ($K_{r,t}$) is equal to accumulated investment minus depreciation:

$$(5.8)\quad K_{r,t} = (1-\delta)K_{r,t-1} + I_{r,t}$$

where the parameter δ represents the depreciation rate, $I_{r,t}$ is total investment supply in region *r* and time *t* as shown in equation (5.7).

Total value of investment supply for product *i* in region *r* and time *t* is equal to the price of the investment goods ($PS_{i,r,t}$) multiplied by investment supply of product *i* in region *r* and time *t* ($I_{i,r,t}$), which is total investments on product *i* from total savings.

On the other hand, investment final demand for product *i* in region *r* and time *t* is equal to the share of investment demand allocated to investment good *i* (denoted as $\alpha^{I}_{i,r,t}$), multiplied by total investment demand in region *r* and time period *t* ($VII_{r,t}$).

In the equilibrium, investment supply is equal to investment demand. (See equation (5.9)).

(5.9) $PS_{i,r,t} \times I_{i,r,t} = \alpha^{I}_{i,r,t} VII_{r,t}$

- **Markets**

The total demand for commodity *i* in region *r* in time period *t* ($QD_{i,r,t}$) is the sum of inter-industry demand for good *i* in region *r* and time period *t* by industry *j* ($A_{i,j,r,t}$), the final demand of consumers ($C_{i,r,t}$), investment ($I_{i,r,t}$), government ($G_{i,r,t}$), and net exports ($X_{i,r,t}$) (equation (5.10)).

(5.10) $QD_{i,r,t} = \sum_{j} A_{i,j,r,t} + C_{i,r,t} + I_{i,r,t} + G_{i,r,t} + X_{i,r,t}$

Equations (5.6) and (5.10) provide us with the supply and demand sides of the market respectively. Commodity prices are adjusted on the market clearing, when total supply is equal to total demand ($QS_{i,r,t} = QD_{i,r,t}$).

5.3 Build the CGE Model in GAMS

The IMPLAN data provides SAMs of 440 industrial sectors, factors (i.e. employee compensation, proprietary income, other property income, and indirect business taxes), and institutions (i.e. households, public entities, corporate entities) for each state. IMPLAN data are first read into GAMS and are converted into data formats that are compatible with GAMS data files. Small values are removed using the filter code in GAMS and the GAMS data files are then recalibrated. Flows of intra-state trade are adjusted in the model to balance exports and imports. State-level SAMs are merged into one single file and are aggregated to five regions: California, Northeast, Midwest, South, and West. The IMPLAN sectors are aggregated to 30 industrial sectors in our study.

Key parameters used in the CGE model are listed in Table 5.1. In the table, *r* represents regions, *g* represents goods, *s* represents sectors, *i* represents institutions, *f* represents factors, *h* represents household, *pub* represents public sector, and *trd* represents trade sector. Equations below show conditions that are required to achieve competitive general equilibrium:

(1) Market clearing: total commodity supply is equal to total commodity demand (equation (5.11)). Total supply is the sum of domestic production $vom_{r,g}$ and goods supply by institutions $\sum_i evpm_{r,g,i}$. Total demand is the sum of domestic intermediate demand $\sum_g vdfm_{r,g,s}$, domestic consumption demand $\sum_h vdpm_{r,g,h}$, domestic investment demand $vdim_{r,g}$, domestic public demands $\sum_{pub} vdgm_{r,f,pub}$, and aggregate exports $vx_{r,g}$.

(5.11)

$$vom_{r,g} + \sum_i evpm_{r,g,i} = \sum_s vdfm_{r,g,s} + \sum_h vdpm_{r,g,h} + v\dim_{r,g} + \sum_{pub} vdgm_{r,f,pub} + vx_{r,g}$$

(2) Income balance: total budget for households and government agents is equal to total expenditure on goods and services. As shown in equation (5.12), factor income for households $\sum_f evom_{r,f,i}$ along with corporate profits $vprf_{r,i}$, institutional

goods supply $\sum_{s} evpm_{r,s,i}$, and inter-institutional transfers $vtrn_i$ are equal to aggregated consumption expenditure vpm_i .

$$(5.12)\quad \sum_{f} evom_{r,f,i} + vprf_{r,i} + \sum_{s} evpm_{r,s,i} + vtrn_i = vpm_i$$

(3) Zero profit: sectors cannot earn extra profits, and the total costs of inputs are equal to values of outputs. This condition applies to the four sectors below:

Sectoral production: total supply is equal to total demand. More specifically, total domestic intermediate demands, $\sum_{s} vdfm_{r,g,s}$, along with imported intermediate demands, $\sum_{trd}\sum_{g} vifm_{r,g,trd,s}$, and factor demands, $\sum_{f} vfm_{r,f,s}$, are equal to aggregate output $vom_{r,s}$. #

$$(5.13)\quad \sum_{s} vdfm_{r,g,s} + \sum_{trd}\sum_{g} vifm_{r,g,trd,s} + \sum_{f} vfm_{r,f,s} = vom_{r,s}$$

Consumers: total consumption demand is equal to aggregate consumption. As shown in equation (5.14), the sum of domestic consumption demand, $\sum_{s} vdpm_{r,s,h}$, and imported consumption demand, $\sum_{trd}\sum_{s} vimp_{r,g,trd,h}$, is equal to the aggregate supply of consumption $vpm_{r,h}$.

$$(5.14)\quad \sum_{s} vdpm_{r,s,h} + \sum_{trd}\sum_{s} vipm_{r,g,trd,h} = vpm_{r,h}$$

Investment: investment demand (the sum of domestic investment demand $\sum_{s} v\dim_{r,s}$ and imported investment demand $\sum_{trd}\sum_{s} viim_{r,s,trd}$) is equal to the aggregate supply of investment, $vinv$.

$$(5.15)\quad \sum_{s} v\dim_{rs} + \sum_{trd}\sum_{s} viim_{r,s,trd} = vinv$$

Public sector: the sum of domestic public demand, $\sum_{s} vdgm_{r,s,pub}$, and imported public demand, $\sum_{trd}\sum_{s} vigm_{r,s,trd,pub}$, is equal to public sector demand, vgm_{pub}.

$$(5.16)\quad \sum_{s} vdgm_{r,s,pub} + \sum_{trd}\sum_{s} vigm_{r,s,trd,pub} = vgm_{pub}$$

Table 5. 1 Key Parameters Used in the CGE Model

aeei	autonomous energy efficiency improvement index
evok0	Capital endowment in benchmark
evol0	Labor endowment in benchmark
evok(r,h)	Capital endowment
evol(r,h)	Labor endowment
evo(r,i,f)	Factor endowment by institution
evom(r,i,f)	Factor supply
evpm(s,i)	Goods supply (make and export)
evpm(r,s,i)	Goods supply
va(r,s)	Armington supply including imports
vdifm(r,g,s)	Total intermediate demand
vdfm(r,g,s)	Domestic intermediate demand
vdfm(r,g,s)	Domestic intermediate demand
vdpm(r,s,h)	Domestic consumption demand
vdgm(s,pub)	Domestic public demands
vdim(s)	Domestic investment demand
vfm(r,f,s)	Factor demand
vifm(r,g,trd,s)	Imported intermediate demand
vfmk(r,s)	Capital demand by sector
vfml(r,s)	Labor demand by sector
vgm(pub)	Public sector demand
viim(r,s,trd)	Imported investment demand
vipm(r,g,trd,h)	Imported consumption demand
vim(s,trd)	Aggregate imports
vinv	Aggregate investment
vinvd(r,g)	Investment demand by commodity
vinvh(r,h)	Investment demand by household
vigm(s,trd,pub)	Imported public demands
vn(g)	Intra-national trade
vom(r,s)	Aggregate output
vprf(r,i)	Corporate profit
vpm(h)	Aggregated consumption
vtrn(r,i)	Transfers
vxm(r,s)	National and international exports
vx(r,g)	Aggregate exports

Note: in the table, r=region, s=region, g=goods, s=sector, i=institution, f=factor, h=households, pub=public sector, trd=trade sector

Key variables for prices and quantities are shown in Table 5.2. The CGE model solves for equilibrium results for these variables.

Table 5. 2 Key price and quantity variables in the CGE Model

Variables	DESCRIPTION
py(s,r)	Sectoral output prices
pfx(s,r)	International trade price
qxf(s,r)	Export
qmf(s,r)	Import
p(s,r)	Price for domestic output
pa(s,r)	Armington aggregate prices
pc(h,r)	Consumption price by household
qc(h,r)	Consumption by households
pn(s)	Intra-national trade price
pinv(r)	New investment price
vpm(r,h)	Aggregate consumption
vgm(r,pub)	Public sector demand
vxm(r,s)	National and international exports
vim(r,s)	Aggregate imports
vinv(r)	Investment
pgov(pub,r)	Price of Public output
qg(pub,r)	Government output
pf (fa,r)	Factor prices
pfx	Foreign exchange
pls	Price of labor supply

Note: in the table, r=region, s=region, g=goods, s=sector, i=institution, f=factor, h=households, pub=public sector, trd=trade sector

To improve the computational speed in solving non-linear programming problems in GAMS, the Mathematical Programming System for General Equilibrium (MPSGE) is used to solve equilibrium results. MPSGE operates as a subsystem in GAMS. It is based on a library of function and Jacobian evaluation routines, which facilitates the process of solving computationally intensive general equilibrium problems. This language provides a convenient way to solve nonlinear inequalities in a complicated system with many constraints. It writes out objective functions for different economic agents based on nested structures for constant elasticity of substitution (CES) utility and production functions.

5.4 Business as Usual (BAU) Scenario

The baseline BAU scenario assumes no climate change impacts on migration. Key parameters such as population, labor productivity, capital productivity, saving rates, depreciation rate, productivity growth rates, autonomous energy efficiency improvement (AEEI) growth rates are parameters that drive regional economic growth. The interest rate in 2010 is obtained from Bureau of Labor Statistics (BLS), which is set to 0.057. The depreciation rate is assumed to be 0.05. The AEEI growth rate is assumed to increase by 2% annually, and the multifactor productivity growth rate, including growth rates of labor and capital productivities, is assumed to be 2.5% annually. Population projections are obtained from the U.S. Census as discussed in Section 3.

The CGE model solves for equilibrium prices and quantities in each time period. Macroeconomic indicators including regional GDP, total consumption, investment, government expenditures, and net exports are computed in the model. Nominal regional GDP in region *r* in time period *t* is calculated as a sum of total consumption, investment, government expenditures, and net exports as shown in equation (5.17). Similarly, nominal regional GDP using benchmark quantities is shown in equation (5.18). These two indicators are used to calculate Laspeyres index and Paasche index that are components of Fisher GDP price index as discussed below.

$$\begin{aligned} gdp\_nom_{r,t} &= \sum_h pc_{r,h,t} \times qc.l_{r,h} + pinv_{r,t} \times \sum_h rhscale.l_{r,h} \times vinv_r \\ &+ \sum_{pub} pgov_{r,pub,t} \times qg.l_{r,pub} + \sum_s pfx_t \times (qxf.l_{r,s,ftrd} - qmf.l_{r,s,ftrd}) \end{aligned} \tag{5.17}$$

where $gdp\_nom_{r,t}$ represents nominal GDP for region *r* in time period *t*, *ftrd* represents foreign trade, quantities ending with *l* represents current year quantities, $\sum_h rhscale.l_{r,h}$ is a rationing constraint to scale transfers and investment with households activity levels. Other parameters are listed in Table 5.2.

(5.18)

$$\begin{aligned} gdp\_nom_{r,b} = & \sum_h pc(r,h,t)\times vpm(r,h) + pinv(r,t)\times \sum_h rhscale.l(r,h)\times vinv(r) \\ & + \sum_{pub} pgov(r,pub,t)\times vgm(r,pub) + \sum_s pfx(t)\times (vxm(r,s,"ftrd") - vim(r,s,"ftrd")) \\ & + \sum_s pn(s,tp)\times (vxm(r,s,"dtrd") - vim(r,s,"dtrd")) \end{aligned}$$

where $gdp\_nom_{r,b}$ represents nominal GDP in region *r* based on quantities in the base year. Since the base year prices are all ones in the CGE model, we do not include those in the calculation. Similar to normal GDP calculated in equation (5.17), nominal GDP in equation (5.18) is the sum of total consumption, investment, government expenditures and net exports. Other variables are listed in Table 5.2.

The Fisher GDP price index is used to minimize inflation errors (Sue Wing, Daenzer, Fisher-Vanden, and Calvin, 2011). This price index is used to obtain real wage rates in the model. Prices in the CGE model are prices that are relative to numeraire, which in the model is foreign exchange. It is found that any nominal price in the CGE model can be chosen as numeraire, and the choice of numeraire has no impact on real prices and quantities in the model (Burfisher, 2011). Since we choose foreign exchange as numeraire, it implies that the value of foreign exchange is equal to one, and serves as the base of all prices in the model. In addition, the price of labor is set to one in the base year which has the effect of defining units to be how much $1 can purchase labor in the base year. As such, the price of labor produced by the CGE model for each time period is actually growth rate of labor price. Although previous studies are aware of this issue, it is challenging to convert the relative price to real values and there is no perfect solution to this (Boehringer and Rutherford, 2006; Aaberge et al., 2004). In order to address this issue, we divide the wage rates produced by the CGE model by the Fisher GDP price deflator to produce real growth rate of wages relative to the base year 2010. The Fisher GDP price index is generated from two indices: the Laspeyres index and Paasche index. The former is calculated using benchmark quantities in the numerator, whereas the Paasche index uses current time *t* and quantities. The formula is shown in equation:

(5.19) $$PGDP_{r,t}^{Fisher} = \sqrt{PGDP_{r,t}^{Laspeyres} \times PGDP_{r,t}^{Paasche}}$$

(5.20)
$$PGDP_{r,t}^{Laspeyres} = \frac{gdp\_nom(r,b)}{\begin{array}{l}\sum_h vpm(r,h) + \sum_h rhscale.l(r,h) \times vinv(r) + \sum_{pub} vgm(r,pub) + \sum_s vxm(r,s,"ftrd") \\ + \sum_s vxm(r,s,"dtrd") - \sum_s vim(r,s,"ftrd") - \sum_s vim(r,s,"dtrd")\end{array}}$$

(5.21)
$$PGDP_{r,t}^{Paasche} = \frac{gdp\_nom(r,t)}{\sum_h qc.l(r,h) + \sum_h rhscale.l(r,h) \times vinv(r) + \sum_{pub} qg.l(r,pub) + \sum_s qxf.l(r,s) - \sum_s qmf.l(r,s)}$$

Real growth rate of wages is then calculated using the following formula: we divide wage rate that the CGE model is producing by Fisher GDP price index.

$$wage\_rate\_real_{r,t} = \frac{wage\_rate\_CGE_{r,t}}{PGDP_{r,t}^{Fisher}}.$$

Fisher GDP price index is also used to produce real GDP and adjust for other macroeconomic indicators by minimizing inflation errors.

To summarize, this section provides an overview of the U.S. inter-regional CGE model and describes the BAU scenario that serves as a baseline scenario in the model. Differences between the results from the BAU scenarios and those from the counterfactual scenario will be discussed in the next section.

Chapter 6

Regional Economic Impacts from Climate Change-Induced Migration

6.1 Introduction

Previous studies that examine regional economic impacts from climate change-induced migration have not considered the endogeneity of labor wages. If more households move into a region due to pleasant amenities including moderate weather, labor supply in that region may increase. Labor wages are likely to respond to changes in labor supply. Assuming an increase in labor supply dominates the change in the equilibrium price of labor, labor wages may drop. Decreasing wages may generate outflow of workers. The opposite occurs in the regions that experience increasing labor wages. An increase in labor wages may attract more people to move into this region. In this sense, ignoring feedbacks from the equilibrium labor market may lead to biased results while examining regional economic impacts. In order to endogenize labor wages, we couple a structural residential sorting model with a CGE model to simulate regional economic impacts. The coupling process allows us to update labor supply in the CGE model, while allowing for re-sorting behaviors in the RUM from changes in both climate and wages.

6.2 Population Shares in the RUM

We employ projected climate data (i.e. extreme hot days, extreme cold days, and annual number of days with heavy rainfall) for the time period 2056-2065 to predict population shares by region in 2065 from changes in climate. Due to the instability of a single-year projected data, we calculate the mean value across ten years from the year 2056 to 2065. Both the A1B and A2 IPCC emission scenarios are used for comparison. The following probability equation based on multinomial logit specification is used to predict changes in population shares across regions under changes in climate extremes:

$$(6.1)\quad P_{ijt}(\ln V_{ijt} > \ln V_{ikt}\ \forall j \neq k) = \frac{e^{\beta_I \ln \hat{I}_{ijt} + \sum_{q=1}^{Q} \beta_q^T (HH_{qt}^i \times T_t^j) + \beta^{EduW}(EDU_t^i \times W_t^j) + \beta_m M_{ijt} + \hat{\Theta}_{jt}}}{\sum_{l=1}^{J} e^{\beta_I \ln \hat{I}_{ilt} + \sum_{q=1}^{Q} \beta_q^T (HH_{qt}^i \times T_t^l) + \beta^{EduW}(EDU_t^i \times W_t^l) + \beta_m M_{ilt} + \hat{\Theta}_{lt}}}$$

where $\hat{\Theta}_{jt} = \beta_x \ln Z_{jt} + \beta_w W_{jt} + \beta_c CLIMATE_{jt}$

In the equation, i represents household, j represents MSA, t represents the starting point where $t = 2000$, and the ending point where $t = 2065$. T_t^j represents both extreme hot days and extreme cold days in MSA j in the time period t. Other variables are the same as used equations (4.1).

In the simulation, we assume that new generation replaces the old generation, and demographics of residents in 2065 stay the same with those in the year 2000 (e.g. age, educational attainment). It is also reasonable to assume that preference for climate amenities holds unchanged in the year 2065 compared to the base year 2000, since the climate relates to a climate zone will not change dramatically in 65 years. In the next step, we endogenize labor wage rates W_t^j using a coupling process, and input the wage responses into the prediction. A challenging issue here relates to the predicted income $\hat{I}_{ijt}$ as shown in equation (6.1). In this model, we simply assume predicted income stays unchanged but address relative changes in wage rates W_t^j . In the future study, we will use income regression in equation (4.10), and decompose the MSA fixed effects α_j into MSA-specific characteristics including sectoral wages at the MSA level. As such, we can predict household income based on changes in sectoral wages in the time period of *t*.

The probability of choosing MSA *j* is aggregated to regional level—the Northeast, Midwest, South, West, and California by adding up the weighted probabilities of choosing MSA *j* that belongs to region *r*.

$$P_{rt} = \sum_{j \in r} \left(weight_{jt} \times P_{jt} \right) = \sum_{j \in r} \left(\frac{pop_{jt}}{pop_{rt}} \times P_{jt} \right) = \sum_{j \in r} \left(\frac{pop_{jt}}{pop_{rt}} \times \frac{1}{N} \sum_{i=1}^{N} P_{ijt} \right) \quad (6.2)$$

where *r* represents one of the five regions in the U.S.; *j* represents one of the 281 MSAs; *t* respectively represents starting point in the year 2000 and ending point in the year 2065; P_r is the probability that region *r* is chosen (population share by region); P_j is the probability that MSA *j* is chosen; P_{ijt} is the probability that the head of household *i* chooses MSA *j* in the time period *t* as shown in equation (4.4); *N* is total number of individuals in the data sample; $weight_{jt} = \frac{pop_{jt}}{pop_{rt}}$, which represents the weight of each MSA *j* within region *r* in the year *t* based on population size; pop_{jt} is the total population in MSA *j* in the time period *t*, and pop_{rt} is the total population in region *r* in the time period *t*.

Both the A2 scenario and the A1B scenario are used in the RUM to simulate population shares by region under changes in climate in terms of extreme hot days, extreme cold days, and annual number of days with heavy rainfall. Population shares by region computed from the RUM under these two scenarios are presented in Table 6.1 and 6.2. Results in the 1st column show the estimated population shares by region in the base year 2000. We change only one variable at a time respectively for extreme hot days, extreme cold days, and extreme precipitation to predict population shares by region under changes in a specific climate variable (column (2), (3), and (4)). Population shares by region under hypothetical changes in all three climate variables are shown in column (5). The population share in the Northeast increases due to changes in climate between the years 2000 and 2065, while other regions lose population shares in 2065 relative to 2000.

Table 6. 1 Population Shares in RUM under Changes in Climate (A1B scenario)

Regions	Baseline scenario (2000)	Only change extreme hot (2065)	Only change extreme cold (2065)	Only change precipitation (2065)	Change extreme hot, extreme cold, and precipitation (2065)
	(1)	(2)	(3)	(4)	(5)
Northeast	0.2100	0.3191	0.3148	0.3183	0.3177
Midwest	0.2334	0.2238	0.2174	0.2228	0.2036
South	0.3540	0.3003	0.3104	0.3038	0.3231
West	0.0970	0.0881	0.0874	0.0864	0.0849
California	0.1053	0.0690	0.0703	0.0688	0.0707

Table 6. 2 Population shares by Region in RUM Under Changes in Climate (A2 Scenario)

Regions	Baseline scenario (2000)	Only change extreme hot (2065)	Only change extreme cold (2065)	Only change precipitation (2065)	Change extreme hot, extreme cold, and precipitation (2065)
	(1)	(2)	(3)	(4)	(5)
Northeast	0.2100	0.3198	0.3140	0.3184	0.3170
Midwest	0.2334	0.2218	0.2169	0.2228	0.2000
South	0.3540	0.3002	0.3108	0.3038	0.3247
West	0.0970	0.0892	0.0873	0.0863	0.0860
California	0.1053	0.0695	0.0707	0.0688	0.0716

6.3 Population Shares from the Iterative Process

The baseline BAU scenario as discussed in Chapter 5 solves for equilibrium wage rates by region in the baseline scenario where climate change does not occur. A constant elasticity of transformation (CET)-constant elasticity of substitution (CES) function is used to allocate labor to 30 sectors including the service sector of our interest based on returns to labor. Particularly in the CGE model, annual growth rates of equilibrium wages are obtained. We compute a real wage rate by dividing the wage rates that the model produces by the Fisher GDP price index. Details of the GDP price index are discussed in the previous section. We iterate between the RUM and CGE model by adjusting regional population in the CGE model and updating labor wages in the RUM. The real wage rates are presented in Table 6.3. and 6.4.

Table 6. 3 Real Wage Growth Rates Relative to the Year 2010 and numeraire (A1B Scenario)

	BAU (2065)	Migration (1st iteration) (2065)	…	Migration (20th iteration) (2065)	Migration (21th iteration) (converged results) (2065)
NE	1.2124	1.1944	…	1.2223	1.2216
MW	1.5143	1.6131	…	1.5403	1.5379
SO	1.3895	1.3897	…	1.4057	1.4055
WE	1.3150	1.1719	…	1.2399	1.2404
CA	1.3769	1.5605	…	1.3776	1.3808

Table 6. 4 Real Wage Growth Rates Relative to the Year 2010 and numeraire (A2 Scenario)

	BAU (2065)	Migration (1st iteration) (2065)	…	Migration (23rd iteration) (2065)	Migration (24th iteration) (converged results) (2065)
NE	1.2124	1.1967	…	1.2218	1.2213
MW	1.5143	1.6248	…	1.5383	1.5381
SO	1.3895	1.3891	…	1.4055	1.4054
WE	1.3150	1.1686	…	1.2402	1.2407
CA	1.3769	1.5552	…	1.3805	1.3809

After we obtain the real wage growth rates, we calculate real wages in the year 2065 measured in dollar value. This real wages is produced by multiplying the real wages for the year 2010 in dollar value obtained from the Bureau of Labor Statistics (BLS) by the real growth rates of wages (Table 6.5 and 6.6). We then compute the difference in the natural log of wages ($) between 2065 and 2000 by region and add the difference into the 2000 wage matrix in the RUM to re-predict population shares based on the new wages for the year 2065. It is assumed that MSAs in the same region experience the same change in wages.

Table 6. 5 Service Wage Rates ($) (A1B Scenario)

Region	2000	2010	BAU (2065)	Migration (1st iteration) (2065)	…	Migration (20^{th} iteration) (2065)	Migration (21th iteration) (converged results) (2065)
NE	$35,794	$63,358	$76,817	$75,678	…	$77,442	$77,396
MW	$33,960	$53,267	$80,662	$85,923	…	$82,045	$81,919
SO	$31,936	$51,849	$72,045	$72,055	…	$72,887	$72,876
WE	$33,821	$55,885	$63,673	$65,494	…	$69,290	$69,320
CA	$34,922	$63,739	$87,764	$99,466	…	$87,808	$88,013

Table 6. 6 Service Wage Rates ($) (A2 Scenario)

Region	2000	2010	BAU (2065)	Migration (1st iteration) (2065)	…	Migration (23th iteration) (2065)	Migration (24^{th} iteration) (converged results) (2065)
NE	$35,794	$63,358	$76,817	$75,822	…	$77,412	$77,380
MW	$33,960	$53,267	$80,662	$86,546	…	$81,939	$81,932
SO	$31,936	$51,849	$72,045	$72,023	…	$72,875	$72,869
WE	$33,821	$55,885	$63,673	$65,308	…	$69,311	$69,337
CA	$34,922	$63,739	$87,764	$99,127	…	$87,989	$88,014

Although population shares are aggregated to the regional level in both the RUM and the CGE model, the regional shares are different from these two models. Population shares predicted by the RUM are based on population shares at the MSA level, while population shares in CGE BAU scenario are based on state-level population projections obtained from the U.S. Census. In order to make the share change consistent between the RUM and the CGE model, we first calculate the percentage difference between RUM-migration scenario and RUM-BAU scenario ($P_{rt}^{RUM-MIG} - P_{rt}^{RUM-BAU}$). The RUM-BAU scenario is the scenario where population shares are predicted reflecting changes in wage rates determined by the CGE BAU scenario. The difference is then multiplied by the share from the CGE-BAU scenario ($P_{rt}^{CGE-BAU}$) to produce new population shares for the CGE-migration scenario ($P_{rt}^{CGE-MIG}$) (Equation 6.3). Population shares calculated from the RUM are shown in Table 6.7 and 6.8.

$$(6.3)\quad P_{rt}^{CGE-MIG} = P_{rt}^{CGE-BAU} \times \left(\frac{P_{rt}^{RUM-MIG} - P_{rt}^{RUM-BAU}}{P_{rt}^{RUM-BAU}} \right)$$

Table 6. 7 Population Shares in the RUM in the year 2065 (A1B Scenario)

Region	RUM-BAU (input wages solved by the CGE BAU scenario into the RUM) (2065)	RUM-MIG_1st (change extreme hot, extreme cold, and extreme precipitation) (2065)	…	RUM-MIG_20th (2065)	RUM-MIG_21st (converged results) (2065)
	Scenario A	Scenario B			Scenario C
	(1)	(2)		(3)	(4)
NE	0.2951	0.3177	…	0.2945	0.2927
MW	0.2388	0.2036	…	0.2349	0.2326
SO	0.3135	0.3231	…	0.3071	0.3076
WE	0.057	0.0849	…	0.0695	0.0689
CA	0.0963	0.0707	…	0.0943	0.0985
All regions	1	1		1	1

Table 6. 8 Population Shares in the RUM in the year 2065 (A2 Scenario)

Region	RUM-BAU (input wages solved by the CGE BAU scenario into the RUM) (2065)	RUM-MIG_1st (change extreme hot, extreme cold, and extreme precipitation) (2065)	…	RUM-MIG_23rd (2065)	RUM-MIG_24th (converged results) (2065)
	Scenario A	Scenario B			Scenario C
	(1)	(2)		(3)	(4)
NE	0.2951	0.3170	…	0.2932	0.2935
MW	0.2388	0.2000	…	0.2317	0.2317
SO	0.3135	0.3247	…	0.3084	0.3084
WE	0.0570	0.0860	…	0.0698	0.0697
CA	0.0963	0.0716	…	0.0973	0.0972
All regions	1	1		1	1

Comparing results across the three scenarios-(a) Scenario A—the scenario reflecting changes in wages without climate change-induced migration in the year 2065 (column (1)); (b) Scenario B—the scenario that considers climate-induced migration without its effect on wages projected for the year 2065 (column (2)); (c) Scenario C—the scenario that incorporates both climate change-induced migration and resulting changes in wages (column (4)). We find that the converged results in Scenario C are close to the results from the scenario that only considers wage effect in Scenario A. This finding provides evidence that wage effects dominate climate effects in residential location choices for working-age population.

After we translate the share difference by comparing RUM-migration and RUM-BAU into the CGE model, the sum of population shares across all regions is not necessarily one (Table 6.9 and 6.10). In order to normalize the population shares and set the total population shares for all regions to one in the CGE model, we divide the regional population share by the sum of population shares to compute the adjusted population shares in the CGE model (Table 6.11 and Table 6.12). Similar to scenarios described above, there are three scenarios in the CGE model—Scenarios D, E, and F. The Scenario D in column (1) represents the CGE BAU scenario without climate change. The Scenario E in column (2) represents the case where climate change-induced migration occurs. In this case, we take the results from the first iteration between the RUM and the CGE models, and assume that wage rates are exogenous. The Scenario F is the case where both climate-induced migration and resulting wage effects are considered. In this case, converged results are achieved after iterating between two models. In this case, labor wages are endogenized by inputting the general equilibrium effects into the prediction of regional population shares. Comparing results from Scenario D to these from Scenario E, we find that the Northeast and West gain population shares due to changes in climate. On the other hand, the South, Midwest, and California lose population shares due to significant increases in both extreme hot and extreme cold days. After we consider feedbacks from the equilibrium labor market, the population share increases in the West and California but decreases for other regions (Scenario D vs. Scenario F in Table 6.11). One reason might be that wage effects dominate climate effects in location choices. Since more people move into the Northeast with changes in climate, labor supply increases. In response to changes in labor supply, labor wages drop. Lower wages lead to outflows of workers from this region. The negative effects from the labor market outweigh the positive effects from climate change-induced migration into the Northeast. On the other hand, an increase in wages rates attracts more people to move to California.

Table 6. 9 Population Shares in the CGE Model in the Year 2065 (non-adjusted) (A1B Scenario)

Regions	CGE-BAU	CGE-MIG_iter1	…	CGE-MIG_iter20	CGE-MIG_iter21 (converged results)
	Scenario D	Scenario E			Scenario F
	(1)	(2)		(3)	(4)
NE	0.1248	0.1344	…	0.1246	0.1238
MW	0.1410	0.1202	…	0.1387	0.1373
SO	0.4623	0.4764	…	0.4528	0.4536
WE	0.1372	0.2044	…	0.1673	0.1659
CA	0.1347	0.0989	…	0.1319	0.1377
All regions	1.0000	1.0343		1.0153	1.0184

Table 6. 10 Population Shares in the CGE Model in the year 2065 (Non-adjusted) (A2 Scenario)

Regions	CGE-BAU	CGE-MIG	…	CGE-MIG_iter23	CGE-MIG_iter24 (converged results)
	Scenario D	Scenario E			Scenario F
	(1)	(2)		(3)	(4)
NE	0.1248	0.1341	…	0.1240	0.1241
MW	0.1410	0.1181	…	0.1368	0.1368
SO	0.4623	0.4788	…	0.4547	0.4547
WE	0.1372	0.2071	…	0.1681	0.1678
CA	0.1347	0.1001	…	0.1361	0.1359
All regions	1.0000	1.0382	…	1.0197	1.0194

Table 6. 11 Population Shares in the CGE Model in the Year 2065 (Adjusted) (A1B Scenario)

Regions	CGE-BAU	Adjusted CGE-MIG_iter1	…	Adjusted CGE-MIG_iter20	Adjusted CGE-MIG_iter21 (converged results)
	Scenario D	Scenario E			Scenario F
	(1)	(2)		(3)	(4)
NE	0.1248	0.1299	…	0.1227	0.1216
MW	0.1410	0.1162	…	0.1366	0.1349
SO	0.4623	0.4606	…	0.4460	0.4454
WE	0.1372	0.1976	…	0.1648	0.1629
CA	0.1347	0.0956	…	0.1299	0.1353
All regions	1	1		1	1

Table 6. 12 Population Shares in the CGE Model in the Year 2065 (Adjusted) (A2 Scenario)

Regions	CGE-BAU	Adjusted CGE-MIG_iter1	…	Adjusted CGE-MIG_iter23	Adjusted CGE-MIG_iter24 (converged results)
	Scenario D	Scenario E			Scenario F
	(1)	(2)		(3)	(4)
NE	0.1248	0.1292	…	0.1216	0.1218
MW	0.1410	0.1138	…	0.1342	0.1342
SO	0.4623	0.4612	…	0.4460	0.4461
WE	0.1372	0.1995	…	0.1648	0.1646
CA	0.1347	0.0964	…	0.1334	0.1333
All regions	1	1	…	1	1

These new population shares in the CGE model are multiplied by the total population projections in the year 2065 obtained from the U.S. Census to produce regional population. The regional population is used in the CGE model to solve for the market clearing wages. Wage responses are fed back into the RUM, and the RUM produces updated population shares under changes in both climate and wages. It takes approximately 25 iterations until convergence is achieved—the locational equilibrium is achieved in the RUM and wage rates in the CGE model do not change between iterations.

Table 6. 13 Regional Population in the CGE Model in the Year 2065 (in million) (A1B Scenario)

Region	CGE-BAU pop (million persons)	CGE-MIG pop	…	CGE-MIG pop_iter20	CGE-MIG pop_iter21
NE	60.26914	62.73239	…	59.23979	58.70160
MW	68.08851	56.12626	…	65.96673	65.12544
SO	223.2121	222.416	…	215.3587	215.0642
WE	66.27104	95.4345	…	79.58589	78.66283
CA	65.02054	46.15221	…	62.71022	65.30733
Total	482.8614	482.8614	…	482.8614	482.8614

Table 6. 14 Regional Population in the CGE Model in the Year 2065 (in million) (A2 Scenario)

Region	CGE-BAU pop (million persons)	CGE-MIG pop	…	CGE-MIG pop_iter23	CGE-MIG pop_iter24
NE	60.26914	62.36237	…	58.7241	58.79882
MW	68.08851	54.92968	…	64.78764	64.80377
SO	223.2121	222.6897	…	215.3383	215.3919
WE	66.27104	96.313	…	79.58495	79.49071
CA	65.02054	46.56663	…	64.42638	64.37618
Total	482.8614	482.8614	…	482.8614	482.8614

Details of the iterative process are summarized in Figure 6.1. The linkage between the CGE and RUM is labor supply and labor wage rates. The RUM solves for the choice probability for MSA *j*, which is aggregated to the regional level to produced regional population shares. The population shares by region produced by the RUM ($P_{r,t=2065}^{RUM-MIG}$)

are converted to regional population shares in the CGE model ($P^{CGE-MIG}_{r,t=2065}$) based on equation (6.3). The population shares are used to multiply total population projection to obtain regional population in the CGE model. In response to changes in regional labor supply, the CGE model solves for equilibrium labor wage rates for each region. In order to obtain real service wages by region projected in the year 2065, we multiply the growth rate for the year 2065 with real service wages for the year 2010 in dollar value acquired from BLS. We then disaggregate real service wages to the MSA level ($W^{MIG}_{j\in r,t=2065}$) and feed back the values into the RUM. Under changes in both climate and service wages, we use the RUM to re-predict population shares that are input back into the CGE model. Iteration continues between these two models until convergence is achieved—locational equilibrium is achieved in the RUM and wage rates stay unchanged over iterations in the CGE model.

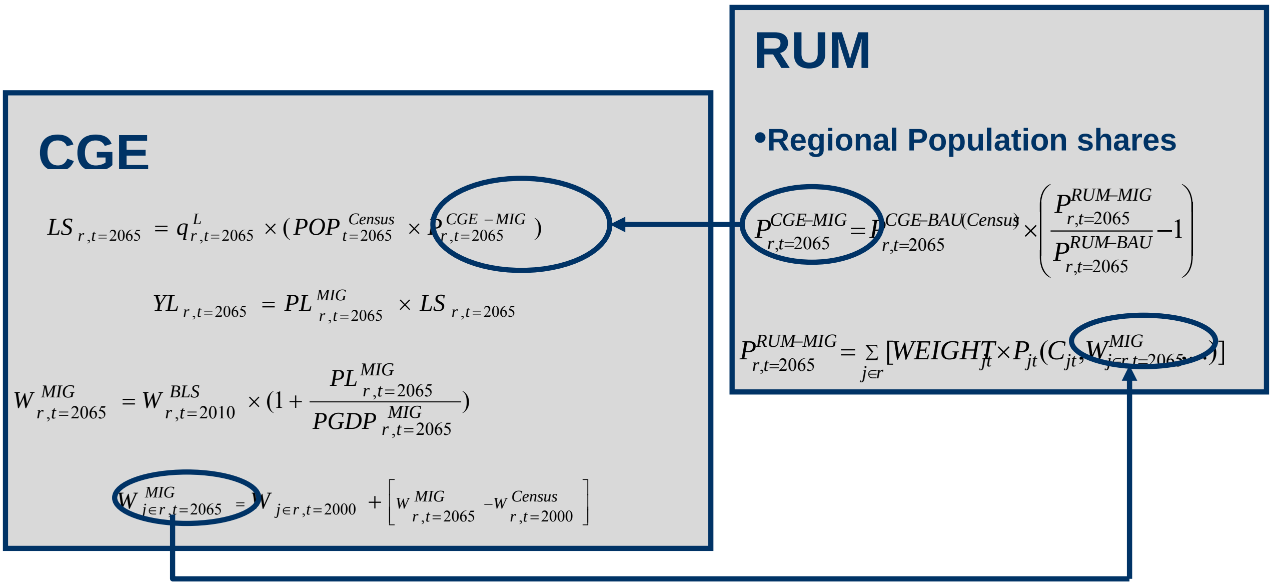

Figure 6. 1 Iterative Process between Two Models

6.4 Results of Economic Impacts from the CGE Model-A1B Scenario

The CGE model produces changes in wage rates along with changes in macroeconomic indicators including gross regional product (GRP), consumption, investment, government, and net exports. We compare the counterfactual scenario of climate change-induced migration to the baseline BAU scenario for the year 2065. Results are presented in Table 6.15 and Table 6.16. The former table lists the difference in results between the case without iterations and the BAU scenario, while the latter represents the difference in results between the scenario that endogenizes wages and BAU scenario. Comparing results with and without iterations, we find that endogenizing wages dampens the impacts on regional economies due to climate change-induced migration. Changes in macroeconomic indicators by region are smaller while considering wage feedbacks due to migration-induced changes in labor supply. In the A1B scenario, the converged results show that the gross regional product (GRP) in the Northeast decreases by 1.77%, the percentage decrease rates for the Midwest and South are 2.88% and 2.40% respectively. GRP in the Western region increases by 12.14%, and GRP in California increases by 0.22% relative to the BAU scenario. Wage rates go down (increase) due to an increase (decrease) in labor supply as more (less) people move to this region. A decrease (increase) in wage rates therefore leads to labor outflow (inflow) from (into) this region. Endogenizing labor wages decreases both losses and gains at the regional level due to climate change-induced migration.

Table 6. 15 Changes in Macroeconomic Indicators across Regions in the U.S. (Climate Change-Induced Migration Scenario vs. Baseline Case -% difference) (w/o iterations) (A1B Scenario)

Region	GRP	Consumption	Investment	Government	Net exports
Northeast	2.58%	2.82%	3.04%	0.25%	3.30%
Midwest	-11.79%	-12.30%	-12.73%	-0.80%	-17.53%
South	-0.26%	-0.20%	-0.18%	0.05%	-0.66%
West	27.84%	29.49%	31.44%	1.06%	33.71%
California	-19.24%	-20.27%	-21.51%	-1.34%	-22.26%

Table 6. 16 Changes in Macroeconomic Indicators across Regions in the U.S. (Climate Change-Induced Migration Scenario vs. Baseline Case -% difference) (converged results-w/ iterations) (A1B Scenario)

Region	GRP	Consumption	Investment	Government	Net exports
Northeast	-1.77%	-1.79%	-1.80%	-0.04%	-2.34%
Midwest	-2.88%	-2.96%	-3.03%	-0.15%	-4.47%
South	-2.40%	-2.49%	-2.56%	-0.11%	-3.30%
West	12.14%	12.89%	13.78%	0.55%	14.61%
California	0.22%	0.32%	0.43%	0.08%	0.18%

Table 6.17-Table 6.21 present equilibrium results for prices of goods and services, outputs, and employment by sector for each region. In the CGE model, the economic impacts due to climate change-induced migration result from both the supply and demand sides of the regional economies. For example, as population share increases in the West, demands for goods and services increase. An increase in demand drives the expansion of production. On the supply side, as labor supply increases, labor-intensive sectors (e.g. service) are likely to expand.

Table 6. 17 Sectoral Impacts from Climate Change-Induced Migration (Migration with Endogenizing Wages vs. BAU -% difference)-Northeast (A1B Scenario)

Northeast			
Sector	Prices	Output	Employment
Grains and oilseeds	0.28%	-0.49%	-1.54%
Fruits, vegetables, and nuts	-0.45%	-2.17%	-3.05%
Greenhouse products	-0.32%	-2.79%	-3.73%
Other crops	-0.68%	-3.37%	-4.34%
Beef	-0.50%	-1.86%	-2.77%
Dairy	-0.09%	-0.13%	-1.43%
Poultry and eggs	0.09%	-0.92%	-1.74%
Other animal production	-0.05%	-1.00%	-2.12%
Forestry	-0.58%	-3.06%	-3.83%
Other agricultural products	-0.05%	-2.61%	-3.61%
Oil and gas	0.02%	-0.68%	-1.87%
Coal	0.35%	-1.02%	-2.18%
Other mining	0.42%	-0.46%	-1.29%
Electricity	-0.35%	-0.89%	-2.20%
Nat gas distribution	-0.19%	-1.35%	-2.36%
Water and sewage	0.11%	-1.88%	-2.57%
Construction	0.20%	-1.73%	-2.31%
Food and tobacco	-0.05%	-1.15%	-2.11%
Wood products	-0.26%	-2.81%	-3.70%
Pulp paper	0.09%	-0.96%	-1.84%
Petro products	-0.07%	-0.63%	-1.60%
Chemicals	0.14%	-0.63%	-1.56%
Rubber plastics	0.22%	-1.27%	-1.95%
Nonmetallic metals	0.06%	-1.54%	-2.39%
Primary metals	0.07%	-1.70%	-2.46%
Heat_aircond	0.17%	-1.29%	-2.01%
Other_mfg	-0.04%	-1.99%	-2.85%
Furniture	0.04%	-2.12%	-2.82%
Services	0.02%	-1.82%	-2.67%
Insurance	-0.10%	-1.13%	-1.97%

Table 6. 18 Sectoral Impacts from Climate Change-Induced Migration (Migration with Endogenizing Wages vs. BAU -% difference)-Midwest (A1B Scenario)

Midwest			
Sector	Prices	Output	Employment
Grains and oilseeds	0.26%	-1.96%	-3.55%
Fruits, vegetables, and nuts	-0.44%	-3.18%	-4.72%
Greenhouse products	-0.31%	-3.84%	-5.41%
Other crops	-0.66%	-4.32%	-6.49%
Beef	-0.37%	-2.74%	-4.72%
Dairy	-0.42%	-1.16%	-3.40%
Poultry and eggs	0.07%	-1.80%	-3.29%
Other animal production	-0.39%	-1.18%	-2.93%
Forestry	-0.57%	-4.70%	-6.03%
Other agricultural products	-0.22%	-4.06%	-5.50%
Oil and gas	0.05%	-1.20%	-3.37%
Coal	0.37%	-2.19%	-3.97%
Other mining	0.44%	-1.31%	-2.74%
Electricity	-0.76%	-1.98%	-3.81%
Nat gas distribution	-0.14%	-2.11%	-3.92%
Water and sewage	0.27%	-3.13%	-4.21%
Construction	0.47%	-2.83%	-3.88%
Food and tobacco	-0.03%	-2.43%	-3.93%
Wood products	-0.18%	-4.65%	-6.03%
Pulp paper	0.14%	-2.52%	-3.93%
Petro products	-0.18%	-0.88%	-2.44%
Chemicals	0.16%	-1.68%	-3.29%
Rubber plastics	0.22%	-2.75%	-3.97%
Nonmetallic metals	0.08%	-2.78%	-4.23%
Primary metals	0.09%	-3.27%	-4.53%
Heat_aircond	0.16%	-2.53%	-3.84%
Other_mfg	-0.03%	-3.50%	-4.95%
Furniture	0.06%	-3.45%	-4.75%
Services	0.12%	-3.16%	-4.47%
Insurance	-0.19%	-2.07%	-3.54%

Table 6. 19 Sectoral Impacts from Climate Change-Induced Migration (Migration with Endogenizing Wages vs. BAU -% difference)-South (A1B Scenario)

South			
Sector	Prices	Output	Employment
Grains and oilseeds	0.29%	-1.55%	-2.99%
Fruits, vegetables, and nuts	-0.43%	-2.51%	-4.02%
Greenhouse products	-0.32%	-2.76%	-4.23%
Other crops	-0.50%	-4.34%	-5.59%
Beef	-0.24%	-2.33%	-3.96%
Dairy	0.03%	-0.07%	-2.03%
Poultry and eggs	0.08%	-1.49%	-2.82%
Other animal production	-0.15%	-1.05%	-2.67%
Forestry	-0.50%	-3.94%	-5.10%
Other agricultural products	-0.03%	-3.38%	-4.73%
Oil and gas	0.15%	-1.19%	-2.89%
Coal	0.37%	-1.75%	-3.38%
Other mining	0.44%	-0.90%	-2.11%
Electricity	-0.52%	-1.54%	-3.11%
Nat gas distribution	-0.08%	-1.70%	-3.24%
Water and sewage	0.21%	-2.56%	-3.58%
Construction	0.36%	-2.41%	-3.27%
Food and tobacco	-0.06%	-1.78%	-3.15%
Wood products	-0.11%	-3.82%	-5.06%
Pulp paper	0.12%	-1.78%	-3.05%
Petro products	-0.16%	-0.94%	-2.25%
Chemicals	0.16%	-1.40%	-2.78%
Rubber plastics	0.23%	-2.13%	-3.18%
Nonmetallic metals	0.08%	-2.33%	-3.55%
Primary metals	0.08%	-2.52%	-3.65%
Heat_aircond	0.15%	-1.94%	-3.06%
Other_mfg	-0.03%	-2.84%	-4.10%
Furniture	0.07%	-3.44%	-4.48%
Services	0.10%	-2.62%	-3.75%
Insurance	-0.06%	-1.90%	-3.23%

Table 6. 20 Sectoral Impacts from Climate Change-Induced Migration (Migration with Endogenizing Wages vs. BAU -% difference)-West (A1B Scenario)

West			
Sector	Prices	Output	Employment
Grains and oilseeds	0.34%	9.70%	16.93%
Fruits, vegetables, and nuts	-0.02%	10.61%	16.54%
Greenhouse products	-0.50%	14.30%	20.06%
Other crops	-0.65%	8.32%	14.64%
Beef	0.11%	10.06%	16.57%
Dairy	1.88%	6.53%	14.68%
Poultry and eggs	0.22%	10.14%	17.27%
Other animal production	0.66%	8.19%	16.34%
Forestry	-0.04%	15.63%	19.92%
Other agricultural products	-1.03%	16.25%	22.24%
Oil and gas	-0.20%	7.29%	16.52%
Coal	0.36%	10.96%	18.08%
Other mining	1.15%	4.78%	11.97%
Electricity	2.00%	8.54%	17.37%
Nat gas distribution	0.49%	9.72%	17.48%
Water and sewage	-1.10%	13.01%	18.07%
Construction	-0.80%	13.64%	18.63%
Food and tobacco	0.05%	12.03%	18.48%
Wood products	-1.05%	17.96%	22.90%
Pulp paper	0.31%	9.77%	16.82%
Petro products	0.48%	4.71%	10.99%
Chemicals	0.27%	8.99%	16.05%
Rubber plastics	0.14%	13.54%	20.10%
Nonmetallic metals	-0.03%	12.66%	19.10%
Primary metals	0.02%	13.21%	19.60%
Heat_aircond	0.15%	13.71%	20.27%
Other_mfg	-0.05%	12.21%	18.66%
Furniture	-0.16%	17.61%	23.75%
Services	-0.58%	12.87%	18.85%
Insurance	0.97%	10.12%	17.89%

Table 6. 21 Sectoral Impacts from Climate Change-Induced Migration (Migration with Endogenizing Wages vs. BAU -% difference)-California (A1B Scenario)

California			
Sector	Prices	Output	Employment
Grains and oilseeds	0.27%	1.02%	1.16%
Fruits, vegetables, and nuts	0.02%	0.25%	-0.22%
Greenhouse products	-0.16%	0.23%	0.15%
Other crops	-0.42%	-0.95%	-1.27%
Beef	-0.26%	0.09%	0.24%
Dairy	-0.03%	0.40%	0.89%
Poultry and eggs	0.06%	0.48%	0.70%
Other animal production	-0.02%	0.25%	0.48%
Forestry	-0.08%	-0.35%	-0.87%
Other agricultural products	-0.26%	-0.06%	-0.08%
Oil and gas	0.00%	0.31%	0.49%
Coal	0.37%	0.75%	0.65%
Other mining	0.49%	0.90%	1.11%
Electricity	0.15%	0.35%	0.61%
Nat gas distribution	0.01%	0.30%	0.48%
Water and sewage	-0.09%	0.29%	0.42%
Construction	-0.12%	0.33%	0.63%
Food and tobacco	-0.01%	0.37%	0.55%
Wood products	-0.29%	0.05%	0.15%
Pulp paper	0.11%	0.60%	0.72%
Petro products	0.04%	0.21%	0.40%
Chemicals	0.12%	0.55%	0.80%
Rubber plastics	0.14%	0.62%	0.82%
Nonmetallic metals	0.04%	0.44%	0.61%
Primary metals	0.03%	0.53%	0.71%
Heat_aircond	0.13%	0.72%	0.91%
Other_mfg	-0.04%	0.31%	0.47%
Furniture	0.00%	0.54%	0.69%
Services	-0.09%	0.29%	0.42%
Insurance	0.08%	0.38%	0.60%

6.5 Results of Economic Impacts from the CGE Model-A2 Scenario

In order to examine the sensitivity of results under changes in climate projections from different emission scenarios, this section displays results of economic impacts by using climate projections from high-emission A2 scenario. Similar to results shown in Section 6.4, endogenizing labor wages dampens regional economic impacts.

There is a slight difference in results between the A1B and A2 climate scenarios. Under the high-emission A2 scenario, the population share in California decreases by 1.04% in 2065 in the migration scenario relative to the BAU scenario, while population share in California increases by 0.45% under low-emission A1B scenario as shown in Table 6.11 and 6.12. The difference in population shares leads to divergence in regional economic impacts. Under the A2 scenario, the regional economy of California is negatively affected by climate change-induced migration (percent change in regional GDP is -0.68% relative to BAU case), while the effects are positive under low-emission A1B scenario (percent change in regional GDP is 0.22% between migration and BAU scenarios). These differences result from different climate projections. Under the high-emission A2 scenario, the maximum of annual extreme hot days is 13 days more than the maximum value projected in the A1B scenario (Tables 3.5 and 3.6).

Table 6. 22 Changes in Macroeconomic Indicators across Regions in the U.S. (Climate Change-Induced Migration Scenario vs. Baseline Case -% difference) (w/o iterations)-A2 Scenario

Region	GRP	Consumption	Investment	Government	Net exports
Northeast	2.18%	2.40%	2.60%	0.23%	2.79%
Midwest	-13.00%	-13.57%	-14.05%	-0.89%	-19.33%
South	-0.18%	-0.12%	-0.09%	0.06%	-0.57%
West	28.64%	30.34%	32.35%	1.09%	34.67%
California	-18.79%	-19.80%	21.01%	-1.30%	-21.74%

Table 6. 23 Changes in Macroeconomic Indicators across Regions in the U.S. (Climate Change-Induced Migration Scenario vs. Baseline Case -% difference) (converged results-w/ iterations)-A2 Scenario

Region	GRP	Consumption	Investment	Government	Net exports
Northeast	-1.66%	-1.68%	-1.68%	-0.03%	-2.20%
Midwest	-3.20%	-3.29%	-3.38%	-0.17%	-4.93%
South	-2.30%	-2.39%	-2.45%	-0.10%	-3.18%
West	12.93%	13.73%	14.67%	0.58%	15.57%
California	-0.68%	-0.64%	-0.59%	0.03%	-0.85%

Table 6. 24 Sectoral Impacts from Climate Change-Induced Migration (Migration with Endogenizing Wages vs. BAU -% difference)-Northeast (A2 Scenario)

Northeast			
Sector	Prices	Output	Employment
Grains and oilseeds	0.32%	-0.39%	-1.34%
Fruits, vegetables, and nuts	-0.39%	-2.04%	-2.78%
Greenhouse products	-0.30%	-2.72%	-3.48%
Other crops	-0.71%	-3.41%	-4.23%
Beef	-0.53%	-1.86%	-2.64%
Dairy	-0.05%	-0.04%	-1.20%
Poultry and eggs	0.10%	-0.88%	-1.57%
Other animal production	-0.04%	-0.97%	-1.97%
Forestry	-0.62%	-3.11%	-3.72%
Other agricultural products	-0.05%	-2.57%	-3.41%
Oil and gas	0.01%	-0.67%	-1.76%
Coal	0.33%	-1.02%	-2.05%
Other mining	0.46%	-0.39%	-1.09%
Electricity	-0.35%	-0.88%	-2.05%
Nat gas distribution	-0.17%	-1.28%	-2.12%
Water and sewage	0.11%	-1.85%	-2.41%
Construction	0.20%	-1.70%	-2.14%
Food and tobacco	-0.04%	-1.11%	-1.94%
Wood products	-0.30%	-2.85%	-3.62%
Pulp paper	0.08%	-0.94%	-1.70%
Petro products	-0.04%	-0.58%	-1.47%
Chemicals	0.15%	-0.59%	-1.41%
Rubber plastics	0.22%	-1.23%	-1.77%
Nonmetallic metals	0.05%	-1.52%	-2.24%
Primary metals	0.08%	-1.66%	-2.27%
Heat_aircond	0.17%	-1.26%	-1.84%
Other_mfg	-0.04%	-1.95%	-2.67%
Furniture	0.04%	-2.09%	-2.64%
Services	0.02%	-1.80%	-2.51%
Insurance	-0.09%	-1.11%	-1.82%

Table 6. 25 Sectoral Impacts from Climate Change-Induced Migration (Migration with Endogenizing Wages vs. BAU -% difference)-Midwest (A2 Scenario)

Midwest			
Sector	Prices	Output	Employment
Grains and oilseeds	0.30%	-2.19%	-3.95%
Fruits, vegetables, and nuts	-0.38%	-3.39%	-5.07%
Greenhouse products	-0.29%	-4.20%	-5.87%
Other crops	-0.69%	-4.70%	-7.04%
Beef	-0.39%	-3.01%	-5.18%
Dairy	-0.45%	-1.27%	-3.74%
Poultry and eggs	0.08%	-2.05%	-3.69%
Other animal production	-0.43%	-1.31%	-3.25%
Forestry	-0.60%	-5.21%	-6.64%
Other agricultural products	-0.21%	-4.47%	-6.02%
Oil and gas	0.05%	-1.35%	-3.77%
Coal	0.35%	-2.52%	-4.46%
Other mining	0.48%	-1.49%	-3.07%
Electricity	-0.85%	-2.21%	-4.24%
Nat gas distribution	-0.12%	-2.30%	-4.27%
Water and sewage	0.30%	-3.49%	-4.67%
Construction	0.52%	-3.16%	-4.30%
Food and tobacco	-0.03%	-2.69%	-4.33%
Wood products	-0.20%	-5.21%	-6.70%
Pulp paper	0.13%	-2.87%	-4.44%
Petro products	-0.17%	-0.95%	-2.68%
Chemicals	0.17%	-1.92%	-3.69%
Rubber plastics	0.23%	-3.11%	-4.47%
Nonmetallic metals	0.08%	-3.13%	-4.73%
Primary metals	0.09%	-3.66%	-5.04%
Heat_aircond	0.17%	-2.88%	-4.33%
Other_mfg	-0.02%	-3.89%	-5.45%
Furniture	0.05%	-3.87%	-5.31%
Services	0.14%	-3.52%	-4.95%
Insurance	-0.21%	-2.32%	-3.95%

Table 6. 26 Sectoral Impacts from Climate Change-Induced Migration (Migration with Endogenizing Wages vs. BAU -% difference)-South (A2 Scenario)

South			
Sector	Prices	Output	Employment
Grains and oilseeds	0.32%	-1.41%	-2.79%
Fruits, vegetables, and nuts	-0.37%	-2.35%	-3.76%
Greenhouse products	-0.30%	-2.66%	-4.03%
Other crops	-0.54%	-4.29%	-5.45%
Beef	-0.26%	-2.29%	-3.86%
Dairy	0.08%	0.05%	-1.80%
Poultry and eggs	0.09%	-1.40%	-2.66%
Other animal production	-0.15%	-1.00%	-2.55%
Forestry	-0.54%	-3.92%	-5.01%
Other agricultural products	-0.03%	-3.27%	-4.56%
Oil and gas	0.14%	-1.14%	-2.79%
Coal	0.35%	-1.70%	-3.26%
Other mining	0.49%	-0.78%	-1.92%
Electricity	-0.50%	-1.48%	-2.98%
Nat gas distribution	-0.04%	-1.57%	-3.02%
Water and sewage	0.20%	-2.47%	-3.43%
Construction	0.35%	-2.31%	-3.11%
Food and tobacco	-0.05%	-1.69%	-2.99%
Wood products	-0.15%	-3.78%	-4.98%
Pulp paper	0.12%	-1.72%	-2.92%
Petro products	-0.13%	-0.87%	-2.13%
Chemicals	0.17%	-1.32%	-2.63%
Rubber plastics	0.23%	-2.02%	-3.01%
Nonmetallic metals	0.08%	-2.24%	-3.41%
Primary metals	0.09%	-2.41%	-3.48%
Heat_aircond	0.16%	-1.85%	-2.90%
Other_mfg	-0.03%	-2.74%	-3.93%
Furniture	0.07%	-3.33%	-4.31%
Services	0.09%	-2.53%	-3.60%
Insurance	-0.05%	-1.82%	-3.09%

Table 6. 27 Sectoral Impacts from Climate Change-Induced Migration (Migration with Endogenizing Wages vs. BAU -% difference)-West (A2 Scenario)

West			
Sector	Prices	Output	Employment
Grains and oilseeds	0.37%	10.43%	18.09%
Fruits, vegetables, and nuts	0.03%	11.50%	17.88%
Greenhouse products	-0.49%	15.40%	21.52%
Other crops	-0.69%	8.94%	15.63%
Beef	0.13%	10.79%	17.67%
Dairy	2.03%	7.05%	15.74%
Poultry and eggs	0.24%	10.85%	18.40%
Other animal production	0.71%	8.78%	17.43%
Forestry	-0.05%	16.74%	21.24%
Other agricultural products	-1.09%	17.49%	23.80%
Oil and gas	-0.22%	7.79%	17.55%
Coal	0.34%	11.68%	19.23%
Other mining	1.24%	5.12%	12.76%
Electricity	2.13%	9.14%	18.51%
Nat gas distribution	0.56%	10.49%	18.74%
Water and sewage	-1.17%	13.96%	19.28%
Construction	-0.84%	14.65%	19.88%
Food and tobacco	0.06%	12.92%	19.74%
Wood products	-1.13%	19.23%	24.36%
Pulp paper	0.32%	10.43%	17.88%
Petro products	0.53%	5.08%	11.73%
Chemicals	0.28%	9.61%	17.08%
Rubber plastics	0.14%	14.50%	21.41%
Nonmetallic metals	-0.04%	13.57%	20.35%
Primary metals	0.02%	14.16%	20.90%
Heat_aircond	0.15%	14.68%	21.58%
Other_mfg	-0.05%	13.11%	19.93%
Furniture	-0.18%	18.88%	25.32%
Services	-0.61%	13.80%	20.11%
Insurance	1.03%	10.84%	19.07%

Table 6. 28 Sectoral Impacts from Climate Change-Induced Migration (Migration with Endogenizing Wages vs. BAU -% difference)-California (A2 Scenario)

California			
Sector	Prices	Output	Employment
Grains and oilseeds	0.30%	0.14%	-0.30%
Fruits, vegetables, and nuts	0.04%	-0.67%	-1.62%
Greenhouse products	-0.05%	-0.85%	-1.42%
Other crops	-0.40%	-2.02%	-2.94%
Beef	-0.28%	-0.80%	-1.26%
Dairy	-0.31%	-0.33%	-0.52%
Poultry and eggs	0.05%	-0.33%	-0.75%
Other animal production	-0.05%	-0.28%	-0.81%
Forestry	-0.06%	-1.54%	-2.59%
Other agricultural products	-0.06%	-1.43%	-1.81%
Oil and gas	0.01%	-0.27%	-0.68%
Coal	0.35%	-0.13%	-0.82%
Other mining	0.52%	0.17%	-0.22%
Electricity	0.01%	-0.23%	-0.77%
Nat gas distribution	-0.11%	-0.38%	-0.66%
Water and sewage	0.03%	-0.63%	-0.96%
Construction	0.01%	-0.60%	-0.76%
Food and tobacco	0.00%	-0.53%	-0.90%
Wood products	-0.27%	-1.22%	-1.50%
Pulp paper	0.13%	-0.46%	-0.80%
Petro products	-0.14%	-0.27%	-0.54%
Chemicals	0.08%	-0.07%	-0.45%
Rubber plastics	0.16%	-0.30%	-0.64%
Nonmetallic metals	0.05%	-0.48%	-0.86%
Primary metals	0.06%	-0.51%	-0.85%
Heat_aircond	0.14%	-0.25%	-0.61%
Other_mfg	-0.03%	-0.61%	-1.01%
Furniture	0.03%	-0.66%	-0.97%
Services	-0.03%	-0.62%	-1.02%
Insurance	0.04%	-0.38%	-0.80%

6.6 Conclusions

Based on estimated results, we simulate population shares across regions under hypothetical changes in climate. We find that the population share in the Northeast increases due to a moderate change in extreme weather, while the population shares in other regions drop due to significant increases in both extreme cold and hot days under climate change. After considering feedbacks from the equilibrium labor market, the population shares in the West and California increase while other regions experience losses in population shares in the low-emission A1B climate scenario. Correspondingly, results from the A1B scenario show that the gross regional product (GRP) in the Northeast decreases by approximately 1.8%. Decrease rate of GRP is 2.9% for the Midwest and 2.4% for the South. GRP in the West increases by 12.1%, and GRP increases in California by 0.22% relative to the BAU scenario in 2065. Different climate projections from different climate scenarios lead to different regional economic impacts in California. Under the A1B scenario, the population share in California increases by 0.45% relative to BAU case, and GRP increases by 0.22%. In contrast, under the A2 scenario, population share in California decreases by 1.04%, and GRP decreases by 0.68%. The results suggest that even minor difference in climate projection can lead to significant divergence in regional economic impacts. In addition, our findings suggest that different mitigating policies should target different regions based on heterogeneous regional impacts. We also find that ignoring feedbacks from the labor market leads to biased results when simulating economic impacts. Specifically, we find that feeding wage information back into the RUM reduces the changes in regional population shares due to climate change and dampens regional economic impacts. Endogenizing labor wages tones down losses in the Midwest and California as a result of climate change-induced migration.

One contribution of this research is that it jointly considers two important factors in location choices—climate amenities and job opportunities and their mutual effects. We find that wage effects dominate climate effects in location choices for working-age population. For example, although population share increases in the Northeast due to moderate increase in frequency of warm weather, an increase in labor supply leads to a decrease in labor prices. The decreasing labor wages prevent further influx of labors and even drives population share down relative to the BAU scenario in 2065. Similarly for Midwest, as extreme weather days increase under changes in climate, population share in the Midwest decreases, and labor wages correspond to changes in labor supply. An increase in labor wages in the Midwest drives population share up relative to the scenario where only climate effect is considered, although the regional population share is still lower relative to the BAU scenario.

Another contribution of this work is that it allows for changes in industrial size and composition in the regional economies in response to changes in local labor supply. Therefore, both direct and indirect impacts across different sectors in the regional economies are captured in this work. We find that the size of labor-intensive sectors (e.g. service sectors) increases in the West due to an increase in labor supply in this region, while labor-intensive sectors shrink in other regions. On the demand side, as population share increases in the West, demands for goods and services increase, industries in this region expand and increase production.

The innovation of this paper is that it endogenizes labor wage rates by linking two models that enables feedbacks resulting from climate change-induced migration. It combines strengths of both the RUM and the CGE models. The RUM captures preference heterogeneity towards climate change for different groups of people, and it allows for the re-sorting decisions of individuals in response to changes in climate and resulting wage changes. At the same time, the CGE model allows us to simulate regional economic impacts by considering interactions across multiple sectors.

Section 7

Concluding Remarks

7.1 Main Findings and Conclusions

This paper employs a RUM that incorporates migration costs and allows for preference heterogeneity in temperature extremes. Results show that people born in different regions have different preferences for temperature extremes. For example, people born in regions that have relatively high exposure to extreme weather (such as the Northeast, South, and California) are more averse to extreme weather than people born in other regions. Other demographic characteristics also have significant impacts on individuals' location decisions. We find that highly educated people (e.g. college graduates) are more averse to extreme temperatures than individuals without college degrees. This finding potentially reflects that college graduates may have more job opportunities and are thus more mobile than people with lower education levels. People over 65 years old are more sensitive to extreme temperatures and factor that when making location decisions. One possible reason is that older retired people relocate to new places for the sake of pleasant amenities, including moderate weather. They are also more mobile since they are not tied to a job. We find that migration costs are significant. If migration costs are high, people are not willing to relocate to the place for the sake of a small improvement in climate.

Besides climate, other factors such as wage rates, natural amenities (e.g. the proximity to bodies of water), arts and entertainment are significant factors in household location choices. Service wage rates are positively significant in one's location choice. In particular, college graduates have stronger preferences for higher service wages. College graduates may have a higher probability of pursuing a business-related job with higher wages, and business-related jobs are categorized into the service sector. Proximity to water as an index of natural amenity is positively related to household location choice. The total number of arts, entertainment, and recreation establishments per square mile, which is a measurement of abundance of recreational opportunities, has a positive effect on residential location choice. Humid summers tend to be a disutility thus people generally prefer to relocate to a cooler and less humid place.

In this study, we compare relative performance of the residential sorting model and conventional wage-hedonic model. The former has advantages of capturing preference heterogeneity, and can control for location-specific unobservables. In addition, the residential sorting model can include migration costs that are important in analyzing location choices. Due to the shortage of addressing these points, the wage-hedonic model is found to underestimate MWTP for climate extremes compared to RUM.

Beyond the empirical analysis, this study couples the RUM with a CGE model. Under changes in climate, the Northeast gains population shares, while other regions lose population shares. Interestingly, wage effects tend to dominate climate effects for working-age population, while climate effects are quite significant for retirees. After we endogenize wages through a coupling process, an initial increase in labor supply in the Northeast turns to an opposite outcome. A decrease in labor wages generates outflow of workers from this region, and the negative effect from decreasing wages outweighs the positive effect due to pleasant climate. Similarly for California, this region experiences a loss in population share, and the corresponding changes in wages lead to an increase in population share in this region in the A1B climate scenario. Another important finding is that endogenizing labor wages dampens regional economic impacts from climate change-induced migration, and the results suggest that ignoring feedbacks from the general equilibrium markets including equilibrium labor market understate economic impacts.

7.2 Future Directions

Although we have addressed the endogenity of labor wages, endogeniety of housing prices is likely to play an important role as well in simulating regional economic impacts. Future research will continue exploring the feedback from the housing market through a coupling process between the empirical model and a CGE model. In addition to the endogeniety issue, further research will involve a comparison of welfare effects between two different models in terms of consumer surplus (CS), compensating variation (CV), and equivalent variation (EV). Given the fact that climate change affects different sectors in the regional economies including climate-sensitive sectors such as agricultural sector, energy, and water, there are future research needs to examine multiple impacts and their mutual effects. Negative impacts on agricultural sectors in the West may surpass the positive impacts from climate change-induced migration, or it can be the other way around.

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